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THE IMPACT OF TECHNOLOGY ON UNEMPLOYMENT

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ABSTRACT

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One of the most important aims of scientific research is to develop methods and tools for the most beneficial use of human labor. Scientific research put forward for this purpose and transformed into technological outputs over time lead to structural changes in existing jobs and cause some professions to disappear completely or to be replaced by new ones. This situation brings us face to face with a socio-economic problem, unemployment, which has existed since the use of labor as a production factor, and its effect is increasing day by day despite all the social and economic precautions taken by the states.

The relationship between technology and employment is a longstanding and highly controversial issue. Although the labor-saving technologies used in the manufacturing sector, in particular, with the Industrial Revolution, kindled the concerns of technological unemployment in the economics literature and focused attention on this issue, the extensive literature in this field has not yet reached a definite conclusion. Based on this conflict, this thesis aimed to examine the relationship between technology and unemployment at the macro level, focusing on both developed and developing countries separately, as well as taking into account different sectors. Using a large data set covering the period 1990-2019, 21 developed and 23 developing countries were discussed separately in the first stage, and in the last stage, three main sectors for 30 developed and developing countries were focused on. In the studies conducted for developed and developing countries, the total unemployment rate was used as the dependent variable in the first place, and the employment rates were defined as the dependent variable in the analyses based on the skill groups. In the sectoral level studies, the dependent variables are the employment rates of the relevant sector. In addition, since the main interest of the study is the effect of technology on employment, per capita gross domestic R&D

expenditures in developed and developing country investigations and per capita business enterprise R&D expenditures in sectoral analyzes were defined as the main technology proxy. Alternatively, although the main theme of the thesis is on the technology-unemployment relationship, macro variables such as per capita income, inflation, worker productivity, real effective exchange rate index, real interest rate, trade openness, public unemployment expenditures, and trade union density were also used in empirical models. Therefore, the relationship between employment and many important macro indicators was also questioned.

In line with the above-mentioned purposes, the empirical process followed in the study consists of three stages. First, unit root tests of the series in the models that are considered to show the technology-unemployment relationship were performed, and it was shown that the first differences of all series were stationary. In the second stage, the long-term relationship of the series was proven by both Pedroni cointegration tests (Pedroni, 1999, 2004) and the Kao cointegration test (Kao, 1999). In the last stage, the coefficient estimates of the relevant models were made using the Panel Dynamic Ordinary Least Squares (PDOLS) proposed by Pedroni (2001a), Kao and Chiang (2001) and Mark and Sul (2003), and Fully Modified Least Squares (FMOLS) developed by Philips and Moon (1999), Pedroni (2001b), Kao and Chiang (2001).

The first empirical analysis on developed economies shows that as R&D expenditures increase, the employment level of high-skilled workers increases, while the opposite is true for low-skilled workers. Thus, in advanced economies, technology has a complementary effect on high skilled workers. However, it can be indicated that the destructive effect of technology outweighs the complementary effect for the low-skilled group. In addition, the estimated coefficient of R&D expenditure in the overall models for the total unemployment dependent variable was positive and significant, providing evidence that higher R&D does indeed have a negative impact on unemployment. The possible reason for this result may be that the density of skilled workers in developed countries is still less than the share of unskilled or low-skilled workers. The impact of technology on overall unemployment could be reversed in the future if the share of low-skilled workers in the workforce declines and the employment structure becomes more skill-intensive and/or low-skilled workers become better equipped and adapt to new technologies. In addition to the findings on the technology-unemployment relationship for developed countries, among other important macro variables, the employment effect of per capita income was found to be positive, while inflation was negative. It was determined that factors such as real interest rate, public unemployment expenditures, and trade union density also increase unemployment. The effects of these macroeconomic indicators on employment by skills are heterogeneous, excluding per capita income. It has been determined that the increase in per capita income has a positive effect on the employment of both skill groups.

The second main finding of the thesis is on developing countries. In the literature on the technology-employment relationship, studies that touch on developing countries are extremely limited. Developing countries have been neglected for a long time because the economics literature concerning the relationship between technology and unemployment, especially since the Industrial Revolution, emerged in developed countries, and the machines also first appeared in developed ones. So naturally, employment concerns first started in these geographies. In order to fill the literature gap on developing countries, in this study, the effect of technology on employment was discussed in a wide country group and time period, specific to developing countries. According to the results, the general unemployment effect of technology in developing countries is in the direction of labor-saving, as in developed countries and the effect sizes are close to each other. While both skill groups appear to be negatively impacted by technology in developing countries, the negative impact on high-skilled employment is relatively low. In addition, low-skilled employment in developing countries is less affected by technology than in developed countries. One of the possible reasons for this is that the relative wages of workers in these countries are low and therefore the comparative advantage of labor persists for a longer period. Then again, the employment effect of per capita income is positive in developing countries as well as in developed countries. The increase in per capita income increases the employment level of both skill groups. The effect of inflation, moreover, is heterogeneous by skill groups but negative on overall employment. The relationship between unemployment and interest rate as well as real effective exchange rate index in developing countries is not strongly significant. In addition, it was determined that trade openness has a strong positive effect on high-skilled employment, but its effect on low-skilled employment is also positive but weak. Finally, it should be noted that there are notable differences between the findings of developed and developing countries. Therefore, both the effect of technology on unemployment and the movement of unemployment with other macro indicators are in a heterogeneous structure among country groups.

The third important finding of the thesis is on the effects of technology on employment in different sectors. The impact of innovation on employment is expected to differ between sectors, and the findings of the thesis support this hypothesis. The results show that the technology produced in agriculture and industry reduces employment in agriculture and industry. The destructive effect of technology in the agricultural sector cannot be suppressed even through income, and the demand, which is inelastic due to the nature of the sector or less flexible than in the past, cannot create additional employment areas where manpower will be used. On the other hand, economic growth is an important compensation mechanism for the industry, but it does not completely eliminate the labor-saving effect of technology, but partially alleviates it. This is true for developed and some developing countries covered in the study. Finally, the effect of technology on employment in the service sector has been identified as positive. In other words, R&D expenditures in the service sector increase employment within the sector. The results obtained in this chapter also indirectly support the routine/task-oriented technological change and job polarization hypotheses.

Keywords: Technology and Unemployment Relationship, Technological Unemployment, Skill Groups, R&D Expenditure, Skill-Biased Technological Change (SBTC), Routine-Biased Technological Change (RBTC), Job Polarization, Panel Cointegration, Pedroni Cointegration, PDOLS, FMOLS.

ÖZ

TEKNOLOJİNİN İŞSİZLİK ÜZERİNDEKİ ETKİSİ

Hami SAKA

Bilimsel araştırmaların en önemli amaçlarından bir tanesi, insan emeğinin en faydalı şekilde kullanılabilmesine yönelik yöntem ve araçlar geliştirmektir. Bu maksatla ortaya konulan ve zamanla teknolojik çıktılara dönüştürülen bilimsel araştırmalar, mevcut işlerde yapısal değişikliklere yol açmakta ve bazı mesleklerin tamamen yok olmasına veya yerlerine yenilerinin gelmesine neden olmaktadır. Bu da bizleri, işsizlik gibi, emeğin bir üretim faktörü olarak kullanılmaya başlanmasından bu yana varlığını sürdüren, dahası devletlerin aldığı tüm sosyal ve ekonomik önlemlere rağmen etkisini her geçen gün artıran bir sosyoekonomik problem ile karşı karşıya getirmektedir.

Teknoloji ve istihdam arasındaki ilişki uzun süredir devam eden oldukça ihtilaflı bir konudur. Sanayi Devrimi ile birlikte özellikle imalat sektöründe kullanılan emek tasarrufu sağlayan teknolojiler, ekonomi literatüründe teknolojik işsizlik kaygılarını alevlendirerek dikkatleri bu konuya yoğunlaştırsa da, bu alandaki genişçe literatür henüz kesin bir sonuca varamamıştır. Bu ihtilaftan hareketle bu tez, hem gelişmiş hem de gelişmekte olan ülkelere ayrı ayrı odaklanarak ve bunun yanı sıra farklı sektörleri de dikkate alarak teknoloji ve işsizlik arasındaki ilişkiyi makro düzeyde incelemeyi amaçlamıştır. 1990-2019 dönemini kapsayan geniş bir veri seti kullanılarak ilk aşamada 21 gelişmiş ve 23 gelişmekte olan ülke ayrı ayrı ele alınmış, son aşamada ise 30 gelişmiş ve gelişmekte olan ülke için üç ana sektör özelinde teknoloji-istihdam ilişkisine odaklanılmıştır. Gelişmiş ve gelişmekte olan ülkeler için yapılan çalışmalarda ilk etapta bağımlı değişken olarak toplam işsizlik oranı kullanılmış, çalışanların beceri gruplarını baz alan ve aynı ülke grupları için gerçekleştirilen analizlerde ise istihdam oranları bağımlı değişken olarak tanımlanmıştır. Sektörel düzeydeki analizlerde tüm modellerde bağımlı değişkenler ilgili sektörün istihdam oranlarıdır. Ayrıca, çalışmanın temel ilgi alanı teknolojinin istihdam üzerindeki etkisi olduğundan, gelişmiş ve gelişmekte olan ülke analizlerinde kişi başı gayri safi yurtiçi AR-GE harcamaları ve sektörel analizlerde ise kişi başı özel sektör AR-GE

harcamaları ana teknoloji değişkeni olarak tanımlanmıştır. Diğer yandan, tezin ana teması teknoloji-işsizlik ilişkisi üzerine olsa da, ampirik modellerde kişi başı gelir, enflasyon, işçi verimliliği, reel efektif döviz kuru endeksi, reel faiz oranı, ticari açıklık, kamu işsizlik harcamaları ve sendika yoğunluğu gibi makro değişkenler de kullanılmış ve dolayısıyla istihdamın birçok önemli makro gösterge ile ilişkisi de sorgulanmıştır.

Yukarıda bahsedilen amaçlar doğrultusunda çalışmada takip edilen ampirik süreç üç aşamadan oluşmaktadır. Öncelikle, teknoloji-işsizlik ilişkisini yansıttığı düşünülen modellerde yer alan serilerin birim kök testleri gerçekleştirilerek, serilerin tamamının birinci farklarının durağan oldukları gösterilmiştir. İkinci aşamada ise serilerin uzun dönemde ilişkili oldukları hem Pedroni eşbütünleşme testleri (Pedroni, 1999, 2004) hem de Kao eşbütünleşme testi (Kao, 1999) ile kanıtlanmıştır. Son aşamada Pedroni (2001a), Kao ve Chiang (2001) ve Mark ve Sul (2003) tarafından önerilen Panel Dinamik En Küçük Kareler (PDOLS) ve Philips ve Moon (1999), Pedroni (2001b), Kao ve Chiang (2001) tarafından geliştirilen Modifiye En Küçük Kareler (FMOLS) yöntemleri ile ilgili modellerin katsayı tahminleri yapılmıştır.

Bu tezde yer alan ampirik analizler sonucunda elde edilen ilk bulgu gelişmiş ülkeler üzerinedir ve bu bölümdeki sonuçlar hem teknolojinin genel işsizlik üzerindeki, hem de iki farklı beceri grubunun istihdam düzeyleri üzerindeki etkileri adına önemli çıkarımlar içermektedir. Temel sonuçlar, gelişmiş ekonomilerde AR-GE harcamaları arttıkça, yüksek vasıflı işçilerin istihdam düzeyinin arttığını, diğer yandan düşük vasıflı işçiler için bunun tersinin geçerli olduğunu göstermektedir. Dolayısıyla gelişmiş ekonomilerde teknoloji, yüksek vasıflı işçiler üzerinde tamamlayıcı bir etkiye sahiptir ve istihdam düzeylerini artırır. Ancak düşük vasıflı grup için teknolojinin tamamlayıcı etkisinden ziyade yok edici etkisinin ağır bastığı söylenebilir . Ek olarak, toplam işsizlik bağımlı değişkeni için oluşturulan genel modellerde AR-GE harcamasının tahmin edilen katsayısı pozitif ve anlamlıdır, bu da daha yüksek AR-GE'nin işsizlik üzerinde gerçekten olumsuz bir etkisi olduğuna dair kanıt sağlar. Bu sonucun olası nedeni, gelişmiş ülkelerde vasıflı işçi yoğunluğunun, vasıfsız veya düşük vasıflı işçi yoğunluğundan hala daha az olması olabilir. Düşük vasıflı işçilerin işgücündeki payı azalırsa ve istihdam yapısı daha beceri yoğun hale gelirse ve/veya düşük vasıflı işçiler daha donanımlı hale gelir ve yeni teknolojilere uyum sağlarsa, gelecekte teknolojinin genel işsizlik üzerindeki etkisi tersine dönebilir. Gelişmiş ülkeler için teknoloji-işsizlik ilişkisine dair bulguların yanı sıra, diğer önemli makro değişkenler arasından kişi başı gelirin istihdam etkisi olumlu, enflasyonun ise olumsuz olarak tespit edilmiştir. Reel faiz oranı, kamu işsizlik harcamaları ve sendika yoğunluğu gibi faktörlerin de işsizliği arttırdığı tespit edilmiştir. Bahsedilen bu makroekonomik göstergelerin becerilere göre istihdam üzerindeki etkileri ise kişi başı gelir hariç olmak üzere heterojendir. Kişi başı gelirdeki artışın her iki beceri grubunun istihdamına da olumlu yönde yansıdığı tespit edilmiştir.

Tezin ikinci ana bulgusu gelişmekte olan ülkeler üzerinedir. Teknoloji-istihdam ilişkisine dair literatürde gelişmekte olan ülkelere dokunan çalışmalar son derece sınırlıdır. İktisat literatürünün özellikle Sanayi Devrimi'nden bu yana teknoloji ve işsizlik ilişkisini konu almaya başlaması ve makinelerin ilk olarak gelişmiş ülkelerde ortaya çıkması nedeniyle gelişmekte olan ülkeler uzun süre ihmal edilmiş, doğal olarak istihdam kaygıları önce bu coğrafyalarda başlamıştır. Gelişmekte olan ülkelere dair literatür boşluğunu doldurmak amacıyla da bu çalışmada teknolojinin istihdam üzerindeki etkisi gelişmekte olan ülkeler özelinde geniş bir ülke grubu ve zaman diliminde tartışılmıştır. Sonuçlara göre gelişmekte olan ülkelerde teknolojinin genel işsizlik etkisi gelişmiş ülkelerde olduğu gibi emek tasarrufu yönündedir. Ayrıca gelişmiş ve gelişmekte olan ekonomilerde teknolojinin istihdam üzerindeki etki büyüklükleri birbirine yakındır. Gelişmekte olan ülkelerde her iki beceri grubunun da teknolojiden olumsuz etkilendiği görülmekle birlikte, yüksek vasıflı istihdam üzerindeki olumsuz etkisi nispeten düşüktür. Ayrıca, gelişmekte olan ülkelerdeki düşük vasıflı istihdam, gelişmiş ülkelere göre teknolojiden daha az etkilenmektedir. Bunun olası sebeplerinden bir tanesi bu ülkelerdeki işçilerin nispi ücretlerinin düşük olması ve dolayısıyla emeğin karşılaştırmalı üstünlüğünün daha uzun süre devam etmesidir. Diğer yandan, gelişmiş ülkelerde olduğu gibi gelişmekte olan ülkelerde de kişi başı gelirin istihdam etkisi olumludur. Kişi başı gelirdeki artış, her iki beceri grubunun istihdam seviyesini de arttırmaktadır. Enflasyonun etkisi ise, beceri gruplarına göre heterojen olmakla birlikte genel istihdam üzerinde negatiftir. Faiz oranı ve reel efektif döviz kuru endeksi ile gelişmekte olan ülkelerdeki işsizlik arasındaki ilişki güçlü değildir. Diğer yandan ticaret açıklığının yükske beceri grubu istihdamını güçlü bir şekilde olumlu yönde etkilediği fakat düşük beceri grubu üzerindeki etkisinin de pozitif fakat zayıf olduğu tespit edilmiştir. Son olarak belirtmek gerekir ki, gelişmiş ve gelişmekte olan ülkeler özelinde elde edilen bulgular arasında dikkate değer farklılıklar çarpmaktadır. Dolayısıyla gerek teknolojinin işsizlik üzerindeki etkisi, gerekse işsizliğin diğer makro göstergeler ile hareketi ülke grupları arasında heterojen bir yapıdadır.

Tezin üçüncü önemli bulgusu, teknolojinin farklı sektörlerde istihdama etkileri üzerinedir. İnovasyonun istihdam üzerindeki etkisinin sektörler arasında farklılık göstermesi beklenmektedir ve tezin bulguları bu hipotezi desteklemektedir. Sonuçlar, tarımda ve sanayide üretilen teknolojinin yine tarım ve sanayide istihdamı azalttığını göstermektedir. Tarım sektöründe teknolojinin istihdamı yıkıcı etkisi gelir üzerinden dahi bastırılamamakta ve sektörün doğası gereği esnek olmayan veya geçmişe nazaran daha az esnek olan talep, insan gücünün kullanılacağı ek istihdam alanları oluşturamamaktadır. Diğer yandan ekonomik büyüme sanayi için önemli bir telafi mekanizmasıdır ancak teknolojinin emek tasarrufu sağlayan etkisini tamamen ortadan kaldırmaz, kısmen hafifletir. Bu durum, çalışmada kapsanan gelişmiş ve bazı gelişmekte olan ülkeler için geçerlidir. Son olarak hizmet sektöründe ise teknolojinin istihdam üzerindeki etkisi olumlu olarak tespit edilmiştir. Diğer bir ifade edile, hizmet sektöründeki AR-GE harcamaları sektör içi istihdamı arttırır. Bu bölümde elde edilen sonuçlar dolaylı olarak rutin/görev yanlı teknolojik değişim ve iş kutuplaşması hipotezlerini de desteklemektedir.

Anahtar Kelimeler: Teknoloji ve İşsizlik İlişkisi, Teknolojik İşsizlik, Beceri Grupları, AR-GE Harcamaları, Beceri-Yanlı Teknolojik Değişim (SBTC), Rutin-Yanlı Teknolojik Değişim (RBTC), İş Kutuplaşması, Panel Eşbütünleşme, Pedroni Eşbütünleşme, PDOLS, FMOLS.

PREFACE

The main motivation underlying this thesis is the concerns of technological unemployment that started especially with the Industrial Revolution. In this direction, I have defined the period from the Industrial Revolution to the use of the internet and personal computers as the age of mechanical effects, and the process starting from that time and continuing today as the age of digital effects. I showed that technological unemployment concerns, which began in the age of mechanical effects, took different forms in today's age of digital effects, and moreover, the employment effects of technology are heterogeneous in terms of skills, sectors, and countries.

This doctoral dissertation makes significant contributions to the economics literature with its method, scope, and findings. I first confirm that this thesis, as currently presented, is not submitted for any other academic award or qualification but is also completely original and independent. Besides, I would like to state that a couple of articles were prepared/will be prepared from various parts of this thesis to be submitted to national and international peer-reviewed journals. One of these articles was published before the thesis defense and it is foreseen that other articles will be published in the period after the dissertation.

I would like to mention the people and institutions that contributed to the completion of this thesis in many ways. Hereby, firstly, I would like to express my gratitude and appreciation for my current thesis advisor, Prof. Dr. M. Kutluğhan Savaş Ökte, and for my former thesis advisor, Prof. Dr. Mehmet Orhan, whose help, guidance, and academic support have been invaluable throughout this process. The most important gain for me has been benefiting from their knowledge, experience, perseverance, and fairness. I am also thankful to the esteemed jury members and all staff of the Institute of Social Sciences, Istanbul University, for their enduring help.

Secondly, I wish to show my appreciation to the Scientific and Technological Research Council of Turkey (TÜBİTAK) for their financial support during my doctoral studies. This dissertation aims to understand the effects of technology on unemployment and in this context, the scholarship I received from one of Turkey's largest science and technology-focused institutions was very appreciated.

I wish to extend my special thanks to my family, for their fortitude, enthusiasm and for sharing this burden with me. The unlimited support they have shown me during my Ph.D. dissertation period, as in my previous education life, is of course irreplaceable. Without the help that they provided me in preparing this thesis and the emotional support that gave me, this thesis would not have been possible.

İstanbul, 2021

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2SLS	:	Two-Stage Least Squares
ADF	:	Augmented Dickey-Fuller
AI	:	Artificial Intelligence
AIC	:	Akaike Information Criterion
ALM	:	Autor-Levy-Murnane
ASEAN	:	Association of Southeast Asian Nations
BCG	:	Boston Consulting Group
BERD	:	Business Enterprise Expenditure on Research and Development
CIS	:	Community Innovation Survey
DGE	:	Dynamic General Equilibrium
DOLS	:	Dynamic Ordinary Least Squares
EU	:	European Union
F-ADF	:	Fisher-Type Augmented Dickey-Fuller
FMOLS	:	Fully Modified Ordinary Least Squares
GERD	:	Gross Domestic Expenditure on Research and Development
GMM	:	Generalized Method of Moments
HSE	:	High-Skilled Employment
IAB	:	Institute for Employment Research
ICT	:	Information and Communication Technologies
ILO	:	International Labor Organization
IPS	:	Im-Pesaran-Shin
IPUMS	:	Integrated Public Use Microdata Series
ISIC	:	International Standard Industrial Classification
LLC	:	Levin-Lin-Chu
LSDVC	:	Least Squares Dummy Variable Corrected
LSE	:	Low-Skilled Employment
MGI	:	McKinsey Global Institute

ML	:	Machine Learning
MSCI	:	Morgan Stanley Capital International
NBER	:	National Bureau of Economic Research
O*NET	:	Occupational Information Network
OECD	:	Organization for Economic Co-operation and Development
PDOLS	:	Panel Dynamic Ordinary Least Squares
PIAAC	:	Program for the International Assessment of Adult Competencies
PISA	:	Program for International Student Assessment
R&D	:	Research and Development
RBTC	:	Routine-Biased Technological Change
REER	:	Real Effective Exchange Rate
SBTC	:	Skill-Biased Technological Change
SIC	:	Schwarz Information Criterion
SME	:	Small and Medium-Sized Enterprise
SMT	:	Survey of Manufacturing Technology
SYS-GMM	:	System Generalized Method of Moment
TBCT	:	Task-Biased Technological Change
TFP	:	Total Factor Productivity
TPF	:	Triadic Patent Families
TUD	:	Trade Union Density
WECD	:	Worker-Establishment Characteristic Database
WTO	:	World Trade Organization

CHAPTER 1: BACKGROUND

While technology makes life easier by deeply affecting many social and economic factors, the idea that it leads to less labor need over time became an important economic phenomenon that has settled in the focus of economists and policymakers, especially after the Industrial Revolution. Incessantly advancing and developing technology and machines, which are among its primary outputs, take away many jobs from human power. Therefore, when this economic issue is evaluated only from this point of view, it can be thought that one day all work areas where human power is needed will be transferred to machines and robots. On the other side, the fact that technology affects many economic dynamics positively by increasing productivity makes the relationship between technology and unemployment an economic dilemma.

The technology-employment relationship, which is an important research area both theoretically and empirically, is examined in many dimensions and, of course, critical contributions are made to the literature. However, neither the theoretical nor the empirical literature can reach a consensus on the ultimate impact of technology on employment. Figuring out whether technological changes have a beneficial effect on employment is particularly important for decision-makers in order to produce solutions for a very important macroeconomic problem called "*unemployment*". In this thesis, the relationship between the two economic indicators is discussed from an overly broad perspective and important contributions were made to the current discussions. First of all, the technology-employment relationship is evaluated separately for developed and developing countries. In addition, the hypothesis that the effect of technology on employment may differ from sector to sector is also investigated and different results are obtained for key sectors of the economy. This section first contains a brief introduction to the study and then details the main motivation, method, and structure of the thesis.

1.1. Introduction

Studies on the direction and intensity of the relationship between technology and un(employment) lead to incompatible results. While some economists assert that technological developments trigger factors like mechanization and innovation to replace labor and increase unemployment, others claim that unemployment decreases with technology and technological progress since these cause new business opportunities accompanied with them and enlarge business in some sectors as well as the entire industries. The examination of economic events under different conditions or the establishment of theories under different assumptions can be effective in the formation of opposing views. Variables included in addition to short and long-term concepts, category of the workforce under investigation, metric to measure technology, type of unemployment as well as the regional and countrywide differences can directly affect the outcome of the analysis. Besides, other factors have a significant influence on the course of the relationship just like productivity and wage. Technology is assumed to fuel productivity and productivity while not increasing cost so that economies of scale is to be preserved. One of the most common views on the effect of technology on the economy is that technological developments increase productivity while reducing the costs of production. This makes productivity an important indicator of technological progress whose effects can be seen in short, medium, and long terms.

In practice, the main factor to stimulus innovation is the R&D investments as the key driver of technological advancements. Large firms are capable of allocating a substantial budget to R&D to enable product innovation. On the other hand, process innovation necessitates investment into machinery, methods, and procedures including managerial tactics to produce higher quality items less costly with properly designed automation. Once the technology in terms of product or process innovation is achieved the shock to different markets is initiated. Knowledge transformation is part of spin-offs from companies in addition to mobility of workers among firms or worker interactions. Innovative firms, employ more workers as well as more qualified/high-skilled personnel and thus pay by large more. They are preferred by their workforce since the working conditions as well as fringe benefits are substantially preferable. Besides, all countries demand such companies since they increase the GDP as well as exports of the sovereign in spite of destroying the income uniformity.

The progress in technology results in a shock to many economies and the ramification of this shock has perplexing effects on labor markets. There are many factors to be considered in such a shock, ranging from the supply and demand at the labor markets to the heterogeneity of the workers' productivity as well as the institutions and regulations and essentially the structure of the markets. Many models are established so far to account for a subset of these factors. These many complications make it very difficult if not impossible to analyze the situation in a theoretical framework managing all details governing the impact of technology on unemployment. That is why we preferred the empirical methodology of analysis. Indeed, conditions governing the empirical study can be pervasive, but the proof of the pudding is in the eating and all such conditions are taken into consideration per se in any typical empirical study.

Technology became the main factor in the globalization process that leads to business competition. Multinationals investing in high tech innovate more and take the pioneering position in new and existing markets. They use resources more efficiently to pay their employees higher remuneration. The other industries enjoy the spillover effects with the cost of adapting their business and personnel to new technology. Such multinationals invest huge funds in R&D bearing the risk since in many industries feasible outcome is very unlikely. Innovation in dominant high-tech industries like aerospace, computation and communication, electronics, and pharmaceuticals requests a huge amount of venture capital. Composite material innovation in the aviation industry, for instance, requests huge funds and in the end, the material innovated cannot be replaced with the existing ones and might be scrapped. Or the medication development efforts by pharmaceutical giants to globally widespread diseases like hepatitis may end up futile making all investment go by the board. Since huge figures are required with high risk, it is almost impossible for SMEs to engage in such R&D activities. Even transferring the innovated technology will exceed the budget of many SMEs. Still, the majority of the

SMEs are interested in high-tech business since low-tech industries like paper printing or textiles promise no or almost zero profit with their own idiosyncratic risk. With one way or another, the introduction of new products and thereby new markets have the job creation effect.

The information revolution changed the phenomena by making the scarce info of the previous era more available to companies. The companies' challenge altered from accessing useful and inevitable knowledge to solicit it from a massive set provided and offered to them by all means. Globalization puts extra pressure on firms to compete in a harsher environment with rivals from the entire globe. This is a perpetual process beyond the power of states to enforce companies to use the most advanced and up-to-date technology where the rapid advance in technology requires even monthly updates with considerable items appended to the passive side of the firm's balance sheets. No company regardless of whether domestic or global can resist technological developments since the spill-over effects of any such progress will surround any market, physical or virtual. While big companies enjoy economies of scale, SMEs have greater difficulty to react by investing in newer technology and surviving. This process deliberately derives the SMEs out of business gradually. Such enterprises can develop products for only very limited and small-scale businesses that the big companies do not want to penetrate since their return on capital employed ratio does not decrement to that low.

Considering that the term automation was coined right after WWII and the technological advancement with information epoch has resulted in driverless cars contemporarily, clear analysis on the debate is essential for labor markets. It has been a century after the Second Industrial Revolution which still has a detrimental and catastrophic impact on the employment. The Information Revolution commenced in the second half of the 20^{th} century made information available under loose conditions, but the conditions for laborers are now worse with longer working hours, greater stress, fewer benefits, and less security. Both revolutions grow structural unemployment as well as temporary and part-time workers. On the other hand, income inequality and the concentration of wealth and power in the hands of elites have increased substantially. The adoption of new technology, as well as the advance of the existing one, comes with many complications to the laborers. How are they going to be trained and who is going to pay for it? Will the company be able to survive after incurring the cost of huge investment expenditures? Should the firm invest in the most advanced technology which is extremely costly or some less advanced one? How are the competitors investing? According to skill-biased technological change discourse, the correlation between wage inequality and economic growth is positive, endogenous production of technological knowledge which fuels economic growth favors skilled labor. This means the unskilled labor is supposed to suffer from such growth and is penalized by growth (Acemoglu, 1998). The main institution to support the basic rights of the unskilled labor in reality is the labor union but in many industries, the union is oligopolistic if it exists. Indeed, the wage of the unskilled labor is rigid and as the wage in addition to fringe benefits of the skilled labor progress, unskilled does not take advantage. The benefits of growth to unskilled and skilled labor are asymmetric and the bargaining power of the unskilled labor stays reluctant as skilled labor enjoys better working conditions including even home offices as well as higher premium paid to skill. Firms willing to compete with advanced technology even in domestic markets cannot simply do this by importing hi-tech machinery and equipment since the labor administering them has to be employed. Such hi-tech facilities and personnel to run them are represented with fixed proportions in related production functions. The proportions constitute the software, maintenance, upgrades, and extra processes in addition to the machinery.

In the light of all these reasons mentioned, detecting how high-skilled and low-skilled workers are impacted by technology at the macro level in advanced economies will make a significant contribution in this field. In this study, the purpose is to provide a comprehensive macro-level contribution to the literature, based on the fact that the macro part of the empirical literature on the effects of technology on employment in developed countries has not been sufficiently filled. With this motivation, the relationship between technology employment in developed and developing countries is empirically examined from three different perspectives: a) Firstly, the effect of technology on overall unemployment at the macro level is investigated in both country groups, and in this respect, the study has common aims with similar studies. As stated before, there is no consensus on this research question yet produced at both micro and macro-level studies. b) Secondly, the effect of technology on employment at the macro level is investigated on the basis of two different skill groups specifically low-skilled and high-skilled. This study differs from its peers in terms of reducing employment effects of technology to skill dimensions and makes a significant contribution to the literature. c) Thirdly, the effect of technology on three main different sectors, namely agriculture, industry, and service at the macro level, was investigated, which is the first of its kind in the literature -as far as is known- in terms of its analysis method, the countries it covers, results and findings. As a result, even though there are substantial studies in the micro-framework, macro analyses are rare, and among them, none is focusing on the country groups we explore, over the period we study, with the analytical method we facilitate, coverage of countries, and the emphasis we make on skill-biased employment.

1.2. Motivation and Objectives

Unemployment is a social and individual reality that has persisted since the beginning of the use of labor as a factor of production, especially in the 20th century, which has increased its influence day by day despite all the social and economic precautions the states have taken. Today, the most important and compelling concern for governments and politicians is the construction of policies emerging employment and to prevent unemployment along with the economic crises. The utilization of science to social demands and human needs, and the regulations produced to satisfy these demands and needs, lies in evaluating human labor in the most useful and convenient way. Over time, scientific research is transformed into technology, and products emerging are presented to the service of human beings through technology. As a result, technological progress leads to structural changes in existing jobs, causing some professions to be destroyed or replaced by new ones. When we look at the change that technology has made in the past, it is evident that the replacement of the labor force by machines evolved from unskilled labor to highly qualified labor.

The relationship between technology and employment is a long-standing and highly controversial issue. A large literature and a considerable amount of studies have not produced a definitive conclusion on the relation between technology and unemployment. On the one hand, especially process innovations lead firms to save labor, and on the other hand, product innovations and other labor-friendly effects of machines via compensation mechanisms show that the relationship between technology and employment must be taken from a broad perspective. Accordingly, this thesis aims to examine the relationship between the two in terms of different skills and sectors based on as wide a range of countries as possible. In this way, it is aimed to determine the effect of technology on employment separately for both developed and developing countries, and to see how and to what extent qualified and unqualified worker groups are affected by innovations in these country groups. The study was not limited to this, it also evaluated various hypotheses about the possible different effects of technology on sectors. It is a fact that especially after the Industrial Revolution, while the agricultural sector was under the influence of automation in developed economies, the existing workforce for industrial jobs was made more qualified by investing in the education of young people. Today, the way to keep up with the new mutations of technology goes through the same processes (Saunders, 2017), so education systems, labor market regulations, workers' and employers' organizations, professional approaches, wage adjustments, and many more should be redesigned, restructured, and reorganized according to the needs of the digital effects period. Young people should be prepared for the dynamic working platforms of the future instead of preparing for the past jobs, and in this direction, schools and universities should allow students to grow up as dynamic, continuous learners, easily adaptable, and able to prepare themselves for innovation. Instead, importance should be given to the education of adults who lag behind technology, and the negative effects of disruptive technologies on the medium-skilled group should be minimized. At this point, it is emphasized by many authors that human skill should not be underestimated and that humanity is the one who has a say in technology. While Denis Gabor (1963) draws attention to the fact that *"the future is something that can be invented, even if it cannot be predicted"*, David Autor

(2015) makes a similar point and states that *"it is difficult to predict the future, but it is arrogant to bet on human creativity skills"*.

In sum, in this thesis, the extent to which unemployment, which is an important socio-economic reality, is affected by technology, has been studied with the following sub-objectives: a) Firstly, how technology affects unemployment in the developed geography where it was born, grown and spread, b) Secondly, how the qualified (high-skilled) and medium or low qualified (low-skilled) groups are affected by technological advances in developed economies, c) Thirdly, what is the impact of technology on employment in developing economies, d) Fourthly, how high and low-skilled workers in developing economies are affected by technology will be explored. These research questions also offer implications for possible differences in the impact of technology on developed and developing countries. Furthermore, it is aimed to figure out whether the effect of technology on employment differs between sectors by evaluating both developed and developing countries together. For this purpose, three broad sectors, agriculture, industry, and service were investigated as well as the two sub-sectors of industry, namely manufacturing and energy.

1.3. Methodology

In this study, the relationship between technology and unemployment has been investigated at the macro level by focusing on both developed and developing countries separately and by considering different sectors. In this context, initially 21 developed countries and in the second stage, 23 developing countries were examined to determine the effect on both overall unemployment and employment by skill. In the last stage, three main sectors were included for 30 developed and developing countries. All data used in the study cover the period 1990-2019. In the sectoral analyses, the total values of employment, technology, and other control variables in the main sectors of the countries were used, and in this respect, the sectoral results are also at the macro level. In the first stage, the total unemployment rate was used as the dependent variable in studies conducted for developed and developing countries, and in the analyses based on two different skill groups, employment rates were defined as dependent variables instead of unemployment. In the empirical part made at the sectoral level, the dependent variable in all models is the employment rate of the relevant sector. The unit of both unemployment and employment rates is the total percentage of the labor force and these values are used as decimal fractions in the analysis. The main area of interest of the study is the effect of technology on employment, and for this purpose, total gross domestic R&D expenditure per capita is used in the first two empirical sections representing technology, and business enterprise R&D expenditure per capita is used in the last section containing sectoral analyses. Other macro indicators such as GDP per capita, consumer price index, output per worker, real effective exchange rate index, trade union density index, real interest rate, per capita public unemployment spending, and trade openness in various model variations created to determine the effect of technology on employment, used as control variables. The variables R&D per capita, GDP per capita, output per worker, and per capita public unemployment spending are used in the constant US Dollar and the base year is 2010 for all. The natural logarithms of all these series were considered in the analyses. For the consumer price index, real effective exchange rate index, trade union density index, and trade openness index variables, the base year was defined as 2010 and these variables were also used in the analysis by taking their natural logarithms. The real interest rate, conversely, was obtained as a percentage and was included in the analyses as a decimal fraction, as was done for dependent variables.

In the study, the existence of the effect of technology on employment was scanned with multiple models using various macro indicators, which are among the determinants of employment, as well as R&D, which is used as a technology proxy. In all of these models, variables representing technology, income, and inflation took their place as core explanatory variables, while other macro variables were tested in different variations for robustness check. In econometric analyses, three main stages were followed in line with these established models. First, it has been shown that the first differences of all series in the models are stationary because this is the prerequisite of the cointegration methods applied in the second stage. At this point, three different unit root tests have been employed, namely the LLC (Levin et al., 2002), the IPS (Im et al., 2003), and ADF-Fisher

(Maddala and Wu, 1999). In the second stage, it was proved that the series in the models are cointegrated in the long term by both the Pedroni cointegration tests (Pedroni, 1999, 2004) and the Kao cointegration test (Kao, 1999). In the last stage, the coefficients of the variables in the models were estimated using different versions of Panel Dynamic Ordinary Least Squares (PDOLS) proposed by Pedroni (2001a), Kao and Chiang (2001), and Mark and Sul (2003) and Fully Modified Ordinary Least Squares (FMOLS) generated by Philips and Moon (1999), Pedroni (2001b), Kao and Chiang (2001). In the application of econometric methods, EViews 12 statistical software was used, following the guidelines described in IHS Markit - EViews (2020a, 2020b). In some additional analyzes and reports, both Stata 16 and Microsoft Excel software were also used.

1.4. Outline of the Thesis

This thesis consists of six main chapters. Chapter 1 contains the sections mentioned so far, and Chapter 2 provides a broad summary of the economics literature on the relationship between technology and unemployment. While Chapter 3 and Chapter 4 contain empirical results for developed and developing countries, respectively, in Chapter 5 the effect of technology on employment is discussed according to different sectors. In the last section, the findings obtained in the study are explained comparatively.

Chapter 2 examines the relationship between technology and unemployment from a historical perspective and presents an extended literature survey on concerns, approaches, and policies on this issue. Then, the approaches of the leading economic thought movements on the concept of technological unemployment are discussed. In the second part of Chapter 2, the relationship between technology and unemployment is discussed theoretically, the distinction between product-process innovation, compensation mechanisms, the functioning, assumptions, and coverage of the skills and task biased technical change hypotheses are discussed. In the last part of Chapter 2, empirical studies on the phenomenon are discussed separately according to the characteristics of employment and duties, as well as micro and macro levels. This section also includes predictions for the future regarding the quality and quantity of the work.

Chapter 3 is the section in which developed countries are discussed in the study. In this direction, it has been investigated how both overall unemployment and according to skills, that is, high-skilled and low-skilled employment, are affected by technology in developed countries. The introduction, literature review, empirical approaches, and results of this section are unique to themselves, but since the path followed is almost the same, it is also possible to compare the results obtained for developing countries.

Chapter 4 was created by extending the steps implemented in Chapter 3 to developing countries. In this section, similar econometric approaches are discussed, but in the sections on both the introduction and the literature review, evaluations are made specifically for developing countries. The main motivation of this part of the study is based on the idea that the technological impact in developing countries will be different than in developed countries.

Unlike the other two empirical chapters, Chapter 5 considers developed and developing countries together and focuses on the technology-employment relationship but taking into account sectoral differences. In this direction, we focused on the technology-employment relationship first in the agriculture sector, then the whole industry, as well as in the manufacturing and energy sectors, which are the two sub-sectors of the industry. In the last stage, the service sector is discussed. Since the R&D expenditures used as a technology proxy in this section are sector-specific, the effects of technological advances in one sector on different sectors could not be observed separately.

Chapter 6 is the last part of the thesis and summarizes the findings from three empirical chapters comparatively. In addition, among the studies in the literature, empirical studies that coincide or agree with the findings of this thesis are also included. Finally, the limitations of the thesis and suggestions for future studies are mentioned.

CHAPTER 2: AN OVERVIEW OF THE RELATIONSHIP BETWEEN TECHNOLOGY AND UNEMPLOYMENT

Although there are indirect examples in history where technology is seen as a serious threat to labor markets, it would not be wrong to say that the special interest of the economics literature on this issue started with the Industrial Revolution. On the one hand, the capitalists aim to increase productivity by including machines in the production process effectively, and on the other hand, the unemployment concerns of the existing workers against the complete replacement of the labor market by the machines have made the situation an issue that needs to be seriously and carefully considered in economic and social terms. Even the painful experiences like the Luddite Movement, in which unemployment concerns went beyond being a harmless feeling, led decision-makers to take radical precautions in this regard.

Technological advances are inherently inevitable; as they have deeply affected the economic dynamics so far, they will continue to have a voice in this issue in the future and will guide societies in many ways. In addition, technology is a complex concept by its nature, it is really difficult to measure and predict the forms it will take in the future. In this direction, the perspectives of the parties in the economics literature on the relationship between technology and unemployment, the methods of handling the issue, the findings they have reached, and their interpretations of these findings contain many differences from the past to the present. On the one hand, the contribution of inevitable technical advances to economic growth through many channels, especially productivity, is seen as very attractive, on the other hand, anxious approaches regarding the negative employment effects of technology shocks, especially in the short term, continue to draw the main framework of these differences. It should be said that, although there is a fairly large literature on the relationship between technology and (un)employment, there is still no clear consensus among the views due to the complex and unpredictable nature of the former and the fact that the latter is an issue affected by many economic dynamics.

It can be stated that the trend in both the theoretical and empirical literature is roughly divided into two, in terms of both the direction and magnitude of the -possible-- effect of technology on employment (or unemployment). Firstly, on the pessimistic side of the issue, approaches that think that technological advances negatively affect the number of existing jobs and increase unemployment, emphasize the "*job destroyer*" or "*labor-saving*" feature of technology. On the optimistic side, it is argued that the positive reflection of technological advances on total output by opening new business areas or offering new products increases employment, which generally emphasizes the "*job creation*" or "*labor-friendly*" feature of technology through the compensation channels. Although there is no clear conclusion in the theoretical literature that there is no relationship between two important economic indicators such as technology and employment, some empirical studies argue that as a third approach, technology does not significantly affect employment in the long run, but these inferences are not common in the literature. Because the starting point of even such approaches is that the negative technological effects in the short term are compensated within the market itself.

The fact that the relationship between technology and employment is such a controversial and unresolved issue is the focus of many theoretical and empirical studies. As mentioned above, on the one hand, there is no consensus on the existence, if any, direction and size of the relationship, and on the other hand, the definition of technology and how it is measured or should be measured has not been clarified. In fact, the concepts of employment or unemployment are economically obvious, but what the concept connotes or encompasses for "*technology*" is open to debate. Such difficulties or differences in approach cause technology to be used or measured differently in the literature at micro and macro levels. In micro-level, sectoral, or company-based studies, both technology investments and the number and quality of used machines, robots, or technical equipment can be used as technology proxies. However, it cannot be expected that only physical capital will be used as an indicator in every sectoral or company-based study as an indicator of technology. It is also important to use non-physical technology indicators since some specific fields such as the service sector are different from other sectors in the way they benefit from technological advances. Alternatively, R&D investments are an important technology proxy in the studies conducted at the macro level. Of course, these expenditures cannot be expected to fully reflect the technology level of the country, because the effectiveness of R&D and its ability to provide added value are highly affected by the dynamics of the country. However, as an overall technology indicator, R&D remains an important variable, as it can quantitatively reflect the country's technology investments as well as reveal the nature of the existing knowledge stock. Some studies may also use variables such as the number of patents, the number of researchers, the number of universities, or the number of scientific research as a macro-level technological indicator. But all these indicators have similar drawbacks with R&D expenditures. For this reason, R&D expenditure continues to be widely used as a technology proxy in both micro and macro-level empirical studies.

In the theoretical literature, both the effect of technology "job creation" or "labor-friendly" and the "job destroyer" or "labor-saving" effect are directly related to whether the innovation is a product or process innovation. Generally, the former is considered positive in this regard, while the latter's impact on labor demand is assumed to be negative. Then again, since technological development in the form of product innovation for one firm or sector may mean process innovation for another firm (Dosi, 1984), both types of innovation are intertwined, especially when considered at the macro level. In addition, assuming that product innovations will also create employment directly through demand and new markets can be interpreted as a simplistic view of the relationship because such inferences are also based on strict market assumptions (Pianta, 2005). Moreover, when examining the relationship between innovation and employment, of course, compensation mechanism channels explaining the market stabilizing effects of both product and process innovations in different ways are also important. However, the empirical literature on this subject focuses specifically on micro-based studies, specific firms, or industries. Although product and process innovations can be considered separately on a micro basis, especially at the company level, but they become concepts that are intertwined on a macro basis, and it is almost impossible to think independently from each other.

The theoretical and empirical literature on the technology-employment relationship, especially at the firm and sectoral level, summarized in great detail in studies such as Freeman et al. (1982), Freeman (1987), Tether et al. (2005), Pianta (2006), Piva and Vivarelli (2013), Vivarelli (2014), Calvino and Virgillito (2018) and Dosi et al. (2021). In this part of the thesis, a broad summary of the theoretical and empirical approaches to the technology-employment issue from the past to the present is documented. In this direction, first of all, historical employment concerns regarding the technology-(un)employment relationship, which is the main focus of the study, and the emergence of the concept of "technological unemployment" are included. In the continuation of the chapter, the theoretical perspectives of leading economists and different economic thoughts are presented, and the assumptions and effectiveness of compensation mechanisms are discussed. In the last part, empirical studies that deal with the effect of technology on (un)employment from the micro level to macro level, both at the aggregate level and by skill and task-based approaches are included.

2.1. Technology and Unemployment: Historical Perspective

In the 16th century, the fear and anxiety underlying the refusal of the Queen of England to patent the stocking frame knitting machines produced for use in spinning mills, for the yarn workers to maintain their current employment positions, is actually "*technological unemployment*". Therefore, ideas about the disruptive impact of technology on employment do not arise solely from the superior skills of today's *"robots"*. As reported by Acemoglu and Robinson (2012), the invention of these machines and Queen Elizabeth's concerns about this situation show that the possible effects of machines on employment were discussed 4-5 centuries ago and precautions were taken according to various apprehensions. The machine's creator, William Lee, did not get the attention he deserved at the time, as the Queen was more concerned with the negative employment effects of the machine on workers of hand-knitting and possible reactions from the workers. In similar examples shared by Karl Marx (1867/1976), workers' reactions and even historical events leading to uprisings and riots against the weaving machines were used almost throughout Europe in the 17^{th} century, the windy sawmill built near London water-powered saws in the 1630s and, water-powered wool clippers and wool carding mills in the first years of the 18th century are among other vital evidence that technological unemployment is not a new phenomenon. Again, the Luddite Movement, also mentioned by Karl Marx, the workers' uprising in response to the destruction caused by electric looms in employment at the beginning of the 19th century, and the forceful measures taken by the British government against this uprising are also examples of how the authorities' attitudes towards technological unemployment have changed over time. In fact, the first response of political authorities to the unemployment problem in history was to limit the use of machines, as Queen Elizabeth did, and it is not difficult to guess that similar protectionist approaches were applied by many countries in the early stages of mechanization. In European countries such as France and England, examples can be increased that the use of some machines was restricted by decision-makers due to employment concerns (Freeman and Soete, 1994). However, in the following examples, the British government of the time chose to suppress the resistance against mechanization (Mantoux, 2013).

Undoubtedly by many, the *"Lancashire early cotton riots"* of 1669-1779 and the *"Luddite movement"* of 1811-1816 in England are a manifestation of the technological change and mechanization anxiety of the workers in the textile industry. It disrupts the understanding of work, and this creates an angry group of workers who are willing to work but cannot find a job. Therefore, the idea that the current skills of workers become obsolete or that they can no longer meet expectations has created a fight to new technologies in the labor market. Thus, the balance between the preservation of existing jobs and technological advances reflects the balance of power in society and how the gains from innovations are distributed (Frey and Osborne, 2017). In practice, the widespread belief in the economic history literature about the causes of machine revolts is the concern of unemployment. However, opinions that offer a different perspective on the issue are also noteworthy. For example, according to Mokyr et al. (2015), although all these confusions about the short-term costs of technology led to the thought that technological unemployment was a serious problem during the Industrial Revolution, to argue that some cases of temporary unemployment arose due to the introduction of machines and to argue that such suggesting that technological unemployment actually occurs on a large scale is a different matter, and indeed, according to the authors, there is no empirical evidence for these situations in history. As stated by the authors, although the events of both Luddite (1811–1816) and Captain Swing (1830–1832) are assumed to be due to technological innovations in textiles when these protests are examined more closely, the real concerns are not the replacement of workers by machinery, but other issues such as low wage practices and poor working conditions emerged for economic and social reasons. At this point, Noble (1995) presents the same approach, noting the Luddite uprising as a technophobic movement, but rather as a *"starvation"*, *"violence against the capitalists"* or *"abolishing the machines"* and choosing the softest protest in front of them refers to the rebellion of the group. But he adds that this does not prevent political authorities from taking drastic measures such as the death penalty. Similarly, according to Mokyr et al. (2015), the fact that machines are targeted by workers in Lancashire is due to the fact that machines are a more suitable target in disputes between employers and employees. According to some, the Swing riots are aimed at the new steam beaters as well as the unemployment problem caused by cheap Irish immigrants (Stevenson, 1979/2014). Mokyr (2015) admits that the main problem with factories at that time was the poor working conditions offered in the mills, and even though he believed that the Industrial Revolution did not change the overall employment balance, it posed a threat to certain types of labor. For example, at the beginning of the 19th century, the group that was most planted in capital goods investments were the workers of the sector, who normally produce with traditional methods such as the handloom weavers and frame knitters, and which normally have low capital and low productivity. As a result, these areas quickly disappeared at that time due to the capital flow in the factories (Bythell, 1964).

Frey and Osborne (2017) summarize two critical issues as the basis for the divergence in British policy makers' attitudes towards technological change over time. First, the differentiation in the administrative system facilitated regulation in favor of the propertied class by making the Parliament more dominant than the Crown (North and

Weingast, 1989). It is clear that manufacturing technologies, i.e., new machines, are not a threat to the possessing class, but rather an opportunity to facilitate their production and increase their exports. Secondly, it is thought that unskilled workers benefited from this mechanization both in terms of wages and employment (Mokry, 1990; Clark, 2008; Frey and Osborne, 2017). In fact, technologies developed in the manufacturing industry in the 19th and 20th centuries can be considered "*complementary*" for "*unskilled workers*". For example, the new assembly line implemented by Ford Motor Company in 1913 provided employment opportunities for 29 people in a one-man operation, while reducing the total working time. This is an example of the displacement of relatively skilled workers or craftsmen, while these mechanizations that occurred in the 19th century were a complement to unskilled workers (Frey and Osborne, 2017). It should be added that the change in question also reveals the discontinuity of the demand for skilled and unskilled labor in terms of economic history, and Acemoglu (2002) states that the demand for skilled labor is actually a 20th-century phenomenon at this point. Because, as both authors emphasized, in the 19th century following the Industrial Revolution, automation was a complement for unskilled workers, while advanced technologies of the 20^{th} century mostly supported and complemented skilled workers. At this point, I would like to open a parenthesis to the historical process and state that I have used the concepts of "mechanical effects" and "digital effects" in this thesis to define the different effects in the 19th and 20th centuries on which both authors emphasized. I define the mechanization brought about by the Industrial Revolution and the employment results of this change as the "mechanical effects period", and the results of more complex and advanced technologies such as today's Information and Communication Technologies (ICT), Artificial Intelligence (AI), and Machine Learning (ML) as the "digital effects period". Because, in the era of mechanical effects, technology is more mechanizable and static, but still requires a certain level of skill, while 20^{th} and 21^{st}-century technologies have the character that can complete or completely take over more dynamic works. In the era of mechanical effects, technology is a complement to unskilled workers, as it automates the tasks of relatively skilled workers of that era, employing low or no-skilled workers for manual tasks that cannot be automated, and creating threats for them. In the era of digital effects, technology is – for now – a complement to skilled workers, increasing their productivity by automating some of their tasks, and working as a kind of assistant.

2.1.1. Classical Approach

Concerns about technology, which amounted to riots and, in some cases, bloody controls, had actually begun to change somewhat, as prominent economists such as Adam Smith and J. B. Say saw technology as a blessing rather than a disaster for employment. These authors, believing in the power of the free market, drew attention to the ability of technology to increase productivity rather than its destructive effect and preferred to look at the issue from the positive side. Therefore, it would not be wrong to say that, with a few exceptions, the early classical economists ignored or, more sharply, rejected the concept of technological unemployment, although the spread of machines that facilitated the work as a blessing of technology caused various social disorders, especially the employment structure. James Steuart, one of the pioneers of Mercantilist thought, which was dominant before the beginning of classical economic theory, discusses whether mechanization is beneficial or harmful for society in his work called *"An Inquiry into the Principles of Political Economy"*, he accepts that sudden mechanization in production causes unemployment, but this is temporary. He argues that this is a temporary issue and that to resolve this temporary issue, state policies should be channeled into various areas such as shifting the workforce to different tasks (Steuart, 1767/1966). Because James Steuart believes that the advantages of technology to humanity are more than various side effects such as temporary unemployment, but he thinks that these technology-related problems cannot be solved on their own, therefore, effective state policies should be engaged. Indeed, James Steuart states that he will not approve of machines if they *"take away the jobs of people who cannot find any other way to earn their living from their current job"* and believes that technology will have a negative effect on unemployment only in sudden emergencies. But even in this case, the author, who thinks that the effect is temporary, does not believe in a permanent unemployment problem in the long term but states that the advantages of productivity arising from technological advances are permanent.

Because James Steuart defends the inevitable effects of technology with the following words: *"Just as an area cannot be swept without dust or a shoe cannot be walked without getting dirty, it is unthinkable to put labor-saving machines into production without rendering human labor unnecessary"*. Therefore, Steuart (1767/1966) argues that the labor savings caused by technology and the subsequent loss of employment cause short-term unemployment, and this situation will be compensated by the increased production in the sectors and the falling prices in this context, increasing the demand for labor in the next period. But, of course, based on Adam Smith's book *"The Wealth of Nations"*, his views on the positive effects of mechanization and the self-regulating nature of the market dominate classical economics (Smith, 1776/1977). While Adam Smith, on the one hand, attributes the causes of unemployment to the high tax systems in the economy and the extravagance of the capital owners, he does not mention any role of the machines among the possible unemployment problems, on the contrary, he emphasizes the importance of the productivity of the land or labor and emphasizes that the machines have duties such as increasing labor productivity and ensuring more efficient distribution of the labor force. While making the connection between greater mechanization of labor and surplus labor, Adam Smith explains that this situation is not perceived as a problem for workers, but rather an opportunity for capital owners, or more generally employers, and states that "more mechanization means more talent and more efficiency. He makes a connection between the division of labor and the increase in labor productivity, with particular emphasis on the importance of the division of labor and believes that technological advances will mean a worker can do more work because machines will increase the productivity of labor. Adam Smith, who also evaluates the issue in terms of technology adaptation or alienation of existing labor from technology, emphasizes the helpless situation that workers who spend their lives doing certain simple jobs will fall after mechanization, and acknowledges that their current knowledge will bring them to the lowest level in terms of skills. In addition, Jean-Baptiste Say, in his book titled *"A Treatise on Political Economy"*, admits that integrating new technologies into the production system in the short run will negatively affect employment, but states that in the long run, the total production in the economy will not exceed the total demand (Say, 1836/1971). In the employment-technology framework drawn by Say, it is stated that a complete replacement of the workforce with machines can only occur if investments remain below the pace of capital productivity, which is not possible because technology adaptation will take time because entrepreneurs are wary of doubts and uncertainties. Then again, Say states that new production methods usually change the basic properties and structure of a good, so rejecting new technologies will actually mean rejecting new products, and this will be a negative situation for the economy. Say (1836/1971) exemplifies the issue with the invention of printing presses in the aforementioned period. He states that printing presses, of course, took away the jobs of many copyists at first, because the printers were able to reach the output they had achieved by employing two hundred people in the past with only one journeyman thanks to the machines. However, by emphasizing the benefits of technology that spread over a longer and wider area, he said that the prices of books decreased in a short time, the demand increased in many areas from education to press and broadcasting; states that this has positively affected mold makers, paper manufacturers, bookbinders, booksellers, and many other related areas, and therefore, at the end of the process, the number of people in charge of book production and the areas touched by book production has increased one hundred times compared to before printing machines. Contrarywise, according to Thomas Robert Malthus, who argues that a continuous increase in per capita income is not possible in *"An Essay on the Principle of Population"*, technological developments and the increase in the productivity of labor, as a result, will push people to have more children as they raise their living standards. This situation will continue until the beginning, which is until the living standards fall to the minimum income level necessary for living (Malthus, 1798/2010). Pointing out that industrialized productions become more and more machine intensive as time progresses, Malthus argues that the incomes of countries may fluctuate over time, but there will not be an upward trend in growth in general, which was partially supported empirically in England until the Industrial Revolution. Contrary to Adam Smith, Malthus, who presents a pessimistic view on economic development, makes predictions that especially low and medium-level workers such as farmers and factory workers will only earn enough money to keep themselves alive in the long run due to technology. As a result, it would not be wrong to say that Adam Smith, J. B. Say and James Stuart think that the net socio-economic effects of technical advances will be positive in the long run, although they accept that there may be some indirect and negative but non-structural employment effects in the short run. The basis of these approaches is the expansion of aggregate demand due to productivity growth in general.

David Ricardo had a similar point of view with Adam Smith and J. B. Say in his early focus on the issue. The main approaches that shaped David Ricardo's early views were that technology created new products and new products created new values, increased productivity lowered prices, and this had a positive impact on aggregate demand. However, in the third edition of his work *"On the Principles of Political Economy and Taxation"*, David Ricardo, modifying his previous optimistic views, took a more pessimistic approach and thought that capitalists might want to constantly replace workers with new technology. In this work, David Ricardo accepted that machines could cause "irreparable unemployment" and formed the basis of the concept of *"technological unemployment"*, which is extremely important in terms of the economics literature. Emphasizing that "labor-saving technological advances can cause long-term problems", Ricardo essentially justifies the employment concerns of the working class (Ricardo, 1821/1911). Ricardo stated that machines used instead of human labor are mostly harmful to the interests of the working class and that this negative effect should be evaluated in terms of both employment and salaries; he thought that if technological growth went in the wrong direction and the labor-destroying impact of technology surpassed its job creation, it would be a disaster for workers. According to David Ricardo, the negative effects cannot be compensated, as the replacement of the workforce by machines may require the use of machines instead of manpower, even in new sectors born with technology; on the contrary, it continues in a cycle over time. With these views, David Ricardo, as one of the rare classical economists who argues that the negative impact of technology on employment will outweigh, conceptualized the idea of progressive mechanization and attributed the capitalists' investment in machinery to increase productivity, as the cost of a good produced by the machine is lower than the cost of the good produced by the worker. In other words, if the increase in workers' wages encourages capital owners to mechanize, and as a result, if the increase in labor productivity exceeds the increase in demand for goods, excess supply will lead to less labor use. At this point, Ricardo states that the factors of production labor and capital are always in competition and that capital will not be used until the price of labor is relatively high compared to capital. In addition to these views, Ricardo presents a dilemma by emphasizing that technological innovations in foreign economies will harm domestic markets if local technological advances are not adequately supported. David Ricardo's introduction of technological unemployment as a concept to the economics literature required classical economists to reconsider the compensation mechanisms from time to time. For example, John Stuart Mill, in his work titled *“Principles of Political Economy With Some of Their Applications to Social Philosophy”*, accepts that workers will suffer in terms of employment in industries where mechanization takes place, but he still argues that gross employment or production will not decrease, especially in rich countries (Mill, 1848/ 2004).

2.1.2. Marxist View

Parallel to Ricardo, Marxist thought argues that capitalism can cause increased productivity and controlled unemployment, that technology in the capitalist system can impoverish workers in the short run, and that the problem can reach a serious level in this respect but sees technology as a part of the social and political structure necessary for prosperity in the long run. It should be emphasized that while technology is accepted as a driving force in terms of economic growth in other economic views, Marx's approach to technology is mostly based on social values. According to Marxists, whether technology is internal or external, the main thing is that it is a trigger for societies, because changes in the system are possible with technological advances. Karl Marx discusses the impact of machines on workers both economically and sociologically and states that unlike those who have optimistic views, whom he defines as *“utopian”*, machines do not save workers from any work and do not offer a wide area of welfare as promised. On the contrary, he claims that some of the workers suffered a loss of income that they were forced to work in factories under difficult conditions and they were exploited. Karl Marx claims that the most important reason for this is that machines take the jobs of adult men by facilitating the jobs that require physical power and that women and children are employed in this field. According to Marxist philosophy, newly developed and labor-saving machines cannot be thought to create enough jobs (Wood, 2004), but still, according to this idea, technology is neither an angel nor a devil in terms of employment. On the one hand, it can replace labor by being used by capitalists, on the other hand, it can create a new social structure by itself by transforming societies: *"Technology shows the way people deal with nature and the production process necessary for their survival; and thus reveals the way in which people's social relations are formed and the intellectual concepts that derive from them"* (Marx, 1867/1976). As a result, Marx considers the entire capitalist process as a distinction between classes and in this direction presents a dilemma by emphasizing the nature of technology that both liberates workers and causes the capitalists to put pressure on workers. Because of this dilemma, Marxists in the next period also differ on whether technology is good or bad for workers, some see technology as a job-destroying devil, while others show more optimistic approaches in this regard (Gera and Singh, 2019). As a result, it is possible to say that Marxists see technology not only as an end but also as a tool that Capitalists use against labor.

2.1.3. Keynesian Approach

The painful consequences of unemployment that emerged in the 1929 Economic Depression caused Keynesian approaches, one of the new paradigms of the period, to draw their attention to this issue. John Maynard Keynes, in his work titled *"Economic Possibilities for Our Grandchildren"*, reminds the economic environment of the concept of technological unemployment once again and explains the issue as *"the speed of technology replacing labor is higher than the speed of creating new jobs for technology-affected labor"* (Keynes, 1930/2010). It is possible to say that Keynes, like Ricardo and Marx, focused on the destructive effect of technology on employment and predicted that working hours would decrease. However, Keynes states that this is a temporary economic problem, and that technology plays a role in solving many economic problems in the long run. Therefore, it would be correct to say that Keynes believes in the positive effects of technology on the economy in the long run rather than a pessimistic view on the effects of technology on employment and that he thinks the concept of technological unemployment is a temporary phenomenon. Moreover, Keynes predicted that technology would reallocate working time in the future, predicting *"15-hour working hours, three hours a day"* for 100 years or so later. Focusing on the structure of jobs that change with technology and the possible improvements in living standards in general, Keynes claims that economic problems will be overcome over time, and this will allow people to spend their time on different issues away from economic concerns. Keynes, in his predictions for the next 100 years, focuses on how to use the free time that science offers to people, and states that people who can survive and reach perfection in this process will be the ones who can benefit from the abundance provided by the economy.

Finally, it should be emphasized that, as we can see in a sub-title, classical and neoclassical economists generally deny the problem of *"permanent technological unemployment"*, while Keynesians accept the existence of the problem of technological unemployment but believe that it can be overcome in the long run with public policies. At this point, Hans Philip Neisser's contributions in the article *"Permanent Technological Unemployment"*, which removed technological unemployment from being a concept and raised it to the list of theories, are important (Neisser, 1942). In the years after the Great Depression, Neisser (1942) emphasized the existence of many involuntarily unemployed despite the optimistic approaches in the compensation theory, emphasized that technological unemployment is actually a permanent phenomenon, and complained about the indifference of the economics scientific community to this problem.

2.1.4. Neoclassical Approach

While the existence of a temporary unemployment situation caused by technology is an economic problem that even neoclassical economists participate in, the main disagreement of the economics literature is over *"permanent technological* *unemployment"*. Accordingly, the criticisms of David Ricardo and Karl Marx on the effectiveness of compensation theory necessitated a reinterpretation of technological unemployment by the representatives of neoclassical economics. While the economics literature reports that classical economists centered around the general view that technological advances cannot permanently suppress employment in a perfectly competitive market, in Alfred Marshall's *"Principles of Economics"*, Knut Wicksell's *"Lectures on Political Economy"* and John Bates Clark's *"Essentials of Economic Theory"* similar thoughts were documented (Marshall, 1890/2013; Wicksell, 1901/1967; Clark, 1907/2013; Kaldor, 1932). Discussions on the technology-employment relationship have changed again with the neoclassical economists' new views on the effectiveness of mechanisms by reconsidering the criticisms of compensation theory. In the early part of the 20th century, Wicksell (1901/1967) states that the marginal product of labor and wages may decrease or increase depending on whether technical advances are labor-saving or labor augmenting and distinguishes the short-long-term effects of technology. According to him, revolutionary inventions from time to time and the industry's use of these new technologies turned many workers into "*beggars"* in the short term, but the subsequent increase in savings and investments removed these evils and increased wages (Wicksell, 1901/2013). Pointing to this issue, Clark (1907/2013) states that *"without temporary displacement of workers, it is not possible to continue progress for the welfare of workers"*. At this point, Kaldor's (1932) statement that *"there is enough evidence to reject claims that new inventions tend to reduce employment"* actually summarizes the neoclassical view.

Wicksell (1901/1967), stating that there is no direct causality between technology and employment, argues that there are different determinants of unemployment and bases his approach on the marginal productivity of the factors of production. Technical advances increase labor supply more than demand, but in a free market economy, an increase in labor supply lowers wages, creating an opportunity to benefit from cheap labor for sectors not yet affected by technology. Thus, Wicksell argues that what really worries or should worry policymakers, in the long run, is not unemployment due to technological productivity, but wage rigidities that hinder the absorption of labor in technologically underdeveloped sectors. While Wicksell (1981), unlike Ricardo, argues that technological advances will create more jobs, he explains in his study what aspects of Ricardo's model are failing at the level of occupations and emphasizes the role of states in terms of implementing *"skill development"* policies to keep up with technology in the context of technology-employment relationship and ideal welfare level. According to Wicksell (1981), David Ricardo ignores the fact that manpower may be needed in the production of machines brought by new technologies. However, David Ricardo states that over time, technological products will take over the comparative advantage of human labor all over the world and this will encourage countries to adapt to machines more, and Wicksell (1981) agrees with this view. However, Wicksell (1981) argues that this situation will lead to an economic expansion in all areas by showing a multiplier effect instead of reducing production over time.

Theoretical models of the technology-employment effect of neoclassical approaches at the firm level explain that technical advances cannot cause permanent unemployment in firms where innovation is accomplished, with the relationship between increased productivity, profit maximization, and increased labor demand under the assumption of fixed wages (Hamermesh, 1996; Filer et al., 1997). Douglas and Director (1931), who stated that such a relationship at the firm level is directly related to the demand elasticity at the industry level, predicts that if the demand elasticity is unitary, the employment losses will be compensated and that if the demand is flexible enough, there will be an increase in employment in this direction. Douglas and Director (1931) actually base their views, like many classical economists, on Say's Law, that all displaced workers will be absorbed in the long run by the labor demand in different sectors. Moreover, they state that in the absence of elastic demand, the compensation mechanism will not work, and they accept that there will be a decrease in employment in this case. In neoclassical approaches, the effect of technological advances on the change in employment is based on obtaining the change in employment by subtracting the total productivity change from the change in total output. Therefore, technological change does not reduce employment if aggregate demand rises sufficiently against aggregate output growth as a reflection of productivity growth. In this direction, Solow (1957, 1965) states that technology does not determine the total employment volume in the country and that the right financial and monetary policies can provide full employment for any level of technical progress in the example he gave on the US economy and argues that the phenomenon called technological unemployment is not different from normal unemployment. Therefore, according to Solow, the increase in total demand and the growth of total output at the same rate means that technology does not cause any employment loss. In other words, preventing the contraction in employment depends on the increase in output and labor productivity at the same rate.

Nevertheless, the expansion in potential output is also based on inputs, in fact, capital goods such as technology, and in other words, it is supply-side, so the increase in demand may not be able to offset the decrease in employment in this situation. Thus, in fact, the decline in employment will prevent potential output from increasing at the same rate as the increase in productivity. The basis of this and similar criticisms are the rigid assumptions of the neoclassical approach. Hansen (1931) argued that in situations of insufficient elasticity of demand or inelasticity, sticky wages and competition or friction between other firms may complicate the flow of workers between sectors. Kliman (1997) draws attention to the fact that these approaches are based on the assumption that each additional worker will increase output in the same way, since technological advances lead to higher output per employee, that is, labor productivity, and states that even at the firm level, not every technical advance that increases productivity is guaranteed to increase employment. He shows with his theoretical model that the neoclassical approach does not provide enough arguments to ignore the possibility that advances in technology can reduce equilibrium employment and that the opposite is also possible. Because neoclassical approaches are based on rigid assumptions such as a perfectly competitive market, perfectly flexible prices and wages, and homogeneous inputs and outputs. Therefore, according to Kliman (1997), it is possible to say that labor supply and demand can be balanced under the assumption of flexible wages and a perfectly competitive labor market, but there is no guarantee that declining wages or output prices will offset the employment contraction caused by technical advances. Douglas and Director (1931) show that under the assumption of unit elasticity, the average cost of firms, and hence the fall in price, is less than the fall in the cost of labor, so that the fall in price is insufficient to increase output per worker at the same rate, resulting in a decline in employment in the industry. Neisser (1942) states that neo-classical theory argues in the long run, a man can always find a job at equilibrium wages because the neo-classical approach completely rejects permanent unemployment. At this point, both Neisser (1942) and Stoneman (1983) show the general conditions under which technological unemployment can occur, the former is by verbal and graphical analyses and the latter is by mathematical modeling at the industry and firm level. John Richard Hicks (1939/1975) states that technology can reduce employment in certain situations, from a point of view that is still managed in different ways today and shows the production of labor-saving equipment as an example. The important point of view put forward by the author here is that the demand for labor may decrease when technology is a substitute for labor, but unemployment cannot be mentioned when technology is complementary to labor. It is interesting that this approach is embodied in skill-biased and task-based technology-employment approaches that are still popular today. As it is mentioned in more detail in the next parts of this thesis, technology can replace labor completely or increase its efficiency by completing that labor. These characteristics of the technology are explored more deeply in the Skill-Biased Technological Change and Routine-Biased Technological Change approaches that address its qualitative impact on employment. Finally, Mokyr (2015) states that the job opportunities created by technology were neglected especially by the 19th-century political economists and that the job opportunities for the children of displaced hand weavers are not only to work in cotton factories, but instead they can continue their lives as trained engineers or operators. Although Mokyr (2015) believes that current technological unemployment estimates are mostly wrong, he states that the existence of many workers who are displaced due to mechanization and technology cannot be ignored. The author strikingly points out that in the long run, wages for workers also increased to reflect their productivity, but in the Industrial Revolution it took longer than an average working life to happen.

2.1.5. Schumpeterian and Neo-Schumpeterian Views

Joseph Alois Schumpeter, in his *"Theory of Economic Development"*, discusses the structure of *"economic evolution"* in terms of some fundamental elements such as the nature of change, credit, monopoly practices, and the effect of prices. Among them, Schumpeter draws attention to the distinction between two phenomena for fundamental changes in the economy: growth and development. According to Schumpeter, growth may be a purely quantitative indicator, but on the other hand, the source of development is mainly qualitative changes (Schumpeter, 1934/2008). In this context, Schumpeter sees business or sector losses caused by technology as a cleaning activity in order to create new business areas or advantages in the market. Contrary to Marx's putting technology at the center of social changes, Schumpeter states that the main driver of innovation is the profit and cost concerns of economic units, and therefore considers technology more focused on businesses. While Schumpeter states that the change in the current balance is in the hands of entrepreneurs, he argues that at this point, technology will only progress with the funds obtained by entrepreneurs.

According to Joseph Alois Schumpeter, there are three main stages of technological change in a free market economy: a) The first stage is the *"invention"* stage, where the idea, product, or a new process is designed. b) In the second stage, *"innovation"* is realized by fulfilling the economic requirements for the invention designed. c) The third stage is the stage of *"spreading"* the new invention by imitating or observing it. Therefore, Joseph Alois Schumpeter argues that technological advances are not produced permanently, but intermittently and explosively, in various periods, that is, technology emerges in the form of shocks in various periods. This suggests that cycles of contraction and expansion in the economy are the result of technological revolutions or rather radical innovations. Therefore, while companies that cannot compete and cannot follow new technologies or adapt to innovations and the outdated technologies they use disappear, competitive and innovative companies continue to stay in the market and introduce new products and new production methods. Schumpeter (1934/2008) defines technology as a tool of *''creative destruction''* that destroys old industries (or makes them obsolete) and replaces them with new sectors or areas, contributing to the development of a free-market economy. At the end of this process, efficient production methods and technologies are selected, and inefficient ones are disabled, which leads to an improvement in the quality of life and many socio-economic dimensions, increasing the level of welfare.

Schumpeter's creative destruction begins when innovations override some existing practices, making resources in existing apps available for use elsewhere, positively impacting productivity. Henry Hazlitt, in his *''Economics in One Lesson''*, describes as an example the cotton spinning machines introduced in the UK in the 1760s and the creative destruction effect of the new technology of the period. While the British textile industry employed about 8,000 workers in the 1760s, the increase in productivity and many other economic advantages brought by the cotton spinning machines, which were the invention of Richard Arkwright, increased the number of people employed in the same field by 4,000% and it reached 320,000 people in just 27 years, according to the estimates for 1787 (Hazlitt, 1946/2010). Therefore, according to the author, the idea that the insurgents opposing the new textile machinery will permanently displace workers has no long-term meaning, and this is exemplified as creative destruction. However, this does not change the fact that machines, even if temporarily, displace a group of workers and negatively affect their living standards. As a matter of fact, for a period close to the previous example, William Felkin emphasized in his publication *''History of the Machine-Wrought Hosiery and Lace Manufactures''* that the vast majority of about 50,000 stocking-knitters in England faced hunger and misery in the following years due to the employment destruction caused by the machines (Felkin, 1867/1967), Levinsohn and Petropoulos (2001), who share statistics from the textile industry for a more recent period, state that job losses from textile machinery in the USA in 1972-1992 amounted to 30%. Therefore, the creative destruction effect does not deny the existence of employment damage, even if it is temporary.

The views of Joseph Schumpeter extend to the present day in the form of a neo-Schumpeterian approach, especially considering the role played by innovative activities and technical advances in the last 30 years, both in economic growth and in the development of competition (Evangelista, 2018). In the neo-Schumpeterian approach, technological advances are placed at the center of economic growth, competition, and innovation; therefore, the technological advances that have reached the present day have caused a kind of renaissance or evolution process in Schumpeter's approach. Freeman (2003) attributes this situation to the rapid technological advances brought about by the increasing acceleration and spread of ICT in recent years, and this new Schumpeterian trend is called *"evolutionary economics"*, *"economics of technological change"* or *"neo-Schumpeterian"* in the literature. In this study, the latter is preferred in order to explain the determinants and effects of new technical advances by taking the Schumpeter reference point (Freeman, 2003; Hall and Rosenberg, 2010; Evangelista, 2018). The neo-Schumpeterian approach has been discussed in pioneering studies such as Freeman et al. (1982), Nelson and Winter (1985), Nelson (1993), Freeman (1987), Fagerberg et al. (2005), Fagerberg et al. (2013), and Winter (2014) after the 1970s.

Neo-Schumpeterian literature shows technology as the most distinguishing factor for entrepreneurship and competition because of its nature that enables the emergence of new firms and industries or makes some existing firms or industries obsolete, and it is generally accepted that technology is one of the most important dimensions for economic growth. The creative destruction process, which defines the effect of technology, is frequently discussed at micro, sectoral or macro levels in the Neo-Schumpeterian approach, and three important features of these approaches can be listed as follows: a) Investigations take the impact of technology on the economy from the macro-level to the micro-level, and in terms of time periods, short-term perspectives are emphasized rather than long-term perspectives. b) The diffusion and adaptation of technology and the possible effects of this situation are discussed with models in which demand is largely ignored and the main determinants are handled with a supply-side approach. c) Very optimistic and problem-free approaches are put forward regarding the economic and social effects of technology in free-market economies, negative effects are completely ignored, or the existence of a permanent net negative effect is not accepted (Evangelista, 2018).

The assumptions of the neo-Schumpeterian approach are summarized under two main headings: a) There is a strong and positive link between technology, economic growth, and employment, technological advances increase the economic capacity and competitiveness of firms, industries, and countries. b) Technological advances are always a positive *"social and economic sum game"*, this applies to both the past, the present and the future. At this point, it should not be ignored that the positive net effects of Neo-Schumpeterian models on employment, social and economic phenomena are based on the idea that technological advances will create their own demands. In both early Schumpeterian and neo-Schumpeterian views, the view that technology would potentially provide a sufficient rate of economic growth for full employment is dominant. While shaping these views, although the destructive effect of technology on employment is not completely ignored, it is assumed that the negative effects will be absorbed by low-skilled employment, and it has been argued that the overall employment effect on the economy will be positive. At this point, Evangelista (2018) specifically objects to the second assumption, stating that although it can be supported by both logical and empirical evidence that technology positively affects employment and social welfare at the micro-level, the assumption of a positive-sum game at the macro level is not always compatible with the facts. Vivarelli (2014) states that there is not enough empirical evidence that the net effect of technology, in the long run, is optimistic due to both modeling and estimation difficulties. It can be said that the net long-term effect becomes even more blurred because the effectiveness of compensation mechanisms, which will be discussed in the following sections, are based on very rigid and sometimes impossible assumptions, and at the same time, today's ICT and artificial intelligence (AI) developments have emerged as more complex structures in terms of innovation than in the past. Today's ICT advances make it difficult to see the course of the total impact due to reasons such as the rapid spread of innovation and the diversity of usage areas (Evangelista et al., 2014). The neo-Schumpeterian approach, in fact, cannot address the impact of technology on the economy in general and employment as a narrower focus, on theoretical or empirical grounds at the macro level. Rather, it represents a fairly optimistic view that technical advances always increase economic growth and social welfare. On the basis of the creative destruction effect of Schumpeter, based on the dynamics and unlimited power of the free-market economy and its neo-Schumpeterian reflections, lies the idea that technological advances will be a solution to the current financial crises, economic growth problems, and employment problems of countries.

2.1.6. A Brief Review on the Technological Unemployment Discussions

Although the concept of technological unemployment has once again come to the fore as a popular phenomenon as technology has reached levels that many cannot anticipate today, as discussed above, such a type of unemployment does not actually exist, according to a considerable number of economists. From another point of view, the fact that the economic theory treats unemployment as frictional and structural in general does not prevent some people from adding the concept of *"technological unemployment"* to the same list. To summarize, technological unemployment is a type of unemployment that is caused by technical advances or innovations, which occurs with the use of machinery, computers, robots, or all other technological equipment instead of human labor and makes some human skills unnecessary over time (Black et al., 2012; Campa, 2017). However, at this point, it is necessary to add that not every technical progress can be considered as a cause of unemployment, and it cannot be denied that technological innovations affect the individual or industrial actors of the economic order or countries in different ways and direct employment. For example, the decline in the share of human labor in the agricultural sector, where traditional methods were once dominant, is quite striking. While approximately 41% of the population was employed in the agricultural sector in the United States in the 1900s, this rate decreased to only 1.9% in the 2000s, and below 1.5% in the 2010s (Dimitri et al., 2005; US Bureau of Labor Statistics, 2021a). Similar patterns are also seen in the manufacturing sector. Again, in the USA, while the share of the manufacturing sector in total employment was 26.4% in 1970, this rate decreased to 22.1% in 1980 and 10% at the end of the 2010s (U.S. Bureau of Labor Statistics, 2021). In

Turkey, between 1990 and 2019, the share of the agricultural sector in employment decreased from approximately 30% to 18%, while the employment share in the total of industries covering sub-sectors such as manufacturing, construction, and energy decreased from approximately 30% to 25% in the same period (ILO, 2020)[1]. Dramatic employment declines in the same sectors, but at different rates in both examples, point to technology-induced productivity gains and, in other words, the need for less manpower for the same output. While technology causes employment transitions from agriculture to manufacturing and, more recently, from manufacturing to the service sector; on the other hand, the increase in productivity created by technology perhaps suppresses or prevents *"technological unemployment"* from turning into a kind of permanent or chronic economic problem, at least for now (Campa, 2017). But of course, this situation does not necessitate ignoring some temporary or partial employment problems caused by technology in employment, on the contrary, despite the thought that everything returns to normal in the long run, it is unclear how long the transition processes will take, and which workers will be negatively affected in this period.

As a result, both the Classical and Neoclassical approaches that started to take shape since the end of the 19th century mostly consider the technology-employment relationship with an optimistic point of view and build their explanations or theories on compensation mechanisms. Indeed, the early classical economists indirectly included technology among the components of the economy instead of addressing them directly, or they preferred to use sub-components of technology such as mechanization and discovery (Mejía, 2017). Some classical economics thinkers such as Adam Smith, Alfred Marshall, Karl Marx, Carl Menger, and Leon Walras did not give enough space to technology in their studies (Hodgson, 1996). In Adam Smith's *"Wealth of Nations"*, words like machine or discovery are used in place of technical progress, while the term technology completely appears in Karl Marx's *"Capital"* and is associated with the use of mechanized machines instead of physically demanding work. Ricardo, alternatively, laid the foundations of the concept of

[1] These statistics were calculated using the data of *"employment by economic activity and occupation"* published by the International Labor Organization (ILO, 2020).

technological unemployment by revising his initially optimistic views in a pessimistic direction. While Keynes popularized this phenomenon in the later period, he made predictions about how weekly working hours will decrease in the coming years, especially by giving observable examples from the manufacturing sector, but his predictions that working hours will decrease do not show that his view of the long-term technology-employment relationship is pessimistic. The general equilibrium view of neo-classicals argues that the effect of technological advances on unemployment is only temporary and that the market somehow prevents the employment problem and overproduction in the long run. According to this view, the temporary problem in labor markets stems from wage adjustments, that is, the absence of an equilibrium wage. On the other hand, the Keynesian approach, which is shaped on an axis opposite to this view in terms of the balance mechanism, states that insufficient employment due to technology cannot adjust itself and if this situation is not intervened, unemployment will become a permanent problem. In addition, since the decreasing demand level in the economy, especially during recession periods, makes the expectations for the future pessimistic, the desired increase in investments may not be achieved. However, solving the unemployment problem is based on high investments and the demand for labor that comes with investments. The Keynesian approach argues that the demand for labor provided by investments is uncertain and cannot provide the expected contribution to employment, so this approach does not support the existence of a system in which technology transforms into new investments. Schumpeterian approaches also consider that there may be short-term negative effects on the way to increased productivity and greater welfare with the effect of creative destruction. Besides, the Schumpeterian approach argues that placing technological advances at the center of the economy shapes the important dynamics of the economy and does not support structural unemployment, which is a claim of the Keynesian approach. Generally, optimistic views are based on the fact that technological unemployment is a short-term problem and even assume it as a temporary side effect that should be accepted rather than a problem. Pessimistic approaches, on the other hand, focus on the significant structural damages of technology in the short or long term. The Luddite movement, which is effective in shaping pessimistic views, is located on the side of technology facing mechanization, that is, in the *"age of mechanical effects"* as its starting point. However, additionally, we may be faced with more important problems brought about by the *"age of digital effects"* because technology is becoming more complex day by day in terms of its structure. In sectors impacted by developments in automation, digitization, computerization, artificial intelligence, machine learning, ICT, or other aspects of technology, it is not certain that productivity gains or new jobs will be generated enough to absorb the displaced workforce back into the labor market. More strikingly, even if the desired level of productivity gains is achieved, increased production may not face a surge in demand that could absorb unemployment. Finally, even though technology creates more jobs than in the past or creates new jobs, the skill or quality of current or future employment may not be sufficient to take over these jobs. All these uncertainties once again reveal the necessity of more qualified forecasts for both economists and policymakers.

2.2. R&D Based Growth Theories

Up to this point, the ideas of leading economists on the effect of technology on employment have been given from a historical perspective. Before moving on to the theoretical foundations of the technology-employment relationship, an overview of the R&D-based growth models, which have a very important place in the literature, will be presented because the growth and productivity dimensions of the economy are very important in terms of theoretical approaches to the technology-employment relationship. As a choice, R&D is used as a proxy for technology in this thesis, and thus how R&D affects growth which is a significant macroeconomic indicator in terms of employment and productivity is also valuable in terms of compensation mechanisms discussed in the next sections.

Economic growth can be defined as the increase in the total production volume, in other words, in the national income, depending on the expansion in the capacity of a country to produce goods and services, namely in the existing production inputs such as labor force, capital, knowledge stock, natural resources, and technology. Research and development (R&D) is a process that includes systematically conducted innovative studies to increase the stock of knowledge and the quality of human capital, and the use of this knowledge to design new products, methods, and applications. R&D is undoubtedly an important factor for economic growth, as both theoretical and empirical models of the link between economic growth and R&D often reveal the positive and strong relationship between the two. In other words, the triggering role of science and technology, which is an important prerequisite for the sustainability of capital accumulation and productivity increase, on the economic growth and social development of countries is indisputable. In this direction, both the exogenous growth theories introduced in the middle of the 20th century and the endogenous growth theories introduced to the economics literature in the 1980s accepted the important and critical role of knowledge and technology. Especially in studies such as Romer (1990), Grossman and Helpman (1991a), Aghion and Howitt (1992), while emphasizing the theoretical foundations of the relationship between R&D and growth in endogenous growth models, the common point emphasized by the authors is that R&D is a kind of trigger for economic growth. For this reason, policymakers should use this tool effectively to achieve their goals.

Although economic growth is not always an indicator that reflects the real living standards of the population, as one of the most important indicators of welfare, it is an economic phenomenon that many studies have been conducted on which driving forces are affected. While economic growth is evaluated in terms of capital accumulation, mechanization, and division of labor in classical economics, determinants of growth have become a striking issue again, especially after the Great Depression of 1929. At this point, the Harrod-Domar Model, based on two different studies by Roy F. Harrod (1939) and Evsey D. Domar (1946), points to savings and efficient use of capital as triggers of economic growth: In the model, the average capital-output ratio is expressed as K / Y and the marginal capital-output ratio is expressed as $\Delta K / \Delta Y$. The inverse of the average capital-output ratio Y / K shows the average productivity level of the capital where *"K"* represents capital and *"Y"* shows output (Domar, 1946). In order to increase the economic growth in the Harrod-Domar Model, either the saving rate or the productivity of the capital must be increased. However, in the 1950s, neoclassical economists identified labor as one of the most important factors in economic growth, in addition to capital, because the Harrod-Domar Model was not supported by strict assumptions and especially real economic data of the US. In this model, the economy is assumed to be in perfect competition and full employment, and the share of the factors of production is determined by the marginal productivity of the factors of production and it is assumed that there is perfect substitution between labor and capital. At this point, Solow states that the increase in economic growth cannot be explained only by capital and labor, and that technological development is also an important factor directing growth, and he defines this situation as a *"residual"* (the Solow residual) in his new model. It should be noted that although leading economists such as Joseph Schumpeter also stated that technological growth is an important factor for economic growth, Solow (1957) was the first to explain this with an economic model and support it with empirical evidence. In the model, saving rates, population growth rate, and technological progress data are considered as observations and therefore these indicators are assumed to be determined exogenously. Therefore, in the model, there are two inputs namely capital and labor, and with the exogenous technological variable the production function in Solow Model is defined as $Y_t = f(K_t A_t L_t)$, where Y_t, K_t, L_t and A_t are output, capital, labor, and technological change in time t, respectively. As a result, under the assumptions of constant returns to scale and positive factors of production ($K > 0$, $L > 0$), the Cobb-Douglas production function of the Solow Model can be formulated as $Y_t = K_t^{\propto}(A_t L_t)^{1-\propto}, 0 < \propto < 1$. In the model, it is assumed that labor and technology grow exogenously at constant *"n"* and *"g"* rates, respectively. Therefore, the value of labor and technology in the time *"t"* are $L_t = L_0 e^{nt}$ and $A_t = A_0 e^{gt}$ respectively.

However, the emergence of technology, which is considered as an exogenous variable in the Solow Growth Model, is not explained and the diminishing marginal productivity is ignored. In addition, historical growth data do not support the hypothesis advocated in Solow (1957) that there will be convergence between rich and poor countries over time. At this point, endogenous growth models are based on how R&D investments and innovations produced as a result of these investments eliminate the decreasing productivity, starting from Schumpeter's putting technology at the center of economic change. Accordingly, endogenous growth models performed more satisfactorily in explaining the differences in growth rates of countries. Romer (1986, 1990), one of the first representatives of endogenous growth models, considered R&D activities as a direct variable in the growth model and placed it at the center of the model, starting from the fact that the research sector uses its human capital and knowledge stock to produce new knowledge or technology. In Romer's (1990) model, R&D activities and R&D employees cumulatively increase the knowledge from the past to the present to create innovations, and therefore more R&D investment in the economy and more R&D employees means more innovation and increases the rate of economic growth. Contrary to the Solow model, endogenous growth theories assume that countries can sustain their economic growth by investing more in technology, and convergence of growth rates between countries is not a requirement. In addition, in endogenous growth models, the ability of countries to produce more goods or services than in the past is associated with the law of increasing returns to scale. Furthermore, endogenous growth models also draw attention to the role of people in the economy and the economic differences between countries.

There are four basic inputs in Romer's (1990) endogenous growth model: physical capital, human capital, labor force, and technological level index. Also, physical capital is measured in terms of consumption goods, and in the measurement of human capital, cumulative education is considered. In Romer's model, human capital (H) and technology (A) are separated from each other, and the technological level index is assumed to grow indefinitely. Since "A" shows the design for the production of each new commodity, it is measured by the total number of designs or projects. The economy consists of three sectors: a) The R&D sector uses existing information stock and human capital to generate new knowledge. b) Using the designs of the R&D sector, the intermediate sector produces durable inputs that the final sector can use. c) The final sector produces final goods, using intermediate goods as inputs produced in the intermediate sector as well as labor and human capital. These final goods are either consumed or saved as capital input. Based on this information and under the assumption of constant population and labor supply, the Cobb-Douglas production function is $Y(H_Y, L, x) = H_Y^{\propto} L^{\beta} \int_0^{\infty} x(i)^{1-\propto-\beta}$ where *"Y"* is the final output, *"L"* is unskilled labor, H_Y is human capital and $x(i)$ shows durable capital goods. In this model, the element that internalizes the technological change is the equation showing the change in the total project or design stock: $\dot{A} = \delta H_A A$ where H_A is total human capital employed in the R&D sector and δ is productivity parameter. The total inputs used in the R&D sector in the model are the accumulation of knowledge that is needed to produce new capital and new information. Also, capital goods in the production function can be substitutes or complete each other. While intermediate goods x_i are different from each other, the final products are homogeneous, and the stock of information is assumed to be open to all researchers. In Romer's (1990) endogenous growth model, the knowledge stock used in the development of the previous product is also used in the R&D activities performed for the development of a new product. In this model, it is expected that the R&D costs to be used in the production of each new product will decrease since the products are assumed to be indestructible. But because of the fact that a new product can make previous products obsolete, the vertical product development model was introduced by Grossman and Helpman (1991a). In this model, it is assumed that entrepreneurs are always in a race to produce a higher quality product, and it is assumed that each successful product development result will be an incentive for further research. The starting point of Aghion and Howitt (1992), another R&D-based growth model, is Schumpeter's "creative destruction". Schumpeter describes creative destruction as a process that constantly revolutionizes the economic structure from the inside, destroying the old and creating the new permanently. Successes as a result of R&D activities provide partial market power and create profit opportunities; this allows the innovator to earn monopoly profits, at least for a limited time. The monopoly profit that encourages new R&D spending ends up with imitation or further innovation by rival firms (Aghion and Howitt, 1998).

While endogenous growth models attribute the source of long-term economic growth to technological advances, the importance of economies of scale becomes prominent at this point. Because the common point of endogenous growth models is the establishment of a linear relationship between R&D activities and growth in the economy. However, it is observed that endogenous growth models cannot be verified in some empirical studies. For example, Jones (1995), while assessing the R&D-based growth model with data from OECD countries, states that during the Second World War until the end of the 1980s, despite the high R&D investments, the growth data did not occur as predicted in the model. Linking the inadequacy of the endogenous growth literature of the period to the scale effect, Jones (1995) advocated quasi-internal growth models that eliminated this effect. In the model developed by Jones (1995), the intertemporal spillover effect is not as severe as in the model of Romer (1990). Because Jones (1995) argues that critical ideas are discovered first and therefore the probability of discovering a new idea is inversely proportional to the current level of knowledge. Similar to Jones (1995), Segerstrom (1998) also investigates the reasons why the per capita growth rates have not increased at the desired level despite the rising R&D in developed countries and shows that R&D investments cannot turn into patents at the desired level over time. Because, according to Segerstrom (1998), the number of patents per capita is decreasing day by day and this shows that the discovery of patentable innovations is getting harder. Therefore, the long-term growth rate of countries is determined by the volume of innovation and population growth rate, as well as how difficult it is for R&D expenditures to turn into an innovation. Young (1998) also eliminates the scale effect by evaluating horizontal and vertical product development approaches together with similar concerns. At this point, the author, who states that the increase in population and product diversity in the horizontal product development dimension does not have a long-term effect on economic growth, asserts that sustainable growth can be achieved in the vertical product development dimension, based on the fact that product quality is independent of the population.

It would not be wrong to say that numerous empirical studies have been conducted scanning the impact of R&D on economic growth. While most of these studies report a strong positive link between the two, in some studies the relationship is meaningless. Empirical studies reporting positive associations between R&D and economic growth include Teitel (1987), Lichtenberg (1992), Goel and Ram (1994), Gittleman and Wolff (1995), Coe and Helpman (1995), Griliches (1998), Freire-Serén (1999), Blackburn et al. (2000), Ballot et al. (2001), Sylwester (2001), Chou (2002), Bebczuk (2002), Guellec and van Pottelsberghe (2004), Ülkü (2004), Zachariadis (2004), Wang (2007), Falk (2007), Goel et al. (2008), Alene (2010), Horvath (2011), Güloğlu and Tekin (2012), Eid (2012), Gülmez and Yardımoğlu (2012), Inekwe (2014), Silaghi et al. (2014), Gümüş and Çelikay (2015). Among the empirical studies that concluded that R&D did not affect growth, had little or no effect, especially public R&D, Mansfield et al. (1977), Bresnahan (1986), Birdsall and Rhee (1993), Jones (1995), Sylwester (2001), Grossman (2007), and Samimi and Alerasoul (2009) can be shown.[2]

As a result, while R&D based growth models reveal the importance of R&D, capital structure, learning, information processing, technology diffusion, and many more education-skill-technology related inputs and outputs in terms of economic growth, development, and welfare (Romer, 1990), there is still a lack of comprehensive approaches to R&D and employment impacts and a general equilibrium model today. One of the main prominences of the growth theory based on R&D is that technical equipment, machinery, information technologies, education, and R&D investments have micro and macro effects far beyond what is expected and that these multiplier effects are still

[2] In Lichtenberg (1992), business enterprise R&D was reported as significant but public R&D is not. Goel and Ram (1994) indicated that there is a causality between R&D and growth, but the causality way is not clear. In Coe and Helpman (1995), both domestic and international R&D were found to increase TPF. Sylwester (2001) reported that R&D was significant to explain economic growth in just G7 countries. In Guellec and Van Pottelsberghe (2004), all three R&D types, domestic private, public, and international R&Ds were found to have a significant effect on economic growth. Goel et al. (2008) stated that public R&D was more significant than private R&D. In Silaghi et al. (2014), private sector R&D was found to have a significant effect on growth. Mansfield et al. (1977) reported too small effect of R&D on growth. Bresnahan (1986) documented very little impact of R&D on growth. Jones (1995) indicated that R&D-based endogenous growth models were not supported by the economic growth data. Sylwester (2001) reported that R&D was not significant to explain economic growth in just OECD countries. Grossman (2007) stated that R&D subsidies did not affect growth. Samimi and Alerasoul (2009) found a negative but insignificant economic growth effect of R&D in developing countries.

consistently demonstrated and in this direction the economy policies need to be developed. Because growth theory reveals that social and societal gains can be achieved with R&D and issues such as productivity increase, investment, and education are much more important than thought.

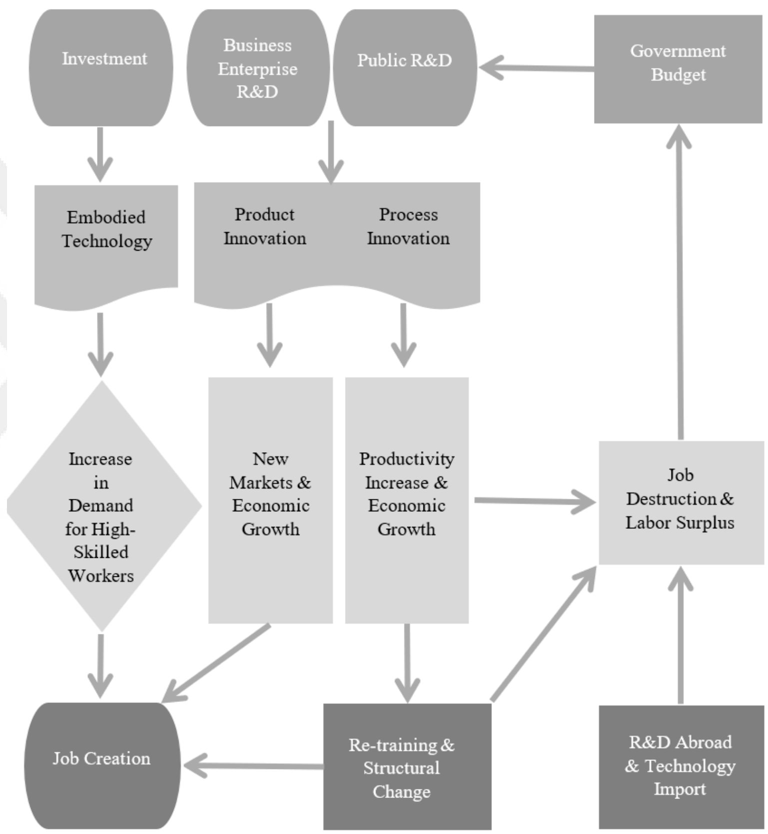

Figure 2.1. R&D, employment, and economic growth
Source: Author's own elaboration based on Welfens et al. (1998) and Dosi et al. (2021).

The employment aspect of R&D investments is a more complex issue than economic growth (Figure 2.1). At this point, it is clear that R&D directly causes two important innovations, such as process and product innovations[3], and the global income and price impact of process innovations and the power of product innovations to create new markets, which are important to explain technology-driven economic development.

[3] More detailed information on this subject has been shared under the title of *"Process and Product Innovations"*.

R&D investments of both companies and governments bring along many innovations, which are very important for the economic units mentioned above to achieve their own relative technological superiority and to contribute to market growth in this direction. Many of the R&D-driven process innovations result in a reduction in absolute prices worldwide, which increases global demand for goods and therefore increases real returns. On the other hand, market expansion provided by process innovations creates sectoral surpluses as a result of increased labor productivity. In addition, as process innovations lead to investments in new machines and other advanced technologies, the demand for skilled labor increases, especially in more complex service sector areas. At the same time, these investments in capital goods pose a threat to unskilled workers if there are no wage advantages, and they end up with the replacement of their labor with capital (Welfens et al., 1998).

2.3. Technology and Unemployment: Theoretical Framework

In the literature, the relationship between technology and employment is an old and highly controversial issue: one side of the debate argues that technological progress is a threat to employment and destroys jobs while, against this background, the opposing view claims technological unemployment is counterbalanced by the benefits associated with productivity. In the previous section, while presenting the historical framework, it was mentioned that one side of the economics literature, especially in the axis of compensation mechanisms, tried to consider the situation as an economic cycle rather than a problem, in the face of concerns about the unemployment caused by technology or the problem of *"technological unemployment"*. In this direction, the theoretical studies on the technology-employment relation are based on the existence of a compensation mechanism that is shaped by process and product innovations. At this point, Freeman et al. (1982), Pianta (2005), Tether et al. (2005), Piva and Vivarelli (2013), Vivarelli (2014), Calvino and Virgillito (2018), and more recently Dosi et al. (2021) presented a rather extensive literature survey which indicates both sides of the controversy in terms of compensation mechanisms. By making use of the studies mentioned in this section, the theoretical approaches from the past to the present on the relationship between technology and unemployment are discussed both at the total level and technical change hypotheses developed in line with skill and task-oriented approaches.

According to the simple definition or assumption, technology develops continuously and allows the same amount of goods or services to be produced with lower use of capital and labor, which naturally leads to technological unemployment (Vivarelli, 2014). Figure 2.2 has been prepared in order to show how capital *"K"* and labor *"L"* react against technological changes in the short term and long term. In terms of the short-term effect of technology, it is seen that the labor decreases from the potential level $\bar{L}$ to *L'* since the same amount of output can be produced with less labor force. However, an important point should be reminded here that this approach was created by considering the process innovations, the details of which are shared in the following sections, because process innovations, by their nature, exhibit labor-saving characteristics. In the long run, under the assumptions of full capital use and full employment, the pre-technology equilibrium point is defined as *"E"*, including production amount ($\bar{y}$), wage (*w)*, and interest rate (*r)*. Since technological progress will require less labor and capital under the assumption of constant output, fixed wages, and fixed interest rate, the isoquant curve will shift to the left and reach the new equilibrium point *E'*, at which point it can be deduced that employment will decrease due to the need for less labor (Vivarelli, 2014).

However, this approach includes very strict assumptions and does not take into account the important dynamics of the economy. Therefore, it can show the direct or immediate effect of technology, and Vivarelli (2013) especially emphasizes that this relationship only reflects the effects of process innovation. For example, the assumption of constant output is unrealistic; an increase in productivity can encourage producers to produce more, which can increase overall output, lower prices, and require a reassessment of the amount of capital and labor used. However, the assumption that wages and the interest rate do not change is not met in reality, because as a result of technical advances, workers may accept to work for lower wages and create resistance to machines.

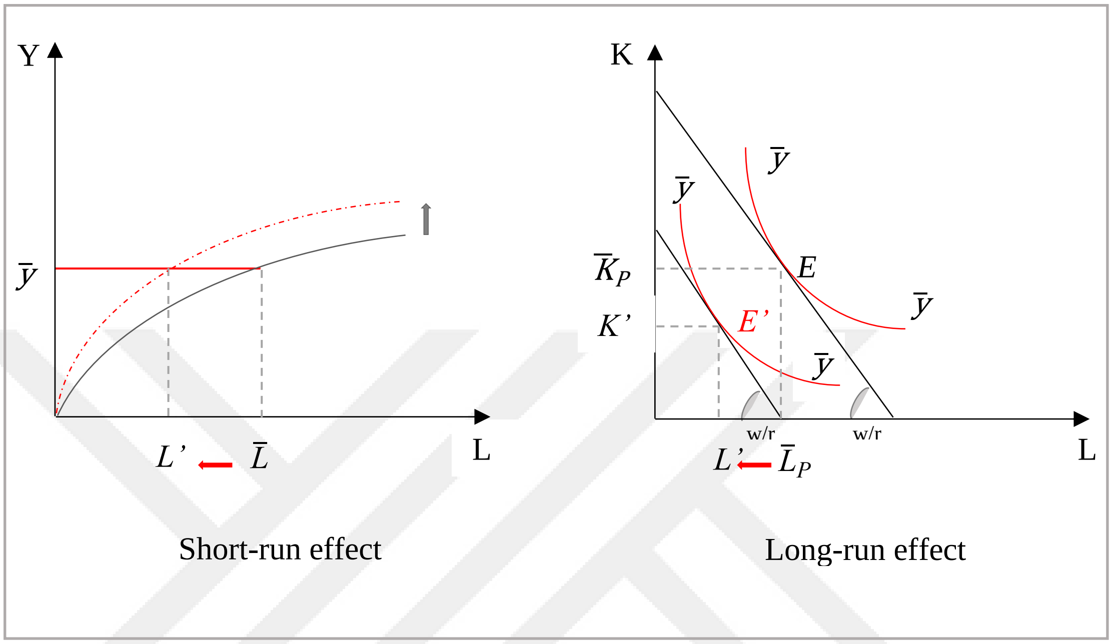

Figure 2.2. Technology and employment relation in the short run and long-run
Source: Autor's own elaboration based on Vivarelli (2013, 2014).

The main issue on which the ideas developed at this point diverge is actually about the ability of employment to reach equilibrium after technological shocks. While technology is considered as a secondary factor in studies within the scope of labor economics, its effect on employment is discussed in the context of wages and it is argued that unemployment created by technology will be temporary and wage adjustments will bring employment back into balance in the long run. These approaches also consider innovations as process innovation in general and do not accept technological unemployment, so they do not talk about structural unemployment. Nevertheless, differing views reject the assumption that labor markets always adapt to technology and argue that there is no evidence of that effect. Technological advances can present or destroy many job opportunities depending on their type; calculating the net effect is very complex and depends on the current adaptability of labor markets. Therefore, the disequilibrium approach mentions the existence of a slowdown in labor markets in the adaptation process and argues that how society will react to technological changes will determine the direction and size of technological unemployment.

The common point of both equilibrium and disequilibrium approaches is that technical changes require a period of adaptation (Freddi, 2018). At this point, even the neo-classical models, which offer the most optimistic approach, accept that it will take time to reach equilibrium as a result of technological changes and the process will involve some negative consequences. Freddi (2018) also refers to the *"diffuse power of technology"*, noting that if there is no diffusion, technical advances will have a limited social or economic impact. What is meant by the diffusion of technical advances is the extent to which all economic units in society, from individual consumers to firms and governments, are able to keep up with or adapt to innovation, and how quickly they replace the new technology with the old (Hall, 2004; Fagerberg et al., 2005).

How the first or direct negative impact of technology on employment is bypassed in market dynamics is a theoretically important issue. At this point, before moving on to the compensation mechanism, which is the most comprehensive theory of the employment-technology relationship, it should be noted that this mechanism is mostly based on process innovation, but in the later periods, a compensation mechanism channel was defined in which product innovations were also included, especially based on Schumpeter's views. To explain briefly, while the operation, method, or tool changes provided by technological developments in the economy are considered as process innovation, innovations that give a new product to the market, increase the product variety or change the structure of an existing product are defined as product innovation. Therefore, economists assess possible discharges that may arise due to product or process innovation over the existence of the compensation mechanism introduced by Karl Marx and discuss whether there is a balance system, in other words, whether negative effects on employment can be offset by technological achievements. Part of the work claim that the negative effects of technology on employment can be fully compensated by the compensation mechanism, and even that employment may increase further, while opponent opinions argue that the mechanism cannot work perfectly, and that technology always leads to job losses and increase unemployment. While Say (1836/1971) states that the employment problems arising from process innovations create new job opportunities in the capital markets, and therefore there is a balance factor, Hicks (1939/1975) says process innovation is not able to positively influence employment in the capital markets. On a side note, Freeman et al. (1982) state that the machines may not be part of any compensation mechanism if they already replace older machines.

As can be examined, to understand the employment effect of technology, it is also important to define the type of technology correctly. However, even if this distinction is made correctly, it cannot be said that both the theoretical and the empirical literature shared in the later chapters fully agree on the impact of process and product innovations. In the next section, firstly, brief information about the process and product innovation is shared, how the distinction is made, and how these two innovation types affect employment from a theoretical perspective are discussed. Then, important details about the basic principles of the compensation mechanism are presented and approaches that defend the effectiveness or explain the ineffectiveness of this mechanism through different channels are presented, and the issue is summarized from a theoretical point of view. In the last part of the theoretical perspective, skills and task-oriented approaches, which are a fresher discussion on the technology-employment relationship, are explained, and the importance of the quality of the workforce and the content of the tasks in the jobs in terms of the effects of technology on employment are discussed.

2.3.1. Process and Product Innovations

It is important to define the differences between process and product innovations in order to understand the structure and nature of technological change, but these two approaches cannot be expected to be completely separated from each other; both types of innovation can be internal. The division of process and product innovation is often considered artificial (Flichy, 2008). In this section, the differences between the two types of innovation are outlined and the possible employment effects of both are evaluated from a theoretical perspective.

Product innovation is an innovation that involves the use of new materials and components, modifying existing products, or the creation of new products in almost every field, from automobiles to mass media, from agriculture and food products to the textile industry. Such innovations improve the quality of life of societies, and with the advancement of technology, it may become possible to produce more products at lower costs. On the other side, process innovations refer to technical or methodological innovations in the organization of production or other operational stages, such as the use of assembly lines or the integration of new automation systems into production (OECD and Eurostat, 2018).[4] Simonetti et al. (1995) evaluate the process and product innovation under five headings: a) Innovations integrated into the economic system are very sensitive to the business cycle. Firms reduce their costs during recession periods; in expansion periods, they tend to discover new products. b) The product life cycle also affects product development. An industry is more focused on new product development in its early days, but as the industry ages, product development is replaced by process improvements. c) Product or process-oriented technological changes bring risks and uncertainties for companies. d) New methods or products used by companies can be imitated. Therefore, the protection of products is provided by patents and various laws, and the protection of processes is provided by confidentiality. e) Finally, and perhaps most importantly, according to the consensus of economists, process innovation reduces the demand for labor force – and therefore reduces employment – while product innovation can increase demand for new products introduced and thus increase employment.

[4] The detailed definitions of both innovation types can be found in Oslo Manual 2018, 4th edition. For definitions and other detailed information see OECD & Eurostat. (2018).

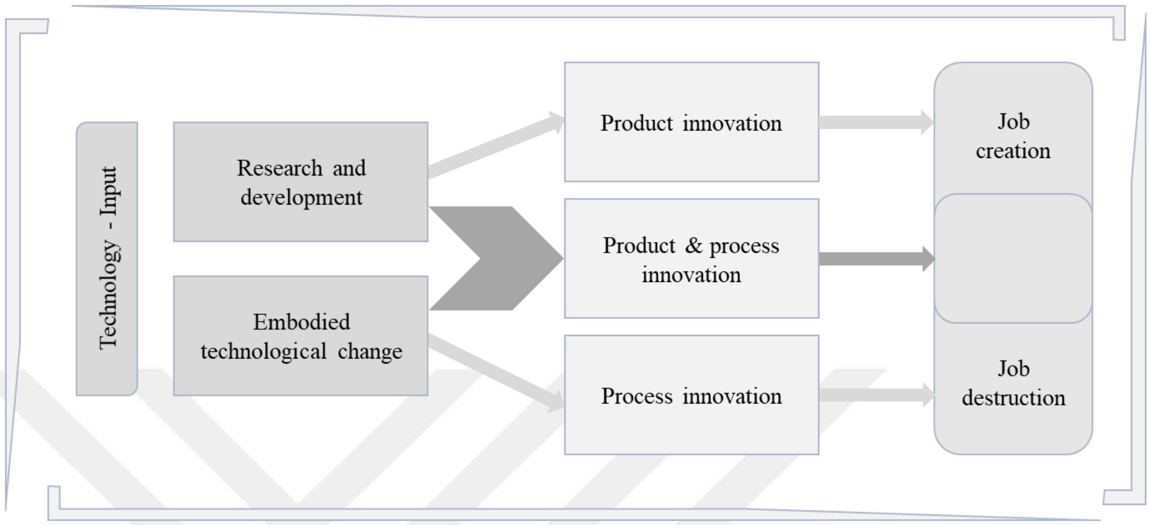

Figure 2.3. The impact of process and product innovation
Source: Author's own elaboration based on Vivarelli (2015)

In line with these explanations, Figure 2.3 deals with the impact of product and process innovations on employment. According to the theoretical approach, while process innovations tend to reduce employment due to their labor-saving characteristic, product innovations are assumed to have a positive response in total demand and are considered to be labor-friendly. However, the spread of both types of innovation to companies, sectors and even countries makes it difficult to model whether the effect is job creative or job destructive. In addition, although product and process innovations can be separated by definition, it is not always easy to determine which category the innovations are in. At this point, the difference between product and process development can be viewed from different perspectives. Generally, when a distinction is made for a firm, a new product or service released is called a product innovation, while a change in production methods is considered a process innovation. However, a technological improvement that is considered a product innovation for that firm may be a process innovation for another firm (Simonetti et al., 1995). For example, a new machine used by a company in the production of goods or services is *"process innovation"* for itself, while it is *"product innovation"* for the company that produces that machine. Besides, in this example, if the firm produces the *"machine"* that will provide innovation in the production method, it will have realized both process and product innovation at the same time. Therefore, it is concluded that this innovation made a negative or positive change in the business cycle; it is not easy to reach the conclusion that it increases (un)employment. While evaluating both process and product innovations in the *"technological innovation"* category, OECD and Eurostat (2018) underline that companies can also invest in areas such as organizational or marketing innovation. On the other hand, according to Brynjolfsson and Hitt (2000), it may not make sense to distinguish between technological and non-technological innovations, because non-technological innovations usually complement technological innovations. As a result, these groupings can be subjective from time to time, and dividing technological changes into product and process innovations is quite tricky as it is much more difficult to categorize at the macroeconomic level. For example, both product and process development may be possible as a result of aggregate R&D expenditures. Similarly, for the reasons mentioned above, patents can mean a new process as well as representing a new product. Therefore, empirically, it is necessary to make the prerequisite that technology proxies at the macro level consider product and process innovations together. For this reason, it is often inevitable to consider technological progress as a whole in macroeconomic studies.

2.3.2. Theory of Compensation

The history of theoretical studies on the direct *"job destructive - labor-saving"* and *"job creative - labor-friendly"* effects of technology on employment mentioned above, is based on the fact that technology-induced labor demand reductions can be compensated by the economy's own dynamics and through various channels, which is *"Compensation Theory"* and although it is a subject emphasized by many economists, such a designation was first made by Karl Marx (Marx, 1867/1976). In fact, Compensation Theory is based on studies in which different authors directly or indirectly addressed the compensatory effect of technology on employment in the past, and in this respect, it is a kind of compilation mechanism. Moreover, since product innovations in the economy are generally considered to be employment-enhancing, the focus of the compensation mechanism is how to eliminate or fulfill the *"labor-saving"* caused by process innovation. Therefore, in this section, the need for less labor as a result of process innovation and the ways in which the decreased employment is compensated in this direction are emphasized, but many recent studies also include the mechanism of creating employment through new products, which Schumpeter emphasizes, into this theory. Tether et al. (2005), Vivarelli (2013, 2014), and Calvino and Virgillito (2018) make important contributions to the literature with a very comprehensive study on the assumptions of compensation mechanisms, activities, and criticisms of mechanisms. This section summarizes the theories mostly compiled from the work of these authors and presents supportive and critical views on the functionality of compensation mechanism channels in this direction. At this point, first of all, five different channels that the compensation mechanism operates in order to suppress the destructive effect of process innovation on employment can be mentioned. While the first four of these five different channels, *"new machines"*, *"decrease in prices"*, *"fall in wages"* and *"new investments"*, are the work of classical and neo-classical approaches; the mechanism that operates through the *"increase in income"* channel is based on Keynesian thought. Finally, the *"new products"* channel, which is a sixth compensation mechanism and based on Schumpeterian approaches in general.

2.3.2.1. Compensation mechanism "via new machines"

The compensation mechanism, which was first discussed in this study, runs through *"employment opportunities offered by new machines to the economy"* and the working principle of this mechanism is based on Say (1836/1971). The main inference in this mechanism is that process innovation that causes employment loss in one area is based on new machines produced in another area, new machines are actually produced in a different sector and create a labor market by needing labor. In other words, machines that take away the jobs of people in an area increase the demand for labor in the area where they are produced.

In fact, as stated in the previous title, a change that is a process innovation for one firm may be a product innovation for another firm. Therefore, job opportunities eliminated by process innovation are actually compensated by product innovation, and in this case, the compensation mechanism that works *"through new machines"* can be considered as a subversion of the *"through new products"* compensation mechanism, which will be discussed later. However, there are serious handicaps for the effective operation of this mechanism. The use of process innovation is labor-saving, and labor-saving innovation may not create the same demand for labor to be employed in introducing that innovation (Vivarelli, 2015). In other words, it can only be partial that the compensation mechanism working with new machines replaces the lost jobs. Technological progress can also occur in capital goods themselves. In other words, process innovations can take place to produce a new machine that offers process innovation in an industry, which ultimately takes shape as a cycle and cannot increase employment to a level that compensates as claimed. A comparable situation is also discussed in Calvino et al. (2018). In the compensation mechanism working through new machines, the effect of labor transfers on total unemployment is not clear, even if technology leads to high volumes of transfers between sectors, shifting employment from agriculture to the manufacturing sector and from there to the service sector.

As a result, new machines can create new jobs in the sectors they are produced while causing employment destruction in the sectors in which they are used, but many dynamics must work together to make up for the lost jobs to the same extent. For example, if the new machines that come with high technological change completely put the old machines out of use, it cannot be assumed that the new machines create new employment areas, and the compensation mechanism cannot work effectively as claimed. Since process innovations, by their very nature, are mostly based on replacing obsolete methods with new ones, it is possible that new machines will make old ones obsolete over time, and this makes the effectiveness of the via new machines channel questionable.

2.3.2.2. Compensation mechanism "via decrease in prices"

The second channel of compensation mechanism works through *"decrease in prices"* and its starting point is the assumption that process innovation will increase efficiency and reduce prices in a perfectly competitive market, thus increasing the demand for the product, which in turn will increase the labor requirement. According to Steuart (1966/1767), *"the new machines produced by developing technology might be cause of* *hundreds of jobs losses but offer thousands of new business opportunities and increase employment"* via a reduction in prices.

However, the assumptions of this mechanism are also not entirely realistic since it may not be immediately possible for firms to reduce their prices at the desired rate. At the same time, this assumption does not take into account the differences in demand elasticity, and a decrease in prices in the market may not increase demand at the same rate. Standing (1984) notes that the mechanism is being founded on Say's Law, but the fluctuations and restrictions in demand are not taken into consideration. Hence, in the case of lower demand elasticity, the reduction in prices might not find an instantaneous response in the market and may not progress the compensation mechanism. Therefore, in order for the compensation mechanism to work effectively through the prices channel, the increase in demand through falling prices must be higher than the general decrease in demand due to the loss of the workforce. Along with classical economists such as Clark (1907/2013) and Pigou (1920/2013), modern economists like Stoneman (1983) and Dobs et al. (1987) defend the existence of an equilibrium mechanism that operates via a decrease in prices. Also, Malthus (1836/1964) emphasizes that labor-saving technological advances do not increase the total demand but reduce it due to the many people who are not able to work because of the new machines. In parallel with Malthus, Mill (1848/2004) suggests that the increasing consumer demands due to technological change will be suppressed by rising unemployment, which is caused by process innovation so that the compensation mechanism through fall in prices deteriorates. Finally, the compensation mechanism with reducing prices is based on the assumption that the market is fully competitive. Therefore, it is not possible to operate the system for oligopolistic markets since oligopolistic firms may not directly reflect the reductions in their costs (Vivarelli, 2013).

2.3.2.3. Compensation mechanism "via new investments"

The third compensation mechanism argues that new job opportunities will arise through *"new investments"*. This approach was discussed in various forms by prominent economists Ricardo (1817/1966), Marshall (1890/2013), Hicks (1939/1975), and Stoneman (1983), and it is based on the fact that reduced costs as a blessing of technological advances bring extra profits for capital and business owners and investors. It is thought that these profits can be transformed into new investments by the capital owners and create new job opportunities.

Similarly, this idea that new profits are transformed instantly and completely into new investments has been criticized in important studies such as Freeman and Soete (1987), Vivarelli (1995), and Pianta (2006). Drawing attention to economic realities like *"animal spirits"* and *"expectations"* at this point, the authors point out that there may be delays in the conversion of profits or profits might not be fully used for new investments. Marx (1867/1976) indicated that the increase in technology-driven profits can be transformed, not directly, but partially, and therefore the effect on the compensation mechanism remains low in the capital-intensive markets. In other words, the idea that the firm will instantly transform its profits into new investments may be too naive or optimistic, since such steps will be risky, and there is a time gap between new business opportunities through new investments instead of destroyed businesses.

In addition, the assumption that new investments will require new labor is also very strict, entrepreneurs can use less labor by turning to capital-intensive investments with the attraction of technology (Vivarelli, 2014; Calvino and Virgillito, 2018). That is, the assumption that all accumulated profits are converted into new investments in the period until prices drop is too assertive, because new investments may turn to labor-saving technologies instead of demanding more labor. Therefore, investments that emerge as a result of higher production may not increase the demand for labor to the extent that this channel advocates. Finally, the assumption that all investments are made as real investments is also quite strict, especially today most of the investments are more directed towards financial activities (Calvino and Virgillito, 2018).

2.3.2.4. Compensation mechanism "via decrease in wages"

The fourth compensation mechanism works through the *"fall in wages"* channel. Here, again, under the assumption of perfect competition and perfect substitution between labor and capital, it is argued that the loss of labor due to technological development is compensated by the decrease in the wages of the workers since the fall in wages makes the labor comparatively superior to technology again and increases its demand. These arguments are used in studies such as Wicksell (1901/1967), Hicks (1939/1975), Sinclair (1981), and Layard et al. (1991/2011) and are summarized in Figure 2.4. Advances in technology initially reduce labor demand from $\bar{L}$ to L', but the adjustment in wages, i.e., the reduction in the w/r ratio, can bring labor demand back to its potential level $\bar{L}$.

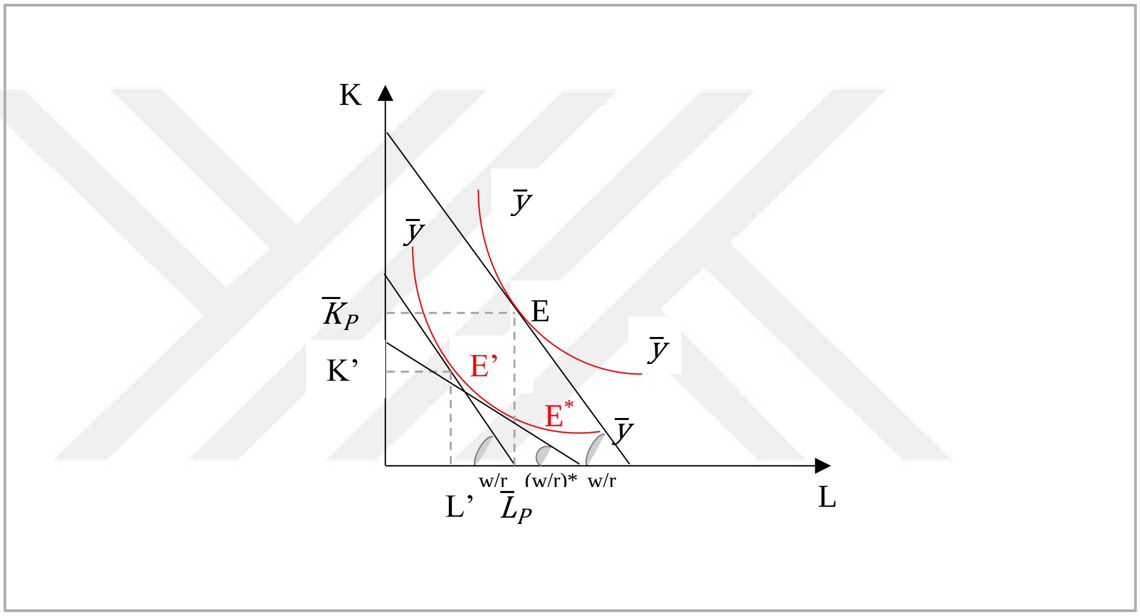

Figure 2.4. The effect of technological development on labor demand and compensation mechanism via decrease in wages
Source: Autor's own elaboration based on Vivarelli (2013, 2014).

Nevertheless, falling wages may reduce the demand for goods or services, so a decrease in demand may prevent employers from increasing employment. In other words, the reduction in wages partly means a decrease in demand and consequently prevents the efficient functioning of the mechanism, which already contradicts the Keynesian effective demand theory. It should be also highlighted that because of the different and complex chemistry of the technology it may not be possible to operate the compensation mechanism fully and perfectly via a decrease in wages (Freeman and Soete, 1987). Even though firms tend to hire new employees since the reduction in wages, the downward trend in wages decreases aggregate demand and worsens workers' prospects for the future. Therefore, they employ fewer workers as needed (Rosenberg, 1976; Vivarelli, 2014).

In addition, the assumption of perfect substitution between labor and capital is also unrealistic, especially for irreversible technological advances, since the transition from labor to capital may be easy once a cost advantage is provided, but the transition from the capital to labor will not be so easy. Technology is not a reversible element over time. After the manufacturers upgrade their existing technologies, they may be affected by the decrease in wages and may not want to do the work they used to do with machines again, because backtracking involves many risks. This issue is discussed in detail especially in Dosi and Nelson (2010). The authors state that once the firm has mastered a certain technological competence, they will not want to replace labor with technology with a change in wages. Similarly, Yu et al. (2015) and Dosi et al. (2016) argue that factor substitution does not exist between capital and labor productivity.

Finally, it should be added that the decrease in wages may not be possible due to regulations such as minimum wage practices in the labor market. For such reasons, wages cannot always be on a downward trend and workers cannot maintain their relative cost advantage over machines indefinitely.

2.3.2.5. Compensation mechanism "via increase in incomes"

Another important contribution of the technological advancements to the economy is that it leads to *"an increase in net income"* based on the Keynesian approach (Pasinetti, 1983) which states savings provided by process improvements increase income first and consumption depending on income, which leads to an expansion in demand. In other words, economists with Keynesian tradition who exemplify the Fordist production process also point out that new technologies may increase savings and expenditures. The increase in income and expenditures causes an increase in total demand and affects employment positively (Pasinetti, 1983). However, contrary to the 1950s and 1960s, studies claim that the compensation mechanism arises from the production approach dissolved in later periods and income growth is not a balancing factor in employment anymore (Boyer and Petit, 1991). As Calvino and Virgillito (2018) stated, it was known that unionized workers had bargaining power in terms of workers' rights in the past, but today, collective initiatives of workers are less frequent and therefore this mechanism is not as flexible as it used to be. Finally, this mechanism partially contradicts the *"through a decrease in wages"* mechanism, since the decrease in the wages of the workers means a contraction in their income, which shows that the wheels of the two mechanisms are turning in opposite directions.

2.3.2.6. Compensation mechanism "via new products"

After the compensation mechanisms for process innovations, how the *"job-creating"* or *"labor-friendly"* characteristic of product innovation works can be examined. Perhaps one of the rare effects that the theoretical economics literature on the technology-employment relationship has agreed upon is that product innovations have an employment-enhancing effect. The theory states that while product innovations create new markets and even new industries, new markets and new industries create new business opportunities. However, as Vivarelli (2014) notes, the contribution of product innovations to employment may be stronger or weaker depending on economic conditions, and in some cases, no significant effect may be observed. Because the welfare or convenience provided by new products or services should at least be balanced with the substitution effect. Say emphasizes the labor-intensive impact of product innovations and Marx states that machines and industrial innovations that come with them create new employment areas, in fact, he mostly criticizes the remaining five mechanisms where process innovations are discussed. In this respect, the *"via new machines"* channel, which is stated as the first compensation mechanism, may intersect with product innovations at some point. In fact, as mentioned before, since new machines are also new products in a sense, the first channel discussed under the title of process innovation can also be considered as a sub-title of the new products channel.

Product development can take place in the form of producing a new product by an existing company or changing the form or structure of an existing product, or it can take place in the form of introducing a new product to the market by a completely new entrepreneur and therefore the company. Freeman and Soete (1987), Vivarelli and Pianta (2000), and Edquist et al. (2001) find that product-oriented technological advances affect employment positively by introducing new products or making changes in product form.

Studies such as Arrighetti and Vivarelli (1999) and Cefis and Marsili (2006) indicate that product development with a new firm has more permanent positive effects and provides higher employment rates. Besides, Dosi (1982) acknowledges that product innovation contributes positively to employment, but the effect depends on the product type, industry and it is influenced by the different periods and institutional structures. Additionally, the author notes that the situation in which the product innovation comes with the process innovation is considerable and emphasizes that the total effect should also be evaluated. In terms of product innovation, Freeman and Soete (1994) state that the production of information and communication technologies is very effective in terms of empowering employment, especially product innovations such as personal computers and cell phones create new job opportunities. In addition, they state that the sectors that use these innovations directly or indirectly actually experience some kind of process innovation.

As it can be seen, the relationship between technology and employment is a long-standing and highly controversial issue. A large literature and a considerable number of studies have not produced a definitive conclusion on the relation between technology and unemployment. On the one hand, process innovation leads firms to labor-saving, and on the other hand, labor-friendly effects of compensation mechanisms and product innovations show that the relationship between technology and employment must be taken from a very broad perspective. In addition, the destructive and creative effects of process and product innovations in terms of employment vary from country to country, from sector to sector, and of course from company to company. Of course, additionally, the type and quality of the product, the economic environment in which the innovation is carried out, the historical process, and many other characteristics are among the determinants of the effect of innovation on employment. For example, Vivarelli (2014) emphasizes that the effects of innovations for automobiles and computers produced for personal use will be different from each other; and states that the automobile industry will have a more employment-increasing effect. Therefore, the existence of a stabilizing effect on employment is investigated with both micro and macro-level empirical studies in addition to theoretical studies. The ultimate impact of technology on employment or unemployment is complex, but considering unemployment is an important macro problem, understanding the current outlook of its relationship and making consistent predictions for the future is very important for policymakers & decision-makers, as well as for workers and employers, who are the main actors of employment.

2.3.3. Technology, Skills and Tasks

When examining the technology-employment relationship, it is a very simple assumption that labor is reduced to a single type and treated as *"homogeneous"*, because the type of labor and skill level of workers are diverse and are affected by many different dynamics. People have different levels of education and, in parallel, different skills, and this makes manpower diverse. In this direction, the skill demand of companies is also affected by innovation, and high technologies increase the need for high-skilled employees. On the other hand, the variety of skills that companies have also determines the direction of innovation, that is, the more skills are used in the innovation process mean the easier and faster the development of market innovations and new products. While Nelson and Phelps (1966) and Griliches (1969) emphasized the necessity of adaptability of existing skills in the adaptation of new technologies, they stated that economies with higher skill levels facilitate the diffusion of innovations; Cohen and Levinthal (1990) emphasized that this is especially true in the diffusion of high technologies that require higher learning. Therefore, the skill need and the level of technology used are closely related, and there is a positive correlation between higher skill use and higher technology, or in general terms, capital investment (Berman et al., 1994; Levy and Murnane, 1996; Doms et al., 1997). Accordingly, companies have to decide on the type and quality of manpower, while choosing between machinery and manpower, together with technology. On account of technology, the issue is not only to decide between capital and labor but also to determine the type of labor. Besides, the more successful individuals and companies are in finding relationships that complement human labor with machines or improve the quality of labor, the more employment growth can be achieved. In this way, more appropriate skills can be assigned to more satisfying and meaningful jobs. While employers are constantly chasing the lowest input costs with the effect of technology, workers and prospective workers continue to see a good job as an important life goal, and especially for the last two centuries, workers have been competing against their machine rivals alongside humans for this purpose. Therefore, skill-occupation matching is becoming a more and more emphasized phenomenon day by day (Tether et al., 2005).

While the fear of automation is not new, it has always been difficult to predict how automation will affect employment. For example, in the early 1900s, nearly half of the population in developed countries and more than three-quarters of the population in developing countries were employed in the agricultural sector (Grigg, 1975). Today, it is difficult to say that people living in that period can predict that the share of this sector in total employment will decrease to 3% for the first and to 20% for the second (World Bank, 2021).[5] Because although it is possible to imagine new business lines born with technology both at that time and today, it is very difficult to turn dreams into consistent predictions. Structural changes in labor markets, in particular, reduce the likelihood of old jobs returning. At this point, two common approaches are discussed to explain the technological change in labor markets in recent years, and these two approaches are generally based on the quality of the labor force and the structure of the occupations. The first is the Skill-Biased Technological Change (SBTC) hypothesis, which is based on the view that changes in employment are accompanied by technological advances, increasing the demand for highly skilled workers. The second is the Routine-Biased Technological Change (RBTC) hypothesis, which is based on the claim that the SBTC cannot explain the occupational structural changes observed in the labor markets, especially since the 2000s, and which is based on the view that technological changes affect employment according to the type and structure of duties. This hypothesis is also known as *"Autor-Levy-Murnane (ALM)"* or *"Task-Biased Technological Change"* in the literature according to the different task definitions it contains (Autor et al., 2003; Goos and Manning, 2007).

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[5] These data published in the World Bank (2021) with the title of *"Employment in agriculture (% of total employment)"* are based on *"ILO Modeled Estimates"*.

Both the SBTC and RBTC hypotheses are covered in more detail in the following sections, both theoretically and empirically. The SBTC hypothesis can be briefly summarized as an approach that states that the demand for skilled labor increases and unskilled labor markets shrink as a result of technology and argues that technology offers a higher and more effective compensation mechanism and higher wages for the skilled workers. Acemoglu (1998) and Kramarz (1998) are among the first studies to establish the relationship between the employment of skilled workers and technology, and Machin and Van Reenen (1998) are early studies that provide empirical evidence for the SBTC hypothesis. However, in studies such as Autor et al. (2003), Goos and Manning (2007), and Nedelkoska (2013), it was argued that the SBTC hypothesis could explain labor polarization from one side but failed to address it as a whole, and the RBTC approach, which revealed the importance of tasks, was discussed. Because, according to the empirical evidence obtained from many developed economies, especially the USA, while the number of high-skilled workers increases, there is a growth in the employment of low-skilled workers, but a contraction is observed in the employment of those who are in the middle-skill group and conduct routine jobs. Whether the point of view of the issue is from the perspective of the SBTC or RBTC hypotheses, the opinion that technological innovations are skill-oriented is common and there is a general view that while the demand for the more educated increases in the labor market, the demand for the uneducated or less educated decreases or does not increase as much as the former (Goldin et al. Katz, 1998; Bekman, Bound and Machin, 1998). Because education improves people's ability to obtain information, solve and understand, and these abilities enable people to keep up with technological changes (Nelson and Phelps, 1966).

As a result, the skill level or quality of employment determines the extent to which technology will benefit, as well as how quickly and easily technology will advance. Additionally, advances in technology affect the demand for different types of skills by changing the structure of existing occupations. An acceptable level of sustainable economic growth can be achieved with an effective bridge of harmony between recent technologies and previous economic and social structures (Pianta, 2006). The adaptation of innovation to economic demands and the expansion of demand with the formation of new markets are directly related to both the skill level and the structure of the jobs. At this point, both SBTC and RBTC approaches deal with the qualitative as well as the quantitative effects of technology on employment. So far, it has been tried to reveal how important the distinctions between technology and the skill quality of the workforce and the content of tasks are in terms of understanding the direction and strength of the relationship, and for this purpose, the SBTC and RBTC hypotheses discussed in the literature have been outlined. In the following sub-headings, the theoretical framework of these two hypotheses is discussed with a deeper perspective and the advantages and disadvantages of both approaches are presented in detail.

2.3.3.1. Skill-biased technological change

Technological progress is an important factor that affects labor demand both qualitatively and quantitatively, which is held responsible for the changes observed in labor demand in technology-intensive countries. Developments in technology, with the effect of globalization and rapid modernization processes, cause fluctuations in employment, especially in developed economies where flexible labor demand is dominant while increasing the demand for highly skilled workers (Autor et al., 2006; Crinò, 2009; Acemoglu and Autor, 2011). Because technology cannot be thought of independently from human skills, technological advances may tend to favor some skills more while rendering some skills worthless or unnecessary. In today's developed countries, while the dominance of machines in many automation-prone jobs, especially textiles, has increased as the effects of the Industrial Revolution, today this effect shows itself in a modified way in the digital arena and results in an increasing demand for qualified workers. In both cases, the mechanical effects of the Industrial Revolution and today’s contemporary digital effects are taking away the repetitive jobs from low or middle-skilled workers, while increasing the demand for high-skilled employment for complex jobs that have emerged as a result of technology. Therefore, today, skills-focused technological change hypotheses are in vogue. This approach, which is called SBTC in the literature, has attracted more attention since the end of the 20th century, especially with the developments in ICT.

The hypothesis that the skilled side of employment is more complementary to physical capital than others (capital-skill complementarity) is presented by Griliches (1969). The main theme of the hypothesis is that new technologies require qualified employment with sufficient skills to be effective and efficient. Lack of a skilled workforce not only makes technology adoption and adaptation difficult but also hinders full employment and leads to human resource scarcity (Amendola and Gaffard, 1988). Labor substitution can occur at different levels for different types of labor, at which point Acemoglu and Autor (2011) emphasize the increasing income inequalities for workers with different education levels over time. While the quality of labor influences the adoption and diffusion of technical advances, technological advances increase the demand for skilled labor to perform complex tasks, deepening wage inequalities through changes in capital and organizational structure (Özcan, 2019). Figure 2.5 has been prepared to explain the SBTC hypothesis, using the studies of Machin (2001), Acemoglu (2002), and Vivarelli (2014). In the left part of the graph (a), the change in the employment of skilled and unskilled workers based on wages is shared under the assumptions of constant output, external technical change, and constant supply, and through this visualization, the effect of both the increase in the supply of skilled workers and the technological advances on the skill premium can be observed. At this point, *"skill premium"* indicates the ratio of wages of skilled workers relative to unskilled workers, and an increase in the ratio means an increase in wage inequality. A possible increase in the supply of skilled employees will shift the supply curve to the right by increasing the S/U ratio, but on the other hand, the skill premium will decrease in the first place due to the abundance of skilled workers. Subsequently, a more skilled workforce will be involved in R&D activities, accelerating technical progress, in other words, SBTC will increase the demand for skilled workers and thus the skill premium. These impacts are approximate and depend on the extent of technical advances and in what areas. The excessive increase in skilled labor supply may not be compensated by SBTC in the next period, which means that the mentioned effect on the skill premium will not be seen. Or the increase in demand can directly increase the skill premium, and the subsequent oversupply of skilled workers and the resulting surplus can continue the cycle, this time in the opposite direction. Consequently, if technical progress is skill-based, in other words, if innovation requires higher skills, the share of skilled workers relative to unskilled will increase over time and the relative demand curve will shift to the right. Acemoglu (2002) states that the rapid increase in the supply of skilled workers during most of the 20th century, but not in the 19th century, encouraged the development of skill-complementary technologies, in other words, the acceleration in skill-based technical change may be due to the rapid increase in the supply of skills in the last few decades. In addition, it should be emphasized that the differences in wages in terms of skill-biased employment vary from country to country depending on the structure of the economy (Vivarelli, 2014). The effects of skill-biased technical change can be seen in the United Kingdom as well as in the United States in terms of both wages and increased demand for skilled labor, but in continental Europe wages and the current employment structure are relatively preserved due to stricter labor market regulations, which in fact leads to higher unemployment rates (Tether et al., 2005). At this point, Mortensen and Pissarides (1999) point to a similar point in their model. According to the theoretical findings on the comparative unemployment experience of the United States and leading European countries in the late 1970s, the main difference between the two groups is the prevalence of unemployment insurance benefits and other workers' rights practices in Europe. The authors note that skill-biased technology shocks, which accordingly increase the spread of productivity among workers, have more severe unemployment effects in Europe than in the United States, even if the initial employment positions are the same. Autor et al. (1998) -for the United States- and Haskel and Slaughter (1998) -for the United Kingdom- point out that wages rise more in favor of high-skilled employment, thus increasing inequality between low-skilled and high-skilled groups, but Goux and Maurin (2000) in France, Abraham and Houseman (1995) in Germany, Casavola et al. (1996) in Italy, and Hansson (2000) in Sweden show that wage differentials are more limited.

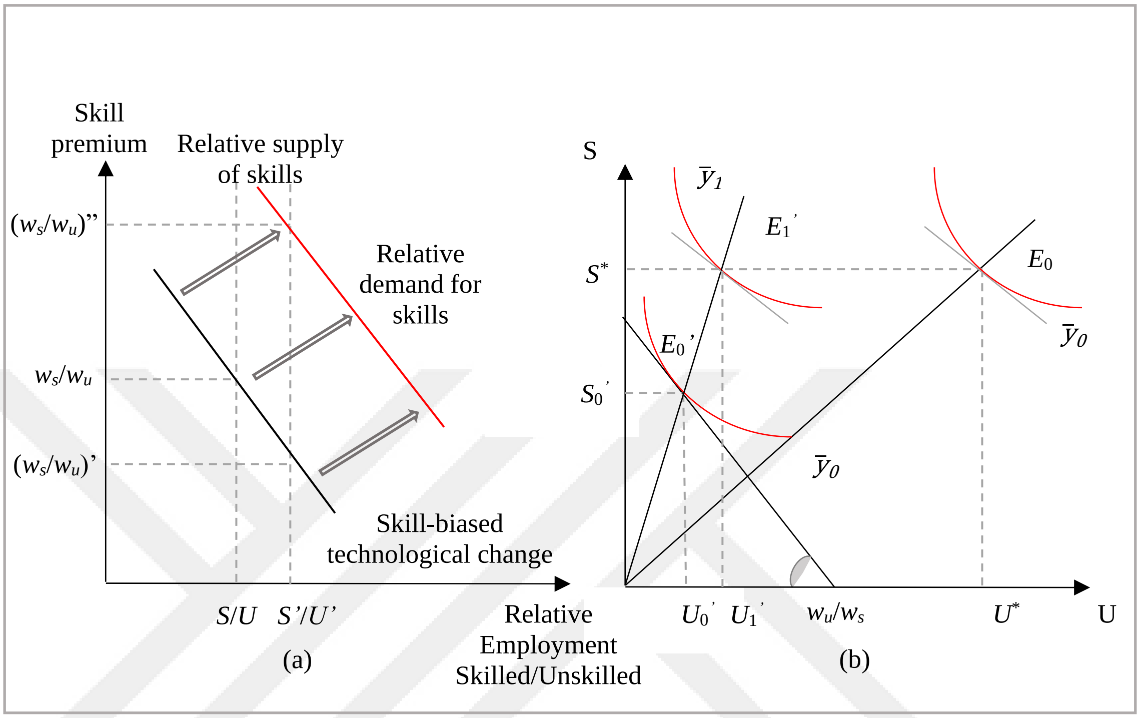

Figure 2.5. Skill-biased technological change and the relative demand for skills
Source: Author's own elaboration based on Machin (2001), Acemoglu (2002), and Vivarelli (2014).

On the right side of Figure 2.5 (b), the full employment rates are indicated for skilled (*S*) and unskilled (*U*) labor forces, and the employment market is at the E_0 equilibrium level. After the labor-saving technological progress, at first, both *U* and *S* decrease and they fall to S_0' and U_0' levels in new equilibrium level, E_0'. At this point, the skill-biased technological change approach states that the compensation mechanism can only provide a partially positive effect for *U* indirectly and, most optimistically, the economy can reach E_1' again. Therefore, although *S* reaches full employment in the new equilibrium state, this is not possible for *U*, and the unemployment problem arises for unskilled workers.

SBTC states that low and medium-skilled jobs disappear over time due to technology, so workers in this skill group are negatively affected by technology; on the other hand, it is based on the idea that there is an increase in the number of jobs requiring high skills due to the increasing importance of cognitive skills. As mentioned in Acemoglu and Autor (2011), SBTC is established under two main assumptions. First, jobs are classified as high-skilled (or sometimes just skilled) and low-skilled (or sometimes just unskilled) based on the skills of the employees. This classification shows that the jobs are divided into certain categories according to the abilities of the employees and the employees in the low skill class cannot do the jobs in the high skill group. Here, whether a job is low or high skilled is mostly determined by the education levels of the employees. Second, in the classification of low- and high-skilled workers or jobs, technology is treated externally, meaning that technical advances are not affected by the current workforce composition or skill level. Although this assumption is incompatible with general equilibrium models, the main claim of the SBTC hypothesis is that all technical changes are skill-biased, that is, a process in which high-skilled people benefit by adapting more easily, but low-skills face consequences such as relocation or job dismissal. Today, most digital tools, especially information and communication technologies, are a complement for skilled workers and a substitute for unskilled workers. Thus, increasing the productivity of the high-skilled and the demand for the high-skilled, resulting in a positive correlation between skill demand and technical change. In addition, the skill-biasedness of technological changes is related to the ability of skilled or highly skilled workers to better use new technology and adapt themselves to technical changes more easily. At the same time, technical advances free high-skilled workers from routine tasks, allowing them to devote more time to creative work. Naturally, the risk of substituting medium and low-skilled jobs with new technologies and new machinery being a threat to the workers in this group is much higher.

As a result, the SBTC hypothesis continued to be a popular phenomenon, especially until the mid-2000s, even though a heterogeneous technology-employment relationship was observed in terms of countries. However, the SBTC hypothesis focuses on the skills determined by the educational status of the employees rather than the content of the occupations, and also ignores the medium-skilled jobs and the workers in these jobs (or considers the medium-skilled in the low skill group). This situation brought about the inability to explain the business polarization with the SBTC and the shift of the focus of the economics literature to the RBTC hypothesis. It should be noted, however, that job polarization also differs between countries, as discussed in detail in the following sections.

In addition, it is predicted that the job polarization may be interrupted in the coming decades and that in the near future technology will reduce the demand, especially for low and middle-income occupations, while high skilled and high paid occupations will be less susceptible to technological destruction (Frey and Osborne, 2013). Therefore, it is difficult to say that the SBTC hypothesis, which left its popularity to RBTC since the mid-2000s, has completely lost its effect and validity. [6]

2.3.3.2. Routine-biased technological change and job polarization

As mentioned above in the SBTC approach, there has been a contraction in the number of medium-wage jobs and thus in medium-skilled employment in developed countries, especially since the mid-2000s. Particularly the labor markets of developed economies have undergone radical transformations in terms of both their professional and industrial structures. As a result of these transformations, the polarization in both the demand for skills and the wages depending on the demand has been experienced in the form of significant labor force transitions in many areas, mainly from the manufacturing sector to the service sector. According to OECD (2017), one-third of the disappearing medium-skilled jobs are replaced by low-skilled jobs, while two-thirds are replaced by high-skilled jobs. So, things are a bit more complicated for the medium-skilled group; statistics show that there is less need for blue-collar workers or white-collar office workers in production and operational positions. While there are job losses due to automation in the manufacturing sector, medium-skilled workers working in this field tend to work in low-skilled jobs, causing jobs to grow in the low-skilled workgroup. This phenomenon is known as job polarization, which is based on the idea that employment shares are mostly shifting towards high-skilled and low-skilled occupations and that shares of middle-skilled jobs are falling. OECD (2018) confirms that job polarization is technology-related in many developed countries. At this point, the SBTC approach, which is insufficient to explain employment structure changes such as job polarization as a reflection of technical advances, due to the inclusion of tasks, has been revised as the RBTC approach, in which

[6] The subject of *"Future of Jobs"* is discussed in more detail in the last part of Chapter 2 and the predictions in the literature about this field are included.

labor and capital are the basic inputs of production and the production function is expressed with tasks. According to this approach, advances in information technologies, in particular, take routine tasks from manpower and assign them to machines (Autor et al., 2003). Here, routine tasks can be defined as well-understood tasks that can be done by a machine, repeated, standardized, and coded (Acemoglu and Autor, 2011). Autor et al. (2003) actually classify tasks in two different dimensions: in the first step of the categorization, it is determined whether the task can be routinized according to the definition mentioned, and accordingly, the grouping is made as *"routine"* and *"non-routine"*. In the second leg of the classification, tasks are divided into *"manual"* or *"cognitive"*. While making this classification, the production process is considered in terms of the definition and content of the tasks, and at this stage, three important characteristics of the tasks are taken into account: a) Degrees of routine (or their propensity for automation, or degrees of repeatability). b) Differences between tasks. c) The final costs of having tasks assigned to machines or humans (whether the machines are cost-effective for that task). The purpose of the RBTC hypothesis is to determine the extent to which capital or machinery is allocated to routinizable work, mostly done by moderately skilled workers. Therefore, whether the jobs are routinizable or not is the underlying element of the RBTC hypothesis, and in this context, technical tools can be expressed as machines, robots, software, or various codes according to the necessity of the tasks. Furthermore, one of the main points that distinguish the SBTC and RBTC hypotheses are the definitions of tasks and skills: Acemoglu and Autor (2011) define a task as *"a unit of work activity performed to produce an output"*, while a skill is *"an employee's -necessary- the ability to perform a specific job or task"*. As a result, combinations of routine-non-routine and cognitive-manual dimensions mainly reveal four different task structures:

i) Routine & manual tasks: Both routine and manual jobs involve repetitive tasks that can be easily performed by machines. It is possible to see routine & manual tasks, especially in production and many operational activities, and these tasks are very prone to automation. For example, many blue-collar factory workers like forklift or metal-press machines operators, home appliance repairers, or production line assembly workers are in this group.

ii) Routine & cognitive tasks: These types of tasks consist of repetitive tasks involving the processing of existing information. Especially, advances in Information and Communication Technologies allow data-based repetitive tasks to be transferred to computers. For example, bank tellers, switchboard operators, office and administrative professionals responsible for static works, filing clerks are examples of employees in this group.

iii) Non-routine & cognitive tasks: This group includes jobs that involve both the production and processing and analysis of information, which are non-coding and non-repetitive, and require cognitive ability. Non-routine cognitive jobs are often performed by professionals, managers, and people who are employed in creative positions and are often described as high-skilled. The RBTC hypothesis states that it is difficult to completely replace non-routine cognitive tasks with technology, technology plays a complementary role for such tasks, and consequently increases their productivity. At this point, again, according to the RBTC hypothesis based on the ALM, two different non-routine & cognitive tasks can be mentioned: a) non-routine interactive cognitive tasks are professions that require creativity, flexibility, and complex communication skills, and involve some managerial and interpersonal responsibilities. b) non-routine analytical cognitive tasks require the ability to solve complex problems and numerical abilities. Today, positions such as judges, psychologists, financial analysts, computer programmers, medical doctors, or human resources specialists are examples of non-routine cognitive jobs.

iv) Non-routine & manual tasks: The definition and examples of tasks in this group may be more problematic than others. Because, according to Autor et al. (2003), non-routine manual tasks are not repetitive and cannot be easily completed with technology, nor can they be fully replaced by technology. However, for example, the *"truck driving"* profession, which is given as an example of non-routine manual tasks in Autor et al. (2003), is among the professions that are trying to be fully automated today, and there are pilot studies conducted by famous truck companies on this subject (Crandall and Formby, 2016; Viscelli, 2018). Besides, Autor (2015) gives the example of The Google Car, citing how technical advances can overcome existing technology barriers to accomplish non-routine tasks, through the vehicle's adaptation to real-time variables, and in fact, he makes a correction to his definition of driving task as *"non-routine and manual"* in Autor (2003), published 12 years before this study. Therefore, a profession that was defined as *"non-routine and manual"* in 2003 is now on the way to becoming *"routine-manual"*, which shows that the degree of the routine of tasks may change over time. Because technology can offer opportunities that are very difficult to predict, the impact of this situation on employment can progress unexpectedly. Notwithstanding, jobs that are not prone to automation for now, such as janitors, home health care services, can be shown as examples of today's non-routine manual jobs.

Table 2.1. Technology effect and automation risk level by skills and job types

Risk Level of Automation by Jobs and Skills			
		High Skill	Low Skill
Automation Risk	High Risk	Routine & Cognitive	Routine & Manual
	Low Risk	Non-routine & Cognitive	Non-routine & Manual
Anticipated Impact of Technology on Employment and Wages by Job Types			
Job Type with Skill Intensity		Employment Effect	Wage Effect
Non-routine & Cognitive		Positive	Positive
Non-routine & Manual		Positive	Negative
Routine & Cognitive		Negative	Negative
Routine & Manual		Negative	Negative

Source: World Bank, (2016); WTO, (2018).

In Table 2.1, the possible employment effects of the technology for both SBTC and RBTC are shared. Although studies at the firm and sectoral level focus on specific areas, especially manufacturing, technological change presents powerful opportunities that can lead to significant transformations and changes not only in the way of production and doing business, but also in the overall economic structure. In addition to many types of robots and machines used in production today, the effects of fields such as big data, artificial intelligence, and machine learning, augmented reality and the internet are indisputable. Therefore, while technology completely takes over unskilled jobs, as the previous literature has focused on, on the other hand, it can complete and even perform cognitive tasks that require more complex abilities. Consequently, the possible impacts in Table 2.1 may change in the future.

The impact of technology on the earnings of employment or occupational groups mostly depends on the labor supply. Non-routine cognitive tasks can be defined as high-skill jobs and these jobs require higher education and cognitive skills. Technological advances are then responded to by increased demand for labor, but because these jobs are executed by highly skilled workers, there is a barrier to entry into this employment group, and in fact, the labor supply is relatively inelastic. Low labor supply elasticity naturally increases average wages. Although recent developments in computerization are targeting high-skilled jobs such as ICT, AI, and Machine Learning, the demand for the workforce is still increasing as developments in this field have not yet reached the point where it will negatively affect high-skilled employment. As a result, firms need skilled labor in return for their R&D investments, and this increases high-skilled employment over time. In contrast, workers in the medium-skill group are likely to gravitate towards low-skill rather than high-skill jobs, as skill upgrading is time-consuming, costly, and in some cases not feasible. This will increase the labor supply in the low-skill group and the surplus in the labor supply will cause average wages to decline over time. As a result, workers in jobs with automation risk have two options: jobs that offer lower wages and less satisfaction and require less skill, and jobs that are more satisfying and desirable but cannot be achieved with the current education and skill level (Saunders, 2017). As listed in Autor et al. (2016), in the USA the shares of two opposite poles increased from 1979 compared to 2016, while the share of middle-skilled workers decreased from 61% to 43%. A similar pattern can be mentioned in Turkey, while the share of medium-skilled employment was around 75% in the early 1990s, this ratio dropped below 64% towards 2020 (ILO, 2021).[7]

Although the RBTC approach replaces SBTC to explain the changes in the structure of existing labor markets, it has some limitations in terms of its applicability (Sebastian and Biagi, 2018). First, the sharp distinction between tasks as routine and non-routine can be problematic in itself. As stated by Matthes et al. (2014), a task that is not perceived as routine by a worker may actually be routine for robots or machines. In parallel with this, Green (2012) states that it is not possible to predetermine routine and non-routine works, and there are some problems in the validity of the routine-non-routine distinction. Another problem with this approach is the uncertainty about what tasks cognitive tasks involve, although the definition of routine and non-routine work can be made sharply in theory and practice. Routine tasks, by definition, involve little or no cognitive tasks; when the reverse of this situation is accepted as true, making a cognitive task distinction becomes meaningless. On the other hand, in many studies, cognitive tasks are defined as tasks that require data processing ability or problem-solving ability, in which case both routine and data processing tasks should not be included in the cognitive class (Eurofound, 2014; Sebastian & Biagi, 2018). Besides, as mentioned earlier, the distinction between routine and non-routine may change over time as in the truck driver example in Autor et al. (2003) and Autor (2015).

In addition, there are some problems with the classification of tasks in the RBTC approach, and task indexes can be determined arbitrarily or subjectively in studies. For example, business areas such as management tasks and quality control are included in the class of non-routine cognitive tasks according to the current RBTC definition, but it would not be wrong to say that both management tasks and quality control tasks can become routine over time depending on the organizational structure and nature of the work. The diversity of data sources and the use of survey techniques, in general, brings with it several disadvantages, which makes it difficult to compare RBTC studies among themselves

[7] These statistics were calculated using *"Employment by economic activity and occupation"* data published by International Labor Organization (ILO, 2020).

(Sebastian and Biagi, 2018). Susskind (2017) also criticizes the task-based employment-technology relationship discussed in Autor (2015), which generally includes an optimistic approach. Susskind (2017) states that, in fact, tasks that cannot be automated are completed with traditional capitals, and the value of these tasks moves in the same direction as the amount and productivity of capital. Also, he argues that labor cannot be integrated with completed tasks indefinitely, but enhanced capital will erode the types of tasks it completes. The increase in quantity and productivity concomitantly reduces the types of completed tasks for which labor retains its comparative advantage, resulting in available labor having to specialize in declining tasks. Thus, Susskind (2017) opposes the optimistic view and instead proposes a new model in which labor is brutally displaced and there is a steady decline in absolute wages.

Susskind (2017) counters Acemoglu and Restrepo's (2018) notion that despite labor shortages producers will tend to create new tasks in which labor has a comparative advantage, through the main example of comparing horses and humans. Acemoglu and Restrepo (2018), as a counterargument for the statement in Leontief (1952) that is *"labor shares the fate of horses; manpower becomes less and less important and is completely replaced by machines"*, emphasize that *"there is a major difference between horses and human labor, that humans have the ability to perform more complex tasks. Horses did not. If this comparative advantage is significant and the creation of new tasks continues, employment and the labor share can remain stable in the long run even in the face of rapid automation"*. But Susskind (2017) opposes Acemoglu and Restrepo (2018) on this point, asking *"if the technological change has also led to declining horse shortages, why hasn't there been an increase in new types of tasks in which horses have a comparative advantage in the 20th century?"* poses a question. Susskind (2017) states that the framework drawn by Acemoglu and Restrepo is the supply-side, based on the fact that producers create new types of jobs to get output. Moreover, he states that the demand for new products and services also shapes the demand-side approach and reveals more optimistic perspectives. At this point, it should be added that Susskind (2017) ignores the differentiation of horses and humans in terms of labor by comparing horses with human power. Because people actually used horses as a machine technology upgraded these machines and offered more advanced ones. Thus, in this example, it may be more accurate to compare horses with robots that complete human labor rather than directly comparing with human labor. Of course, other issues should also be considered here. Even when compared to manpower, for example, there is no employment agency for horses, nor is there any social awareness of equine unemployment issues. On another note, it does not seem possible for horses to adapt themselves to the new workforce structure. This reveals the importance of tasks that require cognitive ability. Finally, Susskind (2017) concludes that being able to talk about optimism in the employment-technology relationship will only come after the new goods and services that need to be produced require tasks in which labor has a comparative advantage and that the destructive effect of technology on employment will occur in cases where capital has a comparative advantage.

As a result, in the RBTC approach, unlike SBTC, the focus is on tasks, and it is thought that routine work is taken from manpower and given to machines with the effect of technology. At this point, the most important pillar of RBTC is job polarization. However, the empirical literature given in the next sections reveals that job polarization is heterogeneous and it is not observed in some countries and may even disappear in the future (Frey and Osborne, 2017).

2.3.4. Technology and Unemployment in Developing Countries

In addition to the many opportunities technology already offers to economies, problems such as the replacement of human labor by machines (Brynjolfsson and McAfee, 2012; Frey and Osborne, 2017), the possibility of increasing income inequality (Acemoglu and Autor, 2011), and the increase in the share of informal jobs that affect the quality of jobs created (OECD, 2018) affect not only developed economies but also developing economies. However, the differences in the initial conditions of developed and developing countries, their different economic dynamics and social structures, and the spread of technology to developing countries, mostly from developed countries, support the idea that its effects may pose a greater threat to developing economies. However, factors such as the comparative advantage of the labor force due to the relatively low cost and the slow technology adoption in developing countries delay the high-risk level to turn into job loss at the same rate. On the other hand, the faster growth of the workforce relative to the population in developing economies already raises concerns that not enough jobs will be created for everyone. With the transfer of routine tasks to machines and the general increase in demand for higher-level skills, the already high-income inequality can become even more tragic in the process (Soto, 2020).

Technological advances in developing countries are mostly imported, in other words, they are related to foreign direct investments and technology transfers (Acemoglu, 2003; Vivarelli, 2014). Technology transfers rapidly from the developed world to middle-income countries, but for low-income developing countries this is still not clear. Rapid technology transfer from high-income countries to middle-income countries enables the upgrading of existing machinery or technology in general (Vivarelli, 2014). In addition, R&D intensity in technological change in developing countries is different than in developed countries. Product innovations based on R&D are less common in developing countries. Compensation mechanisms may also not work efficiently in developing countries: mechanisms that operate through reductions in wages or prices are less effective than in developed countries due to less competitive market conditions. The contribution of new investments or increase in income to employment is less than in developed countries. However, R&D activities in developing countries gain importance over time and become a meaningful technology proxy. Because although the technological progress of developing countries is based on technology imports, it would not be right to completely ignore the impact of R&D expenditures. Technology transfer of countries cannot be considered completely independent of R&D expenditures. In particular, high-tech intermediate or final goods realized at the firm and sectoral level can be the previous or next stage of R&D expenditures. Finally, the intensity of R&D expenditures also indicates the nature of the knowledge stock available in developing countries and thus the level of imported technology, as countries import technologies they can use. It would be appropriate to say that the focus of many studies in the literature on what innovations change in the labor market is advanced economies and that there are limited studies in this field based on the developing world (Vivarelli, 2014; Soto, 2020). Parallel to this, it is an important fact that there are many policy recommendations for developed economies, but the emerging world is also weak in this regard. On the other hand, although theoretically many tasks can be automated in many emerging economies, it is clear that automating them is not as easy and fast as in theory. Because automation is not yet economically attractive in these countries and there is still an abundance of cheap labor. In other words, technology is adopted more slowly due to the relative superiority of labor costs over machines. The expanding scope of automation and potential market disruptions associated with labor polarization are likely to affect emerging economies later than advanced economies. For this reason, the negative impact of technology, especially on low-skill groups, in developing countries may be slower and smaller than in developed countries.[8]

2.3.4.1. Technology, skills and tasks in the DCs

While technology increases the demand for high-skilled workers in developing countries, as in developed countries, it can have a negative effect on low-skilled workers. As discussed in Lee and Vivarelli (2006), the effect on unskilled workers can be just the opposite; specialization in unskilled labor-intensive products in developing countries can increase the demand for unskilled workers. Secondly, if technology and trade are considered as complementary factors when technology transfer from developed countries to developing countries is experienced rapidly, there is a need for high-skilled workers at similar levels in developing countries. However, developing countries may have difficulty in responding to this demand due to the fact that the current average worker skill levels are not suitable (Vivarelli, 2014).

While Berman and Machin (2000) discuss technology transfer between high, middle, and low-income countries within the framework of skill-biased employment, it is stated that rapid technology transfer from high-income countries to middle-income countries ensures rapid skill upgrade and adaptation but indicates that the process is slower in low-income countries. Meschi and Vivarelli (2009) highlight the results in favor of

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[8] A detailed comparison on this topic is covered under the heading *"Future of Jobs"* at the end of Chapter 2.

skill-biased technical change and wage inequality stemming from trade and technology transfer with high-income countries in middle-income countries and reiterate that technology is one of the main factors determining the demand for qualified workers in developing countries.

There are differences in the direction and severity of the impact in studies that focus on individual countries rather than groups of developing countries, and this issue is covered in detail in the empirical literature. As a result, the effect of technology on employment is more uncertain in developing countries, as this group of countries is more heterogeneous in structure. Therefore, it should be taken into account that developed economies are at the center of the theoretical frameworks and presenting the same approaches for developing economies may be misleading.

2.4. Technology and Unemployment: Empirical Evidence

While there are many important empirical studies on the relationship between technology and employment, especially at the micro and sectoral level, it can be said that the studies at the macro level are more limited at this point. Comprehensive literature reviews of these empirical studies are detailed in Tether et al. (2005), Pianta (2005), Vivarelli (2014), and more recent studies Calvino and Virgillito (2018) and Dosi et al. (2021) and these studies present really important literature surveys in this field.

The technology-employment relationship is a complex one, and the direction and severity of the relationship may differ at the micro or macro level. Moreover, the direction and magnitude of the effect may differ in different firms in the same industry, or in the same firms in different periods. R&D investments, which are the source of the advancement of technology, are affected by many external factors. For example, intellectual property rights regulations for the protection of patents or ideas may affect technology positively, but also delay the copying and dissemination of new techniques and products produced.

Measuring technology at the micro level and observing the results of technology-oriented investments such as R&D expenditures are somewhat easier than at the macro level, and thus empirical analyses of the technology-employment relationship at the macro level may involve more methodological problems. In studies conducted at the firm or sectoral level, it is possible to distinguish especially product and process innovations, and thus effects such as labor-saving and labor creation can be detected more easily (Calvino and Virgillito, 2018). However, it should not be overlooked that sectoral analyses are also affected by many factors and may include the same problems. Because it is obvious that companies or different industries are affected by events at the macro level. On the other hand, in studies at the sectoral level, employment is likely to be shaped up or down due to the nature of the industry or the firm. Finally, since micro studies focus on a specific firm, sector, or sector group, it is not correct to generalize the results to the macro-level or to other country groups. In particular, studies at the firm level are often based on technology-intensive companies, which causes biased results. In sectoral level studies, the cross-sectoral transition is often overlooked. In both cases, it can be seen that the technology-intensive firm or sector whose data is used ignores the employment trend in firms or sectors other than themselves and use relatively less technology. This reveals that the way to see the overall effect is again through macroeconometric studies.

In this section, firstly, microeconometric studies are discussed and for this purpose, empirical studies conducted first at the firm level and then at the sectoral level are summarized. Some of the firm- and sector-level results were obtained from the same study, as some of these studies looked at both firm and sectoral impact in a comparative manner. After the micro-level results, macro-level empirical studies that present narrower literature are included. At the end of the chapter, a summary of the studies that deal with the impact of technology on employment according to skill and task-based approaches is presented, followed by predictions for the future.

2.4.1. Micro Level Studies

Empirical studies on the technology-employment relationship have mostly been conducted at the micro-level for reasons such as making the distinction between product and process innovation easier, finding data for more time points, choosing various technology proxies suitable for the chemistry of the sector, and monitoring the differences and transitions between sectors. Although technology proxies used in empirical studies are often difficult to obtain and the extent to which these indicators represent technology is debatable, both R&D investments and patent numbers remain strong indicators for researching the technology. But sometimes embodied technological changes can be more important in areas where in-house R&D activities are limited. Especially in some traditional industries or small or medium-sized enterprises where innovation is achieved with capital goods, technological progress depends on outsourced machinery (Vivarelli, 2015). Therefore, it is not sufficient to measure technology directly by R&D in such sectors or companies and it may be necessary to use different indicators. This is especially important in developing countries, as technology imports are more intense (Frey and Rahbari, 2016; Soto, 2020).

Micro-econometric analyses that deal with the technology-employment relationship also include some disadvantages. First of all, studies carried out at the firm or sectoral level cannot fully demonstrate the effectiveness of the compensation mechanism. Secondly, it is very critical to assess that micro-analyses tend to show the positive effect of employment mostly, there is a kind of *"positive bias"* situation (Vivarelli, 2014). Especially when the empirical analysis is accomplished with a single company, the innovative company increases its employment as it increases its market share. However, if the *"business stealing effect"* is ignored, especially in studies focusing on single-firm or specific companies, the destructive effect of technology on rival companies is not taken into account, and reports are made that technology increases employment at the firm level. However, the new technology used by the company may push some of the rival companies out of the sector, which should be recorded as a negative employment effect.

2.4.1.1. Firm Level Studies

The relationship between technology and employment at the firm level is the main subject of many empirical studies, and there are of course a number of important considerations when examining a relationship at this level and interpreting the results. In empirical analyses of employment-technology relationship at the firm level, technology is usually represented by R&D expenditures, number of patents, innovation intensity, number of machines, number of computers, technical equipment density, and technology-innovation indexes measured by survey data obtained from firms. On the other hand, a significant number of empirical studies also pay attention to the product-process innovation distinction, but mostly the possible negative effects of the latter are ignored. Thus, most firm-based empirical studies share a common characteristic, which often leads to reporting of a positive impact of technology on employment. However, these studies are not sufficient to directly show the effect of technology on employment. Because the compensation mechanism for the technology-employment relationship is a more general and aggregate concept, but company dynamics may contain features and temperaments that are too specific to generalize. Still, of course, these analyses provide valuable insights into the impact of innovation for specific industries.

In this section, while sharing empirical studies at the firm level, a certain chronology has been tried to be adhered to. However, this chronology is occasionally neglected because some studies have common points and focus on similar issues. A list of these studies is shared in Table 2.2.

The common point among the early firm-based studies is that the source of technology and employment data is various labor force surveys and statistics on R&D investments obtained from these surveys. For example, Machin and Wadhwani (1991) determined the positive effect of innovation on employment in the manufacturing sector, with data obtained from the 1984 British Workplace Industrial Relations Survey in the United Kingdom. With survey-based data on more than 850 Dutch manufacturing firms from 1983-1988, Brouwer et al. (1993) find that although the employment effect of product innovation is positive, the overall innovation effect as measured by R&D data is negative. Meghir et al. (1996) and Van Reenen (1997) identify a positive employment-innovation relationship in the manufacturing sector with the Science Policy Research Unit's (SPRU) data covering the years 1976-1982 in the United Kingdom. Using the SPRU innovation database and patents data of the UK, Meghir et al. (1996) found that companies with high innovation levels at the firm level and in the manufacturing sector for the years 1976-1982 had lower adjustment costs than non-innovative companies, and this situation had a positive effect on employment. Van Reenen (1997) states that technological innovations had a positive effect on employment at the firm level between 1976-1982 in a study using a panel of approximately 600 British manufacturing companies.

Using data from more than 8,000 Italian manufacturing firms for the period 1981-1985, Vivarelli et al. (1996), although positive employment effects were observed in some sectors characterized by high engineered products and higher product innovation percentages; they emphasized the overall negative impact of innovation on employment due to the overall dominance of process innovations. Using data on more than four-fifths of manufacturing employment in Norway from 1982 to 1992 in a northern European example, Klette and Førre (1998) found that there was no clear positive relationship between net job creation and the firm's R&D intensity. They claimed that firms with the highest R&D intensity lag behind the rest of the manufacturing sector in terms of employment growth, which differs sharply from studies using similar variables and methods. Blanchflower and Burgess (1998) in their multi-industry study of the Australian and British sample calculated that new technologies increase employment in related firms by an average of 1.5% and 2.5% per year, respectively. Regev (1998), using data from Israeli industrial firms from 1982 to 1993, developed a technology index for these firms and reported that high-tech firms tend to create net jobs and that these firms are important players in industrial performance. In addition, he stated that they have a large share in labor capital and production compared to other companies, and also drew attention to the fact that they are more productive, offer higher salaries, and generate higher added value and profit per worker and capital. Greenan and Guellec (2000) reported a similar effect for more than 15,000 French firms for the 1986-1990 period and found that innovative ones created more jobs. The authors stated that the positive employment-technology relationship at the firm level is valid for both product and process innovation, more so in process innovation, which the study differs from in this aspect because according to the theory, process innovations have labor-saving characteristics. The authors attribute the positive employment contribution of process innovations at the firm level to increased demand through reductions in prices. Greenhalgh et al. (2001), used both R&D

expenditures and patent data for the years 1987-1994 belonging to UK manufacturing companies, state that the R&D effect is higher in high-tech firms, and the patent effect is higher in mature technology firms, both being positive. Smolny (2002) reported that among firms operating in the manufacturing sector in West Germany for the period 1980-1992, innovative ones were generally more successful than non-innovative ones, producing more output and showing greater employment growth. Ali-Yrkkö (2005) examines the effect of public R&D financing on both R&D employment and non-R&D employment, using data from Finnish companies for the 1997-2002 period. In the study, it is stated that R&D funding has a positive and significant effect on employment in the R&D field, while there is no significant effect in non-R&D employment fields. Piva and Vivarelli (2005), state that technology affects employment positively, but the severity of the effect is quite low, based on the innovation data they obtained through surveys in their studies covering the years 1992-1997 and 575 Italian manufacturing companies. In similar studies conducted by Yasuda (2005) with data from Japanese manufacturing firms (1992-1998) and Yang and Huang (2005) Taiwan electronics industry firms (1991-1998), it is stated that R&D expenditures per worker positively affect firm growth as measured by the number of employees. Using a method similar to Piva and Vivarelli (2005), Yang and Lin (2008) found that product innovation had a positive effect on all companies and process innovation only on companies with high R&D intensity between 1999-2003. They found that process innovation shows labor-saving characteristics in low R&D intensive firms.

Table 2.2. Firm level studies

Study	Country	Period	Employment Effect of Technology
Machin and Wadhwani (1991)	United Kingdom	1984	Positive effect of innovation in manufacturing.
Brouwer et al. (1993)	Netherland	1983-1988	Positive effect of product innovation in manufacturing. Negative but weak effect of product & process innovation in manufacturing.
Meghir et al. (1996)	United Kingdom	1976-1982	Positive effect of innovation in manufacturing.
Van Reenen (1997)	United Kingdom	1976-1982	Positive effect of innovation in manufacturing.
Vivarelli et al. (1996)	Italy	1981-1985	Positive effect of innovation in such sectors related to product innovation. Negative overall effect of innovation.
Klette and Førre (1998)	Norway	1982-1992	No net effect of innovation.
Blanchflower and Burgess (1998)	Australia & Britain	1989& 1989-1990	Positive effect of innovation.
Regev (1998)	Israel	1982-1993	Positive effect of innovation in the manufacturing industry.
Greenan and Guellec (2000)	France	1986-1990	Positive effect of product & process innovation in manufacturing firms. Positive effect of process innovation is greater.
Greenhalgh et al. (2001)	United Kingdom	1987-1994	Positive effect of innovation in manufacturing.
Smolny (2002)	Germany	1980-1992	Positive effect of innovation in manufacturing.
Ali-Yrkkö (2005)	Finland	1997-2002	Positive effect of innovation in R&D related firms. Insignificant effect of innovation in non-R&D firms.
Piva and Vivarelli (2005)	Italy	1992-1997	Positive but weak effect of innovation in manufacturing firms.
Yasuda (2005)	Japan	1992-1998	Positive effect of innovation in manufacturing.
Yang and Huang (2005)	Taiwan	1991-1998	Positive effect of innovation in fast growing manufacturing firms.
Yang and Lin (2008)	Taiwan	1999-2003	Positive effect of product innovation in all manufacturing firms. Positive effect of process innovation in high R&D intensity manufacturing firms. Negative effect of process innovation in low R&D intensity manufacturing firms
Harrison et al. (2008, 2014)	France, Germany, Spain, United Kingdom	1998-2000	Positive effect of product innovation in both manufacturing and service firms.
Herstad and Sandven (2008)	Norway	2004-2010	Positive effect of both product and process innovation.

Table 2.2. ***(Continued)***

Study	Country	Period	Employment Effect of Technology
Benavente and Lauterbach (2008)	Chile	1998–2001	Positive effect of product innovation in manufacturing and energy firms. Insignificant effect of process innovation in manufacturing and energy firms.
Zimmermann (2009)	Germany	2003 & 2005 & 2006	Positive effect of both product and process innovation in SMEs. Positive effect of process innovation is greater.
Hall et al. (2009)	Italy	1995-2003	Positive effect of product innovation. Insignificant effect of process innovation.
Stam and Wennberg (2009)	Netherland	1994-2000	Insignificant overall effect of innovation. Positive effect of innovation in fast-growing & young firm.
Meriküll (2010)	Estonia	1994-2006	Positive effect of product & process innovation. Positive effect of process innovation is greater.
Lachenmaier and Rottmann (2011)	Germany	1982-2002	Positive effect of product & process innovation in manufacturing firms. Positive effect of process innovation is greater.
Coad and Rao (2011)	United States	1975-2002	Positive effect of innovation in high employment growing firms. Negative effect of innovation in high jobs losing firms.
Crespi and Tascir (2012)	Argentina, Chile, Costa Rica, and Uruguay	1995-2009	Positive effect of product innovation. Negative but weak effect of process innovation just in Chile.
Bogliacino et al. (2012)	European Firms	1990-2008	Negative but small overall effect of innovation in manufacturing and service firms. Insignificant effect of innovation in traditional manufacturing firms. Positive effect of innovation in service and high technology firms.
Evangelista and Vezzani (2012)	EU	1998-2000 & 2002-2004	Positive effect of product & process innovation manufacturing and service firms. Insignificant effect of process innovation.
Triguero et al. (2014)	Spain	1990-2008	Positive effect of process innovation in manufacturing SMEs. Insignificant effect of product innovation.
Ciarli et al. (2018)	Britain	2001 & 2011	Positive effect of innovation for high-skilled employees in nonroutine jobs. Negative effect of innovation for low-skilled employees in routine jobs.
Van Roy et al. (2018)	European Firms	2003-2012	Positive effect of innovation in high and medium technology manufacturing firms. Insignificant effect of innovation in low technology manufacturing and service firms.
Camiña et al. (2020)	Spain	1990-2016	Negative effect of process innovation in industrial firms.
Ortiz and Fumas (2020)	Spain	2003-2014	Positive effect of both product and process innovations.
Laguna and Bianchi (2020)	Uruguay	2007-2015	Positive effect of both product and process innovations.

Note: This table lists the important work done at the firm level. Some of these studies also cover the sectoral level. Although the technology variables used in the studies may differ, they are all expressed as *"innovation"* in this table. In Crespi and Tascir (2012), the data periods are country-specific and in the table, the broadest period is included.

While previous studies examining firm-level R&D expenditures pay more attention to sector-oriented distinctions and focus specifically on the manufacturing industry, recent studies address the relationship in more than one dimension. In this direction, factors such as the age of the company, the economic size of the company, the level of technology they use, the geography where the company is located, and the current employment profile, in addition to the sector in which the company operates, of course, affect the direction and magnitude of the technology-employment relationship.

With comparable firm-level data from France, Germany, Spain, and the United Kingdom for the 1998-2000 period, Harrison et al. (2008, 2014) found that product innovation in the manufacturing industry is associated with employment growth, but there is no strong evidence that jobs are being destroyed through process innovation. In the study, first of all, a theoretical model that examines the effect of product and process innovations on employment is developed and econometric analysis is applied with the aforementioned data in order to test this model. According to the findings of the study, new jobs created with new products are more than jobs lost due to new products. Instead, they claim that jobs lost due to the problem of *"product stealing"* after product innovation account for one-third of the jobs created. In addition, the authors state that the specified mechanism works with the same efficiency in both the manufacturing and service sectors, which is different in most of the previous studies. In addition, the authors state that the main source of employment increase in firms is product innovations. On the other hand, another finding of the study is that process innovations do not reduce employment. They claim that although some jobs disappeared due to process innovation in the time frame included in the study, the increase in demand compensates for this destruction effect. Therefore, the mechanism of *"increase in demand with decreasing prices"* mentioned in the theoretical literature is also observed in this study empirically. Finally, as noted by the authors, one of the main shortcomings of the study is that it ignores workers in different skill groups. Because both types of innovation can create new jobs; however, not every created job may be a suitable opportunity for every employee whose job has disappeared. The theoretical approach, which is based on the studies of Harrison (2008, 2014) and models the employment-technology relationship at the firm level, has been used in different studies and investigated on data belonging to different countries or country groups. For example, Hall et al. (2009), using data from 1995-2003, examine the displacement of existing jobs due to technology in Italy. In the study, there is no evidence of a job displacement caused by process innovation; On the other hand, it is claimed that employment growth is affected equally by product innovation and the increase in sales of obsolete products. Besides, Hall et al. (2009) estimate the effect size of product innovation on employment to be lower than Harrison et al. (2008). Finally, the authors state that no effect of innovation increase on productivity was observed in the specified period. Parallel results with this study are obtained by Benavente and Lauterbach (2008) in the case of Chile for the years 1998-2001. While it is emphasized that product innovations have a significant and positive effect on employment, in the survey data of the manufacturing and energy sectors and covering 560 companies, no statistically significant relationship can be detected between process innovations and employment. Using different cross-section data from Argentina, Chile, Costa Rica, and Uruguay between 1995 and 2009, Crespi and Tascir (2012) state that one of the main factors in firm-level employment growth is product innovation. The authors also underline that process innovation has a slight negative impact on the labor force.

Stam and Wennberg (2009) examined the employment-innovation relationship using the data of 647 new Dutch companies covering the years 1994-2000. When all firms are taken as a basis, it is concluded that there is no significant relationship between R&D investments in the early stages of firms, that is, in their young years, and their employment levels. According to an essential conclusion of the study, R&D investments in the early stages of fast-growing and high-tech companies play an important role in employment. Hölzl (2009) investigates the relationship between technology, employment, and growth in SMEs using Community Innovation Survey III (CIS III) data and covering the period of 1998-2000 for 16 European countries. The countries analyzed in the study are divided into three groups according to their technology levels, and according to the findings, technology has the highest positive effect on employment in high-growth companies in the countries closest to the technological frontier. While this is the case in small and medium-sized companies that have just entered the sector, Bogliacino et al. (2012), focusing on larger companies, researches the technology-innovation relationship by using the data of 677 European companies operating in the manufacturing and service sectors between 1990 and 2008. According to the prominent results of the study in which the Least Squares Dummy Variable Corrected (LSDVC) method was used, a) R&D investments generally have a labor-friendly effect, but this effect is not very large. b) R&D expenditures do not have a significant effect on employment in manufacturing firms that use low technology or, in other words, *"traditional methods"*. c) R&D expenditures in the service sector and manufacturing sector using high technology positively affect employment. Based on these results, the authors state that one should not expect that R&D has a positive effect on employment in the majority of industrial sectors. Because the R&D investments used in the study are related to product innovation with a labor-friendly effect, the process is insufficient to capture the effect of innovation.

Coad and Rao (2007, 2011) examine high-tech manufacturing firms based in the United States. They use both R&D and innovation indicators such as the number of patents provided by the National Bureau of Economic Research (NBER), covering the years 1975-2002. In their findings obtained by the weighted least squares (WLS) method, the authors state that the effect of innovation on employment may have been underestimated in previous empirical analyses and conclude that the job-creation effect of technology is generally valid in United States manufacturing companies: a) Firms with fast-growing employment owe this to their past innovation activities. b) The job destruction effect in firms experiencing the greatest employment contraction seems to be related to innovation. c) Innovation activities in large firms affect employment more positively than small firms. Then again, the authors mention the highly variable and fluid structure of the American job market compared to other countries as an important limitation of the study and therefore emphasize that the generalization of the results is not correct. In fact, this is true for all firm-level studies. Because the characteristic structures of each firm and the sectors in which the firms operate, as well as the countries in which the sectors operate, are different from each other, it is reasonable to evaluate the results in this direction in firm-based studies. In Herstad and Sandven (2008) and Zimmermann (2009), companies in Norway and Germany, respectively, are studied and the innovation-employment relationship is examined in terms of different innovation types. Herstad and Sandven (2008), with data covering the years 2014-2010, indicate that both process and product innovations affect employment positively; state that the magnitude of the effect is greater when these two innovations are evaluated together. On the other hand, Zimmermann (2009) states that both product and process innovation have an employment-increasing effect in both expanding and contracting SMEs, with the effect of process innovation being higher. Meriküll (2010) investigates the effect of innovation-employment at the firm level for the period 1994-2006 with 2,783 companies operating in Estonia and classified as low, medium, and high-tech, and this study is important in that it deals with a mid-level economy, unlike its counterparts. The results show that, overall, innovation positively and statistically significantly affects firm-level employment; the impact is reported to be greater in terms of process innovation than product innovation, which is in line with Greenan and Guellec (2000) and Zimmermann (2009).

Lachenmaier and Rottmann (2011) examine the relationship between product and process innovations on employment, using both R&D and patent indicators in their study covering the years 1982 and 2002 and involving companies in Germany. According to the results obtained by using the SYS-GMM method, with data containing 1073 firms in total and an average of 9 observations per firm, product innovations mostly affect employment in the second lag, while process innovations affect employment positively and significantly in both the first and second lags. Moreover, by stating that the positive effect of process innovations is greater than that of product innovations, the authors reach a conclusion that overlaps with Greenan and Guellec (2000) and Meriküll (2010) but contradicts the theory. Finally, in the study, there is no significant difference between sectors in terms of innovation effect. Evangelista and Vezzani (2012) examine the effect of process and product innovations on employment by considering the indirect effect of innovation. Using company-level Community Innovation Survey data from the European

Union countries for the years 1998-2000 and 2002-2004, the authors state that process and product innovations together strongly increase employment in the manufacturing and service sectors. On the other hand, according to the authors, process innovation does not have a negative effect on employment when taken alone. Triguero et al. (2014) examine the innovation-employment relationship in Spain between 1990 and 2008 in terms of different types of innovation. The authors show that process innovation has a positive effect on employment in SMEs and large firms, and the impact on SMEs increases as lag increases; reports that there is no significant relationship between product innovations and employment.

Ciarli et al. (2018) state that R&D-intensive superstar firms employ proportionally fewer workers despite their increasing gains from R&D. Ciarli et al. (2018) show that R&D has a positive effect on the high-skilled employment group specializing in non-routine jobs in the UK local labor market, conversely, it has a negative effect on low-skilled employment in routine jobs. In addition, the authors point out that the impact of R&D in the routinized labor market in the short term will lead to more polarization. The authors stated that R&D positively affects employment in the fields of manufacturing, transport, and business and financial services by sectors, regardless of skill and routine-nonroutine distinction; on the other hand, it reports that the effect is negative in the construction and wholesale sectors.

Van Roy et al. (2018) examine the effect of innovation on employment with the data of 2003-2012 covering nearly 20000 patenting companies in Europe and the System GMM method. In their studies, which they measured by the number of patents and considering the quality of the patents as well as the quantity, the authors stated that innovation increases employment in high-tech and medium-tech manufacturing companies; but he states that this result is not valid in low-tech manufacturing or service companies. Alternatively, the authors stated that patented innovations were used in the study, and non-patented innovations (mainly process innovations) were ignored; therefore, the labor-saving effect of the technology was not taken into account. In this direction, it is important that the results are interpreted at the firm level and not considered as an overall conclusion on the technology-employment relationship. Instead, the authors emphasize that the patent is an important technology proxy for the manufacturing sector, but that it may be insufficient to show the innovations in the service sector and emphasize that the statistically insignificant relationship in the service sector should be interpreted in this direction.

Camiña et al. (2020) examine the relationship between automation, employment, and productivity using data from 5511 manufacturing companies in Spain. The model used in the study is adapted from the model of Van Reenen (1997), and the assumption of constant returns to scale and a perfectly competitive market is applied in this model. According to analyses based on data from the Business Strategy Survey covering the years 1990-2016, the use of industrial robots and flexible production systems in Spain reduce employment. However, the authors state that in the long run, investment in automation increases productivity and demand in the long run, and the negative effect on employment can be compensated. Ortiz and Fumas (2020) examine the labor demand effect of firm-level innovation in Spain in their study covering the years 2003-2014. The authors state that the process and product innovations realized together in the period included in the study have a significant and positive effect on labor demand. On the other hand, the authors state that the effect is in the counter-cyclical direction and that it is higher in recession periods considered after 2008 than in expansion periods considered before 2008.

As a result, although a labor-friendly effect is generally observed in firm-based studies where R&D and patent indicators are used as technology-innovation proxies, this positive relationship is mostly valid for high-tech companies in the manufacturing sector. On the other hand, most of the studies are focused on the United States or developed European countries, so the results should be considered in this context. It should also be noted that in most of the studies, no significant effect of technology on employment is observed especially in low-tech manufacturing firms; on the contrary, some of them mention the job-destruction effect of innovation. In addition, whether the studies distinguish between product and process innovations also affects the results. However, to make a general conclusion, product innovations in developed countries have a positive effect on employment, especially in large and/or high-tech companies. Some studies consider process innovation as a whole with product innovation and evaluate the impact in this direction. Some studies state that process innovations cause job loss, albeit a small number, but the gap is closed with product innovations, and in the worst case, job loss is balanced. Finally, few studies reveal that both process and product innovations positively affect employment, whether they are considered separately or together.

2.4.1.2. Sectoral Level Evidence

While examining the literature on the employment-technology relationship at the sectoral level, it should be noted that some studies are shaped by the firm level. On the other hand, it is possible that there are some differences between the findings obtained at the firm level and the sectoral level. Despite the positive technology-employment relationship reported in most of the firm-level studies, it is observed that the situation at the sectoral level is generally in the opposite direction (Feldman, 2013). Pianta et al. (1996) state that a considerable number of sectors in European countries have observed a decrease in employment due to labor-saving, which indicates heterogeneity between sectors and countries. Hence, it is observed that most of the empirical studies carried out at the sectoral level in the literature focus on the manufacturing sector, and it is not difficult to guess that sectoral differences can change the direction or size of the innovation-employment relationship. As Vivarelli (2014) points out, especially in the manufacturing sector, new technologies are directly channeled through labor-saving process innovations. In this case, the negativities of the labor-saving effect towards employment markets can be compensated, but this may not be possible most of the time because it depends on the effective operation of several market dynamics, as mentioned many times.

Automation certainly increases the quality in many business areas at the sectoral level by reducing costs, increasing the quality of output, and producing products in many areas that are impossible to reach with human power. Therefore, it would be correct to say that automation, or more generally technology, benefits the whole economy through various channels by increasing efficiency: a) Increased productivity provides a general sectoral growth within the industry that requires a new labor force. b) Sectors not affected by automation benefit from lower prices and costs in automation-intensive sectors, which accelerates labor transfer between industries. c) Automation is a growth trigger with the effect of capital-augmenting that increases labor demand. d) New jobs that cannot be automated have a positive impact on employment, which in turn contributes positively to aggregate demand and growth. Then again, the argument that automation is disadvantageous in terms of the labor force at the sectoral level is based on the view that productivity growth causes a decrease in labor demand (Compagnucci et al., 2019).

Although studies with common inferences or methods are shared together at some points, sectoral results are generally presented in this section depending on the chronology, and a list of these studies is shared in Table 2.3. Using the 1984 British Workplace Industrial Relations Survey of 721 private sector establishments, two studies from the early 1990s, Blanchflower et al. (1991) and Machin and Wadhwani (1991) obtained a negative raw link between ICT adoption and employment. However, when the model is controlled for work environment features and fixed effects, the same correlation turns out to be positive. Likewise, Zimmermann (1991), using microdata of 3374 companies from 16 German industries, states that technological change was one of the determining factors of the employment decline in Germany in the 1980s, in other words, one of the main causes of the unemployment problem was technological advances. Similarly, Meyer-Krahmer (1992), with various industry data from the 1980s, states that in Germany, employment is negatively affected by innovation, with the magnitude of the effect varying from sector to sector. Brouwer et al. (1993) extended their firm-level work to the sectoral level, using a cross-section of 859 Dutch manufacturing firms. They discovered a cumulative negative relationship between total R&D expenditures and employment, and on the other hand, they reported that the opposite occurs only when product innovation is considered. Contrary to these studies, Entorf and Pohlmeier (1990) and Smolny (1998) studies, which also deal with the German manufacturing sector, confirm the positive effect of product innovation on employment at the sectoral level with data from more than 2,000 companies, the first covering the years 1984 and the second 1980-1992.

Vivarelli et al. (1996), in the study of the manufacturing sector in Italy, observed a generally negative trend between the increase in productivity and employment with the data of 1985. The authors explain that this effect decomposes into a positive effect on product innovations. Doms et al. (1997) investigate the relationship between wages, employment, and technology in the US manufacturing industry with the data obtained from the Survey of Manufacturing Technology (SMT) and Worker Establishment Characteristic Database (WECD). First of all, the authors state that wages are 8-20% higher in high-tech firms compared to others. They argue that the reason for this is the quality differences among the workers. Moreover, with the quality differences, it is obvious that there is more efficiency in high-tech factories both before and after technology. The authors also point out that new technologies are more likely to be adopted in factories with skilled workforces, noting that managers at these facilities may tend to increase workforce numbers and quality in the period prior to technology adoption. As a result, the innovation-employment relationship is observed positively in the United States manufacturing industry between 1987 and 1991.

Table 2.3. Sectoral level studies

Study	Country	Period	Employment Effect of Technology
Entorf and Pohlmeier (1990)	Germany	1984	Positive effect of product innovation.
Blanchflower et al. (1991)	United Kingdom	1984	Negative correlation between ICT adoption and employment.
Machin and Wadhwani (1991)	United Kingdom	1984	Negative correlation between ICT adoption and employment.
Zimmermann (1991)	Germany	1980-1981 & 1983-1984	Negative overall effect of technological advance in manufacturing industries.
Meyer-Krahmer (1992)	Italy	1980s	Negative overall effect of R&D expenditure in various sectors.
Brouwer et al. (1993)	Netherland	1983–1988	Negative but weak overall effect of R&D. Sectors with high product-related R&D intensity
Vivarelli et al. (1996)	Italy	1985	Positive effect of product innovation in manufacturing sectors. Negative effect of process innovation in manufacturing sectors.
Doms et al. (1997)	United States	1987-1991	Positive effect of new technologies especially in high-tech firms
Van Reenen (1997)	United Kingdom	1976-1982	Positive effect of innovation in manufacturing.
Smolny (1998)	Germany	1981-1992	Positive effect of product innovation in manufacturing sectors.
Blanchflower and Burgess (1998)	United Kingdom	1989 & 1989-1990	Positive effect of innovation.
Pianta (2000)	5 European Countries	1989-1993	Job losses are higher in sectors and countries with higher innovation levels.
Greenan and Guellec (2000)	France	1986-1990	Positive effect of product & process innovation in the manufacturing industry. Positive effect of product innovation is greater.
Antonucci and Pianta (2002)	8 European Countries	1994-1999	Job losses are higher in sectors and countries with higher innovation levels.
Díaz and Tomás (2002)	Spain	1987-1996	The proportion of workers employed in high technology sectors is lower than others.
Evangelista and Savona (2003)	Italy	1993-1995	Negative overall effect of innovation in service sector. Positive effect of innovation in small and/or high-tech service firms. Negative effect of innovation in large service companies, finance, and capital-intensive sectors.
Chang and Hong (2003)	United States	1958-1996	Permanent technology shocks decrease working hours in some sectors temporarily but increase working hours permanently in more sectors.
Uçdoğruk (2006)	Turkey	1995-1997 & 1998-2000	Positive effect of process innovation in manufacturing sector especially in low-tech industries. Negative effect of product innovation in medium and high-tech manufacturing industries.
Mastrostefano and Pianta (2009)	10 European Countries	1994-2001	Positive effect of innovation.
Georgiou (2009)	European Countries	1995-2005	There is a critical level of technology use increasing/decreasing employment.
Meriküll (2010)	Estonia	1994-2006	Insignificant overall effect of innovation. Insignificant effect of innovation in the high-tech sectors, positive effect of innovation in the low and medium-tech sectors.

Table 2.3. ***(Continued)***

Study	Country	Period	Employment Effect of Technology
Bogliacino and Pianta (2010)	8 European Countries	1994-2004	Positive effect of product innovation in manufacturing and service sectors. Negative effect of process innovation in manufacturing and service sectors.
Bogliacino and Vivarelli (2012)	European Countries	1996-2005	Positive effect of R&D investments.
Bogliacino et al. (2012)	European Countries	1990-2008	Insignificant effect of innovation in traditional manufacturing sector. Positive effect of innovation in service and high technology sectors.
Buerger et al. (2012)	Germany	1999-2005	Negative effect of innovation in the chemical products sector. Insignificant effect of innovation in the transportation sector. Positive effect of innovation in electrics and electronics and medical equipment sector.
Ebenstein et al. (2015)	United States	1983-2008	Negative effect of high computer uses or capital intensity in all levels of workers.
Autor and Salomons (2017)	19 OECD Countries	1970-2007	Negative impact of productivity at the industry level but positive impact on the aggregate labor demand. Positive impact on the high-skilled workers is greater than low-skilled workers.
Graetz and Michaels (2018)	17 Advanced Economies	1993-2007	Insignificant overall effect of robots. Negative effect of robots on low-skilled workers.
Piva and Vivarelli (2018)	11 European Countries	1998-2011	Positive effect of R&D investments in both manufacturing and service sectors. Insignificant effect of R&D investments in the low-tech manufacturing sector.
Dauth et al. (2018)	Germany	1994-2014	Insignificant overall effect of robots in both manufacturing and non-manufacturing sectors.
Compagnucci et al. (2019)	16 OECD Countries	2011-2016	Negative effect of robots on labor demand in manufacturing industries.
Dang and Vu (2020)	Vietnam	2011-2017	Positive effect of high-tech imports in manufacturing industries.
Wang et al. (2020)	China	2000-2014	Positive effect of internet use and internet technologies at the industrial level.
Paul and Lal (2020)	India	2011-2012 & 2015-2016	Positive effect of ICT.
Adachi et al. (2020)	Japan	1978-2017	Positive effect of a decrease in robot prices and increase in robot adaptation.
Jung and Lim (2020)	42 Mixed Countries	2001-2017	Insignificant overall effect of robot use in manufacturing sector. Positive effect of robot use on high skilled workers but negative on low skilled workers.
Acemoglu and Restrepo (2020)	United States	1990-2007	Negative effect of the number of industrial robots per worker on labor demand.
Bessen (2020)	United States	1820-2007	Negative effect of computer use in manufacturing sectors. Positive but small effect of computer use in other sectors.
Koch et al. (2021)	Spain	1990-2016	Positive effect of robots in sectors with high technology adaptation. Negative effect of robots in sectors with low technology adaptation.

Van Reenen (1997) and Blanchflower and Burgess (1998) have implications for the UK at the industrial level as well as the firm level, and the results are in line with the firm level. Van Reenen (1997), in his study covering approximately 600 manufacturing companies between 1976-1982, found a positive relationship in terms of employment and innovation at the sectoral level using the generalized method of moments (GMM) method. Blanchflower and Burgess (1998) examine the relationship between employment and innovation measured by a dummy variable, with data based on World Industrial Relations Survey specific to the UK and the Australian economy, and state that innovation at the industrial level positively affects employment growth in both countries for the periods 1989 and 1989-1990, respectively. Pianta (2000) and Antonucci and Pianta (2002) found that sectoral job losses in manufacturing industries were higher in sectors and countries with high innovation levels in their studies covering the years 1989-1993 in five European countries and the years 1994-1999 in eight European countries, respectively. Evangelista (2000) and Evangelista and Savona (2003) investigate with data from 1993-1995 that the effect of innovation differs significantly according to firms, industries, and workforce quality.

This study, unlike many other studies, focuses on the service sector and examines the innovation-employment relationship in terms of both the type of innovation and the skill level of the existing labor in Italy and at the sectoral level. Although the authors claim that employment in the service sector, especially in technology-intensive areas, is positively affected by innovation, they report a negative innovation-technology relationship in the Italian economy in general. The main findings of the study are as follows: a) The effect of innovation on employment in Italy is generally negative when the service sector is taken into account, and the authors state that the main reason for this is the de-specialization of the Italian economy. b) Jobs that require lower skills are replaced by jobs that require high-skilled and qualified workers. c) The net effect of technology is positive in small firms, especially in industries that use scientific or technological tools. d) The effect of innovation on employment is negative in large firms, capital-intensive companies, and the finance sector, particularly in banking and insurance.

Greenan and Guellec (2000) investigate the technology-employment relationship in French firms and sectors by constructing a structural model in which product innovations determine the demand function and process innovations determine the production function. In the study, while it is concluded that innovation affects employment positively, it is revealed that product innovations at the sectoral level are more labor-friendly than process innovations. But at the firm level, the situation is the opposite, process innovations are more job creation than product innovations. The study is important in terms of containing results at both the firm and sectoral levels. On the other hand, according to the findings of the study, product innovations do not negatively affect the competitors of the companies in terms of employment. Finally, it is stated that innovative companies provide more employment than non-innovative companies in an average of five years, and more intra-sector job transfer is observed in companies with intensive process innovation. Díaz and Tomás (2002) report that in parallel with studies that include pessimistic results, in the 1980s and 1990s, Spain experienced more job losses, especially in high-tech sectors. Chang and Hong (2003) argue that permanent technology shocks temporarily reduced working hours in some industries, but technology increased working hours in more industries than this, using the VAR analysis of 458 industries in the US manufacturing sector, with data for the years 1958-1996. Some statistical data also confirm that there is a contraction in employment with rapid productivity growth in technology-intensive growing sectors in some countries. For example, despite the significant productivity increases in the manufacturing sector in Germany and the USA between 1970 and 2011, a decrease in employment share is observed. Between 1993 and 1997, the density of robots used per hour increased by 160% in Germany and approximately 237% in the USA, which explains the labor savings in related industries as a result of similarly increased automation (WTO, 2017).

Üçdoğruk (2006) studied the effects of process and product innovation on employment in the Turkish manufacturing industry for the 1995-1997 and 1998-2000 periods by considering the low, medium, and high-tech industries separately. According to the results, process innovations have an increasing effect on employment in general, and this effect is larger and more significant for industries using low-tech, unlike similar studies in the literature. Besides, according to another interesting finding of the study, the relationship between product innovations and employment growth in manufacturing industries using medium and high-tech is negative.

Mastrostefano and Pianta (2009) and Bogliacino and Pianta (2010) examine the employment-innovation relationship at the sectoral level using the Community Innovation Survey database. In the first study, 10 European countries with data from 1994-2001, and in the second study, eight European countries with data from 1994-2004 are included. In the study of Mastrostefano and Pianta (2009), a positive relationship between employment and innovation is observed at the sectoral level, and this relationship is stronger in long-term lags. In addition, labor costs affect employment negatively, while the density of innovative firms affects the sector positively in terms of employment. In their study, which deals with the manufacturing and service sectors together, Bogliacino and Pianta (2010), on the other hand, focus on the same relationship at the sectoral level with the distinction between process and product innovation, and they state that process innovations affect the change in employment negatively but product innovations positively. Bogliacino et al. (2012) found that the employment-innovation relationship was positive in the manufacturing sectors using service and high technology, but no labor-friendly effect was observed in the traditional manufacturing sector. Taking 25 manufacturing and service sectors in developed European countries, Bogliacino and Vivarelli (2012) show that R&D expenditures, which are an indicator of product innovation, have a job creation effect at the sectoral level between 1996 and 2005.

It was claimed in Georgiou (2009)'s study in which he discussed the manufacturing sector in Western European countries between the years 1995 and 2005 that there was a critical level of technology use increasing/decreasing unemployment. While the technology use below this critical level increased unemployment, the one above the critical level reduced unemployment. In other words, if the use of technology is not at a level to reduce the production costs, it will trigger unemployment; it increases employment in the opposite case. Georgiou (2009) explained this situation by advocating that the increase in employment rates of high-skilled workers would suppress the increase in unemployment rates of low-skilled workers with the use of technology above the critical level and thus, the total employment would decrease.

Meriküll (2010), in his study, which was previously included in the empirical literature at the firm level, also includes outputs at the sectoral level and states that the employment-innovation relationship is weaker at the sectoral level than at the firm level. At the sectoral level, product innovation affects employment positively and process innovation negatively affects employment, but the net effect of innovation on employment is statistically insignificant. Finally, Meriküll (2010) states that the impact of innovation on the high-tech sector is insignificant, while the other level sectors, namely low and medium-tech industries, are influenced positively and significantly. Buerger et al. (2012) emphasize that the employment-innovation relationship differs from sector to sector in their studies covering four different sectors in Germany. In studies conducted with data from 1999-2005, both patent and R&D investments are used as technology indicators. According to the results, the innovation relationship represented by employment and patent numbers is reported as a) negative but weak in the chemical products industry, b) meaningless in the transportation equipment manufacturing industry, c) positive in the electrics and electronics industry, and d) positive in the medical products industry.

Ebenstein et al. (2015), on the other hand, argue that, contrary to optimistic sectoral evidence, more technology and capital equipment usage means lower employment, higher unemployment rates, and lower workforce participation in all occupations in the US. Bessen (2015) states that in the example of cloth weaving in the 19th century, increased demand for cloth through declining prices despite the automation of 98% of labor led to net job growth in the industry. In another example, he states that ATMs, which started to become widespread in the USA in 1970 and increased fourfold between 1995 and 2010, did not reduce the number of tellers, but on the contrary, the number of full-time tellers increased by 2% annually on average after 2000. This rate is higher than the annual workforce growth of the USA. However, here, of course, this situation cannot be interpreted as the fact that ATMs increase the number of tellers, because the banking sector has undergone many structural changes and developed different business areas and models over time; as a natural consequence of this, it needed more labor force. Bessen (2020), in his study covering the manufacturing industry in the USA and the period of 1984-2007, reports that computer use has a negative employment effect in the sector, on the other hand, it has a positive but very small employment creation ability on different industries. As a result, according to Bessen (2015, 2020), the elasticity of demand in the manufacturing sector, which was sufficient to compensate for job losses in the 19th century, is not valid in the 20th century.

The sectoral employment effect of the increase in productivity provided by technology has also been the subject of some empirical studies. Autor and Salomons (2017) investigate the relationship between productivity growth and employment at the country and industry level for 19 OECD countries with approximately 37 years of data, and they observe a decrease in employment at the industry level as productivity increases. But according to the authors, the negative impact of increased productivity on industry-level employment is suppressed by positive spillovers to the rest of the economy, so employment generally grows as total productivity at the country level increases. Graetz and Michaels (2018) discuss 17 developed countries and 14 industries in their study covering the 1993-2007 period. According to the results obtained in the study, the increase in robot density provides an annual increase of 0.36% in labor productivity in the relevant period. The authors emphasize that this rate is close to the labor productivity increase brought by steam engines (0.35% per year), but the growth rate of that period covered about 60 years, 1850-1910. Finally, it is claimed that robots do not reduce overall employment but reduce the employment share of low-skilled workers.

Dauth et al. (2018) evaluate how automation affects labor markets and how companies adapt to robotization, with data presented by the Institute for Employment Research (IAB) covering the years 1994-2014 in the German labor market. The study, which deals with 53 manufacturing industries, also focuses on 19 non-manufacturing industries for 1998 and beyond. The authors point out that robots do not only replace humans in production, but also indirectly affect the overall balance, and point out that the use of robots in tasks that complement production steps may increase labor demand in other areas. Therefore, according to the findings of Dauth et al. (2018), losses in manufacturing industries due to robots are offset by increased employment opportunities in business services. In other words, the authors state that robots change the structure of jobs and sectors in the German economy, there has been a decrease of approximately 23% in employment in the manufacturing sector between 1994 and 2014, nevertheless, all of this loss is compensated by the new jobs created in the service sector which mean overall employment was not affected. The authors find the destruction effect approach to the employment impact of robots too pessimistic; they believe that a large part of the adaptation process to robots has taken place and this situation can even be stated to increase job stability and wages for high-skilled workers. In addition, the authors point out that manufacturing workers in the manufacturing sector do not lose their jobs, and that technology reduces future employment opportunities for young people in this sector. But it means low wages for low-skilled workers. Because the authors state that according to the data of the International Federation of Robotics (2016), robot stocks in North America, Europe, and Asia have increased fivefold from 1993 to 2015 and those industries have already made various changes in their production organizations compared to robots. They also argue that economically companies react to automation by changing the roles and responsibilities of their employees, which prevents layoffs. Finally, in the study, it is stated that employment in industries dominated by robots in Germany for 20 years did not suffer, on the contrary, employment stability was achieved, but a decrease in wages was observed as a negative result.

Piva and Vivarelli (2018) use OECD-STAN and OECD-ANBERD databases for the period 1998-2011 in their studies covering the manufacturing and service sectors in 11 European countries. In the study, R&D intensity is used as a technology proxy and econometric analyses are mostly based on System GMM and LSDVC methods. When both sectors are considered together, R&D expenditures based on product innovations are in a labor-friendly structure, but the positive effect of R&D originates from medium and high-tech sectors, and no significant effect is detected in low-tech industries. Koch et al.

(2021) investigate which companies have adapted to robot technology, the effects of robot adaptation on labor demand, and how the heterogeneity between companies affects the balance in the entire industry, in their studies covering the years 1990-2016, specifically for the Spanish manufacturing industry. The authors note that large and efficient firms are more likely to adapt to robots than skill-intensive firms. Secondly, the authors state that in Spanish manufacturing companies, robots provide a 20-25% increase in productivity within four years, which reduces labor costs by around 5-7%, while creating a new job of 10%. Finally, the authors reveal that there are job losses in companies that do not have robot adaptation or that are slow and that worker displacement in the industry is from non-adopters to adapters. Compagnucci et al. (2019) investigate how the increase in robotization affects wages and employment in the manufacturing sector in 16 OECD countries with the P-Var method for the period 2011-2016 and claims that robotization increases hourly wages while reducing total working time. The authors estimate that a 1% increase in the number of robots reduces working hours by an average of 0.16%, resulting in less demand for manpower at the industry level. Besides, the authors state that the increase in wages is slower in sectors where robotization is fast compared to other sectors, which shows that the substitution effect caused by robotization is more than the complementarity effect.

Dang and Vu (2020) investigate the relationship between imported capital goods, technology imports, and employment by combining all sub-categories of the manufacturing industry with data obtained from the Vietnam Enterprise Survey between 2011 and 2017 in Vietnam. In the study, the authors state that imported capital goods and high-tech imports increased labor productivity in Vietnam during the aforementioned years. Then again, it is determined that technology import has an increasing effect on employment in large companies and industrial zones. As a result, it is emphasized that productivity-enhancing technologies in Vietnam lead to more employment, not unemployment, and it is stated that the job-creation effect outweighs it. In addition, the authors underline that this effect may differ from firm to firm or from sector to sector. Wang et al. (2020) investigate how internet technologies in China affect employment. In the study covering the years 2000-2014 and covering 47 industries, the authors use the World Input-Output Database data to reach the conclusion that internet technology positively affects employment through positive industry spillover and positive direct effect. Paul and Lal (2020), in a study covering the service and manufacturing sectors for the 2011-2012 and 2015-2016 periods, investigate the relationship between technology intensity and employment in India and report the labor-friendly effect of expenditure on Information and Communications Technology at the sectoral level. Adachi et al. (2020) examine the impact of automation on labor demand with data covering the years 1978-2017, specific to Japan and at the industry level. The authors show the effect of automation-labor demand in their study with a cost-based definition method, and according to the findings obtained in the study, robots and labor are gross complements to each other. According to a result put forward in the study, a 1% decrease in the prices of robots used in automation in Japan increases the labor demand by 0.44%. Additionally, the 1% increase in robot adoption due to the decrease in the prices of robots increases employment by 0.28%. Jung and Lim (2020) use annual shipments of industrial robots per 10,000 manufacturing workers as a technology indicator, with data from 2001-2017 in 42 countries. In the study, the effect of both robots on employment and the employment structure on technology is examined with the simultaneous equation system, that is, the relationship is looked at from two sides. The authors summarize the findings as follows: a) The increase in labor costs increases the tendency to prefer industrial robots. b) The expansion in the number of industrial machines depends on the innovation capacity of the firms. c) The increase in the number of industrial robots reduces the growth in labor demand due to the replacement effect, but it affects the workforce positively by reducing labor costs with productivity increase. d) Robotization in the manufacturing sector affects low-skilled workers negatively and shifts labor demand to skilled workers.

Finally, in this section, the studies of Acemoglu and Restrepo (2019), Acemoglu and Restrepo (2020), and Bessen (2020) are given in more detail. These studies actually contain theoretical and empirical findings from a broader perspective on the relationship between technology and employment, and with these aspects, they also include contributions to both the theoretical approaches presented at the beginning of the chapter and the macro-level empirical findings mentioned in the next chapter. However, all three studies contain more sector-oriented analyses and therefore the studies are mentioned in this section.

Acemoglu and Restrepo (2019) investigate the effects of technological change on labor demand and productivity with a task-based approach. Because production is possible with the combination of many tasks and automation enables the production of some or all of these tasks with machines. For this reason, it is important to allocate the tasks to the factors of production, but the traditional production function does not consider the tasks. Acemoglu and Restrepo (2019) first formulate the effect of technological changes on labor demand as *"the effect of automation on labor demand = productivity effect + displacement effect"* and this formulation is established for a sector. Here, the efficiency effect arises as automation increases the added value and thus the demand for labor for non-automated jobs. The displacement effect is based on the displacement of work previously performed by automation, and the authors make an analogy here, stating that *"automation actually increases the size of the pie, but a smaller slice falls on the employees"*. The authors point out that *"brilliant"* technological changes do not reduce employment and wages, but *"so-so"* technologies that are not high enough cannot provide productivity gains to offset the negative impact on employment and wage. Besides, in the study, two more important effects of technology are formulated: *"effect of new tasks on labor demand = productivity effect + reinstatement effect"* and *"effect of factor-augmenting technologies on labor demand = productivity effect + substitution effect"*. Finally, with a multisectoral point of view, adding the *"composition effect"*, which includes the displacements between sectors, to the equation, the automation effect is formulated as follows: *"the demand for the total workforce of the new automation in a sector = productivity effect + displacement effect + composition effect"*. The authors state that similar composition effects should be considered in both new tasks and factor-augmenting technologies.

Acemoglu and Restrepo (2019) examine the employment data of six broad sectors in the USA, namely construction, services, transportation, manufacturing, agriculture, and mining, by focusing separately on two periods, with the theoretical model mentioned above. Between the years 1947-1987, which is the first period, no significant decrease is observed in the labor sharing rates of the other four sectors, except for mining and transportation, which has a relatively small proportion compared to the others. There is even a slight increase in employment in the manufacturing and service sectors. Furthermore, there are serious changes in the GDP shares of the sectors. While the share of the service sector in GDP is increasing, a serious decrease is detected in manufacturing. In addition, the wage bill is growing by 2.5% annually in the specified period, while the rate of increase in productivity explaining this growth is 2.4% annually. However, in this period, the effects of substitution, composition, and task content are determined to be very small. Perhaps the most striking statistic about this period is that labor demand, which decreased by an average of 0.48% per year due to the displacement effect, increases by an average of 0.47% annually thanks to the reinstatement effect. A similar pattern is also observed when focusing only on the manufacturing sector. As a result, the authors reveal that in the forty-year period following the Second World War, the decreased labor demand due to automation was offset by new tasks, and the economy, especially manufacturing, was balanced in terms of employment in general. The authors present the image for the 1987-2017 period in the study and state that, contrary to the previous forty-year period, a serious decrease was observed in the share of the manufacturing, mining, and construction sectors in the workforce between 1987-2017. Another important point is that after 1987, reinstatement effect increased labor demand by only 0.35% per year, while the displacement effect decreased labor demand by 0.7% per year. Therefore, while the reinstatement effect is decreasing compared to the previous period, the displacement effect is increasing. Moreover, this outlook is more serious in the manufacturing sector. While there was no significant difference in terms of displacement and reinstatement between the overall employment pattern and manufacturing in the previous period, this time the displacement effect is observed as 1.1% per year for manufacturing, the total cumulative effect is approximately 30%.

Acemoglu and Restrepo (2019) state that the effect of composition and substitution on wage bills is very small, and besides, a strong composition effect that contributes to labor demand cannot be mentioned. In summary, the authors attribute the slowdown in labor demand growth over the past 30 years to weak productivity growth and the effect of automation, which cannot be offset by the creation of new jobs. As reasons why the creation of new tasks cannot suppress the negative impact of automation, the authors consider the possibility that automation may make the creation of new tasks more difficult, the incentives for automation increased more than any other in the US economy, and the possibility of exhaustion of highly productive ideas. Finally, the authors emphasize that the framework they established in the study has clear implications for the future of work, but neither the empirical results nor their conceptual approaches contain an optimistic or pessimistic inference about the impact of technology on human labor. Rather, the authors argue that the relative status of labor will decline if automation continues to be the source of future productivity growth. In addition, the creation of new tasks and other technologies that increase the labor intensity and labor share of production is a very important condition for a wage increase in proportion to the increase in productivity.

Acemoglu and Restrepo (2020) investigate how industrial robots affect labor markets in the United States with data from 722 commuting zones covering the years 1990-2007. Adhering to the definition of The International Federation of Robotics, the authors consider “automatically controlled, programmable multi-purpose machines” as robots in the selected sample. An important assumption of the study at this point is naturally based on the competition of human power and robots. The authors emphasize that the number of robots per worker is low in the US economy compared to many developed European countries. Additionally, the most important emphasis of the study is that robots have a strong negative effect on both employment and wages in the US economy. The employment/population ratio of a one-unit increase in the number of robots per thousand workers in the selected period is 0.2%; moreover, it is shown that it reduces wages by 0.42% on average. Acemoglu and Restrepo (2020) state that if robotic technology continues to grow aggressively in the future, the magnitude of its devastating effect on employment will increase. For example, the authors calculate that if the predictions that the number of robots in the world will quadruple by 2025 are realized, the employment ratio to the total population will decrease by 1% and the average wages by 2%.

Bessen (2020) evaluates with a fairly wide range of data whether new technologies will lead to greater unemployment in industries, requiring new policies to address mass unemployment. In his study, the author deals with three different industries in the US economy, namely textile, steel, and automobile, and explores why the demand for employment, which increased with productivity in these manufacturing sectors, has moved in the opposite direction since the middle of the twentieth century. This study is very important in that it not only looks at the issue from both theoretical and empirical perspectives but also focuses on the *"price elasticity of demand"* dimension, which compensation mechanisms often ignore with an assumption. In his study, which uses 200 years of data from three selected industries, Bessen (2020) states that technology initially increased employment because the price elasticity of demand was quite high in previous periods. Furthermore, the author, who states that the demand has reached saturation in the more recent period, reveals that the increase in productivity, therefore, leads to employment losses. Therefore, rather than the effect of automation on mass unemployment, it is clear that technology can cause the decline of some industries and the expansion of others. Another issue is that workers may have to make disruptive transitions to different fields or industries that require new skills, competencies, specialties, or occupations. The risk that some work thought to be done by machines will soon lead to high rates of mass unemployment calls for new policies. However, it is not correct to assume that automation has a devastating effect on employment in every sector in which it is involved. The author supports with data that in the previous centuries, employment in some manufacturing industries in the USA was positively affected by productivity. However, as stated before, recent data in many manufacturing industries such as textiles and steel show that automation leads to job losses in these industries. Bessen (2020) expresses this situation with an inverted U-shape for all three sectors. The author explains the importance of this model from two perspectives: a) It is not true that productivity-enhancing technology always leads to workforce loss. b) Productivity-enhancing technology may or may not reduce total employment. This indicates that different effects can be seen in different industries at different times, that is, the heterogeneous effect.

Both empirical and theoretical studies on the relationship between productivity, technology, and employment almost agree that employment will increase if there is sufficient demand expansion despite productivity growth. Therefore, Bessen (2020) emphasizes at this point that the price elasticity of demand (or elasticity with respect to labor productivity) determines whether the technology that increases productivity will increase employment. This is because a major factor in the expansion of demand in response to new technology is that increased productivity lowers prices in competitive markets. The author also explains the relationship between demand and labor productivity descriptively and shows that the increase in labor productivity over time is evident in all three sectors. However, the author repeats the inverted U-shape pattern mentioned earlier for the request. While all three sectors expand rapidly at different times, each sector consistently and relatively produces more output per worker overtime. While employment also increases over time, all three sectors exhibit a concave pattern after a point, because the fact that the demand has now assumed a *"horizontal"* structure indicates that *"demand saturation"* has been reached. At this point, it should be noted that demand saturates over time despite increasing income (income elasticity of demand). As a result, demand is initially very elastic, enabling employment to grow with productivity growth; however, then demand loses its elasticity and employment decreases with the increase in productivity. However, many industries and different markets have different elasticities of demand, so the employment effect of technology is heterogeneous. This may require workers to acquire new skills and make transitions to new fields and industries in line with technological developments. As a result, Bessen (2020), using both empirical evidence and theoretical model, claims that the elasticity of demand with respect to labor productivity significantly impacts the direction and severity of the impact of technological progress on employment. At this point, the author reveals that the speed of productivity growth resolves the magnitude of the change in employment, while the elasticity of demand defines the direction of the effect. The fact that the data and the model show that there is heterogeneity between industries necessitates employment policies to be complicated in this direction.

Although it was predicted under the leadership of Keynes that automation would reduce the demand for labor -or at least by reducing working hours- at the beginning of the 20th century, it is not possible to say that the increase in productivity has completely eliminated the need for labor force today or will soon. However, it can still be seen that the increase in productivity affects employment negatively in many sectors in this period, and therefore, although the increase in productivity reverses the direction of employment compared to the past, the demand for more goods and services prevents or slows the technology-induced deepening of mass unemployment for a while. At this point, Bernes (2020) states that today's change is faster and wider than in the past, conversely, it is not possible for human needs and demands to undergo major changes in the short term, and therefore, policies should be shaped in this direction. Because demand may not remain elastic enough to compensate for the destructive effect of technology.

As a result, the findings of sectoral analyses are somewhat more complex and *"inconclusive"* than firm-level studies. However, it can be said that sectoral studies, especially in the last ten years, are rather more pessimistic. Acemoglu and Restrepo (2019) attribute this situation to the fact that the productivity increase provided by automation is no longer at a level that can compensate for the loss of the workforce. Bessen (2020) also draws attention to the saturation of demand in general and states that the elasticity of demand in the historical process has lost the power to compensate for employment in some sectors over time. Therefore, the use of new tasks that increase the labor intensity and labor share of production in the future, as well as the use of new technologies that will bring productivity to levels that will compensate for employment, are important for the course and direction of employment.

2.4.2. Macro Level Studies

Overall, the vast literature examining technological advances, skill change, and their interrelationships often reveals a significant relationship between these factors, while inferences on some key points remain weak due to the lack of a macroeconomic perspective. Among the micro-level studies that deal with the technology-employment relationship, those that focus specifically on firms mostly focus on innovative ones and do not take into account changes in competitors within the sector or impacts in other sectors. In addition, studies at the sectoral level also focus on a specific sector and do not predict the net employment effect, ignore the transition between sectors and the qualitative and quantitative effect of new sectors on employment, and at the same time do not make a holistic unemployment inference possible. For this reason, it is not enough to focus only on firms or sector groups with a narrow labor market perspective. Macroeconomic studies, which take into account the aggregate socio-economic context, are important in terms of seeing a general and clear employment effect. A limited number of macro-level empirical studies are discussed in this section. Although some of these studies use sectoral data, they are discussed here because they are based on assumptions about aggregate economics and include overall inferences.

Although there are more alternatives to measure technology at the micro level, technology measurement at the macro level is not easy because technical progress is characterized by multiple economic dynamics. Still, two important macro variables such as R&D expenditures and patent numbers, which are widely used to measure the technology levels of countries, can be mentioned. While R&D expenditures quantitatively reflect an overall technology level, they can also be qualitatively superior to the number of patents, since variables such as the number of patents per capita ignore patent quality. Alternatively, Triadic Patent Families (TPF), which has been used as a patent indicator especially recently, includes innovations registered in patent offices located in three major economic regions, European Patent Office, US Patent, and Trademark Office, and Japanese Patent Office. Due to the high standards of these major patent organizations, the TPF indicator can be reliable (Feldman, 2013). However, the TPF variant does not separate product and process innovation and is often of interest to large companies because patents are not attractive to small and medium-sized businesses. However, in most developed and developing countries, a significant share of employment comes from small and medium-sized enterprises, so the number of patents that do not cover small and medium-sized enterprises may be insufficient to explain employment as a technology proxy. Besides, some industries tend to have a higher patent propensity than other industries, which can cause industry bias. Feldman (2013) also states that the TPF variable may be affected by different evaluations on the basis of the three major patent institutions. On the other hand, R&D expenditures may not completely transform into technology, so it cannot be said that it fully reflects the technological level of countries. Such reasons constitute the main disadvantages of macro-level studies that use R&D and patent numbers as technology proxies.

Macro-level empirical studies (see Table 2.4) investigating the employment-technology or unemployment-technology relationship include approaches in the early stages in line with the compensation mechanism and general equilibrium. Sinclair (1981) explains the effect of technology on employment in terms of the IS/LM principle with the assumption of a single country (the US) and a single sector. Sinclair (1981), using US data between 1900-1965, indicates that the relationship between technology and employment is positive when demand elasticity and factor substitution are high. In the same study, it is revealed that the compensation mechanism over the same data is valid via decrease in wages, but the decline in prices is not efficient. As the author emphasizes, the study is based on strict assumptions. For example, capital stock is considered stable and homogeneous, and the economy is assumed to be closed and has one sector. Therefore, the results should be interpreted accordingly.

Layard and Nickell (1985a, 1985b), in their macro-level studies covering France, Germany, Japan, the UK, and the US countries and the years 1966-1986, emphasize that technical changes increase the need for labor in four countries except for Japan. In their study, the authors reiterate that the elasticity of demand is an important factor in the increase in labor demand due to technology, and they claim that sufficient elasticity increases productivity and labor demand together. For example, Layard and Nickell (1985b), in the UK-specific macro results, empirically investigated whether technical change increases the demand for labor under labor productivity and adequate demand elasticity, with 1954-1983 data. Based on the results, the demand elasticity in the UK economy was 0.9, which was seen as sufficient to compensate for technology-related job losses. Therefore, the authors stated that capacity utilization was below the average when the unemployment rate in the UK was 12%, and therefore the increase in unemployment rates cannot be attributed to the increased use of machines in the production process. Similarly, Nickel and Kong (1989) investigate UK firms from nine different industries covering the 1974-1985 period in order to demonstrate whether compensation mechanism via decrease in prices is valid. Based on the estimations, only two of the nine sectors - bricks/glass and textiles - are found to have no employment effect of the reduction in prices, while the remaining seven sectors have sufficiently high demand elasticity and the positive overall effect of technology on employment. It should be noted that the studies of both Layard and Nickell (1985) and Nickell and Kong (1989) report a positive technology-employment relationship under the assumption of high elasticity of demand at the macro level. However, it may not be correct to conclude that the need for labor directly increases employment in such studies. It is unclear whether the new labor demands are met or will be met with manpower or machines. For this reason, although it is assumed that the need for labor is met directly by people in the early studies, which may be true for that period, many sectors today are much more technology-intensive than in the past. Therefore, the more labor needs that arise with the increase in productivity can be met again with the opportunities offered by technology and may not compensate for the job losses.

Pini (1995) is one of the few studies that both theoretically models and empirically examines the early technology-employment relationship at the macro level. The study covers the years 1960-1990 and nine developed OECD countries. Six of them are European countries (Belgium, France, Italy, Netherlands, Germany, and the United Kingdom) and 3 are other developed economies namely the USA, Canada, and Japan, which are not members of the EU. The empirical findings of the study reveal that, on the one hand, the increase in physical capital provided by technology stimulated by R&D negatively affects employment. According to Pini (1995), there is an *''equal compensation mechanism''* that works by encouraging export directly or indirectly through the innovation process itself and the outputs it produces. In addition to these, the author emphasizes that the production of physical capital also provides value added for employment, and this constitutes important evidence for the multiplier effect of technology. Contrary to these, the study does not provide evidence for the existence of a compensation mechanism that works through changes in nominal income. As another issue, the author emphasizes that the model reports different results between countries. He states that while the strong impact of the innovation process on employment as an *''input''* in EU countries is clear, it is not possible to talk about the existence of a compensation mechanism through exports as an *''output''*. Besides, it is concluded that the situation is the opposite for non-European countries, namely the USA, Canada, and Japan. At this point, the author draws attention to a possible break in the mid-1970s and claims that technology inputs, which are considered as R&D expenditures in the post-1976 stage, have no positive effect on productivity, and similarly, he reports that there is no evidence observed that the output of innovative activities has a positive effect on exports. In the literature on regional differences, it is possible to encounter many similar findings and different interpretations of their causes. For instance, while studies, such as Oliner and Sichel (2000) and Jorgenson and Stiroh (2000), drew attention to regional differences in technological progress, they claimed that Europe was left behind the United States in adaptation to technology. Duernecker (2008) argued that the difference between technological levels and unemployment rates of the countries and so-called lack of adaptability was coincidental and placed technological heterogeneity at the source of differences in labor market outcome between the countries. Rubart (2007) showed the main source of unemployment in some European countries such as Germany and France, as the unemployment of low-skilled workers. Although highly educated workers had low unemployment volatility both in Europe and the United States compared to less-educated workers, the unemployment of less-skilled workers was either stable or in the direction of decline in the economies of Anglo-Saxon countries such as the US and UK. For instance, the unemployment rate of low-skilled workers in the US was 13% in 1988, this rate dropped to 6% in 2004. On the other hand, the rate for the same skill group in Germany was 13% in 1988, it increased to 20% in 2004 (Rubart 2007). Gottschalk and Smeeding (1997) and Acemoglu (2002) attributed the territorial differences in the unemployment of low-skilled workers to increasing wage spread in Anglo-Saxon countries and the stable orientation of it in continental Europe. In other words, the European countries, such as Germany and France, have more strict sticky prices compared to the United States and Britain. While the employment rates were maintained in the US and Britain as low-skilled workers were willing to work for lower wages with the developing technology, the inability to lower the wages led to an increase in the unemployment rate in other European countries.

Table 2.4. Macro level studies

Study	Country	Period	Employment Effect of Technology
Sinclair (1981)	United States	1900-1965	Technology has a positive effect on employment when demand elasticity and factor substitution are high.
Layard and Nickell (1985a)	U.K., U.S., France, Germany, Japan	1957-1984	Technical changes increase employment because demand elasticity is sufficient to compensate job losses except for Japan.
Layard and Nickell (1985b)	United Kingdom	1954-1983	Technical changes increase employment because of the sufficient demand elasticity.
Nickel and Kong (1989)	United Kingdom	1974-1985	Job losses are compensated via reduce in prices since demand elasticity is sufficient.
Pini (1995)	9 OECD Countries	1960-1990	Decrease in employment because of technology is compensated by increase in productivity and its effect on export dynamics.
Vivarelli (1995)	United States, Italy	1960-1988	Decrease in employment because of technology is partially compensated via decrease in prices.
Shea (1998)	United States	1959-1991	Technology shocks lead to increase in labor input in the short run but decrease in the long run.
Galí (1999)	G7 Countries	1948-1994	Positive technology shocks decrease labor hours in G7 countries except for Japan.
Simonetti et al. (2003)	France, Italy, Japan, U.S.	1965-1993	Compensation mechanisms (especially via decrease in prices and increase in incomes) are efficient in the selected countries.
Christiano et al. (2003)	United States	1948-2001	Positive technology shocks increase hours worked.
Uhlig (2004)	United States	1889-2002	Technology shocks have no initial effect but lead increase in labor input in the long run.
Francis and Ramey (2005)	United States	1947-2003	Positive technology shocks decrease hours in the short run.
Basu et al. (2006)	United States	1949-1996	Technology shocks cause a sharp decrease in labor input in the short run.
Michelacci and Lopez-Salido (2007)	United States	1972-1993	Investment-specific technology shocks have a weak positive effect on labor input while neutral technological progress decreases hours worked.
Weis and Garloff (2011)	14 Advanced Countries (Continental Europe, the U.K., the U.S.)	1975-2005	SBTC increases overall unemployment in Continental Europe but not in the U.S. and the UK. SBTC increases unskilled unemployment in all selected 14 advanced economies.

Table 2.5. ***(Continued)***

Study	Country	Period	Employment Effect of Technology
Feldmann (2013)	21 Advanced Countries	1985-2009	Increase in the number of Triadic Patent Families increases unemployment in the short run.
Gallegati et al. (2016)	G7 Countries	1962-2012	Technology has a negative effect on labor input in the short and medium runs, positive effect in the long run.
Matuzeviciute et al. (2017)	25 European Countries	2000-2012	Both R&D and the number of patents have no significant effect on unemployment.
Graetz and Michaels (2018)	17 Developed Countries	1993-2007	Robots reduce low and medium-skilled worked hours but rise high-skilled ones. Robots have no significant overall effect on labor input.
Autor and Salomons (2018)	17 OECD Countries	1970-2007	Technology has a positive effect on the aggregate employment level.
Bertulfo et al. (2019)	12 Developing Asian Countries	2005-2015	Technical progress decreases overall labor demand, but domestic consumption expenditures are able to compensate for job losses.
Aly (2020)	25 Developing Countries	2017	Digital transformation has a heterogeneous effect on labor demand in developing countries. In some countries, it is transformed into more job opportunities but in some others, it is not.
Baş and Canöz (2020)	15 OECD Countries	1996-2017	R&D expenditures are the Granger cause of unemployment.
Cengiz and Şahin (2020)	Turkey	1990-2018	Increase in R&D expenditures decreases unemployment.
Grigoli et al. (2020)	23 Developed Countries	1985-2016	Technology has a negative effect on labor participant rate and as the degree of routinizability of the job increases, the negative effect size of automation increases.
Yıldırım et al. (2020)	12 EU Countries	1998-2015	The number of patents has a negative impact on employment in both low-innovation and high-innovation degree countries. The magnitude of negative effects in low-innovation countries is higher.
Lydeka and Karaliute (2021)	28 EU Countries	1992-2016	Both R&D and the number of patents have no significant effect on unemployment.

Vivarelli (1995) and Simonetti et al. (2003), in which the macro-level functionality of compensation mechanisms is discussed, it is stated that the most effective and meaningful channel is based on the principle of *"decrease in prices"* and product innovations offer new business opportunities through this channel. Vivarelli (1995) examines the job-creating effect of product innovation and the labor-saving effect of process innovation, given by the American and Italian economies over the period of 1960-1988 and he finds that the most effective of the six mechanisms is via decrease in prices, and indeed the effect is partial; that is, the decrease in the need for labor due to technology is partially compensated by the decrease in prices and the destroyed works cannot be fully compensated. In addition, the author states that other mechanisms are less important or do not work at all (for example, the existence of a mechanism that works through a reduction in wages is not observed). At the same time, technological advancements have a positive employment effect and exhibit labor-friendly characteristics in the US since the American economy is more product-oriented. However, in Italy, different compensation mechanisms cannot balance labor-saving effects resulting from process innovations. Simonetti et al. (2003) found that the most effective compensation mechanisms channels were via decline in prices and rise in incomes for the US, France, Italy, and Japan from 1965 to 1993. While the authors emphasized in their study that other mechanisms are less significant as balancing elements, technological advances based on product innovation in leading countries such as the United States have a much more positive effect on employment than the others.

Weiss and Garloff (2011) discussed the technology-unemployment relationship in terms of skill-biased in 14 developed countries with both theoretical modeling and empirical approach at the macro level. The authors report that skill-biased technological change has increased unemployment in European countries excluding the United Kingdom, while the skill premium has increased in the United Kingdom and the United States. Technology negatively affects the employment of unskilled workers in all countries included in the study. This study is very important in that it deals with the SBTC approach at the macro level in the recent period.

Feldmann (2013), who is among the important studies examining the technology-unemployment relationship at the macro level recently, uses the macro data of 21 industrial countries from 1985 to 2009 and prefers the ratio of triadic patent families (TPF) to the population as a technology proxy. The 2SLS regression method was used throughout the study and the predictions were validated with a few specifications. In all models applied by the author, the triadic patent families coefficient is positive, leading to the conclusion that technology increases unemployment. The author shows that one standard deviation increase in the number of patents increases unemployment by 2.3% to 3.0%. Feldman (2013) states that his findings are compatible with the theoretical model proposed by Weiss and Garloff (2011). However, the author adds that there is no significant evidence for the effectiveness of reverse transmission mechanisms, namely market compensation mechanisms, in the long run. Feldman (2013) interprets his results separately in the short and long term and emphasizes that while the effect of technology is compatible with the creative destruction stated in Aghion and Howitt (1994) in the first 3 years, this effect is balanced with the capitalization effect in the next period. It also confirms the findings of Gatti (2000) that the radical increase in the stock of knowledge increases the impact of intense competition in decentralized market economies and thus unemployment. According to the author, the negative short-term impact and further negative impact on unskilled workers in Şener (2000, 2001) are also supported, but in fact, the empirical analyses in Feldman (2013) do not address the skilled-unskilled worker distinction. Matuzeviciute et al. (2017) is one of the studies examining the employment-technology relationship at the macro level in the more recent period. The model discussed in the article follows Feldman (2013) in terms of the variables used. The authors use both R&D and triadic patent families data from 25 European countries as their proxy. In the study covering the years 2000-2012, panel data regression model and two-step generalized method of moments (GMM) methods are used. The main finding of the authors is that both technological variables do not have a significant effect on unemployment at the macroeconomic level. Graetz and Michaels (2018), with similar results, state that despite all the ongoing discussions about the potential effects of robots, robots do not have a significant effect on employment. The authors state that there has been a significant decrease in robot prices from the past in the major developed countries they have studied, and this is a driving factor that increases the use of robots in industries. However, while this situation increased labor productivity, total factor productivity, value-added, and wages in 1993-2007 and 17 developed economies, it did not reveal a significant effect on total hours worked in relation to employment. According to the authors, robots reduce the working hours of both low-skilled and middle-skilled workers, but still the overall employment effect is insignificant.

Bertulfo et al. (2019) first discuss three approaches to the relationship between technology and jobs and examine how employment responds to consumption, trade, and technological advances in 12 countries that account for 90% of employment in developing Asia during the 2005-2015 period. While the authors draw attention to the fact that there is an increase in non-routine-cognitive and non-routine-manual jobs compared to routine and task-intensive occupations in the labor markets of many countries in the world, they contribute by examining the changes in the work structure in developing Asian countries in this direction. Using the demand-based input-output approach, the authors demonstrate that technological progress in all sectors reduces labor demand while showing that technological change tends to reduce demand for routine jobs more than for low- and high-paying non-routine jobs. But on the other hand, the study argues that the demand for labor triggered by domestic consumption compensates for the job destruction caused by technology. Aly (2020) analyses the relationship between digital transformation and some important macroeconomic indicators, including employment, using 2017 cross-sectional data from 25 developing countries. In the article, which is one of the limited number of studies focusing on developing countries, some important findings obtained by using the feasible generalized least squares method are as follows: a) Digital transformation has a significant and positive effect on both economic development and labor productivity. b) While high levels of digital transformation are transformed into more job opportunities in some countries such as Malaysia, Chile, and China, in some other countries such as Turkey, South Africa, and Jordan, digital transformation cannot create new job opportunities at the desired level. c) Digital transformation provides more job opportunities for women. The study provides no evidence for the overall employment impact of digital transformation.

Baş and Canöz (2020) examine the unemployment effect of R&D expenditures in a study covering 15 OECD countries and the years 1996-2017. Although no cointegration is found between R&D expenditures and unemployment in the preliminary results of the study, the authors explore the presence of hidden cointegration between R&D and unemployment shocks in the second stage and obtain significant findings in this direction. According to the results, *"the negative shock of the R&D is the Granger cause of the negative shock of the unemployment rate"* and *"the positive shock of the R&D is the Granger cause of the positive shock of the unemployment rate"*. Cengiz and Şahin (2020) again inspect the effect of R&D on unemployment through the example of Turkey. In the study, the unemployment indicator is used as the dependent variable as a ratio to the total labor force, and R&D expenditure and GDP are used as independent variables as total values, taking the first difference. In the article covering the years 1990-2018 and using the quantile regression method, it is claimed that a 1% increase in R&D expenditures reduces unemployment by 5.7% and it is determined that the growth in GDP does not have the power to create employment.

Grigoli et al. (2020) are among the rare studies that examine the relationship between workforce participation and technology for tasks that can be routinized, both on a micro and macro basis. The authors focus on two fundamental issues in their work: a) Whether employees whose jobs become obsolete by reason of automation are at risk of being permanently cut off from the workforce. b) Whether technological advances can explain recent trends in total workforce participation rates in advanced countries. For these purposes, the authors, who applied with complementary analyses covering 23 developed countries and the years 1985-2016 at the macro level and covering the years 2000-2016 and 24 developed countries at the micro-level, report the significant negative effect of technology on the labor force participation rate. According to another result obtained in the study, as the degree of the routine of occupations increases, the negative effect of automation on labor force involvement also increases. According to the results of the analysis at the individual level, it is confirmed that workers engaged in routinizable tasks are more likely to leave the workforce than others. On the other hand, various labor market programs and especially higher investments in education reduce the negative effects of technological change on labor force participation. Grigoli et al. (2020) underscore the existence of empirical evidence showing that declined demand for occupations involving routine tasks owing to technological advancement contributes to the decline in male labor force participation in the United States. The authors' findings show that long-term changes in labor demand as a result of technological advances are strongly and negatively related to male and female participation rates. Additionally, it is emphasized that the adjustment costs allied with technological change might be longer-term than previously thought. Employees who lose their jobs due to automation face difficulties in finding alternative jobs, leading to workforce separation. The authors note that these findings explain the large job losses in domestic labor markets in the US, which has greater exposure to robots as documented in Acemoglu and Restrepo (2017). As a result, having a profession that is more vulnerable to routinization is associated with lower labor force participation rates. On the other hand, another important finding of the study is that education and labor market policies have significant positive effects on workforce involvement. The rise in the portion of workers with secondary and particularly tertiary education is linked with significantly higher participation, expressly for female workers. Higher education is similarly positively associated with male participation.

Yıldırım et al. (2020) cover 12 EU countries, which have a higher degree of innovation in the world compared to other countries. While scanning the relationship between innovation and unemployment for EU countries in the study, countries are divided into two classes according to their technology degrees, and the panel threshold model is used in the analysis, based on the assumption that the technology-employment relationship is not linear. According to the findings obtained in the study, in which the data of 1998-2015 is used and innovation is measured by *“patent numbers”*, innovation increases unemployment in countries with both low innovation and high innovation levels, with a higher effect size in the former.

Lydeka and Karaliute (2021) followed two previous similar studies, Feldman (2013) and Matuzeviciute et al. (2017), with data from 28 European Union countries covering the years 1992-2016. The authors followed Matuzeviciute et al. (2017) as a technology proxy in their studies, discussed both R&D and patent numbers, and used the two-step system generalized method of moments (GMM-SYS) in the analysis. According to the findings of the study, although there is significant evidence that R&D reduces unemployment in two of the six models established with R&D, the coefficients are insignificant in all models including triadic patent families. Except for public unemployment expenditures, most of the variables like important macro indicators such as GDP and inflation are insignificant in their models. In addition, the authors consider R&D as product innovation and patent numbers as process innovation, but at the macro level, product and process innovations are intertwined. The purpose of Aggregate R&D spending is to achieve new products and new production processes, so the assumption that R&D expenditure only leads to product innovation is strict.

Empirical studies on how technology shocks affect labor demand are also noteworthy, which generally treat *"labor input"* as *"total working hours"* and approach the issue in terms of productivity increase. In fact, these studies generally follow an empirical path from sectoral level to macro inferences, and with these aspects, they are micro-level studies based on theoretical modeling rather than a macro-level empirical study, but they are open to generalization to the macro level in terms of their scope. On the other hand, it is not possible to talk about a general consensus in the findings of these studies. For instance, according to the studies of Cooley and Prescott (1995), Shea (1998), Galí (1999), Francis and Ramey (2005), Basu et al. (2006), Galí and Gambetti (2009), and Barnichon (2010), the main reason for business cycle fluctuation was the positive technology shock and these technology shocks decreased the labor input. Moreover, Fisher (2002), Christiano et al. (2003), and Michelacci and Lopez-Salido (2007) showed that technology shocks increased the labor input through findings indicating the opposite.

Quarterly data of the United States for the years 1948-1994 was used in Galí (1999) and the results compatible with Keynesian models were obtained. According to Galí (1999), the conditional correlation between productivity and working hours was negative (-0.81) and the decline in working hours generated from the positive technology shock was permanent. Like demand shock, the conditional correlation between non-technology shocks and productivity growth was positive (0.35). In the same study, remaining G7 countries were also analyzed, and it was found that the overall negative correlation between technology shocks and labor hours was -0.56 and except for Japan, in all G7 countries labor input decreases when there was a positive technology shock. Francis and Ramey (2005) obtained similar results in their study in which they used Dynamic General Equilibrium (DGE) and argued that the technology-driven real business cycle model disappeared because positive technology shocks induce a decline in hours. Shea (1999) also reached the same results as Galí (1999) using R&D expenditures and patent applications as a measure of technology input. According to the author, technology shock leads to an increase in labor inputs in the short run but declines them in the long run. Christiano et al. (2003), in his study, achieved different results although he used the same assumptions as Galí (1999). While Galí (1999) claimed that the hours worked was strongly pro-cyclical and therefore, technological changes had a strong effect on business cycle fluctuations, Christiano et al. (2003) declared that the effect of technological changes on the business cycle was limited and claimed that the positive technology shocks increase variables such as per capita hours worked, consumption, investment, and output. The findings of Christiano et al. (2003) contained results similar to those of Chang and Hong (2003). While Francis and Ramey (2005), who mentioned of inverse correlation between technology shocks and hours, used the growth rate of hours worked in their study, Christiano et al. (2003) dealt with the level of hours worked. Uhlig (2004), who administered on the US data with Bayesian VAR model, argued that in what way the working hours changed against the technology shocks can best be understood by medium run identification. According to the results of the analysis, the correlation between technology shocks and hours worked had the hump-shaped effect that, meant that the effect of technology was initially close to zero, then it developed in a positive direction. According to Basu et al. (2006), the input use and non-residential investments experience a sharp decline, the production changes very little with the development of technology in the short-run, and these results contradict the standard RBC models. In their study in which they used quarterly data of the US between the years 1972 and 1993 and the VAR model, Michelacci and Lopez-Salido (2007) considered technologic advances from two different aspects as neutral technology and investment-specific technology. While more effective software and production tools with powerful hardware were shown here as investment-specific technological progress, product and service innovations can be given examples for neutral technology advancement. Michelacci and Lopez-Salido (2007) indicated that the existing production units cannot be adapted to the new technology and thus the companies would upgrade themselves to the new technology with investment-specific technologic advancements. Based on the Solow (1960) growth model, the authors found that investment-specific technologies in the US between 1972 and 1993 reduced job destruction over time, but investment-neutral technological advances caused more job destruction and job reallocation. Gallegati et al. (2016) argued that studies on the technology-employment relationship were usually based on VAR analysis, but the relationship in question needed to be examined separately in the short, medium, and long-terms. They examined the relationship between employment and productivity in the short, medium, and long-terms in their study in which they paid attention to G7 countries between the years 1962-2012 and to the US between the years 1948-2013 and concluded that while a correlation was present in positive direction between unemployment and productivity in the short and medium-terms, this correlation was opposite in the long-term. In other words, while technology led to the contraction in employment in the short-medium terms, an increase in employment was achieved in the long term with the new job opportunities brought by technology. Finally, Autor and Salomons (2018) analyze the labor-displacing effect of automation via micro-macro channel using data from 19 developed OECD countries in 32 different industries from 1970-2007. The authors point out that many technological innovations provide the use of automation or machinery instead of manpower, but this capital-labor substitution does not mean that aggregate labor demand will be reduced. Because the labor-capital effect causes different effects on input and output levels both within the industry and between industries, it causes shifts between industries and changes in final demand. As a result, the authors stated that the increase in total factor productivity caused by technology increases the demand for labor in general.

As a result, the literature on macro-level studies investigating the technology-employment relationship using direct technology proxies in the literature contains large gaps compared to firm and sectoral-level studies, and especially the literature after the 2000s is relatively pessimistic. Besides, these macro-level studies have doubts that the technology-induced labor-saving effect can be compensated by the labor creative effect.

2.4.3. Technology, Employment Quality and Job Structures

2.4.3.1. Empirical evidence on SBTC

It was stated in the previous sections that the quality of the workforce is not homogeneous, therefore the employment effect of technology is also experimented for different skill groups. In this section, empirical studies that directly or indirectly address the SBTC hypothesis are discussed. Empirically, especially in the USA and subsequently, in other developed countries, the fact that technological advances increase the demand for skilled workers while producing machines that replace unskilled workers has revealed the SBTC approach, and theoretical approaches to this issue are built on data obtained from labor markets.

New computers and, more generally, the technological revolution change the wage structure and on the other hand require the existing labor force to acquire new knowledge and acquire skills (Acemoglu, 2002). Because every new technology requires an adaptation process, and skill both facilitates and accelerates this process. Acemoglu (2002) defines the purpose of technical changes as *"to divide and simplify the work performed by manpower by expanding the division of labor"*. The situation is similar when we look at the issue not only from the perspective of *"new computers"* but also from the perspective of R&D expenditures. R&D activities directly affect the firm's market share and knowledge stock by leading the creation, adoption, and application of new technologies at all stages of the production processes (Freeman and Soete, 1987). Therefore, R&D can increase the demand for high-skilled workers, especially in high-tech countries (Autor and Dorn, 2013; Eeckhout et al., 2014). Moreover, R&D activities in sectors or fields with highly specialized high-skilled workforces can encourage higher-skilled or skilled workers to work in R&D activities or related ancillary areas. On the other hand, R&D expenditures may adversely affect the demand for labor in areas where there is a high density of jobs that are prone to automation since those who work in these jobs are mostly unskilled for new jobs (Autor and Dorn, 2013; Mazzolari and Ragusa, 2013). But the historical perspective shows that the SBTC is not always an active phenomenon. Along with the Industrial Revolution, in the 19th century, new technologies took the place of the skilled workers of the period in England, making the unskilled workforce attractive especially in the production processes, but the increase in the skilled workforce in the 20th century was characterized by SBTC and enabled the completion of the jobs requiring skill with technology (Acemoglu, 2002). Therefore, according to this approach, technology in the 19^{th} century negatively affected the relatively skilled people of the period and increased the demand for the unskilled. However, the phrase *"19^{th}-century skilled workers"* is important because the workforce group that was laid off due to automation in the 19^{th} century is actually mostly blue-collar workers in the intermediate skill group according to today's skill definition. Therefore, it should be taken into account that the definition of a skilled workforce is highly influenced by the dynamics of time.

Empirical studies focusing on how employment is affected by technology by dividing the workforce into two groups as low and high skill in terms of quality are generally built on firm or sectoral data, at a micro level, and most of these studies were carried out before the mid-2000s. Because, after this date, empirical data led economists to consider the professions in terms of their duties, that is, to the RBTC approach. In fact, at this point, it should be noted that the difference in the perspectives of the SBTC and RBTC approaches to the issue stems from the definition of *"medium-skilled workforce"*. In the SBTC approach, empirical approaches are put forward by including the medium-skilled workforce in the low-skilled or unskilled group. In this section, the studies that deal directly or indirectly with the effect of technological change on employment in terms of skills are summarized by considering the chronology.

In studies of the SBTC approach, labor force skill is generally defined according to the education level of the worker. For example, Berman et al. (1994), in their study covering some 450 manufacturing sectors in the USA, obtain empirical evidence that R&D investments and increased computerization are shifting employment towards the high-skilled group. In the study, it is shown that the technological advances in the manufacturing sector in the 1980s increased the demand for high-educated workers within the sector, and therefore the employment of low-educated workers, although slightly increased by the expansion in international trade, lags behind the demand for high-skilled workers in general. A similar pattern was observed in all sectors in the study. Howell (1996) claims that the SBTC perspective is not valid for the US labor markets, and although the skill structure in the country changed between 1973-1983, there was no technology-induced change in the skill composition, especially in the years when ICT began to spread.

Autor et al. (1998), covering the years 1940-1996, state that skill-upgrading was observed in the manufacturing and non-manufacturing sectors in the USA, especially after the 1970s. The authors reveal that this situation occurs more rapidly in companies that use computers intensively and invest more at this point. Dunne et al. (1997), with a similar approach, found a significant and positive but weak relationship between R&D and skilled labor in the manufacturing sector. The authors attribute the weakness of the relationship to the fact that the companies have already increased their skilled labor since before the innovation, in other words, they state that what triggers the innovation is the increase in the supply of skilled labor already. Morrison Paul and Siegel (2001) examine the effects of both technology and trade on the employment of different skill groups. In a study covering 450 manufacturing industries operating in the USA and the years 1958-1989, it is stated that technology affects the demand for high-skilled workers more than trade, while it is claimed that both trade and technology reduce the demand for workers who do not have a college degree. Bresnahan et al. (2002) also state that the use of ICT and organizational changes based on ICT are key indicators for skill-biased technological change in the US manufacturing and service sectors. Bartel et al. (2007), in their study covering the years 1997-2003, found that the adoption of IT equipment in the USA led to the demand for more skilled and skilled workers in the manufacturing industry. Burstein et al. (2015) state that in the US economy, computerization is the most important driver of changes in skill premium and explains more than 60% of the total change in wages. The results of Betts (1997) and Gera et al. (2001), in which similar situations were questioned in the Canadian economy after the US economy, are also in line with the US findings. While Betts (1997) confirmed the skill bias of technology in 11 of 18 industries in Canada between 1962 and 1986, Gera et al. (2001) reach the same conclusion in their study covering 1981-1994 and the manufacturing industry. In South American cases, the issue is more heterogeneous. Robbins (1996b) shows that increases in imports of machinery and equipment for Colombia also increase the demand for skilled labor. Contrary to this study, Pavcnik (2003) claims that the purchase of foreign technologies and other technical inputs for more than 4000 companies in Chile during the 1979-1986 period did not directly affect the demand for skilled workers.

Machin (1995) -both at the firm and sectoral level- and Haskel and Heden (1999) -at the firm level- tests the skill-biased technology change hypothesis with the use of computers in the UK and states that technology increased the need for skilled labor in the 1980s. Nickell and Nicolitsas (2000) investigate whether the R&D and fixed capital investments of some 580 manufacturing firms in the UK are affected by the quality of the available workforce. The authors concluded that a 10% growth in the number of firms reporting a shortage of skilled labor in an industry leads to a 10% permanent decline in fixed capital investment and a 4% temporary reduction in R&D investments.

Tether et al. (2005) link the employment skill composition with R&D investments, using the results of the 2001 UK Innovation Survey. The authors state that the rate of employees with a high level of education in R&D-intensive companies is more than 90%, and the employment rate of graduates from fields such as science and engineering in these companies is much higher than in non-R&D-intensive or non-R&D companies. The authors reveal that similar results are seen when firms are categorized as innovative and non-innovative. For example, it reveals that while the graduate rate in innovative companies is more than 80%, it is around 50% in non-innovative companies, so the skill density of companies that bring a new product innovation or process innovation to the market is significantly higher than the others. Mairesse et al. (2001), in their cross-sectional analysis covering the period 1986-1994, reveal that ICT increased skilled labor demand in France. Goux and Maurin (2000) state that 15% of the change in labor demand in the manufacturing sector in France can be explained by computers and new technologies. Falk and Seim (2001) in their study covering 933 companies and the period 1994-1996 emphasize that ICT-intensive companies in the service sector in Germany tend to demand more skilled labor and show that those who invest more in technology employ more university-educated workers.

Casavola et al. (1996) examine the effect of technology on employment and wages in Italy in the 1986-1990 period and show that technological advances increase the demand for skilled workers. In addition, the authors reveal that the effect of technology on wage differentials is not as high as in other countries. Piva and Vivarelli (2001) in their study covering more than 400 manufacturing companies and the period 1991-1997 show that the effect of technology, measured by R&D expenditures, on employment in Italy is not skill-biased. Piva et al. (2005), indicate that the main source of skill-biased changes in Italian firms is the organizational structure changes. The authors, in their work focusing solely on the machinery industry in Italy, show that both skilled and unskilled workers are adversely affected by technological advances. Again, in Italy, but this time covering the textile industry, Baccini, and Cioni (2010) show that new technologies often replace unskilled jobs with machines, but in a few empirical cases, high-skilled jobs can also be replaced by machines. In Spain, Aguirregabiria and Alonso-Borrego (2001) analyzed data from Central de Balances del Banco de Espana, owned by over 1000 manufacturing firms, for the period 1986-1991, indicating that technology capital confirmed the skill-biased employment change. However, the author reported that no significant effect was observed when R&D was used as the technology proxy.

Since the middle of the 2000s, in terms of studies on the relationship between labor demand and technology, the needle of the economics literature has shifted from the SBTC hypothesis to the RBTC hypothesis, so there are not many skill-oriented studies in the recent period. Koren et al. (2017), which is a remarkable study among the limited number of recent studies in that it focuses on one of the developing economies, examines the effects of imported technology products on the employment structure by using the data of machine operators working in Hungary between 1992-2004. The authors support with a case study that imported machines are used by more reliable and more skilled workers. On the other hand, the authors argue that in the Hungarian manufacturing industry, imported machines operators are paid on average 5% more than others, and that trade liberalization is responsible for about a third of wage inequality. Ultimately, the authors state that imported machines facilitate the diffusion of skill-biased technological change.

Silva and Lima (2017), in their study, examine an average of 2.5 million employees and 200000 companies per year in Portugal between 1995 and 2007. The authors demonstrate with the Portuguese example that the skill complement effect of technology is observable in terms of job duration, especially in medium or high technology firms, where the risk of *"job separation"* of highly skilled workers is lower than in others. The authors explain this by the fact that the complexity of jobs in high-tech firms makes it difficult to acquire technology-specific skills, resulting in the firm placing greater emphasis on available human capital. As a result, the increase in technology intensity affects the relationship between skilled employment and job duration in favor of employment, and this situation significantly reduces the job separation risk of high-skilled employment in high-tech firms. Lordan and Neumark (2018), in their studies covering the years 1980-2015, discuss how the change in the minimum wage in the USA affects the demand for jobs that are prone to automation, especially on the axis of low-skilled workers. The authors reveal that the increase in the minimum wage reduces the employment of low-skilled workers. Then again, as a more specific finding, a decrease is observed in the employment share of relatively older workers, especially those employed in the manufacturing sector. The authors point out that the negative impact on low-skilled workers is eliminated by increasing the number of high-skilled jobs through the creation of new job opportunities.

Aldieri et al. (2019) emphasize that the empirical literature examining the technology-employment relationship at the regional level is quite limited, and the literature at the regional level does not separately discuss the impact between low and high skilled workers. At this point, this study investigates whether regional innovation activities in Finland have an impact on regional labor demand for different skill levels. Their work is twofold: a) First, they use employment data from 70 subregions of Finland, including innovation R&D, and examine the impact of skill-based technological change, taking the period 2000-2013. b) In the second stage, they investigate the employment effect of interregional knowledge spillovers. The authors confirm that local innovation activities and knowledge spillovers from other regions increase the demand for high-skilled workers, while innovation has a negative impact on the low-skilled, but they state that knowledge spillovers have no significant impact on the second group. Therefore, innovation and knowledge spillovers in Finland positively affect the high-skilled group, and this effect is greater in the long run than in the short run. On the other hand, the negative effect towards the low-skilled group weakens in the long run.

In addition to the studies that deal with the countries individually, there are also studies in which the SBTC is tested directly and indirectly with groups consisting of developed and developing countries. For example, Machin and Van Reenen (1998), in their study of seven developed economies, reveal that R&D expenditures increase the demand for skilled employee. Moreover, the authors note that the variation between wages by skill in the USA and UK is also quite high and significant, which is in line with previous empirical findings. Robbins (1996a), with a pooled data set consisting of Argentina, Chile, Colombia, Costa Rica, Malaysia, and the Philippines countries, detects a positive correlation between imported capital products and especially higher education graduate labor demand. Görg and Strobl (2002) show that imports of foreign machinery for 200 manufacturing companies in Africa increase the demand for high-wage workers. In their study covering 28 manufacturing industries in 23 low- and middle-income countries, Conte and Vivarelli (2011) discuss the effects of technology imports on different types of skills in the 1980-1991 period. The authors conclude that the import of skill-complementary capitals and embodied technologies is one of the likely causes of the increase in demand for highly skilled or skilled labor. Michaels et al. (2014), in their study covering the USA, Japan, and nine developed European countries, report that only 25% of the differences between countries in terms of increasing demand for highly skilled workers between 1980 and 2004 could be explained by ICT. In summary, average skill increases and variations in skill intensities across all countries are common among countries with different levels of development and are directly related to technology use and adaptation. According to the authors, this is also an indication of a global SBTC presence.

According to the data obtained from developed countries, it can be said that innovation is mostly skills-oriented (Tether et al., 2005), although the demand for skilled workers in developing countries has increased over time, the current bottleneck in the supply of skilled workers makes the process more complex than in developed countries. The skill-biasedness of innovation is a threat to the low-skilled group of workers, as technical change facilitates the automation of low-skilled jobs, and with the complementarity of trade, this process reduces the demand for low-skilled workers in developed countries. But it does not adversely affect the demand for labor for unskilled jobs that are difficult to automate and will not be affected by trade openness. Based on the fact that technology complements skills, technologies increase the demand for high-skilled people. Typically, however, these innovations are used first by highly skilled workers, as they may benefit more from technology than lower-skilled workers. Technical diffusion is also associated with organizational change, and higher-skilled workers are thought to benefit more from organizational changes than lower-skilled workers.

The effects of skills supply on the scope and nature of innovation in society, and what kinds of skills intensify innovation activities are another issue of concern. Qualified employees working in the fields of information and technology certainly contribute to the expansion of their fields. For example, the fact that the UK has qualified people in fields such as biotechnology and nanotechnology, especially in the pharmaceutical sector, and countries such as Germany and Japan are pioneers in sectors such as automobiles and electronics with their qualified engineers, are important observations that not only does technology affect the demand for skills, but also existing skills affect technology (Tether et al., 2005). On the other hand, while the high-skilled employment structure affects innovations positively, various skill deficiencies can delay technology or make it difficult to adapt. For example, in the innovation survey reports obtained from various countries in Europe, it is revealed that the biggest obstacles to innovation are the lack of skilled personnel, such as not finding sufficient human resources, lack of personnel with high technical and commercial capabilities, and inability to fill vacant positions with sufficient qualified personnel (Tether et al., 2005). At this point, as stated in Gary Becker's *"Human Capital Theory"*, employers may not be investing in training because they may be concerned that the skills gained as a result of training will provide more benefits to other firms than to add value to their own firm (Becker, 1964/1993). Howells (2005) states that this situation can be experienced especially in high-tech sectors that require high education costs. Thus, in real and inefficient markets, employers and individuals are likely not to invest enough in human capital, which can reduce the efficiency or speed of innovation. In summary, it is seen that companies complain about the lack of technical and commercial personnel, especially the lack of basic skills in the innovation process, and the inadequacy of the supply of university graduates. Also, innovation does not only require a trained workforce, but it also requires managerial skills for effective implementation.

As a result, the SBTC hypothesis has been frequently tested, especially with labor market data obtained from developed countries. According to the findings of almost all studies, the aspect of high-skilled employment is clear: technical progress increases the demand for skilled labor. However, the side of the demand for unskilled labor is a little more blurred. These blurriness and post-2000 employment data from developed countries, especially the USA, gave rise to the RBTC hypothesis, whose empirical literature is summarized below. However, this does not mean that the SBTC hypothesis has been empirically overruled completely. On the contrary, future projections show that low-skilled employment will decline, but demand for high-skilled workers will continue to increase (Frey and Osborne, 2017).

2.4.3.2. Empirical evidence on RBTC

The SBTC hypothesis was insufficient to explain the increase in the share of low-skilled jobs along with the share of high-skilled jobs, while jobs that mostly appeal to the medium-skilled workforce contracted in many developed countries, especially the USA. Both RBTC and SBTC hypotheses explain the increase in the demand for high-skilled employment with technological advances, the point where the two hypotheses diverge is for the middle-level employment group, which SBTC already considers this group together with the low-skilled level in general. Autor et al. (2003) state that computerization or digitalization increases the likelihood that routine work can be done automatically, as they are more easily differentiated and more prone to mechanization. On the other hand, if the tasks require unclear information, may change over time or are open to interpretation, and contain unpredictable dynamics and characteristics, there is no routine, and tasks cannot be digitized or done with the same ease. Of course, when explaining job polarization based on routine jobs, the definition of the routine job is very important. Differently defined jobs or tasks influence inferences on the existence or extent of polarization. The RBTC hypothesis is a successful approach to explain job polarization, increased demand for highly skilled workers, and other changes in employment structures, especially in industrialized countries. Furthermore, the tasks that are theoretically an element of the production function in the model are assigned according to the comparative advantages of workers and robots, which may present difficulties for empirical applications. In this field, data collection techniques are mostly based on two methods such as *"databases such as O*NET containing job descriptions based on professional evaluations of experts"* and *"surveys containing questions based on employees' definitions of their own duties and skills"* (Raquel and Biagi, 2018). Both data collection techniques have their advantages and disadvantages. One of the handicaps of the O*NET database, which is generally used in studies involving the RBTC approach, is that it is not possible to compare the outputs over time because the job descriptions change over time.

On the other hand, the surveys answered by the workers reflect the opinions of the workers and may be far from subjectivity. In addition, although a group of workers is formally doing the same job, some of their duties may differ, this situation may differ between sectors and there may be significant divergences in approach between countries. These data can then be expanded at a sectoral or macro level by coding routinely or non-routinely, cognitively or manually, but of course, the subjective nature of these definitions from time to time can make inferences difficult and make measurements problematic (Raquel and Biagi, 2018). Another important point is that the SBTC hypothesis classifies workers, not occupations, according to their skills, often taking into account education level, roughly dividing them into *"skilled"* and *"unskilled"*. However, as emphasized in the previous chapters, the main focus in the RBTC hypothesis is the classification of tasks, and inferences are made about the skill levels of the workers working in these jobs, following the task classifications. In this direction, the evidence in the RBTC hypothesis is mostly on the classifications of *"high"*, *"medium"* and *"low"* skill-requiring jobs. However, another point to be considered here is to what extent the job classifications reflect the skill levels of the employees. It would not be wrong to say that the majority of workers in developed countries work in jobs that match their skill level, but job shortages in the labor market, especially in developing countries, may force people with high skills to do lower-level jobs. In other words, new labor-saving technologies may lead highly educated people to work in low-skilled jobs. Thus, task-based approaches do not give a clear idea of the skill levels of workers currently employed, especially in low-skilled task classifications, even though they take into account the level of training the task requires (Cirillo et al., 2021).

Empirical evidence for the RBTC hypothesis, as with other technology-employment analyses, is mostly for developed countries. As a general approach, these studies are based on the idea that technology causes different automation risks for different tasks, but studies may differ in terms of the definition and classification of tasks. For example, the ALM hypothesis, which was put forward in 2003 and is one of the pioneers of the task-oriented technological change approach, divides tasks into five (Autor et al., 2003), but later this approach was revised by Autor et al. (2006) and defined as three tasks. In the following period, Spitz-Oener (2006) and Goos and Manning (2007) deal with the tasks in 5 different ways based on the ALM taxonomy and evaluate the RBTC hypothesis in this direction. Besides, Autor et al. (2006), Autor and Handel (2013), Autor and Dorn (2013), Goos et al. (2014), and Sebastian (2018) examine tasks under three main headings as routine, manual and abstract tasks. In these studies, routine tasks represent routine manual and routine cognitive tasks, while abstract tasks involve tasks that require high cognitive abilities (such as problem-solving and managerial positions). Finally, manual jobs include flexible jobs that require physical effort and manual dexterity, which have low automation risks. Matthes et al. (2014), on the other hand, reduce tasks to five dimensions, slightly different from previous studies: autonomy, analytic, interactive, routine, and manual. The "autonomy" title, which is addressed differently from the previous literature, stems from organizational changes or structure rather than the positions of the tasks against technology. Fernández-Macías and Hurley (2016) evaluate the "social interaction" sub-task dimension in addition to the routine and cognitive categories in their study, which argues that such tasks are not prone to computerization by their nature. Marcolin et al. (2016) focus on measuring how routinely intensive occupations are, while Fernández-Macías and Bisello (2017) distinguish between the content of tasks and the ways in which tasks are performed. In this respect, Fernández-Macías and Bisello (2017) study can be considered as a further extension of RBTC as it evaluates the degree of the routinization of work by considering both technology and organizational structure. All these differences in task definitions also affect the course of empirical studies because a task defined as routine in one study may be defined as non-routine in another study, and even the same author may have changed his approach over time depending on the developments in technology. In fact, Frey and Rahbari (2016) state that historically computerization has mostly been limited to tasks based on clear rules that can be easily encoded by the computer, but that ICT has made it more possible as time progresses to automate non-routine tasks as well. The authors, who give examples of actions such as driving and handwriting recognition, say that both activities were shown among the tasks that could not be automated a very short time ago, but today such tasks can be automated to a large extent or are very close to being fully automated. Therefore, it will not be difficult to foresee that these job definitions will change in the future.

RBTC-based analyses that evaluate the employment impact of technological changes by considering tasks notably Goos and Manning (2007) in England, Autor et al. (2006), Autor and Dorn, (2013) and Autor (2015) in the USA, and Goos et al. (2014) in 16 European countries, are processed together with job polarization. The starting point of job polarization is wages, as mentioned earlier; According to this approach, employment growth occurs at the extremes of the wage distribution, based on the observation that low- and high-wage jobs grow faster in terms of job creation than middle-wage jobs. According to the job polarization, jobs consisting of manual & routine tasks are prone to automation, and workers in this field will likely be replaced by machines. Workers in this group mostly have a low level of education and their wages are the lowest in this context.

Workers with medium education and whose wages are also characterized as middle-income often work in *"high routine-intensive"* jobs, and these *"standardized, monotonous"* jobs are most likely to be automated. Cognitive and non-routine workers perform tasks that are difficult to replace with technology, but they can increase the productivity of the tasks they perform with technology, in which case technology or more specifically *"computers"* take on a *"complementary"* role for them. Finally, manual but non-routine tasks that require dexterity or special attention are not adversely affected by technology. Such jobs can be performed by low- or medium-skilled or educated workers. The demand for the workforce working in these roles may increase due to the aging and enriching population (Mazzolari and Ragusa, 2013) and the general equilibrium effect from technology, that is, the increased demand with productivity (Autor and Dorn, 2013).

Autor et al. (2006), one of the pioneering studies empirically testing job polarization and the RBTC hypothesis, reveal that routine tasks are shrinking compared to non-routine jobs in the current US labor market. Similarly, Goos and Maning (2007) examine the UK employment structure for the years 1979-1999 and make three important links that explain the substitution of middle-wage jobs with technology as a result of RBTC and are an important reference point for further studies: a) Non-routine manual tasks mostly involve low-paying jobs. b) Mid-wage jobs often consist of cognitive but routine tasks. c) Both cognitive and non-routine jobs are high-paying jobs.

Cortes et al. (2016) report that the employment rate in routine jobs, which was 40% in 1979 for employees aged 20-64 in the USA, decreased to 31% in 2014; states that employment in non-routine manual jobs increased by 3.9% and employment in non-routine cognitive jobs increased by 6.7% in the same period. The author points out that the rates are more striking for the low-education group. While more than 60% of the low-educated employment group was working in routine jobs in 1979, this rate decreased to 20% in 2014. Finally, the authors point out that routine US workforces are less likely to engage in high-paying non-routine cognitive jobs, especially low-skilled routine workers are more likely to shift to non-routine manual jobs. More recently, Lee and Clarke (2019) explore how the growth of the high-tech industry in Britain, particularly between 2009 and 2015, affected low and middle-skill employment. Stating that high-tech industries are in an important position for economic growth and generally provide high-paid-high-skilled employment, the authors state that the literature is divided into two at this point: a) According to optimistic views, the high-tech industry is a tradeable sector and has a *"multiplier"* effect on employment, while the sector has a job creation effect within itself, it also creates new jobs in other *"non-tradeable"* sectors. b) Pessimistic views are shaped within the framework of inequality and polarization in wages. The authors on this viewpoint out that in the high-tech industry, technology benefits the skilled group while lowering the wages of the low-skilled group. Examining the impact of high-technology industries on less-well-educated workers in their studies, the authors reach three important findings: a) There is a significant multiplier effect in the high-tech industry. Each new high-tech job creates 0.7 non-treatable jobs. b) High-tech industry growth reduces the wages of low-skilled workers. c) Contrary to similar studies, positive findings are reached for middle-skilled workers in this study, and high-tech growth is beneficial for workers in this group.

Contrary to studies focusing on a single country sample such as the USA and the UK, the findings on the effect of technological change on business polarization in studies dealing with continental Europe are more complex and heterogeneous. Instead, these studies analyze country groups rather than focusing on individual countries. Goos et al. (2014), in their study covering the years 1993-2010 and 16 European countries, states that technology is mostly responsible for employment polarization with the exception of a few EU countries, in other words, there is evidence in favor of the RBTC hypothesis in these countries. Similarly, Naticchioni et al. (2014) confirm that investments in digital technology are positively related to job polarization with the European sample of the 1995-2007 period but argue that there is no evidence that technology causes wage polarization at the sectoral level. Michaels et al. (2014), in their study covering the USA, Japan, and some of the developed EU countries, find that the demand for highly educated people is increasing in sectors with high ICT investment growth, but the demand for medium education is decreasing. In his study, Peters (2016) categorizes eight different occupational groups in EU15 countries according to their average wages for three different periods, 1995-2001, 2001-2008, and 2008-2015, and shows that while the share of high-paid professionals and low-paid service workers in employment increases, middle-wage occupations tend to increase. According to the data, an average of 4.6% decrease was observed in the share of medium-wage occupations in the period of 1995-2015, while an increase of 3.1% in low-wage occupations and 1.3% in high-paid occupations. The study shows that the changes are more dramatic for the period after the global financial crisis, that is, after 2008, nevertheless, although the share of high-paying professions on average has increased, the share of some high-paid professions such as the manager position has decreased slightly over 3% after 2008. However, a decrease is observed in the employment share of middle-wage occupations in all three periods.

Although Marcolin et al. (2016) did not directly address the effect of technology in their studies, it was also found important for this thesis in terms of focusing on routine occupations. The authors state that the routine or non-routine of a profession can be defined by whether it is designed according to a set of specific rules or according to tasks that involve complex activities such as creativity problem solving and decision making. In this direction, the routine intensity index (RII) is created with the questions asked by using the OECD International Assessment of Adult Competencies (PIAAC) questionnaire to measure the degree of routineness of the professions. This index provides information on employees' self-assessments: a) Freedom in determining the order of tasks. b) Degrees of freedom in deciding the type of tasks performed at work. c) Freedom to make their own decisions for their own activities. d) Freedom to organize their own time. In the classification of Marcolin et al. (2016), it is seen that while the employment share of the high-skilled group is highest in non-routine or low-level routine jobs, medium and highly routine intensive occupations generally appeal to medium-skill employment. It reveals that 73% of all high routine intensive jobs and 68% of all medium routine intensive jobs can be categorized as medium-skilled employment, indicating that middle-skilled workers are the group most affected by job disruptions. Marcolin et al. (2016) also show the said categorization on a country basis. The authors show that Italy, Spain, and Ireland are the EU countries with the highest proportion of high routine intensive occupations. However, when high and medium-level routine intensive occupations are considered together, he states that the country ranking has changed this time and that the United Kingdom, Ireland, Slovakia, and Poland are the countries with the highest ratio of routine intensive occupations.

The countries with the highest share of non-routine jobs are Austria, Germany, and Denmark. On the other hand, the proportion of work that is not routine or has a low routine intensity is maximum in Luxembourg (55%) and lowest in Italy (20%). As reported in the study, the change in Turkey is as follows: while the total of low routine and non-routine in manufacturing is 28%, the sum of medium routine and high routine is 72%. In service, as expected, the weight of nonroutine and low routine is 34% higher than in manufacturing, and the rate of high and medium routine is 66%. Finally, the proportion of workers with a high routinization rate overall is 41% in manufacturing versus 28% in the service sector.

Salvatori and Manfredi (2019) provide evidence of how middle-skilled labor and income structures were shaped in 18 OECD countries between the mid-1990s and mid-2010s. Many workers in middle-income households are middle-skilled, so job polarization puts pressure on the average income of this group. Because the distribution of occupations in the middle-income group changes over time, the increase in the share of high-skilled jobs may reduce the share of middle-skilled jobs on the one hand and may prevent or compensate for the decline in the average income of the middle-income group, on the other hand, thus making the income share of middle-income households less affected. . Since the distribution of different occupational groups by income groups has changed significantly recently, the changes observed in the share of workers in middle-income households are explained by the changes in the tendency to belong to different occupational groups. First, there is a shift in the job composition of the middle-income group. From the mid-1990s to the present, the proportion of high-skilled workers in the middle-income group has increased from 35% to 47%, while the proportion of middle-income workers has decreased from 41% to 32%. The authors note that the polarization of the occupational structure is a very common finding in OECD countries, with employment showing a clear shift mostly towards high-skilled occupations. On average, the share of high-skilled occupations in employment increased by 10.6%, according to the data presented in the study. While the decrease in jobs requiring medium skills is 7.8%, the share of low-level occupations is 2.8%. The total share of medium-skill jobs is shrinking in 16 of the 18 OECD countries included in the study, while no such trend is observed in the two developing countries, Mexico and Slovakia. Also, decreases in the share of medium-skill jobs in 14 countries are mostly offset by high-skill jobs, except for Hungary and the USA, where low-skilled occupations are increasing more. Thus, the overall implication in terms of job polarization in OECD countries is that the share of medium-skill jobs is falling relative to both high- and low-skill occupations, while most gains are achieved by high-skilled jobs. In addition, the authors state that the polarization of household income classes is not as widespread as the polarization of occupations and is mostly caused by the shift of working adults to the lower classes. But the different patterns observed in changes in occupation shares suggest that job polarization is not necessarily related to a shrinking middle-income class. Although the decrease in the employment share of middle and low-skilled workers pushes the middle-income class down, the middle-income group is stabilized because the share of high-skilled workers has increased. The increase in the share of highly skilled workers contributes to the strengthening of the middle class in all OECD countries except the USA. On average, the higher share of high-skilled workers in OECD countries contributes 8.4% to middle-income class growth, and overall, changes in the distribution of highly skilled workers by class contribute positively to middle-class growth in 12 of the 18 OECD countries. Overall, the impact of job polarization on the size of the middle class across countries is small. This is because the decline in the share of middle-skilled and some low-skilled workers has been suppressed by the growth of high-skilled jobs. Thus, the middle-income class is becoming much less middle-skilled and much more highly skilled. It is therefore clear that some jobs are increasingly failing to deliver on the promise of income growth associated with skill levels.

Many studies in the literature on what RBTC has changed in the labor market focus on advanced economies, and the emerging world remains weak in terms of policy recommendations since the number of studies based on the developing world in this field is limited (Soto, 2020). On the one hand, there is a lot of solid evidence to support the RBTC hypothesis regarding the relationship between job polarization and technology in developed countries, while the situation is more heterogeneous for developing countries. Frey and Rahbari (2016) point out that technology and automation may have deeper effects in developing countries. In the World Bank (2016) report, between 1995 and 2012, with the exception of China, job polarization is observed in developing countries, with the decrease in medium-level jobs being approximately 8%, which is slightly below the rate of industrialized countries, 12%. The reason China is an exception here is due to the relocation of manufacturing jobs from developed countries to this country, but they suggest that China may be the last country to use industrialization as an important tool on the road to prosperity in this field. According to Rodrik (2016), one of the reasons for the early deindustrialization in developing countries may be technology. According to Frey and Rahbari (2016), the effects of automation on employment may be more severe in developing countries because while the share of agriculture and industry in employment is 26% in developed countries, this rate is around 55% in developing countries. However, Maloney and Moline (2016) state that the impact of technology on job polarization in developing countries has not yet been more severe than in developed countries, as claimed in Frey and Rahbari (2016), on the contrary, there is not enough evidence that mid-level jobs are lost. The authors explore the polarization of labor markets in developing countries by following Autor and Dorn (2013) in studies for the USA and categorize job categories for 21 developing countries in Africa, Latin America, and Asia in the Integrated Public Use Microdata Series (IPUMS). They show that the effects of job polarization in developed countries are not yet seen in developing countries. The authors report that there has not been a significant decrease in occupations such as plant and machine operator and assembler, which are among the most important categories for medium skill jobs and emphasize the possibility that this situation may not remain the same in the future, and state that there is no evidence supporting job polarization in developing countries yet. On the other hand, the authors mention exceptions on a country-by-country basis. They note that in countries such as Brazil, Indonesia, and Mexico, a significant decline in the category of machine operators has been observed, while in China, robotization may accelerate the decline in routine work in the future. Among some other studies, including developing countries, Medina and Posso (2010) confirm the existence of job polarization in Mexico and Colombia, while finding no evidence for job polarization in Brazil for the period 1991-2001, but the findings for Mexico are weaker. The World Bank (2016) does not observe job polarization in Argentina, China, Costa Rica, Peru, Russia, Turkey, and South Africa for the data range from 1995 to 2012, but these analyses exclude agriculture. Rejinders and Vries (2018) found job polarization in China and Mexico in their analysis, which did not include the agriculture sector while providing evidence to the contrary in Turkey, Indonesia, and India. The authors also find that technology increased the number of non-routine jobs in both developed and developing countries over the period 1999-2007.

Much more recently and from a broader perspective, Soto (2020) looks at 13 emerging countries, including Turkey, to fill the literature gap on how technology is shaping labor markets in emerging economies. The author states that theoretically many tasks can be automated in many emerging economies, but their automation is not as easy and fast as in theory. Because automation is not yet economically attractive in these countries and there is still an abundance of cheap labor. Thus, technology is being adopted more slowly and the expanding scope of automation is likely to affect emerging economies later than advanced economies. Soto (2020) states that since the employment density in the agricultural sector in developing countries is still higher than in developed countries, this situation should be taken into account when checking the existence of job polarization. Today, agricultural employment in developed countries is very small, because employment in these countries has already shifted to manufacturing and service sectors. Therefore, the inclusion of agricultural employment does not have a significant effect when explaining the existence of job polarization. But, ignoring the share of agriculture in employment in developing countries, there is little evidence in favor of job polarization. Although the share of middle-skilled jobs in employment in these countries decreases over time, if agricultural employment is ignored, a job polarization pattern similar to that in developed countries is observed only in countries such as Chile, Costa Rica, Mexico, and South Africa. Conversely, job polarization is observed in most developing countries when agricultural employment is included. The most important reason for this is the decrease in the share of the agricultural sector in employment, which mostly requires middle-level skills in these countries. In addition, wages in agricultural occupations in developing countries are lower than in other occupations, so shifting employment from agriculture to other sectors seems to increase both job quality and wages. While the share of medium-skilled occupations decreases in almost all sectors of the economy in more developed economies, this share does not decrease in all sectors in developing economies. Only the construction, manufacturing, and energy sectors show some signs of polarization in some emerging economies. Therefore, understanding job polarization in developing countries requires addressing sectoral transformations on an individual basis. Soto (2020) states that the share of high- and low-skilled occupations in total employment in developing countries increased by about 2.6% on average between 2000 and 2015, including the agriculture sector. In addition, the author states that 78% of this increase in polarization can be explained by job reallocation between sectors and 22% by job reallocation within sectors. The decline in certain sectors plays a significant role in the loss of medium-skill jobs relative to high- and low-skill occupations in most developing countries. The cross-industry effect is observed in Indonesia, Costa Rica, Turkey, Russia, and Peru, while the intra-industry effect is more prevalent in Chile, Mexico, Brazil, and South Africa. Thus, the polarization observed in many developing countries is the result of a process of structural change involving the reallocation of employment from less polarized sectors such as agriculture and manufacturing to more polarized service sectors. As part of economic development, emerging economies are shifting large labor shares from low-wage agriculture to service sectors that promise high wages. This process, which started in the 1980s and accelerated in the last two decades, brings along a great decrease in employment shares in manufacturing and especially agriculture sectors while increasing the share of all service sectors in total employment. These changes in economic activity are part of a fairly natural process, as people tend to consume more services as they have better economic conditions (IMF, 2018; Soto, 2020).

As a result, the removal of routine jobs, or in other words, medium-skill tasks, can occur in two ways: a) Factors causing job polarization eliminates medium-skill jobs, and the share of low- or high-skill jobs in the same industry increases. Thus, while technology is a driving force for both the upper and lower groups in terms of employment skills, the routine jobs of those in the middle group are now old-fashioned for the employment world. b) While the increase in demand for goods or services in some sectors increases the demand for employment, in some other industries the demand may decrease, and employment may be adversely affected. In the face of this situation, workers can reallocate across industries. If the weight of routine jobs is high in the shrinking industry, while the low and high-skilled share is high in the expanding industries, the reallocation of the workers will again trigger job polarization. And consequently, as technology changes the character of the job, how people adapt to the new job has become an important problem, and considering the size and speed of technological transformation, it is very critical how people will respond to the skill requirements of the employment market. At this point, Autor et al. (2015) argue that US citizens whose jobs are taken away or displaced as a result of automation are discouraged from seeking employment and prefer not to participate in the labor market. On the other hand, when the issue is evaluated in Germany, it has been determined that employees who lose their routine jobs are more inclined to change professions rather than be unemployed. In addition, it has been reported that workers in this situation do not lose wages if they upgrade themselves to higher skills, but if they turn to low-skill jobs, they experience a loss of wages (Nedelkoska, 2013; Nedelkoska et al., 2015). So, if contracting sectors with larger shares of medium-skilled jobs are leading to job polarization, labor market policies should focus on helping displaced workers in shrinking sectors transition into other sectors with new opportunities. If job polarization is due to changes in employment within the sector, policies should ensure that workers in medium-skill jobs are encouraged and acquire the necessary skills to hold high-skilled jobs. Although both situations involve a training or skills development process, the way of implementation and the type of skills and support required may be different. If intra-industry displacements are due to technology, workers need to adapt to new technology and acquire technical skills. Alternatively, if there is a transition between sectors, such as the transition from the manufacturing sector to the service sector, workers will be expected to have completely different skills than they have, and measures and policies will need to be determined accordingly.

2.4.4. Future of Jobs

As computerization possibilities increase and robots become cheaper, it is inevitable that such machines will be used in production and spread to all sectors. Economic history shows that inventions such as electricity, early production machines, and first-generation computers affected all sectors and all dynamics of the economy in the past. It is highly likely that today's and tomorrow's technologies will similarly spread to all sectors and cause the same or greater effects. In this respect, a significant part of the recent studies on the relationship between technology and employment contain predictions about the future. These studies usually calculate the automation risk of different occupational groups and make predictions about their probability of extinction in the future, while also making predictions about occupations that are likely to be popular in the future or to be in high demand in the labor market. However, technologies of today and future have some differences compared to the past, and these differences are an important handicap of the estimations. For example, while past technologies mostly provided the opportunity to mechanize routine works, more complex works can also be digitized today (Autor, 2015; Acemoglu and Restrepo, 2018), and it would not be unreasonable to expect humanity to produce more successful technologies in more complex areas in the future.

In today's conditions, the average citizen of a developed country has access to better health care, educational opportunities, travel, and communication tools than the wealthiest of the recent past, and similar opportunities will continue to increase in the future as a blessing of technology. For example, at the beginning of the 1800s in the USA, the product that a farmer obtained in approximately 300 hours could be produced in 50 hours with machines that complement the labor of horses at the end of the same century, while this duration was reduced to 3-4 hours with the help of advanced tractors and combines at the end of the 20^{th} century. Therefore, obtaining more output with the same inputs in agriculture resulted in lower production costs and cheaper food, and reduced *"starvation death"* rates (Saunders, 2017). Autor (2015) also states that historical data indicate that gains in productivity in the very long run do not lead to a decrease in demand for goods and services, on the contrary, household consumption mostly keeps pace with household incomes. The author states that today's worker, who desired to live at the income level of an average worker in the USA in 1915, could reach this aim by working approximately 17 weeks a year, but most citizens would not intend this trade-off between hours and income because consumption increased with increasing productivity. However, it should be taken into account that workers in developed countries have shorter annual working hours, take more holidays, and retire earlier when compared to an average of 100 years ago, and therefore prefer to spend a part of their increased income on more leisure time. Autor (2015) states that this is a good indicator of well-being in general and claims that it cannot mean demand saturation. Therefore, he states that elements such as consumption and leisure complement each other, people spend their free time in more activities that will make them happy, and that the Marxist concern that workers will gradually weaken at this point is not true. But although technologies in the past have almost halved working hours in both the US and Europe and have allowed keeping unemployment low, while also increasing female labor market participation, current technologies have far exceeded the average full-time working time in EU countries. The average working time has decreased from 41.9 hours to 41.1 hours in the last ten years until 2015. According to Dachs (2018), the effects of worktime reduction are not clear for the future, since shortening the working time, on the one hand, helps workers to establish a better work-life balance, on the other hand, it may lead to the labor shortage.

The increase in productivity in agriculture brought about the migration of farmworkers to the cities and thus the development of industry, resulting in the creation of new goods and services and an increase in consumption. While Autor (2015) attributes the share of agricultural employment, which was approximately 41% at the beginning of the 1900s, to 2% in the 2000s, naturally to automatic machines used in the sector and various other technologies; states that similar employment effects can be seen in many professions, from construction workers to accountants today and in the future. Because the main purpose of workplace technologies is to save labor and to include less error-prone machines into the production and service process instead of manpower. While such technologies produced for the purpose of labor-saving are successful in most cases, the author questions why there is still so much work and states that labor and capital play an important role for each other. Thus, the author declares that improvement in one does not necessarily remove the need for the other, that improvements in productivity within a task sequence increase the economic value of all tasks in the business chain. However, in addition to such wonderful gains, the negative effects of mechanization on the workforce cannot be ignored. For example, although there were similar increases in the incomes of workers at all levels in the USA between 1940 and 1970, income inequality began to reach serious dimensions after those years, because while those at the top saw significant increases in their wealth, the lower class made more modest gains (Saunders, 2017). It is not surprising that such productivity gains and employment losses will continue. At this point, Autor (2015) underlines three important factors that determine the risk of automation in employment: a) If workers do a job that is replaced by automation rather than completed by automation, they will be negatively affected by automation, which will lead to job loss or a decrease in wages. b) The flexibility of the labor supply can erode wage gains; because if there are plenty of workers who can do complementary tasks, this can lead to a reduction in wages. c) Output elasticity of demand and income elasticity of demand can both affect the gains from automation; while the increase in productivity in some sectors reduces the share of that sector in total expenditures, technological advances in sectors such as health increase the amount spent on health.

The studies by Carl B. Frey and Michael A. Osborne are the most popular on automation risk and the future of work and serve as both a guide and inspiration for similar research and a reference point for new predictions in these studies. For example, Frey and Osborne (2013, 2017) are one of the most striking analyses of recent times that includes insights into how technology affects the future of employment and occupations in general. The authors estimate the probability of computerization of 702 different occupations in the US employment market, stating that the main motivation for the study is Keynes' statement that *"technological unemployment will occur if the production of tools that make the use of labor less costly is faster than creating new areas for the use of labor"*. According to estimates based on testing O*NET data provided by the US Department of Labor with the model developed based on advances in machine learning and mobile robotics, 47% of total employment in the US will be at risk of high automation within one to two decades. The authors note that most jobs in the shipping and transport industries, administrative support workers, construction work, and employment involved in manufacturing will suffer in the first place. Algorithms, computerized tools, and similar technologies involving the use of big data are the main reason for the decreasing need for manpower in these areas. The tendency of production professions to automation is similarly due to the use of advanced robots in these areas. The authors state that fields that require social skills and creativity such as fine arts, social perception and negotiation/communication, and occupations based on hand or finger dexterity are in the low-risk group. Therefore, he concludes that areas of expertise that involve tasks that require people's intuitive knowledge, and the development of new ideas and artifacts are those least susceptible to computerization. The authors attribute the engineering and science professions' low susceptibility to computerization to the high degree of the creative intelligence they require. However, they state that the algorithms developed now offer the ability to recognize patterns thanks to big data opportunities, and therefore non-routine cognitive tasks are also at risk of computerization. Finally, the study emphasizes that the forecasts for job polarization have been interrupted and it is stated that in the near future computerization will reduce the demand especially for low- and middle-income occupations, while high-skilled and high-paying occupations will be less susceptible to computerization. Therefore, the SBTC hypothesis, which left its popularity to RBTC since the mid-2000s, may refocus on it in the future, as the forecasts in the study report that the demand for low-skilled occupations will also decrease. While applying the same methodology to the European sample by Bowles (2014), it was stated that the jobs included here are at risk of automation in the range of 40% to 60%, and it was claimed that the European countries that would be most affected by this situation would be Bulgaria, Greece, Portugal, and Romania. David (2017) investigated the potential job disruption of computer technology in Japan by following the study of Frey and Osborne (2013) with approximately 70 occupations and found that 55.6% of current occupations are *“highly likely”* to be interchangeable with technology in the future. He calculated that 19% had a low risk of automation. The author also states that those working part-time, or temporary jobs will suffer more from automation.

Arntz et al. (2016) and Nedelkoskaa and Quintini (2018) claim that the automation risk is overestimated in the studies given above. Based on Frey and Osborne (2013) in their study, Arntz et al. (2016) argue that the occupation-based approach, instead of dividing jobs into tasks, causes some jobs that are difficult to automate to be classified as high-risk jobs, so the automation risk is overestimated. In the study, in which the authors took into account the heterogeneity of the tasks by taking a task-based approach rather than an occupation-based approach, they examined the automation susceptibility of jobs for 21 OECD countries and determined the average of high automation risk as 9%.[9] Drawing attention to the differences in automation risk between countries, the authors estimate the rate of jobs with high automation risk to be 6% in Korea, 9% in the USA, and 12% in Austria. Organization, education, and technology investment differences between countries are suggested as the reasons for this situation. On the other hand, the authors present a critical approach to the way the threat of computerization is handled and base it on three reasons: a) The use of technologies progresses more slowly than expected due to economic, legal, and social barriers, indicating that technology substitution will not occur at the predicted level. b) Even if new technologies are used directly, employees can adapt to technology by changing duties. c) New technologies create new jobs with increasing demand and competitiveness. Parallel to the literature, since the cost of automation adjustment will be borne by low-skilled workers, the main issue arising from technical advances is not the effect on total employment, but the unfair wage distribution and the process of retraining workers to become skilled. In a similar study, Nedelkoska and Quintini (2018) estimate the risk as 14%. Both estimates are well below the 47% risk estimate in Frey and Osborne (2017). In the study of Bonin et al. (2015), which only focuses on Germany and focuses on tasks rather than occupations, it is estimated that job loss due to ICT will be 12%. Wolter et al. (2015) predict that ICT for the German economy will only lead to a 1% reduction by 2030. At this point, Egana-delSol (2019), emphasizing the importance of defining a job as a *"collection of tasks"* to understand whether a job can be automated or not, attributes the reason for the different estimates between studies to whether the jobs are divided into tasks or not. For example, according to Frey and

[9] In the study, the definition of *"high automation risk"* was made for jobs with at least 70% probability of being automated.

Osborne (2017), it is estimated that 92% of employees working in retail sales are at risk of automation, while this rate is only 4% in Arntz et al. (2016). The reason for the difference in the estimates of the studies is again whether occupations are divided into tasks, as ICTs can replace or take over the routine parts of a profession, but this does not mean that the profession is completely abstracted from manpower.

Sachs et al. (2015) make the issue clearer by stating that the impact of technology on economic well-being, in general, is still unclear, given the already positive effects of increasing output and enabling the production of more goods and services, but the negative effects of reducing the number of jobs and investment in complementary capital goods. It develops a theoretical model based on OLG for this purpose. The authors point out that under the assumption of low savings rate and the substitutability of automatable and non-automatable goods in consumption, more robots will lower the well-being of the current younger generation and future generations, hence the importance of policies that redistribute income between generations. As in Sachs et al. (2015), Benzell et al. (2015) investigate the effects of robots on employment by drawing a theoretical model and show the decrease in the share of labor in income as the cause of long-term impoverishment. The authors' question is simple and includes a quote from years ago: *"Will technology do to human power what internal combustion engines do to horses and obsolete labor?"*. In fact, in the continuation of this question, the authors somewhat oppose the view that demand will continue to increase, that is, unlimited elasticity of demand, adding that *"if technology is making people more unemployed, or at least depriving people of better jobs; doesn't this prevent people from buying products made by smart machines?"*. The authors state that the answer to these questions is yes in their model, and they add: *"If the redistribution channels are carefully prepared, the bad effects of this situation can be mitigated."* According to the authors' two-period OLG models, the following long-term consequences are likely: a) A decrease in the labor force's share of income. b) Technical bankruptcies following technology explosions. c) Increasing dependence of current output on past technical investments.

So how is the situation in developing countries? In many studies, it is pointed out that there are serious differences between developed and developing countries in the predictions of the future of work because there is more uncertainty about the effects of automation on developing economies. Developed and developing countries have different initial conditions, and the rapid decline in communication costs also facilitates the acceleration of technological diffusion between the advanced and emerging world (Soto, 2020). Therefore, technology can affect developing countries both by bringing new opportunities for industrial development and creating new risks in terms of employment as they become increasingly integrated into emerging international markets and production systems. While initial estimates of automation risk fuel fears that technology will lead to mass job losses, this will be even more striking in emerging economies as they contain low-wage and low-skilled occupations that are easier to automate. The share of employment in developing countries that may experience significant automation is higher in these countries than in developed countries because many of these jobs have already disappeared in developed countries (Frey and Osborne, 2013). In developing countries, due to their current stages, the majority of employment is in sectors with a high risk of automation, such as manufacturing and agriculture. The share of the agricultural sector tends to fall in the early stages of economic development, and then, in the middle-income stage, the share of manufacturing industries rises. As these sectors peak and then begin to decline, they typically show an inverted U-shaped trend in employment share. As a result, countries grow by shifting their workforce from low-productivity areas such as agriculture to high-productivity industries such as manufacturing and services (Soto, 2020).

Another important point is that although automation took place later in developing economies, they were already indirectly affected by the automation that emerged in developed economies. The decline in industrial employment in many developed economies is demonstrated by both data and empirical studies on this subject (Fort et al., 2018). Nevertheless, the share of the manufacturing sector in employment is beginning to decrease in some developing countries. In some countries such as Turkey, the share of manufacturing in employment reaches its peak at a lower point than in developed countries. In other words, manufacturing employment in developing economies reaches its peak at much lower rates than developed countries and experiences a kind of *"premature deindustrialization"* (Rodrik, 2016). According to Frey (2020), although many studies focus on developed countries, he thinks that the main problem will be experienced in developing countries due to early deindustrialization. For example, manufacturing employment in the UK peaked at 45% of total employment at the beginning of the 20th century, while emerging economies, including Brazil and India, peaked at an employment share of no more than 25%. The reason for this is that the manufacturing processes in developing economies are more automated today than in the past. However, some emerging economies have experienced declines in production output that cannot be explained by the increasingly automated production processes. Automation technology in developed countries may also have some indirect effects on developing countries. For example, Kugler et al. (2020) state that robotization in the automobile industry in the United States will negatively affect the same industry in Colombia, leading to loss of employment. Therefore, industrial employment loss in developing countries is not only related to internal automation but also automation in trading partner countries.

Predictions about the different effects of automation on developed and developing countries are also supported by empirical analysis. For example, the Boston Consulting Group (2015) estimates that replacing humans with robots will result in 16% global workforce savings in 2025 while switching from humans to robots in manufacturing shows the most cost savings in developed countries such as South Korea, Japan, and the United States, where manufacturing labor costs are the highest. Furthermore, it is reported that the use of robots will be less costly in 2025 in developing economies such as Mexico and Brazil, where labor costs are relatively lower, and such as in China, where labor costs are starting to increase. In this regard, Frey and Rahbari (2016) state that the average rate of jobs under the risk of automation is 57% in OECD countries, while they estimate that this rate varies between 69-77% in developing countries.

In the report published by Oxford Economics and Cisco (2018), technology and its impact on workers are examined in a study that covers 6 Association of Southeast Asian

Nations (ASEAN) member countries and 433 different professions in 21 industries in these countries. The study covers the future situation of approximately 275 million workers working in Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam, and according to the main findings, current output by 2028 can be achieved with 10% less labor input than the current workforce. In parallel, the work of approximately 6.6 million workers in the countries considered will be negligible by that date. The sector that will be adversely affected by this situation in the region is agriculture, which is expected to require a net 5.7 million fewer workers in total. On the other hand, the authors state that there will be a net increase in job demands by 2028 in many sectors and argue that the productivity increase that comes with technology will more than offset the displacement effect. A net increase of 4.3 million jobs is expected by 2028 in sectors such as wholesale and retail, manufacturing, construction, and transportation in the region. In the study, it is also estimated that among 433 professions, the highest increase in demand will be for managers and professionals with 4.4%, and the highest decrease in demand will be for agricultural workers and primary school graduates, 6.9% and 2.7%, respectively. In parallel, Chang et al. (2016) state that many manufacturing branches, especially automotive, electronics and textile sectors, are at risk of automation in ASEAN countries. Though, Asian Development Bank (2018) has a more optimistic attitude on this issue. In the Asian Development Outlook report they published, they state that technology automates only certain jobs and mostly automates routine tasks, creating time for other complex tasks.

According to the McKinsey Global Institute (2017), which uses a task-based approach, countries such as Mexico, Colombia, Brazil, India, China, and Russia are estimated to have a higher number of jobs that can be automated than most advanced economies. Similarly, for the three emerging economies Russian Federation, Chile, and Turkey, Nedelkoska and Quintini (2018) show that automation risk in Turkey and Chile is higher than the OECD average, while Russia is less sensitive to automation than a few advanced economies such as Germany or Japan. Many jobs in emerging economies can technically be automated, but lower wages and slower technology adoption are slowing automation. For example, in the World Development Report published by the World Bank (2016), it is estimated that 55% of jobs in China and 44% of jobs in India can be automated. However, these rates will be less than developed countries in the coming years, according to McKinsey Global Institute (2017) forecasts, because adaptation to automation is slow in developing economies. For example, while the McKinsey Global Institute (2017) estimates a transition to automation as 9% in India and 18% in Russia, these estimates for the same period in developed countries such as Japan and the United Kingdom are 26% and 20%, respectively. Acemoglu and Restrepo (2017) draw attention to this issue and states that although there has been an increase in wages in developing countries recently, these values are far from developed countries. Countries with higher wage levels are also more susceptible to automation, but despite this rise in wages in emerging economies, wages are still far from levels seen in more developed economies. Therefore, automation is not yet economically attractive in many developing countries due to the abundance of cheap labor. On the other hand, higher wages lead to higher labor costs, making it more attractive to replace humans with machines with potentially higher cost savings. Therefore, although the number of jobs that are prone to automation is higher in developing countries, low wages and the slowness of technology adoption keep the developing economies' level of automation at lower levels than developed countries.

Egana-delSol (2020) explains the impact of routine and non-routine work, the differentiation of employment by education, and the automation risks gap between developing and developed countries, using data from the World Bank's STEP Skills Measurement Program Database for 10 developing countries. The author explains the estimated level of automation in terms of both productivity and displacement, confirming that routine jobs have a higher risk of automation than non-routine jobs. In addition, the author tests the hypothesis that the more educated population is less affected by automation. It is emphasized here that as automation intensifies, more complex tasks are assigned to more skilled workers. Egana-delSol (2020) explains the hypothesis that developing countries inherently have a higher risk of automation. According to the results obtained when calculating the automation risk individually in developing countries in the study, the high automation risk ranges from 7.7% (China) to 42.2% (Ghana) in developing countries, and the median is calculated as approximately 23% for 11 developing countries. The author points out that the values found by OECD for 21 developed countries with a similar approach vary between 6% and 12% (with a 9% median). Therefore, the number of tasks with high automation risk in developing countries is approximately 2.5 times higher than in developed countries. He also finds in his study that people with higher education rates in developing countries have less risk of automation.

There are also studies focusing on developing countries individually in the recent period. Zemtsov (2020) explores how robots and machines in Russia can affect employment in the long run and why compensation mechanisms may not work effectively. In his study, the author estimates that up to 30% of workers in Russia are working in jobs that may be subject to high automation in the future and that in 2030, close to half of current jobs will need to adapt to technology, as many of them are routine tasks. Finally, the author claims that the technology-related injuries of employment in Russia will be lighter than the world average. Similarly, Zhou et al. (2020) examine the employment structure of 2005, 2010, and 2015 in China with the technology variable that measures the use of AI in different industries with the AI adaptation rate. The authors estimate that by 2049, about 36% of existing jobs in China will be replaced by AI. Furthermore, the authors state that AI has a substitution effect especially in females, old age, low education, and low wage groups, revealing that this change has gender segregation as well as being skill-biased.

So how will the job structure change? In addition to the computerization of routine production tasks, Autor and Dorn (2013) draw attention to the structural change caused by technology; document the structural shift in the market, with the reallocation of the labor supply from middle-income manufacturing to low-income service occupations. One of the possible reasons for this situation is that the manual tasks of service professions require a higher degree of flexibility and physical adaptability, so they are less susceptible to robotization, in other words, they can show more resistance (Goos and Manning, 2007; Autor and Dorn, 2013). However, more strikingly, Brynjolfsson and McAfee (2012) state that today, complex software technologies have changed the structures of labor markets more, that computerization is no longer limited to only affecting routine jobs, and jobs that require high cognitive abilities will also suffer from computerization. Saunders (2017) emphasizes that it is very difficult to expect a machine to write a novel or take care of a child, although coding and computerizable jobs are more open to substitution and draws attention to the importance of routine-non-routine job separation in terms of automation effect. When machines enable people to be more productive, they make it easier for them to focus on tasks such as generating ideas or solving problems by completing their labor rather than taking away their jobs. For example, spreadsheets or calculators have made many accountants' jobs simpler, but instead of eliminating the accounting profession, they have changed its structure, allowing people working in this position to work more effectively in providing insight or strategic advice. The author emphasizes the importance of the population giving up looking for a job because of being discouraged by unemployment rates in America. According to the statistics given in the study, the unemployment rate in the country was about 5% in 2007 and this rate decreased to 4.2% in 2017, while the ratio of employment to the total population over the age of 16 was over 60%. However, the author states that as of the end of 2017, there were roughly 6.8 million unemployed in the USA, while the number of people who were not included in the labor force was approximately 1.6 million. In other words, there are about 1.6 million unemployed people in the United States who are also not actively seeking employment, and half a million of these workers, or almost 1 in 3, are not looking for a job because they think it is not a suitable job for them and are discouraged. The author explains this situation as follows: *"Imagine a high school coal miner in West Virginia with an annual salary of $80,000; when this worker is laid off due to the use of more advanced technologies in the mines, he may not be willing to work as a cashier in the same region for a salary of one-third of what he was earning before. The motivation to look for a job will be broken, as it will not be possible to return to the mining sector due to the use of existing technology. As a result, this discouraged worker will not be included in the current unemployment rate."* The author also draws attention to an important job statistic in the USA, how skill shortages affect unemployment rates. In 2009, just after the Great Recession, 14.6 million unemployed were recorded while the number of job postings in the United States dropped to 2.2 million. In August 2017, 6.1 million job postings were recorded with increasing job opportunities especially in the service sector and construction, while it is stated that the number of unemployed was 8.4 million. Overall, at least 6.1 million of the 8.4 million unemployed could benefit from current job positions. However, this is not so easy in practice because people cannot be matched with existing jobs, especially because they do not have sufficient qualifications. For this reason, Saunders (2017) draws attention to the fact that private employment has been stagnant since 2000, although productivity has increased.

While Autor (2013, 2015) states that there is a technology-induced displacement or automation in existing mid-level jobs, but many jobs requiring medium skill will continue to exist in different formations, he gives a few examples in this regard. Stating that medical support professions such as radiology technicians, nurses, and phlebotomists working in the health sector are jobs that require intermediate skills, the author emphasizes these professions require qualifications such as medium skill mathematics, mastery in analytical thinking and life sciences, which in most cases requires a two-year associate degree or four-year undergraduate degree. Declaring that these examples can be applied to trade and many office professions, the author thinks that *"an important middle-skill profession group that combines basic medium skill levels such as literacy, mathematics, adaptation, problem solving and common sense with certain professional skills"* will continue to exist in the coming decades. As for how this will happen, the author states that *"most future medium-skill jobs will combine routine technical tasks with non-routine tasks such as interpersonal interaction, flexibility, adaptability, and problem-solving, in which employees have a comparative advantage."* Thus, the main focus in the US economy, according to the author, is not that *"middle-class workers are doomed to automation and technology,"* but rather that *"human capital investment should be at the center of any long-term strategy to produce skills that are complemented rather than substituted."* At this point, Autor (2015) states that the employment effects of technology can be mitigated or positively increased through three main factors: first of all, if the tasks of the employees are completed with automation, the effect is likely to be positive, but if it is replaced by automation, the effect will be negative. Second, the flexibility of the labor supply directly affects the average wages of occupations, so the emergence of new groups of workers for these tasks may reduce wage gains if technology-complementary tasks are abundantly available in the market. Finally, the output elasticity of demand, or income elasticity of demand, also influences the gains from automation in both directions: as productivity in the agricultural sector has increased by leaps and bounds, it has caused consumers to lose their share of their income for agricultural products. But the opposite situation overflowed in health services, technical advances in health caused people to allocate more shares in this sector. Therefore, a decrease in demand in a sector does not mean a negative effect on the whole economy.

In 2013, McKinsey Global Institute reports that although technological advances with higher added value and requiring skills increase productivity, they can also cause unemployment because new technologies can raise the lower limit of skills needed. Another view in MGI (2013) again emphasizes the importance of public policy: *"The potential consequences of the split between high-skilled and low-skilled workers should not be ignored, as the problem of the current workforce that fits the demands of high technology will grow over time"*. However, while Campa (2017) emphasizes that this approach in the report is an old solution proposal of the Neoclassical view, he states that the optimistic approach claims more free time and more benefits for workers. However, according to the author, examples such as self-driving cars or drones used in transportation mean unemployment, not useful free time for those working in this field. At this point, some authors draw attention to the fact that technology changes are a complex, non-linear, and non-deterministic process and state that technology takes place in different stages, and therefore both job destructive and job creator effects are seen together.

As a result, technology has changed the structure of jobs so far and will continue to do so in the future. Provided the potentially transformative, destructive and modifier effect of mechanization and associated technological trends on job markets, conclusive and significant policy responses will be required, including measures such as improving quality, to ensure that the profits and benefits are shared, and the losses compensated. Both optimistic and pessimistic forecasts for the future show that some professional groups will not be able to resist automation any longer. On the other hand, just as there are professions or duties where technology cannot negatively affect employment, there will also be new business areas that technology will reveal itself. This is a big probability for most countries but developing economies might experience it even more problematic due to lower government efficiency and less elastic economic and political structures. In addition, these countries will probably be less able to take advantage of many of the opportunities proposed by new technologies. This is because, in a significant part of the developing world, a large proportion of the population lacks the skills to complement new technologies. For example, literacy rates in Turkey and Chile are lower than in developed countries. Therefore, adapting to technological change can be particularly difficult in emerging economies because many of the new jobs require significantly higher skill levels, especially those related to the use of ICT. However, it should not be overlooked that there are great differences between the skill levels of the labor force population in developing countries from country to country. The skill gap is not only a problem today, the Program for International Student Assessment (PISA) data shows that the skills of the young population are less in developing countries than in developed countries, and this reveals that the quality of the workforce in the future will also be different (Soto, 2020). It would not be wrong to say that there will be a significant difference between developed and developing economies in the future, as basic skills such as numeracy and literacy are the basis of employability and the ability to raise oneself to new skills and learn. Therefore, it is important for countries to have sufficient skilled workers at all times in order to establish a balance between the jobs that are lost and the jobs that are created and to prevent potential unemployment problems.

CHAPTER 3: THE RELATIONSHIP BETWEEN TECHNOLOGY AND UNEMPLOYMENT IN DEVELOPED COUNTRIES

3.1. Introduction and Motivation

The starting point of technological unemployment concerns in terms of economic literature is the Industrial Revolution. The discontent of the European workers who had to be replaced by machines in the 19th century sometimes extended to violent uprisings. At this point, although there were examples of the restriction of the use of some machines due to employment concerns in the early periods (Freeman and Soete, 1994), the governments could not resist the contribution of machines to productivity and chose to suppress the resistance to technology, as the British government of that period did (Mantoux, 1905/ 2013). But were workers' concerns about technological unemployment in vain at that time? Or is it just an exaggerated worry that technology will cause unemployment today? The answer to this question is *''yes''* according to prominent classical economists such as Adam Smith and JB Say, because they saw technology not as a disaster for employment, but rather as a blessing, believing that mechanization is an opportunity for employers in line with the power of the free market economy. They argued that *''more mechanization means more talent and more efficient labor distribution''*. According to classical economists, technology does not cause structural unemployment, because temporary labor savings are compensated by market dynamics over time. However, the classics' reluctance to see technology as a permanent structural problem was interrupted by David Ricardo's acknowledgment that machines could create irreparable unemployment. Ricardo stated that the negative effects that emerged with the replacement of the labor force by the machines could be too large to be compensated by the market's own dynamics, and in fact laid the foundations of the concept of technological unemployment at that time. This phenomenon was later conceptualized by John Maynard Keynes and defined as *''the rate at which technology replaces labor is faster than the rate* *at which new jobs are created for technology-affected labor"* and acknowledged the negative impact of technology, which is destructive but can be made temporary in the long run by constructive policies. According to Keynes, technological unemployment is not a permanent problem but has a structure that can provide more leisure and welfare to workers by reducing their working hours in the future with effective policies. The ideas of both classical economists and Keynes that the effect of labor-saving technical advances is compensated overtime was termed *"Theory of Compensation"* by Karl Marx, but the net employment effect of technology has remained controversial because the flawless functioning of the wheels of this mechanism is based on very rigid market assumptions. At this point, although the criticisms of David Ricardo and Karl Marx against the extreme optimism of compensation theory require a reinterpretation of technological unemployment by the representatives of neoclassical economics, leading neoclassical economists such as Alfred Marshall and Knut Wicksell continued the optimistic classical views and argued that in a perfectly competitive market, technological advances could not permanently suppress employment. Finally, in the Schumpeterian view, technological advances were defined as a kind of *"creative destruction"* process, and job or sector losses caused by technology were seen as cleaning activities that create new business areas or advantages in the economic system.

While the job creation or job disruptive feature of the technology is emphasized in the theoretical literature, inferences regarding the compensation mechanism vary depending on which characteristic outweighs, and this is directly related to the type of innovation, that is, whether it is a product or process innovation. For example, product-oriented technological changes should result in a better product being produced at a lower cost. Assuming that the market is perfectly competitive, a decrease in total cost increases aggregate demand by lowering product prices, which means more workers are employed to meet demand. In addition, new products spread rapidly all over the world as a result of globalization, and an increase in total output is achieved due to the introduction of new products and/or upgrading of existing products, and technology results in more labor requirements. On the other hand, if large investments in R&D are process-oriented, that is, aiming at the development of new robots or machines to change production methods, this directly results in labor savings because one of the most important goals of process innovations is to obtain the same amount of output or more by using less labor input. In this case, people who lost their jobs due to technological developments cannot demand as much as before; this leads to a decrease in aggregate demand and a further increase in unemployment. At this point, these examples, which deal with the issue from both perspectives, are actually based on the assumption in the literature that product and process innovations affect employment in different ways, namely the idea that the first has labor-creating and the second has labor-saving characteristics (Tether et al., 2005). Another perspective is based on classifying workers according to their skills or job content rather than considering employment as a whole. Advanced technologies threaten workers in routinized jobs, lowering their relative wages over time. The reduction in relative wages gives human labor a comparative advantage over technology for a while, leading to more demand for labor. But workers who earn less also demand fewer goods or services as consumers, causing a decrease in aggregate output, and hence the demand for labor, again. This is generally true for those in jobs prone to automation, which is low- or mid-level workers. In another aspect of employment, technical advances increase the demand for specialized labor, leading to higher payouts to high-skilled workers, which increases aggregate demand, resulting in more output and thus employment.

As a result, the effectiveness of the compensation mechanism is based on the assumptions of a perfectly competitive market such as perfect substitution and high elasticity of demand, which makes the operability of the mechanism questionable. At this point, the economics literature has often turned to empirical studies at both micro and macro levels, much more to the former, in order to see which of the *"labor-saving"* and *"labor creating"* effects outweigh net employment or net unemployment. However, micro-level studies are too firm or sector-specific to draw an overall conclusion and contain significant handicaps. For example, firm-level analyses often focus on firms that already have innovative practices and do not take into account changes in competitors within the industry or impacts in other industries, resulting in a kind of biased estimates.

Besides, studies at the sectoral level, especially in the early period, mostly focus on the manufacturing sector, and therefore, they cannot predict the net employment effect and do not make a holistic employment inference possible by ignoring the transition between sectors and the qualitative and quantitative effects of new sectors on employment.

The common feature of the studies on firm data of developed countries is that the net effect of product innovations on employment is reported positively in almost all of them. On the other hand, the results are somewhat more heterogeneous in process innovations, in some firm-level studies it has been claimed that the labor-saving effect of process innovations is compensated by product innovations or that innovations do not have a significant effect on employment in general. In a small number of firm-level studies, it has been reported that the labor-saving effect of process innovations will outweigh the labor-friendly effect of product innovations. Sectoral implications are more complex. A significant portion of the studies focused on the manufacturing sector concluded that the effect of process innovation negatively affects overall employment in the sector. Macro-level empirical studies investigating the employment-technology relationship include approaches in the early stages in line with the compensation mechanism and general economic balance. For example, Sinclair (1981), under the assumption of one country and one sector and in line with the IS/LM principle, with data covering the years 1900-1965 in the United States; Layard and Nickell (1985a, 1985b) with data covering the years 1966-1986 in France, Germany, Japan, the UK, and the US; reported that adequate demand flexibility plays an important role in overcoming labor losses with compensation mechanisms. While Pini (1995) presents evidence that the increase in physical capital caused by technology stimulated by R&D activities in nine developed OECD countries negatively affects employment, on the other hand, there is an *"equal compensation mechanism"* based on promoting exports through the productivity increase channel provided by technology. In Vivarelli (1995) study, which also discussed the effectiveness of compensation mechanisms at the macro level, it was stated that the most effective compensation channel for the United States and Italy between 1960-1988 was based on the principle of *"reduction in prices"* and product innovations offered new business opportunities through this channel. In the study, it is also stated that the effect is different from each other in Italy and the USA, while the labor-friendly effect is seen because the innovations in the American economy are more product-oriented, the labor-saving effect caused by process innovations in the Italian economy cannot be compensated. Simonetti et al. (2003), argue that the most effective and meaningful channel is based on the principle of *"decrease in prices"* and *"increase in income"*, with the country group consisting of the US, France, Italy, and Japan, and the data set covering the years 1965-1993, and they argue that in terms of compensating the labor-saving effect of technology on employment, the most advantageous country is the USA. Among the more recent macro-level studies using a technology proxy such as direct R&D or patent numbers, Feldman (2013) reports that technology, which he measured with triadic patent families in 21 advanced economies between 1985 and 2009, increased unemployment in the short term; Matuzeviciute et al. (2017), who analyzed 25 European countries with similar profiles for the years 2000-2012, claimed that both R&D and triadic patent families did not have a significant effect on employment. Yıldırım et al. (2020) divided the 12 EU countries, which have a higher degree of innovation in the world compared to other countries, into two groups as having low and high innovation levels, with the data of 1998-2015. The study concluded that technology, as measured by patent numbers, increases unemployment in countries with both low and high innovation levels, with a larger effect size in the former.

On the one hand, while the studies deal with technology and employment as a whole, on the other hand, the fact that both workers and occupations are not uniform has brought different approaches to the issue. Technical advances are a process in which high-skilled people adapt more easily and benefit both in terms of employment and wages, but low-skilled people face consequences such as displacement or a decrease in wages. While routine jobs require fewer human resources due to skill-oriented technological changes, non-routine jobs that require analytical and cognitive skills increase the need for highly skilled workers (Acemoglu and Autor, 2011). Developed economies can adapt their labor markets to technological changes more easily, as they have a denser and higher quality high-skilled workforce compared to developing countries, and they can also strengthen technical advances by increasing the skilled labor supply faster (Caselli and Coleman, 2006). In addition, the effects of technological changes affecting demand for different skills in countries may be heterogeneous. For example, according to a theoretical model that was established to understand whether skill-biased technological changes explain different unemployment patterns in Europe and the United States by Mortensen and Pissarides (1999), because of the unemployment insurances and tax on the displacement of workers, negative SBTC effects on employment is higher in Europe than the United States. But this theoretical model did not touch on empirics. At the micro-level, empirical studies that take into account, the skill levels of employees and the routine intensities of tasks have proven that increased use of technology requires high skill. For instance, Berman et al. (1994), empirically explored the skill-biased technological shift in early periods and proved the existence of a robust association between industry skill-enhancing and enlarged investment in R&D and computer technology in the U.S. manufacturing sector. Similarly, Bartel et al. (2007), Haskel and Heden (1999), and Falk and Seim (2001) obtained empirical evidence of technology skill bias at the sectoral level for the United States, the United Kingdom, and Germany respectively. At the macro level, Weis and Garloff (2011) demonstrated that technology increases lower-skilled unemployment in 14 developed countries, including the United States and the United Kingdom, with a theoretical model based on unemployment benefits and wages, but the model was not examined directly using a technology proxy and employment by skills data. In the RBTC part of the issue, while the studies focused on the disappearance of jobs requiring medium skill, they investigated the reasons for the increase in the number of jobs requiring low and high skills and ignored the net employment effect with a few exceptions. For example, in the pioneering work Goos and Manning (2007) in England; Autor et al. (2006), Autor and Dorn, (2013) and Autor (2015) in the USA and Goos et al. (2014) in 16 European countries concluded that technological advances have led to job polarization in developed countries, but these studies do not contain an inference on the net employment effect of technology. Grigoli et al. (2020), on the other hand, investigated the relationship between labor force participation and technology for routinizable tasks at the macro level, with analyses covering the years 1985-2016 and 23 developed countries. The authors concluded that the overall effect of technology on the labor force participation rate in developed countries is significantly negative, and as the degree of the routine of occupations increases, the negative effect of automation on labor force participation also increases.

Both sectoral and macro-level studies, especially after 2010, are relatively more pessimistic, and there are great doubts that the technology-induced labor-saving effect can be compensated by the labor creative effect. For example, Acemoglu and Restrepo (2019) stated that the productivity increase provided by automation is no longer at a level that can compensate for the loss of workforce, that the displacement effect of technology is two times higher than the reinstatement effect in the USA after 1987. They stated that industrial robots per worker reduced both the employment rate and wages. Even more strikingly, the authors noted that the relative advantages of labor would be further diminished if automation continued to be the source of future productivity growth. Bessen (2020) also draws attention to the saturation of the demand in general and stated that the elasticity of demand has lost its power to compensate for employment in the historical process. In the 19th century, technology negatively affected the relatively skilled workers and increased the demand for the unskilled, but the 20th-century effects developed as a demand for more skilled workers (Acemoglu, 2002). Therefore, the fact that technology has undergone many changes over time, as well as the differentiation in productivity and demand dynamics, carries its employment effect to a different dimension. Today, complex software technologies also change the structures of labor markets more, showing that technology is no longer limited to only affecting automation jobs or simple routine jobs and that jobs that require high cognitive skills will also suffer from computerization (Brynjolfsson and McAfee, 2012). At this point, empirical studies including how technology will affect employment in the future, in terms of its quantity, quality, and structure, especially after 2010, are also popular, and most of these studies draw attention to the density of jobs with high automation risk in developed economies. According to some predictions, 47% of jobs in the USA (Frey and Osborne, 2017), 40-60% of jobs in Europe (Bowles, 2014), and 56% of jobs in Japan (David, 2017) have a high risk of automation and that these jobs will be completely handed over to technology in the coming decades.

Consequently, although the empirical literature on the technology-employment relationship in developed countries generally contains positive conclusions at the micro-level, the results and expectations in recent years are more pessimistic, as can be understood from the limited number of macro perspectives and various predictions about the future of work. As stated in the report published by World Economic Forum (2018), 71% of total work hours in 12 industries were functioned by humans in 2018, while machines conducted 29%. World Economic Forum (2020) stated that human share dropped to 67% in 2020 and it is expected that until 2025, it will decrease to 53%. Hence, do these estimates mean that total employment will diminish? The later report explains that the current 85 million jobs will be taken from people and assigned to machines by 2025; in other words, technology will demolish employment. On the other hand, 97 million new job opportunities will arise due to technology. In spite of this, the vital point here is to what extent the existing human resources will be able to adapt to new opportunities to be created with the qualifications they currently have. In the same report, it is estimated that 50% of all employees will need reskilling by 2025, but it is difficult to predict at what speed employees will upgrade themselves.

In light of all these reasons mentioned, identifying how high-skilled and low-skilled workers are affected by technology at the macro level in developed countries will make a significant contribution in this area. In this study, it is aimed to provide a comprehensive macro-level contribution to the literature, based on the fact that the macro part of the empirical literature on the effects of technology on employment in developed countries has not been sufficiently filled, and with this motivation, the relationship between technology employment in developed countries is empirically discussed from two different perspectives: a) First of all, the effect of technology on overall unemployment at macro level is investigated in developed countries, and in this respect, the study has common aims with similar studies. As stated before, there is no consensus on this research question yet produced by both micro and macro-level studies. b) In the second stage, the effect of technology on employment at the macro level is investigated on the basis of two different skill groups as low-skilled and high-skilled. Considering this, this study differs from its peers in terms of reducing employment effects of technology to skill dimensions and makes a significant contribution to the literature. Accordingly, even though there are extensive studies in the micro-framework, macro analyses are scarce, and including them, none is focusing on the country list we have, over the time period we consider, with the empirical method we facilitate, and the stress on employment by skills. With these four important highlights specified, our research is unique to fill the literature gap and Section 3 and Section 4 prepared for these purposes include data and methodology respectively. Section 5 reports estimation results and interprets them and finally, Section 6 concludes with remarks.

3.2. Data

The developed countries used in the study are determined in line with the MSCI Market Classification Framework (MSCI, 2020) based on the countries' performance in criteria such as economic development, liquidity requirements, and market accessibility. Although the number of developed countries varies according to the classification method used, 21 countries that are among the developed countries favorably many methods and given in Table 3.1 are covered in the study. In line with their qualifications and availability, the data obtained from various sources listed in Table 3.1 covers a period of 30 years, 1990-2019, wherefore the data set includes the balanced panel with $N \times T = 630$ observations ($N = 21$ and $T = 30$).

Table 3.1. List of the developed countries

ID	Country Name	Abbreviation	ID	Country Name	Abbreviation
1	Australia	AUS	12	Japan	JPN
2	Austria	AUT	13	Netherlands	NLD
3	Belgium	BEL	14	New Zealand	NZL
4	Canada	CAN	15	Norway	NOR
5	Denmark	DNK	16	Portugal	PRT
6	Finland	FIN	17	Spain	ESP
7	France	FRA	18	Sweden	SWE
8	Germany	DEU	19	Switzerland	CHE
9	Ireland	IRL	20	United Kingdom	GBR
10	Israel	ISR	21	United States	USA
11	Italy	ITA			

Note: There are 23 countries in the current Developed Markets list of MSCI, but data from 21 countries were used in this study.

The main purpose of the thesis is to clarify how the unemployment rates of developed countries are affected by technology and to determine whether the relationship between these two variables differs by skills. For this object, the unemployment rate is used as the dependent variable for the first research question which investigates the overall employment impact of technology, while for the second research question, high-skilled and low-skilled employment rates are on the left-hand side of the different equations. The list of the variables with their symbols, explanations, units, and sources are portrayed in Table 3.1. The unemployment rate refers to the ratio of the population not working in the country to the total labor force in accordance with the International Labor Organization (ILO) definition (ILO, 2020a). Employment rates by skill levels show the percentage of employees by skills in the total labor force. ILO (2020b) scaled the skill levels from 1 to 4, combining groups 3 and 4 as *"high-skilled"* and classifying groups 1 and 2 as *"low-skilled"* and *"medium-skilled"*, respectively. In this thesis, *"low"* and *"medium"* groups were combined, and the *"low-skilled employment"* group was created and recognized into a single variable. Research and development (R&D) expenditure, which is the core independent variable of this study, and GDP were used as per capita in constant US$. Output per worker was employed as a productivity measure, and it is also in the form of constant US$. Besides, variables such as consumer price index (CPI), public unemployment spending, trade union density (TUD), real effective exchange rate index (REER), and real interest rate were also identified as other control variables.

Table 3.2. List of variables and data sources

Variable Type	Description and Units of Variables	Symbol	Source
Dependent Variables	Unemployment rate (% of total labor force)	*U*	ILO (2020a), World Bank (2020a)
	High-skilled employment rate (% of total labor force)	*HSE*	ILO (2020b), Author's calculations
	Low-skilled employment rate (% of total labor force)	*LSE*	ILO (2020b), Author's calculations
Core Independent Variables	R&D Expenditure per capita (constant 2010 US$)	*RD*	OECD (2020a), World Bank (2020b), Author's calculations
	GDP per capita (constant 2010 US$)	*GDP*	World Bank (2020c)
	Consumer price index (2010 = 100)	*CPI*	World Bank (2020d)
	Productivity (output per worker, constant 2010 US$)	*PRD*	ILO (2020c), Author's calculations
Other Independent Variables	Public unemployment spending per capita (constant 2010 US$)	*PUS*	OECD (2020b), Author's calculations
	Trade union density index (2010 = 100)	*TUD*	OECD (2020c), Author's calculations
	Real effective exchange rate index (2010 = 100)	*EXC*	World Bank (2020e), Author's calculations
	Real interest rate (%)	*INT*	World Bank (2020f), Author's calculations

Notes: The dependent variables namely *U, HSE,* and *LSE* were obtained as a percentage of the total labor force but used as a decimal fraction in the analyses. *RD* was obtained as a percentage of total GDP and calculated as R&D per capita based on constant 2010 US$. *TUD* is the ratio of workers that are trade union members, divided by the total number of workers. It was obtained as a percentage but used as an index with the base year of 2010. In all estimation results, *GDP, CPI,* and *PRD* variables were considered as core variables in baseline specifications in addition to *RD*. Other control variables were employed in different model variations.

Starting from the main research question of our study, coefficient and sign of *RD* were mainly questioned in this part and as stated in the empirical and theoretical literature review, there is no consensus on the coefficient of technology proxies. In this study, besides R&D, the effect of other factors that were found to affect unemployment -or employment- in the literature was also controlled. In this regard, the first and the most important control variable is GDP per capita. It is a widely accepted view that the rate of growth in an economy's total income increases employment, theoretically, the effect of GDP on unemployment is negative. This approach, which is based on Okun's Law (Okun, 1962) and relates output and unemployment, has become one of the most famous concepts in macroeconomics and has proven its validity many times in developed countries empirically (Attfield and Silverstone, 1997; Lee, 2000; Knotek, 2007).

Another control variable in the study is inflation, even though the traditional representation of the inflation-unemployment relationship is mostly based on research by Philips (1958), and states that there is a negative trade-off between inflation and unemployment, but according to the historical patterns of unemployment and inflation figures and also empirical studies this relationship is much more controversial especially in the long-term relationship. It is not surprising to expect high inflation rates to adversely affect investments and economic growth, and thus employment, in the long run, by preventing the efficient allocation of resources and reducing the investment returns to enterprises (Feldman, 2013). Thus, although the relationship between unemployment and inflation is often known as the Philips Curve in the economic literature, this approach does not always find empirical evidence to support it. Looking at the unemployment and inflation data of the developed countries for the last thirty years, it is seen that low inflation does not always mean high unemployment or vice versa. For example, according to ILO (2020a) and World Bank (2020g) data, the average unemployment rates of 21 countries covered in this study decreased from 6.9% to 5.4% in the period from 1990 to 2019, but inflation also fell from 7.8% to 2.61% in the same period. Moreover, while the average unemployment and inflation rates in developed countries were 7.8% and 2.8%, respectively, in the 15-year period covering 1990-2004, these values decreased to 7% and 1.5%, respectively, in the last 15-year period covering the years 2005-2019. Therefore, in the long-term, high rates of inflation decreases in developed countries have been accompanied by less unemployment decreases, and unemployment and inflation data in the historical process show that both the short and long-term relationship between these two have been broken many times. On the other hand, the skill-related part of employment is also important in terms of the direction of its relationship with inflation. Because the negative unemployment-inflation relationship in Philips Curve is based on the idea that the increase in labor wages in low unemployment situations also increases inflation over time, and it has also been supported empirically for certain periods. But today there is an abundance in the supply of low-skilled workers due to technology and an increase in the demand for high-skilled workers, resulting in an increase in the skill premium in the economy (Machin, 2001; Acemoglu 2003). Therefore, the relationship between high-skilled employment and low-skilled employment rates with inflation may be in different directions.

Findings related to the relationship between productivity and unemployment may contain differences in the literature due to the diversity in the definitions of productivity. The productivity variable used in this study is worker productivity which is obtained by dividing total output by the total number of workers. Due to the nature of the *"output per worker"* variable used in productivity measurement, which is total employment is the denominator and total output is the numerator, a negative relationship between productivity growth and employment is always a strong possibility. This result is not surprising because technology is developing with an increasing momentum day by day, and it allows to produce more output with less labor force. However, a positive effect may be possible if the growth in output is greater than the growth in output per worker. As a matter of fact, there is empirical evidence in both directions of the employment-productivity relationship in studies in the literature where labor input is mostly measured as total worked hours. For example, Cooley and Prescott (1995), Shea (1998), Galí (1999), Francis and Ramey (2005), Basu et al. (2006), and Galí and Gambetti (2009) provide evidence that increased productivity due to technology shocks reduces labor input. Contrary to these studies, Fisher (2002), Christiano et al. (2003), Michelacci and Lopez-Salido (2007), and Autor and Salomons (2018) reported that the increase in productivity was caused by technology shocks increased the labor input requirement overall. On the other hand, Barnichon (2010) argues that before the 1980s, the relationship between productivity and unemployment is negative but weak, while it is positive and strong after the 1980s because of the technology shocks while Gallegati et al. (2016) concluded that correlation was positive between unemployment and productivity in the short and medium terms but became negative in the long-term.

Other control variables used for robustness check in the study are real interest rate, public unemployment spending, trade union density, and real effective exchange rate index. The increase in real interest rate is theoretically expected to adversely affect employment because the increase in interest rates increases the cost of capital use, making investments relatively less advantageous, and under the assumption that wages are fixed, less labor demand follows the decrease in investments (Phelps, 1994; Blanchard and Katz, 1999; Ball, 1999) and this theoretical approach is supported by several empirical evidence (Blanchard and Wolfers, 2000; Fitoussi et al., 2000; Nickell et al., 2005; Baccaro and Rei, 2007; Feldman, 2013b). Social benefits, such as public unemployment spending, both reduce the economic cost of unemployment and thus the unemployed persons' desire to seek a job, and raise workers' wage expectations, which both channels mean higher unemployment rates (Nickell et al., 2005; Bertola et al., 2007). At this point, Meyer (1988) and Moffitt (1985, 2014) provide empirical evidence that benefits such as unemployment insurance prolong job search. In addition, Mortensen and Pissarides (1999) stated that the difference in unemployment rates between the United States and European countries in the 1970s, experienced higher in Europe, was due to unemployment insurance benefits and other workers' rights practices in Europe. On the other hand, trade union density is calculated as the ratio of workers that are trade union members, divided by the total number of workers, and high union membership rates mean higher bargaining power and an increase in equilibrium unemployment rates. This situation especially negatively affects the employment of low-skilled or unskilled workers, as higher wage pressure by unions increases average wages and leads employers to employ fewer workers, causing workers who are willing to work for lower wages to be unemployed (Ashley and Jones, 1996; Baccaro and Rei, 2007). Lastly, the real effective exchange rate is obtained by removing the relative price effects from the weighted average value of the domestic currency relative to a group of foreign currencies, and empirical literature has reported the significant impact of REER on employment (Frenkel and Ros, 2006; Feldman, 2011). The appreciation or depreciation of the local currency can affect unemployment in both ways through different channels. For example, its overvaluation may reduce the competitiveness of exported goods, reducing exports and thus employment. On the other hand, economic growth may affect employment negatively by slowing down economic growth in export-oriented countries. In addition, the appreciation of the local currency can reduce the relative costs of capital goods, making the manufacturing sector capital-intensive and reducing the demand for labor. However, all these negative effects are related to the overvaluation of the real effective exchange rate and are mostly developed as a result of approaches based on the manufacturing industry. Conversely, the appreciation of the local currency may increase employment in developed countries, especially in the service sector, because the economy of developed countries is based on the service sector rather than agriculture or industry, and with the appreciation of the local currency, the orientation to financial channels increases. Finally, exchange rate shocks aside, smoother changes in both directions would not be expected to have a drastic positive or negative impact. As a matter of fact, while the average REERs of the 21 developed countries included in the thesis decreased by approximately 7% in the 10-year period between 1990-1999, the average unemployment rates increased by approximately 0.5 percentage points in the same period. In the 20-year period covering the years 2000-2019, the average REER decreased by approximately 1.7%, while the average unemployment rates decreased by around 1.7 percentage points (ILO, 2020a; World Bank, 2020e).

According to Table 3.3, which shows the overall summary statistics of developed countries, the average unemployment rate of 21 advanced economies in the relevant thirty-year period is 7.38%, while the average of per capita R&D expenditures is approximately $948 and the average of GDP per capita is approximately $43534. Besides, the average high-skilled employment rate is 36.3% while the low-skilled employment rate is 56.3%.

Table 3.3. Overall descriptive statistics for developed countries

Variables	Mean	Std. dev.	Max.	Min.	Skewness	Kurtosis
U	7.382	3.764	26.090	1.780	1.677	7.102
HSE	36.254	7.247	50.193	17.234	-0.546	2.700
LSE	56.338	6.574	78.524	45.317	1.169	4.307
RD	948.249	507.789	2717.794	77.276	0.604	3.121
GDP	43533.640	14661.440	92556.320	16667.580	1.091	4.493
CPI	90.380	15.638	120.270	32.520	-0.417	2.562
PRD	93474.790	25667.540	182984.800	36347.000	0.938	4.904
INT	4.337	2.906	15.010	-5.630	0.188	3.517
EXC	100.077	10.762	146.752	67.569	0.455	5.494
TUD	110.111	26.051	275.271	70.192	3.022	16.078
PUS	532.184	401.270	2161.406	45.403	1.203	4.090

Note: U, *HSE*, *LSE*, and *INT* are in percentages. *RD*, *GDP*, *PRD*, and *PUS* are in constant 2010 US$. *CPI*, *EXC*, and *TUD* are indexes that has the base year of 2010=100.
Source: Author’s own calculations based on World Bank, OECD, and ILO data.

Figure 3.1 shows the distribution of countries by average unemployment rates and average per capita R&D expenditures between 1990 and 2019. While Israel and Finland drew attention among the countries with both high R&D and high unemployment averages in this period, Switzerland, Sweden, Denmark, and Norway took the lead among the countries with lower unemployment and higher R&D rates than the average of developed countries. Continental Europe, with a few exceptions, is seen to have higher unemployment patterns than the average of developed countries, based on the 30-year period. Finally, countries with below-average R&D and unemployment rates are Great Britain, New Zealand, the Netherlands, and partially Australia. At this point, it should be noted that these values show an average of three decades and it may be misleading to make a general inference. For example, while Israel was above the average of developed countries with an unemployment rate of more than 12% in 1990 when it comes to 2019, this rate is below the average of the same country group with 3.9%.

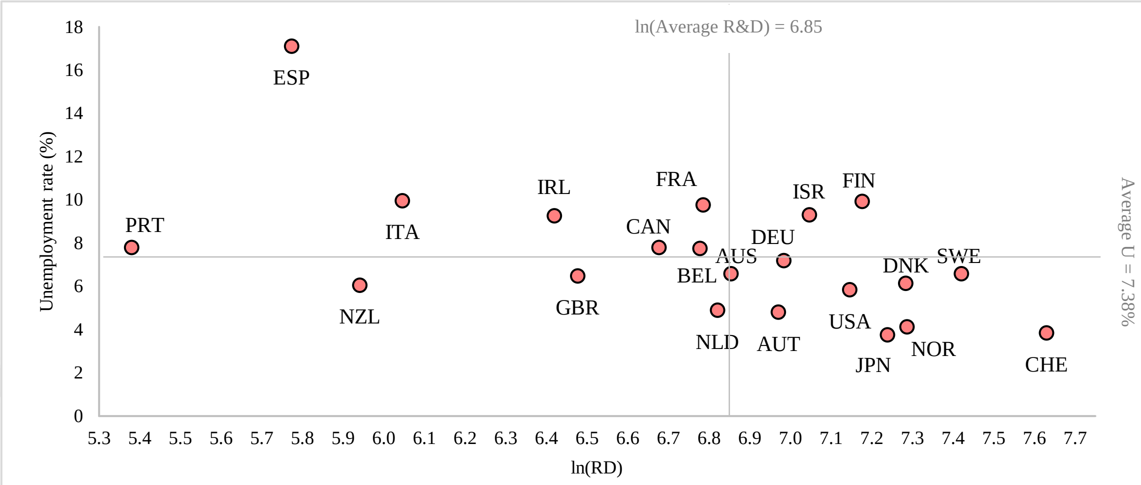

Figure 3.1. Average unemployment rate (%) and R&D per capita by country
Source: Autor's own elaborations based on ILO (2020a), OECD (2020a), World Bank (2020b).

Figure 3.2 shows the distribution of average R&D expenditures and low-skilled and high-skilled employment rates of selected developed countries for the period 1990-2019. The graph shows a negative (positive) correlation between low-skilled (high-skilled) employment distribution and R&D expenditures. Per capita, R&D expenditures, and employment rates by skill levels are spotted over a 30-year horizon with averages for developed economies. The graph illustrates that as per capita R&D increases, high skilled employment rates also increase, which is very reasonable. Especially Switzerland, Sweden, Norway, Denmark, Finland, United States, Israel, and Germany stand out with their above-average *RD* and *HSE* rates, while Mediterranean countries such as Portugal, Italy, and Spain, as well as Ireland and France, have below-average *RD* and *HSE* rates. There is a similar pattern in *LSE* rates. With a few exceptions, such as the United Kingdom, Belgium, Canada, and the Netherlands, countries with low *RD* averages have high *LSE*s, while countries with high *RD* spending have low *LSE* rates.

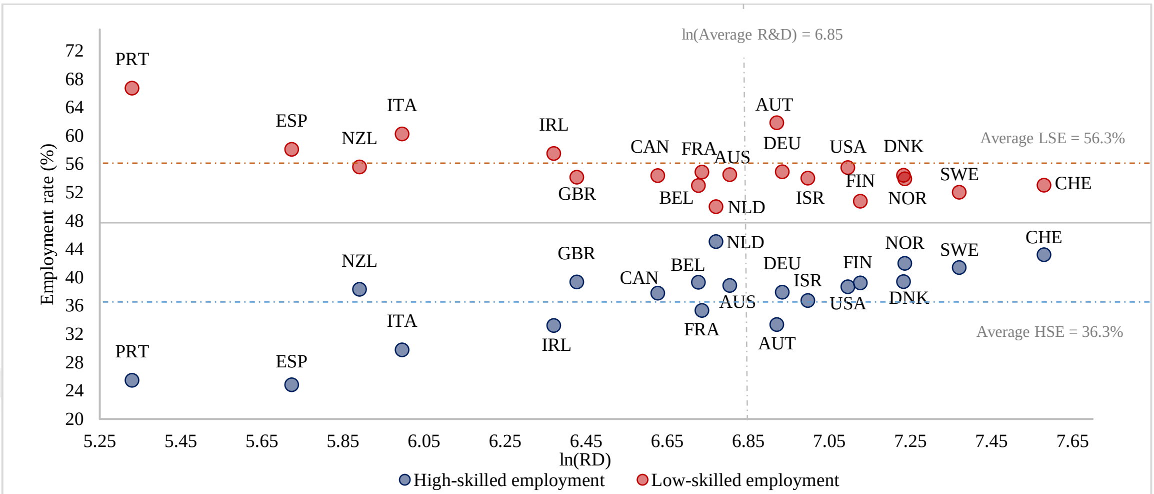

Figure 3.2. Average low and high-skilled employment rates and R&D per capita by country
Source: Autor's own elaborations based on ILO (2020a), OECD (2020a), World Bank (2020b).

In Table 3.4, the data are summarized by country, in Table 3.5 by years. Based on the average of the 1990-2019 period, the country with the highest unemployment rate among developed countries is Spain with 17.1%, the country with the highest per capita R&D expenditure is Switzerland with $1958, and the countries with the highest high-skilled employment are Switzerland and the Netherlands with 43% and 45%, respectively. Special mention should be made of Japan in this regard, as it is among the countries with the highest low-skilled employment rates despite very low unemployment rates and high R&D expenditure. As discussed in detail in OECD (2021) and Ganelli and Miake (2015), the reason for this situation is the labor shortage in Japan and the low-skilled labor force demand increasing above the OECD average. On the other hand, occupations requiring low and medium skill have been merged and grouped as *"low-skilled"* in this thesis, which has caused this rate to be higher than the OECD average in Japan because the middle-skilled employment share in the country is still quite high (OECD, 2021).

Based on annual averages, it is observed that the unemployment rate decreased from 6.9% to 5.4% in developed countries from 1990 to 2019, with some fluctuations in some periods, the rate of change is around 22%. This average peaked at 9.6% in 1995 and declined to 5.7% before the 2008 Global Financial Crisis. In the years following the crisis, it started to increase again, reaching the level of 8.5% in 2013, and then re-entering the downward trend, it decreased to the lowest unemployment level of the last 30 years, which is 5.7%. However, it should be noted that the data range covers the period before the Covid-19 pandemic, as the average for developed countries started to rise again in 2021, reaching 6.6% (ILO 2021). On the other hand, while the average per capita income increased by 51.9% in developed countries in the same period, R&D expenditures per capita rose from $628 to $1303, which shows that the change is 107.5%, which is more than twice the change in GDP. Finally, there is a dramatic change in the average skill distribution of developed countries. While the high-skilled employment rate was 30.7% in 1990, the average for 2019 was 41.3%, which indicates that the high-skilled employment rate has increased by 35.4% in the intervening 30 years.

Table 3.4. Descriptive statistics for the main indicators by country

Statistics	Ct.	U	HSE	LSE	RD	GDP	Ct.	U	HSE	LSE	RD	GDP
Mean	AUS	6.58	38.84	54.48	902	47053	JPN	3.75	22.33	73.91	1324	43519
Std. dev.		1.84	3.50	2.08	287	7365		1.03	1.81	2.26	203	3095
Max.		10.87	43.53	57.76	1336	57071		5.37	24.89	78.52	1620	49188
Min.		4.23	33.42	51.31	452	35035		2.09	19.39	71.64	993	38074
Mean	AUT	4.80	33.33	61.85	1013	43252	NLD	4.90	45.05	49.97	872	46785
Std. dev.		0.74	4.37	4.86	386	5346		1.61	2.00	1.00	150	6203
Max.		6.01	38.97	70.50	1641	50655		7.42	47.63	52.79	1226	55690
Min.		3.25	26.08	55.92	458	33889		2.12	40.43	48.16	650	35703
Mean	BEL	7.76	39.30	52.95	835	40796	NZL	6.06	38.30	55.57	362	31627
Std. dev.		1.08	3.21	3.00	249	4823		1.93	4.18	3.17	93	4662
Max.		9.65	44.20	58.88	1402	47541		10.67	44.13	59.78	532	38993
Min.		5.36	33.97	48.94	498	32672		3.60	32.36	51.01	223	23660
Mean	CAN	7.81	37.78	54.36	755	42748	NOR	4.13	41.98	53.90	1389	82117
Std. dev.		1.56	2.85	1.78	145	6812		1.00	4.84	4.37	274	10047
Max.		11.38	41.70	56.82	926	51589		6.31	49.60	59.00	2037	92556
Min.		5.66	33.21	51.39	499	32503		2.49	36.04	46.33	920	60227
Mean	DNK	6.15	39.41	54.42	1385	55826	PRT	7.80	25.48	66.73	206	20978
Std. dev.		1.77	3.74	3.11	425	5886		3.51	3.91	6.19	96	2165
Max.		10.72	43.50	59.88	2017	65147		16.18	33.39	75.50	350	24590
Min.		3.43	32.74	50.43	677	44569		3.82	20.31	55.97	77	16668
Mean	FIN	9.94	39.23	50.75	1244	41578	ESP	17.11	24.81	58.08	306	28509
Std. dev.		3.40	2.59	1.81	380	6735		5.35	3.86	4.87	91	3479
Max.		17.00	42.69	55.77	1754	49441		26.09	29.20	66.84	422	33350
Min.		3.07	34.45	48.39	607	29684		8.23	17.23	49.22	176	22513
Mean	FRA	9.77	35.34	54.88	842	38684	SWE	6.58	41.37	52.00	1589	47708
Std. dev.		1.52	4.53	3.97	78	3674		2.28	4.00	3.73	308	7618
Max.		12.59	41.11	62.43	975	44317		10.36	48.20	59.32	2023	57975
Min.		7.06	28.44	49.63	736	32524		1.83	36.00	46.22	948	35495
Mean	DEU	7.19	37.90	54.91	1027	39769	CHE	3.84	43.18	52.99	1958	70139
Std. dev.		2.31	3.34	2.87	240	4626		0.87	4.98	5.72	449	6080
Max.		11.17	43.01	62.20	1499	47628		4.92	50.19	64.66	2718	79407
Min.		3.14	32.38	51.34	730	32427		1.78	33.73	45.32	1440	61603
Mean	IRL	9.27	33.18	57.48	584	46863	GBR	6.47	39.36	54.15	618	37064
Std. dev.		4.33	5.41	3.57	213	15158		1.85	4.34	3.56	77	5070
Max.		15.78	39.35	63.11	928	79703		10.35	46.49	58.88	758	43688
Min.		3.68	23.50	49.83	193	24315		3.74	32.91	48.18	498	28291
Mean	ISR	9.30	36.71	53.99	1093	28446	USA	5.84	38.65	55.49	1207	45843
Std. dev.		3.12	8.26	5.90	360	3965		1.60	2.04	2.17	213	5970
Max.		14.08	49.78	63.59	1777	35293		9.63	41.65	58.52	1599	55670
Min.		3.90	24.77	46.05	538	21520		3.67	34.94	49.73	878	35542
Mean	ITA	9.96	29.76	60.25	402	34904	TOT	7.38	36.25	56.34	948	43534
Std. dev.		1.85	5.09	4.18	57	2136		3.76	7.25	6.57	508	14661
Max.		12.68	38.23	68.37	505	38272		26.09	50.19	78.52	2718	92556
Min.		6.08	22.30	55.65	308	30871		1.78	17.23	45.32	77	16668

Note: U, *HSE*, and *LSE* are percentages of total labor force. *RD* and *GDP* are in constant US$.
Source: Author's own calculations based on World Bank, OECD, and ILO data.

Table 3.5. Descriptive statistics for the main indicators by year

Stat.	Yr.	U	HSE	LSE	RD	GDP	Yr.	U	HSE	LSE	RD	GDP	Yr.	U	HSE	LSE	RD	GDP
Mean	1990	6.9	30.7	61.3	628	34331	2000	6.5	35.2	58.3	868	42314	2010	8.1	38.4	53.5	1092	46561
Sd.		3.9	6.3	6.1	352	11326		3.2	6.7	6.4	428	13342		3.6	6.6	5.8	504	14483
Max.		16.3	40.7	78.4	1483	64344		13.8	46.7	75.5	1647	81653		19.9	47.4	71.7	2207	87694
Min.		1.8	17.5	51.2	77	16668		2.7	20.7	49.2	155	21498		3.5	22.8	48.2	345	22499
Mean	1991	7.9	30.7	61.5	622	34368	2001	6.0	35.5	58.5	902	42837	2011	7.9	38.3	53.8	1115	47090
Sd.		4.0	6.3	6.1	331	11330		2.8	6.5	6.4	444	13481		4.1	6.9	5.7	523	14477
Max.		15.9	40.4	78.5	1440	62962		11.8	47.1	75.5	1780	82927		21.4	46.9	73.7	2306	87413
Min.		1.8	17.2	52.3	90	17436		2.1	20.7	49.3	166	21761		3.2	21.7	48.4	323	22150
Mean	1992	8.6	31.0	60.5	634	34585	2002	6.4	35.4	58.2	915	43241	2012	8.4	38.9	52.7	1121	47083
Sd.		4.1	6.5	6.4	336	11426		2.8	6.4	6.1	448	13536		4.9	6.9	5.3	534	14766
Max.		17.7	41.7	78.3	1480	63630		12.9	47.5	74.5	1742	83674		24.8	47.9	71.6	2390	88605
Min.		2.2	17.4	51.5	98	17639		2.6	21.1	50.0	157	21809		3.1	24.1	47.7	294	21337
Mean	1993	9.6	31.1	59.3	643	34658	2003	6.8	35.7	57.6	929	43580	2013	8.5	39.3	52.1	1132	47240
Sd.		4.6	6.5	6.7	336	11476		2.7	6.4	6.1	453	13525		5.1	7.1	5.5	545	14819
Max.		22.2	43.8	77.6	1477	65052		13.5	47.6	72.4	1746	83941		26.1	48.7	72.4	2453	88445
Min.		2.5	18.2	48.6	95	17258		3.6	21.6	48.8	150	21525		3.4	23.6	46.6	282	21257
Mean	1994	9.5	31.3	59.2	661	35637	2004	6.7	36.9	56.3	942	44696	2014	8.1	40.0	51.9	1151	47891
Sd.		4.8	6.4	6.5	342	11790		2.6	5.7	5.5	454	14040		4.7	7.1	5.7	551	14996
Max.		24.2	43.7	77.1	1495	67952		13.0	46.3	72.2	1843	86759		24.4	49.8	72.4	2531	89176
Min.		2.9	18.9	48.4	93	17378		4.0	23.1	49.0	159	21858		3.5	24.1	45.5	278	21541
Mean	1995	8.9	31.8	59.3	681	36571	2005	6.6	37.2	56.2	965	45606	2015	7.7	40.1	52.2	1167	49031
Sd.		4.5	6.0	6.2	354	11911		2.3	5.6	5.6	466	14412		4.1	7.1	5.8	576	15481
Max.		22.7	42.3	76.5	1504	70410		11.3	45.2	72.2	1897	88433		22.1	49.7	72.3	2581	90029
Min.		3.2	20.1	48.6	93	18059		3.8	23.4	50.1	166	21988		3.3	24.4	45.5	274	22018
Mean	1996	8.9	32.3	58.9	707	37400	2006	6.2	37.7	56.2	1013	46756	2016	7.1	40.5	52.4	1198	49650
Sd.		4.3	6.0	6.1	363	12254		2.2	5.9	5.8	484	14765		3.7	7.0	5.8	588	15501
Max.		22.1	44.1	76.2	1518	73576		10.7	45.6	72.5	1970	89828		19.6	49.7	72.4	2620	90196
Min.		3.4	20.6	49.4	102	18622		3.4	23.4	50.5	213	22305		3.1	24.5	45.4	289	22534
Mean	1997	8.6	32.7	58.7	739	38580	2007	5.7	38.0	56.4	1057	47955	2017	6.4	40.9	52.7	1230	50657
Sd.		4.1	6.2	6.3	374	12725		2.0	6.1	5.8	494	15077		3.3	6.9	5.9	598	15826
Max.		20.7	44.7	75.8	1529	77045		9.4	46.6	72.6	2042	91566		17.2	49.9	72.5	2620	91549
Min.		3.4	20.8	49.5	109	19355		2.5	22.4	50.3	257	22820		2.8	24.7	45.3	311	23381
Mean	1998	8.0	33.7	58.3	769	39652	2008	5.7	38.5	55.8	1094	47723	2018	5.7	41.3	53.0	1275	51573
Sd.		3.8	6.4	6.5	386	12949		2.1	6.3	5.6	510	15001		2.9	6.8	6.0	611	16247
Max.		18.7	45.9	75.0	1549	78598		11.3	47.6	71.9	2069	90862		15.3	49.9	72.8	2717	92120
Min.		3.6	20.3	49.8	126	20183		2.6	22.7	49.8	330	22859		2.4	24.8	45.4	328	24036
Mean	1999	7.3	34.6	58.1	814	40837	2009	7.7	38.4	53.9	1082	45768	2019	5.4	41.5	53.1	1303	52138
Sd.		3.4	6.7	6.5	399	13019		3.2	6.5	5.7	496	14501		2.7	6.8	6.0	629	16470
Max.		15.5	46.6	74.7	1547	79633		17.9	47.6	71.9	2082	88174		14.1	50.2	72.7	2718	92556
Min.		3.2	20.7	49.5	142	20853		3.1	23.1	49.0	350	22125		2.4	24.9	45.4	340	24590

Note: U, HSE, and *LSE* are percentages of total labor force. *RD* and *GDP* are in constant US$.
Source: Author's own calculations based on World Bank, OECD, and ILO data.

Figure 3.3 shows the patterns of change in developed countries' average unemployment, high-skilled employment, and low-skilled employment rates. It is seen that the most serious increase in unemployment occurred in 2009 as a reflection of the global financial crisis of 2008, besides this, the decrease in employment was mostly on the low-skilled employment side, and the decreases in high-skilled employment were observed at milder rates. In addition to these, while low-skilled employment rates of developed countries mostly decreased until 2015, an increase is observed in both low-skilled and high-skilled employment with the year 2015.

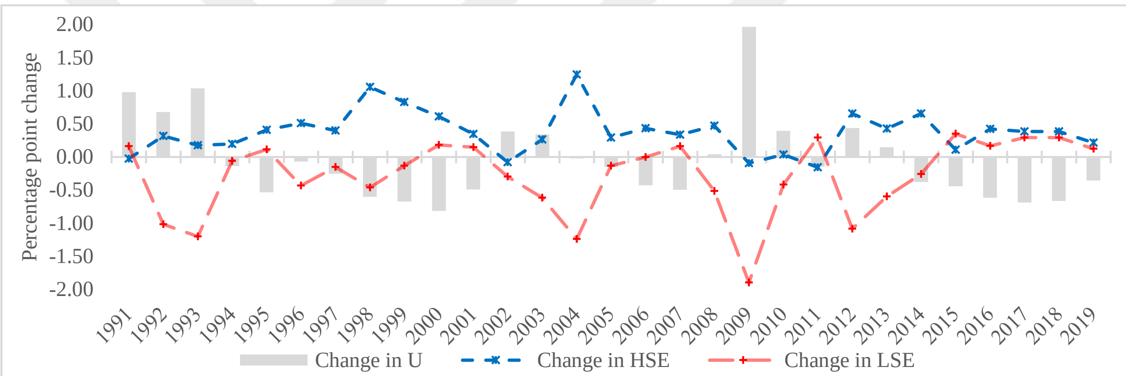

Figure 3.3. Changes in average unemployment, high-skilled and low-skilled employment rates in developed countries by year
Note: In this figure, percentage point changes in *U*, *HSE*, and *LSE* are shown on the primary axis (left).
Source: Author's own calculations based on World Bank and ILO data.

Figure 3.4 shows the unemployment rates, R&D expenditures, and GDP per capita changes in developed countries over years. In developed countries, growth in R&D per capita has been greater than growth in GDP per capita, except for the years 1991, 2004, 2010, and 2015. Apart from that, *GDP* and *RD* change trends follow each other. Although the frequency of increase in average unemployment rates was less frequent than the frequency of decrease, the magnitude of the increase on an annual basis was generally more severe than the decline.

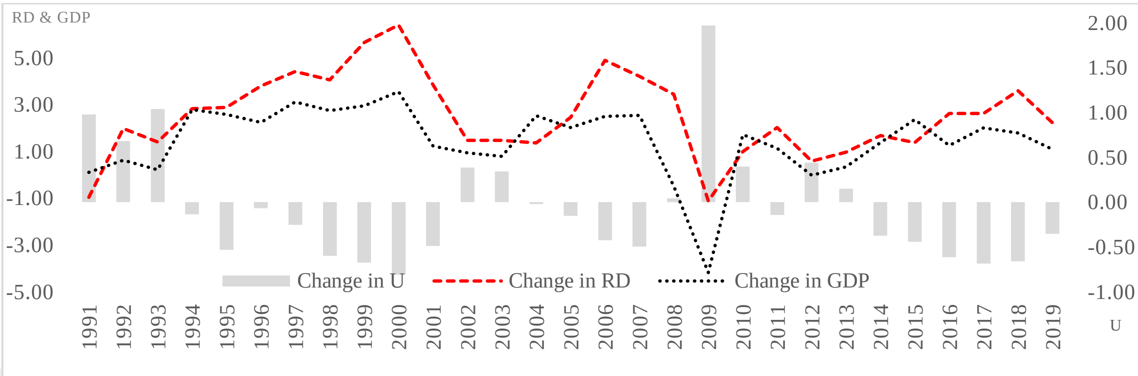

Figure 3.4. Changes in average unemployment, GDP per capita and R&D per capita in developed countries by year

Note: In this figure, percentage changes in per capita GDP and per capita R&D are shown on the primary axis (left) while the percentage change in unemployment is located on the secondary axis (right).
Source: Author's own calculations based on World Bank, OECD, and ILO data.

As a result, in this part of the study, the data used, data sources, and various descriptive statistics and figures are shared. Unemployment, high-skilled employment, and low-skilled employment, which are used as dependent variables in the study, and real interest rate, one of the control variables, are used as decimal fractions in the analysis. All other explanatory variables, especially R&D, were used by taking their natural logarithms. The empirical methods discussed in the next section are yielded in detail.

3.3. Empirical Methodology

Pedroni Cointegration and Panel Dynamic Ordinary Least Squares methods constitute the main scheme of empirical analysis in this study. The implementation of the Pedroni Cointegration method depends on whether the dependent and independent variables used in the models are integrated of order one, $I(1)$. Therefore, before proceeding to cointegration and model estimation steps, unit-root results are reported, and the stationarity status of the series is determined.

Both time series and panel data analyses begin with possible unit root detection. If the variables do not contain a unit root, the long-term relationship can be specified in levels by Ordinary Least Squares or other similar methods. However, if the variables contain unit root -which is a problem for one or more variables in many panel data- a spurious regression problem arises when long-term relationships are estimated by standard methods. Long-term relationships can still be predicted in these situations, but only if the variables are cointegrated. Therefore, if variables contain a unit root that is indicated in the first step, it is checked whether they are cointegrated in the second step because the concept of cointegration implements a mechanism for identifying long-run relationships. Finally, the power and direction of long-term relationships between variables that are proven to be cointegrated are estimated in panel data using Panel Dynamic OLS and Fully Modified OLS methods.

In this study, three types of panel unit root tests that have three different characteristics are used. LLC (2002), one of these tests, has a homogeneous unit root test process as mentioned before, while the other two tests, IPS (2003) and Fisher Type (Maddala and Wu, 1999), perform heterogeneous unit root tests. In the research, unit root test results are reported both with and without a trend for all three methods. In addition to these, to mention again all three LLC, IPS and F-ADF operate under a null hypothesis of a nonstationary and as emphasized before, the coefficient in the LLC test is identical, while the coefficients in the IPS and Fisher Type ADF tests is possible to diversify according to cross-sections.

3.3.1. Equations to be estimated

Since the main purpose of this study is to explain the changes in unemployment rates of countries with technology using a panel data set, besides the technology proxy, other macro variables that have been proven to have a critical effect on unemployment, following previous studies, are also selected for inclusion in the models. In this study, the effects of technology on both overall unemployment and employment by skill are examined. While examining the overall unemployment effect of technology, U_{it} which reflects unemployment rate is used as the dependent variable. Moreover, in order to test the effect of technology on employment by skill levels, HSE_{it} and LSE_{it} are used as dependent variables. In this study, a total of seven models, two of which are baseline models, are proposed in the specifications in which unemployment is used as an independent variable, while three models are defined each to examine the technology employment relationship on the basis of skills. Details of these models are given in the next section.

3.3.1.1. Equations for the overall unemployment rate

Here, the dependent variable used in the model, regardless of skill, is the overall unemployment rate. As stated before, this variable is obtained as the percentage of the total labor force, but it is used as a *"decimal fraction"* in models. Since the main purpose of the study is to determine the effect of technology on unemployment -or employment-, the technology variable R&D takes its place as the core independent variable in all models. On the other hand, based on previous empirical studies and theoretical literature, per capita GDP and inflation are defined as the baseline model variables and are included in all models in the study. With i (=1, ..., N) denoting countries and t (= 1, ..., T) representing year, the estimated initial baseline model is as follows:

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+e_{it} \qquad \textit{Model 3.1}$$

where U_{it} represents unemployment rate for country i (= 1,2, ..., 21); RD_{it}, is the natural logarithm of per capita research and development expenditure and it is used as technology proxy; GDP_{it}, shows the natural logarithm of per capita GDP; CPI_{it}, denotes the consumer price index and is in natural logarithm form as other two, and finally e_{it} represents an error term that indicates other factors affecting unemployment. The main coefficient of interest in the thesis, β, is the partial effect of technology on unemployment, and hence β is expected to be positive if an increase in technology leads to an increase in unemployment or vice versa. In addition, income plays an important role in reducing unemployment, so α_1 is expected to be negative. Finally, details on both the empirical and theoretical literature on the direction of the relationship between inflation and unemployment are presented in the previous sections, and the coefficient can be estimated in either direction. Likewise, Model 3.2 is created by adding the productivity variable to Model 3.1 below:

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+e_{it} \qquad \textit{Model 3.2}$$

where PRD_{it} represents productivity and is calculated as *"output per worker"*. Although there is consensus on the effect of productivity on unemployment, in the long run, the direction of the relationship is controversial. Since the output per worker is calculated based on the formula $total\ output/total\ employment$, it is clear that the direction of the effect is influenced by both income and employment. In addition to the two base specifications given above, the following five models with other control variables are also included and estimated:

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_4 INT_{it}+\alpha_5 PUS_{it}+e_{it} \qquad \textit{Model 3.3}$$

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_4 INT_{it}+\alpha_6 TUD_{it}+e_{it} \qquad \textit{Model 3.4}$$

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_4 INT_{it}+\alpha_5 PUS_{it}+\alpha_7 EXC_{it}+e_{it} \qquad \textit{Model 3.5}$$

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_5 PUS_{it}+\alpha_6 TUD_{it}+\alpha_7 EXC_{it}+e_{it} \qquad \textit{Model 3.6}$$

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_5 PUS_{it}+\alpha_6 TUD_{it}+e_{it} \qquad \textit{Model 3.7}$$

Model 3.3 includes INT_{it} and PUS_{it} as well as core independent variables and they represent real interest rate and per capita public unemployment spending respectively. On the other hand, Model 3.4 contains TUD_{it} which shows trade union density and excludes PUS_{it} from Model 3.3. In Model 3.5, the natural logarithm of real effective exchange rate index, which is EXC_{it} is added. Finally, Model 3.6 and Model 3.7 show the other variations including the same variables.

3.3.1.2. Equations for employment by skills

While examining the impact of technology on unemployment at the macro level, this study primarily focuses on country groups and evaluates developed and developing countries separately. This section focuses on developed countries and considers two different skill groups, high-skilled and low-skilled. At this stage, it is primarily estimated in Model 3.8 where HSE_{it} is the dependent variable:

$$HSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+e_{it} \qquad \textit{Model 3.8}$$

As mentioned earlier, HSE_{it} represents the high-skilled employment rate and is used as a decimal fraction in the analysis. Explanatory variables, on the other hand, represent the natural logarithms of per capita R&D expenditure, per capita GDP, and CPI variables, respectively, as in the previous title. In addition to Model 3.1, the following two specifications are estimated for the high-skilled employment rate dependent variable:

$$HSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+e_{it} \qquad \textit{Model 3.9}$$

$$HSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_4 INT_{it}+e_{it} \qquad \textit{Model 3.10}$$

where PRD_{it} is the natural logarithm of output per worker and INT_{it} is the real interest rate. In developed countries, the β coefficient is expected to be positive, especially in line with the SBTC and RBTC hypotheses regarding the effect of technology on high-skilled workers.

After the dependent variables U_{it} and HSE_{it}, models established to explain low-skilled employment are also mentioned under this title. First, as in HSE_{it}, here also in the baseline model RD_{it}, GDP_{it}, and CPI_{it} explanatory variables are included for LSE_{it}:

$$LSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+e_{it} \qquad \textit{Model 3.11}$$

where, LSE_{it} is the dependent variable representing low-skilled employment, and the other variables are the same as the previous models. In this regard, the other two models for LSE_{it} are as follows:

$$LSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+e_{it} \qquad \textit{Model 3.12}$$

$$LSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_4 INT_{it}+e_{it} \qquad \textit{Model 3.13}$$

Of course, as the main focus of the study, the effects of explanatory variables on HSE_{it} and LSE_{it} are expected as different in terms of their signs or magnitudes in the light of both SBTC and RBTC approaches. So far, details about the specifications discussed in the study are given. The following sections show some technical details about the methods used in the analysis.

3.3.2. Unit root testing procedure

Today, one of the most important issues to be considered in order to reach correct and consistent results in the empirical analysis is the stationarity of time series. Since the panel data models also include a time dimension, the stationarity analysis should be applied first. Two basic conditions can be mentioned for stationarity: a) the mean and time-series variance are constant over time and b) the covariance among the time periods is governed by the distance between the two periods, not the period of the variables that observed. If the series are not stationary, the average cannot be maintained in the long run and the variance value goes to infinity as the time come close to infinity. As the lag of the series increases, high R^2 and t statistics values are obtained due to the autocorrelation values moving away from zero. Thus, the long-term model estimates cannot give accurate and consistent results and a spurious regression model appears.

There are many alternative tests available today to find out if the series are stationary. The unit root test is one of the methods that test the stationarity of the series by checking whether the time series contains unit root or not. It is well known that unit root tests generally have low power in small sample sizes, and it is considered as a solution to add the cross-section size to the time dimension to increase the power of unit root tests. Since the number of observations increases, it is accepted that panel unit root tests are statistically stronger than time series unit root tests and that is why panel unit root has also taken an important place in the empirical data analyses. (Maddala and Wu, 1999; Hadri, 2000; Levin et al., 2002).

The first-generation tests like Fisher Type (Maddala and Wu, 1999; Choi, 2001) and some other alternatives recommended by Breitung (2001), Levin et al. (2002), and Im et al. (2003) are used to perform unit root tests in panel data models. The establishment of hypotheses in these tests and the calculation of test statistics are based on the Dickey-Fuller (1979) and Augmented Dickey-Fuller (ADF) unit root tests.

In the Levin-Lin-Chu (LLC) test by Levin et al. (2002), the ρ coefficient for all units is assumed to be homogeneous, whereas, in the Im, Pesaran, and Shin (IPS) by Im et al. (2003) test, the coefficient of ρ is allowed to be heterogeneous. In the IPS test, the unit root test is applied separately for each unit without combining the data, and IPS test statistics are calculated by taking the average of the obtained statistics (Im et al., 2003). Maddala and Wu (1999) and Choi (2001) propose the non-parametric Fisher-type tests based on combining unit root test statistics for each cross-section as an alternative. In this test, as in LLC (2002) and IPS (2003) tests, panel data need not be balanced. In addition, different lag lengths can be used in ADF regressions for each unit and can be applied for any derived unit root test.

The tests included in this study are first-generation tests designed for cross-sectionally independent panels. Undoubtedly, this very strong assumption significantly simplifies the derivation of asymptotic distributions of panel unit root and stationarity tests. In the following sections, the LLC test presented by Levin et al. (2002), the IPS test introduced by Im et al. (2003), and the Fisher-type unit-root test using ADF and PP by Maddala and Wu (1999) is explained.

3.3.2.1. The Levin-Lin-Chu Test (LLC)

The first method used in the study is developed by Levin and Lin (1993) and Levin, Lin and Chu (2002); is the Levin-Lin-Chu Test (LLC) that performs a unit-root test on pooled data series by handling panel data as homogeneous cross-sections. The first version of the test developed by Levin and Lin (1993) is based on the following model:

$$y_{it} = \rho_i y_{i,t-1} + z_{it}\gamma + u_{it} \qquad \textit{Eq. 3.1}$$

where, $i=1, 2, 3, \ldots, N; t=1, 2, 3, \ldots, T$ and z_{it} is defined as a deterministic component while u_{it} represents the stationary process. Accordingly, the hypotheses of the test can be expressed as follows:

$$H_0: \rho_i = \rho = 1, \qquad for\ all\ i = 1, 2, 3, \ldots, N$$
$$H_1: -1 < \rho_i = \rho < 1, \qquad for\ all\ i = 1, 2, 3, \ldots, N$$

in other words,

H_0: Each time series contains unit roots-which means nonstationary

H_1: Each time series is stationary-which means no unit root

At this point, firstly, Augmented Dickey-Fuller (ADF) for each cross-section on the equation is run, and the important point to consider is that the coefficient of the lagged dependent variable is assumed to be homogeneous in all units of the panel. On the other hand, the current LLC test procedure is based on the following model:

$$\Delta y_{it} = \rho y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta y_{it-j} + \delta_{mi} d_{mt} + \varepsilon_{it} \qquad \textit{Eq. 3.2}$$

The null and alternative hypotheses for this model are as follow:

$$H_0: \rho_i = \rho = 0, \qquad for\ all\ i = 1, 2, 3, \dots, N$$

$$H_0: \rho_i = \rho < 0, \qquad for\ all\ i = 1, 2, 3, \dots, N$$

After running the model above, residuals are obtained using the following two auxiliary regressions:

$$\hat{e}_{it} = \Delta y_{it} - \sum_{j=1}^{p_i} \hat{\pi}_{ij} \Delta y_{it-j} + \hat{\delta}_{mi} d_{mt} \qquad \textit{Eq. 3.3}$$

$$\hat{v}_{i,t-1} = y_{i,t-1} - \sum_{j=1}^{p_i} \tilde{\pi}_{ij} \Delta y_{it-j} + \tilde{\delta}_{mi} d_{mt} \qquad \textit{Eq. 3.4}$$

After this step, residuals can be standardized as follows:

$$\tilde{e}_{it} = \frac{\hat{e}_{it}}{\hat{\sigma}_{\varepsilon_i}} \qquad \textit{Eq. 3.5}$$

$$\tilde{v}_{i,t-1} = \frac{\hat{v}_{it}}{\hat{\sigma}_{\varepsilon_i}} \qquad \textit{Eq. 3.6}$$

where σ_{ε_i} expresses the standard error from each ADF and finally, the current LLC test is the result of combining all cross-sectional and time series to estimate the following model:

$$\tilde{e}_{it} = \rho \tilde{v}_{i,t-1} + \tilde{\varepsilon}_{it} \qquad \textit{Eq. 3.7}$$

In this time, the null hypothesis is $\rho = 0$ and the t-statistic is described as conventional. The fundamental requirement for the LLC test is $\sqrt{N_T} / T \rightarrow 0$, while adequate conditions would be $N/T \rightarrow 0$ and $N/T \rightarrow k$. The models with homogeneous dynamics are crucial because of the small time-series dimension of most panels. For this reason, Levin et al. (2002) state that the statistic works well when N ranges between 10 and 250 and when T is between 5 and 250. A very tiny T means that the test is under-dimensioned and has low power. One important downside of the LLC test statistic is that it depends rigorously on the presumption of cross-sectional independence. Furthermore, the null of all cross-sections are nonstationary is very definitive which means it is not allowed that some units have unit root, and some have not. If the dimension of T is very wide, then Levin et al. (2002) recommend individual unit root time-series tests. If N is very high -or T very small- typical panel data methods can be implemented. Lastly, the adjusted t-statistics for this test are calculated as follows:

$$t_\rho^* = \frac{t_\rho}{\sigma_T^*} \; NT\hat{S}_N \left(\frac{\hat{\sigma}_{\hat{\rho}}}{\hat{\sigma}_{\tilde{\varepsilon}}^2}\right) \left(\frac{\mu_T^*}{\sigma_T^*}\right) \qquad \textit{Eq. 3.8}$$

$$\hat{S}_N = \frac{1}{N}\sum_{i=1}^{N} \hat{\sigma}_{y_i} \Big/ \hat{\sigma}_{\varepsilon_i} \qquad \textit{Eq. 3.9}$$

where μ_T^* is the mean adjustment and σ_T^* is standard deviation adjustment which are reported by authors for different sample sizes (Levin et al., 2002). Besides, $\hat{\sigma}_{y_i}$ is a long-run variance kernel estimator of the country *i*.

3.3.2.2. The Im-Pesaran-Shin Test (IPS)

The Im-Pesaran-Shin (IPS) test developed by Im, et al. (2003) is not as restrictive as the LLC test as it allows for heterogeneous coefficients: ρ_i. Accordingly, ρ is removed from the model used in the LLC test and ρ_i is added to obtain the following model:

$$\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta y_{it-j} + \delta_{mi} d_{mt} + \varepsilon_{it} \qquad \textit{Eq. 3.10}$$

In the IPS test, the null hypothesis is as follows:

$$H_0: \rho_i = 0, \qquad for\ all\ i = 1, 2, 3, \dots, N$$

On the other hand, the alternative hypothesis is exhibited as follows:

$$H_1: \begin{cases} \rho_i < 0, & for\ i = 1, 2, 3, \dots,\ N_1 \\ \rho_i = 0, & for\ i = \ N_1 + 1, \dots, N \end{cases}$$

In other words, according to the null hypothesis, *"all individuals contain a unit root"*, whereas the alternative hypothesis states, *"not all individuals include a unit root, some are stationary"*. Therefore, in the IPS test, instead of pooled data, separate unit-root tests are performed for N number of cross-sections, and the average t-statistics is used:

$$t_{NT} = N^{-1} \sum_{i=1}^{N} t_{\rho_i} \qquad \textit{Eq. 3.11}$$

The IPS test requires the determination of the deterministic part of each cross-section ADF and the number of lags. In addition, individual fixed or individual constant and trend terms can be used in this test. According to Monte Carlo simulations, the IPS test performs better than LLC's, especially in small samples. The IPS test requires $N/T \rightarrow 0$ condition as the cross-section number approaches infinity. As T goes to infinity, the values of t_{ρ_i} converge to the DF distribution and are independently and identically distributed. In addition, in both LLC and IPS tests, if N is too small or too large compared to T, some size distortions can be examined.

3.3.2.3. Fisher Type Tests: Maddala and Wu (1999) and Choi (2001)

As pointed out in the earlier section, panel unit root tests are established on a heterogeneous model and composed of testing the significance of the results obtained from N independent tests. In this regard, IPS uses an average statistic, but there is an alternative testing strategy based on combining the significant levels observed from individual tests. The approach based on p values has a long history in meta-analysis. In panel unit root tests, such a strategy, based on Fisher (1925/1992) type tests, is used especially by Maddala and Wu (1999) and Choi (2001). Fisher-type tests practice the same hypotheses as to the IPS test:

$$H_0: \rho_i = 0, \qquad for\ all\ i = 1, 2, 3, \ldots, N$$

$$H_1: \begin{cases} \rho_i < 0, & for\ i = 1, 2, 3, \ldots,\ N_1 \\ \rho_i = 0, & for\ i =\ N_1 + 1, \ldots, N \end{cases}$$

The Fisher type unit root test, generated by Maddala and Wu (1999), based on the fact that t-statistics are continuous, and p-values are uniform variables in the range of 0 and 1, defines the test statistic as follows:

$$P_{MW} = -2 \sum_{i=1}^{N} ln\rho_i \qquad \textit{Eq. 3.12}$$

which has X^2 distribution with $2N$ degrees of freedom ($T_i \rightarrow \infty\ for\ finite\ N$). This test is very favorable because it enables working on unbalanced panel data and allows different lag lengths. For larger N samples, Choi (2001) suggests the following similar and standardized statistics:

$$Z_{MW} = \frac{N^{0.5}[N^{-1}P_{MW} - E|-2ln\rho_i\,|]}{[Var|-2ln\rho_i\,|]^{0.5}} = -\frac{\sum_{i=1}^{N} ln\rho_i + N}{N^{0.5}} \qquad \textit{Eq. 3.13}$$

Besides, in the Maddala and Wu (1999) test, the number of lags used in each cross-section ADF regression should be determined, while in the Choi (2001) test, it is necessary to calculate the kernel as an autocorrelation correction method.

3.3.3. Panel cointegration tests

In panel data analyses, which are frequently used by economists today, the next step after unit root analysis is to examine the properties and attributes of non-stationary time series in panel form. The sources of two tests commonly used to examine these characteristics are Pedroni (1999, 2004) and Kao (1999) cointegration studies. Cointegration is one of the widely used methods in experimental studies in order to detect the existence of long-term relationships between panel time series. Here, the method introduced by Pedroni (1999, 2004) presents seven different statistics in two groups or sets; the four statistics in the first set give the cointegration results for the homogeneous panels, and the three statistics that belong to the second set give the results in the heterogeneous panels. On the other hand, the Kao cointegration test (Kao, 1999) test is performed for homogeneous panels.

Cointegration tests in panel data have recently attracted the attention of experimental researchers in the economics and finance fields. Of course, one of the most important reasons underlying this is that economic or financial indicators have unit-roots. Because of the unit root, regressions give false but statistically significant coefficients which mean *"spurious"* results. Besides, cointegration tests are quite successful in preventing false regression results; and it is an important method that has become popular and useful, especially with the availability of data accessible over longer time intervals. Therefore, it is inevitable that cointegration will continue to be a popular and useful tool in the future, especially for examining long-term relationships.

This study is based on the results achieved from the cointegration method developed by Pedroni (1999, 2004). In addition, it is aimed to support the results gathered by Pedroni cointegration method with Kao (1999) cointegration test. Both tests provide a residual-based cointegration test process in panels and the null hypothesis is set up as *"no cointegration"*. The presupposition of both tests is *"independency across cross-sections"* and of course, this assumption can be seen as both unrealistic, restrictive, and unattainable.

3.3.3.1. Pedroni cointegration test

Based on the unit root tests, the finding that all variables are $I(1)$ is a sufficient condition for detecting the existence of a long-term relationship with Pedroni cointegration. As mentioned before, Pedroni (2004) offers seven different test statistics, and these statistics are based on residuals of panel cointegration regressions. The first four statistics are called panel statistics, and these statistics are based on estimators that pool the autoregressive coefficient across countries to perform a unit root test on predicted residuals. On the other hand, the remaining three statistics are called group statistics and these tests are based on estimating the autoregressive coefficients separately for all countries in the panel and then averaging them. For both types of test statistics, the null hypothesis is set as "*no cointegration*", i.e., the autoregressive coefficient of the estimated residuals is equal for all countries, $\rho_i = 1$. The alternative hypothesis is different between the two groups: a) the alternative hypothesis for panel statistics is that the autoregressive coefficient has a common value for all countries and this value is less than one, $\rho_i < 1$; b) the alternative hypothesis for group statistics is that the autoregressive coefficient may have less than one value for all countries, but different values between countries, so group statistics allow for additional cross-sectional heterogeneity in cointegration tests. Considering the fact that Pedroni cointegration reports seven test statistics, in cases where some tests reject the null hypothesis and other tests cannot, the overall decision about cointegration may be arbitrary or relative to some extent. The criterion chosen for this study is that at least one panel and one group of test statistics at a 5% significance level give meaningful results. In addition, it is important to note that Pedroni (2004) states the group ρ statistics have lower power than other test statistics. Consequently, four statistics of Pedroni cointegration are reported in this study: Panel PP t, Panel ADF, Group PP t, and Group ADF test statistics. The panel ADF statistic is comparable to the LLC panel unit root test while the group ADF statistic is parallel to the IPS panel unit root test. Lastly, the PP statistics are panel versions of the Phillips Perron t-statistics.

According to Pedroni (1999, 2004), the following model can be considered:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + ... + \beta_{Mi} x_{Mi,t} + e_{i,t} \qquad \textit{Eq. 3.14}$$

where, T is the time dimension, N is the number of individual members and M is the number of regressors. At this point, slope coefficients β_{1i}, β_{2i}, …, β_{Mi} and intercept α_i (also the trend term δ_i if added) may alter according to cross-sections. In order to calculate Pedroni panel cointegration test statistics, the above cointegration regression is estimated for each cross-section with OLS. Besides, panel (within-dimension) statistics are calculated using the first differences of the original series with the help of the following regression:

$$\Delta y_{i,t} = \sum_{m=1}^{M} \hat{\beta}_{mi} \Delta x_{mi,t} + \hat{\eta}_{i,t} \qquad \textit{Eq. 3.15}$$

By using the residuals given in the above equation (differenced regression), the long-term variance of $\hat{\eta}_{i,t}$ which is used to obtain $\hat{L}_{11i}^{-2}$ is calculated with the Newey and West (1987) estimator.

As discussed, in the Pedroni cointegration process, there are two different test types: parametric and non-parametric. Practicing the residuals of the cointegration regression, the next equation is estimated to calculate the non-parametric test statistics:

$$\hat{e}_{i,t} = \rho_i \hat{e}_{i,t-1} + \hat{u}_{i,t} \qquad \textit{Eq. 3.16}$$

where $t = 1, \dots, T; i = 1, \dots, N; m = 1, \dots, M$. Then, the long-term and contemporaneous variances of $\hat{u}_{i,t}$, which are represented as $\hat{\sigma}_{i,t}^2$ and $\hat{s}_i^2$ respectively, can be calculated. On the other hand, the parametric test statistics are calculated by the following regression, again using the residuals $\hat{e}_{i,t}$ in the cointegration equation:

$$\hat{e}_{i,t} = \rho_i \hat{e}_{i,t-1} + \sum_{k=1}^{K} \varphi_{i,k} \Delta \hat{e}_{i,t-k} + \hat{u}_{i,t}^{*} \qquad \textit{Eq. 3.17}$$

where $t = 1, \dots, T; i = 1, \dots, N; m = 1, \dots, M$. After this equation is also estimated, the variance of $\hat{u}_{i,t}^{*}$ is calculated and expressed as $\hat{s}_i^{*2}$.The calculation steps for both parametric and non-parametric Pedroni cointegration calculations can be summarized as follows:

$$\hat{s}_i^{*2} = T^{-1} \sum_{t=1}^{T} \hat{u}_{i,t}^{*} \qquad \textit{Eq. 3.18}$$

$$\tilde{s}_{N,T}^{*2} = N^{-1} \sum_{n=1}^{N} \hat{s}_i^{*2} \qquad \textit{Eq. 3.19}$$

$$\hat{L}_{11i}^{-2} = T^{-1} \sum_{n=1}^{N} \hat{\eta}_{i,t}^{2} + 2T^{-1} \sum_{s=1}^{k_i} \left(1 - \frac{s}{k_i + 1}\right) \sum_{t=s+1}^{T} \hat{\eta}_{i,t} \hat{\eta}_{i,t-s} \qquad \textit{Eq. 3.20}$$

$$\hat{\lambda}_i = T^{-1} \sum_{s=1}^{k_i} (1 - \frac{s}{k_i+1}) \sum_{t=s+1}^{T} \hat{u}_{i,t}\hat{u}_{i,t-s} \qquad \textit{Eq. 3.21}$$

$$\hat{s}_i^{*2} = T^{-1} \sum_{t=1}^{T} \hat{u}_{i,t} \qquad \textit{Eq. 3.22}$$

$$\hat{\sigma}_i^2 = \hat{s}_i^2 + 2\hat{\lambda}_i \qquad \textit{Eq. 3.23}$$

After the steps given above finally, the seven statistics can then be constructed from the following equations. It must be noted that Pedroni (1999, 2004) should be reviewed for a comprehensive examination of how these test statistics are formed.

$$panel\ v: T^2 N^{1.5} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \qquad \textit{Eq. 3.24}$$

$$panel\ \rho: TN^{0.5} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i) \qquad \textit{Eq. 3.25}$$

$$panel\ t: \left(\tilde{\sigma}_{N,T}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-0.5} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i) \qquad \textit{Eq. 3.26}$$

$$panel\ ADF: \left(\tilde{s}_{N,T}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-0.5} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*} \Delta \hat{e}_{i,t}^{*} \qquad \textit{Eq. 3.27}$$

$$group\ \rho: TN^{-0.5} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{t=1}^{T} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i) \qquad \textit{Eq. 3.28}$$

$$group\ t: N^{-0.5} \sum_{i=1}^{N} \left(\hat{\sigma}_i^2 \sum_{t=1}^{T} \hat{e}_{i,t-1}^2 \right)^{-0.5} \sum_{t=1}^{T} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i) \qquad \textit{Eq. 3.29}$$

$$group\ ADF: N^{-0.5} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{s}_i^{*2} \hat{e}_{i,t-1}^{*2} \right)^{-0.5} \sum_{t=1}^{T} \hat{e}_{i,t-1} \Delta \hat{e}_{i,t} \qquad \textit{Eq. 3.30}$$

Here, $\hat{\lambda}_i$ is equal to $(\hat{\sigma}_i^2 - \hat{s}_i^2)/2$ and $\tilde{s}_{N,T}^{*2}$ can be represented as $N^{-1} \sum_{i=1}^{N} \hat{s}_i^{*2}$. After the panel cointegration test statistics are determined, mean and variance correction terms are practiced in order to obtain the statistics asymptotically normally distributed.

Although Pedroni cointegration suggests seven different test statistics, the null hypothesis for all these statistics is the same:

$$H_0: \rho_i = 1 \ \ for\ all\ i = 1,2,3, \dots, N.$$

In other words, the null hypothesis is stated as *"there is no cointegration"*. Furthermore, the alternative hypothesis is shown differently according to group (between dimension) and panel (within dimension) statistics. The alternative hypothesis for group statistics:

$$H_1: \rho_i < 1 \;\; for\ all\ i = 1,2,3, \dots, N.$$

The alternative hypothesis for panel statistics:

$$H_1: \rho_i = \rho < 1 \;\; for\ all\ i = 1,2,3, \dots, N.$$

As it can be seen, there is a common value assumption for ρ_i in panel statistics, which can only be represented with ρ by dropping the cross-section term i.

3.3.3.2. Kao cointegration test

Kao (1999) assumes homogeneity under the $\beta_i = \beta$ constraint for the cointegration test he proposes. The Kao cointegration test is similar to Pedroni cointegration in the general process but specifying a cross-section-specific intercept differentiates it from Pedroni cointegration. On the other hand, while it is possible to add a trend to the model in Pedroni cointegration, trend specification is not enabled in Kao. In this direction, the following standard panel equation is remembered:

$$y_{it} = \alpha_i + \beta x_{i,t} + e_{i,t} \qquad \textit{Eq. 3.31}$$

In this equation, as in Pedroni cointegration, y_{it} and x_{it} are $I(1)$ and are noncointegrated. The null hypothesis of the Kao cointegration test indicates that there is no cointegration between series, and two methods can be mentioned to test this hypothesis, namely DF-type and ADF test statistics. However, since the ADF method is used in this study, the ADF test statistics calculation steps for Kao cointegration are briefly explained. For the ADF test, the following regression is run first:

$$\hat{e}_{i,t} = \rho_i \hat{e}_{i,t-1} + \sum_{j=1}^{p} \varphi_j \Delta \hat{e}_{i,t-j} + \nu_{i,t} \qquad \textit{Eq. 3.32}$$

where, $\Delta \hat{e}_{i,t-j}$ is the j^{th} lag and $j = 1,2,3, \dots, p$, while p refers to the number of lags in the equation. As in Pedroni cointegration, many methods can be used to determine the number of lags in Kao cointegration. Finally, in the ADF version, the test statistic is calculated as follows:

$$Kao\ ADF = \frac{t_{ADF} + \frac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_v}}{\sqrt{\frac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v^2} + \frac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}^2}}} \qquad \text{Eq. 3.33}$$

Accordingly, the null hypothesis can be re-expressed as $H_0\colon \rho = 1$ for the ADF version of Kao cointegration. Then again, the main method for cointegration is Pedroni (1999, 2004) in this study. The results of the Kao cointegration are also reported to verify and support the results obtained from Pedroni cointegration.

3.3.4. Estimation in panel cointegration models

Today, it is quite popular to observe and practice long-term cointegrating relationships in panel time series. Accordingly, in the previous sections, two important methods of whether time series are cointegrated in the long run are discussed. In this section, two methods, Panel Dynamic Ordinary Least Squares (PDOLS) and Fully Modified Ordinary Least Squares (FMOLS) estimations which are widely used to estimate the models of the panel series that are confirmed to be cointegrated are examined.

Before moving on to panel versions of these methods, it is useful to first review how they are applied in standard time series. While the PDOLS method used in panel time series today is based on the Dynamic OLS method developed by Saikkonen (1992) and Stock and Watson (1993) for use in time series; the origin of the FMOLS method is the estimators presented by Philips and Hansen (1990) and Hansen (1992).

Now, the estimators cited above can be reviewed: first, the $n+1$ dimensional time series is remembered by the following cointegration regression:

$$y_t = X_t'\beta + D_{1t}'\gamma_1 + u_{1t} \qquad \text{Eq. 3.34}$$

$$\Delta X_t = \hat{\Gamma}_{21}'\Delta D_{1t} + \hat{\Gamma}_{22}'\Delta D_{2t} + \hat{u}_{2t} \qquad \text{Eq. 3.35}$$

where $D_t = (D_{1t}', D_{2t}')'$, $X_t = \hat{\Gamma}_{21}' D_{1t} + \hat{\Gamma}_{22}' D_{2t} + \hat{\epsilon}_{2t}$, $\hat{u}_{2t} = \Delta\hat{\epsilon}_{2t}$ and X_t are directed by the system of specifications. Besides, according to Hansen (1992), u_t are strictly stationary. On the other hand, Σ contemporaneous covariance matrix, Λ is a one-sided long-run covariance matrix and Ω is a covariance matrix, these variables can be expressed in u_t as follows:

$$\Sigma = E(u_t u_t') = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \Sigma_{22} \end{bmatrix} \qquad \textit{Eq. 3.36}$$

$$\Lambda = \sum_{j=0}^{\infty} E\left(u_t u_{t-j}'\right) = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \Lambda_{22} \end{bmatrix} \qquad \textit{Eq. 3.37}$$

$$\Omega = \sum_{j=-\infty}^{\infty} E\left(u_t u_{t-j}'\right) = \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \Omega_{22} \end{bmatrix} = \Lambda - \Lambda' - \Sigma \qquad \textit{Eq. 3.38}$$

In the previous chapters, it is mentioned that making estimations with OLS causes erroneous results in non-stationary time series. Besides, although the β coefficient estimated by static OLS in line with the above equation is consistent, it is biased and asymmetric, and therefore static OLS is not recommended for cointegrating model predictions. In this direction, in the following chapters, first the origin points of FMOLS and PDOLS methods and then the employment process of these estimates in panel time series are mentioned.

In the standard time series, the cointegrating estimation procedure is as above, whereas in the panel series the process is more complicated. The revised version of the equation given above for the time series, which is based on Philips and Hansen (1990) and Hansen (1992), for panel series is as follows:

$$y_{it} = X_{it}'\beta + D_{1it}'\gamma_{1t} + u_{1it} \qquad \textit{Eq. 3.39}$$

As it can be seen, in addition to the time dimension in the previous cointegrating equation, an individual dimension “i” (cross-sections) is added to the model. Moreover, as in standard time series, $D_{it} = (D_{1it}', D_{2it}')'$ is defined as deterministic trend regressors, while stochastic regressors can be represented as:

$$X_{it} = \hat{\Gamma}_{21i}' D_{1ti} + \hat{\Gamma}_{22i}' D_{2it} + \hat{\epsilon}_{2it} \qquad \textit{Eq. 3.40}$$

$$\hat{u}_{2it} = \Delta\hat{\epsilon}_{2it} \qquad \textit{Eq. 3.41}$$

On the other hand, in terms of deterministic trend, the version of the model in which the model is mostly expressed only with cross-section dimension is as follows:

$$y_{it} = X'_{it}\beta + \gamma_i + u_{1it} \qquad \textit{Eq. 3.42}$$

$$\Delta X_{it} = u_{2it} \qquad \textit{Eq. 3.43}$$

Now, to adapt the standard time series equations given above for the panel series by adding the "i" dimension:

$$\Sigma_i = E(u_{it}u'_{it}) = \begin{bmatrix} \sigma_{11i} & \sigma_{12i} \\ \sigma_{21i} & \Sigma_{22i} \end{bmatrix} \qquad \textit{Eq. 3.44}$$

$$\Lambda_i = \sum_{j=0}^{\infty} E\left(u_{it}u'_{it-j}\right) = \begin{bmatrix} \lambda_{11i} & \lambda_{12i} \\ \lambda_{21i} & \Lambda_{22i} \end{bmatrix} \qquad \textit{Eq. 3.45}$$

$$\Omega_i = \sum_{j=-\infty}^{\infty} E\left(u_{it}u'_{it-j}\right) = \begin{bmatrix} \omega_{11i} & \omega_{12i} \\ \omega_{21i} & \Omega_{22i} \end{bmatrix} = \Lambda_i + \Lambda'_i - \Sigma_i \qquad \textit{Eq. 3.46}$$

where $\hat{u}_{it} = (\hat{u}_{1it}, \hat{u}'_{2it})'$ is the long-run covariance matrices for the errors in cross-section which are strictly stationary and ergodic with the mean of zero, Σ_i is the contemporaneous covariance matrix, Λ_i is the one-sided long-run covariance matrix, and finally Ω_i is the long-run covariance matrix. According to Phillips and Moon (1999), the long-run average covariance matrices can be defined as $\Lambda = E(\Lambda_i)$ and $\Omega = E(\Omega_i)$. Finally, the independence assumption between cross-sections should be noted, as emphasized in panel cointegration methods. Now, under these conditions, it can be explained how the panel versions of FMOLS and DOLS methods, which are originally produced for time series, can be employed. In the study, at first, FMOLS steps are explained, and then technical details about PDOLS are given.

3.3.4.1. Fully modified OLS in panel series (FMOLS)

In this section, firstly, the Fully Modified OLS method (FMOLS), which is developed by Philips and Hansen (1990) and then adapted to panel series by Philips and Moon (1999), Pedroni (2001), and Kao and Chiang (2001), is introduced. Among these techniques, the method developed by Philips and Moon (1999) is considered as pooled FMOLS and the method produced by Pedroni (2001) and Kao and Chiang (2001) is considered as pooled-weighted FMOLS. Although the starting point and application purpose of the methods are the same, there are some technical differences between them.

a. Pooled FMOLS

Based on the standard cointegration estimation process given above, the modified dependent variable created for use in time series is defined as follows:

$$y_t^+ = y_t - \widehat{\omega}_{12}\widehat{\Omega}_{22}^{-1}\hat{u}_2 \qquad \textit{Eq. 3.47}$$

In addition, the panel version of this model is as follows where $\widehat{\Lambda}$ and $\widehat{\Omega}$ are long-term covariance matrices calculated using $\hat{u}_t$ as defined earlier:

$$\tilde{y}_{i,t}^+ = \tilde{y}_{it} - \widehat{\omega}_{12}\widehat{\Omega}_{22}^{-1}\hat{u}_2 \qquad \textit{Eq. 3.48}$$

Besides that, the estimated biased error correction term is calculated as follows, where $\widehat{\omega}_{12}$, stands for the long-term average variance of $\hat{u}_{1it}$:

$$\hat{\lambda}_{12}^+ = \hat{\lambda}_{12} - \widehat{\omega}_{12}\widehat{\Omega}_{22}^{-1}\widehat{\Lambda}_{22} \qquad \textit{Eq. 3.49}$$

Consequently, the pooled FMOLS estimator proposed by Phillips and Moon (1999) is a simple modified version of the standard Phillips and Hansen estimator for panel data. Finally, the pooled FMOLS estimator (hereinafter P-FMOLS) is defined as follows, with

$$\hat{\beta}_{P-FMOLS} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{X}_{i,t}\tilde{X}_{i,t}'\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(\tilde{X}_{i,t}\tilde{y}_{i,t}^+ - \widehat{\Lambda}_{12}^{+\prime}) \qquad \textit{Eq. 3.50}$$

where, $\tilde{y}_{it} = y_{it} - \bar{y}_i$ and $\tilde{X}_{it} = X_{it} - \bar{X}_i$. Again, as stated before estimates of the terms $\widehat{\Lambda}_i$ and $\widehat{\Omega}_i$ are computed using the common approximation, $\hat{u}_{it}$. Then $\widehat{\Lambda}$ and $\widehat{\Omega}$ are obtained directly taking average by cross-sections: $\widehat{\Lambda} = \sum_{i=1}^{N}\widehat{\Lambda}_i$ and $\widehat{\Omega} = \sum_{i=1}^{N}\widehat{\Omega}_i$.

Instead of directly calculating the asymptotic variance in the P-FMOLS used today, the moments of the explanatory variables are obtained by performing the following steps based on the revised approach presented by Pedroni (2001b) and Mark and Sul (2003):

$$\hat{V}_{P-FMOLS} = \widehat{\omega}_{12}\widehat{M}_{P-FMOLS}^{-1} \qquad \textit{Eq. 3.51}$$

$$\widehat{M}_{P-FMOLS} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{T^2}\sum_{t=1}^{T}\tilde{X}_{i,t}\tilde{X}_{i,t}'\right) \qquad \textit{Eq. 3.52}$$

In this study, the *“sandwich estimator form”*, a modified version of the above approach offered by Mark and Sul (2003), is employed, which allows heterogeneous variances:

$$\hat{V}_{P-FMOLS} = \hat{M}^{-1}_{P-FMOLS}\hat{D}_{P-FMOLS}\hat{M}^{-1}_{P-FMOLS} \quad \textit{Eq. 3.53}$$

$$\hat{D}_{P-FMOLS} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\omega}_{12,i}\frac{1}{T^2}\sum_{t=1}^{T}\tilde{X}_{i,t}\tilde{X}'_{i,t}\right) \quad \textit{Eq. 3.54}$$

b. Pooled-weighted FMOLS

In the pooled-weighted Panel Dynamic OLS estimation (PW-FMOLS), which is an extension of P-FMOLS and presented by Pedroni (2001b) and Kao and Chang (2001), the data is weighted by cross-section specific covariance estimates for heterogeneous cointegrated panels including unequal variances:

$$\hat{\lambda}^{+}_{12,i} = \hat{\lambda}_{12,i} - \hat{\omega}_{12,i}\hat{\Omega}^{-1}_{22,i}\hat{\Lambda}_{22,i} \quad \textit{Eq. 3.55}$$

As can be seen, unlike P-FMOLS, in PW-FMOLS, “*i*” cross-section term is attached to the above model of long-term variance and in this regard, the adjusted dependent variable is denoted as below:

$$\tilde{y}^{++}_{i,t} = \tilde{y}_{it} - \hat{\omega}_{12}\hat{\Omega}^{-1}_{22}\hat{u}_2 - \hat{\omega}^{0.5}_{12,i}[\hat{\omega}^{-0.5}_{12,i}\tilde{X}'_{i,t} - (\hat{\omega}_{12,i}\tilde{X}_{i,t})']\beta_0 \quad \textit{Eq. 3.56}$$

in where the weighted variables are calculated as follows:

$$\tilde{X}^{*}_{i,t} = \hat{\Omega}^{-0.5}_{22,i}\tilde{X}_{i,t} \quad \textit{Eq. 3.57}$$

$$\tilde{y}^{*}_{i,t} = \hat{\omega}^{0.5}_{12,i}\tilde{y}^{++}_{i,t} \quad \textit{Eq. 3.58}$$

$$\hat{\lambda}^{*}_{12,i} = \hat{\omega}^{-0.5}_{12,i}\hat{\lambda}^{+}_{12,i}\hat{\Omega}^{-0.5}_{22,i} \quad \textit{Eq. 3.59}$$

Hence and finally, the PW-FMOLS estimator is calculated as:

$$\hat{\beta}_{PW-FMOLS} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{X}^{*}_{i,t}\tilde{X}^{*\prime}_{i,t}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(\tilde{X}^{*}_{i,t}\tilde{y}^{*}_{i,t} - \hat{\lambda}^{*\prime}_{12}) \quad \textit{Eq. 3.60}$$

Lastly, asymptotic covariance is obtained using the following equation as suggested by Pedroni (2001b):

$$\hat{V}_{PW-FMOLS} = \left(\frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{T^2}\sum_{t=1}^{T}\tilde{X}_{i,t}^{*}\tilde{X}_{i,t}^{*\prime}\right)\right)^{-1} \quad \textit{Eq. 3.61}$$

3.3.4.2. Dynamic OLS in panel series (PDOLS)

In this section, Dynamic OLS, which is started to be used in parallel with FMOLS and originated from the studies of Saikkonen (1992) and Stock and Watson (1993), is declared. The word *"dynamic"* in the method expresses the lags and leads added to the model, and these leads and lags of the differenced regressors eliminate the long-term correlations between u_{1t} and u_{2t}:

$$y_t = X_t'\beta + D_{1t}'\gamma_1 + \sum_{j=-q}^{r}\Delta X_{t+j}'\,\delta - v_{1t} \quad \textit{Eq. 3.62}$$

In this section, as in the FMOLS title, details of two methods are mentioned, namely, pooled Panel Dynamic OLS (P-PDOLS) and pooled-weighted Panel Dynamic OLS (PW-PDOLS). PDOLS estimation method is a modified extension for panel data of the DOLS model, which is tried to be expressed by the above equation by Kao and Chiang (2001), Mark and Sul (2003), and Pedroni (2001a). Therefore, it is a promising idea to add the dimension i to the equation above first to understand the extension for panel series:

$$\tilde{y}_{i,t} = \tilde{X}_{i,t}'\beta + \sum_{j=-q_i}^{r_i}\Delta\tilde{X}_{i,t+j}'\,\delta_i - \tilde{v}_{1it} \quad \textit{Eq. 3.63}$$

The most imperative point to be considered here, nevertheless, can be stated as one of the most important advantages of the method; adding cross-section specific leads and lags of ΔX to the model eliminates the asymptotic endogeneity and serial correlation problem in the specification. On the other hand, $\tilde{y}_{i,t}$ and $\tilde{X}_{i,t}$ data in the model are purged from the individual deterministic trend.

After the adaptation of Dynamic OLS to panel data has been stated, in the next section, the technical details of the pooled Panel Dynamic OLS (P-PDOLS) developed by Kao and Chiang (2001) and the pooled-weighted Panel Dynamic OLS (PW-PDOLS) methods developed by Mark and Sul (2003) are shared. As in FMOLS, while the initial point and employment purpose of the methods are similar in PDOLS, the calculation processes contain some technical differences.

a. Pooled PDOLS

In the standard pooled PDOLS method presented by Kao and Chiang (2001), deterministic components are redeemed from both dependent and explanatory variables:

$$\tilde{y}_{i,t} = \tilde{X}'_{i,t}\beta + \sum_{j=-q_i}^{r_i} \Delta\tilde{X}'_{i,t+j}\,\delta_i - \tilde{v}_{1it} \qquad \textit{Eq. 3.64}$$

In this model where the augmented cointegrating regression equation is estimated, as can be seen, δ_i includes a cross-sectional dimension, and in this direction, the pooled PDOLS estimation can be denoted as follows:

$$\begin{bmatrix}\hat{\beta}_{P-PDOLS}\\ \hat{\gamma}_{P-PDOLS}\end{bmatrix} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widetilde{W}_{i,t}\widetilde{W}'_{i,t}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widetilde{W}_{i,t}\tilde{y}'_{i,t}\right) \qquad \textit{Eq. 3.65}$$

Here, equivalence in the form of $\widetilde{W}'_{i,t} = (\tilde{X}'_{i,t}, \tilde{Z}'_{i,t})'$ can be established if $\tilde{Z}_{i,t}$ is defined as regressors formed by the interaction of $\Delta\tilde{X}'_{i,t+j}$ with cross-section dummy variables. Additionally, Kao and Chiang (2001) state that the asymptotic distribution for the P-PDOLS estimation method is the same as P-FMOLS. Hence the covariance matrix of $\hat{\beta}_{P-PDOLS}$:

$$\hat{V}_{P-PDOLS} = \hat{\omega}_{12}\widehat{M}^{-1}_{P-PDOLS} \qquad \textit{Eq. 3.66}$$

$$\widehat{M}_{P-PDOLS} = N^{-1}\sum_{i=1}^{N}\left(T^{-2}\sum_{t=1}^{T}\widetilde{W}_{i,t}\widetilde{W}'_{i,t}\right) \qquad \textit{Eq. 3.67}$$

Like P-FMOLS, the sandwich estimator presented by Mark and Sul (2003) can be used in the P-PDOLS, and this method is preferred in the analysis of this thesis:

$$\hat{V}_{P-PDOLS} = \widehat{M}^{-1}_{P-PDOLS}\widehat{D}_{P-PDOLS}\widehat{M}^{-1}_{P-PDOLS} \qquad \textit{Eq. 3.68}$$

$$\widehat{D}_{P-PDOLS} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\omega}_{12,i}\frac{1}{T^2}\sum_{t=1}^{T}\widetilde{W}_{i,t}\widetilde{W}'_{i,t}\right) \qquad \textit{Eq. 3.69}$$

b. Pooled-weighted PDOLS

Following P-PDOLS, the pooled-weighted Panel Dynamic OLS (PW-PDOLS) method, which is proposed by Mark and Sul (2003) and allows heterogeneity in long-run variances using cross-section-based estimates, is mentioned. Simply PW-PDOLS estimation:

$$\begin{bmatrix}\hat{\beta}_{PW-DOLS}\\ \hat{\gamma}_{PW-PDOLS}\end{bmatrix} = \left(\sum_{i=1}^{N}\hat{\omega}_{12,i}^{-1}\sum_{t=1}^{T}\widetilde{W}_{i,t}\widetilde{W}_{i,t}'\right)^{-1}\left(\sum_{i=1}^{N}\hat{\omega}_{12,i}^{-1}\sum_{t=1}^{T}\widetilde{W}_{i,t}\tilde{y}_{i,t}'\right) \qquad \textit{Eq. 3.70}$$

Subsequently, like PW-FMOLS, the covariance matrix of $\hat{\beta}_{PW-PDOLS}$ is calculated as follows:

$$\hat{V}_{PW-PDOLS} = \left[N^{-1}\sum_{i=1}^{N}\hat{\omega}_{12,i}^{-1}\left(T^{-2}\sum_{t=1}^{T}\widetilde{W}_{i,t}\widetilde{W}_{i,t}'\right)\right]^{-1} \qquad \textit{Eq. 3.71}$$

To summarize, the pooled panel FMOLS estimator is an estimation proposed by Phillips and Moon (1999) as an extension of the FMOLS estimator, which presents estimators after correcting the deterministic components in the explanatory variables. The pooled-weighted FMOLS is proposed by Pedroni (2001b) and Kao and Chiang (2001) as a method that allows different long-term variances across the cross-section for heterogeneous panels. Unlike the FMOLS, augmented regression with different leads and lags used in the DOLS eliminates the problems of asymptotic endogeneity and serial correlation. While Kao and Chiang (2001) propose the pooled Panel DOLS, which allows short-term dynamics to be cross-section specific, Mark and Sul (2003) extend the same method to pooled-weighted panel DOLS, which yields heterogeneity between long-term variances. Finally, there are two grouped versions of both methods developed by Pedroni (2001a, 2001b, 2004). The grouped FMOLS and DOLS estimators introduced by Pedroni (2001a, 2001b) are calculated by averaging the individual cross-section FMOLS and DOLS estimates. Technical details of the grouped FMOLS and grouped PDOLS techniques are discussed in Chapter 4.

3.4. Empirical Results

In this section, firstly, the unit root test results are shared and the basis for the Pedroni cointegration test is established. Models proven to be cointegrated in the long term by the Pedroni cointegration test are estimated by PDOLS and FMOLS methods in the next section.

3.4.1. Unit root test results

LLC, IPS, and ADF-Fisher type unit root test results, the technical details of which were shared in the previous sections, are shown in the section. Table 3.6 presents the unit root test statistics of the variables in both levels and $I(1)$ without trend. According to this table, the LLC test results show that the null hypothesis could not be rejected at the level for the HSE_t and PUS_t variables, but for the first difference, all the variables were stationary. Additionally, while the variables that are $I(0)$ according to the IPS test results are U_t, CPI_t, PRD_t, INT_t, PUS_t and EXC_t and others are not stationary at level, parallel to LLC results, all variables are $I(1)$. Finally, ADF – Fisher results show that all variables are $I(1)$, although some variables are stationary at the level, and some are nonstationary. Besides, following the unit-root results without trend, the unit-root test results with the trend are also presented in Appendix Table A1. According to LLC, IPS, and ADF-Fisher results, the number of non-stationary variables for level is higher than Table 3.6. But still, after taking the first differences, it appears that the null hypothesis of nonstationarity is rejected for all variables which means according to all three unit-root test results, all the variables are treated as $I(1)$ - nonstationary process. Consequently, taking the first difference of variables, though, the result would incline to approve the hypothesis that the series is $I(1)$ variable, as differencing rejects the null and therefore eliminates the unit root.

Table 3.6. Panel unit root test results without trend

Variables	LLC		IPS		ADF - Fisher	
	Level	First Difference	Level	First Difference	Level	First Difference
U_t	-3.445 [0.000]***	-9.894 [0.000]***	-4.428 [0.000]***	-10.926 [0.000]***	92.877 [0.000]***	196.921 [0.000]***
HSE_t	-1.226 [0.110]	-18.005 [0.000]***	2.689 [0.996]	-17.085 [0.000]***	23.141 [0.992]	315.131 [0.000]***
LSE_t	-4.119 [0.000]***	-15.283 [0.000]***	-1.492 [0.068]	-15.345 [0.000]***	61.593 [0.026]*	286.842 [0.000]***
RD_t	-2.383 [0.009]**	-11.609 [0.000]***	2.048 [0.980]	-12.363 [0.000]***	38.217 [0.638]	229.033 [0.000]***
GDP_t	-4.300 [0.000]***	-10.799 [0.000]***	1.200 [0.885]	-11.986 [0.000]***	28.606 [0.943]	215.402 [0.000]***
CPI_t	-6.157 [0.000]***	-11.835 [0.000]***	-1.955 [0.025]*	-12.428 [0.000]***	73.446 [0.002]**	224.465 [0.000]***
PRD_t	-8.578 [0.000]***	-13.718 [0.000]***	-3.211 [0.001]***	-12.596 [0.000]***	80.824 [0.000]***	236.499 [0.000]***
INT_t	-5.743 [0.000]***	-18.910 [0.000]***	-4.163 [0.000]***	-18.733 [0.000]***	90.743 [0.000]***	359.222 [0.000]***
PUS_t	2.452 [0.993]	-14.097 [0.000]***	-1.710 [0.044]*	-6.826 [0.000]***	57.750 [0.054]	137.348 [0.000]***
TUD_t	-1.704 [0.044]*	-13.570 [0.000]***	2.692 [0.997]	-13.003 [0.000]***	28.274 [0.948]	227.886 [0.000]***
EXC_t	-2.679 [0.004]**	-15.178 [0.000]***	-3.219 [0.001]***	-14.861 [0.000]***	79.733 [0.000]***	272.091 [0.000]***

Note: All the variables include a constant. In order to detect the optimal lag length, the Akaike Information Criterion (AIC) is used. Newey-West bandwidth selection with Bartlett kernel is applied for the LLC test. All the variables are in natural logs, excluding U_t, HSE_t, LSE_t, and INT_t. *Rejection of the null hypothesis of nonstationarity at the 0.05 level, **Rejection of the null hypothesis of nonstationarity at the 0.01 level, ***Rejection of the null hypothesis of nonstationarity at the 0.001 level.
Source: Author's calculations.

3.4.2. Panel cointegration and estimation results for unemployment

After proving that all the variables are $I(1)$, we make use of Pedroni's cointegration tests that require the same order of integration for all variables, with at least one being stationary at its level. The same degree of integration for most of the variables provides the impression that the panel cointegration test is likely to conclude a stable relationship among the variables in the long run. Panel cointegration results of all seven models with unemployment identified as the dependent variable are summarized in Table 3.7. It is determined that Model 3.1 and Model 3.2 are baseline specifications with core independent variables, while the other five models are constructed with additional control variables. The Kao panel cointegration test results are also presented in addition to Pedroni's to support the initial findings. According to Pedroni cointegration tests which are executed without trend, the null hypothesis of *"no cointegration"* is rejected with at least two statistics at the 0.05 significance level in all models. Models with the trend are also in the same direction with an exception, there is no cointegration in Model 3.5. As a result, based on the overall results for all models, it can be highlighted that there is a long-run stable relation among variables.

Table 3.7. Pedroni and Kao cointegration test results for unemployment

Test	Statistics	Model 3.1	Model 3.2	Model 3.3	Model 3.4	Model 3.5	Model 3.6	Model 3.7
		RD, GDP, CPI	*RD, GDP, CPI, PRD*	*RD, GDP, CPI, PRD, INT, PUS*	*RD, GDP, CPI, PRD, INT, TUD*	*RD, GDP, CPI, INT, PUS, EXC*	*RD, GDP, CPI, PUS, TUD, EXC*	*RD, GDP, CPI, PRD, PUS, TUD*
					w/o trend			
Pedroni	Panel PP t	-0.105	-1.853*	-2.055*	-3.071***	0.384	0.510	-2.168*
	Panel ADF t	-2.957**	-3.708***	-2.319**	-2.656**	-0.970	-1.734*	-3.188***
	Group PP t	0.257	-1.856*	-3.289***	-4.342***	1.242	-2.585**	-2.720**
	Group ADF t	-4.346***	-3.380***	-2.097*	-2.985**	-1.659*	-1.659*	-1.659*
Kao	ADF t	-6.200***	-5.565***	-5.735***	-5.453***	-5.740***	-5.835***	-5.854***
					w/ trend			
Pedroni	Panel PP t	-0.157	-2.781**	-2.794**	-4.383***	0.556	-0.883	-3.010**
	Panel ADF t	-1.921*	-4.632***	-3.397***	-4.639***	-0.518	-0.968	-4.688***
	Group PP t	-0.670	-3.077***	-3.764***	-6.711***	0.692	-1.156	-4.173***
	Group ADF t	-3.779***	-4.106***	-3.049***	-3.486***	-1.391	-2.202*	-3.788***

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the AIC is used. In panel PP and ADF results, weighted statistics are reported. All the variables are in natural logs, excluding U_t and INT_t. P-values are given in brackets. *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

After proving the existence of the long-run relation empirically, we make use of PDOLS to estimate the coefficients of the variables. In addition to panel DOLS estimation, FMOLS results are also reported as a robustness check. For the two baseline specifications, Model 3.1 and Model 3.2, results are displayed in Table 3.8. In the analyses, the decimal fraction of U_t is used. Since the number of variables to be included in a panel with short periods has to be limited, this constraint is taken care of to elaborate on the equations to keep the number of variables as low as possible. The coefficient vector β has close estimates in baseline equations, and both PDOLS and FMOLS estimates of RD_t are significant at 5%. Based on these results, the coefficient of RD_t is positive and between 0.019-0.034, which means technology proxied by R&D expenditures increases overall unemployment. Our findings lead to the particularly important inference that in developed economies, technological progress makes job creation outweighed by job destruction and the compensation mechanism with different channels is not fully effective.

Table 3.8. PDOLS and FMOLS estimates results for the baseline models of unemployment

Variables	Model 3.1 (Baseline Model)			Model 3.2 (Baseline Model)		
	PDOLS pooled w.	PDOLS pooled	FMOLS pooled	PDOLS pooled w.	PDOLS pooled	FMOLS pooled
RD_t	0.0317	0.0274	0.0344	0.0213	0.0193	0.0220
	$(4.429)^{***}$	$(2.625)^{**}$	$(3.706)^{***}$	$(5.026)^{***}$	$(2.543)^{*}$	$(3.938)^{***}$
GDP_t	-0.2171	-0.2176	-0.1740	-0.4405	-0.4173	-0.4029
	$(-14.426)^{***}$	$(-11.048)^{***}$	$(-8.090)^{***}$	$(-29.208)^{***}$	$(-18.280)^{***}$	$(-20.446)^{***}$
CPI_t	0.0665	0.0652	0.0380	0.0455	0.0402	0.0442
	$(5.529)^{***}$	$(4.230)^{***}$	$(2.609)^{**}$	$(5.789)^{***}$	$(2.786)^{***}$	$(5.241)^{***}$
PRD_t				0.3761	0.3579	0.3407
				$(18.271)^{***}$	$(11.743)^{***}$	$(14.042)^{***}$
	PDOLS results for the baseline models of unemployment with fixed lead & lags					
Variables	Model 3.1 (Baseline Model)			Model 3.2 (Baseline Model)		
	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)
RD_t	0.0253	0.0177	0.0309	0.0203	0.0136	0.0235
	$(3.459)^{***}$	$(2.281)^{*}$	$(3.631)^{***}$	$(4.539)^{***}$	$(2.980)^{**}$	$(3.763)^{***}$
GDP_t	-0.2141	-0.2206	-0.2520	-0.4396	-0.4429	-0.4726
	$(-13.924)^{***}$	$(-12.718)^{***}$	$(-14.505)^{***}$	$(-27.841)^{***}$	$(-26.556)^{***}$	$(-22.614)^{***}$
CPI_t	0.0754	0.0815	0.0989	0.0476	0.0374	0.0424
	$(6.227)^{***}$	$(6.707)^{***}$	$(6.876)^{***}$	$(5.852)^{***}$	$(4.557)^{***}$	$(4.132)^{***}$
PRD_t				0.3751	0.4034	0.4177
				$(17.475)^{***}$	$(14.910)^{***}$	$(14.802)^{***}$

Note: In the first part PDOLS estimates, the AIC is used to determine the leads & lags. The second part of the table is prepared to support findings in the first part and PDOLS pooled-weighted estimation method is used with the fixed leads & lags. As a panel method, both pooled-weighted and pooled estimation results are used and reported. For the FMOLS estimator, pooled estimation is used as the panel method and the sandwich method is used in estimating covariance. As the dependent variable, decimal fractions of U_t are used. All the independent variables are in natural logarithms, and t-statistics are given in parentheses. *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Besides, GDP_t has a negative coefficient, consistent with the theory and previous empirical studies. The coefficient of GDP_t ranges between -0.174 and -0.441 in baseline models. It can be seen that when the PRD_t is added to the models to represent the output per worker, the coefficient of the GDP_t variable α_1 increases. PRD_t as well as the measure of inflation CPI_t are positively correlated with unemployment in baseline specifications. In the second part of Table 3.9, tahini is also given for different fixed lead and lag variations of the PDOLS results given in the previous table. Although these results are parallel to the results in Table 3.9 in terms of the direction of the coefficients, there are negligible differences in the magnitudes of the estimates.

Table 3.9 includes variations of other control variables in addition to baseline models. PDOLS results are shared in the first part of the table and FMOLS results are given in the second part. In all model variations estimated by both methods, the signs of the coefficients of the variables given in the previous two baseline models are the same. Based on all the models evaluated in the study, it is seen that the technology coefficient β varies between 0.013 and 0.034. Also, the coefficient of the variable INT_t is positive and statistically significant in both PDOLS and two FMOLS estimations, which means an increase in real interest rates causes a rise in unemployment in developed countries. The coefficient PUS_t, a variable of public unemployment spending is positive as expected, but significant in two of the four PDOLS estimations and insignificant in the other two. Trade union density is also among the factors that increase unemployment according to empirical results, and its coefficient varies between 0.018 and 0.036 according to the statistically significant PDOLS and FMOLS results. The real effective exchange rate index is used in Model 3.5 and Model 3.6. Although the coefficient of the variable is negative, it is statistically insignificant according to the PDOLS results. To remember, a very weak result is reported in the cointegration test applied for the variables in Model 3.5. In addition, no significant results are obtained in the Pedroni cointegration test, which is with a trend for Model 3.6. Considering these results and the relatively smooth REER movements in developed countries, it can be concluded that EXC_t does not have a significant effect on unemployment.

Table 3.9. PDOLS and FMOLS estimates results for the additional specifications of unemployment

Variables	Model 3.3	Model 3.4	Model 3.5	Model 3.6	Model 3.7
			PDOLS		
RD_t	0.0125	0.0260	0.0178	0.0218	0.0141
	(2.454)*	(4.663)***	(2.303)*	(2.216)*	(2.628)**
GDP_t	-0.3806	-0.4017	-0.2079	-0.1680	-0.4129
	(-19.148)***	(-23.958)***	(-9.290)***	(-6.569)***	(-24.489)***
CPI_t	0.0518	0.0525	0.1029	0.0681	0.0583
	(5.070)***	(5.096)***	(7.966)***	(4.035)***	(5.526)***
PRD_t	0.3263	0.3512			0.3996
	(13.265)***	(13.042)***			(17.081)***
INT_t	0.0759	0.1087	0.2399		
	(1.573)***	(2.599)*	(3.313)**		
PUS_t	0.0056		0.0049	0.0144	0.0075
	(1.505)		(1.264)	(4.154)***	(2.264)*
TUD_t		0.0249		0.0076	0.0359
		(2.567)*		(0.686)	(3.795)***
EXC_t			-0.0124	-0.0119	
			(-0.931)	(-0.939)	
			FMOLS		
RD_t	0.0154	0.0231	0.0222	0.0246	0.0185
	(3.079)**	(4.714)***	(3.157)**	(3.327)***	(3.793)***
GDP_t	-0.3643	-0.3742	-0.1229	-0.1355	-0.3719
	(-19.269)***	(-24.572)***	(-7.210)***	(-7.312)***	(-23.502)***
CPI_t	0.0447	0.0500	0.0364	0.0222	0.0416
	(5.558)***	(7.010)***	(3.234)**	(1.835)	(5.634)***
PRD_t	0.3220	0.3279			0.3298
	(14.234)***	(18.606)***			(17.753)***
INT_t	0.0801	0.1136	0.1652		
	(2.778)**	(4.913)***	(3.851)***		
PUS_t	0.0090		0.0149	0.0161	0.0086
	(5.231)***		(6.676)***	(6.814)***	(5.226)***
TUD_t		0.0179		-0.0041	0.0112
		(2.970)**		(-0.443)	(1.683)
EXC_t			-0.0344	-0.0219	
			(-4.038)***	(-2.606)**	

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags, and the pooled-weighted estimation is used as the panel method. For the FMOLS estimator, pooled estimation is used as the panel method and the sandwich method is used in estimating covariance. As the dependent variable, decimal fractions of U_t are used. All the independent variables are in natural logs excluding INT_t. Besides, t-statistics are given in parentheses. *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Consequently, according to the findings obtained from both PDOLS and FMOLS estimations, the effect of technology proxied by R&D on unemployment is positive and statistically significant, which means in developed economies, higher technology increases unemployment. However, the β coefficient is estimated to be smaller in terms of effect compared to the coefficients of other core variables. Another critical point is that the compensation mechanism working through the increase in income is partially effective in developed countries because in the PDOLS estimates where the per capita income and output per worker variables take place simultaneously, the coefficient of GDP_t varies between -0.38 and -0.44, while this range is between 0.33 and 0.40 in the PRD_t coefficients. is in the form. Productivity, calculated as output per worker, is not the result of technology alone but is of course affected by technology and non-technology shocks. Therefore, the factors that lead to the use of fewer workers, in the long run, can only be partially compensated by the increase in per capita income.

3.4.3. Panel cointegration and estimation results for employment by skills

In addition to the technology unemployment relation, we are interested in detailing this relation to different skill groups. Both skill-biased and routine biased technological change approaches and comments on job polarization claim that the impact of technology on workers with different skills is varying. Starting from this point, we enlarge our analysis to account for the skill levels with the same methodology and procedure of Model 3.1 to Model 3.7.

To this end, Table 3.10 reports panel cointegration test results of three models for high-skilled employment. The null hypothesis is rejected at the 5% significance level for all models, with and without trend, underlining the long-term relationship. Kao's cointegration test results support Pedroni’s again. These results document that in developed countries, high-skilled employment rates have a long run significant relation with R&D and other macro variables included.

Table 3.10. Pedroni and Kao cointegration test results for high-skilled employment

Test	Statistics	Model 3.8		Model 3.9		Model 3.10	
		RD, GDP, CPI		*RD, GDP, CPI, PRD*		*RD, GDP, CPI, PRD, INT*	
		w/o trend	w/ trend	w/o trend	w/ trend	w/o trend	w/ trend
Pedroni	Panel PP t	-2.529**	-3.098***	-2.711**	-3.535***	-2.868**	-3.827***
	Panel ADF t	-4.046***	-7.046***	-4.569***	-4.707***	-5.008***	-5.049***
	Group PP t	-2.566**	-3.240***	-3.225***	-3.869***	-3.467***	-3.889***
	Group ADF t	-4.768***	-7.620***	-4.625***	-3.868***	-4.203***	-4.295***
Kao	ADF t	-1.648*		-1.807*		-2.837**	

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the AIC is used. In panel PP and ADF results, weighted statistics are reported. All the variables are in natural logs, excluding HSE_t and INT_t. P-values are given in brackets. *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

We go one step ahead after proving the existence of the long-run nexus among variables of interest to diagnose the direction and magnitude of the relation. Estimation results of PDOLS are reported in Table 3.11 and FMOLS results are given in Appendix A2. The coefficients of R&D in Model 3.8, Model 3.9, and Model 3.10 established for high-skilled employment are positive as expected. These results are in line with the assertion that the impact of technological progress shock on employment is skill-biased. Also, the rise in per capita GDP increases high-skilled employment. Besides, it is concluded that the coefficient of productivity is positive but insignificant in most of the PDOLS estimations. This result is important because, in the models constructed for overall unemployment, the productivity coefficient is positive and significant. The insignificance of the output per worker effect in high-skilled employment suggests that the source of the significant adverse effect in overall unemployment is low-skilled employment. Furthermore, the interesting conclusion is that our results on the high-skilled employment effect of inflation are parallel with the classical Philips Curve. Finally, there is a negative relationship between high-skilled employment and real interest rate which is in line with the theory.

Table 3.11. PDOLS estimates results for the high-skilled employment specifications

Variables	Model 3.8				
	pooled w.				pooled
	leads & lags AIC (*)	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)	leads & lags AIC (*)
RD_t	0.0416	0.0493	0.0612	0.0545	0.0310
	(4.438)***	(4.816)***	(5.451)**	(4.476)***	(2.205)*
GDP_t	0.1121	0.1173	0.1035	0.1031	0.1144
	(5.092)***	(4.813)***	(3.826)***	(3.636)***	(3.692)***
CPI_t	0.0550	0.0389	0.0338	0.0484	0.0799
	(3.531)***	(2.431)*	(2.167)*	(2.446)*	(3.219)**

Variables	Model 3.9				
	pooled w.				pooled
	leads & lags AIC (*)	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)	leads & lags AIC (*)
RD_t	0.0500	0.0616	0.0763	0.0660	0.0459
	(5.011)***	(5.336)***	(4.985)***	(4.613)***	(2.985)**
GDP_t	0.1124	0.0991	0.0854	0.0456	0.1448
	(3.868)***	(2.667)**	(1.764)	(1.041)	(3.259)**
CPI_t	0.0482	0.0366	0.0291	0.0722	0.0666
	(2.653)**	(1.665)	(0.847)	(2.522)*	(2.363)*
PRD_t	-0.0178	-0.0138	0.0421	0.0418	-0.0555
	(-0.687)	(-0.405)	(-0.275)	(-0.056)	(-1.158)

Variables	Model 3.10				
	pooled w.				pooled
	leads & lags AIC (*)	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)	leads & lags AIC (*)
RD_t	0.0517	0.0579	0.0390	0.0507	0.0558
	(4.945)***	(4.563)***	(2.442)*	(3.219)**	(2.841)**
GDP_t	0.1247	0.1139	0.1745	0.0238	0.1632
	(3.631)***	(2.821)**	(3.191)**	(0.360)	(2.960)**
CPI_t	0.0501	0.0459	0.0472	0.0912	0.0486
	(2.464)*	(1.913)	(1.556)	(2.698)**	(1.328)
PRD_t	-0.0804	-0.0647	-0.1257	0.0336	-0.1176
	(-2.306)*	(-1.534)	(-2.220)*	(0.553)	(-1.936)
INT_t	-0.1546	-0.1830	-0.5548	-0.2686	-0.2912
	(-2.117)*	(-1.979)*	(-5.288)***	(-2.199)*	(-2.277)*

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags, and both pooled-weighted and pooled estimation results are used and reported. Besides, PDOLS pooled-weighted method estimation results are also reported under the fixed leads & lags. As the dependent variable, decimal fractions of HSE_t are used. All the independent variables are in natural logs excluding INT_t. Besides, t-statistics are given in the parentheses. *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

The steps followed for high-skilled employment are also applied to low-skilled employment. Accordingly, Table 3.12 shows the Pedroni cointegration test results of the models established for low-skilled employment. In the majority of both trended and non-trend models, the null hypothesis is rejected at least at the 5% level and the existence of cointegration between variables is proven.

Table 3.12. Pedroni and Kao cointegration test results for low-skilled employment

Test	Statistics	Model 3.11		Model 3.12		Model 3.13	
		RD, GDP, CPI		*RD, GDP, CPI, PRD*		*RD, GDP, CPI, PRD, INT*	
		w/o trend	w/ trend	w/o trend	w/ trend	w/o trend	w/ trend
Pedroni	Panel PP t	-1.581	-1.232	-2.002^{*}	-2.404^{**}	-3.421^{***}	-4.127^{***}
	Panel ADF t	-3.410^{***}	-2.391^{**}	-3.914^{***}	-3.377^{***}	-3.508^{***}	-3.930^{***}
	Group PP t	-1.107	-1.066	-2.557^{**}	-2.416^{**}	-4.331^{***}	-4.176^{***}
	Group ADF t	-3.106^{***}	-2.116^{*}	-3.881^{***}	-2.496^{**}	-3.449^{***}	-3.348^{***}
Kao	ADF t	-3.911^{***}		-3.671^{***}		-3.804^{***}	

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the AIC is used. In panel PP and ADF results, weighted statistics are reported. All the variables are in natural logs, excluding LSE_t and INT_t. In Base Model 1, RD_t, GDP_t, and CPI_t are used as the independent variables. Base Model 2 includes PRD_t in addition to the variables in Base Model 1. P-values are given in the brackets. *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

PDOLS and FMOLS methods are used to estimate the models established for low-skilled employment, as in the previous section, and the results are shared in Table 3.13 (and FMOLS results are in Appendix Table A3). Coefficients of technology proxied by R&D in Model 3.11, Model 3.12, and Model 3.13 constructed for low-skilled employment are negative. These results are again in line with the assertion that the impact of technological progress on employment is skill-biased. The β coefficient varies between -0.040 and -0.083 in the models estimated by the PDOLS method. The upper bound for this spread is greater than the estimated values for high-skilled employment, which explains the estimated negative coefficient for unemployment, and it appears that the positive effect of technology on high-skilled employment does not increase overall employment sufficiently to offset the job-destructive effect in low-skilled employment. Besides, the increase in per capita GDP increases low-skilled employment as in high-skilled employment. However, it is determined that the GDP_t coefficients estimated for low-skilled employment are generally higher than those estimated for high-skilled employment. Besides, it is estimated that the coefficient of productivity is positive and significant in all the PDOLS estimations. Therefore, an increase in productivity decreases especially low-skilled employment not high-skilled. In some of the models, while the coefficient of GDP_t is larger than the coefficient of PRD_t in terms of size, the situation is the opposite in some of them. Considering the magnitude of the negative RD_t coefficient, the increase in income is an important compensation mechanism channel for low-skilled employment, in other words, the effect of this increase on transformation to low-skilled employment is bigger than high-skilled employment, but it can be concluded that the balance factor is insufficient, and it still causes the loss of employment in this skill group. Contrary to the findings in high-skilled employment, inflation negatively affects low-skilled employment, which contradicts Philips Curve but can be explained by skill premium. Finally, according to the PDOLS results, it is determined that although the coefficients of interest rates are positive, they do not have a significant effect on low-skilled employment.

Table 3.13. PDOLS estimates results for the low-skilled employment specifications

Variables	Model 3.11				
	pooled w.				pooled
	leads & lags AIC (*)	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)	leads & lags AIC (*)
RD_t	-0.0398	-0.0434	-0.0568	-0.0480	-0.0668
	(-3.130)**	(-3.047)**	(-3.809)***	(-2.882)**	(-4.046)***
GDP_t	0.0843	0.0680	0.0626	0.1070	0.1056
	(3.625)***	(2.484)*	(1.958)*	(3.591)***	(3.720)***
CPI_t	-0.1292	-0.1204	-0.0977	-0.1578	-0.1236
	(-5.864)***	(-5.082)***	(-3.761)***	(-5.644)***	(-4.764)***

Variables	Model 3.12				
	pooled w.				pooled
	leads & lags AIC (*)	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)	leads & lags AIC (*)
RD_t	-0.0494	-0.0674	-0.0700	-0.0747	-0.0565
	(-4.030)***	(-5.231)***	(-4.473)***	(-4.895)***	(-3.121)**
GDP_t	0.2394	0.2635	0.2763	0.3699	0.2358
	(6.659)***	(6.464)***	(5.370)***	(7.276)***	(4.996)***
CPI_t	-0.1116	-0.0982	-0.0924	-0.1468	-0.1303
	(-5.289)***	(-4.145)***	(-3.376)***	(-5.024)***	(-4.243)***
PRD_t	-0.2564	-0.2890	-0.2953	-0.3381	-0.2221
	(-6.531)***	(-6.592)***	(-5.791)***	(-6.204)***	(-4.062)***

Variables	Model 3.13				
	pooled w.				Pooled
	leads & lags AIC (*)	leads & lags (1 1)	leads & lags (1 2)	leads & lags (2 1)	leads & lags AIC (*)
RD_t	-0.0654	-0.0709	-0.0723	-0.0835	-0.0735
	(-5.456)***	(-5.288)***	(-6.808)***	(-6.505)***	(-3.529)***
GDP_t	0.2373	0.2362	0.2493	0.3044	0.2492
	(6.068)***	(5.411)***	(5.205)***	(4.708)***	(4.251)***
CPI_t	-0.1128	-0.1005	-0.0831	-0.1178	-0.1158
	(-5.029)***	(-3.955)***	(-3.124)**	(-3.494)***	(-3.023)**
PRD_t	-0.2096	-0.2206	-0.2061	-0.2765	-0.2261
	(-4.813)***	(-4.564)***	(-3.733)***	(-4.346)***	(-3.264)**
INT_t	0.0017	0.0017	0.0047	0.0026	0.0017
	(1.944)	(1.638)	(4.026)***	(1.926)	(1.312)

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags, and the both pooled-weighted and pooled estimation results are used and reported. Besides, PDOLS pooled-weighted method estimation results are also reported under the fixed leads & lags. As the dependent variable, decimal fractions of LSE_t are used. All the independent variables are in natural logs excluding INT_t. Besides, t-statistics are given in the parentheses. *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.
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3.5. Concluding Remarks

In this part of the thesis, the effect of technology on employment is investigated both in general and by considering two different skill groups separately. To this end, we make use of annual data from 21 developed countries over 1990-2019 to document that there is cointegration among the set of variables including R&D expenditures and (un)employment. Our time span includes the hit of the global financial crisis to reveal the resilience of the relationship even along with the shock and thereafter. In the first model, it is evaluated whether R&D, which is considered as a technology variable and some other important macroeconomic indicators that have been proven to be associated with unemployment in the literature, are cointegrated with unemployment. With one exception, the existence of a strong cointegration between variables is demonstrated in seven different models established. We detail the analysis to explore the impact of technology on the employment of high and low-skilled labor.

The main interest of the study is β, the coefficient of Research and Development. The PDOLS and FMOLS estimates are positive for unemployment models and statistically significant at the 5% level. While the β coefficient is estimated between 0.0125 and 0.0317 for PDOLS estimators using two different panel methods, this range is between 0.0154 and 0.0344 for the FMOLS estimator. Apparently, technology proxied by R&D appears to have an adverse effect on employment, ceteris paribus; an increase in R&D expenditures increases unemployment in developed countries. Of another interest are the coefficients on the income, the estimated effect of the per capita GDP on unemployment is negative and statistically significant at least at the 5% level. The coefficient ranges for GDP per capita were -0.4405 and -0.1680 according to PDOLS, and -0.4029 and -0.1229 according to FMOLS. On the other side, according to PDOLS, the coefficient range of labor productivity is between 0.3263 and 0.3996. Hence, the adverse effect of R&D and worker productivity together on overall employment is bigger than or at most equal to GDP per capita impact implying that any positive income effect on employment is not able to counterbalance the adverse effect of technology in developed countries.

In the second stage of the study, the technology-employment relationship was investigated according to skill groups. Based on the PDOLS estimator, the coefficient of R&D per capita in models established for high-skilled employment is between 0.0310 and 0.0558, while this range is -0.0735 to -0.0398 for low-skilled employment. Hence it is worth mentioning that the estimated coefficients of R&D for low-skilled employment are much bigger than those of high-skilled employment in terms of effect size. This explains the negative impact of R&D on overall employment. The estimated range of GDP per capita according to PDOLS is between 0.1121 and 0.1632 for high-skilled employment, and 0.0843 0.2492 for low-skilled employment. As can be seen, economic growth is an important labor creation channel for both skill groups, but the coefficient range and coefficient limits are wider for low-skilled employment. Just like R&D, the effect of inflation on high and low-skilled employment is contradictory because inflation is known to be increasing due to demand-pull as economic activity revives. The interesting conclusion is that our results on the high-skilled employment effect of inflation are parallel with the classical Philips Curve, while low-skilled employment is not. Finally, the real interest rate has a negative impact on high-skilled employment while it is insignificant in explaining low-skilled employment. Although the relationship between labor productivity and high-skilled is negative based on PDOLS results, most models and estimates made with different lag specifications reveal that the variable is statistically insignificant. On the other hand, the effect size of the estimated negative coefficients is lower than the effect size of GDP per capita. Therefore, the negative effects that cause labor savings for high-skilled employment in developed countries are eliminated by technological progress and economic growth, and the new job areas that emerge through these channels are much more than the jobs that disappear. For low-skilled employment, the PDOLS results show that the labor productivity coefficient is between -0.2096 and -0.2564. Therefore, the labor-saving effect of the increase in productivity caused by technology and non-technological shocks in developed countries on low-skilled employment cannot be fully compensated by the income channel and therefore the net effect is negative.

In a summary, estimation results with PDOLS and FMOLS demonstrate that:

a) As R&D expenditures increase, employment rates of the high-skilled workers increase, whereas the opposite is true for the low-skilled workers in advanced economies. The compensation mechanism via increase in income is effective for high-skilled workers, not the low-skilled ones. In developed economies, technology has a complementary effect for high-skilled workers and increases their employment levels. However, low-skilled employment is affected even more by developing countries, as will be seen in the next section.

b) The estimated coefficient of the R&D expenditure is positive and highly significant, providing evidence that higher R&D indeed has an adverse effect on unemployment. The probable reason for this result is that in developed countries, the intensity of skilled workers is still less than the intensity of unskilled or low-skilled employees. If low-skilled workers become more equipped and are able to adapt to new technologies, the impact of technology on overall unemployment may reverse in the future.

c) Growth declines unemployment as expected, and this result is valid and in the same direction for both skill groups.

d) To the contrary, productivity increases unemployment. However, there is no significant relationship between labor productivity and employment for high-skilled employment. Low-skilled employment does not have the ability to compensate for the loss of employment resulting from the increase in productivity resulting from both technical and non-technical shocks, through channels such as income growth. Since low-skilled employment in developed countries is adversely affected by wage competition in the developing world, the destroyer effect on employment for the low-skilled group is relatively faster and higher.

e) Public unemployment spending and unemployment are positively related as the positive coefficients suggest. This is also plausible and in line with previous empirical studies. Social benefits reduce the motivation and willingness of workers to seek a job and extend the duration for workers to find a job or be employed.

Our investigation asserts concrete empirical evidence on the research and development expenditure unemployment relation coupled with skill groups, but further analyses are required, and there is room to explore the same relation along with other key variables headed by wage, working conditions, and more detailed skill and occupation groups. It is important to note that, although technology has a vital role in causing an increase in unemployment as found empirically, interfering with technological progress is not possible and technological advances are inevitable. Therefore, policies that enable the existing workforce to adapt to new technologies are particularly important.[10]

[10] This part of the thesis was published as Saka et al. (2021).

CHAPTER 4: THE RELATIONSHIP BETWEEN TECHNOLOGY AND UNEMPLOYMENT IN DEVELOPING COUNTRIES

4.1. Introduction and Motivation

In addition to the economic and social benefits of technology, the concerns that it replaces human labor, especially through channels such as automation (Frey and Osborne, 2013, 2017), the possibility of worsening income inequality by increasing the skills premium among workers (Acemoglu, 2003; Acemoglu and Autor, 2011) and negatively affecting the existing workforce by changing the structure, content, and quality of tasks (Autor, 2010; OECD, 2018) are important areas of interest not only for developed countries but also for developing economies. However, developing countries have been neglected for a long time because the economics literature has focused on technology and unemployment since the Industrial Revolution, and because the machines first appeared in developed countries, employment concerns first started in these geographies. On the other hand, the differences in the initial conditions and current economic dynamics of both country groups (Vivarelli, 2014) and the fact that technology is mostly imported to the economies of developing countries from developed ones (Acemoğlu, 2003) make the direction and magnitude of the impact on these countries in terms of employment more uncertain compared to developed countries. Therefore, although the empirical literature on the technology-employment relationship is rich in advanced economies, especially at the micro-level (Pianta, 2005; Vivarelli, 2014; Calvino and Virgillito, 2018; Dosi et al., 2021), studies addressing the issue in developing countries are limited, and the majority of these works report the positive employment impact of product innovations in developing economies, either at the firm or sectoral level (Yang and Huang, 2005; Yang and Lin, 2008; Benavente and Lauterbach, 2008; Meriküll 2010; Crespi and Tascir, 2012; Laguna and Bianchi, 2020). Moreover, technological development is an essential factor that is responsible for the variations observed in the labor force need, affecting the demand qualitatively as well as quantitatively. Because, labor type, tasks of the occupations, and the skill requirements vary and are affected by many different dynamics. Whether the propensity to the issue is the skill of the labor (Acemoglu, 1998) or the task-oriented content of the occupations (Autor, 2003, Autor et al., 2006), it is a common belief that while technological innovations increase the demand for more educated and qualified in the labor market, the demand for the uneducated or less educated decreases or does not increase as much as the former (Goldin and Katz, 1998; Bekman et al., 1998). In line with this common belief, empirical evidence is presented that technology is mostly skill-biased in developing economies as well as in developed countries (Robbins, 1996; Görg and Strobl, 2002; Edwards, 2004; Tether et al., 2005; Conte and Vivarelli, 2011; Araújo et al., 2011)

Some predictions for the future, especially made with occupation and task-based approaches, draw attention that although automation occurs later in developing countries than in developed ones, developing economies experience *"premature deindustrialization"* (Rodrik, 2016) because they are already indirectly affected by the emerging technologies in developed economies and this could lead to technology inflicting deeper wounds on employment in the developing world (Frey and Rahbari, 2016). In studies such as the World Bank (2016), Egana-delSol (2020), and Soto (2020) it is noted that due to the current stages of developing countries, most of the employment is in sectors with high automation risks such as agriculture and manufacturing, and it is stated that the automation risk in emerging economies is higher than the average automation risk in advanced countries. However, the fact that the automation risk is high does not mean that the rate of transition to automation or the rate of being affected by machines is equally high. Although many jobs can be automated technically and theoretically in developing countries, the transition to automation is not as fast as in developed countries due to factors such as low wages and slower technology adoption, and thus employment is not yet affected to the same extent. McKinsey Global Institute (2017) predicts that in the coming decades, automation rates in developed countries such as Japan and the United Kingdom will be higher than in emerging economies such as India and Russia. Acemoglu and Restrepo (2017) draw attention to a similar issue and state that despite the increase in wages in developing countries in recent years, average wages remain far from developed economies. In countries with high wage levels, sensitivity to automation is also high due to rising costs. However, despite the increase in wages in developing economies over time, the fact that they are still far from the level of developed countries brings about the existence of cheap labor resources and therefore does not make automation economically attractive in many developing countries. However, Frey (2020) argues that the cost advantage of cheap labor against technology in emerging economies will end soon, and states although many studies focus on developed countries, the main problem will be experienced in developing countries due to the early deindustrialization mentioned above. Because, according to some estimates, in emerging economies such as China, Mexico, and Brazil, where labor costs are relatively low, labor may lose its comparative advantage, as the use of robots will be less costly in the coming decades (Boston Consulting Group, 2015). In addition to these, the efficiency of benefiting from the employment opportunities opened by technology is lower in developing economies. Most new jobs require significantly higher skill levels but even basic education indicators such as literacy rates in developing economies are lagging behind developed countries and therefore there is a lack of skills to complement new technologies. As a result, developing countries cannot fully exploit the many opportunities offered by new technologies as quickly as developed countries. (Soto, 2020).

Unemployment is a social and individual fact that has persisted since the beginning of the use of labor as a production factor, especially in the 20th century, which has expanded its importance day by day notwithstanding all the social and economic precautions the policymakers have taken. Today, the most relevant and compelling issue for states and politicians is the development of policies expanding employment and preventing unemployment along with the economic crises. The employment of science to human needs, and the efforts done to meet these needs, lie in evaluating human labor in the most useful and convenient way. Over time, scientific research is transformed into technology, and products emerging are presented to the service of human beings through technology. As a result, technological progress leads to structural changes in existing jobs, causing some professions to be destroyed or replaced by new ones. When we look at the change that technology has made in the past, it is evident that the replacement of the labor force by machines evolved from unskilled labor to highly qualified labor.

The relationship between technology and employment is a long-standing and highly controversial issue. A large literature and a considerable amount of studies have not yielded a definitive conclusion on this relation. Moreover, the studies where this vast literature touches on developing countries are extremely limited. For these reasons, in this part of the study, the effect of technology on employment is discussed with a wide country group and timespan, specific to developing countries. At the macro level, this study explores how technology separately affects two skill groups, high-skilled and low-skilled employment, in developing countries, as well as overall unemployment. The dependent variables used for this purpose are clear. Countries' overall unemployment rates and employment levels by skills are treated as dependent variables in different models. Although the technology measure for developing countries is a bit more complicated, per capita R&D expenditures are preferred in the study, as in the earlier section, and in the models, this main proxy is supported by core independent variables such as GDP per capita and output per worker. In practice, the main factor to spark innovation is the R&D expenditure as the main driver of technological progress. Large firms are capable of distributing a considerable budget to R&D to enable product innovation. On the other hand, process innovation needs investment into machinery, methods, and procedures including managerial tactics to produce higher quality items less costly with meticulously designed automation. Once the technology in terms of product or process innovation is achieved the shock to different markets is initiated. Knowledge transformation is part of spin-offs from companies in addition to mobility of workers among firms or worker interactions. Innovative firms, employ more workers as well as more qualified/high-skilled personnel and thus pay by large more. They are preferred by their workforce since the working conditions as well as fringe benefits are substantially preferable. Also, all countries demand such companies since they increase the GDP as well as exports of the sovereign despite destroying the income uniformity. In fact, as stated above, a massive portion of the technology used by developing countries is imported (Vivarelli, 2014), and therefore, R&D expenditures of developed countries or imported high-tech inputs are used as a technology proxy in some studies conducted for developing countries (Mohnen, 2001; Piva, 2004). However, high R&D investments in developed countries do not guarantee that developing countries will be able to use technology produced abroad with the same efficiency and prominent level of adaptation. Because in developing countries, there may be problems such as cost and expertise in the use of innovations from developed countries (Piva, 2004). Secondly, domestic R&D expenditures may also determine the nature of high-tech products imported by a developing country from abroad, since R&D reflects the country's adaptability to that technology. Besides, no country tends to import high-tech products that it cannot use. Therefore, in developing countries, even though the R&D expenditure of that country does not reflect the technology in a comprehensive way, it has the power to be a technology proxy for this group of countries, as it actually shows the technology adaptation of the countries at the macro level. Because R&D has a vital role in the adoption and learning of innovative technologies (Cohen and Levinthal, 1989), it would not be wrong to think that the current R&D investments of developing countries show their technology adaptation levels on behalf of these countries. Besides, developing countries' R&D expenditures not only facilitate their adaptation to the technologies they will transfer from developed countries, but also the level of current R&D expenditures determines the nature of the technologies they transfer. Therefore, R&D is an important technology proxy in developing as well as developed countries and reflects the technical levels and technology adaptations of countries.

In this part of the study, accordingly, we attempt to contribute to the existing technology-un(employment) literature by estimating the effect of R&D expenditure on both unemployment and employment by skills using Pedroni's panel cointegration framework. The empirical study is presented to the examination of the effects of technology, income, inflation, productivity, real interest rate, exchange rate, and openness on un(employment) using panel data of 21 emerging economies. To estimate the coefficients of the panel series proven to be cointegrated, grouped PDOLS and FMOLS by (Pedroni 2001a, 2001b) are applied. The limited number of previous studies shared above usually focus on the company or industry or make predictions about the risk of automation for the future. Hence, to the best of our knowledge, this study is the first investigation to examine the technology, productivity, and employment linkage for different skill groups based on developing countries within the framework of a panel cointegration. In the remaining sections of the study, the data section, in which the type, source, and various characteristics of the data used are introduced, followed by the empirical methodology, the findings, and conclusions.

4.2. Data

In this section, the relationship between technology and unemployment is examined at the macro level, based on developing countries. The list of countries covered for this purpose in line with the MSCI Market Classification Framework (MSCI, 2020) is given in Table 4.1. According to the MSCI classification, this list is actually the list of emerging market economies, and therefore, these countries include Korea, one of the leading Asian economies in terms of the size of their economy, and Greece, one of the deep-rooted members of the European Union, as well as geographies such as Argentina and Egypt, which have recently struggled with economic crises. At this point, although the number of developing countries is much larger, 23 developing countries, including Turkey, are included in the study due to reasons such as data availability and accuracy. The gap between the macroeconomic indicators of these countries is larger than that of developed countries. Table 4.1 also includes the countries' ID numbers and abbreviated names in the panel series of this study. All of the countries given in the table are used in models that both explain the overall unemployment-technology relationship and approach the same subject according to skill groups.

The variables in Table 4.2 are the indicators used in the study to explain the technology-employment relationship in terms of developing countries. Although it shows similar features to the section prepared for developed countries, some of the auxiliary arguments used are different. The dependent variables are *U*, *HSE*, and *LSE* represents unemployment and employment by skills, and as in the previous chapter, unemployment rate (% of total labor force), the high-skilled employment rate (% of total labor force), and low-skilled employment rate (% of total labor force) respectively. All of these variables are obtained as a percentage and are reported in this format in the descriptive statistics section. However, in the estimation results, they are used as a decimal fraction for easier interpretation of the data and visual consistency and statistical comfort in the tables. All data on unemployment and employment are obtained from the database of the International Labor Organization (ILO). According to the classification made by the ILO, employees are divided into four categories according to their skill groups. “3” and “4” of these categories are defined as *“high-skilled”* by the ILO, “2” as *“medium-skilled”* and “1” as *“low-skilled”*. In this study, skill classes are divided into two and “3” and “4” are grouped as “*high-skilled”*. Correspondingly, “1” and “2” are considered as *“low-skilled”* which is the combination of low and medium skills.

Table 4.1. List of the selected developing countries

ID	Country Name	Abbreviation	ID	Country Name	Abbreviation
1	Argentina	ARG	13	Korea, Rep.	KOR
2	Brazil	BRA	14	Malaysia	MYS
3	Bulgaria	BGR	15	Mexico	MEX
4	China	CHN	16	Pakistan	PAK
5	Colombia	COL	17	Poland	POL
6	Cyprus	CYP	18	Romania	ROU
7	Czechia	CZE	19	Russia	RUS
8	Egypt, Arab Rep.	EGY	20	Slovakia	SVK
9	Greece	GRC	21	South Africa	ZAF
10	Hungary	HUN	22	Thailand	THA
11	Iceland	ISL	23	Turkey	TUR
12	India	IND			

Note: 23 countries included in the MSCI Emerging Markets Indexes are used.

The variable *RD* denotes per capita research and development expenditures, and its unit is real US$. The GDP per capita indicator is expressed with the *GDP* symbol in the study and shows the real per capita income of the countries in constant US$. The *CPI* variable is the consumer price index of the countries, based on 2010. Productivity shows the output per worker, again in real US$. These four variables, including *RD*, which is used as a technology variable, are defined as core regressors as in the previous section.

On the other hand, real interest rate and real effective exchange rate variables are used in different specifications as other explanatory variables in this section. The real interest rate is obtained as a percentage but is used as a decimal fraction in estimations. The real effective exchange rate is treated as an index and the base year is 2010, as in other variables. The expected signs of the coefficients of all these variables are discussed in the previous section. Unlike the previous section for developed countries, this time the openness variable is also included in the models with the *OPN* symbol. Openness is a statistic that expresses the ratio of the sum of the export and import activities of the countries to the total income. In this study, the ratio in question is converted into an index by accepting the year 2010 as the base year. Theoretically, Heckscher-Ohlin and Stolper-Samuelson (Samuelson, 1948; Stolper and Samuelson, 1941; Berman et al., 1998; Helpman and Krugman, 1985) models demonstrate the advantage of global trade and its positive consequence for employment. Heckscher-Ohlin model specifies a rise in openness growths employment in developing countries since international trade increases demand for unskilled labor that the density of unskilled labor is high in developing countries. The empirical literature contains evidence in both directions, positive (Grossman and Helpman, 1991b; Goldberg and Pavcnik, 2003; Burange et al., 2019) and negative (Revenga, 1997; Furusawa; 1999; Greenaway et al., 1999; Autor et al., 2016) on the possible effects of openness on employment. Krugman (1995) argues that under the assumption of rigid wages, trade openness increases the export of unskilled labor products in developing countries, and therefore has a positive effect on unskilled labor demand. Mesghena (2006) also finds in his study that this time in the USA, openness has increased the employment of unskilled workers. But according to Autor et al. (2016), high openness between the USA and China increases unemployment, decreases labor force participation and wages in the USA. On the other hand, Baldwin (1995) reports that trade activities do not have a significant employment effect in OECD countries. Macro variables such as public unemployment spending and trade union density included in Chapter 3 analyses designed for developed countries couldn’t be used for developing countries due to lack of data.

Table 4.2. List of the variables

Variable Type	Description and Units of Variables	Symbol	Source
Dependent Variables	Unemployment rate (% of total labor force)	*U*	ILO (2020a), World Bank (2020a)
	High-skilled employment rate (% of total labor force)	*HSE*	ILO (2020b), Author's calculations
	Low-skilled employment rate (% of total labor force)	*LSE*	ILO (2020b), Author's calculations
Core Independent Variables	R&D Expenditure per capita (constant 2010 US$)	*RD*	OECD (2020a), World Bank (2020b), Author's calculations
	GDP per capita (constant 2010 US$)	*GDP*	World Bank (2020c)
	Consumer price index (2010 = 100)	*CPI*	World Bank (2020d)
	Productivity (output per worker, constant 2010 US$)	*PRD*	ILO (2020c), Author's calculations
Other Independent Variables	Real effective exchange rate index (2010 = 100)	*EXC*	World Bank (2020e), Author's calculations
	Real interest rate (%)	*INT*	World Bank (2020f), Author's calculations
	Trade openness (2010 = 100)	*OPN*	World Bank (2020h), Author's calculations

Note: The dependent variables namely *U*, *HSE*, and *LSE* were obtained as percentage of total labor force but used as decimal fraction in the analyses. *RD* was obtained as a percentage of total GDP and calculated as R&D per capita based on constant 2010 US$.

Figure 4.1 shows the percentage point changes in the average unemployment, high-skilled employment, and low-skilled employment rates of the 23 developing countries included in this thesis between 1990-2019. As the chart shows, most of the increase in unemployment rates in developing countries comes from the change in the *LSE*. Of course, one of the most important reasons for this is that, as can be seen from the descriptive statistics in Table 4.3, the weight of unskilled workers in developing countries is almost three times that of skilled workers. Except for the 1998 and 2008-2011 periods in developing countries, it is seen that the change in *HSE* is always positive. Therefore, it is concluded that the 2008 global financial crisis negatively affected high-skilled employment in these countries. On the other hand, the change in the *LSE* ratio in developing countries was negative until 2004, and after this date, the direction and trend of the relationship are more fluctuating. While interpreting the graph, it should be kept in mind that the analysis covers developing countries with different profiles. Because while the rate of high-skilled employment in the total workforce has increased dramatically in some countries, the rate of unskilled workers in some countries continues to be well above the average.

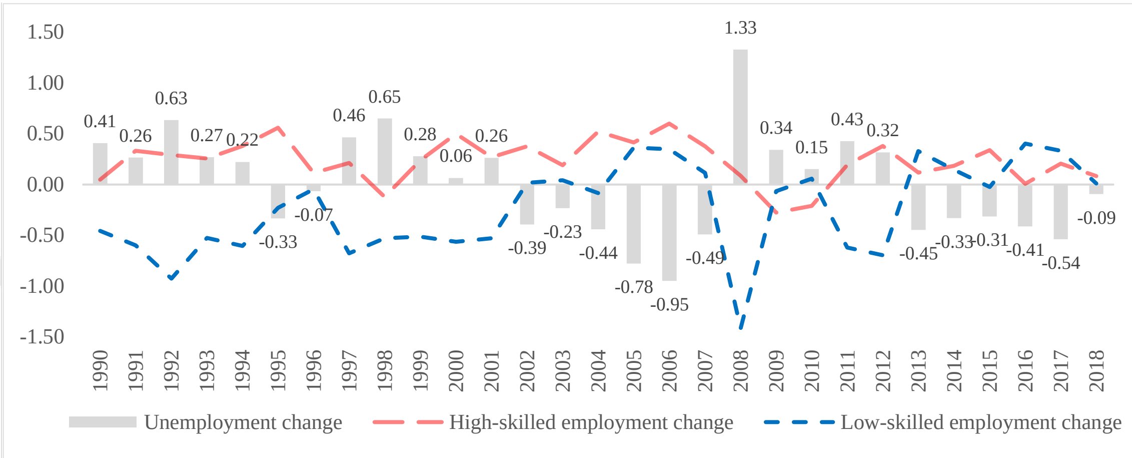

Figure 4.1. Average unemployment, high-skilled and low-skilled employment changes in developing countries

Note: In this figure, average percentage point changes in unemployment, high-skilled, and low-skilled employment rates are given.

Source: Author's own calculations based on World Bank and ILO data.

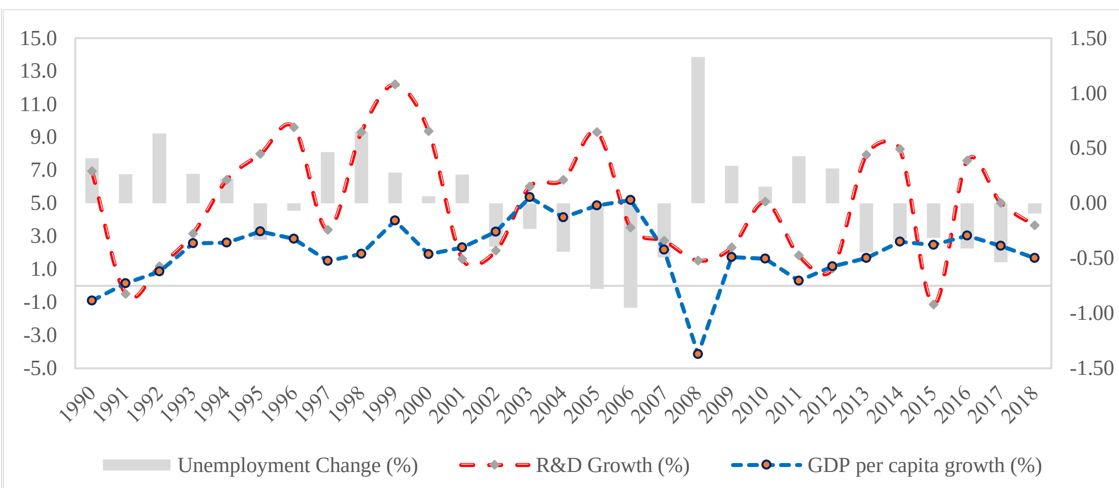

Figure 4.2. Average R&D growth, GDP per capita growth and unemployment changes of developing countries

Note: In this figure, percentage changes in per capita GDP and per capita R&D are shown on the primary axis (left) while the percentage point change in unemployment is located on the secondary axis (right).

Source: Author's own calculations based on World Bank and ILO data.

Figure 4.2 presents the average of the changes in R&D expenditures, per capita incomes, and unemployment rates of developing countries between 1990 and 2019. While the change in the average R&D expenditures of developing countries by years is always positive, except for 1991 and 2015, it is not possible to talk about a constant *"increase"* or *"decrease"* acceleration for change. Interestingly, until the 2008 crisis, it is observed that the change in average unemployment rates followed the change in average R&D expenditures 1-2 years behind; However, it has been determined that this pattern has deteriorated after 2008. Of course, the graph alone cannot prove the difference of a long-term relationship between the two variables; but it may contain an important indication of the direction of the relationship. On the other hand, an important detail is that the average increase in unemployment rates in developing countries was the highest in 2008.

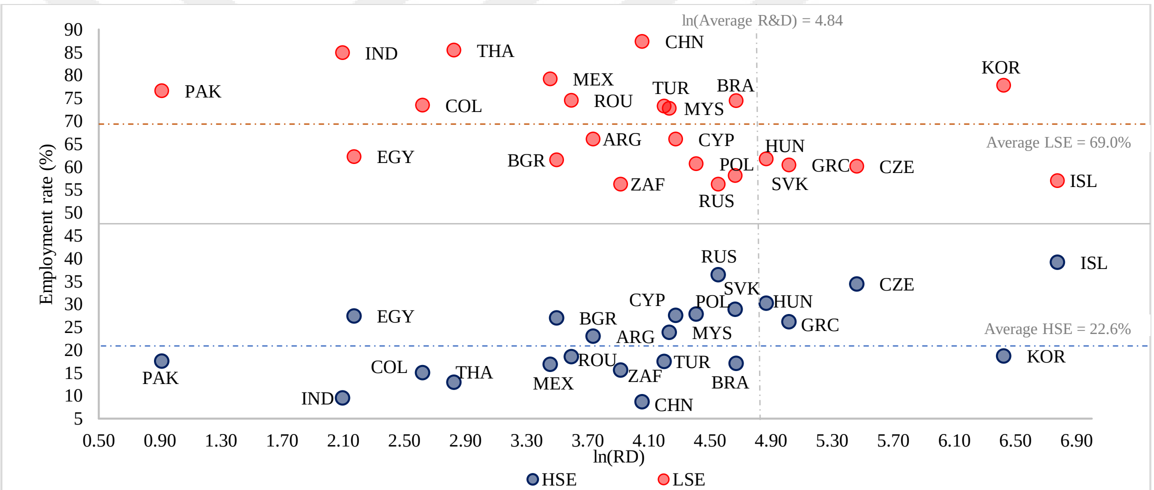

Figure 4.3. Average low and high-skilled employment rates and R&D per capita by country
Source: Autor's own elaborations based on ILO (2020a), OECD (2020a), and World Bank (2020b).

Besides, Figure 4.3 shows the distribution of average *HSE*, *LSE*, and *RD* by the country for the 1990-2019 period. It is difficult to talk about an obvious relationship pattern here since average values are taken for a fairly considerable time period. Furthermore, countries with per capita R&D and high-skilled employment above the emerging market average are identified as Iceland, Korea, Czechia, Greece, and Hungary. Turkey, on the other hand, is below the emerging market average in terms of technology investments and skilled workers. While the country with the lowest R&D average is Pakistan, it is striking that the low-skilled employment rate is higher in manufacturing-intensive Asian countries such as China, Thailand, and India.

Table 4.3. Descriptive statistics of the dependent variables

Statistics	Ct.	U (%)	HSE (%)	LSE (%)	Ct.	U (%)	HSE (%)	LSE (%)	Ct.	U (%)	HSE (%)	LSE (%)
Mean		10.9	23.0	66.1		13.4	26.1	60.4		11.4	27.9	60.7
Median		9.5	22.9	67.8		10.2	25.4	60.8		10.6	26.1	59.8
Std. dev.	ARG	4.0	0.9	4.1	GRC	6.5	2.6	5.7	POL	4.6	5.2	4.1
Max.		19.6	25.2	71.8		27.5	31.5	69.0		19.9	36.3	72.6
Min.		5.4	21.8	58.1		6.8	22.9	48.7		3.5	20.1	55.3
Mean		8.5	17.1	74.4		8.0	30.2	61.8		6.9	18.6	74.5
Median		8.4	16.7	73.9		7.8	31.5	61.9		6.9	19.0	73.8
Std. dev.	BRA	2.1	2.0	3.5	HUN	2.4	3.4	2.8	ROU	1.5	2.4	2.0
Max.		12.8	20.3	81.6		12.1	34.8	67.2		11.0	21.9	78.4
Min.		4.3	13.6	68.0		3.4	23.3	57.1		4.0	15.2	71.4
Mean		11.5	27.0	61.5		3.9	39.1	57.0		7.3	36.4	56.2
Median		12.2	26.8	61.6		3.3	38.2	58.8		6.8	35.2	56.7
Std. dev.	BGR	3.8	2.0	3.1	ISL	1.6	6.4	7.0	RUS	2.4	3.9	2.8
Max.		19.9	31.2	67.1		7.6	47.3	67.8		13.3	42.3	61.8
Min.		4.3	23.4	52.1		1.8	30.4	47.6		4.6	30.1	52.5
Mean		3.9	8.7	87.4		5.6	9.5	84.9		13.0	28.9	58.1
Median		4.3	8.1	87.4		5.6	8.0	86.3		12.7	28.7	58.4
Std. dev.	CHN	0.8	1.8	2.5	IND	0.1	3.2	3.2	SVK	3.5	1.9	3.6
Max.		4.7	11.6	91.1		5.7	14.4	88.5		19.4	32.2	65.3
Min.		2.4	6.5	83.8		5.3	6.0	80.1		5.6	24.1	52.6
Mean		11.5	15.0	73.4		3.5	18.7	77.8		28.2	15.6	56.2
Median		10.6	14.7	73.6		3.5	19.9	76.1		29.4	15.1	56.4
Std. dev.	COL	3.1	1.2	2.6	KOR	1.1	2.6	3.1	ZAF	2.8	3.2	1.8
Max.		20.5	17.0	77.5		7.0	21.8	84.4		33.5	20.7	59.3
Min.		8.4	13.4	66.1		2.0	13.2	75.0		22.4	11.2	52.1
Mean		6.4	27.6	66.1		3.4	23.9	72.8		1.6	12.9	85.5
Median		4.8	27.8	67.7		3.3	24.6	72.3		1.4	13.3	85.3
Std. dev.	CYP	4.2	3.7	7.2	MYS	0.4	1.8	1.8	THA	0.8	1.3	1.5
Max.		16.1	33.6	76.6		4.7	27.2	75.5		3.4	14.7	88.6
Min.		1.9	21.6	53.5		2.5	20.8	69.2		0.7	10.6	83.3
Mean		5.5	34.4	60.1		3.9	16.9	79.2		9.2	17.5	73.3
Median		5.6	34.4	59.0		3.6	17.1	78.6		8.8	17.5	72.8
Std. dev.	CZE	2.1	2.9	3.9	MEX	1.0	1.3	1.6	TUR	1.7	1.5	2.7
Max.		8.8	38.9	69.6		6.9	18.6	82.3		13.5	20.6	77.2
Min.		1.9	28.4	54.4		2.5	14.3	76.6		6.5	15.2	68.2
Mean		10.3	27.4	62.2		5.8	17.5	76.6		8.4	22.6	69.0
Median		10.4	28.2	62.9		5.8	17.0	76.2		7.0	21.9	69.1
Std. dev.	EGY	1.6	3.1	4.0	PAK	1.3	1.4	1.5	TOT	6.0	8.6	10.4
Max.		13.2	31.9	68.6		8.3	19.7	80.6		33.5	47.3	91.1
Min.		8.0	22.5	55.3		3.1	15.7	74.8		0.7	6.0	47.6

Note: U, HSE, and *LSE* are percentages of total labor force. *RD* and *GDP* are in constant US$.
Source: Author's own calculations based on World Bank, OECD, and ILO data.

In Table 4.3, the descriptive statistics of *U*, *HSE*, and *LSE*, which are considered as dependent variables in the study, are shared on the basis of developing countries. According to this table, the average unemployment rate in the developing countries in the mentioned period is 8.4% with a 6.0% standard deviation, the average high-skilled employment rate is 22.6% with 8.6% standard deviation, and low-skilled employment rate 69% with 10.4% standard deviation. In parallel, the table shows that between 1990 and 2019, the developing country with the highest average unemployment rate was South Africa with 22.4%, while the country with the lowest average unemployment rate was Thailand with 1.6%. On the other hand, Thailand's average low-skilled employment rate is 85.5%, and in this respect, Thailand ranks second in the employment of low-skilled workers. Therefore, it can be concluded that the low unemployment rate in this country is actually achieved by high unskilled or low skilled employment. In addition to Thailand, the other countries with the highest low-skilled rate are China with 87.9% and India with 84.9%, so a comparable situation in Thailand is seen in China and India. Table 4.3, on the other hand, shows that the top three countries with the highest high-skilled employment rates are Iceland with 39.1%, Russia with 36.4%, and Czechia with 34.4%, respectively. Also, between 1990 and 2019, the average unemployment rate in Turkey is 9.2%, the average high-skilled employment rate is 17.5% and the average low-skilled employment rate is 73.3%. Turkey is below the average of developing countries in unemployment rates. However, the high-skilled employment rate of Turkey is below the average, while the low-skilled employment rate of Turkey is above the average of developing countries.

In Table 4.4 given in the continuation of Table 4.3, descriptive statistics of core explanatory variables are shared. According to the table, between 1990 and 2019, the average R&D expenditure of developing countries was $126, while the average per capita income was $10,286. The country with the highest average per capita R&D expenditure is Iceland with $875, and the average per capita income of this country is $40,557, well above other countries in its category. The other two countries with the highest average per capita R&D spending are South Korea at $616 and Czechia at $235. As can be seen, there are serious differences even among the top three countries in terms of technology investments in developing countries.

Table 4.4. Descriptive statistics of the core independent variables

Statistics	Ct.	RD ($)	GDP ($)	CPI	Ct.	RD ($)	GDP ($)	CPI	Ct.	RD ($)	GDP ($)	CPI
Mean		41.92	8892	76.46		151.03	23675	79.62		82.31	10427	77.39
Median		37.04	8675	61.92		152.66	22942	83.86		55.51	9780	85.96
Std. dev.	ARG	15.96	1392	47.67	GRC	62.28	3282	22.57	POL	49.20	3601	32.59
Max.		67.62	10883	232.80		288.79	30055	104.88		206.41	17387	114.11
Min.		12.60	6246	15.84		57.18	19304	29.80		39.84	5511	6.98
Mean		106.92	9772	77.67		130.09	12083	72.01		36.31	7123	61.97
Median		94.54	9441	76.99		116.78	12786	75.59		35.36	6610	71.03
Std. dev.	BRA	28.16	1392	49.71	HUN	58.59	2630	36.40	ROU	11.95	2380	46.41
Max.		154.28	11993	167.40		273.23	17466	121.64		67.76	12131	123.78
Min.		71.54	7792	0.00		56.60	8550	9.23		17.93	4350	0.02
Mean		32.98	5788	65.47		875.43	40557	77.33		95.14	9051	69.13
Median		24.83	5401	70.98		1047.27	42359	65.78		102.30	9316	57.99
Std. dev.	BGR	18.96	1655	41.64	ISL	305.65	7244	30.46	RUS	33.87	2346	59.80
Max.		74.60	9026	114.42		1298.20	51593	129.00		181.08	12208	180.75
Min.		15.27	3784	0.04		302.11	29708	39.95		47.02	5506	0.02
Mean		57.80	3427	88.28		8.12	1140	81.84		106.20	13459	77.65
Median		32.85	2600	85.75		7.99	1010	64.70		90.95	12818	85.66
Std. dev.	CHN	57.30	2359	23.55	IND	3.47	487	47.64	SVK	43.66	4582	29.99
Max.		182.03	8254	125.08		14.07	2169	180.44		221.42	21039	115.34
Min.		5.01	729	40.44		3.40	576	22.95		62.22	6161	25.41
Mean		13.72	5850	74.85		616.36	18739	84.26		50.18	6617	81.92
Median		14.36	5315	77.76		486.32	18848	85.00		53.33	6601	73.76
Std. dev.	COL	4.71	1153	39.90	KOR	394.07	6271	22.08	ZAF	11.56	797	39.02
Max.		22.77	7843	140.95		1428.61	28606	115.16		66.01	7583	158.93
Min.		6.32	4467	9.40		118.80	8496	44.55		32.61	5518	25.43
Mean		71.95	20189	85.16		68.96	8148	89.24		16.84	4376	85.90
Median		76.08	20410	87.66		47.35	7848	86.50		9.63	4264	84.69
Std. dev.	CYP	35.54	2656	16.65	MYS	58.43	2213	19.41	THA	19.00	1162	20.58
Max.		131.13	23802	105.76		190.61	12478	121.46		65.29	6503	113.27
Min.		17.53	15248	53.28		4.54	4537	56.81		0.01	2504	49.76
Mean		235.23	17417	82.87		31.64	9138	75.76		66.67	9991	71.36
Median		202.19	17471	86.18		33.36	9222	78.96		50.21	9351	63.36
Std. dev.	CZE	120.10	3658	24.90	MEX	10.24	780	39.60	TUR	44.23	2756	67.33
Max.		465.67	23834	116.48		45.88	10404	141.54		160.12	15069	234.44
Min.		82.19	12313	30.00		12.19	7718	11.75		15.97	6709	0.07
Mean		8.77	2204	88.10		2.49	927	76.14		126.39	10826	78.28
Median		5.42	2121	56.42		2.67	918	53.46		54.20	8528	80.01
Std. dev.	EGY	6.72	469	71.42	PAK	1.53	137	50.93	TOT	230.19	9123	41.05
Max.		22.29	3009	279.71		6.28	1198	182.32		1428.6	51593	279.71
Min.		1.73	1539	19.15		0.74	737	18.00		0.01	576	0.00

Note: RD and *GDP* are in constant US$. CPI is an index with the base year of 2010.
Source: Author's own calculations based on World Bank, OECD, and ILO data.

The developing country with the lowest per capita R&D expenditure is Pakistan with an average of $2.5, which is about 0.3% of Iceland. The second country which has the lowest average R&D spending is India, with $8.8, followed by Egypt with $8.8. It shows that the gap based on technology investments among developing countries is quite large. Table 4.4 also indicates that between 1990 and 2019, Turkey's average R&D

investment was $67, and the average per capita income was $9,991. Turkey remains below the general average of developing countries in terms of both statistics. Finally, the highest inflation was observed in Argentina and Egypt as well as Pakistan, India, and Brazil.

Table 4.5. Descriptive statistics of the other independent variables

Stat.	Ct.	PRD	INT	OPN	EXC	Ct.	PRD	INT	OPN	EXC	Ct.	PRD	INT	OPN	EXC
Mean		22451	3.2	68	150		61965	8.5	86	92		24994	7.1	79	87
Med.		22652	2.1	78	120		65315	8.3	95	91		26300	7.4	67	92
Sd.	ARG	2620	9.8	29	73	GRC	7284	3.2	25	5	POL	7237	4.1	48	16
Max.		26085	29.1	112	276		72104	14.6	124	101		37321	14.8	178	112
Min.		16494	-11.6	21	55		50932	3.2	47	83		12860	-1.4	23	39
Mean		22937	38.9	86	85		30193	3.7	78	84		15906	1.7	85	85
Med.		21983	35.2	93	86		32618	4.3	78	89		15664	5.1	72	90
Sd.	BRA	1947	13.7	32	16	HUN	4819	3.1	36	14	ROU	6038	12.0	40	18
Max.		26193	77.6	136	115		37068	9.5	134	105		27260	12.7	168	113
Min.		20249	18.5	36	58		21788	-2.9	23	56		8848	-43.1	36	42
Mean		13801	4.1	89	78		71615	7.6	78	128		18535	6.3	90	79
Med.		13778	4.6	77	83		74622	8.0	70	129		18443	0.7	94	80
Sd.	BGR	3743	31.5	37	24	ISL	11016	3.3	32	16	RUS	4048	20.3	24	25
Max.		20007	139.8	151	104		89064	14.4	130	157		24242	72.3	166	134
Min.		8028	-69.1	38	26		55981	0.9	36	97		13079	-19.0	46	12
Mean		6219	1.9	65	99		3262	5.5	66	87		31429	6.8	79	75
Med.		4648	2.7	67	96		2746	5.6	56	81		31191	6.9	71	76
Sd.	CHN	4361	3.4	45	15	IND	1454	2.4	49	14	SVK	8968	4.2	43	23
Max.		15332	7.3	133	130		6460	9.2	148	113		44616	15.4	153	105
Min.		1219	-8.0	7	71		1618	-2.0	10	68		17433	-1.0	13	45
Mean		13762	9.5	93	86		36951	3.7	66	125		24683	5.4	85	99
Med.		13304	8.8	84	84		37667	3.5	60	131		24826	4.7	81	98
Sd.	COL	1513	6.6	32	12	KOR	10020	2.8	36	22	ZAF	1354	2.8	32	19
Max.		16341	23.4	153	106		51755	10.8	123	164		26752	13.0	128	134
Min.		11446	-11.1	52	69		19622	-0.4	18	92		22804	2.2	39	70
Mean		58879	4.6	90	95		19317	3.5	87	102		7879	4.4	77	99
Med.		61533	4.6	91	94		19220	3.5	98	98		7609	3.6	84	101
Sd.	CYP	6501	2.1	27	5	MYS	3732	3.5	27	12	THA	1917	3.0	33	9
Max.		65891	8.0	144	105		26341	11.8	124	125		11745	11.9	123	113
Min.		44552	-3.4	44	88		12694	-3.9	30	85		4965	-0.4	25	84
Mean		36536	3.1	80	78		23271	2.9	88	100		30837	-1.6	96	78
Med.		37628	3.3	79	81		23301	2.8	87	101		31977	4.4	83	77
Sd.	CZE	7425	2.3	37	19	MEX	583	4.7	38	13	TUR	7776	22.7	51	13
Max.		47681	7.4	139	104		24131	15.1	164	123		42962	27.6	217	100
Min.		25316	-5.7	34	43		21963	-13.2	31	75		18041	-76.7	32	54
Mean		8046	3.8	78	91		3042	1.4	82	109		25500	5.9	81	95
Med.		7786	3.2	79	93		2991	1.5	76	107		22499	4.7	83	95
Sd.	EGY	1414	4.6	29	18	PAK	292	3.8	25	10	TOT	18731	12.8	36	28
Max.		10961	11.9	136	122		3714	8.3	134	127		89064	139.8	217	276
Min.		5956	-6.3	44	61		2619	-7.4	48	96		1219	-76.7	7	12

Note: PRD is constant US$. *OPN* and *EXC* are indexes with base year of 2010.
Source: Author's own calculations based on World Bank, OECD, and ILO data.

The statistics in Table 4.5 contain descriptive statistics for other macro variables used in the study. Between 1990 and 2019, the country with the highest average output per worker is Iceland with $71,615, and the lowest country with $,3042 is Pakistan. Finally, Turkey’s average productivity is 30,837$, which is above the average of 25,500$ for developing countries.

Table 4.6. Descriptive statistics of R&D and employment variables by year

Stat.	Year	U	HSE	LSE	RD	Year	U	HSE	LSE	RD	Year	U	HSE	LSE	RD
Mean		6.9	18.9	74.2	54		9.7	21.2	69.1	98		8.4	24.3	67.3	154
Med.	1990	5.4	20.9	74.5	18	2000	7.8	22.7	66.1	39	2010	7.6	23.2	69.1	85
Sd.		6.0	7.2	8.8	71		7.1	7.8	10.6	203		4.8	9.3	11.2	258
Mean		7.3	18.9	73.7	58		9.8	21.7	68.5	108		8.6	24.1	67.4	162
Med.	1991	6.3	20.1	75.2	27	2001	8.0	23.2	68.7	40	2011	7.2	23.4	69.4	93
Sd.		6.0	7.2	8.8	79		7.2	8.2	11.1	230		5.1	9.0	11.1	266
Mean		7.6	19.3	73.2	58		10.0	22.0	68.0	110		9.0	24.3	66.8	165
Med.	1992	6.4	20.8	75.5	29	2002	8.1	22.4	69.1	45	2012	7.2	22.9	69.9	100
Sd.		6.0	7.5	9.4	85		7.7	8.2	10.9	228		6.0	9.1	11.6	256
Mean	1993	8.2	19.6	72.2	58		9.6	22.4	68.0	112		9.3	24.6	66.1	167
Med.		6.0	20.8	73.8	29	2003	8.2	22.6	67.8	46	2013	7.1	23.9	68.6	105
Sd.		6.1	7.6	9.8	86		6.9	8.3	10.6	224		6.5	9.0	11.7	249
Mean		8.5	19.8	71.7	60		9.4	22.5	68.1	119		8.8	24.7	66.4	180
Med.	1994	8.1	21.3	73.5	31	2004	7.8	22.2	68.5	46	2014	6.8	22.4	70.3	114
Sd.		6.1	7.7	10.1	93		6.4	8.3	10.4	240		6.4	9.0	11.3	272
Mean		8.7	20.2	71.1	64		8.9	23.1	68.0	127		8.5	24.9	66.6	196
Med.	1995	7.6	21.7	72.7	33	2005	7.7	23.6	67.6	55	2015	6.8	22.3	69.9	122
Sd.		6.4	7.7	10.3	104		6.0	8.6	10.3	251		6.2	9.2	10.9	292
Mean		8.4	20.8	70.9	70		8.2	23.5	68.4	139		8.2	25.3	66.5	194
Med.	1996	6.7	22.2	72.0	34	2006	7.3	22.9	67.2	57	2016	5.9	22.2	68.9	127
Sd.		6.3	7.9	10.2	117		5.6	8.6	9.9	279		6.2	9.4	10.6	296
Mean		8.3	20.9	70.8	77		7.2	24.1	68.7	144		7.8	25.3	66.9	209
Med.	1997	6.8	22.6	71.5	34	2007	6.4	23.8	67.7	64	2017	5.4	22.1	68.0	130
Sd.		6.2	7.8	10.0	132		5.0	8.9	9.7	269		6.1	9.6	10.4	316
Mean		8.8	21.1	70.1	79		6.7	24.5	68.8	148		7.3	25.5	67.3	220
Med.	1998	7.0	22.4	70.5	35	2008	5.8	24.2	67.9	70	2018	4.8	21.9	68.4	129
Sd.		5.9	7.9	9.9	146		4.2	9.5	10.0	267		6.0	9.7	10.2	329
Mean		9.4	21.0	69.6	87		8.1	24.5	67.4	150		7.2	25.6	67.3	228
Med.	1999	7.7	22.5	67.2	38	2009	7.2	24.5	66.5	75	2019	4.5	21.9	68.4	131
Sd.		6.5	7.8	10.2	170		4.4	9.4	10.8	263		6.1	9.7	10.0	342

Note: U, HSE, and *LSE* are percentages of total labor force. *RD* and *GDP* are in constant US$.
Source: Author’s own calculations based on World Bank, OECD, and ILO data.

Finally, Table 4.6 contains the descriptive statistics of developing countries' *U, HSE*, *LSE*, and *RD* values by years. The year in which the average unemployment rate in developing countries was highest was 6.7% in 2008, which is considered to be the date when the last global financial crisis started. Although there is an increase in the average *HSE* and a decreasing trend in the *LSE*, the highest *HSE* is observed in 2019 and the lowest *LSE* in 2013. On the other hand, it is determined that the average per capita R&D expenditures have always increased except for 2013, including 2008. While the increase in R&D expenditures between 1990 and 2019 was approximately 322%, the increase in *HSE* is determined as 35% (6.7 percentage points) and the decrease in *LSE* ratio is determined as 9% (6.9 percentage point). Despite the sharp upward trend in *HSE*, the downward trend in *LSE* appears to have reversed, especially between 2005-2008 and 2013-2019, but increases in *LSE* are more modest, despite significant increases in *HSE*.

One of the most important issues to be mentioned here is the differences between developing and developed countries in light of these variables. To recall, in the same period, the increase in *HSE* in developed countries is approximately 35.2% (10.8 percentage points) and the decrease in *LSE* is determined as 13.4% (8.2 percentage points). Although the increase rates are almost the same, the average *HSE* rate of developing countries is 25.6% in 2019, while the *HSE* rate of developed countries is already 30.7% in 1990, and in this respect, it is seen that developing countries have not yet reached the rate of skilled workers that developed countries had in 1990.

4.3. Empirical Methodology

In this thesis, the empirical parts of the sections prepared for developed and developing countries include pretty similar steps. The cointegration and estimation methods used in this section, which examines the relationship between technology and unemployment in developing countries, are the same as the methods used in the previous section. Here, first, it is determined whether the series are cointegrated in the long term with the Pedroni Cointegration method; the specifications are then estimated by the PDOLS and FMOLS methods. The main difference between the methods used in Chapter 3 and Chapter 4 is in the estimation part. In Chapter 3, both PDOLS and FMOLS methods use pooled and pooled-weighted estimation approaches. In this section, grouped PDOLS and grouped FMOLS, which are also proposed by Pedroni (2001a, 2001b) and newer than the other two, are preferred as estimation methods.

As mentioned before, whether the panel time series are stationary or not is a particularly important detail in both the cointegration and the panel estimation process. In this section, as in the previous chapter, technical information about the preferred unit-root test methods is shared, but this time these details are presented in summary. After the unit root part, the panel cointegration methods are summarized again but briefly, and then the technical backgrounds of grouped PDOLS and grouped FMOLS estimation processes are discussed. Of course, before moving on to these sections, it is useful to discuss the models estimated in the study.

4.3.1. Equations to be estimated

In this part of the study, the models created to define the relationship between technology and (un)employment in developing countries are explained. In this direction, baseline models with core variables are established, as in the specifications prepared for developed countries, and additional models including other explanatory variables that are thought to be important and proved to be important in the literature are estimated. All models on the technology-unemployment relationship can be grouped under three main subjects: a) Models established to explain the overall unemployment-technology relationship, independent of skill, where U_{it} is the dependent variable b) Models where HSE_{it} is determined as the dependent variable, the technology-employment relationship is explained in terms of high-skilled workers c) Models where LSE_{it} is the dependent variable and the effects of technology on low-skilled employment are explained. All three dependent variables are obtained as a percentage of the total labor force as in the previous empirical section but are used as a decimal fraction in the estimation progress. The characteristics and units of the main core explanatory variable RD_{it} and the other regressors used in the analyses are the same.

4.3.1.1. Equations for the overall unemployment rate

Now, firstly, it can be mentioned about the models established to examine the technology-unemployment relationship in developing countries. For the purpose of clarifying this relationship, six models are established, two of which are baseline models, and in all six models, RD_{it}, which represents the per capita R&D expenditure, is included as the main core explanatory variable. Similarly, GDP_{it} and CPI_{it} variables are included in all models by taking their natural logarithms, representing the macro variables of per capita income and inflation, which have been repeatedly proven to directly affect unemployment in both empirical and theoretical literature. In line with these considerations, the first baseline model is as follows:

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+e_{it} \qquad \textit{Model 4.1}$$

where U_{it} represents unemployment rate in decimal fraction while RD_{it}, GDP_{it}, and CPI_{it} show natural logarithms of per capita R&D expenditure, per capita GDP, and consumer price index respectively, for country *i (=1, …, 23)* and year *t (=1990, …, 2019)*. And of course, e_{it} represents error terms including other factors that affect unemployment.

The following specification is obtained by adding the productivity variable to Baseline Model 1:

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+e_{it} \qquad \textit{Model 4.2}$$

where PRD_{it} represents the natural logarithm of productivity that is calculated as *"total output/total workers."* In addition to the two base models above, additional specifications formed using the other imperative regressors are as follows:

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_4 INT_{it}+e_{it} \qquad \textit{Model 4.3}$$

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_5 OPN_{it}+e_{it} \qquad \textit{Model 4.4}$$

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_6 EXC_{it}+e_{it} \qquad \textit{Model 4.5}$$

$$U_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_5 OPN_{it}+\alpha_6 EXC_{it}+e_{it} \qquad \textit{Model 4.6}$$

where INT_{it} denotes real interest rate while OPN_{it} and EXC_{it} are indexes that are used to show openness and real effective exchange rate. The explanatory variables are added to the models by taking their natural logarithms, except for INT_{it}.

Consequently, to determine the interaction between unemployment and technology, the main core explanatory variable RD_{it} and two other core regressors GDP_{it}, and CPI_{it}

are included in all models. In terms of the consistencies and reliabilities of the models and the method, both the magnitudes and the signs of the coefficients are expected to be close to each other.

4.3.1.2. Equations for employment by skills

Although the most important focus of the thesis is how the progress in technology affects unemployment at the macro level, looking at the issue only in terms of overall unemployment leads to an incomplete definition of the relationship. Because employment includes workers with different qualifications and characteristics. Therefore, each group of workers can be affected differently by technology. With the aim of explaining this issue at the macro level, the distribution of employment rates of countries according to skill groups is used in this study.

On the other hand, it should be kept in mind that the dependent variable is taken as "employment" rather than "unemployment" when analyzing the effect of technology on employment by skill. In other words, the coefficients in the models created according to skill groups should be interpreted in the opposite direction to the models created for unemployment. For example, the negative effect of GDP per capita on unemployment means that it actually has a positive impact on employment.

Based on this information, the first base model for high-skilled employment of this part in the study is as follows:

$$HSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+e_{it} \qquad \textit{Model 4.7}$$

where, HSE_{it} shows the high-skilled employment rate as a decimal fraction of the total labor force while the natural log of R&D per capita, the main core explanatory variable, is expressed as RD_{it}. Besides, GDP_{it} and CPI_{it} represent per capita GDP and consumer price index in natural logarithms. Finally, e_{it} is the error term containing all other factors that affect the high-skilled employment rate for country i *(=1, ..., 23)* and year t *(=1990, ..., 2019)*. Like the previous empirical models, the following specification variations includes are also tested:

$$HSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+e_{it} \qquad \textit{Model 4.8}$$

$$HSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_4 INT_{it}+e_{it} \qquad \textit{Model 4.9}$$

$$HSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_5 OPN_{it}+e_{it} \qquad \textit{Model 4.10}$$

where PRD_{it} is output per worker, INT_{it} is the real interest rate and OPN_{it} is trade openness like in the previous models for unemployment.

Finally, in this stage, specifications to explain the relationship between technology and low-skilled employment are shared. The explanatory variables and constructed model combinations are the same as those prepared for HSE_{it} in the previous part. However, on the other hand, the signs or effects of the variables are expected to be different from HSE_{it} of course. For example, the change in GDP per capita may affect both HSE_{it} and LSE_{it} in the same direction, but the magnitude of the effect is expected differently for low-skilled and high-skilled workers. In addition, the impact of the direction and strength of per capita R&D expenditure, which is the core explanatory variable, may, of course, differ, which is actually the main purpose to reach these findings. Consequently, analyses made separately by country and skill groups are important in terms of showing us how the effect of technology reflects on different skill groups in different development categories of countries. Accordingly, four specifications in which the low-skilled employment variable is used as a dependent variable are constructed as follows:

$$LSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+e_{it} \qquad \textit{Model 4.11}$$

$$LSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+e_{it} \qquad \textit{Model 4.12}$$

$$LSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_4 INT_{it}+e_{it} \qquad \textit{Model 4.13}$$

$$LSE_{it}=\alpha_0+\beta RD_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRD_{it}+\alpha_5 OPN_{it}+e_{it} \qquad \textit{Model 4.14}$$

where LSE_{it} shows the low-skilled employment rate as a decimal fraction of the total labor force. Finally, it is worth remembering that in this study, the parameter β is used as the coefficient of RD_{it} in all models, and the letter α is used for the coefficients of intercept and other explanatory variables.

4.3.2. Unit root testing procedure

The unit root tests used in this section are the same as in Chapter 3, and since these tests are discussed previously in more detail, brief technical information about unit root tests is shared in Chapter 4. As it is widely known, accurate, consistent, and unbiased estimators in panel time series are based on stationarity. In this direction, when working on panel time series, the stationarities of the series are examined first. For this, many methods have been produced from past to present and these methods can be easily applied today by courtesy of advanced statistical and econometric software packages.

The stationarity of the series in panel data means that the mean, variance, and covariance values of the series remain constant over time. Changes in these values over time cause high t and R^2 values, causing spurious regressions, which means there is no relationship between the variables but the estimated models to be interpreted as if there exist. Therefore, in non-stationary panel series, the coefficient estimates made by classical methods such as OLS are invalid. In addition, for the $I(1)$ series, which are not stationary at the level, but the first differences are stationary, the proposed estimation methods such as Pedroni PDOLS and FMOLS are extremely useful, which also eliminate endogeneity and serial correlation problems.

It can now be discussed how to determine whether these data contain unit root or not. Although there are many methods in the literature, including first and second-generation unit root tests, the LLC, IPS, and Fisher-Type ADF tests are used in this study. The technical details of these methods are discussed in the previous chapter particularly. In this chapter, it is briefly summarized again, however, not too comprehensive.

All the LLC by Levin et al. (2002), the IPS by Im et al. (2003), and Fisher type test by Maddala and Wu (1999) are the unit root tests based on Dickey Fuller (1979) and Augmented Dickey-Fuller procedures. While in the LLC test, the ρ coefficient for all components is assumed to be homogeneous, the coefficient of ρ can be heterogeneous in the IPS test. Besides, in the IPS test, the unit root test is applied separately for each cross-section without pooling the data, and the test statistic is calculated by averaging all obtained statistics (Im et al., 2003). On the other hand, Maddala and Wu (1999) propose an alternative method that is a non-parametric Fisher-type test based on combining unit root test statistics for each cross-section. Lastly, it is important to mention that in IPS and Fisher-type tests, panel data does not have to be balanced.

The IPS test that is proposed in Im et al. (2003), instead of using pooled data, takes the average of the test statistics calculated for each cross-section at the end of the process:

$$\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta y_{it-j} + \delta_{mi} d_{mt} + \varepsilon_{it} \qquad \textit{Eq. 4.1}$$

where p_i is the lag order, δ_{mi} is the deterministic component, and of course "Δ" is the operator of the first difference. As it can be seen, the coefficient p_i contains the dimension "i" in the equation, and accordingly, the null hypothesis is expressed as follows:

$$H_0: \rho_i = 0, \qquad \forall\, i = 1, \ldots, N$$

that is *"each series contain unit root"* while the alternative hypothesis is stated as *"at least one of the cross-sections is stationary"*. Additionally, the t-statistics is calculated as follows:

$$t_{NT} = \frac{1}{N} \sum_{i=1}^{N} t_{\rho_i} \qquad \textit{Eq. 4.2}$$

The LLC test is based on estimating the following equation:

$$\Delta y_{it} = \rho y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta y_{it-j} + \delta_{mi} d_{mt} + \varepsilon_{it} \qquad \textit{Eq. 4.3}$$

As evidenced before, the structure of the equation is almost the same as the IPS test, but here, based on the assumption of homogeneity between sections, the coefficient ρ does not contain the *i* dimension. The null hypothesis for the LLC is expressed as follows:

$$H_0: \rho_i = \rho = 0, \qquad \forall\, i = 1, \ldots, N$$

Then again, the adjusted *t-statistics* for the LLC can be computed using the following formula:

$$t_\rho^* = \frac{t_\rho}{\sigma_T^*}\, NT \left[\frac{1}{N} \sum_{i=1}^{N} {}^{\hat{\sigma}_{y_i}}\!\big/_{\hat{\sigma}_{\varepsilon_i}}\right] \left(\frac{\hat{\sigma}_{\hat{\rho}}}{\hat{\sigma}_{\tilde{\varepsilon}}^2}\right) \left(\frac{\mu_T^*}{\sigma_T^*}\right) \qquad \textit{Eq. 4.4}$$

where μ_T^* is the mean adjustment and σ_T^* is standard deviation adjustment which are proposed in Levin et al. (2002) for different sample sizes and $\hat{\sigma}_{y_i}$ is a kernel estimator of long-run variance for the country *i*.

On a final note, Fisher type ADF test by Maddala and Wu (1999) is based on combining the significant levels obtained from individual tests. The null hypothesis for the Fisher-type ADF unit root is the same as the IPS test, H_0: $\rho_i = 0$ for all i=1, 2, 3, . . . , N and accordingly the test statistic with X^2 distribution and $2N$ degrees of freedom is calculated in the following way:

$$P_{MW} = -2\sum_{i=1}^{N} log(\rho_i) \qquad \textit{Eq. 4.5}$$

Many simulations are performed for assessing the performance of unit root tests in the literature. These simulations show the advantages and disadvantages of the IPS, LLC, and Fisher-type tests for different samples; it also reveals their superiority against each other. As a result, the LLC test is based on pooled regression, while the IPS test combines test results for all cross-sections. On the other hand, although Fisher-type tests also have a similar approach to the IPS test, one of the main differences between these two tests is the IPS test employs a combination of the test statistics while the Fisher-type test is produced combining the significance levels of the different individual tests. On the other hand, the IPS test is evaluated as parametric as the Fisher-type test is considered a nonparametric test, and the asymptotic structure of the IPS test is governed by $N \rightarrow \infty$ while for the Fisher-type test it depends on $T \rightarrow \infty$ (Im et al., 2003). According to Maddala and Wu (1999), the IPS is more influential than Fisher-type tests if there is no cross-sectional correlation in the error terms and, both are superior to the LLC test. However, Banerjee and Wagner (2009) state that if the cross-country relationships exist, the LLC test performs better than the IPS and Fisher-type test under the size distortion issues.

As highlighted, some advantages and disadvantages are discussed regarding the working principles of the aforementioned unit root tests. In this thesis, the results of three types of unit root tests are reported in order to support each other's results, and possible unclear points are tried to be removed.

4.3.3. Panel cointegration test

Throughout this thesis, Pedroni (1999, 2004) and Kao (1999) cointegration methods are used in relevant analyses and technical information on the subject is shared in Chapter 3. In this section, both methods are briefly summarized again.

It should be recalled that cointegration is one of the most employed approaches to investigate the long-term relationships in panel data studies. While Pedroni cointegration presents seven different statistics in two groups for both homogenous and heterogeneous panels, the Kao cointegration is performed for homogeneous panels. Both tests work under the independency assumption between cross-sections.

The use of Pedroni cointegration depends on the fact that all series are $I(1)$, that is, the first differences are stationary. If it is proved that the series are $I(1)$ by applied unit root methods, Pedroni cointegration can be used to show the existence of the long-term relationship between variables. As indicated earlier, Pedroni cointegration reports a total of seven different test statistics, four of which are panel statistics and three are group statistics. But for all tests in both categories, the null hypothesis is the same:

$$H_0: \rho_i = 1, \qquad for\ all\ i = 1, \dots, N$$

Also, the alternative hypothesis varies according to whether the test statistics is a panel or a group. For panel statistics:

$$H_1: \rho_i = \rho < 1, \qquad for\ all\ i = 1, \dots, N$$

This hypothesis is a *"homogeneous alternative"* and states that the coefficient ρ has a common value for all units and this value is less than 1. Pedroni cointegration panel statistics are also called *"within-dimension statistics"*.

Over and above, heterogeneous *"between-dimension"* test statistics' alternative hypothesis which allows different ρ coefficient across countries as follows:

$$H_1: \rho_i < 1, \qquad for\ all\ i = 1, \dots, N$$

Obviously, because of the seven different test statistics and the two different approaches for the alternative hypothesis, it is not common for all test statistics to be significant at the same time and is not expected in this study. However, based on the approach used in this study, the series must be determined cointegrated by at least one within-dimension and one between dimension test results. On the other hand, Panel PP t, Panel ADF, Group PP t, and Group ADF test statistics of Pedroni cointegration are presented in this study since Pedroni (2004) states that the ADF and PP t statistics are superior to group ρ statistics. Besides, it is important to note that, the panel ADF procedure is in common with the LLC test while the group ADF statistic is related to the IPS test.

In an attempt to apply Pedroni cointegration, all the models are given under the *"equations to be estimated"* title should be run first for each cross-sectional unit. Then, for the purposes of obtaining residuals, the following first differenced equation should be estimated:

$$\Delta y_{i,t} = \sum_{m=1}^{M} \beta_{mi} \Delta x_{mi,t} + \eta_{i,t} \qquad \textit{Eq. 4.6}$$

where *M* is the number of regressors. After the estimation progress above, the long-run variance of $\hat{\eta}_{i,t}$, that is $\hat{L}_{11i}^{2}$ is calculated employing the Newey-West kernel estimator. Subsequently, with $\hat{e}_{i,t}$ of the initial cointegration models, the autoregression is estimated using the equations of a) $\hat{e}_{i,t} = \rho_i \hat{e}_{i,t-1} + \hat{u}_{i,t}$ or b) $\hat{e}_{i,t} = \rho_i \hat{e}_{i,t-1} + \sum_{k=1}^{K} \varphi_{i,k} \Delta \hat{e}_{i,t-k} + \hat{u}_{i,t}^{*}$. The first equation is estimated for the non-parametric statistics while the second one is applied for the parametric statistics. For the non-parametric statistics, the long-run variance $\hat{\sigma}_{i,t}^{2}$ is calculated using the residuals, $\hat{u}_{i,t}$. If $\hat{s}_i^2$ is set as the simple variance of $\hat{u}_{i,t}$, then the term of $\hat{\lambda}_i$ is computed as $\hat{\lambda}_i = (\hat{\sigma}_{i,t}^{2} - \hat{s}_i^2)/2$. On the other hand, in the calculation process of parametric statistics, the residuals are used to calculate $\hat{s}_i^{*2}$, the simple variance of $\hat{u}_{i,t}^{*}$. With these steps, the seven test statistics which are reported in Pedroni (1999) can be computed and aftermath of that, the null hypothesis of $\rho_i = 1$ is analyzed.

As stated before, the Kao cointegration approach is used to check the robustness of Pedroni cointegration results. In this method, the residual terms are obtained by first estimating the original regression. Accordingly, the following equation is run:

$$\hat{e}_{i,t} = \rho \hat{e}_{i,t-1} + \sum_{j=1}^{p} \varphi_j \Delta \hat{e}_{i,t-j} + \nu_{i,t} \qquad \textit{Eq. 4.7}$$

where, p denotes the number of lags in the model. Then, the test statistic of Kao cointegration is expressed as follows:

$$Kao\ ADF = \left(t_{ADF} + \frac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_v}\right) / \sqrt{\frac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v^2} + \frac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}^2}} \quad \textit{Eq. 4.8}$$

where t_{ADF} represents the t-statistic of ρ. The null hypothesis of Kao cointegration is $H_0: \rho=1$ that states "no cointegration".

4.3.4. Estimation in panel cointegration models

In the study, the specifications including the series shown to be $I(1)$ and proven to be cointegrated in the long term are estimated by Panel Dynamic OLS and Fully Modified OLS methods as in the previous section. Preferred PDOLS and FMOLS methods are based on grouped means in this section. Grouped PDOLS and grouped FMOLS approaches are first employed in Pedroni (2001a), and these methods employ average between groups in estimating the panel long-term coefficients. These estimators cause fewer scale distortions than within-group estimators and in parallel, if the cointegration vectors exhibit a heterogeneous structure, these estimators provide more accurate estimates.

4.3.4.1. Grouped PDOLS

When describing the grouped-mean PDOLS estimator, a cointegrated panel system is considered as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it} \quad \textit{Eq. 4.9}$$

where x_{it} and y_{it} are integrated processes of $I(1)$, $x_{it} = x_{it-1} + \varepsilon_{it}$ and $y_{it} = y_{it-1} + \upsilon_{it}$ and both are cointegrated with slopes β_i which might or might not be homogenous among i. This model can be extended to panel data and applied a DOLS estimation on each country in the above equation as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} \sum_{j=-p_i}^{p_i} \gamma_{ik}\, \Delta x_{it-k} + u_{it}^{*} \quad \textit{Eq. 4.10}$$

where $i=1, 2, 3, \dots, N$ is the cross-sectional dimension, country, $t=1, 2, 3, \dots, T$ is the time period, p_i is the number of lags and leads, β_i is the coefficient of slope and x_{it} is the explanatory variable. From this regression, the group-mean panel DOLS estimator can be formed as:

$$\hat{\beta}^{*}_{G-PDOLS} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} z_{it}z'_{it}\right)^{-1}\left(\sum_{t=1}^{T} z_{it}\tilde{y}_{it}\right)\right] \qquad \textit{Eq. 4.11}$$

where $\tilde{y}_{it} = y_{it} - \bar{y}_i$ and z_{it} is the regressors' vector; $z_{it} = (x_{it} - \bar{x}_i, \Delta x_{it-K}, \dots, \Delta x_{it+K})$. Then the grouped-mean PDOLS estimator is simplified by:

$$\hat{\beta}^{*}_{G-PDOLS} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}^{*}_{DOLS,i} \qquad \textit{Eq. 4.12}$$

where, $\hat{\beta}^{*}_{DOLS,i}$ is the standard DOLS estimator, employed to the i^{th} panel member. The test statistic for the standard DOLS estimator is:

$$t_{\hat{\beta}^{*}_{DOLS,i}} = (\hat{\beta}^{*}_{DOLS,i} - \beta_0)\left[\hat{\sigma}_i^{-2}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2\right]^{\frac{1}{2}} \qquad \textit{Eq. 4.13}$$

where, $\hat{\sigma}_i^2$ is the long-run variance of the residuals u^{*}_{it} that is computed using Bartlett kernel estimator by Newey and West (1987). Then the related t-statistic for the grouped-mean PDOLS estimator can be computed as:

$$t_{\hat{\beta}^{*}_{G-PDOLS}} = N^{-0.5}\sum_{i=1}^{N} t_{\hat{\beta}^{*}_{DOLS,i}} \qquad \textit{Eq. 4.14}$$

Since the main purpose of this study is to explain unemployment, the dependent variable y_{it} represents U_{it}. Besides, U_{it} and explanatory variables are cointegrated with slopes β_i, which may or may not be homogeneous across countries i. It should be noted that HSE_{it} and LSE_{it} are also used as dependent variables with the same regressors in different specifications.

4.3.4.2. Grouped FMOLS

As discussed before, grouped-mean PDOLS results are reported with the grouped-mean FMOLS results to demonstrate the consistency of the outcome of the empirical findings. Like grouped PDOLS, Pedroni (2001b) recommends an estimator which takes the average of all individual units' FMOLS estimates. Again, based on Eq. 4.9 the grouped-mean FMOLS estimator can be computed as:

$$\hat{\beta}^{*}_{G-FMOLS} = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2\right)^{-1}\left(\sum_{t=1}^{T}(x_{it} - \bar{x}_i)y^{*}_{it} - T\hat{\gamma}_i\right) \qquad \textit{Eq. 4.15}$$

Again, the grouped FMOLS estimator can be simplified as:

$$\hat{\beta}^{*}_{G-FMOLS} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}^{*}_{FMOLS,i} \qquad \textit{Eq. 4.16}$$

where, $\hat{\beta}^{*}_{FMOLS,i}$ is the standard FMOLS estimator for the country *i*. The test statistic for the standard FMOLS estimator is computed as follows:

$$t_{\hat{\beta}^{*}_{FMOLS,i}} = (\hat{\beta}^{*}_{FMOLS,i} - \beta_0)\left(\hat{\Omega}^{-1}_{11i}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2\right)^{\frac{1}{2}} \qquad \textit{Eq. 4.17}$$

Then, the t-statistic for the grouped FMOLS is calculated as:

$$t_{\hat{\beta}^{*}_{G-FMOLS}} = N^{-0.5}\sum_{i=1}^{N} t_{\hat{\beta}^{*}_{FMOLS,i}} \qquad \textit{Eq. 4.18}$$

As a result, following cointegration tests, PDOLS and FMOLS methods are particularly useful choices to estimate the long-term relationship. Due to the non-stationary regressors, it is well known that the OLS estimate reports asymptotic biased results despite its super consistency; PDOLS and FMOLS methods, on the other hand, generate unbiased estimators asymptotically. Another advantage of these approaches is that they allow the accumulation of long-term information in the panel while allowing short-term dynamics and fixed effects to be heterogeneous among different members of the panel (Pedroni, 2001a).

In the following chapters, the results of the analysis performed based on the empirical methodology stated above are reported.

4.4. Empirical Results

The process similar to that applied to developed countries in the previous chapter is repeated for developing countries as well. Under this heading, unit root test results are shared first, and then the basis for estimating the coefficients is established by proving that the variables are cointegrated in the established models. In the last section, coefficient estimates obtained by both PDOLS and FMOLS methods are given.

4.4.1. Unit root test results

Table 4.7 presents the unit root test statistics of the variables in both levels and $I(1)$ without trend, while Appendix Table B1 contains the test results performed by adding the trend. One of the ten variables according to the LLC test, six of the ten variables according to the IPS test, and four of the ten variables according to the ADF-Fisher type test are not stationary at the level because the null hypothesis of *"each series contain unit root"* cannot be rejected even at the 5% level. However, for all three test types, the series are *I*(1), because the null of nonstationarity cannot be rejected for the levels of all series but is rejected for the first differences. So, taking the first difference of variables, though, the result would incline to approve the hypothesis that the series is *I*(1) variable, as differencing rejects the null and therefore eliminates the unit root. The trended results in Appendix Table B1 also report more non-stationary variables at the level but contain similar findings for the first difference. As a result, according to the results of three different unit-root tests performed both with and without trend, after taking the first difference, all variables are treated as *I*(1).

Table 4.7. Results of panel unit root tests (w/o trend)

Variables	LLC		IPS		ADF - Fisher	
	Level	First difference	Level	First difference	Level	First difference
U_t	-3.081 [0.001]***	-13.492 [0.000]***	-3.801 [0.000]***	-13.850 [0.000]***	82.636 [0.001]***	262.961 [0.000]***
HSE_t	-1.690 [0.046]*	-16.090 [0.000]***	0.934 [0.825]	-16.064 [0.000]***	46.465 [0.453]***	308.470 [0.000]***
LSE_t	-2.692 [0.004]**	-15.399 [0.000]***	-1.340 [0.090]	-14.947 [0.000]***	50.619 [0.296]	287.732 [0.000]***
RD_t	-3.861 [0.000]***	-7.363 [0.000]***	0.830 [0.797]	-12.732 [0.000]***	62.959 [0.049]*	253.435 [0.000]***
GDP_t	-2.132 [0.017]*	-11.995 [0.000]***	3.199 [0.999]	-12.912 [0.000]***	29.373 [0.973]	247.637 [0.000]***
CPI_t	-7.060 [0.000]***	-13.853 [0.000]***	-10.738 [0.000]***	-13.359 [0.000]***	258.569 [0.000]***	256.577 [0.000]***
PRD_t	-1.398 [0.081]	-15.641 [0.000]***	1.958 [0.975]	-17.683 [0.000]***	49.638 [0.330]	338.215 [0.000]***
INT_t	-4.228 [0.000]***	-24.497 [0.000]***	-7.124 [0.000]***	-25.278 [0.000]***	138.956 [0.000]***	498.441 [0.000]***
OPN_t	-5.216 [0.000]***	-21.245 [0.000]***	0.270 [0.606]	-19.357 [0.000]***	52.452 [0.238]	374.168 [0.000]***
EXC_t	-3.395 [0.000]***	-15.991 [0.000]***	-1.910 [0.028]*	-16.571 [0.000]***	69.819 [0.013]*	325.173 [0.000]***

Note: All the variables include a constant. In order to detect the optimal lag length, the Schwarz Information Criterion (SIC) is used. Newey-West bandwidth selection with Bartlett kernel is applied for the LLC test. All the variables are in natural logs, excluding U_t, HSE_t, LSE_t, and INT_t. P-values are given in the brackets. *Rejection of the null hypothesis of nonstationarity at the 0.05 level, **Rejection of the null hypothesis of nonstationarity at the 0.01 level, ***Rejection of the null hypothesis of nonstationarity at the 0.001 level.
Source: Author's calculations.

4.4.2. Panel cointegration and estimation results for unemployment

After obtaining convincing evidence that all panel series are $I(1)$ processes, Pedroni's panel cointegration test is employed to confirm the existence of the long-run relationship among variables in Model 4.1 to Model 4.6. Table 4.8 shows the different test results attributable to Pedroni as well as Kao. The test statistics present that the null of no cointegration can be strongly rejected in all the models except Model 4.6. In Model 4.6, cointegration is not as statistically significant and powerful as in other models. In conclusion, looking at all cointegration tests, even though the selected series in different model variations themselves might be nonstationary, they however incline to move firmly together according to established models over time and the difference between them is constant.

Table 4.8. Results of panel cointegration tests for unemployment

Test	Statistics		Model 4.1	Model 4.2	Model 4.3	Model 4.4	Model 4.5	Model 4.6
			RD, GDP, CPI	*RD, GDP, CPI, PRD*	*RD, GDP, CPI, PRD, INT*	*RD, GDP, CPI, PRD, OPN*	*RD, GDP, CPI, PRD, EXC*	*RD, GDP, CPI, PRD, OPN, EXC*
Pedroni	Panel	Panel PP t	-0.390	-2.595^{**}	-1.784^{*}	-2.338^{**}	-1.327^{+}	-0.764
		Panel ADF t	-3.916^{***}	-3.843^{***}	-3.239^{***}	-3.159^{**}	-3.981^{***}	-1.448^{+}
	Panel weighted	Panel PP t	-0.786	-1.054	-1.376^{+}	-1.197	-0.598	0.055
		Panel ADF t	-3.537^{***}	-2.750^{**}	-3.443^{***}	-2.744^{**}	-2.407^{**}	-0.641
	Group	Group PP t	0.229	-0.729	-0.872	-2.019^{*}	-1.332	-1.875^{*}
		Group ADF t	-4.131^{***}	-2.647^{**}	-1.938^{*}	-2.735^{**}	-1.866^{*}	-0.764
Kao		ADF t	-4.802^{***}	-4.343^{***}	-4.170^{***}	-4.630^{***}	-4.508^{***}	-4.668^{***}

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the AIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the variables are in natural logs, excluding U_t and INT_t. $^{+}$Rejection of the null hypothesis of no cointegration at the 0.1 level, *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

With robust evidence in favor of cointegration in five of the 6 different models, from Model 4.1 to Model 4.6, the coefficients of the series in the models are estimated by both PDOLS and FMOLS methods. The estimates made according to the PDOLS and FMOLS methods for Model 4.1 and Model 4.2, which were first selected as the baseline specifications, are shared in Table 4.9. The main focus of the study is technology, and therefore it primarily focuses on β estimates, which is the coefficient of R&D chosen as a technology proxy. Positive β coefficients show that there is a positive relationship between technology and unemployment in developing countries, which indicates technology causes labor-saving more than labor-creating.

Table 4.9. PDOLS and FMOLS estimates results for the baseline models of unemployment

Variables	Model 4.1			Model 4.2		
	PDOLS			PDOLS		
	leads & lags AIC (*)	leads & lags (1 1)	FMOLS	leads & lags AIC (*)	leads & lags (1 1)	FMOLS
RD_t	0.0304	0.0267	0.0346	0.0351	0.0306	0.0332
	(3.557)***	(3.034)**	(6.246)***	(5.127)***	(3.513)***	(8.699)***
GDP_t	-0.1703	-0.1679	-0.2053	-0.4456	-0.4113	-0.3449
	(-8.713)***	(-8.182)***	(-15.327)***	(-17.321)***	(-10.697)***	(-21.997)***
CPI_t	0.0558	0.0579	0.0727	0.0502	0.0560	0.0573
	(3.265)**	(3.286)**	(13.835)***	(4.532)***	(3.501)***	(11.324)***
PRD_t				0.3389	0.3043	0.2157
				(11.256)***	(6.600)***	(11.541)***

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags, and fixed leads & lags results are also reported. The grouped estimation is used as a panel method for both estimators. As the dependent variable, decimal fractions of U_t are used. All the independent variables are in natural logarithms and t-values are given in the parentheses. $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

In addition to the baseline models, four different models including variations of other control variables are estimated and the results are given in Table 4.10. Although the direction of β does not change in these estimates, its magnitude varies from model to model. When all six models are considered, the β coefficient varies between 0.02 and 0.05. It should be noted that this range is between 0.01 and 0.03 in developed country estimations obtained by the same methods. Therefore, the devastating impact of technology proxied by R&D on overall employment is greater in developing countries than in developed countries.

When other control variables are examined, it is seen that GDP per capita is inversely related to unemployment, and in this respect, the findings are in line with those in developed countries. According to PDOLS results, α_1, GDP per capita coefficient varies between -0.17 and -0.51. Although the range of the estimated coefficients is wider in both directions compared to the findings for developed countries, there is no significant divergence in the sizes. In this respect, the partial compensatory effect of the increase in income in developing countries can be mentioned. The effect of inflation on unemployment is parallel to the findings obtained in developed countries and the relationship between inflation and unemployment is positive.

Table 4.10. PDOLS and FMOLS estimates results for the additional specifications of unemployment

Variables	Model 4.3		Model 4.4		Model 4.5		Model 4.6	
				PDOLS				
RD_t	0.0204	(2.369)*	0.0443	(5.363)***	0.0207	(2.309)*	0.0480	(4.102)***
GDP_t	-0.3224	(-7.312)***	-0.5116	(-12.574)***	-0.3586	(-10.166)***	-0.4734	(-7.168)***
CPI_t	0.0652	(4.513***	0.0569	(6.473)***	0.0905	(7.241)***	0.0377	(1.981)*
PRD_t	0.2202	(4.718)***	0.3897	(7.815)***	0.2082	(4.403)***	0.5331	(6.131)***
INT_t	0.1065	(3.019)**						
OPN_t			-0.0047	(-0.376)			-0.0372	(-1.752)$^{+}$
EXC_t					0.0104	(0.625)	0.0029	(0.134)
				FMOLS				
RD_t	0.0347	(9.798)***	0.0261	(7.110)***	0.0300	(7.537)***	0.0252	(7.894)***
GDP_t	-0.3381	(-22.152)***	-0.3794	(-23.979)***	-0.3641	(-24.949)***	-0.3763	(-24.880)***
CPI_t	0.0568	(11.618)***	0.0513	(12.486)***	0.0559	(11.651)***	0.0522	(13.969)***
PRD_t	0.2077	(11.707)***	0.2766	(15.267)***	0.2557	(13.766)***	0.2913	(17.757)***
INT_t	0.0256	(2.512)*						
OPN_t			0.0031	(0.655)			-0.0022	(-0.471)
EXC_t					-0.0169	(-3.793)***	-0.0120	(-2.508)*

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags and the grouped estimation is used as a panel method. As the dependent variable, decimal fractions of U_t are used. All the independent variables are in natural logarithms excluding INT_t and t-values are given in parentheses. $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

There is a direct correlation between another control variable, output per worker, and unemployment, as in developed countries. In this respect, the results are in parallel with those in developed countries. According to the PDOLS results, the PRD_t coefficient α_3 ranges between 0.22 and 0.51, which is wider than the estimates obtained for developed countries. In developing countries, the increase in income can partially compensate for job losses due to technology-induced productivity gains. But the overall technology impact on employment is adverse.

As expected, the real interest rate is among the factors that increase unemployment. In Model 4.3, where the variable is used, the INT_t coefficient is estimated as 0.107 with

PDOLS and 0.027 with FMOLS. OPN_t, which is represented by the ratio of countries' export and import activities to total income, is negatively related to unemployment according to PDOLS results, but the statistical significance of the coefficients is not strong enough. Only the OPN_t coefficient estimated in Model 4.6 is negative and significant at 10%. Therefore, it is concluded that there is a positive but weak relationship between the openness levels of countries and employment. Finally, the EXC_t variable is insignificant, as in developed countries, according to PDOLS estimations.

4.4.3. Panel cointegration and estimation results for employment by skills

After empirical reporting of the effect of technology on overall employment in developing countries, the analyses are extended to two different skill groups. Firstly, in Table 4.11, the cointegration results of the variables in the four models established for the high employment group are shown. According to almost all Pedroni's cointegration test statistics in all models, the null hypothesis of *"no cointegration"* is rejected, so it is concluded that the series in the model have a significant relationship with each other in the long run. All of the Kao cointegration results are also significant at the 5% significance level and support the Pedroni test statistics.

Table 4.11. Results of panel cointegration tests for high-skilled employment

Test	Statistics		Model 4.7 *RD, GDP, CPI*	Model 4.8 *RD, GDP, CPI, PRD*	Model 4.9 *RD, GDP, CPI, PRD, INT*	Model 4.10 *RD, GDP, CPI, PRD, OPN*
Pedroni	Panel	Panel PP t	-1.044	-2.126^{*}	-1.354^{+}	-2.338^{**}
		Panel ADF t	-2.068^{*}	-2.491^{**}	-2.015^{*}	-4.264^{***}
	Panel weighted	Panel PP t	-3.111^{***}	-3.682^{***}	-2.303^{*}	-4.102^{***}
		Panel ADF t	-4.044^{***}	-4.972^{***}	-3.268^{***}	-4.823^{***}
	Group	Group PP t	-1.606^{+}	-3.131^{***}	-2.263^{*}	-3.904^{***}
		Group ADF t	-2.559^{**}	-2.812^{**}	-2.099^{*}	-3.516^{***}
Kao		ADF t	-1.688^{*}	-1.925^{*}	-2.195^{*}	-2.204^{*}

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the variables are in natural logs, excluding HSE_t and INT_t. $^{+}$Rejection of the null hypothesis of no cointegration at the 0.1 level, *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

After proving that the series are cointegrated, the coefficients of the variables in the models are estimated with the PDOLS and FMOLS methods. At this point, it is striking that the effect of technology on high-skilled and low-skilled employment is strongly differentiated in developing countries compared to developed countries. According to PDOLS estimates in Table 4.12 (FMOLS results are shared in Appendix Table B2), β ranges between -0.004 and -0.008 in developing countries, and all coefficients are statistically significant. Therefore, contrary to the findings for developed countries, technology negatively affects high-skilled employment in developing countries. However, it should be emphasized that the impact of R&D on high-skilled employment in developing countries is exceedingly small compared to other coefficients. Although there are many important reasons for this, one of the important reasons that can be mentioned here is that the use of technology in developing countries is based on imported high-tech products as well as R&D investments, but the second factor mentioned here is not included in the models. Therefore, R&D has a significant impact, but the power to stand for technology shocks alone in developing countries is lower than in developed countries. However, the R&D stock of developing countries gives an idea of the nature of the technology they use, as R&D investments give an idea of the ability of countries to use the technology. As a result, while technology is skill-biased in developed countries, the demand for skilled employment in developing countries cannot turn into employment at a level to compensate for worker losses. One of the reasons for this may be that the skill upgrade in the current skill composition of developing countries cannot adequately respond to the speed of technology diffusion.

GDP per capita, which is one of the other control variables added to the model, is among the factors that increase high-skilled employment as expected. It should be noted that α_1, GDP per capita coefficient for high-skilled employment varies between 0.07 and 0.09 in developing countries. These values are lower than the values found for developed countries. Therefore, it can be said that the efficiency of the employee compensation mechanism through the increase in income is lower than that of developing countries in the case of high-skilled employment. Inflation, another important control variable, moves in the same direction as high-skilled employment, as in developed countries, and this result is in line with Philips Curve. The *"skill premium"* may be an explanation for the trend in inflation and high-skilled employment in both developed and developing countries. The demand for high-skilled workers, which increases with the use of technology in these countries, can also increase the average wage of high-skilled workers, causing inflation. This means that the Philips Curve approach is satisfying for high-skilled employment.

Table 4.12. PDOLS estimates results for high-skilled employment

Variables	Model 4.7		Model 4.8		Model 4.9		Model 4.10	
RD_t	-0.0042	$(-2.520)^{*}$	-0.0049	$(-1.926)^{+}$	-0.0084	$(-2.622)^{**}$	-0.0073	$(-2.682)^{**}$
GDP_t	0.0716	$(15.150)^{***}$	0.0815	$(6.445)^{***}$	0.0857	$(4.660)^{***}$	0.0663	$(4.899)^{***}$
CPI_t	0.0058	$(5.335)^{***}$	0.0057	$(5.232)^{***}$	0.0083	$(4.399)^{***}$	0.0065	$(4.990)^{***}$
PRD_t			-0.0137	(-1.120)	-0.0071	(-0.442)	-0.0350	$(-2.822)^{**}$
INT_t					0.0282	(1.663)		
OPN_t							0.0163	$(3.964)^{***}$

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags. The pooled weighted estimation is used as the panel method for the PDOLS estimator. All the independent variables are in natural logarithms excluding INT_t. Besides, t-values are given in the parentheses. As the dependent variable, decimal fractions of HSE_t are used. $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Although the coefficient of PRD_t, α_3, which is one of the other control variables, is estimated as negative for high-skilled employment, as in developed countries, according to the PDOLS results, it is insignificant in two of the three models, and it is half the effect of GDP in the model that is significant. Therefore, there is a potential for high-skilled employment to be compensated by the increase in income in developing countries as a result of the increase in productivity with the effect of technology and non-technology shocks. In the last two control variables, real interest rate and openness, the results show that the first has no significant effect on high-skilled employment, while the second is more significant at the 1% level and has a positive effect on high-skilled employment.

Table 4.13 shows the results of the cointegration tests of the models established for low-skilled employment in developing countries. Strong cointegration is reported between series in the three specifications, but not for Model 4.7. In Model 4.7, while one of the six Pedroni cointegration test statistics is significant at 5% and two at 10%, the results are not as strong as in other models because the other three test statistics are insignificant. In addition, the Kao test statistic is significant even at the 1% level in all models. As a result, there is a statistically significant cointegration between the series in the models established for low-skilled employment in developing countries.

Table 4.13. Results of panel cointegration tests for low-skilled employment

Test	Statistics		Model 4.7 *RD, GDP, CPI*	Model 4.8 *RD, GDP, CPI, PRD*	Model 4.9 *RD, GDP, CPI, PRD, INT*	Model 4.10 *RD, GDP, CPI, PRD, OPN*
Pedroni	Panel	Panel PP t	-0.203	-1.664^{*}	-0.732	-2.144^{*}
		Panel ADF t	-2.037^{*}	-3.886^{***}	-2.717^{**}	-4.179^{***}
	Panel weighted	Panel PP t	-0.683	-2.968^{**}	-1.833^{*}	-3.886^{***}
		Panel ADF t	-1.537^{+}	-4.858^{***}	-2.911^{**}	-5.311^{***}
	Group	Group PP t	0.963	-1.049	0.260	-2.170^{*}
		Group ADF t	-1.341^{+}	-2.091^{*}	-1.160	-2.791^{**}
Kao		ADF t	-3.143^{***}	-2.998^{***}	-2.809^{**}	-3.503^{***}

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the variables are in natural logs, excluding LSE_t and INT_t. $^{+}$Rejection of the null hypothesis of no cointegration at the 0.1 level, *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

Having detected the powerful cointegration in the panel series, the PDOLS and FMOLS estimators are employed to estimate long-run parameters as in previous parts. PDOLS results are given in Table 4.14 and FMOLS results are in Appendix Table B3. Technology adversely affects low-skilled employment in developing countries as well as in developed country results since β estimates are negative which ranged between -0.018 and -0.028. These results lead the study to two important findings. First of all, the effect of technology on employment in developing countries is 3.5 to 4.5 times higher for low-skilled workers than for high-skilled workers. Second, perhaps more importantly, the negative low-skilled employment impact of technology proxied by R&D in developing countries is milder than in developed countries. Especially in the first chapters of the thesis, this subject is mentioned, and it is stated that in developing countries, manpower still has a comparative advantage in terms of wages against technology in many areas, and therefore technology spreads more slowly in developing countries. For this reason, low-skilled workers working in jobs prone to automation in these countries are affected more slowly by technology. Therefore, although the effect of technology on low-skilled employment is negative in both developed and developing countries, the effect is less severe in developing countries. On the other hand, this negative effect seems to be less compensated, that is, it cannot be fully compensated by other channels of low-skilled employment in developing countries. For example, when the estimated coefficients of GDP per capita, which is among the core independent variables, are examined, it is seen that the values are higher than high-skilled employment. Therefore, the increase in GDP has more power to compensate for the losses in low-skilled employment, but since the loss of workers as a result of increased productivity due to technological and non-technological shocks is much higher in this group than in high-skilled, it can be concluded that the difference cannot be balanced only with the increase in income. Finally, when this situation is combined with the negative effect in high-skilled employment, it causes the overall employment to be negatively affected by technology. Having detected the powerful cointegration in the panel series, the PDOLS and FMOLS estimators are employed to estimate long-run parameters as in previous parts.

Table 4.14. PDOLS estimates results for low-skilled employment

Variables	Model 4.7		Model 4.8		Model 4.9		Model 4.10	
RD_t	-0.0181	(-2.261)**	-0.0268	(-3.935)***	-0.0280	(-3.259)**	-0.0221	(-2.022)*
GDP_t	0.1074	(5.806)***	0.3758	(13.829)***	0.3483	(7.310)***	0.4004	(8.596)***
CPI_t	-0.0833	(-4.523)***	-0.0628	(-4.130)***	-0.0776	(-3.852)***	-0.0871	(-5.481)***
PRD_t			-0.3719	(-10.882***	-0.3671	(-6.858)***	-0.3675	(-5.903)***
INT_t					-0.0976	(-1.649)		
OPN_t							0.0167	(1.126)

Note: For the PDOLS estimator, the SIC is used to determine the leads & lags and grouped estimation is used as the panel method. All the independent variables are in natural logarithms excluding INT_t. Besides, t-values are given in parentheses. As the dependent variable, decimal fractions of LSE_t are used. $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

The coefficient of inflation, which is one of the other control variables, is negative, unlike high-skilled employment estimates. This conclusion is also plausible, as the reduction in low-skilled employment in developing countries causes low-skilled workers to be willing to work for lower wages, lowering their wages, which in turn reverses the relationship between inflation and low-skilled employment. The coefficients of the real interest rate and openness variables are as expected, the first is negative and the second is positive. However, according to the PDOLS results, both variables are statistically insignificant.

4.5. Concluding remarks

In this section, the effect of technology on employment has been investigated on the basis of two different skill groups in developing countries. In the study, data from 23 different developing countries covering the years 1990-2019 were used. The effects of technology on the current demand for low-skill or routine jobs in developing countries are more limited than in developed economies. Because technology adaptation takes more time in developing countries. Second, the average wages of the current workforce in these countries are relatively low, which enables the workforce to maintain its comparative advantage over technology. Therefore, automation does not become attractive as early as in developed countries. On the other hand, if technology is ready for use in developing countries, the skill constraint in countries reveals that few employees or firms can benefit from it. However, this does not mean that the entire developing country pool cannot benefit from technological change. Asian countries such as China and India have switched from traditional methods to modern technologies, especially in the manufacturing sector, and have achieved significant gains.

In light of the foregoing, the chapter first analyzes how and to what extent per capita R&D expenditure used as a technology proxy is related to overall unemployment in developing countries. Secondly, employment in developing countries is divided into high-skilled and low-skilled and how these two groups are affected by technology is investigated. In this direction, three different unit-root tests, the LLC, the IPS, and ADF-Fisher, have been proved that all of the variables used in the different model variations are

I(1). Then, it has been shown by both Pedroni (1999, 2004) and Kao (1999) cointegration methods that the series proven to be *I*(1) have a statistically significant relationship with each other in the long run in line with the different models established. In five of the six models created for the dependent variable of unemployment, evidence of the presence of strong cointegration was found. All four models that were established to explain high-skilled employment, and three of four models for low-skilled employment again indicate the presence of strong cointegration. After the findings in favor of cointegration, the coefficients of the variables in the models established for all three dependent variables were estimated by grouped mean PDOLS (Pedroni, 2001a) and grouped mean FMOLS (Pedroni, 2001b) methods. The results obtained at the end of all these stages are summarized as follows:

i) Unemployment, R&D expenditures, and other control variables included in the study are cointegrated in the long run in developing countries. The validity of this statistically significant relationship has been proven in different models established. The coefficients obtained with the PDOLS and FMOLS estimators show that technology is among the factors that increase unemployment in developing countries. Six different models established for the dependent variable of unemployment were estimated by both the PDOLS method and different levels of lag specifications within the method, as well as the FMOLS method, and all R&D coefficients were calculated as negative, consistent with each other. The R&D coefficient, which is β, was calculated in the range of 0.0204 to 0.0480 according to the PDOLS estimation results, in which leads and lags are automatically determined by the AIC. The range of R&D coefficients estimated by the FMOLS method was determined as 0.0252 to 0.0347. Although the signs of the coefficients obtained by both methods are the same, the FMOLS method estimated the effect size as a narrower range. The coefficient of GDP per capita, which is the leading among the key control variables, was calculated as negative as expected. The coefficients were estimated between -0.1703 and -0.5116 based on the PDOLS method and between -0.2053 and -0.3763 based on the FMOLS method. Therefore, the increase in income is an important employment booster, but the compensation mechanism can only be mentioned superficially since it is not taken into account in this study how much of the income increases due to technological advances. Because the coefficient of employee productivity affected by technical and non-technical shocks is negative, the same output is achieved with less labor over time. The coefficient of the productivity variable was estimated as 0.2202 to 0.5331 based on the PDOLS, which has an effect size greater than the GDP per capita effect size. Therefore, although the increase in income in developing countries is an important compensation channel to suppress unemployment, it does not have the power to completely eliminate the labor-saving effect of both technological and non-technological shocks. Considering baseline models, inflation is among the factors that increase unemployment in developing countries. Among the other control variables, the interest rate coefficient was estimated as 0.1065 as reported by the PDOLS method and as 0.0256 based on the FMOLS. Subsequently, real interest rates are among the factors that increase unemployment in developing countries. As estimated by the PDOLS method, trade openness seems to be among the factors reducing unemployment in developing countries, but its statistical significance is weak. Finally, the real exchange rate coefficient is positive in the models established for unemployment according to the PDOLS method, but it is not statistically significant.

ii) Secondly, the coefficients of the series in the four models in which both high-skilled and low-skilled employment are established and proven to be cointegrated in developing countries are estimated by PDOLS (Pedroni, 2001a) and FMOLS (Pedroni, 2001b). The results show that both high-skilled and low-skilled employment in developing countries is negatively affected by technology. However, while all other effects are equal, the effect of technology on high-skilled employment is quite low since the R&D coefficient in the four models estimated by PDOLS is between -0.0042 and -0.0073. According to the FMOLS method, the effect size was calculated lower than PDOLS, the coefficients ranged from -0.0028 to -0.0067. On the other hand, the effect of economic growth on the high-skilled group in developing countries is positive and significant, with the GDP per capita coefficient estimated between 0.0639 and 0.1445. Considering the negative but low productivity coefficients compared to the GDP per capita coefficient, it is seen that the negative but low impact of technology on high-skilled employment in developing countries can be compensated by the increase in income channel. For low-skilled employment, the results are more striking. The technology coefficients estimated by PDOLS range from -0.0181 to -0.0221, indicating that the disruptive impact of technology on low-skilled employment in developing countries is 2.5 to 5.3 times greater than that estimated for high-skilled employment. Furthermore, in the models established for low-skilled employment, the coefficient of income varies between 0.1074 and 0.4004, while the productivity coefficient varies between -0.3675 and -0.3719. In the models estimated by FMOLS, the coefficients are located in a narrower range, but the signs are parallel with PDOLS. In this respect, it is seen that the increase in income is an important compensation channel in developing countries, but the labor-saving effect from technical and nontechnical shocks cannot be fully compensated. When the inflation effects for high-skilled and low-skilled employment are controlled separately, it is seen that the effect direction is different for both skill groups. Philips Curve is held for high-skilled employment, but low-skilled employment is negatively affected by inflation. There is no statistically significant effect of the interest rate for both groups. The effect of trade openness on both high-skilled and low-skilled employment is positive, but the coefficient calculated for low-skilled employment is not statistically significant.

iii) In developing countries, the effect of technology on employment is negative, as in developed countries, but there are differences in the size of the coefficients for both groups of countries. In the models established for unemployment, based on all the β coefficients estimated by both estimators, the coefficient range is estimated to be 0.0204 to 0.0480 in developing countries, and 0.0125 to 0.0344 in developed countries. It should be noted that these ranges are coefficients based on different models estimated by both PDOLS and FMOLS. Thus, a higher labor-saving impact range was estimated, which could be negligible in developing countries. On the other hand, GDP per capita coefficients in developed countries are estimated between -0.4405 and -0.1229 based on all estimators and all models used, while this range is between -0.5116 and -0.1703 in developing countries. Therefore, the employment-increasing effect of economic growth in developing countries is greater than in developed countries. While the labor-saving effect of increased worker productivity with the effect of technological and non-technological shocks is estimated between 0.2077 and 0.5331 in developing countries, this range is narrower and smaller for developed countries; 0.3220 to 0.3996. Therefore, it can be concluded that the increase in income in developed countries has the power to balance the labor-saving effect experienced with technical and non-technical effects, but the effect of labor-saving in developing countries is higher than the effect of labor-saving gained with income increase. The reason for this, as mentioned in the next step, is the share of the highly skilled workforce in the total workforce in developed countries.

iv) When the technology effect on employment groups by skills is compared with respect to two different country groups, more striking results are obtained. First of all, while technology affects high-skilled employment positively in developed countries, the effect is in the opposite direction in developing countries, although its size is very low. The effect size of R&D on high-skilled employment in developing countries varies between -0.0084 and -0.0042 according to PDOLS results, while this range is between 0.0310 and 0.0558 in developed countries. While the GDP per capita effect is calculated between 0.0633 and 0.0857 according to the PDOLS estimator in developing countries, these values are between 0.1121 and 0.1632 in developed countries. Therefore, the power of income growth to create additional employment for the high-skilled group is higher on average in developed countries. The relationship between labor productivity and employment with high-skilled employment is negative but mostly statistically insignificant in both country groups. Of course, the most important reason for this situation is that technology plays a labor complementary role rather than a labor substitute for the high-skilled group. Secondly, although the effect of technology on low-skilled employment is negative in developed and developing countries, the magnitude of the negative effect is greater in developed countries. As a result of estimating the models established for developed countries with PDOLS, the technology coefficient is estimated between -0.0735 and -0.0398, while it is between -0.0280 and -0.0181 in developing countries. Therefore, the negative impact of technology on low-skilled employment in developed countries is 1.4 to 4.1 times higher than in developing countries. This result is reasonable because, as mentioned in the previous sections, low-skilled employment is retained longer in developing countries due to lower wages and late technology adoption. The low-skilled employment-increasing effect of GDP per capita is higher in developing countries. Because while PDOLS coefficients are estimated between 0.3483 and 0.4004 in developing countries, the effect range is 0.0843-0.2492 in developed countries. Therefore, while the labor-creating effect of GDP per capita for high-skilled employment is higher in developed countries than in developing countries, the labor-creating effect for low-skilled employment in developing countries is higher than in developed countries. While the coefficients of labor productivity are between -0.2096 and -0.2564 in developed countries, it is between -0.3719 and -0.3671 in developing countries.

As a result, the overall unemployment effect of technology in developing countries is in the direction of labor-saving, as in developed countries, and in this respect, the effect sizes are close to each other. Although it is seen that both skill groups are negatively affected by technology in developing countries, the negative effect on high-skill employment is relatively low. On the other hand, the increase in income channel is an effective compensation mechanism for high-skilled employment. In addition, low-skilled employment in developing countries is less affected by technology than in developed countries, since the wages of workers in these countries are relatively low, so the comparative advantage of labor continues for longer. However, considering the fact that this situation will not continue forever, developing countries should make effective use of public policies to reduce threats in the future. In this context, measures such as eliminating bottlenecks, restrictions, and inequalities in access to technology, providing affordable and reliable internet, and advanced digital payment systems are important. In addition, supporting the participation of education systems in the digital world with the necessary equipment, IT-oriented workforce models and the effective integration of online work platforms into labor markets will help the workforce to become qualified for jobs that require higher skills today and will require them in the future. The direct and indirect effects of technology are inevitable and continuous. The cost advantage of labor in developing countries is not permanent and this advantage disappears as robots become cheaper. Thus, the destructiveness of the labor-saving effect may be more sudden and severe in developing countries. Mitigating or eliminating this impact depends on increasing the adaptability of both the economic structure as a whole and the current and future potential workforce individually.

CHAPTER 5: THE RELATIONSHIP BETWEEN TECHNOLOGY AND UNEMPLOYMENT AT THE SECTORAL LEVEL

5.1. Introduction

The impact of innovation on employment is expected to differ across sectors. Because industries differ from each other, including the diversity of technological innovations they achieve, their cumulative knowledge, and their ability to preserve the gains from innovation (Dosi and Nelson, 2010). In developed and developing countries, the workforce is shifting from agriculture to manufacturing and then from manufacturing to the service sector. For example, there is a significant gap between the service and the manufacturing sectors in the European employment structure, and higher employment increases in the service sector are reported in the region. Dachs (2018) states that the sectors with the fastest increase in employment in Europe between 2008 and 2013 are market knowledge-intensive services and high-tech knowledge-intensive services. One reason for this is that service sector products have higher income elasticity. Another result is that the manufacturing sector has shifted from Europe to countries with lower labor costs due to the higher trade openness in the sector (Veugelers, 2013). Thirdly, process innovation brings higher productivity gains in the manufacturing sector than in the service sector (Baumol, 2012). Process innovations in the service industry are based on changes that require less technical, more customer interaction, and higher social skills, and are mostly the result of user-manufacturer interaction, as service products are less standardized than manufacturing products (Tether et al., 2001; Dachs, 2018).

The extent to which employment transitions between sectors are affected by technology is an important pillar of the debate. Pianta (2005) states that there are generally technology-related job losses in some sectors but points out that there is heterogeneity between sectors. The author shows that employment is positively affected in high-tech sectors that provide high product innovation, while employment is negatively affected in traditional sectors such as textile or leather, which have high process innovation, due to the high substitutability of the sector. In this direction, especially in studies dealing with developed countries, the findings on the effect of innovation on employment in the manufacturing sector are mostly heterogeneous. While some studies empirically prove the labor-saving effect of technology on manufacturing employment, especially process innovations (Zimmerman, 1991; Brouwer et al., 1993; Vivarelli, 1996; Yasuda, 2005; Bogliacino and Pianta, 2010; Compagnucci et al., 2019), some studies report that product innovations, in particular, have a positive net employment impact in the manufacturing sector (Van Reenen, 1997; Hall et al., 2009; Lachenmaier and Rottmann, 2011; Evangelista and Vezzani, 2012; Harrison et al., 2014). In Van Roy et al. (2018), manufacturing companies are categorized as high, medium, and low-tech, and it was found that innovation creates labor demand in high and medium-tech manufacturing companies but does not significantly affect employment in low-tech firms. Bogliacino et al. (2012), in parallel with Van Roy et al. (2018), found the employment effect of innovation in traditional manufacturing firms as insignificant. In the service sector, the empirical literature mostly presents a positive employment-technology relationship (Bogliacino and Pianta, 2010; Bogliacino et al., 2012; Harrison et al., 2014; Piva and Vivarelli, 2018,). In more recent studies that offer a multi-sectoral perspective, it is claimed that technology-related employment losses especially in the manufacturing sector are balanced with the increasing labor demand in other areas like mainly service sector (Autor and Salomons, 2017; Graetz and Michaels, 2018; Dauth et al., 2018). In addition, job polarization and routine-biased technological change approaches are also related to sectoral differences in employment and to what extent this differentiation is affected by technology. The decline in certain sectors plays a significant role in the loss of medium-skill jobs relative to high- and low-skill occupations in most developed and developing countries. The polarization in both the demand for skills and the wages depending on the demand has been experienced in the form of significant labor force transitions from less polarized sectors such as agriculture and manufacturing to more polarized service sectors (IMF, 2018; Soto, 2020). As stated by Autor et al. (2006), Goos and Maning (2007), Autor and Dorn (2013), Goos et al. (2014), and Lee and Shin (2017), routine tasks shrink compared to non-routine jobs in developed economies and these studies provide empirical evidence of a workforce transition especially from the middle-income manufacturing sector to the low-income service sector. Goos and Maning (2007) indicate three important links that explain the substitution of middle-wage jobs with technology and are an important reference point for further studies: a) Non-routine manual tasks mostly involve low-paying jobs. b) Mid-wage jobs often consist of cognitive but routine tasks. c) Both cognitive and non-routine jobs are high-paying jobs. Therefore, technical advances increase the demand for high-paying high-skill jobs especially in the service sector, while removing the middle-level routine jobs from the manpower causes these workers to shift to low-paid positions in the service sector or become unemployed.

Finally, Acemoglu and Restrepo (2019) and Bessen (2020) come to the fore among recent studies including how employment has been affected by technology in the past and today in the different sectors. While Acemoglu and Restrepo (2019) investigate the employment data of six broad sectors in the USA, namely construction, services, transportation, manufacturing, agriculture, and mining, Bessen (2020) focuses on the U.S. cotton textile, primary steel, and motor vehicle industries which are mainly sub-sectors of the industry. As stated by Acemoglu and Restrepo (2019), between the years 1947-1987 no significant decrease was observed in the labor sharing rates of the construction, services, manufacturing, and agriculture sectors. But there was a slightly small decrease in mining and transportation sectors which have a relatively small proportion compared to the others. In this period, the effects of substitution, composition, and task content on employment are determined to be very small. Perhaps the most striking statistic about this period is that labor demand, which decreased by an average of 0.48% per year due to the displacement effect, increases by an average of 0.47% annually thanks to the reinstatement effect. As a result, the authors reveal that in the forty-year period following the Second World War, the decreased labor demand due to automation was offset by new tasks, and the economy, especially manufacturing, was balanced in terms of employment in general. Similarly, in Bessen (2020) the hypothesis that the elasticity of demand in these industries is less than one is rejected with parametric analysis. These findings mean that demand in selected industries was quite elastic in the early stages of automation. Nevertheless, both studies show that the effects of automation are different from the past. Acemoglu and Restrepo (2019) present the image for the 1987-2017 period in the study and state that, contrary to the previous forty-year period, a serious decrease was observed in the share of the manufacturing, mining, and construction sectors in the workforce between 1987-2017. Another crucial point is that after 1987, reinstatement labor demand increased only 0.35% per year, while the displacement effect decreased labor demand 0.7% per year. Therefore, on the one hand, the reinstatement effect decreases compared to the previous period, the displacement effect increases. Moreover, this outlook is more serious in the manufacturing sector. While there was no significant difference in terms of displacement and reinstatement effects between the overall employment pattern and manufacturing in the previous period, this time the displacement effect is observed as 1.1% per year for manufacturing, and the total cumulative effect is approximately 30%. Similarly, Bessen (2020) draws attention to the weakening of demand elasticity in the recent period. The author mentions the existence of unmet and great needs in the first years and therefore emphasizes that technology creates employment by strongly increasing demand through the decline in prices. Notwithstanding, although the technological developments that continue as time passes, reduce prices by providing an increase in productivity, this decrease in prices cannot increase employment. The most important reason for this is that over time, the demand reaches saturation and loses its elasticity. In this case, although the compensation mechanism is effective in the first years through the decrease in prices, it is far from the effect of creating a labor force in the near term and cannot prevent the employment losses caused by technology.

Table 5.1. Country list

ID	Country Name	Abbreviation	ID	Country Name	Abbreviation
1	Australia	AUS	16	Korea, Rep.	KOR
2	Austria	AUT	17	Mexico	MEX
3	Belgium	BEL	18	Netherland	NLD
4	Canada	CAN	19	New Zealand	NZL
5	Czechia	CZE	20	Norway	NOR
6	Denmark	DNK	21	Poland	POL
7	Finland	FIN	22	Portugal	PRT
8	France	FRA	23	Romania	ROU
9	Germany	DEU	24	Slovakia	SVK
10	Greece	GRC	25	South Africa	ZAF
11	Hungary	HUN	26	Spain	ESP
12	Iceland	ISL	27	Sweden	SWE
13	Ireland	IRL	28	Turkey	TUR
14	Italy	ITA	29	United Kingdom	GBR
15	Japan	JPN	30	United States	USA

In this part of the thesis, the employment-technology relationship is explored from a sectoral perspective in parallel with the previous chapters. A possible vulnerability of the existing literature is that the empirical importance has often been on industry and country-specific research interest with firm or sectoral level data. Previous sectoral studies were conducted with data obtained from a narrow group of firms or sectors, mostly ignoring the effects on competitors or other industries. Therefore, earlier investigations are that no adequate consideration has been given to sectors at the aggregate level in terms of the employment-technology relationship. This study, on the other hand, deals with the sectors at the macro level and does this by covering the country group with a very wide time interval. Empirical attentiveness is given to the research of the impacts of business enterprise R&D expenditure, income, inflation, worker productivity, and openness on sectoral employment using panel data of 30 developed and developing countries that are given in Table 5.1. The panel cointegration methods revealed by Pedroni (2001a, 2001b) are employed to prove the existence of the long-term relationship, and PDOLS and FMOLS estimators are used to calculate the coefficients of the cointegrated panel series. To the best of our knowledge, this study is the first to investigate the R&D expenditures and sectoral employment link at the macro level within a panel cointegration framework, which can have substantive developments in statistical power yet has been mostly neglected by past studies. The remaining parts include empirical methodology, estimations results, and concluding remarks.

5.2. Empirical Methodology

5.2.1. Equations to be estimated

Since the main purpose of this section of the thesis is to reveal the sectoral differences in the effect of technology on employment at the macro level, business enterprise R&D expenditures in the relevant sector are determined as the technology proxy. Besides, per capita GDP, inflation, productivity, and openness variables are defined as other control variables. In this context, two models are estimated for each of the three main sectors namely agriculture, industry, and service as well as two sub-sectors of industry, manufacturing, and energy sectors. Since the starting sector is agriculture and the final stop is the service sector in the economic development chains of the countries, this order is also followed in the formulation of the models. In this regard, Model 5.1 and Model 5.2 are estimated in order to examine the employment-technology relationship in the agricultural sector first:

$$EMPA_{it}=\alpha_0+\beta RDA_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDA_{it}+e_{it} \qquad \textit{Model 5.1}$$

$$EMPA_{it}=\alpha_0+\beta RDA_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDA_{it}+\alpha_4 OPN_{it}+e_{it} \qquad \textit{Model 5.2}$$

where, $EMPA_{it}$ is the decimal fraction of employment in agriculture for country i ($i = 1,2,\ldots,30$); RDA_{it} is the natural logarithm of per capita business enterprise R&D expenditure in the agriculture sector; GDP_{it} is the natural logarithm of per capita income; CPI_{it} is the natural logarithm of consumer price index; $PRDA_{it}$ is the natural logarithm of output per worker in the agriculture sector; OPN_{it} is the natural logarithm of openness index; and finally e_{it} is an error term including other factors which impact agricultural employment.

Model 5.3 and Model 5.4 are models created for industrial employment, which includes sub-dimensions such as manufacturing, construction, and energy. In these models, while GDP_{it} and OPN_{it} are the same as in the models for the agriculture sector, $EMPI_{it}$ is the decimal fraction of employment in industry for country i (($i = 1,2,\ldots,30$);

RDI_{it} is the natural logarithm of per capita business enterprise R&D expenditure in the industry; and $PRDT_{it}$ is the total output per worker for all sectors in the economy, unlike the previous models.

$$EMPI_{it}=\alpha_0+\beta RDI_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDT_{it}+e_{it} \quad \textit{Model 5.3}$$

$$EMPI_{it}=\alpha_0+\beta RDI_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDT_{it}+\alpha_4 OPN_{it}+e_{it} \quad \textit{Model 5.4}$$

Model 5.5 and Model 5.6 are designed for manufacturing including construction, which is one of the most important sub-sectors of the industry.

$$EMPM_{it}=\alpha_0+\beta RDM_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDT_{it}+e_{it} \quad \textit{Model 5.5}$$

$$EMPM_{it}=\alpha_0+\beta RDM_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDT_{it}+\alpha_4 OPN_{it}+e_{it} \quad \textit{Model 5.6}$$

where $EMPM_{it}$ is the decimal fraction of employment in manufacturing for country i ($i = 1,2,\ldots,30$) and RDM_{it} is the natural logarithm of per capita business enterprise R&D expenditure in the manufacturing sector.

Model 5.7 and Model 5.8 are created only for the energy sector because it is thought that the energy sector holds distinctive characteristics in the industry compared to manufacturing. Despite the possibility that both sectors will be affected by technology in separate ways, such a distinction is made to determine the difference:

$$EMPE_{it}=\alpha_0+\beta RDE_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDE_{it}+e_{it} \quad \textit{Model 5.7}$$

$$EMPE_{it}=\alpha_0+\beta RDE_{it}+\alpha_1 GDP_{it}+\alpha_2 CPI_{it}+\alpha_3 PRDE_{it}+\alpha_4 OPN_{it}+e_{it} \quad \textit{Model 5.8}$$

where $EMPE_{it}$ is the decimal fraction of employment in energy for country i ($i = 1,2,\ldots,30$) and RDE_{it} is the natural logarithm of per capita business enterprise R&D expenditure in the energy sector.

Finally, Model 5.9 and Model 5.10 are created in order to understand the impact of technology on employment in the service sector. Similar to the models shared above $EMPS_{it}$ represents the decimal fraction of employment in service sector for country i ($i = 1,2,\ldots,30$) and RDS_{it} is the natural logarithm of per capita business enterprise R&D expenditure in the service sector.

$$EMPS_{it} = \alpha_0 + \beta RDS_{it} + \alpha_1 GDP_{it} + \alpha_2 CPI_{it} + \alpha_3 PRDS_{it} + e_{it} \qquad \textit{Model 5.9}$$

$$EMPS_{it} = \alpha_0 + \beta RDS_{it} + \alpha_1 GDP_{it} + \alpha_2 CPI_{it} + \alpha_3 PRDS_{it} + \alpha_4 OPN_{it} + e_{it} \qquad \textit{Model 5.10}$$

While the workforce in developed countries first shifted from agriculture to the manufacturing sector during and after the Industrial Revolution, there is a rapid transition from manufacturing to the service sector today. Developing countries also experience an analogous situation due to the *"premature deindustrialization"* mentioned in the previous chapters, but this transition takes place more slowly than developed countries due to the relative superiority in technology adaptation and labor costs. In this section, developed and developing countries are considered together, and a pool of 30 countries, consisting of 28 OECD countries, as well as Romania and South Africa, is included in the scope of the study. Both OECD and past job polarization literature reveal that the share of industry in employment has decreased in both developed and developing countries, while a significant increase has been experienced in the service sector. At this point, technology has a labor displacement effect by providing rapid mechanization in the agriculture and industrial sectors, while it has the labor creative characteristic in the service sector. Therefore, the direction and severity of the β coefficient, which is the main focus of the study, is expected to differ between sectors. Especially with the Industrial Revolution, the industrial sector, which has employment opportunities for many people, is one of the areas where the most technology investments are made. For example, as reported by Rodrik (2016), approximately two-thirds of R&D expenditures in Europe are made in the manufacturing sector. Intensive R&D expenditures trigger process innovations and increase productivity in the industry, resulting in a labor-saving effect. In addition, as process innovations lead to investments in new machines and other advanced technologies, the demand for skilled labor increases, especially in more complex service sector areas (Welfens et al., 1998). As mentioned in the previous chapters, economic growth, one of the core control variables, is expected to be mostly related to overall employment growth, but its effect on sectoral employment may be different. For example, historical data shows that long-term economic growth and technology-induced productivity increase are accompanied by labor displacement in the agricultural sector (Headey et al., 2010). For example, at the beginning of the 19^{th} century in the USA, the output that a farmer produced in approximately 300 hours could be obtained in 50 hours using machines that complement horses at the end of the same century, while this duration was reduced to just 3-4 hours with the help of advanced tractors at the end of the 20^{th} century (Saunders, 2017). There is detailed information in the previous chapters about the theory and empirical literature on the relationship between other control variables in the study, namely inflation, productivity and openness, and employment. Therefore, no further comments will be made on the expected signs of these variables.

5.2.2. Panel cointegration approach

The existence of unit root may cause misinterpretation of the estimation results. Therefore, unit root tests, which have become the primary priority in all empirical studies involving time series, are commonly applied before using standard estimation techniques such as OLS (Harris and Sollis, 2003; Baltagi, 2005). The recent interest in the problem of econometrics of panel data stems from the numerous applications of time series procedures to panels where issues such as nonstationarity, spurious regressions, and cointegration have become important. Adding the cross-section dimension to the time series size provides an advantage when testing for non-stationarity and cointegration because the cross-section expands the number of observations used in these tests and thus leads to an increase in the power of the test. It may also cause some other problems, such as the presence of cross-section dependence especially in small samples, which makes panel unit root test results controversial. These problems are reduced or eliminated only when the panel has large cross-sectional and time-series dimensions.

The starting point of panel unit root tests is time series unit root tests. As mentioned before, the biggest difference between the unit root tests performed in the panel data analysis and the tests performed for the time series is that the asymptotic behavior of the time series dimension T and the cross-sectional dimension N should be taken into account. In other words, there is a difference regarding the homogeneity-heterogeneity problem between unit root tests of time series and panel data. In the case of time series, heterogeneity is not an issue as the unit root hypothesis is investigated on a particular model for a given individual. In panel data analysis, the approach is different because whether the same model can be used to check the unit root hypothesis on various individuals may pose a problem. The availability of the same model means that the panel is homogeneous, while if the individuals are characterized by different dynamics, this indicates that the panel is heterogeneous. Therefore, even if tests based on pooled estimates of autoregressive parameters can be consistent against a heterogeneous alternative, panel unit root tests should take this heterogeneity into account (Moon & Perron, 2004). After incredibly important articles proposed by Levin and Lin (1993) and Levin et al. (2002) based on a pooled estimator of the autoregressive parameter, numerous tests based on alternative heterogeneous specifications are presented by Im et al. (2003), Maddala and Wu (1999), Breitung (2000), Choi (2001) and Hadri (2000). In this study, before proceeding to the cointegration test, whether series are $I(1)$ is tested using three different unit root methods, namely the LLC (Levin et al., 2002), the IPS (Im et al., 2003), and Fisher type ADF (Maddala and Wu, 1999). Since detailed technical information about these tests is shared in Chapter 3 and Chapter 4, it will not be repeated in this section.

If the series contain a unit root, that is, they are not stationary at level, panel cointegration tests are appropriate to investigate whether individual series have a long-term relationship. The panel cointegration approaches employed in this part are Pedroni (1999, 2004) and Kao (1999) cointegration techniques which are the same as the previous chapters. In order to apply these cointegration methods, each model given above should be estimated first and then $\hat{e}_{i,t} = \rho_i \hat{e}_{i,t-1} + \sum_{k=1}^{K} \varphi_{i,k} \Delta \hat{e}_{i,t-k} + \hat{u}_{i,t}^{*}$ should be run to get residuals. For both cointegration methods, testing the null hypothesis of *"no cointegration"* purports $H_0: \rho_i = 1$ against the alternative hypothesis of cointegration amounts $H_0: \rho_i < 1$, for all $i = 1,2,3,\ldots, N$ noting that dissimilar to the Pedroni cointegration tests, homogeneity is required in the Kao test which means the slopes in estimated models are not permitted to differ across i. In the last stage, when the variables in different models are proved to be cointegrated, the following procedure is to estimate the cointegration vectors. For this purpose, the long-run parameters in Model 5.1 to 5.10

are calculated applying the panel dynamic OLS (Pedroni, 2001a; Mark and Sul, 2003) and fully modified OLS (Phillips and Moon, 1999; Pedroni, 2001b; Mark and Sul, 2003) estimators. It should be noted that both approaches eliminate the endogeneity and serial correlation problems, and on the one hand, the PDOLS estimator is a parametric method where lagged the first-differenced series are precisely calculated, and alternatively, the FMOLS is a non-parametric version. The technical details of these approaches are not reproduced here as they have been yielded in the early parts.

5.2.3. Data

The data including a period of 30 years (1990–2019) are obtained for employment in broad sectors, business enterprise R&D expenditures, GDP per capita, consumer price index, output per worker, and trade openness in 30 countries given in Table 5.1. Based on the availability of the data for all the variables, these 30 countries are selected mainly from the OECD countries. The data set comprises the balanced panel with $N \times T = 900$ observations ($N = 30$ and $T = 30$). Since the employment effects of technology proxied by business enterprise R&D expenditure are investigated in this section, sectoral distinctions are used, based on the classification of economic activities published by the United Nations (2008), and presented by the ILO (2020b). In line with this classification, three main sectors as agriculture, industry, and service, and three sub-sectors of the industry as manufacturing, construction, and energy listed in Table 5.1 are focused separately. The agriculture sector includes economic activities such *as "crop and animal production, forestry and logging and fishing and aquaculture"*. The coverage area of the industry is quite wide. It includes business activities from the manufacture of many products, especially *"food, beverages, textiles, chemicals, motor vehicles, trailers, machinery, computer, and electronic products"* to the energy sector such as *"electricity, gas, steam and water supply"* and construction activities in many fields. Finally, the service sector includes market services such as *"trade, transportation, business, and administrative* *services"* and non-market services such as *"public administration, social and community activities"*.[11]

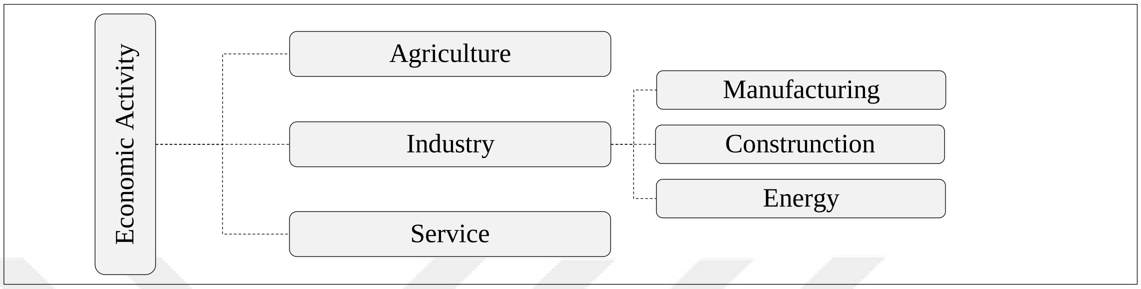

Figure 5.1. Economic activity classification
Source: United Nations (2008) and ILO (2020b).

Table 5.2 contains a list showing the short definitions, abbreviations, and data sources of the dependent and independent variables used in the study. Regarding the three broad sectors in Figure 5.1, the *EMPA*, *EMPI*, and *EMPS* variables show the employment rates in agriculture, industry, and service, respectively, for the three main models established in the study. In addition to the employment rates in these three main categories, models are also estimated for the manufacturing and energy sectors in the industry. Accordingly, EMPM represents employment in manufacturing and construction, while EMPE represents employment in the energy sector. All data on employment rates are derived from the ILO (2020b) as *"share in total employment"* and then calculated as *"percentage of the total labor force"* in this study. While descriptive statistics and figures are shared, these ratios are again expressed as percentages, but they are used as decimal fractions in the analyses. The core explanatory variable of the study, R&D expenditure, is handled differently in the previous sections as *"business enterprise R&D expenditure by sector"*. These data are classified and published by the OECD (2020d) based on the International Standard Industrial Classification (ISIC). At this point, *RDA*, *RDI*, and *RDS* represent per capita business enterprise R&D expenditure in agriculture, industry, and service sectors, respectively. In addition, *RDM* and *RDE* are used to represent per capita R&D in manufacturing (including construction) and energy sectors, respectively. All

[11]All economic activities are published by the ILO (2020b) and the United Nations (2008). For detailed definitions, see https://unstats.un.org/unsd/classifications/Econ/ISIC.cshtml.

R&D expenditures in business enterprise sectors are in constant US$. It should be noted that since the sectoral R&D data are used when investigating how sectoral employment is affected by technology, this study examines how technology produced within the sector relates to the sector's own employment and ignores technological changes in other sectors. But the cross-sectoral impact is also important. For example, R&D expenditures in the manufacturing sector may indirectly affect employment in the service sector. However, since this study is limited to R&D expenditures within the sector itself, indirect effects between sectors are ignored. But still, it is worth noticing that sectoral business enterprise R&D expenditures are the direct and relevant measures for sectoral technology patterns.

Table 5.2. List of the variables

Variable Type	Description and Units of Variables	Symbol	Source
Dependent Variables	Employment in agriculture (% of total labor force)	*EMPA*	ILO (2020b), Author's calculations
	Employment in industry (% of total labor force)	*EMPI*	ILO (2020b), Author's calculations
	Employment in service (% of total labor force)	*EMPS*	ILO (2020b), Author's calculations
	Employment in manufacturing & construction (% of total labor force)	*EMPM*	ILO (2020b), Author's calculations
	Employment in energy (% of total labor force)	*EMPE*	ILO (2020b), Author's calculations
Core Independent Variables	Business enterprise R&D expenditure in agriculture (per capita, constant 2010 US$)	*RDA*	OECD (2020d), Author's calculations
	Business enterprise R&D expenditure in industry (per capita, constant 2010 US$)	*RDI*	OECD (2020d), Author's calculations
	Business enterprise R&D expenditure in service (per capita, constant 2010 US$)	*RDS*	OECD (2020d), Author's calculations
	Business enterprise R&D expenditure in manufacturing (per capita, constant 2010 US$)	*RDM*	OECD (2020d), Author's calculations
	Business enterprise R&D expenditure in energy (per capita, constant 2010 US$)	*RDE*	OECD (2020d), Author's calculations
Other Independent Variables	GDP per capita (constant 2010 US$)	*GDP*	World Bank (2020c)
	Consumer price index (2010 = 100)	*CPI*	World Bank (2020d)
	Productivity in agriculture (output per worker, constant 2010 US$)	*PRA*	World Bank (2020j), Author's calculations
	Productivity in service (output per worker, constant 2010 US$)	*PRS*	World Bank (2020k), Author's calculations
	Productivity (total) (output per worker, constant 2010 US$)	*PRT*	ILO (2020c), Author's calculations

Other control variables used in the study are GDP per capita, consumer price index, productivity, and trade openness. GDP per capita is calculated in terms of constant US$, based on total GDP in all models, with the base year of 2010, and no sectoral distinction has been made for this variable. As in the previous sections, the consumer price index is used for inflation and the base year is 2010. Productivity variable is calculated in constant US$ as output per worker, again the base year is 2010. In the agriculture and services sector, sector-specific productivity values expressed as *PRA* and *PRS* were calculated by dividing the sectoral total output by the total number of employees in these sectors. The productivity variable used for the industry is calculated over the total output and is represented by the symbol *PRT*. Finally, the openness variable is a ratio that expresses the ratio of the total import and export volumes of the countries to their total output, and in this study, it was converted into an index based on 2010.

Table 5.3. Overall descriptive statistics

Variable	Mean	Median	Std. dev.	Max.	Min.	Skewness	Kurtosis
EMPA	7.29	4.57	7.64	45.01	0.91	2.46	9.52
EMPS	60.21	61.64	10.88	79.20	25.03	-0.78	3.30
EMPI	24.22	23.54	5.44	44.96	11.01	0.68	3.41
EMPM	22.60	22.32	5.29	40.16	9.73	0.45	2.92
EMPE	1.62	1.25	0.94	4.81	0.31	1.12	3.31
RDA	2.49	0.89	3.96	30.28	0.01	3.10	15.09
RDS	124.01	68.55	137.00	619.66	0.04	1.34	4.13
RDI	276.37	204.87	273.43	1136.84	0.69	1.07	3.31
RDM	266.76	181.61	271.40	1131.93	0.66	1.13	3.42
RDE	9.61	3.38	21.63	195.29	0.01	5.08	33.53
GDP	32828.26	34639.94	18207.67	92556.32	4349.93	0.49	3.34
CPI	85.43	89.07	26.72	234.44	0.02	-0.61	5.57
PRA	34891.57	26799.70	27181.08	133661.20	1705.04	1.03	3.72
PRS	65614.73	72157.95	27825.45	127341.40	10791.85	-0.26	1.81
PRT	71769.10	78123.70	35805.32	182984.80	8847.76	0.30	2.96

Note: EMPA, *EMPS*, and *EMPI* are the employment rates for the broad sectors. *EMPMC* and *EMPE* are the employment rates for the subsectors: *EMPMC* stands for employment in manufacturing & construction sector while *EMPE* denotes employment in energy sector. All employment rates are in percentages. *RDA*, *RDS*, *RDI*, *RDMC* and *RDE* represent per capita business enterprise research and development expenditure by sector. All R&D expenditures are in constant US Dollars. *GDP* represents GDP per capita in constant US Dollars. *CPI* is consumer price index with a base year of 2010. *PRA*, *PRS* and *PRT* represent productivity in agriculture, productivity in service and total productivity respectively and all productivity data are in constant US Dollars.
Source: Author's own calculations based on World Bank, OECD, and ILO data.

Table 5.3 presents summary data for all variables covering the years 1990-2019 and all countries. In 30 selected countries and over a period of thirty years, the average employment rate in agriculture is 7.3%, while in the industry it is 24.6% and in the service sector, it is 60.2%. While the average business enterprise R&D per capita in agriculture is about $2.5, this value is $276 in industry and $124 in the service sector. As previously reported by Rodrik (2016), R&D expenditures in the manufacturing sector in European countries were two-thirds of the total R&D. The average values calculated for 28 OECD and 2 non-OECD countries in this thesis are also remarkably similar to the statistics by Rodrik (2016). R&D expenditures in industry, especially in manufacturing, constitute a large part of total R&D expenditures.

Figure 5.2 shows the average of sectoral employment and R&D expenditures by country over a 30-year period and provides valuable information in this respect. First of all, the first quadrant includes employment rates in agriculture and the distribution of R&D expenditures in the agricultural sector by country. Mexico, Turkey, Greece, Poland, Portugal, and Romania have agricultural employment above the average of the selected country group and agricultural R&D investments below the average of this country group. Sweden, Canada, United States, Australia, New Zealand, Iceland, the Netherlands, and Norway, conversely, have below-average agricultural employment and above-average agricultural per capita BERD. A striking thing about this chart is that in countries with below-average agricultural R&D, agricultural employment moves in the opposite direction to R&D. In the country group above the R&D average, this pattern becomes blurred. In the same figure, the second quadrant shows the employment and R&D distribution in the industry by country. Note that these ratios include a 30-year average, so they are important to give an idea of the situation rather than make a general inference. The US, Sweden, Denmark, Belgium, the Netherlands, Norway, and France have above-average industrial BERD per capita and below-average industrial employment. The industrial employment rates of Czechia, Slovakia, Hungary, Poland, Romania, Mexico, Portugal, and Italy are above the average, while the industrial BERD values are below the average. On the other hand, Turkey's per capita BERD in industry and industrial employment statistics are below the average of thirty countries.

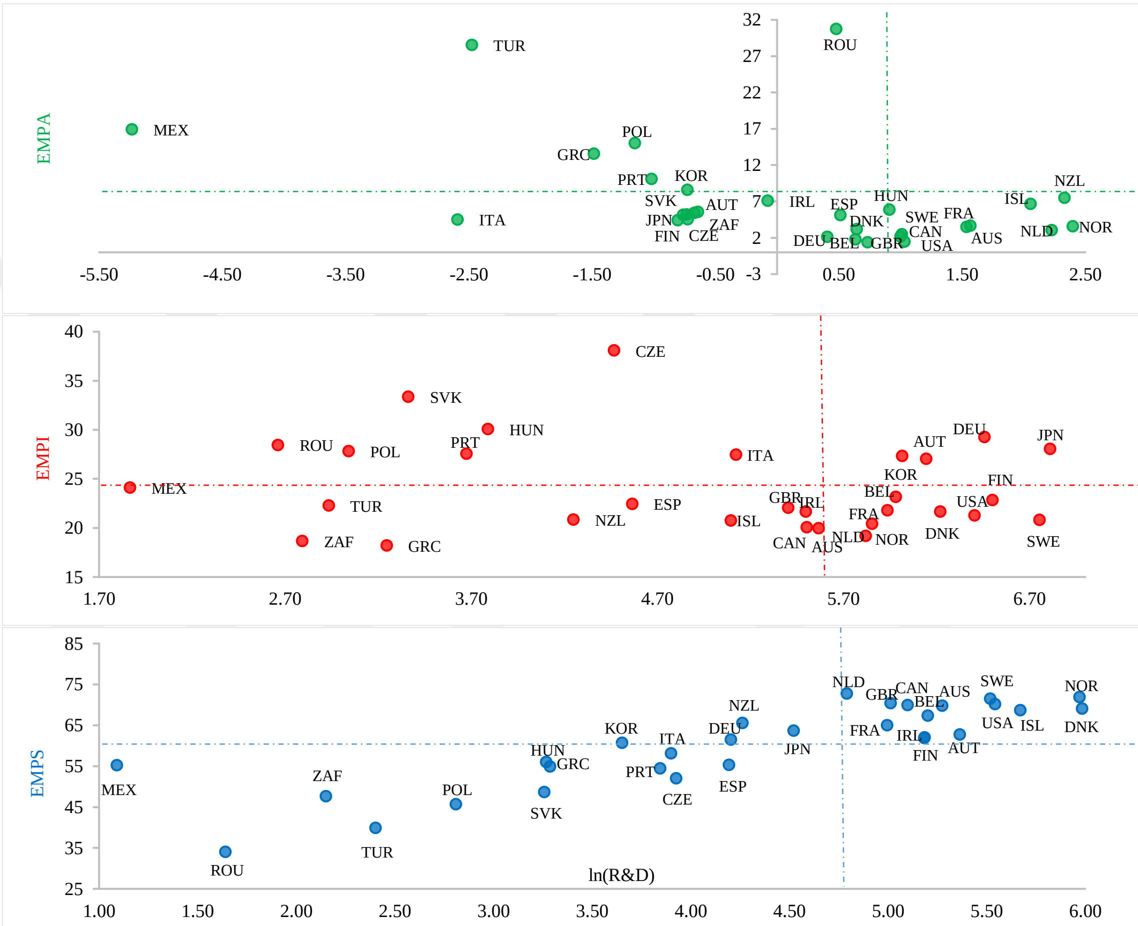

Figure 5.2. Countries' average employment rates and R&D expenditures by sector

Note: Vertical axes show sectoral employment rates and horizontal axes represent the natural logarithm of per capita sectoral business enterprise R&D expenditures.

In the third and last quadrant of Figure 5.2, the employment rates in the service sector and the average distribution of R&D expenditures per capita by countries for a 30-year period are given. Unlike the other two sectors, there is a clear positive pattern between R&D and employment in the service sector and this pattern has not yet been broken apart from one or two exception countries. In the agricultural and industrial sectors, especially in countries with below-average R&D expenditures, an inverse correlation draws attention, while more heterogeneous figures stand out in the country group with above-average R&D expenditures. One of the possible reasons for this situation may be that the agriculture and industry sectors in the selected country group have reached their peak in terms of employment. As mentioned earlier, developing countries experience *"premature deindustrialization"* and reach top employment rates earlier, especially in industry (Rodrik, 2016). However, it cannot be said that the service sector has reached saturation in all countries in terms of employment. This explains the more homogeneity of the employment and technology relationship in the service sector between countries.

Table 5.4 and Table 5.5 contain descriptive statistics for the manufacturing and energy sub-sectors as well as the broad sectors covered in the graphic above. According to the tables, the three countries with the highest average employment in the agricultural sector are Romania, Turkey, and Mexico, respectively. In industry, the top three countries in terms of employment are Czechia, Slovakia, and Hungary, while the top three rankings in terms of R&D per capita are Japan, Sweden, and Finland. Finally, when the employment rates in the service sector are considered, the first three countries are the Netherlands, Norway, and the United States, and when the per capita R&D expenditures are taken into account, the first three rankings are Denmark, Norway, and Iceland. Statistics for R&D expenditure are calculated on a per capita basis, so the ranking of countries by total R&D investment may differ. Finally, Table 5.6 shows the distribution of mean values of other control variables by country. Regardless of the sector, the country with the highest productivity per worker is Norway with an average of $162000 for a thirty-year period, which is well above other countries in this area. The countries that follow Norway are Denmark, Ireland, and Belgium and their average output per worker for thirty years is around $50,000-60,000 less than Norway. Turkey's productivity per worker is estimated to be around $31,000 on average over a thirty-year period.

Table 5.4. Descriptive statistics of sectoral employment by country (%)

Stat.	Ct..	EMP A	EMP S	EMP I	EMP M	EMP E	Ct.	EMP A	EMP S	EMP I	EMP M	EMP E
Mean	AUS	3.66	69.79	19.97	17.70	2.27	KOR	8.58	60.67	27.32	26.77	0.56
Sd.		0.98	3.34	0.94	1.36	0.61		3.15	6.71	4.23	4.24	0.16
Max.		5.67	73.63	21.88	19.68	3.46		15.06	67.59	38.09	37.41	0.78
Min.		2.43	63.36	18.22	15.30	1.44		4.61	46.37	23.62	22.83	0.31
Mean	AUT	5.43	62.71	27.04	25.88	1.16	MEX	16.90	55.18	24.09	23.13	0.96
Sd.		1.22	3.67	2.97	3.01	0.13		4.80	3.62	1.91	1.91	0.13
Max.		7.61	67.97	33.00	31.87	1.38		27.44	59.18	28.37	27.53	1.24
Min.		3.42	55.93	23.55	22.35	0.85		12.18	49.05	20.26	19.62	0.64
Mean	BEL	1.75	67.33	23.17	22.06	1.11	NLD	3.02	72.75	19.17	18.39	0.78
Sd.		0.61	3.82	2.91	3.07	0.24		0.64	4.04	2.79	2.87	0.15
Max.		2.79	74.00	29.15	28.36	1.50		3.97	79.20	23.24	22.46	1.04
Min.		0.91	61.02	19.29	17.87	0.66		1.94	63.53	15.02	14.17	0.55
Mean	CAN	2.14	69.93	20.07	17.44	2.63	NZL	7.49	65.56	20.84	19.97	0.87
Sd.		0.61	2.89	1.22	1.19	0.21		1.45	4.10	1.45	1.55	0.18
Max.		3.26	74.60	21.70	19.25	3.17		10.35	71.71	23.70	22.70	1.16
Min.		1.37	65.14	18.29	15.87	2.35		5.43	58.50	18.57	17.52	0.55
Mean	CZE	4.42	52.04	38.07	34.90	3.17	NOR	3.55	71.87	20.43	17.82	2.61
Sd.		1.86	3.87	2.71	2.10	0.69		1.36	3.21	1.16	1.67	0.60
Max.		8.66	58.83	44.96	40.16	4.81		5.91	75.77	22.36	20.17	3.87
Min.		2.58	43.98	34.90	32.14	2.43		1.92	66.62	18.56	15.19	1.91
Mean	DNK	3.15	69.03	21.66	20.76	0.90	POL	15.04	45.71	27.83	24.48	3.34
Sd.		0.94	4.37	2.95	3.16	0.26		4.46	6.97	2.53	2.41	0.40
Max.		5.21	75.36	25.54	24.75	1.39		25.00	56.78	34.01	30.33	4.18
Min.		2.08	61.38	17.53	16.36	0.50		8.91	33.62	22.86	19.82	2.64
Mean	FIN	5.17	62.05	22.85	21.72	1.13	PRT	10.07	54.47	27.57	26.50	1.07
Sd.		1.63	5.15	2.02	2.06	0.15		2.27	4.17	4.42	4.51	0.15
Max.		9.17	69.24	28.02	26.70	1.32		13.28	64.93	33.57	32.60	1.34
Min.		3.37	53.66	19.67	18.53	0.77		5.47	48.50	19.86	18.80	0.78
Mean	FRA	3.47	64.97	21.79	20.62	1.17	ROU	30.73	34.02	28.45	25.20	3.25
Sd.		0.93	4.03	2.39	2.57	0.24		6.27	6.89	2.78	2.63	0.44
Max.		5.29	70.93	26.39	25.32	1.59		42.06	46.28	36.64	32.96	4.01
Min.		2.24	59.00	18.26	16.87	0.81		20.84	25.03	24.00	20.80	2.64
Mean	DEU	2.12	61.46	29.25	27.85	1.40	SVK	5.19	48.64	33.36	30.55	2.81
Sd.		0.71	4.95	3.26	3.24	0.22		2.74	4.46	2.01	1.73	0.55
Max.		3.41	69.49	36.38	34.77	1.67		11.31	58.14	37.60	34.12	3.96
Min.		1.17	55.07	26.19	24.70	1.04		2.06	41.81	29.88	27.01	2.14
Mean	GRC	13.55	54.90	18.19	16.84	1.35	ZAF	5.55	47.65	18.66	15.37	3.29
Sd.		4.07	4.00	4.26	4.25	0.16		1.74	4.83	1.08	0.82	0.82
Max.		21.49	61.47	24.63	22.86	1.77		8.39	54.02	20.80	17.58	4.50
Min.		9.46	48.56	11.01	9.73	1.10		3.47	42.02	16.45	13.96	2.26
Mean	HUN	5.88	56.03	30.06	27.50	2.56	ESP	5.10	55.30	22.45	21.47	0.98
Sd.		2.00	4.05	1.77	1.73	0.58		1.80	5.74	4.80	4.89	0.12
Max.		10.90	61.22	32.64	30.19	3.69		8.67	64.96	28.20	27.29	1.17
Min.		3.98	46.47	26.51	24.00	1.78		3.17	45.67	14.60	13.58	0.77
Mean	ISL	6.63	68.68	20.76	19.65	1.11	SWE	2.44	70.16	20.80	19.87	0.93
Sd.		2.24	5.15	3.15	3.27	0.19		0.68	4.09	2.77	2.88	0.16
Max.		10.71	77.37	25.89	24.98	1.44		4.03	77.15	25.64	24.79	1.20
Min.		3.65	59.62	15.97	14.55	0.75		1.58	63.83	16.93	15.73	0.69
Mean	IRL	7.08	61.86	22.06	20.85	1.21	TUR	28.55	39.90	22.29	21.21	1.08
Sd.		2.69	7.07	4.75	4.82	0.13		9.72	6.94	1.85	1.79	0.19
Max.		13.14	72.92	28.29	27.10	1.59		45.01	48.93	25.11	23.79	1.37
Min.		4.39	49.35	14.49	13.36	1.02		15.90	28.60	17.98	17.05	0.80
Mean	ITA	4.51	58.10	27.44	26.21	1.24	GBR	1.38	70.42	21.65	20.30	1.35
Sd.		1.41	4.19	2.76	2.89	0.28		0.34	5.26	3.65	3.79	0.31
Max.		8.17	63.44	31.92	30.44	1.56		2.01	78.06	28.11	26.51	1.77
Min.		3.16	50.70	23.07	21.54	0.72		0.98	60.64	17.21	15.44	0.91
Mean	JPN	4.54	63.69	28.03	27.46	0.57	USA	1.46	71.49	21.26	19.64	1.61
Sd.		1.00	4.52	3.82	3.76	0.07		0.20	2.52	2.41	2.41	0.07
Max.		6.85	70.57	34.46	33.79	0.72		1.81	75.96	24.75	23.04	1.73
Min.		3.34	57.01	23.69	23.23	0.45		1.22	66.81	17.75	16.14	1.48

Table 5.5. Descriptive statistics of sectoral per capita R&D expenditure by country

Stat.	Ct.	RDA	RDS	RDI	RDMC	RDE	Ct.	RDA	RDS	RDI	RDMC	RDE
Mean	AUS	4.80	195.44	261.91	170.77	91.14	KOR	0.48	38.57	409.95	404.57	5.38
Sd.		3.06	92.73	88.08	33.10	60.21		0.23	25.58	269.95	268.18	2.06
Max.		12.01	339.82	416.83	224.70	195.29		1.24	92.50	929.79	919.86	10.01
Min.		1.06	66.72	113.18	99.37	13.81		0.05	4.97	71.76	67.39	2.85
Mean	AUT	0.51	213.55	466.55	463.04	3.51	MEX	0.01	2.98	6.46	6.29	0.17
Sd.		0.33	141.42	158.59	160.34	2.35		0.02	1.72	3.73	3.65	0.22
Max.		1.42	471.41	669.17	669.14	10.09		0.10	6.79	14.18	14.02	0.89
Min.		0.14	19.72	224.02	213.93	0.03		0.01	0.07	0.69	0.66	0.01
Mean	BEL	1.89	181.64	396.18	392.63	3.55	NLD	9.28	120.51	337.33	329.54	7.79
Sd.		1.02	112.40	53.67	51.21	3.73		5.78	81.63	33.61	33.01	4.47
Max.		3.70	424.46	501.98	495.14	11.80		25.95	320.91	450.78	445.01	19.45
Min.		0.66	42.28	298.65	297.93	0.57		3.57	21.75	281.57	281.12	0.45
Mean	CAN	2.72	163.95	245.79	217.29	28.50	NZL	10.29	70.99	70.08	69.23	0.85
Sd.		0.91	58.96	44.05	49.35	13.38		6.92	47.13	21.76	21.88	0.52
Max.		5.59	245.86	333.11	317.79	48.74		22.46	181.11	108.66	107.53	2.21
Min.		1.44	60.22	178.37	132.78	13.46		1.19	16.74	39.71	37.70	0.03
Mean	CZE	0.45	50.69	87.18	86.44	0.74	NOR	11.03	391.88	348.81	295.20	53.61
Sd.		0.24	32.62	33.93	33.77	0.39		8.00	114.25	32.94	34.50	8.17
Max.		0.82	116.22	162.22	161.36	2.03		30.28	619.66	426.67	377.56	71.71
Min.		0.02	11.12	40.94	40.64	0.15		0.56	211.27	290.94	241.45	41.22
Mean	DNK	1.91	397.21	503.77	499.02	4.75	POL	0.32	16.59	20.96	20.20	0.76
Sd.		2.40	171.95	140.47	137.79	5.11		0.17	21.86	15.84	15.81	0.67
Max.		11.13	609.75	737.99	731.92	26.12		0.65	82.15	69.73	68.60	2.32
Min.		0.20	103.03	280.72	280.05	0.67		0.04	2.26	6.39	6.36	0.03
Mean	FIN	0.47	178.59	666.35	656.50	9.84	PRT	0.36	46.79	39.43	37.23	2.20
Sd.		0.30	86.89	228.95	228.82	4.41		0.50	37.45	22.30	20.83	2.74
Max.		1.18	305.29	1054.04	1042.78	16.73		1.83	100.09	80.59	79.40	11.26
Min.		0.08	31.19	305.51	294.23	2.10		0.01	4.50	13.88	12.65	0.20
Mean	FRA	4.65	147.84	379.21	367.15	12.06	ROU	1.62	5.16	14.32	11.95	2.38
Sd.		1.72	116.31	64.52	63.57	2.17		1.09	6.64	7.99	6.03	2.11
Max.		7.66	303.91	473.40	460.41	16.91		3.61	22.25	34.26	27.19	7.07
Min.		1.58	17.31	295.47	284.94	8.29		0.08	0.15	5.78	5.55	0.08
Mean	DEU	1.50	66.99	637.98	635.04	2.94	SVK	0.48	25.99	28.85	28.51	0.34
Sd.		0.74	45.66	121.84	121.58	1.14		0.28	13.37	16.08	16.10	0.17
Max.		2.71	135.42	886.12	882.75	6.21		1.08	59.37	67.56	67.30	0.74
Min.		0.01	1.82	473.77	470.34	0.58		0.13	9.56	11.69	11.58	0.06
Mean	GRC	0.23	26.78	25.68	24.15	1.53	ZAF	0.53	8.59	16.32	10.53	5.80
Sd.		0.10	22.37	11.67	10.42	1.97		0.10	4.27	3.10	2.12	1.31
Max.		0.39	82.91	56.72	49.89	8.75		0.77	14.91	24.55	15.63	9.38
Min.		0.04	4.50	10.07	8.61	0.32		0.43	2.32	13.36	7.86	4.27
Mean	HUN	2.49	26.22	44.28	43.69	0.59	ESP	1.67	66.25	96.11	92.20	3.91
Sd.		1.93	31.90	22.82	22.88	0.29		0.63	41.02	13.74	13.33	1.66
Max.		7.83	115.66	83.14	82.95	1.23		3.13	122.26	123.75	118.04	6.91
Min.		0.44	1.23	15.11	14.23	0.19		0.55	11.35	69.51	66.23	0.87
Mean	ISL	7.82	290.58	163.50	153.24	10.26	SWE	2.76	255.57	857.52	848.16	9.36
Sd.		3.45	176.29	85.84	82.68	8.74		2.10	125.67	119.96	121.48	3.45
Max.		13.13	525.48	373.32	348.50	26.27		8.13	432.24	1068.17	1059.80	16.26
Min.		2.18	4.75	49.17	45.49	0.99		0.08	23.46	610.67	597.39	4.43
Mean	IRL	0.93	178.34	222.13	220.58	1.55	TUR	0.08	11.06	18.82	18.54	0.27
Sd.		0.75	130.59	41.55	41.67	1.13		0.06	12.99	15.52	15.35	0.20
Max.		2.77	364.22	304.57	302.26	4.70		0.25	39.94	59.96	59.17	0.79
Min.		0.12	3.88	109.01	108.23	0.34		0.01	0.04	3.20	3.10	0.01
Mean	ITA	0.07	49.45	167.96	164.58	3.38	GBR	2.08	150.55	244.41	238.11	6.30
Sd.		0.07	25.20	27.20	26.89	1.45		1.58	96.87	58.43	57.57	3.50
Max.		0.26	100.96	232.25	228.01	6.29		4.60	284.50	317.26	306.16	14.12
Min.		0.00	15.06	133.23	128.54	0.86		0.20	50.61	151.98	147.88	1.65
Mean	JPN	0.48	92.04	908.43	900.57	7.86	USA	2.82	249.40	604.72	597.80	6.92
Sd.		0.26	49.49	141.39	143.62	2.45		1.31	65.42	105.54	101.18	4.83
Max.		0.93	159.57	1136.84	1131.93	12.49		5.14	328.59	823.55	806.27	17.28
Min.		0.17	15.94	687.82	675.33	3.95		0.94	121.29	457.87	456.07	1.44

Table 5.6. Descriptive statistics of the other independent variables by country

Stat.	Ct.	GDP	CPI	PRA	PRS	PRT	Ct.	GDP	CPI	PRA	PRS	PRT
Mean	AUS	47053	87.4	58922	84882	97554	KOR	18739	84.3	12391	32892	36951
Sd.		7365	19.5	18665	9133	11301		6271	22.1	4510	6350	10020
Max.		57071	119.8	86650	102193	114070		28606	115.2	19908	43425	51755
Min.		35035	59.8	32490	67508	78000		8496	44.6	6067	22179	19622
Mean	AUT	43252	91.7	23596	83755	91514	MEX	9138	75.8	4617	23967	23271
Sd.		5346	15.4	6158	4693	8849		780	39.6	978	1020	583
Max.		50655	118.1	38281	89495	102335		10404	141.5	6057	25400	24131
Min.		33889	65.7	14669	74636	76595		7718	11.8	2972	21491	21963
Mean	BEL	40796	90.8	43294	94698	103313	NLD	46785	90.8	58134	83746	96055
Sd.		4823	15.5	16293	3973	7753		6203	15.6	15848	5805	8000
Max.		47541	117.1	71388	100337	112311		55690	115.9	88094	91008	107890
Min.		32672	66.4	16305	87899	89220		35703	64.4	40471	71831	82798
Mean	CAN	42748	91.1	52148	75813	89457	NZL	31627	88.3	64983	57337	64254
Sd.		6812	14.8	28267	4772	7554		4662	16.3	11564	4412	5581
Max.		51589	116.8	99708	83989	99946		38993	114.2	83129	63637	71672
Min.		32503	67.3	6488	68219	75000		23660	64.7	41999	49072	54000
Mean	CZE	17417	82.9	17621	37086	36536	NOR	82117	90.1	75487	109416	162906
Sd.		3658	24.9	6302	5027	7425		10047	16.1	38224	11695	15805
Max.		23834	116.5	27380	45169	47681		92556	120.3	133661	127341	182985
Min.		12313	30.0	7773	28460	25316		60227	65.0	27473	88470	129638
Mean	DNK	55826	89.5	41769	95477	111312	POL	10427	77.4	4847	26865	24994
Sd.		5886	14.7	13019	8148	12271		3601	32.6	1224	5292	7237
Max.		65147	110.3	63773	107752	128877		17387	114.1	6729	36000	37321
Min.		44569	66.1	15944	80017	88000		5511	7.0	2905	17865	12860
Mean	FIN	41578	93.0	45243	79569	92229	PRT	20978	87.5	9840	48903	45014
Sd.		6735	12.6	15583	7253	12860		2165	18.7	3227	2636	4445
Max.		49441	112.3	73215	85424	105942		24590	110.6	18141	52212	50858
Min.		29684	71.6	22927	60499	65000		16668	48.0	6716	44112	36347
Mean	FRA	38684	91.8	43185	91747	95175	ROU	7123	62.0	3523	20842	15906
Sd.		3674	11.9	12795	4400	7258		2380	46.4	1243	6665	6038
Max.		44317	110.0	65685	99710	106462		12131	123.8	6548	32000	27260
Min.		32524	71.2	22893	83118	81111		4350	0.0	1705	10792	8848
Mean	DEU	39769	92.4	33756	77789	85110	SVK	13459	77.6	17035	32983	31429
Sd.		4626	12.8	11053	4541	6764		4582	30.0	16016	5155	8968
Max.		47628	112.9	52537	82096	93593		21039	115.3	57082	39339	44616
Min.		32427	67.5	18982	64484	71053		6161	25.4	2400	23867	17433
Mean	GRC	23675	79.6	15499	66049	61965	ZAF	6617	81.9	8928	21897	24683
Sd.		3282	22.6	3457	4830	7284		797	39.0	2889	951	1354
Max.		30055	104.9	21299	75760	72104		7583	158.9	14267	23093	26752
Min.		19304	29.8	10205	57276	50932		5518	25.4	4969	19682	22804
Mean	HUN	12083	72.0	18958	27672	30193	ESP	28509	86.1	35736	71313	74031
Sd.		2630	36.4	6768	3333	4819		3479	18.8	11164	3366	3568
Max.		17466	121.6	34233	34590	37068		33350	111.0	51936	78647	80080
Min.		8550	9.2	7003	21796	21788		22513	51.9	17304	66170	67142
Mean	ISL	40557	77.3	87514	57710	71615	SWE	47708	92.9	70345	81942	97081
Sd.		7244	30.5	21712	9516	11016		7618	10.8	23057	9650	14865
Max.		51593	129.0	131122	70685	89064		57975	110.5	108588	94814	115393
Min.		29708	40.0	56195	38539	55981		35495	68.6	31659	63602	69000
Mean	IRL	46863	88.2	19914	97752	107926	TUR	9991	71.4	10332	37938	30837
Sd.		15158	16.4	4372	8359	30244		2756	67.3	3788	2848	7776
Max.		79703	106.6	32910	121846	174181		15069	234.4	16809	43535	42962
Min.		24315	61.0	14563	88717	70000		6709	0.1	5094	32537	18041
Mean	ITA	34904	88.5	36927	93351	92879	GBR	37064	90.5	39736	70218	77828
Sd.		2136	16.8	9109	3832	4680		5070	16.8	8940	7659	8579
Max.		38272	110.6	48233	100692	99262		43688	119.6	51040	78661	87100
Min.		30871	55.8	18854	87620	80762		28291	61.1	25277	55330	60000
Mean	JPN	43519	101.4	23490	90011	85823	USA	45843	88.8	68975	94824	95232
Sd.		3095	2.2	2199	2686	6459		5970	17.6	13864	9070	12983
Max.		49188	105.5	27026	93299	93898		55670	117.2	90947	107394	114003
Min.		38074	94.5	19556	83786	75482		35542	59.9	45625	79465	72000

5.3. Empirical Results

As technically shared both in previous empirical chapters and in the methodology section of this chapter, the prerequisite for panel cointegration tests is to determine that the series contain a unit root. For this purpose, the findings obtained from three different unit root methods are shared in Table 5.7. The results in Table 5.7 are for models without a trend, the results of models including a trend are shared in Appendix Table C1. First of all, LLC test results show that all variables used for agriculture and service sectors are stationary at level, but *RDI* is not $I(0)$ in models established for the industry. According to the IPS test results, the number of variables that are stationary at the level is less. Only 5 of the 16 dependent and independent variables used are stationary at level. According to the results of the AFD-Fisher test, at least two explanatory variables are not stationary at the level in both models created for all sectors. However, three different test results show that the null hypothesis of unit-root is rejected as a result of taking the first differences of the series. Therefore, it is proved by the three unit-root methods that the dependent and independent variables used in all models are $I(1)$. In other words, it is plausible to decide that all the variables in Model 5.1 to Model 5.10 can be interpreted as nonstationary $I(1)$ processes.

With potent indication that all of the panel series are $I(1)$ processes, the Pedroni and Kao panel cointegration tests are implemented to determine the presence of the long-run equilibrium relationship between the variables in all models for different sectors. After the existence of long-run relationships among the selected variables were proved, the long-run parameters were estimated. In the next sections, cointegration and then estimation results are given according to sectors. First, the results of the agricultural sector were shared, then the results of the second broad sector, industry, and the two sub-sectors of the industry, manufacturing, and energy, were included. Finally, the analyses were completed with the results of the service sector. At this point, it should be added that since the manufacturing sector covers a large part of the total industry in terms of employment, share in total income, and R&D expenditures, the manufacturing sector is generally used to represent the whole industrial activities in most studies. For example, an average of

93.3% of the employment in the industry and an average of 96.5% of the R&D expenditures in the 30-year period of the selected 30 countries belong to the manufacturing (including construction) sub-sector.[12] In this study, the results for both the whole industry and manufacturing, excluding the energy sector, are included separately. Therefore, explanations should be assessed in this direction.

Table 5.7. Unit root tests results (w/o trend)

Variables	LLC		IPS		ADF - Fisher	
	Level	First Difference	Level	First Difference	Level	First Difference
$EMPA_t$	-14.288	-18.651	-6.257	-18.482	172.076	420.519
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
$EMPS_t$	-2.145	-17.994	4.649	-18.557	39.458	408.646
	[0.016]*	[0.000]***	[0.981]	[0.000]***	[0.785]	[0.000]***
$EMPI_t$	-4.132	-10.728	-0.862	-11.012	58.278	222.139
	[0.000]***	[0.000]***	[0.194]	[0.000]***	[0.256]	[0.000]***
$EMPM_t$	-3.578	-10.937	-0.360	-10.761	55.169	216.924
	[0.000]***	[0.000]***	[0.360]	[0.000]***	[0.356]	[0.000]***
$EMPE_t$	-0.884	-11.578	-0.103	-12.463	42.793	251.202
	[0.188]	[0.000]***	[0.459]	[0.000]***	[0.815]	[0.000]***
RDA_t	-6.750	-26.035	-2.750	-23.411	98.054	514.743
	[0.000]***	[0.000]***	[0.003]**	[0.000]***	[0.001]***	[0.000]***
RDS_t	-5.934	-25.349	-0.932	-22.572	86.075	413.859
	[0.000]***	[0.000]***	[0.176]	[0.000]***	[0.015]*	[0.000]***
RDI_t	-1.474	-10.066	2.132	-10.076	38.160	203.872
	[0.070]	[0.000]***	[0.984]	[0.000]***	[0.924]	[0.000]***
$RDMC_t$	-1.794	-16.968	2.368	-16.021	40.766	326.147
	[0.036]*	[0.000]***	[0.991]	[0.000]***	[0.870]	[0.000]***
RDE_t	-0.440	-21.306	-0.847	-21.442	63.958	451.391
	[0.330]	[0.000]***	[0.199]	[0.000]***	[0.124]	[0.000]***
GDP_t	-5.184	-14.775	1.476	-16.059	50.908	350.520
	[0.000]***	[0.000]***	[0.930]	[0.000]***	[0.792]	[0.000]***
CPI_t	-12.679	-15.864	-9.031	-15.048	233.970	329.108
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
PRA_t	-4.123	-24.151	1.284	-25.566	54.887	584.489
	[0.000]***	[0.000]***	[0.009]**	[0.000]***	[0.663]	[0.000]***
PRS_t	-6.893	-16.172	-1.475	-16.010	86.335	356.389
	[0.000]***	[0.000]***	[0.070]	[0.000]***	[0.015]*	[0.000]***
PRT_t	-10.526	-18.993	-3.211	-17.614	112.300	384.911
	[0.000]***	[0.000]***	[0.001]***	[0.000]***	[0.000]***	[0.000]***
OPN_t	-2.925	-24.191	1.540	-21.803	46.615	485.717
	[0.002]**	[0.000]***	[0.938]	[0.000]***	[0.897]	[0.000]***

Note: All variables include a constant. In order to detect the optimal lag length, the Schwarz Information Criterion (SIC) is used. Newey-West bandwidth selection with Bartlett kernel is applied for the LLC test. All independent variables are in natural logs. *Rejection of the null hypothesis of nonstationarity at the 0.05 level, **Rejection of the null hypothesis of nonstationarity at the 0.01 level, ***Rejection of the null hypothesis of nonstationarity at the 0.001 level.
Source: Author's calculations.

[12] These data were calculated using the overall statistics in Table 5.3.

5.3.1. Results for agriculture

In this section, firstly, the panel cointegration test results of Model 5.1 and Model 5.2, which were created for agricultural employment, are given. Pedroni and Kao cointegration tests with and without trend in Table 5.8 show that the null of no cointegration is rejected at the 1% level based on almost all test results except one for Model 5.2 including a trend. These results signify the existence of a long-run relationship among the five series in Model 5.1 and six series in Model 5.2. Therefore, even supposing the five variables in Model 5.1 and six variables in Model 5.2 themselves might comprise stochastic trends like being nonstationary, they nevertheless perform to behave collectively in time and the difference among them is constant.

Table 5.8. Results of panel cointegration tests for employment in the agriculture sector

Test	Statistics		Model 5.1 *RD, GDP, CPI, PRA* w/o trend	Model 5.1 w/ trend	Model 5.2 *RD, GDP, CPI, PRA, OPN* w/o trend	Model 5.2 w/ trend
Pedroni	Panel	Panel PP t	-12.408***	-9.888***	-11.670***	-9.544***
	Panel	Panel ADF t	-12.445***	-9.423***	-2.585**	0.708
	Panel weighted	Panel PP t	-5.014***	-6.570***	-4.203***	-6.532***
	Panel weighted	Panel ADF t	-5.526***	-6.121***	-4.439***	-5.649***
	Group	Group PP t	-6.453***	-8.337***	-5.826***	-8.027***
	Group	Group ADF t	-6.453***	-5.828***	-4.439***	-5.175***
Kao		ADF t	-3.933***		-5.511***	

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the independent variables are in natural logs, and the dependent variable $EMPA_t$ is used in decimal fractions. *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

After proving the existence of a long-term relationship in the models established to explain agricultural employment with various macro variables, especially agricultural R&D spending, the coefficients of the variables were estimated using the PDOLS and FMOLS estimators developed by Pedroni (2001a, 2001b) and the results were shared in Table 5.9. As in the other sections, our main focus in this section is the direction and intensity of the β coefficient. According to both estimators, *RDA* affects agricultural employment negatively. In Model 5.1 and Model 5.2, both coefficients obtained by the PDOLS method are approximately -0.0014 and are significant at 1%. According to FMOLS results, in Model 5.1, β was predicted as negative but less effective. The coefficients estimated as -0.0007 and -0.0008, respectively, are statistically significant at 10% and 1% levels, respectively. The results are not surprising, R&D expenditures in the agricultural sector reduce employment in this sector. In the previous periods, the agricultural sector, which was based only on human and animal power, was completed with the Industrial Revolution and the following years with simple machines that complemented human and animal power. Then it became much more technology-intensive, much less labor-intensive, with advanced machinery such as tractors. However, the coefficient of R&D per capita is less effective in terms of magnitude than the coefficient of other variables. The most important reason for this is that the share of R&D expenditures in the agricultural sector in total R&D is quite low. For example, over a thirty-year period, only 0.6% of the average per capita R&D expenditure of thirty selected countries belonged to the agricultural sector. In addition, R&D investments in the industrial sector also directly affect the equipment to be used in the agricultural sector. Therefore, the size of the R&D coefficient given in Table 5.9 should be interpreted accordingly. As stated before, in this study, the sectoral employment effect of technology proxied by intra-sector R&D is investigated and the inter-sectoral technological effect is ignored. This situation does not make it possible to compare the R&D coefficients between sectors in this study but allows them to be evaluated only in terms of their signs. The impact of R&D expenditures in other sectors or total R&D investments on employment in the agricultural sector may be an important area of research for future studies.

Table 5.9. FMOLS and PDOLS estimates results for the agriculture sector

Variable	Broad sector: Agriculture							
	Model 5.1				Model 5.2			
	PDOLS		FMOLS		PDOLS		FMOLS	
RDA_t	-0.0014	$(-2.983)^{**}$	-0.0007	$(-1.917)^{+}$	-0.0014	$(-2.729)^{**}$	-0.0008	$(-2.659)^{**}$
GDP_t	-0.0097	$(-2.583)^{**}$	-0.0192	$(-6.914)^{***}$	-0.0135	$(-1.934)^{+}$	-0.0177	$(-5.063)^{***}$
CPI_t	-0.0233	$(-10.028)^{***}$	-0.0232	$(-12.054)^{***}$	-0.0350	$(-9.810)^{***}$	-0.0245	$(-11.978)^{***}$
PRA_t	-0.0326	$(-15.036)^{***}$	-0.0320	$(-20.855)^{***}$	-0.0324	$(-13.285)^{***}$	-0.0313	$(-23.243)^{***}$
OPN_t					0.0039	(1.168)	-0.0023	(-1.228)

Note: For the PDOLS estimator, the SIC is used to determine the leads & lags and. The grouped estimation is used as a panel method for both estimators. As the dependent variable, decimal fractions of $EMPA_t$ are used. All the independent variables are in natural logs. $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

When the other control variables are examined, the relationship between the growth in per capita income and employment in the agricultural sector is negative, and it is seen that the coefficients estimated by both PDOLS and FMOLS methods vary between -0.010 and -0.018. These results are in line with previous empirical findings. Secondly, it is seen that the relationship between inflation and employment in the agricultural sector is also inversely. *CPI* coefficients obtained with both PDOLS and FMOLS estimators range from -0.023 to -0.035. Third, productivity per worker, which is affected by both technological and non-technology shocks, is inversely proportional to employment in agriculture, as the coefficients range from -0.031 to -0.033 according to the two estimators. Finally, it is observed that *OPN*, which is the trade openness variable analyzed in Model 5.2, does not have a statistically significant effect on employment in agriculture. One of the possible reasons for this situation is the economic development level of the selected countries. 28 of the countries are OECD countries and the remaining two are Romania and South Africa, which have similar economic performances to the developing countries in this country group. In developed and developing countries, the weight of the agricultural sector in the economy is not at a level that will be affected by the trade openness and create additional employment in the sector or cause employment loss.

As a result, technology leads to a loss of employment in the agricultural sector. On the other hand, the effect of R&D expenditures within the sector is smaller than the effect of other control variables. An important reason for this is that the share of R&D

expenditures within the sector is quite low in total R&D. Alternatively, the technology used in the agricultural sector is not only determined by sectoral R&D expenditures, but also new technologies produced in the industry directly affect the agricultural sector. Therefore, the effect of innovation activities in all other sectors on employment in agriculture is an important research topic. Finally, it is seen that the increase in income in the agricultural sector is one of the factors causing the loss of employment rather than being a compensation mechanism because the *GDP* coefficients are negative in both models. Therefore, the increase in income not only alleviates the loss of employment caused by the increase in productivity caused by technology or non-technological factors but inflames it even more.

5.3.2. Results for industry

In this section, panel cointegration and estimation results for the entire industry sector are reported. Unlike agriculture and the service sector given under the next heading, the number of countries whose data is used for the industry is 26. Mexico, Norway, South Africa, and Romania are excluded and therefore 26 OECD countries are used in this section due to issues such as data availability and adequacy. The results in Table 5.10 include both Pedroni and Kao test results on whether the series in Model 5.3 and Model 5.4 are cointegrated in the long run. According to all of the Pedroni tests, the series in both trend and non-trend models are significantly correlated in the long run. Because the null hypotheses of no cointegration among series in Model 5.3 and Model 5.4 separately are rejected at least 1% level based on the Pedroni results. On the other hand, Kao test results are not significant at 5% but significant at 10%. All this means that the series in Model 5.3 and Model 5.4 may not be stationary at level, that is, these series may contain stochastic trends. However, the cointegration results show that these series have a significant relationship in the long run and the differences between them are constant. Therefore, the fundamental principle for the estimation of the parameters of the created models has been satisfied.

Table 5.10. Results of panel cointegration tests for employment in industry

Test	Statistics		Model 5.3 *RD, GDP, CPI, PRT*		Model 5.4 *RD, GDP, CPI, PRT, OPN*	
			w/o trend	w/ trend	w/o trend	w/ trend
Pedroni	Panel	Panel PP t	-4.134^{***}	-4.795^{***}	-4.502^{***}	-4.457^{***}
		Panel ADF t	-4.213^{***}	-6.009^{***}	-3.581^{***}	-4.751^{***}
	Panel weighted	Panel PP t	-3.901^{***}	-4.743^{***}	-4.330^{***}	-4.855^{***}
		Panel ADF t	-4.106^{***}	-5.266^{***}	-3.926^{***}	-4.734^{***}
	Group	Group PP t	-5.487^{***}	-5.511^{***}	-5.713^{***}	-5.980^{***}
		Group ADF t	-4.771^{***}	-4.939^{***}	-3.836^{***}	-4.348^{***}
Kao		ADF t	-1.536^{+}		-1.567^{+}	

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the independent variables are in natural logs, while dependent variable $EMPI_t$ is used in decimal fraction. Mexico, Norway, South Africa, and Romania are excluded. $^{+}$Rejection of the null hypothesis of no cointegration at the 0.05 level, *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

After proving that the series are cointegrated in the long run, the coefficients of the variables were estimated using the PDOLS and FMOLS estimators generated by Pedroni (2001a, 2001b), as in the previous title, and the results are given in Table 5.11. According to the PDOLS results, the *RDI* coefficient in Model 5.3 is -0.0125 and it is statistically significant at the 5% level. On the other hand, although the RDI coefficient in Model 5.4 is negative, it is not statistically significant. According to FMOLS results, the RDI coefficients were estimated as -0.0138 and -0.0132, respectively, and the coefficients were statistically significant at least at a 1% level in both models. Therefore, it can be concluded that business enterprise R&D expenditures affect employment negatively in the industry. In fact, this result is mostly consistent with the RBTC hypothesis and job polarization. Because employment in the industry is mostly composed of blue-collar workers and workers in routine jobs. At this point, the coefficient of *RDI* is negatively much larger than the *RDA* coefficients estimated in the previous section, but the direct comparison may be misleading as these variables indicate intra-industry R&D expenditures.

The coefficient of GDP per capita, which is one of the other control variables, is estimated positively for employment in the industry. According to both PDOLS and

FMOLS results, the coefficients vary between 0.184 and 0.210 and all are significant at 1%. Therefore, unlike the agriculture sector, the increase in income continues to be an important compensation channel for the loss of employment in the industrial sector. However, on the other hand, the coefficient of the productivity variable, namely PRT, which is affected by both technological and non-technological shocks, varies between -0.170 and -0.206, which is remarkably close to the GDP coefficient. Considering the productivity coefficient together with the *RDI* coefficient, it is seen that although the increase in income is an important compensator for the loss of employment in the industry, it cannot prevent the loss of technology-induced net employment in the industry. Besides, the CPI coefficient is also negative, and therefore, the increase in inflation causes a loss of employment in the manufacturing sector. In addition, the effect size of inflation for manufacturing is higher than that estimated for the agriculture sector. Finally, although the coefficient of the *OPN* variable in Model 5.4 is positive, it is statistically insignificant. As a result, it can be said that trade openness has the power to increase employment in the industries of the countries, albeit slightly. It is necessary to draw attention to the heterogeneity between countries for all coefficients. Grouping and re-evaluation of countries with similar characteristics in order to make clearer inferences may be a meaningful research area for future studies.

Table 5.11. FMOLS and PDOLS estimates results for the industry

Variable	Broad sector: Industry							
	Model 5.3				Model 5.4			
	PDOLS		FMOLS		PDOLS		FMOLS	
RDI_t	-0.0125	$(-2.218)^{*}$	-0.0138	$(-3.923)^{***}$	-0.0069	(-0.866)	-0.0132	$(-3.869)^{***}$
GDP_t	0.2139	$(9.655)^{***}$	0.2194	$(17.009)^{***}$	0.1836	$(7.025)^{***}$	0.2090	$(17.602)^{***}$
CPI_t	-0.1283	$(-9.765)^{***}$	-0.1575	$(-19.232)^{***}$	-0.1278	$(-8.143)^{***}$	-0.1683	$(-20.724)^{***}$
PRT_t	-0.2057	$(-8.684)^{***}$	-0.1969	$(-13.366)^{***}$	-0.1959	$(-8.108)^{***}$	-0.1696	$(-11.356)^{***}$
OPN_t					0.0084	(1.166)	0.0018	(0.405)

Note: For the PDOLS estimator, the SIC is used to determine the leads & lags. For both estimators, grouped estimation used as panel method. As the dependent variable, decimal fractions of $EMPI_t$ are used. All the independent variables are in natural logs. Mexico, Norway, South Africa, and Romania are excluded (N = 26). $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

As stated before, the industry has a fairly wide list of sub-sectors, according to the industry division made by the United Nations (2008). In addition, manufacturing, one of the sub-sectors of the industry, has an important share in terms of both employment and R&D investments. At this stage, the cointegration (Table 5.12) and estimation (Table 5.13) results of Model 5.5 and Model 5.6, which were established for the manufacturing (including construction) sector by excluding energy from the industry, were shared. According to the Pedroni cointegration results, there is a statistically significant cointegration between the series in Model 5.5 and Model 5.6 because the null hypothesis of no cointegration is rejected at a minimum level of 1% according to all test results. According to Kao test results, while the cointegration in Model 5.5 is weak, the long-term relationship is significant at 10% in Model 5.6.

Table 5.12. Results of panel cointegration tests for employment in manufacturing and construction

Test	Statistics		Model 5.5		Model 5.6	
			without trend	with trend	without trend	with trend
Pedroni	Panel	Panel PP t	-3.099^{***}	-4.038^{***}	-3.370^{***}	-3.574^{***}
		Panel ADF t	-3.863^{***}	-5.543^{***}	-2.864^{**}	-3.989^{***}
	Panel weighted	Panel PP t	-3.316^{***}	-4.328^{***}	-3.579^{***}	-4.966^{***}
		Panel ADF t	-3.991^{***}	-5.526^{***}	-3.434^{***}	-5.309^{***}
	Group	Group PP t	-3.521^{***}	-5.666^{***}	-4.379^{***}	-6.011^{***}
		Group ADF t	-3.879^{***}	-5.211^{***}	-2.764^{**}	-4.533^{***}
Kao		ADF t	-1.220		-1.258^{+}	

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the independent variables are in natural logs, while the dependent variable $EMPM_t$ is used in decimal fractions. Mexico, Norway, South Africa, and Romania are excluded. $^{+}$Rejection of the null hypothesis of no cointegration at the 0.05 level, *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author’s calculations.

After proving the existence of long-term relationships between the series in Model 5.5 and Model 5.6, the coefficients of the variables were estimated and shared in Table 5.13. As for the whole industry, the coefficient of sectoral R&D expenditures in the manufacturing sector is negative. But this time the coefficients are estimated between -0.0142 and -0.0115 according to PDOLS, and between -0.0133 and -0.0140 according to

FMOLS. This means that when the energy sector is purged from the industry and focused only on manufacturing, the effect size of the technology increases slightly in the negative direction. In addition, the *GDP* coefficient is also positive and slightly larger than predicted for the industry. The *CPI* and *PRT* coefficients also have a negative sign. As a result, the effect of R&D in the manufacturing sector is negative and this effect is more severe than in the entire industry that includes the energy sector. On the other hand, the effect of the increase in income seems to be higher, albeit slightly. Income is an important compensation channel also for employment in the manufacturing sector but is likely to lose its effectiveness over time.

Table 5.13. FMOLS and PDOLS estimates results for the manufacturing sector

Variable	Sub-sector: Manufacturing and construction							
	Model 5.5				Model 5.6			
	PDOLS		FMOLS		PDOLS		FMOLS	
RDM_t	-0.0142	$(-2.406)^{*}$	-0.0140	$(-3.848)^{***}$	-0.0115	(-1.403)	-0.0133	$(-3.912)^{***}$
GDP_t	0.2332	$(10.130)^{***}$	0.2214	$(16.510)^{***}$	0.1918	$(6.725)^{***}$	0.2076	$(16.708)^{***}$
CPI_t	-0.1456	$(-10.943)^{***}$	-0.1699	$(-20.487)^{***}$	-0.1539	$(-9.449)^{***}$	-0.1802	$(-21.965)^{***}$
PRT_t	-0.2031	$(-8.620)^{***}$	-0.1751	$(-11.647)^{***}$	-0.1774	$(-6.299)^{***}$	-0.1500	$(-9.802)^{***}$
OPN_t					0.0138	(1.571)	0.0042	(0.907)

Note: For the PDOLS estimator, the SIC is used to determine the leads & lags. For both estimators, grouped estimation is used as the panel method. As the dependent variable, decimal fractions of $EMPM_t$ are used. All the independent variables are in natural logs. Mexico, Norway, South Africa, and Romania are excluded (N = 26). $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Table 5.14 and Table 5.15 have been prepared for results on how employment in the energy sector is affected by sector-specific R&D expenditures. According to the cointegration results in Table 5.14, there is a long-term significant relationship between the series in Model 5.7 and Model 5.8 because the null of no cointegration is rejected for all test results that are statistically significant.

Table 5.14. Results of panel cointegration tests for employment in energy

Test	Statistics		Model 5.7		Model 5.8	
			without trend	with trend	without trend	with trend
Pedroni	Panel	Panel PP t	-1.901^{*}	-2.711^{**}	-2.109^{*}	-4.015^{***}
		Panel ADF t	-2.426^{**}	-3.873^{***}	-2.774^{**}	-4.120^{***}
	Panel weighted	Panel PP t	-2.976^{**}	-3.020^{**}	-3.358^{***}	-4.023^{***}
		Panel ADF t	-4.075^{***}	-4.795^{***}	-5.074^{***}	-5.673^{***}
	Group	Group PP t	-3.414^{***}	-2.903^{**}	-4.396^{***}	-4.875^{***}
		Group ADF t	-4.164^{***}	-4.682^{***}	-5.095^{***}	-5.581^{***}
Kao		ADF t	-3.157^{***}		-2.951^{**}	

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the independent variables are in natural logs, while the dependent variable $EMPE_t$ is used in decimal fractions. Mexico, Norway, South Africa, and Romania are excluded. $^{+}$Rejection of the null hypothesis of no cointegration at the 0.05 level, *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations.

The coefficient estimates in Table 5.15 are different from the whole industry and manufacturing sector. According to both PDOLS and FMOLS results, the *RDE* coefficient is positive, but according to the PDOLS results, these coefficients are not statistically significant. Therefore, R&D expenditures in the energy sector have a slight employment-increasing effect. However, at this point, it is useful to repeat once again that the R&D expenditures used in the study are unique to each sector. Therefore, the cross-sectoral effect is ignored. The effect of R&D investments made in the entire industry on employment in the energy sector can be the subject of a separate study.

The effect of *GDP*, one of the control variables, is positive as in the industry, but the effect size is smaller. According to an interesting finding of the study, the relationship between *CPI* and employment in the energy sector is positive, and in this respect, the findings differ with the industry results and are compatible with the Philips curve. The *PRT* coefficient is negative, and this shows that the increase in productivity resulting from technical and non-technical effects also reduces employment in the energy sector. This result should be related to the fact that advanced technologies require less manpower, especially in areas such as mining. Finally, trade openness and energy sector employment are negatively related, but this relationship is not statistically significant.

Table 5.15. FMOLS and PDOLS estimates results for the energy sector

Variable	Sub-sector: Energy							
	Model 5.5				Model 5.6			
	PDOLS		FMOLS		PDOLS		FMOLS	
RDE_t	0.0001	(0.257)	0.0006	$(3.882)^{***}$	0.0003	(0.571)	0.0006	$(4.043)^{***}$
GDP_t	0.0091	(1.186)	0.0031	(1.269)	0.0149	$(1.734)^{+}$	0.0053	$(2.164)^{*}$
CPI_t	0.0182	$(6.641)^{***}$	0.0137	$(10.682)^{***}$	0.0168	$(4.712)^{***}$	0.0132	$(10.408)^{***}$
PRT_t	-0.0411	$(-3.405)^{**}$	-0.0275	$(-7.790)^{***}$	-0.0474	$(-3.245)^{**}$	-0.0298	$(-8.711)^{***}$
OPN_t					-0.0019	(-1.099)	-0.0009	(-0.933)

Note: For the PDOLS estimator, the SIC is used to determine the leads & lags. For both estimators, grouped estimation is used as a panel method. As the dependent variable, decimal fractions of $EMPE_t$ are used. All the independent variables are in natural logs. Mexico, Norway, South Africa, and Romania are excluded (*N* = 26). $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

5.3.3. Results for the service sector

Finally, in this section, it is investigated how employment in the service sector is affected by R&D activities. It should be noted that technological developments affecting the service sector are not only affected by R&D expenditures in this field. In particular, technical advances in the industry may also affect employment and other economic dynamics in this sector. Therefore, the results should be evaluated in this direction, and it should not be forgotten that technical advances in other sectors are not taken into account. Secondly, although the significance of the panel cointegration results in Table 5.16 is more moderate than the other two broad sector results, again, most test results prove the existence of a long-run relationship for five variables in Model 5.9 and six variables in Model 5.10. At this point, results with a trend are stronger than results without a trend for both models.

Table 5.16. Results of panel cointegration tests for employment in the service sector

Test	Statistics		Model 5.9 *RD, GDP, CPI, PRS* w/o trend	Model 5.9 *RD, GDP, CPI, PRS* w/ trend	Model 5.10 *RD, GDP, CPI, PRS, OPN* w/o trend	Model 5.10 *RD, GDP, CPI, PRS, OPN* w/ trend
Pedroni	Panel	Panel PP t	-2.013*	-4.164***	-0.041	-2.245*
	Panel	Panel ADF t	-2.267*	-6.139***	-1.248	-3.982***
	Panel weighted	Panel PP t	-1.573+	-4.118***	-1.268	-4.135***
	Panel weighted	Panel ADF t	-2.487**	-6.200***	-2.605**	-5.415***
	Group	Group PP t	-2.303*	-4.490***	-1.524+	-4.916***
	Group	Group ADF t	-2.183*	-6.497***	-2.560**	-4.907***
Kao		ADF t	-3.634***		-3.623***	

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the independent variables are in natural logs, and the dependent variable $EMPS_t$ is used in decimal fractions. +Rejection of the null hypothesis of no cointegration at the 0.05 level, *Rejection of the null hypothesis of no cointegration at the 0.05 level, **Rejection of the null hypothesis of no cointegration at the 0.01 level, ***Rejection of the null hypothesis of no cointegration at the 0.001 level.
Source: Author's calculations

After proving the existence of a long-term relationship between the panel series, long-term coefficients were estimated by PDOLS and FMOLS methods, as in all previous analysis stages. For estimators, pooled weighted and pooled panel methods developed by Philips and Moon (1999), Mark and Sul (2003), and Pedroni (2001b) were preferred, and the results are shared in Table 5.17. According to both PDOLS and FMOLS results, the coefficient of *RDS* used as a technology proxy is positive and statistically significant. The coefficients for both estimators vary between 0.0164 and 0.0189. When these results are evaluated in terms of RBTC and job polarization, they are in line with the literature because non-routine cognitive tasks in the service sector are heavy and such jobs are completed by technology. Secondly, especially in developed economies routine job market shrinks compared to non-routine jobs. And based on the previous empirical results developed economies experience labor force transition especially from the middle-income manufacturing sector to the low-income service sector. Consequently, the service sector is experiencing an expansion in employment due to increased demand for high-skilled workers for non-routine cognitive jobs driven by technical advances within the sector. Moreover, sectoral growth and cross-sector employment transitions can create additional spaces for low-skills in the service sector.

Table 5.17. FMOLS and PDOLS estimates results for the service sector

Variable	Broad sector: Service							
	Model 5.9				Model 5.10			
	PDOLS		FMOLS		PDOLS		FMOLS	
RDS_t	0.0179	(9.905)***	0.0189	(11.592)***	0.0164	(8.816)***	0.0184	(12.272)***
GDP_t	0.1818	(15.107)***	0.1963	(17.753)***	0.1790	(15.538)***	0.1975	(18.773)***
CPI_t	0.0118	(2.926)**	0.0004	(0.129)	0.0081	(2.037)*	-0.0002	(-0.067)
PRS_t	-0.0603	(-4.159)***	-0.0983	(-5.115)***	-0.0656	(-3.726)***	-0.1051	(-5.681)***
OPN_t					0.0122	(2.479)*	0.0037	(0.714)

Note: For the PDOLS estimator, the SIC is used to determine the leads & lags and the panel weighted is used as panel method. For the FMOLS estimator, panel pooled results are given, and the sandwich method is used in estimating covariance. As the dependent variable, decimal fractions of $EMPS_t$ are used. All the independent variables are in natural logs. +Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Authors' calculations.

When the coefficients of other control variables used in the study are examined, it is seen that the increase in per capita income also affects employment in the service sector positively, but the estimated coefficients are slightly lower than those estimated for the industry. Inflation is positive and significant according to PDOLS results, but not statistically significant according to FMOLS results. In this respect, it can be concluded that the PDOLS results are in parallel with the Philips Curve, but the effect size of the coefficient is much lower than that estimated for other sectors. Output per worker, i.e., *PRS* coefficient, is negative, which is consistent with the whole study, but this coefficient is much lower compared to the *GDP* coefficient. Although the service industry is a non-routine cognitive work-intensive industry, low- or medium-skill workers who are already employed in jobs prone to automation, or high-skilled workers who do routine cognitive work, are also employed in this industry. Technology is complementary to non-routine cognitive tasks as well as a substitute for labor in routine cognitive tasks. Therefore, the small but negative coefficient of productivity here can be explained by the technical and non-technical technology shocks, which require fewer low- or medium-skilled workers in routine jobs in the service sector. In addition to all these, since the increase in productivity is calculated as output per worker, the rate of increase in technology and the resulting increase in productivity does not mean that employment has increased at the same rate. Because technology allows achieving the same amount of output over time with fewer workers. Finally, trade openness is also significant at the 5% level according to PDOLS results and positively affects employment in the service sector.

5.4. Concluding Remarks

In this section, the technology-employment relationship is discussed from a sectoral point of view, but at a macro level, in a wide country sample and time range. In the study, three different broad sectors, agriculture, industry, and service defined by United Nations (2008), and manufacturing and energy sectors which are among the sub-sectors of the industry, are analyzed. In this direction, R&D expenditures within each sector are used as a technology proxy. Therefore, the main focus of this study is how and to what extent sectoral employment is affected by the innovations produced within the sector. Employment data are also sector-specific and sector-specific employee numbers are divided by the total labor force in the country and sectoral employment data are obtained. In the established models, in addition to the R&D variable, per capita income representing economic growth, consumer price index representing inflation, output per worker representing labor productivity, and the ratio of total export and import activities to total income representing trade openness are considered as control variables. In this direction, two models were established for each sector, and whether the variables in the models were related in the long term were evaluated primarily with the Pedroni (1999, 2004) and Kao (1999) cointegration methods. The coefficients in the models of the series that are proven to be cointegrated in the long run are estimated with the estimators PDOLS (Kao and Chiang, 2001; Pedroni, 2001a; Mark and Sul, 2003) and FMOLS (Phillips and Moon, 2000; Pedroni, 2001b; Kao and Chiang, 2001). In this direction, the main findings obtained in the study are as follows:

i) In models established for all sectors, especially R&D, GDP per capita, consumer price index, output per worker, and openness series and sectoral employment are cointegrated in the long term. These results are very strong for agriculture and industry, manufacturing, and energy sub-sectors. According to almost all of the Pedroni and Kao test results in these sectors, the null hypothesis is rejected, and the existence of a strong long-term significant relationship is statistically demonstrated. Although the cointegration results for the service sector are not as strong as for other sectors, especially trend models prove the existence of a long-term significant relationship.

ii) Technology in the agricultural sector affects employment negatively. The β coefficient was estimated as -0.0014 for both models according to the PDOLS estimator, as -0.0007 for the first model and -0.0008 for the second model according to the FMOLS estimator. The effect size of the variables is lower than the effect sizes of the other control variables. One possible reason for this is that R&D expenditures in the agricultural sector make up a relatively small proportion of total R&D activities. Another possible reason is that the shift from the agricultural sector to other sectors has already taken place, especially in the developed countries that are the subject of the study, and a kind of sectoral saturation has been reached. Finally, the explanatory variable used indicates industry R&D and does not reflect technology influence from other industries. Therefore, this result does not indicate that technology affects employment in agriculture to a small extent. In this respect, the sign of the β coefficient rather than its size is remarkable. The agricultural sector is now much more technology-intensive and much less labor-intensive than in the past, so these results are quite reasonable. Under the assumption of a fixed population, the demand for products produced in the agricultural sector cannot be expected to have high income and price elasticity because these products are mostly essential products. Therefore, it is not possible to talk about the existence of a compensation channel that can balance the negative impact of technology on employment in the agricultural sector. Secondly, the relationship between economic growth and employment in the agricultural sector is also negative. The GDP per capita coefficient was estimated as -0.0097 to -0.0135 according to the PDOLS estimator, and as -0.0192 to -0.0177 according to the FMOLS estimator. As countries develop economically, employment shifts from traditional sectors such as agriculture to sectors with higher added value. Thirdly, inflation negatively affects employment in the agricultural sector, with the coefficients estimated according to both methods between -0.0232 and -0.0350. Although these results are inconsistent with the Philips Curve, it is an expected result that the increase in the price level will adversely affect investments in the sector and thus employment. Increasing productivity due to technical and non-technical shocks in the agricultural sector is also negatively related to employment. Finally, no significant relationship was found between trade openness and employment in the agricultural sector. It is also reasonable because, in developed and most developing economies, the share of the agricultural sector in the economy is not at a level that will be affected by the trade openness and create additional employment in the sector or cause employment loss.

iii) The entire industry is also negatively affected by technology in terms of employment. According to the significant PDOLS and FMOLS results, the coefficient of sectoral R&D expenditures is around -0.0123 to -0.0138. The industry sector especially experiences process innovation intensively because routine jobs that are prone to automation due to the structure of the sector are predominant. This situation causes the R&D expenditures within the sector and the innovations obtained as a result of these to cause employment loss in the sector. The output coefficient per worker also varies between -0.1696 and -0.2057, which indicates that the increased labor productivity as a result of technical and non-technical shocks does not translate into employment growth at the same rate. On the other hand, income growth is an important compensation mechanism channel for the industrial sector. The per capita income coefficient is positive in all models and is statistically significant. However, the increase in per capita income is not sufficient to balance the employment loss alone, and it only alleviates the labor-saving effect of the increased productivity with technical and non-technical shocks. The coefficient of inflation in the industry is also estimated as negative and it is striking that the effect sizes of the coefficients are much higher than in the agriculture sector. These results show that the increase in the general level of prices in the country leads to a contraction in employment in the industrial sector. High inflation situations increase the risk expectations of investors, and this situation causes a decrease in employment by reducing investments. Finally, although the coefficient of the openness variable is positively estimated according to both estimators, it is not statistically significant. Therefore, the intensity and openness in the commercial activities of the countries affect the employment in the industry positively, but very slightly.

iv) Separate models were created and estimated for the two sub-sectors of the industry, manufacturing, and energy. Because the impact of technology on the manufacturing and energy sectors can be in different directions. First of all, it has been determined that R&D affects employment negatively in the models established for the manufacturing sector. At this point, it should be noted that the manufacturing sector actually constitutes a large part of the industry in terms of income, employment and R&D. Therefore, it is not surprising that the manufacturing results are parallel to the industry results. In addition, income in the manufacturing sector is again an important compensation channel and alleviates the labor-saving effect of technology. The most important difference between the manufacturing sector and the agricultural sector is that the elasticity of demand is still high in some areas of the manufacturing sector, in other words, the consumer demand has not yet reached saturation. Therefore, the increase in income is strong enough to increase the demand and thus employment for this sector. However, considering the increased productivity with technology and non-technology shocks, it is seen that income mitigates the negative effect rather than offsetting the loss of employment. Secondly, in the energy sector, the results are different according to the whole industry. According to the PDOLS results, R&D does not affect employment in the energy sector in a statistically significant way. According to FMOLS results, the results are significant, but the effect size of the coefficient is quite low. Interestingly, the effect of income growth on employment in the energy sector is also positive but weak. The relationship between labor productivity and employment, measured by output per worker, is negative according to both estimators. At this point, it is necessary to draw attention to the heterogeneity of the energy sector. The sector has both routine and non-routine job sub-sectors such as mining, which mostly includes blue-collar jobholders, and more developed such as oil and natural gas. Therefore, it is normal to experience loss of employment in routine work-intensive areas in this sector. Due to concerns such as occupational safety, machines are now preferred instead of manpower in many areas. For deeper results specific to the energy sector, it may be helpful to focus on the subcategories of the sector.

v) Finally, models of the service sector were estimated in the study. Unlike agriculture and industry, technology in the service sector has a labor-friendly characteristic. The estimated β coefficient according to PDOLS and FMOLS results is between 0.0164 and 0.0189. The service industry is an area that is less prone to automation and is mostly dominated by cognitive skills. For this kind of work, technology is not a substitute, it is complementary. Therefore, it is reasonable for technology to be job-creating in the service sector. However, it should be noted here that the tasks in the service sector are not classified as routine or non-routine in the study. That is, the results are not task-based or skill-based, but cover all jobs in the service sector, routine or non-routine, high or low skill. Secondly, the reflection of the increase in income on employment in the service sector is also positive, but the effect size is slightly lower than in the industry. Thirdly, in the service sector, unlike the other two main sectors, the relationship between inflation and employment is positively determined, which is in line with the Philips Curve. A possible reason for this situation may be that investors tend to focus more on services in banking and other financial fields instead of physical capital investments in areas such as the industry due to risk uncertainties in high inflation situations. Shifting investments to financial activities rather than real investments can also increase the demand for labor in the service sector. Fourth, the increase in output per worker in the service sector is greater than the increase in employment. In other words, the relationship between productivity and employment is negative, but the coefficient is considerably lower than that estimated for other sectors. One possible reason is routine cognitive work in the service industry that is prone to automation. Although the service sector mostly includes jobs that require high skills and are complementary to technology, cognitive but routine jobs such as bank tellers and standard office staff also have a considerable share in the service sector. And due to the automation tendency of such jobs, it is possible to achieve the same output with less workforce than in the past. Finally, employment in the service sector is positively affected by trade openness in a statistically significant way. Contrary to industry, the relationship in the service sector is clearer. Trade openness in areas such as manufacturing may not create the expected positive employment effect, especially since developed countries are deindustrialized. On the contrary, local employment may decrease due to production shifted to countries where labor is cheaper. However, this is not the case for the service sector because companies in this field are located in developed countries and the possible benefits from commercial activities increase the need for highly skilled employees due to the structure of the sector.

As a result, the findings obtained in the study show that the technology produced in agriculture and industry itself reduces employment in agriculture and industry. Economic growth is an important compensation mechanism for the industry, but it does not completely eliminate the labor-saving effect of technology, it partially alleviates it. In the agricultural sector, the employment-destroying effect of technology cannot be suppressed even through income, and the demand, which is inelastic or less elastic due to the nature of the sector, cannot create additional employment areas where manpower will be used. This is true for developed and some developing countries covered in the study. Underdeveloped countries whose economy is based on agriculture can be the subject of different studies. On the other hand, in the service sector, technology has a positive effect on employment. It can be said that the service sector has the power to eliminate the labor-saving effect experienced in other sectors. However, since these results are revealed by estimating the employment rates within the sector with sectoral technology data, in this study, it is not possible to make an inference about how much the employment losses experienced in the agriculture and manufacturing sectors can be compensated in the service sector. Because it is not possible for those who lost their jobs in the industry sector, which is the result of routine intensive work, to work in similar positions in the service sector. One possible reason is that industry workers are mostly in the medium-skill group, and they are likely to fall towards low-skill positions rather than high-skill jobs, as skill upgrading is time-consuming, costly, and in some cases not possible. Therefore, while the demand and number of skilled workers due to technology increases, the supply of unskilled workers also increases in the sector. The surplus in the labor supply will cause average wages to decline over time.

The findings of this study indirectly support the RBTC, and job polarization approaches introduced in Autor et al. (2006), Goos and Maning (2007), Autor and Dorn (2013), Goos et al. (2014), and Lee and Shin (2017). supports. Because while the manufacturing sector is an area where blue-collar workers mostly work and routine intensive tasks are involved, cognitive work is dominant in the service sector. The fact that technology harms employment in the manufacturing sector and increases employment in the service sector, especially for the skilled, may be due to the automation of non-cognitive routine works in the first and the completion of non-routine cognitive tasks with technology in the second. This supports approaches that explain business polarization with RBTC. Secondly, the results obtained from the study are also compatible with the results obtained in the studies of Acemoglu and Restrepo (2019) and Bessen (2020) especially for the manufacturing sector and revealing that the labor-saving effect outweighs the technology in these areas. Since the automation risk estimations made by Frey and Osborne (2017) also indicate that technology will adversely affect those who work in routine jobs and that the risk of those who work in cognitive jobs is lower, at least for now, the evidence obtained for the industry and the service sector in general in this study also overlaps with the predictions of the authors. Finally, studies such as Vivarelli (1996), Yasuda (2005), Bogliacino and Pianta (2010), and Compagnucci et al. (2019), which indicate that the effect of process innovations on employment is negative, especially in the manufacturing sector, is in line with the empirical evidence obtained in this chapter of the thesis.

CHAPTER 6: CONCLUSION

6.1. Summary of Findings

In this study, the relationship between technology and unemployment was investigated at the macro level by focusing on both developed and developing countries separately and by considering different sectors. In this context, 21 developed countries and 23 developing countries were managed separately in the first stage, while three main sectors were included for 30 developed and developing countries in the last step. All data used in the study belong to the period 1990-2019. In the sectoral analyses, the total values of employment, technology, and other control variables in the main sectors of the countries were used, and in this respect, the sectoral results are also at the macro level. In the studies conducted for developed and developing countries in the first place, the total unemployment rate was used as the dependent variable, and employment rates were defined as dependent variables instead of unemployment in the discrimination based on skills. In the sectoral level analyses, the dependent variables in all models are the employment rates of the relevant sector. The units of both unemployment and employment rates are the total percentage of the labor force and these values are used as decimal fractions in the analysis. The main area of interest of the study is the effect of technology on employment. In this direction, data of total gross domestic R&D expenditure per capita in the first two empirical sections representing technology, and data of business enterprise R&D expenditure per capita in the last section, which includes sectoral analyses, are used. In various model variations created macro indicators such as GDP per capita, consumer price index, output per worker, real effective exchange rate index, trade union density index, real interest rate, per capita public unemployment spending, and trade openness are used in addition to R&D. The variables R&D per capita, GDP per capita, output per worker, and per capita public unemployment spending are used as the constant US Dollar and the base year is 2010. The natural logarithms of all these series were considered in the analyses. For the consumer price index, real effective exchange rate index, trade union density index, and trade openness index variables, the base year was defined as 2010 and these variables were also used in the analysis by taking their natural logarithms. Real interest rate, on the other hand, was obtained as a percentage and was included in the analyses as decimal fractions, as in employment dependent variables.

In the light of the information given above, three main stages were followed in three different empirical sections. In the first stage, it was determined whether the series were *I*(1), and in the second stage, it was shown that the series proved to be *I*(1) were cointegrated with each other with different models. In the last stage, the coefficients of the series that were found to be cointegrated were estimated. EViews 12 statistical software was used in all analyses and the guidelines in IHS Markit - EViews (2020a, 2020b) were followed. As a first step, it has been proven that the series are *I*(1) according to three different unit root tests, namely the LLC (Levin et al., 2002), the IPS (Im et al., 2003), and ADF-Fisher (Maddala and Wu, 1999). At this point, it should be noted that this result is valid for all series in different models in the three empirical chapters and there is no exception. Whether the series proved to be *I*(1) are related to each other in the long term in the relevant models is shown by the different cointegration test statistics generated by Pedroni (1999, 2004) and Kao (1999). Summary results of cointegration tests can be shared as follows:

i) In developed countries, strong evidence was found that the series were cointegrated in six of the seven different models established for the unemployment dependent variable. In the specification expressed as Model 3.5, the cointegration between the series is weak and therefore the estimation results of this model should be interpreted in this context.

ii) In all three different models established for the high-skilled employment dependent variable in developed countries, the cointegration between the series is statistically significant according to all test results. Among the models established for low-skilled employment, statistical significance is strong in all test variations except for the series in the Model 3.11 specification, which is tested by including trends. Therefore, it has been proven that the series in the models established for both skill groups in developed countries are cointegrated in the long run.

iii) In developing countries, six different models have been established for the dependent variable of unemployment. In all models, according to at least three of the six test statistics obtained using the Pedroni cointegration method, the results are cointegrated in the long run. The Kao cointegration method shows that the series in all models are cointegrated even at the 1% significance level.

iv) In developing countries, four models were created for two different skill groups. Variables in the models established for both high-skilled and low-skilled employment are related in the long run based on the Pedroni and Kao cointegration test results. The cointegration results of Model 4.7 established for low-skilled employment are slightly weaker than the others.

v) In the section where sectoral analyses are presented, a total of ten specifications were evaluated, including three main sectors, namely agriculture, industry, and service, and two models each for manufacturing and energy, which are sub-sectors of industry in addition to these main sectors. The existence of a strong relationship has been revealed in the cointegration results of all series in these specifications.

As stated, for almost all models, with a few exceptions, the existence of a long-term significant relationship between the series they contain has been proven by different cointegration tests. In this context, the coefficients of the cointegrated series were estimated by PDOLS (Pedroni, 2001a; Kao and Chiang, 2001; Mark and Sul, 2003) and FMOLS (Philips and Moon, 1999; Pedroni, 2001b; Kao and Chiang, 2001) methods designed for panel data sets. The main focus of the study is the relationship between technology and employment, and at this point, the coefficient of the R&D variable is shown with β in all models. Summary information on the technology-employment relationship in line with the β coefficients estimated according to the PDOLS and FMOLS results is shown in Table 6.1:

i) In models estimated for the dependent variable of Unemployment in developed countries, the β coefficient is estimated between 0.013 and 0.032 for PDOLS estimators using two different panel methods, this range is between 0.015 and 0.034 for the FMOLS estimator. Apparently, technology proxied by R&D appears to have an adverse effect on employment, ceteris paribus; an increase in R&D expenditures increases unemployment in developed countries. On the other hand, GDP per capita coefficients were estimated between -0.441 and -0.168 according to PDOLS, and the effect of the worker productivity variable was measured between 0.326 and 0.400 according to the same method. In the same models, based on the PDOLS results, it was determined that the variables of inflation, real interest rate, public unemployment spending, and trade union density moved in the same direction as unemployment, but no statistically significant effect of the real effective exchange rate index was observed.

ii) With the PDOLS estimator for developed countries, the R&D coefficient was estimated between 0.031 and 0.056 in the models established for the high-skilled employment dependent variable, and between -0.040 and -0.074 in the models established for the low-skilled employment dependent variable. The estimated range of GDP per capita according to PDOLS is between 0.112 and 0.163 for high-skilled employment, and 0.084 0.249 for low-skilled employment. The relationship between labor productivity and employment is statistically insignificant based on PDOLS results for highly skilled workers. For low-skill employment, the PDOLS results show that the labor productivity coefficient is between -0.2096 and -0.2564. Therefore, the labor-saving effect of the increase in productivity caused by technological and non-technological shocks in developed countries on low-skilled employment cannot be fully compensated by the income channel and it makes the net effect is negative. Lastly, just like the effect of R&D investments, the impact of inflation on high and low-skilled labor is different since inflation is known to be increasing due to demand-pull as economic activity improves. The interesting outcome is that our findings on the high-skilled employment effect of inflation are parallel with the classical Philips Curve, while the results for low-skilled employment are not. Also, the real interest rate has a negative impact on high-skilled labor, but it is insignificant in explaining low-skilled employment.

Table 6.1. Main findings on the relationship of technology and (un)employment

Country Group	Developed Countries	Developing Countries
Unemployment (Employment)	Positive (Negative) *-The magnitude is slightly lower than in developing countries.*	Positive (Negative) *-The magnitude is slightly higher than in developed countries.*
High-skilled employment	Positive *-The magnitude is lower than low-skilled employment in developed countries.* *-The magnitude is greater than high-skilled employment in developing countries.*	Negative *-The magnitude is weak and smaller than low-skilled employment in developing countries.* *-The magnitude is lower than high-skilled employment in developed countries.*
Low-skilled employment	Negative *-The magnitude is greater than high-skilled employment in developed countries.* *-The magnitude is greater than low-skilled employment in developing countries.*	Negative *-The magnitude is greater than high-skilled employment in developing countries.* *-The magnitude is lower than low-skilled employment in developed countries.*
Agriculture	Negative	
Industry	Negative	
Manufacturing	Negative *-The effect size is slightly higher than in the entire industry.*	
Energy	Positive but insignificant	
Service	Positive	

iii) Models for unemployment in developing countries β was calculated in the range of 0.020 to 0.048 according to the PDOLS and 0.025 to 0.035 based on the FMOLS. Although the signs of the coefficients obtained by both methods are the same, the FMOLS method estimated the effect size as a narrower range. The coefficient of GDP per capita was estimated between -0.170 and -0.512 based on the PDOLS method and between -0.205 and -0.376 based on the FMOLS method. On the other hand, the coefficient of the productivity variable was estimated as 0.220 to 0.533 based on the PDOLS which indicates that the effect size of technical and non-technical shocks is greater than the magnitude of economic growth in developing countries. When other control variables are considered, as in developed countries, inflation and real interest rates are among the factors that increase unemployment, while openness affects employment positively. The real effective exchange rate index, in contrast, was statistically insignificant, as in developed countries, according to the PDOLS results.

iv) When the skill groups are considered in developing economies the results show that both high-skilled and low-skilled employment in developing countries is negatively affected by technology. However, the R&D coefficient in the four models of high-skilled employment is estimated between -0.004 and -0.007 by the PDOLS while this range was between -0.018 and -0.022 for low-skilled employment. Therefore, the magnitude of R&D per capita on high-skilled employment is lower than the R&D effect on low-skilled employment. In addition, the effect of economic growth on the high-skilled group in developing countries is estimated between 0.064 and 0.145. On the other hand, in the models established for low-skilled employment, the coefficient of income varies between 0.107 and 0.400. PDOLS results show that there is no significant relationship between labor productivity and high-skilled employment in developing countries. However, the productivity coefficients for low-skilled employment are between -0.368 and -0.372 and are statistically significant. These results show that the increase in income is an important compensation channel for both high-skilled and low-skilled employment in developing countries, but technological and non-technological shocks are a serious threat for low-skilled employment. And also, the magnitude of the increase in economic growth is the highest for the low-skilled employment in developing countries compared to the other three combinations. When the inflation effects for high-skilled and low-skilled employment are controlled separately, it is seen that the effect direction is different for both skill groups. Philips Curve is held for high-skilled employment, but low-skilled employment is negatively affected by inflation. There is no statistically significant effect of the interest rate for both groups. The effect of trade openness on both high-skilled and low-skilled employment is positive, but the estimated coefficient for low-skilled employment is not statistically significant.

v) According to the parameter estimations made for the specifications established for the sectors: a) The β coefficient in the agricultural sector is estimated as -0.001 on average according to the PDOLS and FMOLS estimators, and therefore the R&D expenditures in the agricultural sector negatively affect agricultural employment. In addition, the relationship between economic growth and employment in the agricultural sector is also negative because the GDP per capita coefficient is between -0.001 and -0.014 according to the PDOLS estimator. The effect of inflation and labor productivity, which are other control variables, on agricultural employment is negative, while the effect of trade openness is statistically insignificant. b) The industrial sector is also adversely affected by technology in terms of employment because the coefficient of sectoral R&D expenditures is between -0.012 and -0.014 according to the statistically significant PDOLS and FMOLS results. GDP per capita is an important compensation channel and mitigates the labor-saving impact of technology. c) The results of the manufacturing and energy sectors, which are the two sub-sectors of the industry, show that while R&D affects employment negatively in the manufacturing sector, it does not affect employment in the energy sector in a statistically significant way according to the PDOLS results. In the manufacturing sector, the R&D coefficient is slightly larger than the estimates for the entire industry. d) Finally, the estimated β coefficient in the service sector is between 0.0164 and 0.0189, which indicates that technology in the sector as a whole plays the role of complementing the workforce rather than replacing it. On the other hand, the reflection of the increase in income on employment in the service sector is also positive, but the effect size is slightly lower for the industry.

6.2. Concluding Remarks and Contribution

The relationship between technology and employment is a long-standing and highly controversial issue. A large literature and a considerable amount of studies have not yielded a definitive conclusion on this relation. The Industrial Revolution and the following years, especially labor-saving technologies used in the manufacturing sector, included the concerns of technological unemployment in the economic literature, and David Ricardo separated his views from the optimistic classics of the period and laid the foundations of the concept of technological unemployment, arguing that if technology could not create more jobs than it lost, it could lead to unemployment in the long run. While Karl Marx focused on the social dimension of the issue and its negative effects on the working conditions of workers, Keynes defined technological unemployment as a concept but thought that technology would increase the welfare of workers with central adjustments, even if it reduced working hours in the long run. In later periods, while neoclassical economists focused on the power of markets to compensate for the short-term negative effects of technology in parallel with classical views, the Schumpeterian approach defined technological innovations as a kind of creative destruction process. However, although the relationship between technology and unemployment is not only a matter of today, but the enormous level also reached by the former and its unpredictable potential for the future have made the subject more popular and important than ever before. In spite of the fact that the studies that deal with the issue at the micro-level in the empirical literature mostly focus on the negative or meaningless effect of process innovations but the positive effect of product innovations, inferences about the net effect of technology have always been lacking. At the macro level, a very limited number of empirical studies have been conducted and the findings included fuzzy predictions in both directions. Considering the fact that the subject is conducted at the macro level in the empirical literature is quite limited, this study focuses on sectoral differences in technological unemployment as well as investigating how employment is affected by technology in developed and developing countries in general and according to two different skill groups.

The first conclusion of the thesis is on developed countries, and the results in this section contain important implications for both the effect of technology on overall unemployment and the employment effects for two different skill groups. Main findings show that as R&D expenditures increase, employment of the high-skilled workers increases, whereas the opposite is true for the low-skilled workers in advanced economies.

The compensation mechanism via increase in income is effective for high-skilled workers, not the low-skilled ones. In developed economies, technology has a complementary effect on high-skilled workers and increases their employment levels. However, low-skilled employment is affected negatively even more than in developing countries. In addition, the estimated coefficient of the R&D expenditure is positive and highly significant, providing evidence that higher R&D indeed has an adverse effect on unemployment. The possible reason for this result is that in developed countries, the intensity of skilled workers is still less than the intensity of unskilled or low-skilled employees. If the share of low-skilled workers decreases and the employment structure becomes more skill-intensive and/or low-skilled workers become more equipped and are able to adapt to new technologies, the impact of technology on overall unemployment may reverse in the future. In addition, increased labor productivity with the effect of R&D expenditures and other technical and non-technical shocks enables much more output to be obtained with less manpower over time. On the other hand, the increase in income in developed countries is an important employment generator. However, in developed countries, it is not possible to compensate for the labor-saving effect only with the increase in income. These results are especially consistent with the findings of the leading studies of the recent period. Acemoglu and Restrepo (2019) stated that the productivity increase provided by automation is no longer at a level that can compensate for the loss of workforce, that the displacement effect of technology is two times higher than the reinstatement effect in the USA after 1987. They stated that industrial robots per worker reduced both the employment rate and wages. Even more strikingly, the authors noted that the relative advantages of labor would be further diminished if automation continued to be the source of future productivity growth. Bessen (2020) also draws attention to the saturation of the demand in general and stated that the elasticity of demand has lost its power to compensate for employment in the historical process. In this regard, empirical studies including how technology will affect employment in the future are also popular nowadays, and most of these studies draw attention to the density of jobs with high automation risk in developed economies. According to some predictions, 47% of jobs in the USA (Frey and Osborne, 2017), 40-60% of jobs in Europe (Bowles, 2014), and 56% of jobs in Japan (David, 2017) have a high risk of automation and that these jobs will be completely handed over to technology in the coming decades. According to the skill group-based results obtained for developed countries, while high-skilled employment is positively affected by technology, low-skilled employment is negatively affected. At the same time, the effect size of the technology on the latter is greater than on the former. Acemoglu (2002) and Frey and Osborne (2017) stated that the demand for skilled labor is actually a 20th-century phenomenon at this point. Because, as both authors emphasized, in the 19th century following the Industrial Revolution, automation was a complement for unskilled workers, while advanced technologies of the 20th century mostly supported and complemented skilled workers. Low-skilled people face consequences such as displacement or a decrease in wages. While routine jobs require fewer human resources due to skill-oriented technological changes, non-routine jobs that require analytical and cognitive skills increase the need for highly skilled workers (Acemoglu and Autor, 2011). Developed economies can adapt their labor markets to technological changes more easily, as they have a denser and higher quality high-skilled workforce compared to developing countries, and they can also strengthen technical advances by increasing the skilled labor supply faster (Caselli and Coleman, 2006). In addition, today, not only low-skilled workers but also relatively skilled people working in occupations that require higher education but involve routine tasks are adversely affected (Brynjolfsson & McAfee, 2012).

The second main finding of the thesis is on developing countries. The studies where this vast literature touches upon developing countries are extremely limited. Developing countries have been neglected for a long time because the economics literature has focused on technology and unemployment since the Industrial Revolution, and because the machines first appeared in developed countries, employment concerns first started in these geographies. For these reasons, in this study, the effect of technology on employment is discussed with a wide country group and timespan, specific to developing countries. Based on the results, the overall unemployment effect of technology in developing countries is in the direction of labor-saving, as in developed countries, and in this respect, the effect sizes are close to each other. Although it is seen that both skill groups are negatively affected by technology in developing countries, the negative effect on high-skill employment is relatively low. Among the possible reasons why technology may negatively affect the high-skilled group in developing countries, the intensity of cognitive but routine work in these countries and the differences in the definitions of high-skilled workers can be shown. On the other hand, the increase in income channel is an effective compensation mechanism for high-skilled employment. In addition, low-skilled employment in developing countries is less affected by technology than in developed countries, since the wages of workers in these countries are relatively low, so the comparative advantage of labor continues for longer. However, considering the fact that this situation will not continue forever, developing countries should make effective use of public policies to reduce threats in the future. In this context, measures such as eliminating bottlenecks, restrictions, and inequalities in access to technology, providing affordable and reliable internet, and advanced digital payment systems are important. In addition, supporting the participation of education systems in the digital world with the necessary equipment, IT-oriented workforce models and the effective integration of online work platforms into labor markets will help the workforce to become qualified for jobs that require higher skills today and will require them in the future. The direct and indirect effects of technology are inevitable and continuous. The cost advantage of labor in developing countries is not permanent and this advantage disappears as robots become cheaper. Thus, the destructiveness of the labor-saving effect may be more sudden and severe in developing countries. Mitigating or eliminating this impact depends on increasing the adaptability of both the economic structure as a whole and the current and future potential workforce individually. Some predictions for the future, especially made with occupation and task-based approaches, draw attention that although automation occurs later in developing countries than in developed ones, developing economies experience *"premature deindustrialization"* (Rodrik, 2016) because they are already indirectly affected by the emerging technologies in developed economies and this could lead to technology inflicting deeper wounds on employment in the developing world (Frey and Rahbari, 2016). In studies such as the World Bank (2016), Egana-delSol (2020), and Soto (2020) it is noted that due to the current stages of developing countries, most of the employment is in sectors with high automation risks such as agriculture and manufacturing, and it is stated that the automation risk in emerging economies is higher than the average automation risk in advanced countries. Nevertheless, the fact that the automation risk is high does not mean that the rate of transition to automation or the rate of being affected by machines is equally high. Although many jobs can be automated technically and theoretically in developing countries, the transition to automation is not as fast as in developed countries due to factors such as low wages and slower technology adoption, and thus employment is not yet affected to the same extent. McKinsey Global Institute (2017) predicts that in the coming decades, automation rates in developed countries such as Japan and the United Kingdom will be higher than in emerging economies such as India and Russia. Acemoglu and Restrepo (2017) draw attention to a similar issue and state that despite the increase in wages in developing countries in recent years, average wages remain far from developed economies. In countries with high wage levels, sensitivity to automation is also high due to rising costs. However, despite the increase in wages in developing economies over time, the fact that they are still far from the level of developed countries brings about the existence of cheap labor resources and therefore does not make automation economically attractive in many developing countries. However, Frey (2020) argues that the cost advantage of cheap labor against technology in emerging economies will end soon, and states although many studies focus on developed countries, the main problem will be experienced in developing countries due to the early deindustrialization mentioned above. Because, according to some estimates, in emerging economies such as China, Mexico, and Brazil, where labor costs are relatively low, labor may lose its comparative advantage, as the use of robots will be less costly in the coming decades (Boston Consulting Group, 2015). In addition to these, the efficiency of benefiting from the employment opportunities opened by technology is lower in developing economies. Most new jobs require significantly higher skill levels but even basic education indicators such as literacy rates in developing economies are lagging behind developed countries and therefore there is a lack of skills to complement new technologies. As a result, developing countries cannot fully exploit the many opportunities offered by new technologies as quickly as developed countries. (Soto, 2020).

The third crucial finding of the thesis is on the employment effects of technology in different sectors. The impact of innovation on employment is expected to differ across sectors, and the findings of this thesis support the mentioned hypothesis. In all developed economies and partially developing ones, initially, most of the workforce shifted from agriculture to manufacturing and later from manufacturing to the service sector. The findings show that the technology produced in agriculture and industry itself reduces employment in agriculture and industry. Economic growth is an important compensation mechanism for the industry, but it does not completely eliminate the labor-saving effect of technology, it partially alleviates it. In the agricultural sector, the employment-destroying effect of technology cannot be suppressed even through income, and the demand, which is inelastic or less elastic due to the nature of the sector, cannot create additional employment areas where manpower will be used. This is true for developed and some developing countries covered in the study. Underdeveloped countries whose economy is based on agriculture can be the subject of different studies. On the other hand, in the service sector, technology has a positive effect on employment. It can be said that the service sector has the power to eliminate the labor-saving effect experienced in other sectors. However, since these results are revealed by estimating the employment rates within the sector with sectoral technology data, a general inference cannot be made in this study as to what proportions of the employment losses experienced in the agriculture and manufacturing sectors can be compensated in the service sector. It is not possible for those who lost their jobs in the industry sector, which is the result of routine intensive work, to work in similar positions in the service sector. Because, in industry, workers are mostly in the medium skill group and they are likely to fall towards low-skill positions rather than high-skill jobs, as skill upgrading is time-consuming, costly, and in some cases not possible. Therefore, while the demand and number of skilled workers based on technology increases, the supply of unskilled workers increases in the sector. The surplus in the labor supply will cause average wages to decline over time. The findings obtained in the study indirectly support the RBTC and job polarization approaches introduced in studies such as Autor et al. (2006), Goos and Maning (2007), Autor and Dorn (2013), Goos et al. (2014), and Lee and Shin (2017). Because while the manufacturing sector is an area where mostly blue-collar workers work and routine intensive tasks are involved, cognitive work is dominant in the service sector. The fact that technology harms employment in the manufacturing sector and increases employment in the service sector, especially for the skilled, may be due to the automation of non-cognitive routine works in the first and the completion of non-routine cognitive tasks with technology in the second. This supports approaches that explain business polarization with RBTC. Secondly, the results obtained from the study are also compatible with the results obtained in the studies of Acemoglu and Restrepo (2019) and Bessen (2020) especially for the manufacturing sector and revealing that the labor-saving effect outweighs the technology in these areas. Acemoglu and Restrepo (2019) investigate the construction, services, transportation, manufacturing, agriculture, and mining sectors, and stated that between 1987-2019, technology had two major effects, namely the reinstatement effect and the displacement effect; and the latter outweighed the former, resulting in job losses in the aforementioned sectors. Bessen (2020) also focuses on the U.S. cotton textile, primary steel, and motor vehicle industries and states that demand reaches saturation and loses its elasticity. As a result, demand for labor in these industries decreased. Since the automation risk estimations made by Frey and Osborne (2017) also indicate that technology will adversely affect those who work in routine jobs and that the risk of those who work in cognitive jobs is lower, at least for now, the evidence obtained for the industry and the service sector in general in this thesis also overlaps with the predictions of the authors. Finally, studies such as Vivarelli (1996), Yasuda (2005), Bogliacino and Pianta (2010), and Compagnucci et al., (2019) that stated that the negative effect of process innovations on employment especially in the manufacturing sector are in parallel with the empirical evidence obtained in this section.

Unemployment is a social and individual fact that has persisted since the beginning of the use of labor as a production factor, especially in the 20th century, which has expanded its importance day by day notwithstanding all the social and economic precautions the policymakers have taken. Today, the most relevant and compelling issue for states and politicians is the development of policies expanding employment and preventing unemployment along with the economic crises. This thesis also makes significant contributions to the relationship of such an important issue with technology. Over time, scientific research is transformed into technology, and products emerging are presented to the service of human beings through technology. As a result, technological progress leads to structural changes in existing jobs, causing some professions to be destroyed or replaced by new ones. When we look at the change that technology has made in the past, it is evident that the replacement of the labor force by machines evolved from unskilled labor to highly qualified labor. While the mechanical effects of the past replaced the skilled workers and complemented the relatively unskilled ones, today's digital effects show that technology has become a complement for skilled workers. Our investigation asserts concrete empirical evidence on the research and development expenditure unemployment relation coupled with skill groups, but further analyses are required, and there is room to explore the same relation along with other key variables headed by wage, working conditions, and more detailed skill and occupation groups. It is important to note that, although technology has an important role in causing an increase in unemployment as found empirically, interfering with technological progress is not possible and technological advances are inevitable. Therefore, policies that enable the existing workforce to adapt to new technologies are very important.

6.3. Limitations and Suggestions for Future Research

As in any study containing technical and empirical details, there are some limitations in this study and the results should be interpreted in this context. In this part of the thesis, these limitations and various suggestions for future studies on the subject are mentioned and the study is terminated.

Firstly, R&D expenditures of countries were used as technology proxy in the study. Therefore, the claimed technology effect is limited with the power of R&D to reflect the technological levels of the countries. As stated in the previous sections, the level of technology that developed countries produce and use is related to their current R&D investments, and therefore R&D is a powerful technology proxy for them. However, the technology used by developing countries is imported rather than domestic production, so there are concerns that their own R&D expenditures may not reflect current technology levels. Nevertheless, in this study, it is assumed that R&D is also an important technology indicator in developing countries because countries' R&D investments are directly related to their current knowledge stocks and technology adaptation strengths. At this point, innovation proxies such as imported high technology, the quality of machinery and robots used, and R&D expenditures in the outside world can be considered in further studies examining the relationship between unemployment and technology in developing countries. In macro-level studies covering developed countries, variables such as the number and quality of patents, the number and quality of researchers, scientific publications, the number and quality of machinery, robots, and technical equipment used can be addressed, intercalarily R&D.

Another important limitation of the study is related to the methods used. Every empirical study is based on the analytical power of the applied method. A notable limitation is that a maximum of seven variables are allowed in the method proposed by Pedroni (1999, 2004) used to prove the existence of cointegration between series in the long run. Another important issue is related to the power of PDOLS and FMOLS methods used in the estimation of the models to calculate the coefficients consistently. In the study, the first constraint was tried to be overcome by supporting the results of Pedroni's cointegration tests with the method proposed by Kao (1999). In addition, the consistency in the coefficient estimations was ensured by using the PDOLS and FMOLS estimators of more than one model, and these estimators with different variations and different lag options.

The third limitation that can be mentioned in the study is the possibility that other important factors that may affect unemployment have been checked. Although macro indicators such as economic growth, inflation, productivity, unemployment benefits, trade activities, interest rate, and value of the domestic currency, which are frequently shown in the literature to be related to unemployment, are used in this study; limitations on the maximum number of variables and data availability included in the methods have resulted in ignoring other possible factors that may affect unemployment, such as wages, foreign direct investment, and taxes. In addition, the employment structure of countries is highly dependent on their internal economic dynamics. For example, wage adjustments such as the minimum wage can affect unemployment. However, the effect of these factors was not discussed in this study. By taking into account the effects of such additional variables or internal differences between countries, a more comprehensive empirical path can be followed in the future.

The fourth point is that the seasonal employment effects are ignored in the time period covered in the thesis. In the 1990-2019 period, important economic crises, such as the 2008 Great Recession, were overcome both globally and on a country basis. Analyses that take into account the effects of such important events are important for a more effective understanding of the issue.

The fifth point is the possible limitations of dividing employment into two as high-skilled and low-skilled. Three different skill groups, namely low, medium, and high-skilled employment, obtained on the basis of the International Labor Organization, are considered in this study as two different levels by combining the low and medium-skilled groups. However, in order to understand economic phenomena such as job polarization, a detailed analysis of middle-skilled employment is required. Furthermore, directly defining the middle-skilled employment group as low-skilled makes this group more heterogeneous and leads to a fuzzier estimation of the effect of technology on the relevant employment groups. Therefore, in future studies, employment can be grouped in more detail to provide clearer estimates of the impact of technology.

The sixth point is the limitations on sectoral analysis. In the study, the effect of technology on employment within the sector is discussed using business enterprise R&D expenditures in the sector. However, product or process innovations in a sector may also affect employment in different sectors, causing labor reallocation between sectors or directly causing labor savings/labor creation. Therefore, in this study, inferences about the cross-sectoral impact of technology are lacking. Another issue on this subject is that the technology proxy discussed in the section on sectors is not gross domestic R&D expenditure, but business enterprise R&D expenditure. This means addressing a more limited level of technology impact. Finally, in the study, three main sectors, agriculture, industry and service, and the manufacturing and energy sub-sectors under the industry were analyzed. However, the assumption that the main and sub-sectors are completely homogeneous is an extremely strict assumption. Today, there are many sub-sectors, and it is worth investigating separately the direction and size of the technology-employment relationship in each of them. In order to evaluate the inter-sectoral impact in future studies, a more detailed focus on the main and sub-sectors that affect each other in terms of technology may provide clearer inferences.

As a result, in this thesis, despite the various constraints mentioned above, the relationship between technology and employment has been investigated from a very multi-perspective, covering a wide time period and many countries. In this sense, the contribution to the literature is multidimensional and in many ways worthy of both examination and future development. Considering the aforementioned issues, future studies may focus on how and at what level an important fact such as unemployment is affected by unavoidable and/or irrational technological advances.

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APPENDICES

Appendix A: Additional Results for Chapter 3

Table A1. Unit root test results with trend

Variables	LLC		IPS		ADF - Fisher	
	Level	First Difference	Level	First Difference	Level	First Difference
U_t	-2.198	-6.120	-3.861	-7.316	80.329	132.429
	[0.014]*	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
HSE_t	-0.823	-14.649	-1.918	-14.350	59.788	259.935
	[0.205]	[0.000]***	[0.028]*	[0.000]***	[0.037]*	[0.000]***
LSE_t	-1.585	-13.556	-2.563	-13.076	64.385	231.952
	[0.057]	[0.000]***	[0.005]**	[0.000]***	[0.015]**	[0.000]***
RD_t	2.366	-12.206	0.703	-13.250	45.993	233.878
	[0.991]	[0.000]***	[0.759]	[0.000]***	[0.310]	[0.000]***
GDP_t	-1.301	-8.325	0.093	-9.746	47.301	164.704
	[0.097]	[0.000]***	[0.537]	[0.000]***	[0.265]	[0.000]***
CPI_t	0.514	-8.821	-0.644	-8.617	58.660	158.586
	[0.697]	[0.000]***	[0.260]	[0.000]***	[0.045]*	[0.000]***
PRD_t	-3.013	-13.290	0.735	-13.290	33.315	232.769
	[0.001]***	[0.000]***	[0.769]	[0.000]***	[0.828]	[0.000]***
INT_t	-5.686	-16.970	-5.768	-18.202	104.870	351.498
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
PUS_t	-	-	1.478	-2.951	38.941	83.011
	-	-	[0.930]	[0.002]**	[0.606]	[0.000]***
TUD_t	-0.874	-15.187	-1.512	-13.347	60.370	426.949
	[0.191]	[0.000]***	[0.065]	[0.000]***	[0.033]*	[0.000]***
EXC_t	-1.124	-12.622	-4.576	-12.859	90.178	217.386
	[0.131]	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Note: All the variables include a constant and a trend. In order to detect the optimal lag length, the Akaike Information Criterion (AIC) is used. Newey-West bandwidth selection with Bartlett kernel is applied for the LLC test. All the variables are in natural logs, excluding U_t, HSE_t, LSE_t, and INT_t. LLC results with trend for PUS_t are not reported. *Rejection of the null hypothesis of nonstationarity at the 0.05 level, **Rejection of the null hypothesis of nonstationarity at the 0.01 level, ***Rejection of the null hypothesis of nonstationarity at the 0.001 level.
Source: Author's calculations

Table A2. FMOLS estimates results for the high-skilled employment specifications

Variables	Model 3.8		Model 3.9		Model 3.10	
	Beta	p-value	Beta	p-value	Beta	p-value
RD_t	0.0096	0.000***	0.0130	0.000***	0.0146	0.000***
GDP_t	0.0974	0.000***	0.1724	0.000***	0.1622	0.000***
CPI_t	0.1066	0.000***	0.1060	0.000***	0.1017	0.000***
PRD_t			-0.1099	0.000***	-0.1083	0.000***
INT					-0.1445	0.000***

Note: For the FMOLS estimator, pooled-weighted estimation is used as the panel method. Also, for the dependent variable, decimal fractions of HSE_t are used. All the independent variables are in natural logs excluding INT_t and p-values are given in the parentheses. *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Table A3. FMOLS estimates results for the low-skilled employment specifications

Variables	Model 1		Model 2		Model 3	
	Beta	p-value	Beta	p-value	Beta	p-value
RD_t	-0.0409	(0.000)***	-0.0333	(0.000)***	-0.0336	(0.000)***
GDP_t	0.0843	(0.000)***	0.2471	(0.000)***	0.2487	(0.000)***
CPI_t	-0.1536	(0.000)***	-0.1549	(0.000)***	-0.1541	(0.000)***
PRD_t			-0.2385	(0.000)***	-0.2388	(0.000)***
INT					0.0349	(0.001)***

Note: For the FMOLS estimator, pooled-weighted estimation is used as the panel method. Also, for the dependent variable, decimal fractions of LSE_t are used. All the independent variables are in natural logs excluding INT_t and p-values are given in the parentheses. *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Appendix B: Additional Results for Chapter 4

Table B1. Results of panel unit root tests (w/ trend)

Variables	LLC		IPS		ADF - Fisher	
	Level	First difference	Level	First difference	Level	First difference
U_t	-2.701	-11.342	-4.009	-11.231	94.026	198.253
	[0.004]**	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
HSE_t	-1.314	-14.824	-0.830	-14.486	52.123	262.740
	[0.094]	[0.000]***	[0.203]	[0.000]***	[0.248]	[0.000]***
LSE_t	-0.323	-14.077	0.020	-13.369	46.882	240.150
	[0.373]	[0.000]***	[0.508]	[0.000]***	[0.436]	[0.000]***
RD_t	4.384	-4.241	-0.710	-12.027	47.640	221.405
	[1.000]	[0.000]***	[0.239]	[0.000]***	[0.406]	[0.000]***
GDP_t	-3.042	-7.235	-3.690	-8.824	83.458	160.103
	[0.001]**	[0.000]***	[0.000]***	[0.000]***	[0.001]***	[0.000]***
CPI_t	-0.573	-7.829	-5.996	-10.092	158.376	210.503
	[0.283]	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
PRD_t	-0.294	-14.426	0.388	-16.358	40.521	305.553
	[0.384]	[0.000]***	[0.651]	[0.000]***	[0.700]	[0.000]***
INT_t	-4.912	-17.264	-8.245	-24.508	156.820	502.707
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
OPN_t	-1.384	-17.278	-0.902	-17.358	66.118	318.042
	[0.083]	[0.000]***	[0.184]	[0.000]***	[0.028]*	[0.000]***
EXC_t	-1.845	-15.633	-1.382	-17.997	82.866	511.359
	[0.033]*	[0.000]***	[0.083]	[0.000]***	[0.001]***	[0.000]***

Note: All the variables include a constant and a trend. In order to detect the optimal lag length, the Schwarz Information Criterion (SIC) is used. Newey-West bandwidth selection with Bartlett kernel is applied for the LLC test. All the variables are in natural logs, excluding U_t, HSE_t, LSE_t, and INT_t. P-values are given in the brackets. *Rejection of the null hypothesis of nonstationarity at the 0.05 level, **Rejection of the null hypothesis of nonstationarity at the 0.01 level, ***Rejection of the null hypothesis of nonstationarity at the 0.001 level.
Source: Author's calculations.

Table B2. FMOLS estimates results for high-skilled employment

Variables	Model 4.7		Model 4.8		Model 4.9		Model 4.10	
RD_t	-0.0028	(-0.950)	-0.0038	$(-3.269)^{***}$	-0.0053	$(-1.952)^{*}$	-0.0067	$(-2.569)^{*}$
GDP_t	0.0639	$(9.375)^{***}$	0.1379	$(22.985)^{***}$	0.1445	$(8.401)^{***}$	0.0950	$(4.762)^{***}$
CPI_t	0.0045	$(4.613)^{***}$	0.0043	$(12.381)^{***}$	0.0049	$(5.339)^{***}$	0.0036	$(3.560)^{***}$
PRD_t			-0.0793	$(-14.937)^{***}$	-0.0849	$(-5.165)^{***}$	-0.0651	$(-4.158)^{***}$
INT_t					-0.0016	(-0.174)		
OPN_t							0.0230	$(4.912)^{***}$

Note: For the FMOLS estimator, the pooled estimation is used as the panel method and the sandwich method is used in estimating covariance. All the independent variables are in natural logarithms excluding INT_t. Besides, t-values are given in the parentheses. As the dependent variable, decimal fractions of HSE_t are used. $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Table B3. FMOLS estimates results for low-skilled employment

Variables	Model 4.7		Model 4.8		Model 4.9		Model 4.10	
RD_t	-0.0273	$(-4.321)^{***}$	-0.0289	$(-6.172)^{***}$	-0.0302	$(-7.110)^{***}$	-0.0157	$(-3.604)^{***}$
GDP_t	0.1203	$(7.607)^{***}$	0.3263	$(16.372)^{***}$	0.3000	$(15.640)^{***}$	0.3319	$(16.245)^{***}$
CPI_t	-0.0772	$(-7.617)^{***}$	-0.0706	$(-8.771)^{***}$	-0.0702	$(-9.046)^{***}$	-0.0567	$(-7.719)^{***}$
PRD_t			-0.3100	$(-12.291)^{***}$	-0.2783	$(-11.558)^{***}$	-0.3363	$(-13.849)^{***}$
INT_t					-0.0338	$(-2.325)^{*}$		
OPN_t							-0.0090	$(-1.724)^{+}$

Note: For the FMOLS estimator, grouped estimation is used as the panel method. All the independent variables are in natural logarithms excluding INT_t. Besides, t-values are given in parentheses. As the dependent variable, decimal fractions of LSE_t are used. $^{+}$Significance at the 0.1 level, *Significance at the 0.05 level, **Significance at the 0.01 level, ***Significance at the 0.001 level.
Source: Author's calculations.

Appendix C: Additional Results for Chapter 5

Table C1. Unit Root tests results (w/ trend)

Variables	LLC		IPS		ADF - Fisher	
	Level	First Difference	Level	First Difference	Level	First Difference
$EMPA_t$	-2.866	-21.419	1.288	-21.602	57.613	500.334
	[0.002]**	[0.000]***	[0.901]	[0.000]***	[0.564]	[0.000]***
$EMPS_t$	-0.499	-15.903	-0.925	-16.108	75.878	332.689
	[0.309]	[0.000]***	[0.178]	[0.000]***	[0.081]	[0.000]***
$EMPI_t$	-1.689	-9.134	-1.053	-8.936	58.656	176.607
	[0.046]*	[0.000]***	[0.146]	[0.000]***	[0.245]	[0.000]***
$EMPM_t$	-1.625	-9.289	-0.990	-8.500	57.641	169.805
	[0.052]	[0.000]***	[0.161]	[0.000]***	[0.275]	[0.000]***
$EMPE_t$	-1.225	-9.188	0.218	-9.973	44.746	190.903
	[0.110]	[0.000]***	[0.586]	[0.000]***	[0.752]	[0.000]***
RDA_t	-3.396	-23.609	-2.935	-21.133	106.212	500.341
	[0.000]***	[0.000]***	[0.002]**	[0.000]***	[0.000]***	[0.000]***
RDS_t	-0.905	-23.983	-0.056	-21.773	64.073	736.672
	[0.183]	[0.000]***	[0.478]	[0.000]***	[0.336]	[0.000]***
RDI_t	-1.173	-16.432	-1.145	-14.541	73.542	275.964
	[0.120]	[0.000]***	[0.126]	[0.000]***	[0.026]*	[0.000]***
$RDMC_t$	-1.174	-16.069	-0.755	-15.089	70.171	285.922
	[0.120]	[0.000]***	[0.225]	[0.000]***	[0.047]*	[0.000]***
RDE_t	-1.676	-17.401	-2.046	-19.615	80.400	432.282
	[0.047]*	[0.000]***	[0.020]*	[0.000]***	[0.007]**	[0.000]***
GDP_t	-1.065	-10.620	0.702	-12.308	55.704	251.881
	[0.143]	[0.000]***	[0.759]***	[0.000]***	[0.633]	[0.000]***
CPI_t	-4.822	-12.211	-3.080	-12.259	112.123	260.943
	[0.000]***	[0.000]***	[0.001]***	[0.000]***	[0.000]***	[0.000]***
PRA_t	-2.933	-22.520	-3.944	-26.120	112.817	554.929
	[0.002]**	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
PRS_t	-5.038	-17.778	-0.277	-16.979	78.506	345.208
	[0.000]***	[0.000]***	[0.391]	[0.000]***	[0.055]	[0.000]***
PRT_t	-3.013	-17.613	1.977	-17.143	39.076	349.226
	[0.001]***	[0.000]***	[0.976]	[0.000]***	[0.983]	[0.000]***
OPN_t	-4.407	-21.701	-3.258	-19.257	100.389	399.264
	[0.000]***	[0.000]***	[0.001]***	[0.000]***	[0.001]***	[0.000]***

Note: All variables include a constant and a trend. In order to detect the optimal lag length, the Schwarz Information Criterion (SIC) is used. Newey-West bandwidth selection with Bartlett kernel is applied for the LLC test. All independent variables are in natural logs. *Rejection of the null hypothesis of nonstationarity at the 0.05 level, **Rejection of the null hypothesis of nonstationarity at the 0.01 level, ***Rejection of the null hypothesis of nonstationarity at the 0.001 level.
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