

YEDITEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES

**EMPLOYMENT GENERATION AND PRODUCTIVITY: EVIDENCE
FROM TURKISH MANUFACTURING INDUSTRY**

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TURKISH MANUFACTURING INDUSTRY

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DECLARATION OF ORIGINALITY

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ABSTRACT

EMPLOYMENT GENERATION AND PRODUCTIVITY: EVIDENCE FROM TURKISH MANUFACTURING INDUSTRY

Studies on productivity at the firm level have shown significant differences in productivity between large and small companies. These variations could be due to differences in the distribution of factors that affect Total Factor Productivity (TFP) across companies of different sizes, as well as differences in the returns on these factors. In this thesis, we analyze the productivity of Turkey using a large dataset of the Turkish manufacturing industry, obtained from Entrepreneur Information System (EIS), which shows that small firms are less productive than large firms, and there is a significant productivity gap between them. We use the Blinder-Oaxaca decomposition technique to identify the overall endowment and return effects and quantify each factor's contribution to the productivity gap. While many works use the Oaxaca-Blinder decomposition, our study addresses the identification issue when more than a set of dummy variables are employed in the model, using the solution proposed by Yun (2005) to estimate the Turkish size productivity gap. To calculate TFP, we use the method proposed by Akerberg et al. (2015), which takes into account the endogeneity issue that arises when firms that seek to maximize profits can observe their TFP early on and adjust their factor input decisions accordingly. The dissertation tracks 59,560 firms that existed in 2006 to investigate the contribution of firms of different sizes and ages to employment generation, taking into account the differences in survival rates of these firms. The Two-part model is used to estimate the growth rate of employment in 2020 and decompose it across groups of sizes and ages.

Keywords: Blinder-Oaxaca decomposition, Identification Issue, TFP, Two-part model

ÖZET

İstihdam Yaratma ve Verimlilik: Türk İmalat Sanayisinden Kanıtlar

Firma düzeyinde üretkenlik üzerine yapılan çalışmalar, büyük ve küçük şirketler arasında önemli üretkenlik farklılıkları olduğunu göstermiştir. Bu varyasyonlar, şirketler arasındaki Toplam Faktör Üretkenliği'ni (TFP) etkileyen faktörlerin dağılımındaki farklılardan kaynaklanabileceği düşünülmektedir. Ayrıca bu faktörlerin getirilerindeki farklılıkların da bunda etkili olabileceği ön görülmektedir. Bu tezde, Türkiye'nin üretkenliği, Türk imalat endüstrisine ait geniş bir veri setini kullanılarak analiz edilmiştir. Girişimci Bilgi Sistemi'nden (EIS) elde edilen veriler, küçük işletmelerin büyük işletmelerden daha az üretken olduğunu göstermektedir, bu bakımdan aralarında önemli bir üretkenlik farkı bulunmaktadır. Bu üretkenlik farkına her faktörün katkısını belirlemek için Blinder-Oaxaca ayrıştırma tekniği kullanılmıştır. Bu teknik, birçok çalışmada kullanılmaktadır. Çalışmamızda birden fazla set dummy değişkeni kullanılarak ortaya çıkan tanımlama sorununu ele alınmıştır. Ayrıca Yun (2005) tarafından önerilen çözüm kullanarak Türkiye'nin boyut üretkenlik farkı tahmin edilmiştir. TFP'yi hesaplamak için Akerberg (2015) tarafından önerilen yöntemi kullanıyoruz; bu yöntem, kârı maksimize etmeye çalışan firmaların TFP'yi erken aşamada gözlemleyebileceklerini ve buna göre faktör giriş kararlarını ayarlayabileceklerini ele almaktadır. Tezde, 2006 yılında var olan 59,560 firmayı izlenerek, farklı boyut ve yaş gruplarındaki firmaların istihdam oluşturmaya katkısı araştırılmış ve bu firmaların yaşama oranlarındaki farkları ele alınmıştır. İstihdamın 2020'deki büyüme oranını ve bu oranın boyut ve yaş grupları arasındaki dağılımını tahmin etmek için İki Bölümlü model kullanılmıştır.

Anahtar Kelimeler: Blinder-Oaxaca ayrıştırma, Tanımlama sorunu, TFP, İki Bölümlü model.

DEDICATION

To My Beloved Mother



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LIST OF SYMBOLS

$n_{i,t}$	Log employment
$k_{i,t}$	Log capital stock
$\ln\gamma_{i,t}$	log value added
$TFP_{i,t}$	Logarithm of the total factor productivity in firm i at time t
$c_{i,t}$	Log capital intensity
$w_{i,t}$	Logarithm of the average annual gross wage per worker.
$AGE_{i,t}$	Age of the firm
$dte_{i,t}$	Ratio of total liabilities to total equity expressed as a logarithmic value.
$INOV_{i,t}$	Dummy variable of innovation activity
ε_{it}	An error terms
EX	Dummy variable of firm export status
$TECH$	High technology
$TECMH$	Medium high technology
$TECML$	Medium low technology
$TECML$	Low technology
δ_i	Unobserved firm specific effect
$\gamma_{i,t}$	Possibly autoregressive productivity shock
Y_i	output
x_i	a vector of the input variables
β	The vector of technology parameters that must be estimated
vi	The disturbance or random error term $vi \sim N(0, \sigma_v^2)$
ui	The technical inefficiency or the non-negative error term.
$ui \sim N^+(0, \sigma_v^2)$	Takes the truncated normal distribution.
$TE_{it} = e^{-uit}$	The efficiency level of an entity i at period t
ε_{it}	Serially uncorrelated measurement errors
$EM_{i,t}$	The number of employees at time t
Φ	The cumulative distribution functions of the standard normal distribution.
X_i	The set of explanatory variables
$EM_{i,2006}$	The initial number of employees

$A_{i,2006}$	The age of firm at the initial time 2006
D_s	Sectors dummy at Nace-2-digit level



LIST OF ABBREVIATIONS

AISS	Annual Industry and Service Statistics
AMS	Annual Manufacturing Survey
BR	Business Register dataset
DEA	Data Envelopment Analysis
EIS	Entrepreneur Information System
GMM	Generalized Methods of Moments
KOSGEB	Small and Medium Enterprises Development Organization of Turkey
LP	Levinsohn and Petrin
LRD	Longitudinal Research Database
NACE	Classification of Economic Activities in the European Community
OECD	Organization for Economic Cooperation and Development
OP	Olley and Pakes
R&D	Research and Development
SFA	Stochastic Frontier Analysis
SMEs	Small and Medium-Sized Enterprises
TFP	Total Factor Productivity
TUIK	Turkish Statistical Institute
U.S	the United States
UK	the United Kingdom

1. INTRODUCTION

Until the early 1970s, it was widely accepted that economic development could be carried out through mass and specialized products in capital-intensive industries. Therefore, large enterprises were considered economic engines because they were supposed to be best suited to realize gains from economies of scale.

However, the oil crisis in the 1970s became a turning point for this growth story. The long-standing trend toward centralization in business organizations ceased and reversed. In many countries with advanced economies, the percentage of people employed in small and medium-sized businesses has gone up (Audretsch and Zoltan, 1993; Choi and Lee, 2020). Empirical evidence using data from the six largest OECD countries was provided by Loveman and Sengenberger (1991) to explore why the size advantages seem to diminish. They argue that small and medium-sized firms often enjoy lower labor costs and flexibility in the specialization. In contrast, large firms are often subject to inflexibility in adapting to changing market conditions.

Carlsson (1992) argues that changes in the economic environment include intensified global competition and uncertainty. Moreover, technological progress (flexible automation) has resulted in a structural shift towards small firms.

Alongside the increasing importance of SMEs, new and young firms' role in economic growth and job creation has also been recognized (Davis and Haltiwanger, 1992). Geroski (1995) Argues that entrepreneurial activities play a vital role in evolving the market's structure and performance by promoting new product innovation helps discover new markets and replace inefficient incumbents.

As a result of these significant contributions, many countries worldwide have developed new policies that support establishing, organizing, and protecting SMEs' economic activities (Storey, 2003)

In 1990, KOSGEB (Small and Medium Enterprises Development Organization of Turkey) was established to promote small firms and entrepreneurship, emphasizing their importance for the future prosperity of the Turkish economy by increasing competition among SMEs (KOSGEB, 2020).

Although numerous SMEs support programs have been implemented by developed and developing countries worldwide, empirical evidence confirms that large productivity gaps exist between large and small firms in favor of large ones (Snodgrass and Biggs, 1996; Taymaz, 2005; Castany et al., 2005; Zhang, 2014). As was mentioned in the OECD (2005) report, micro and small firms dominate a considerable proportion of the total manufacturing enterprises in many OECD countries. However, the productivity gaps between size groups are particularly large in Turkey.

Recent studies on entrepreneurial firms show that young and small firms play a significant role in employment generation, employment growth rate, and innovation (Calvo, 2006; Toma et al., 2014; Özlale and Polat, 2019; Méndez-Picazo et al., 2021). However, the positive consequences of young and small firms are conditional on their survival.

Davis and Haltiwanger (1992) notice that young firms, especially if they are small, have a high mortality rate than incumbent firms. Decker et al. (2014) report that while young and small enterprises play a substantial role in creating new jobs and productivity growth in the short run, their survival rate within the first ten years is low, and most surviving young businesses' growth rate is also low. However, a small fraction of newly created companies that survive grow fast and contribute significantly to new job creation in the long run.

Many small firms, besides a few large firms, shape the Turkish manufacturing sector. Manufacturing firms whose staff number is more than 500 workers make up less than one percent of all manufacturing sectors. Nevertheless, those corporations account for 28 percent of employment and fifty-three percent of overall manufacturing value-added. Because of their significant share in total value-added, these large-scale enterprises drive the weighted average of productivity in the completely manufacturing industry (World Bank, 2019).

The purpose of this dissertation is to investigate and analyze the differences in Total Factor Productivity (TFP) between large and small Turkish manufacturing firms for the period spanning from 2006 to 2020. The study aims to identify the extent to which these differences are influenced by the characteristics of the variables or are driven by the return of these variables. Specifically, the study explores the impact of variables such as firm export status, capital intensity, sector technology level, firm age, average annual wages paid to employees, ratio of total liabilities to equity (debt to equity ratio), and innovation activity of the firm on the observed TFP differences.

In addition, the study analyzes which type of firms, based on size and age, generate the most employment growth during the sample period. This have been accomplished by considering the employment growth contributed by enterprises that continue to flourish and those that continue to operate, as well as the employment loss resulting from the closure or exit of firms.

Overall, the study aims to provide valuable insights into the factors that affect the productivity and employment growth of Turkish manufacturing firms. By identifying the key drivers of TFP differences and employment growth, the study aims to offer recommendations that can help firms enhance their productivity and boost employment in the sector. For instance, the generation of employment opportunities is a crucial policy matter. If a large company goes bankrupt, many employees are at risk of losing their jobs. This issue has significant implications for both the economy and society. The thesis aims to shed light on the role of small and young companies in employment growth and job creation, including firms that survive and those that exit. This contribution is essential in addressing relevant policy questions, such as whether policymakers should support policies that prevent the failure of large firms to save jobs or help new small firms emerge and contribute to job creation.

The thesis contributes to the existing literature in the following aspects: First, contrary to the literature strand that depends on the firms that survived during the sample period to calculate the employment growth rate, this study is interested in calculating the survival rate, the exit rate, and growth rate of employment, which consist of employment growth in the continuing firms and employment loss due to firms exits.

Second, this study will provide an answer to the following question: whether most of the employment change occurred in the continuing firms or was driven by firms that exited the market?

Third, previous studies that analysed firms' dynamics, job creation, and productivity estimates in Turkey have used several datasets. However, these datasets have some drawbacks. For instance, the Annual Industry and Service Statistics (AISS) dataset provided by the Turkish Statistical Institute (TurkStat) lacks age information (Grun et al., 2013; Dogan et al., 2017). The Annual Manufacturing Survey (AMS) not comprehensive in coverage (Taymaz, 2005) Although the Business Register dataset (BR) covers all firms in

Turkey and has information about their ages, it does not have any output measures. As a result, it precludes any analysis of productivity (Atiyas et al., 2017).

Lastly, the thesis empirical investigations will be based on the Entrepreneur Information System (EIS) database from the Ministry of Industry and Technology. (EIS) have advantages over the other datasets have been mentioned above; for instance, EIS include all the Turkish firms in the BR over the period 2006-2020 and have their balance sheets and income statements data, information on the sector of activity, years of establishments, and the number of employees. These firms account for more than 90 percent of the total employment in Turkey. It should also be mentioned that Özlale and Polat (2019) have used the EIS database over 2006-2016 to analyze firms' role in creating new job opportunities. Still, they have applied a different methodology and estimation methods.

The Total Factor Productivity (TFP) is estimated by the translog production function. This model allows for heterogeneity, places no restrictions on elasticities of substitution between inputs and allows returns to scale to vary with the level of output (Pavelescu, 2011). So, this model is suited to the thesis objective to investigate the differences in TFP across firms of different sizes

Different estimation approaches available in the productivity literature to estimate the translog production function: an Ordinary Least Squares (OLS), a fixed-effect (within-effect) model, a dynamic panel model with the generalized method of moments (GMM), and the approach proposed by Akerberg et al. (2015). We are utilizing the Akerberg Caves and Frazer (ACF) methodology in this thesis to compute TFP. This methodology is an extension of the Levinsohn and Petrin (2003) LP technique and takes into account endogeneity, which occurs when firms that aim to maximize profit observe TFP early enough to alter their factor input decisions.

This study employs the Oaxaca-Blinder decomposition technique to investigate the reasons for the productivity gap between two groups. By breaking down the gap into endowment and return effects, the study helps us comprehend the factors that contribute to the difference in the average level of a variable between the two groups. Moreover, the study provides insight into the factors that influence TFP at the firm level. Additionally, the thesis examines the uncertainty related to using more than one dummy variable and applies a proposed solution to the Turkish case.

This dissertation tracks the firms that existed in 2006; only these firms will be selected to investigate firms' contribution of different sizes and ages in employment generation, taking into account the differences in survival rates. Firm exit variable is determined when the firm does not emerge in the following year. Following the methodology proposed by (Wooldridge, 2009; Erhardt, 2017). The Two-part model is estimated. The first part of the model the Probit model is used to estimate survival rate and the exit rate. However, the growth rate of employment is estimated by means of Ordinary Least Squares (OLS) in the second part of the two- part model.

It is significant to mention that the empirical findings that are presented in the thesis were obtained utilizing Stata v.17 software. Specifically, the following commands were employed: `oaxaca`, `acfest`, `translog`, `twopm`, and `xtreg` in the panel data module.

The organization of this thesis is as follows: The following section presents the literature review. The methodology and descriptive statistics for empirical analysis are elaborated in the third section. The estimation of econometric models for the empirical analysis is conducted and the results will be reported in the fourth section. The last section concludes the dissertation.

2. LITREATURE REVIEW

2.1. Employment Generation among Firms of Different Sizes and Ages

This section presents a comprehensive literature review analyzing the employment generation patterns among firms of varying sizes and ages. A review of the existing literature on the subject aims to provide insights into the relationship between the size and age of a firm and its potential to create employment opportunities.

2.1.1. Which Firms Create more Jobs Small or Large?

Substantial research has been conducted on the correlation between the size and growth of firms since the pioneering study by Gibrat in 1931. Named the Gibrat law (of proportionate effect), it claims an independent relationship between a firm's growth rate and size; regardless of the firm's size, the rate of growth for each has the same probability of happening every time period. In other words, this implies arguing about the random nature of firm development. As a result, the law predicts that some businesses will flourish; however, others will decline or stay in their current size class. Prior studies, focusing on large firms generally, revealed that the link between firm size and its growth was either positive or unrelated to each other (Hart and Prais, 1956; Chesher, 1979).

However, whether small firms generate more employment than large firms have been heavily debated, following David Birch's findings, that small firms create more jobs in his controversial works (Birch, 1979, 1981, 1987), several empirical papers have examined the importance of small firms in providing new job opportunities seriously. Birch's seminal studies (1979, 1981) provided the first empirical proof that small firms are the main driver of job growth in the US economy. Additionally, he claimed that job loss caused by large businesses creates a dynamic mechanism inside a sector, leading to the creation of small-business jobs and the destruction of large-business jobs. Birch made a similar argument (1987).

Findings by Birch were initially met with suspicion. The first criticism was directed at the reliability of the data used to measure job change (MacDonald, 1985). Davis et al. (1996)

directed the second criticism to the calculation of job creation, which separates firms into size groups. Davis et al. (1996) claimed that Birch's estimates about job growth variation among different size groups suffer from a "regression fallacy." As a result, the calculated contributions of small businesses to employment growth are biased upward. Davis et al. (1996) used data from the Longitudinal Research Database (LRD) on the US manufacturing industry from 1972 to 1988, and an estimation that they believed is not subject to this bias to conclude that net job growth has no structural correlation with average firm size.

Brown et al. (1990) contributed to the debate about Birch's findings; They argued that a firm's employment share could not be considered a sign of success in the industry. Brown et al. (1990) used empirical data from several sources in the United States to compare small firms to their larger counterparts as employers in the mid-1980s. Brown et al. (1990) found that while small businesses created more new jobs, the majority of these jobs were temporary, and small businesses paid low wages; Furthermore, small businesses have more unsatisfactory working conditions and higher employee turnover, according to the findings. While earlier it was not possible to get a full dataset on the U.S. economy as a whole that covers several sectors, recent advancements have made it possible to get such data. Neumark et al. (2011), for example, utilized the "National Establishment Time Series" dataset to reopen the debate over small businesses' contribution to job creation (Birch 1979, 1981, 1987) and the criticism by Davis et al. (1996). In their methodological study, Neumark et al. (2011) used two methods: one dependent on scale class to avoid the "regression fallacy" argued by Davis et al. (1996). A nonparametric approach that does not include the definition of an arbitrary employer size group was also available. Birch's observation that small businesses created more employment was supported by Neumark et al. (2011).

It is not easy to make a conclusive statement when the findings are not conclusive. Some studies, such as Birch's, revealed a negative association between firm size and job creation. As an example. Baldwin and Picot (1995) used Canadian manufacturing data and applied various techniques to account for the "regression fallacy" problem put forward by Davis et al. (1996). According to Baldwin and Picot's (1995) study, small manufacturing firms contributed more to net job creation than large manufacturing firms. Broersma and Gautier (1997) looked at how small, and large businesses behaved in terms of net job growth in the Dutch manufacturing sector from 1978 to 1991. Small businesses' contribution to net employment creation exceeded that of large ones, according to Broersma and Gautier (1997)

Data at the firm-level of UK manufacturing was used by Barnes and Haskel (2002), they investigated employment creation and job destruction processes in small and large firms in the United Kingdom. Between 1980 and 1991, small plants were the main responsible for net job growth in the UK, according to Barnes and Haskel (2002). Voulgaris et al. (2005) examined job creation and destruction trends in the Greek manufacturing industry from 1995 to 1999 using a longitudinal sample of 6145 companies. Voulgaris et al. (2005) demonstrated the dynamic role of small and medium businesses in creating new jobs in the Greek manufacturing sector. Furthermore, the findings revealed that manufacturing sectors with a high degree of technology and capital intensity contributed the most to Greece's net employment growth. Larger firms contribute less to job growth in comparison with smaller firms in the EU as a whole, according to de Kok and de Wit (2012), and net job creation rates decline for each firm size class.

Based on firm-level panel data from Ethiopian manufacturing from 1996 to 2007, Shiferaw and Bedi (2013) reported that smaller firms in Ethiopia have higher employment growth. The effect of the firm size, especially the role of micro and small firms that used to be neglected in most of the previous studies that deal with developing countries on employment growth rates, was addressed by Li and Rama (2015). The findings revealed that gross employment generation is related negatively to firm size. In developing nations, when the role of micro and small firms is taken into consideration, the investigation showed that micro and small businesses are the main employers.

Bakhtiari (2017) studied the Australian economy using a firm-level dataset. The study found that small businesses were responsible for creating 20 percent and losing 9 percent of full-time jobs. The research analyzed the firm population across all industries in Australia between 2004 and 2014. The findings show that small businesses, that were newly established, created 2.0 million out of the 2.5 million new full-time jobs during this period. According to Bakhtiari (2017), most of Australia's net job growth in the past ten years has been driven by small start-ups and entrepreneurs.

Hohti (2000) on the other hand, investigated employment share and growth behavior across different sizes of firms in the Finnish manufacturing sector from 1980 to 1994. Hohti (2000) came to the same conclusion as Davis et al. (1996). Namely, no obvious link tied a firm size and net job change. Fornaro and Luomaranta, (2015) analyzed monthly firm-level data from January 1998 to September 2014 in Finland, covering all sectors. They confirmed

Hohti's (2000) findings and rejected Gibrat's law. The study found that small companies had higher growth rates compared to large businesses. Additionally, the research looked at the contribution of small and large businesses to Finland's net job growth. The results showed that smaller businesses, except for the governmental sector, created the most employment growth across all sectors in the Finnish economy. In Tunisia, Rijkers et al.(2015) discovered a strong correlation between net job creation and firm size.

2.1.2. Dose All Small Firms Grow? Which Firms Are Responsible for the Majority of Job Creation?

"Gazelles" was the word used by Birch and Medoff (1994) to describe a few numbers of high-growth firms responsible for creating most of the new net jobs in the economy. the period 1988- 1992, around four percent of all U.S. firms account for about 70 percent of all net new jobs created by all of the surviving firms, according to Birch and Medoff (1994). Also, these four percent created nearly 60 percent of all new jobs in every economic sector at the same span of time. For every "gazelle" firm, the average employee number was 61 in 1993. They were rather small. Birch and Medoff (1994) discovered "gazelles" in all industries, with about equal percentages of fast-growing firms in each.

However, there is a well-established finding from the literature that smaller firms either do not expand or they expand at a slow pace. Therefore, the interest in rapidly growing firms "gazelles" was increased due to the fact that job creation within an economy could be achieved by few numbers of (rapidly growing) firms or a small proportion of all firms (see Storey, 1994; Davidsson & Henrekson , 2002). According to the findings of these empirical studies, around 4 percent of firms are responsible for more than 50 percent of all new jobs created each year. Therefore, the traditional thinking regarding the importance of smaller firms in creating new employment opportunities has been changed. Several empirical papers started to increase their focus on the importance of high-growth firms and the features and factors that shape their growth rates (Coad et al., 2014). For instance, Delmar et al. (2003) examined high-growth firms' own attributes; namely, they looked at whether these firms were small, young, or belonged to the enterprise group. In contrast, Davidsson et al. (2006); Mason and Brown (2013) explored whether high-growth firms developed in a specific industry. Furthermore, the analysis was extended to establish if these fast-growing firms

originated in a particular area or nation (Acs and Mueller 2008; Bravo-Biosca et al. 2016). The following facts could be drawn from the existing literature: The average age of high-growth firms is younger than that of non-high-growth firms; gazelles are not always small but may be of any size; and they operate in a variety of industries rather than just high-tech (Moreno & Coad, 2015).

To summarize, the research indicates that a few fast-growing firms drive employment generation in manufacturing. Here, Henrekson and Johansson (2010) highlight the importance of gazelles in economic downturns as they continue to expand. Additionally, the evidence implies that young firms generate unique job opportunities. However, there was no clear conclusion on the influence of size in the literature. According to Henrekson and Johansson (2010) and Coad et al. (2014), though small firms are better represented, gazelles of any size, especially if they are large, are vital for employment generation.

2.1.3. Which Firms Create Jobs Size and Age Combinations?

Recently, another strand of micro-data analysis studies investigating the role of small and young firms in generating employment deals with Gibrat's law. Gibrat (1931) argued that mean growth rates in firm size, as determined by the number of workers, are the same for all firm sizes regardless of historical growth background. Utilizing firm-level data for manufacturing firms in the United States, Evans (1987) identified a negative link between firm growth and firm size (while keeping constant the age factor). Gibrat's Law was refuted in this study, which considered significant early research that highlighted the role of firm age in the dynamics of growth.

However, the research was conducted using data with significant constraints for tracking new enterprises and start-ups, as Evans (1987) stated. By studying firm growth and size, age, death, and survival among a comprehensive sample of UK businesses from 1975 to 1985, Dunne and Hughes's (1994) empirical findings violated Gibrat's law. According to Dunne and Hughes (1994), smaller firms grew faster than larger ones, and they became less vulnerable to acquisitions by larger corporations. As a result, when compared to medium-sized businesses, they had a lower death rate. Dunne and Hughes (1994) discovered that younger firms grew faster than mature ones for a given size class.

Furthermore, the Gibrat law has been challenged in several recent studies (e.g., (Audretsch et al. 1999; Heshmati, 2001; Lotti and Santarelli, 2004; Calvo, 2006). Calvo (2006) used the least-squares and Heckman models to assess the validity of Gibrat's law in Spain. The findings refuted Gibrat law's validity, demonstrating that small businesses grew at a higher rate than larger businesses. On the other hand, Numerous empirical research, including (Cabral and Mata, 2003; Lawless, 2014; Lotti et al. 2009; Daunfeldt and Elert, 2013), demonstrated that once firms reach an efficient scale, company size and job development became separate, confirming Gibrat's Law.

There is a substantial body of literature that has addressed the differentiation between the effect of firm size and the impact of firm age. One such study is that of (Haltiwanger et al. (2013), which utilized data from the Business Dynamics Statistics and Longitudinal Business Database of the Census Bureau., which are not affected by the same restrictions faced the early study by Evans (1987). Haltiwanger et al. (2013) shed light on the crucial role of start-ups and young enterprises in the U.S. economy as major employment generators. According to Haltiwanger et al. (2013), young firms usually dominate small firms in net job creation; these young firms tend to have relatively small capacities upon their foundations. Thus, the lack of control for firm ages in the literature leads to the majority of these young firms being classified as small. So, the negative association between firm size and net job growth was found in previous studies. As a result, when the firm's age is taken into account, the strong negative correlation between firm size and job generation disappears. Similar findings were found for Slovenia by Banerjee and Jesenko (2016).

Criscuolo et al. (2014) provided evidence that extended to that seen in the United States, revealing a prominent role for young businesses in net job creation across 18 countries over ten years from 2001 to 2011. Esaku (2020) provided evidence from Kenya demonstrating that almost all net employment growth is due to the age of firms rather than their size. According to Bravo-Biosca et al. (2016), young businesses contribute disproportionately to overall employment growth. Using survey results from a vast number of developing economies, Ayyagari et al. (2014) illustrated that small young firms create more jobs than larger mature firms. While the contribution of young firms to employment growth was lower than that of large firms.

A study by Ochieng and Park (2017) suggests that young and elderly enterprises have a significant impact on employment creation and job destruction in transitioning economies.

Conversely, according to Aterido et al. (2019), most new jobs are created by large and old businesses. As per their analysis of firm-level data from South Africa Eslava et al. (2019) reported that the youngest firms were responsible for the majority of this employment growth.

Dogan et al. (2017) utilized firm-level data to explore the correlation between business size and job creation among all non-agricultural companies in Turkey with at least 20 workers from 2003 to 2010. The data came from the Turkish Statistical Institute's annual enterprises (firms) survey. In the manufacturing and service sectors, Dogan et al. (2017) discovered that company size is inversely related to net job growth. To account for age impact, Dogan et al. (2017) used a small sample and found that the negative relation between firm size and net job growth still exists. Furthermore, Özlale and Polat (2019) showed that firm size did not influence job creation when they controlled for age and accounted for the regression to-the-mean effect. Özlale and Polat (2019) conducted the study utilizing the "Entrepreneur Information System" dataset, which spanned from 2006 to 2016.

The positive consequences of young and small firms (e.g. for employment growth) are conditional on their survival. Davis and Haltiwanger (1992) and Haltiwanger et al. (2013) noticed that young firms, especially if they are small, have a high likelihood to exit than incumbent firms. According to Quatraro and Vivarelli (2015), new firms in developing countries have a survival rate of fewer than 50 percent in the first five years of their operations. Prior studies, for example, Dunne et al. (1988) for the United States, Reid (1991), for Portugal Mata et al. (1995), and Johnson (2005) for North East England, have all observed similar low survival rates. In the four-digit US manufacturing industries for the period 1963-1982, Dunne et al. (1988) investigated firms' entrance, growth, and exit patterns. According to the inquiry findings, there were significant failure rates; for instance, on average across four-digit industries, 61.5 percent of all firms exit within five years after their entrance. Further, on average, 79.6 percent of all firms fail within 10 years after their founding.

According to the results of Audretsch et al. (1999), new manufacturing firms in Italy have a survival rate of just 59 percent after five years in operation. Johnson (2005) presented that about 60 percent of the new entrants in North East England within five years. For the United States, Decker et al. (2014) report that young and small enterprises' role in creating new jobs and productivity growth is substantial in the short run. However, the survival rate

among these startups is low within their first ten years, and the growth rate of most surviving young businesses is low. At the same time, a small fraction of survived newly created businesses grow fastly and contribute disproportionately to new job creation in the long run.

According to a study by Huber et al. (2016), young firms in Austria have the highest net job creation rates, but this is subject to their survival. The study found that variations in firm size alone cannot fully account for the differences in net job creation rates. Huber et al. (2016) also noted that young and small businesses tend to experience the highest job loss rates, mainly due to market exit.

For Turkey, Atiya's et al. (2017) confirmed the crucial role of small and young firms in job creation. However, these jobs do not long-lasting. Furthermore, about 50 percent of small firms and new entrants do not survive for more than five years. Özlale and Polat (2019) proposed strong support for young firms' importance in generating new jobs in the Turkish economy. The OECD Economic Survey (2021) shows that the average growth rate of startups in Turkey was roughly 1.1 percent throughout the 2010-2014 period. Between 2015 and 2019, it slowed to about 0.3 percent. This drop-in of new entrants, along with an increase in exit rates, is alarming for Turkey, considering the importance of young businesses in creating new jobs (e.g. Atiyas et al., 2017; Özlale and Polat, 2019).

2.1.4. Net Employment Growth and Sample Selection Bias

The negative relationship between firm size and growth in several studies is consistent with industry evolution models “passive and active learning” effects (Nelson and Winter, 1982; Jovanovic , 1982; Ericson and Pakes,1995). However, an earlier study by Mansfield (1962) showed that this result might be due to sampling selection bias, which occurs when small businesses with low or negative performance have a higher probability to be excluded from the sample compared to their larger counterparts. Many large firms move to lower size class and take a significantly longer time to exit, whereas firms in the lower size class more likely to get through the exit threshold earlier. Because only surviving firms were included, the link between size and growth could be overestimated.

2.2. Which Firms Drive Productivity?

Kerr et al. (1960) emphasized the importance of large-scale firms as an economic engine in their considerable book -Industrialism and Industrial Man. Kerr et al. (1960) stated, "The technology and specialisation of the industrial society are necessarily and distinctively associated with "large-scale organizations" and that "economic activity" is carried on by large-scale enterprises which require extensive coordination of managers and workers"(p. 39).

Prior to the early 1970s, corporations of significant size were widely acknowledged as key drivers of the economy, largely due to their exceptional levels of productivity and innovation. These entities were considered instrumental in fostering economic growth, innovation, and driving economic development (Du Boff and Chandler, 1990; Schumpeter, 1942). According to Bartelsman et al.(2003) large businesses are well-suited to develop and benefit from economies of scale and scope. However, the oil crisis in the 1970s changed all of that; Loveman and Sengenberger (1991) pointed that size advantages diminished because large firms are often subject to inflexibility in adapting to changing market conditions. In contrast, small and medium-sized firms often enjoy lower labor costs and flexibility in the specialization. According to Storey's (1994) findings, the productivity of smaller enterprises is relatively lower and they tend to offer lower wages (i.e., less stable), and have less satisfactory working conditions. The empirical research has continued to show the shortcomings of small firms in the marketplace. For example, according to (Winter-Ebmer and Zweimüller, 1999), SMEs often hired less-educated and less-experienced human capital. Moreover, SMEs have less capital-skill complementarity, according to (Troske, 1999).

The relationship between the size factor and labor productivity has been extensively explored in academic and business literature. Ark and Monnikhof (1996) described this relation for five OECD countries (the United States, the United Kingdom, France, Japan, and Germany). Ark and Monnikhof (1996) utilized "censuses of manufacturers and industrial surveys"; to combine data on "gross output" (the net sales value of all products sold for France, Japan, and the United States. While it equals the value of all products sold and unsold For Germany and the United Kingdom). And "value-added" (gross output minus intermediate inputs) with data on the number of employees to calculate relative productivity performance by size category represented as a percentage of productivity for the whole

manufacturing sector. The findings revealed that larger-sized units more productive than smaller-sized units when examining the rate of (gross output per employee) and, likewise, (the value-added per employee). The estimate indicated that the disparity in labor productivity levels between the smallest and larger units existed for all five countries. The highest gap between the smallest enterprises and their largest counterparts was presented in 1990 in Japan. While Snodgrass and Biggs (1995) provided proof for nations that are less-developed such as India, the Philippines, South Korea, Bangladesh, Turkey, and Taiwan, the results revealed a big difference in labor productivity between the large and small firms.

Baldwin (1995) in a similar cautionary vein from Canada, reported that new small manufacturing plants fall behind larger ones in terms of labor productivity over the 1970s and 1980s. The entrance of new small firms, according to (Baldwin, 1995) may have increased the employment share of small plants. However, their value-added share could not be increased at a rapid pace like employment share. This meant that, compared to larger plants, the labor productivity of small plants, which is usually smaller, decreased over time (Baldwin et al., 2002). Moreover, (Van Biesebroeck, 2005) introduced evidence from nine African countries showed that large firms were the most productive ones. In addition, a large gap in labor productivity between large and small firms leads to a high divergence between the individual share of these firms to the growth of productivity at the aggregate level.

Using World Bank Enterprise Survey for developing economies, Ayyagari et al. (2011) illustrated that large enterprises are more productive than small enterprises. The World Bank (2012) reexamined the same hypothesis based on the same form of surveys. However, the sample extended to 102 nations. The findings confirmed what was reported by Ayyagari et al. (2011). In addition to a positive correlation was drawn between business size and export success. It also found that a larger business entity is more likely to engage in various emerging product developments, introduce new technologies, outsource, and form international partnerships.

2.3. The Factors behind Productivity Gap between Small and Large Firms

Some researchers try to emphasize the superiority of large firms over small ones. Since large firms can take advantage of economies of scale and more easily absorb the high fixed costs involved with research and development, they are better at innovating and increasing

productivity than small businesses (Herman, 2012). Cohen and Klepper (1996) discovered that firm size increases net innovative output. For example, they referred to the benefits of big firms in terms of innovation, citing the ability of large firms to minimize duplicative activity and carry on tasks that might be unprofitable for small firms. According to Pagano and Schivardi (2001), there was a stronger association between average enterprise size and innovation rates in Europe. Kim et al. (2009) reexamined the firm size-innovation relationship by using data set covering Pharmaceutical and Semiconductor industries in the United States. The empirical results reflected a positive relationship between patents per inventor (R&D measure) and the size in the Semiconductors industry.

However, Acs and Audretsch (1987) claimed that small firms in "high-tech" sectors in the U.S. have higher rates of innovation. According to Audretsch and Thurik (2000), economic activities focused on innovation and novel ideas evolve as a competitive advantage for Europe. Baumann and Kritikos (2016) demonstrated that micro businesses could gain from R&D and innovation practices to raise labor productivity in the same way that their larger peers can. Hall et al. (2009) showed that small and medium-sized enterprises contributed considerably to innovation output. Firm size is positive with the likelihood of having a process or product innovation, and that only product innovation improves labor productivity. According to Calligaris et al. (2016), innovation, as measured by intangible assets such as branding, marketing, and research and development, leads to an increase in productivity growth. In a similar vein, Crass and Peters (2014) conducted a study using panel data from German enterprises between 2006-2010 to examine how intangible assets impact productivity at the firm level. Their research revealed that R&D and human capital (represented by training expenditure and a high proportion of skilled workers) had significant productivity-enhancing effects.

On the other side, a substantial body of literature on the size-productivity relationship focuses on models incorporating the selection impact process associated with industry dynamics. Jovanovic (1982) suggested a "passive learning" paradigm in which businesses join the market with no previous knowledge of their level of productivity. However, they could be sure of their actual productivity after evaluating their performance in the industry. According to Jovanovic (1982), large firms are more productive because only efficient firms survive to grow large, whereas inefficient firms struggle to expand and stay small. Furthermore, Ericson and Pakes (1995) modified Jovanovic's (1982) model to include

random events that may harm even the most productive firms. Under competitive pressure, for example, firms that can consistently improve their productivity have a better chance of growing and surviving; this is an “active learning” model. Taymaz (2005) for Turkey built his analysis based on industry evolution models and stochastic frontier approach, found significant and persistent productivity gaps between large and small firms in the manufacturing industry from 1987 to 1997.

The “active learning” model proposed by Ericson and Pakes (1995) assumed that firms with lower productivity would be forced out of business by higher-productivity firms. However, the empirical investigations of different economies introduced evidence that showed diverse and persistent productivity levels (Nightingale and Coad, 2014). For instance, (Castany et al., 2005 for Spain and Brouwere et al., 2005 for the Netherlands) showed that small firms achieved low labor and total factor productivity levels than their larger counterparts. Recently, Cowling et al. (2011) as in Nightingale and Coad (2014), by utilizing a sample from the U.K., showed that it is difficult for new competitors to compete at the same level as their incumbents. According to Cowling et al. (2011), new entrants faced significant disadvantages; for instance, young firms required at least five years to learn about new technologies. Nevertheless, they need more long time extended to several decades to achieve better productivity levels than older firms. As a result, the remarkable new entrant productivity is often explained by the emergence of pre-existing firms (i.e., the entrance from existing chains), not by the entrance of new ones (see Disney et al. (2003) for the UK and Foster et al. (2008) for the US). The literature on the TFP of firms suggests that the decline in productivity with age is primarily due to the difficulty of keeping up with technological advancements and the changing demands of the market. Additionally, as firms age, they may accumulate more sunk costs, which can make it difficult for them to adapt to changing market conditions (Harris and Moffat, 2015; Goncalves and Martins, 2016; Camino-Mogro, 2021). However, some scholars, such as Jovanovic and Nyarko (1996), proposed the learning-by-doing hypothesis, which suggests that older firms attain greater levels of productivity.

Financial constraints have a significant impact on economic growth as they affect decisions related to savings and investment, ultimately affecting Total Factor Productivity (TFP) growth. In an ideal scenario, perfect financial markets would facilitate long-term investments in projects that enhance productivity, leading to better TFP growth (Aghion et

al., 2005). Access to credit has a notable impact on the productivity and growth of firms. Therefore, enabling long-term investments that enhance productivity can boost growth and reduce volatility (Aghion et al., 2010). However, in reality, investments in risky opportunities, such as research and development (R&D) investments, may be restricted as companies must maintain financial stability to secure lending from banks (Fazzari et al., 1988). However, access to credit remains a significant obstacle for small firms, particularly in developing countries. This issue is of greater concern for small enterprises than for larger corporations, and it may adversely affect productivity growth at the lower end of the firm-size distribution (Van Biesebroeck, 2005).

The relationship between debt and total factor productivity (TFP) growth remains a topic of debate. Empirical evidence suggests that the association varies across different contexts. For example, the study conducted by Goncalves and Martins (2016) highlights a negative correlation between debt and TFP growth in Portuguese manufacturing firms. On the other hand, Van Biesebroeck (2005) found that African manufacturing firms that receive credit tend to have higher levels of productivity compared to those that do not. Similar results are reported by Villalpando (2014) for Mexico. However, Coricelli et al. (2012) argue that the relationship between debt and TFP growth is non-linear, and there is a threshold level of debt that can positively impact TFP growth. Beyond this threshold, the effect becomes negative. In the same vein, Camino-Mogro (2022) found similar results in his analysis of the TFP determinants of Ecuadorian manufacturing firms.

Based on Olley and Pakes' approach (1996), Bartelsman et al. (2013) presented empirical proof from Central and Eastern European countries that the labor productivity and size proportions among industries were strongly linked. Bertelsmann et al. (2013) showed that connection differed considerably from country to country. According to the results recorded, the size/productivity connection was greater in developed nations. In addition, within this community of economies, though, there are significant variations, which became even more noticeable as the shift to a market economy progresses. Using data from Vietnam, Pham et al. (2020) showed substantial heterogeneity in productivity across business sizes in all industries.

An additional factor contributing to the disparity between large and small firms in terms of productivity is their export status; according to (Papadogonas and Voulgaris, 2005) exporters face more competitive pressure. Therefore, exporters are motivated to minimize

inefficiencies and boost productivity. The first empirical research to study the connection between exporting and business performance was performed by Bernard et al. (1995), according to the results, the non-exporters are less productive, less capital-intensive, and less technologically advanced than exporters. Numerous empirical studies conducted in many countries and at the firm level have examined the effects of exporting. As an example, Papadogonas and Voulgaris (2005) found that exporters in Greece have higher labor productivity and rate of productivity growth because of intense competition in global markets. Clerides et al. (1998) supported the claim that export-oriented enterprises in developing countries are more efficient than non-exporting enterprises. Their analysis over Morocco, Mexico, and Colombia, revealed that firms that cease to export are usually less efficient. Aldan and Gunay (2008) analyzed the link between firm export status and productivity; they used firm-level data from the Central Bank of the Republic of Turkey. Turkish exporters were considered to have higher productivity levels and growth rates based on Aldan and Gunay's (2008) analysis. According to a recent study, Turkish exporters are financially stronger, more productive, and invest more in R&D than non-exporters (Atabek Demirhan, 2016).

OECD Economic Surveys (2021) showed that, on average, Turkish companies have less exporting involvement, while those exporting mostly produce commodities consumed outside Turkey as final goods. Along with low levels of Foreign Direct Investment inflows. In most of the literature on Foreign Direct Investment, there is a broad assumption that firms owned by foreign countries are more productive. (See, Harris and Robinson (2003), for the U.K., Rao et al. (2009) for Canada). Foreign affiliates have better management and marketing skills, more specific knowledge about manufacturing, export contracts, and excellent ties with suppliers and customers. Furthermore, since they are part of a worldwide network that connects them to innovation and have the capacity to capitalize on multiplant economies of scale, foreign-owned enterprises outperform domestically owned plants (Papadogonas and Voulgaris, 2005).

3. METHODOLOGY AND DESCRIPTIVE STATISTICS

In the following section, a detailed explanation of the hypotheses, empirical model, and definitions of variables used in this thesis is provided. The empirical models and the specific variables used in the analysis are defined precisely. The research methodology is also explicated, with a clear and detailed description of the steps taken to conduct the study, including the dataset and its sources, the sample size, and any statistical procedures employed. Preliminary results are presented in the form of both numerical and graphical summaries.

3.1. The Hypotheses and Empirical Models

The thesis will test the following hypotheses:

Hypothesis 1:

H₀₁: Capital intensity explains the differences in total factor productivity.

H₁₁: Capital intensity not explains the differences in total factor productivity.

Hypothesis 2:

H₀₂: The wages paid to employees explain the differences in total factor productivity.

H₁₂: The wages paid to employees not explain the differences in total factor productivity.

Hypothesis 3:

H₀₃: Firm age explains the differences in total factor productivity.

H₁₃: Firm age not explains the differences in total factor productivity.

Hypothesis 4:

H₀₄: Firm's financial constraints explain the differences in total factor productivity.

H₁₄: Firm's financial constraints not explain the differences in total factor productivity.

Hypothesis 5:

H₀₅: A firm's exporting status has a role in explaining total factor productivity gap.

H₁₅: A firm's exporting status has not a role in explaining total factor productivity gap.

Hypothesis 6:

H₀₆: A firm's innovations activity explains differences in TFP

H₁₆: A firm's innovations activity not explain differences in TFP

Hypothesis 7:

H₀₇: A firm's sectors technology level explains differences in TFP

H₁₇: A firm's sectors technology level not explain differences in TFP

Hypothesis 8:

H₀₈: Small and young firms contribute the same as large and old firms to employment growth.

H₁₈: Small and young firms contribute more than large and old firms to employment growth.

To test the above hypotheses the following models are suggested.

3.1.1. Modeling Total Factor Productivity Gap between Small and Large Firms

The analysis specification is a regression model that determines the Total Factor Productivity (TFP) based on several factors. These factors include capital intensity, average annual gross wage per worker, age of the firm, debt-to-equity ratio, which indicates financial constraints, the firm's export status, business innovation activities, and the technological levels of the sector to which the firm belongs. The empirical model can be described as follows:

$$TFP_{i,t} = \beta_0 + \beta_1 c_{i,t} + \beta_2 w_{i,t} + \beta_3 AGE_{i,t} + \beta_4 dte_{i,t} + \beta_5 EX + \beta_6 INOV_{i,t} + \beta_{TECH} TECH + \beta_{TECMH} TECHM + \beta_{TECML} TECML + \varepsilon_{it} \quad (3.1)$$

where:

$TFP_{i,t}$: is the logarithm of the total factor productivity in firm i at time t

$c_{i,t}$: Log capital intensity

$w_{i,t}$: Logarithm of the average annual gross wage per worker.

$AGE_{i,t}$: Age of the firm.

$dte_{i,t}$: Ratio of total liabilities to total equity expressed as a logarithmic value.

EX : Dummy variable of firm export status.

$INOV_{i,t}$: Dummy variable equal one if the ratio of firm's fixed intangible assets to total assets greater than zero at time t , zero otherwise.

$TECH, TECMH, TECML$, : Sector's technological levels are Classified as follows:

$TECH$: High Technology.

$TECMH$: Medium- High Technology.

$TECML$: Medium- Low Technology.

The reference group is tech $TECL$, which is Low Technology.

ε_{it} : An error terms.

3.1.2. The Measurement and Decomposition of TFP

TFP describes additional elements contributing to economic growth after capital and labor inputs are removed from the equation. TFP goes into greater detail about the issue of whether or not the impact of technological advancement on output has improved (Liu et al., 2023). TFP is a valuable tool for accurately assessing productivity levels and variations when compared to productivity based on a single factor. There are three standard techniques used to calculate TFP, including the non-parametric Data Envelopment Analysis (DEA), the total parameter estimation Stochastic Frontier Analysis (SFA), and the semi-parametric

estimation proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Akerberg et al. (2015).

Each of the methods mentioned above has both strengths and weaknesses. Semi-parametric estimation (OP & LP) is particularly useful for handling sample selection and simultaneity bias. However, the OP approach works only if investment is a strictly monotonic function of productivity. DEA, on the other hand, requires only input and output quantities as additional information and measures efficiency by the highest observed performance, rather than using an average (Hjalmarsson and Veiderpass, 1992). However, DEA-based estimates are susceptible to measurement errors or other types of data noise, as DEA is deterministic and attributes all deviations from the frontier to inefficiencies (Hossain et al., 2012).

SFA is a method that considers random fluctuations in data and enables statistical evaluation of production structure and inefficiency-related hypotheses. However, SFA has some limitations, such as the need to assume a particular distribution for inefficiency terms and the imposition of a specific parametric functional form that represents the underlying technology (Hossain et al., 2012)

3.1.2.1. *Parametric Stochastic Frontier Analysis (SFA) Panel Data.*

Aigner et al. (1977) and Meeusen and van Den Broeck (1977) first introduced the SFA economic modeling method. The production frontier model, without the random component, is expressed as follows:

$$Y_i = (x_i, \beta) TE_i \quad i = 1, 2, 3 \dots \dots \dots N \quad (3.2)$$

The producer's observed scalar output is denoted as Y_i , where i is a subscript that ranges from 1 to A vector of N inputs used by the producer. The vector of technology parameters that must be estimated is represented by β in the production frontier ($; \beta$). The technical efficiency of the producer, denoted as TE_i , is calculated by dividing the observed output by the maximum practicable output. If TE_i is less than 1, it means that the observed output is less than the maximum feasible output. A TE_i value of 1 implies that the i -th firm reached its highest attainable level of production (Castillo et al., 2014; Kınacı et al., 2016).

To address the possibility of unpredictable disruptions to the production process, a stochastic component designated as $\exp(vi)$ has been incorporated into equation (3.2). This adjustment, in turn, has resulted in the modification of the stochastic production frontier.

$$y_i = f(x_i; \beta) \cdot TE_i \cdot \exp(vi), \quad i = 1, 2, 3, \dots, N \quad (3.3)$$

TE_i is also a stochastic variable is written as an exponential = $\exp(ui)$ the equation (3.3) above is converted to the following one

$$Y_i = (x_i, \beta) e^{vi - ui} \quad i = 1, 2, 3, \dots, N \quad (3.4)$$

where:

Y_i : is output

x_i : is a vector of the input variables

β : The vector of technology parameters that must be estimated

vi : Is the disturbance or random error term $vi \sim N(0, \sigma_v^2)$

ui : The non-negative error term representing technical inefficiency or

$ui \sim N^+(0, \sigma_v^2)$: Takes the truncated normal distribution.

It's important to note that ui and vi are disturbances that occur randomly and are not related to each other or the regressors. They can be defined as $\varepsilon_i = vi - ui$ and have a specific distribution that needs to be identified (Kınacı et al., 2016). The most commonly used distributions for ui are Exponential, Half-Normal, Truncated Normal, and Gamma, while Normal distribution is often used for vi (Kumbhakar and Lovell, 2000). The model was modified by (Battese and Coelli , 1995) for panel data is widely used in the literature.

$$\ln Y_{it} = \beta_0 + \sum \beta_j \ln x_{it} + v_{it} - u_{it} \quad (i = 1 \dots \dots, N; t = 1 \dots \dots T) \quad (3.5)$$

where:

Y_{it}, x_{it} : are the output and input variables of an entity i at specific time t , respectively

vi : is the random error term.

$u_{it} = u_i e^{-\eta(t-T)}$: is a non-negative error term

And η is an estimated parameter.

$TE_{it} = e^{-\eta_{it}}$ Express the efficiency level of an entity i at period t

3.1.2.2. *The Semi Parametric Estimation.*

In panel data, firm "i" is observed several times at the period "t" of analysis. If the production function estimated by Ordinary Least Squares (OLS), it's crucial to consider that can pose significant challenges. When a productivity shock happens, businesses focused on profit-maximizing will quickly adjust their inputs primarily capital to adapt to the changes. As a result, input levels are linked to these shocks. Given that productivity shocks are not directly detectable, they're incorporated into the error term of the regression equation. OLS estimates of production functions are therefore biased. Furthermore, it is evident that the instrumental variables, fixed-effects, or within groups estimators don't seem to yield substantial improvements (Griliches and Mairesse, 1995).

To tackle a particular issue, Levinsohn and Petrin (2003), as well as Olley and Pakes (1996) developed two related semi-parametric estimation techniques. Olley and Pakes, (1996) suggest using a low-order polynomial to approximate the unknown control function, which takes into account the correlation between the unobservable productivity shocks and the input levels. A proposed method for measuring productivity is to use a company's investment as a proxy variable. However, in cases where businesses face significant adjustment costs, such an approach may not be entirely adequate. The investment variable may not fully reflect changes in productivity and may become severely truncated around zero (Tran, 2019), Levinsohn and Petrin (2003) suggest a different strategy that relies on intermediate inputs instead of investments in the control function. This approach is often the only one accessible since acquiring data on firm-level investments is challenging (Manjón and Mañez, 2016).

Akerberg et al. (2015) have pointed out that the estimation methods suggested by Levinsohn and Petrin (2003) may face identification issues. When attempting to estimate a nonparametric function using a low-order polynomial, it is crucial to consider that the labor input may not vary independently unless further assumptions about the data generation processes are taken into account (Guo and Zhang, 2023). To address this challenge, Akerberg et al. (2015) propose using an estimation technique that combines features of two-stage methods proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). In this

proposed technique, the estimation of all input coefficients, including the labor stock coefficient, is done as a second process. The first stage of the process does not estimate any coefficient of the regressors.

This dissertation utilizes the ACF methodology to compute TFP, which extends the LP technique. This methodology deals with the endogeneity and potential collinearity between labor and the proxy variable.

3.1.3. A Description of the Model Used to Estimate Total Factor Productivity (TFP)

In this section, we will discuss the model used to estimate Total Factor Productivity (TFP). Our goal is to provide clarity on the process and methods involved in calculating TFP. For this study, we chose the transcendental logarithmic production function to construct the model. We made this choice because it has a flexible function form that can handle high levels of variability, and it is easy to estimate. This function is advantageous because it is compatible with a wide range of production behaviors and have an ability to prevent the constant scale return and substitution elasticity issues that the Cobb-Douglas production function typically faces (Liu et al., 2023).

$$\ln \gamma_{i,t} = \beta_0 + \beta_k \ln k_{it} + \beta_n \ln n_{it} + \frac{1}{2} \beta_{kk} (\ln k_{it})^2 + \frac{1}{2} \beta_{nn} (\ln n_{it})^2 + \beta_{kn} \ln k_{it} \ln n_{it} + (\delta_i + \gamma_{i,t}) + \varepsilon_{it} \quad (3.6)$$

Where:

$\ln \gamma_{i,t}$: log value added

$n_{i,t}$: log employment

$k_{i,t}$: log capital stock

$(\delta_i + \gamma_{i,t})$: δ_i Unobserved firm specific effect $\gamma_{i,t}$ is possibly autoregressive productivity shock and ε_{it} is serially uncorrelated measurement errors (Blundell and Bond , 2000).

3.1.4. Static Blinder-Oaxaca Decomposition

The Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973), it has frequently been used to examine wage differences between various worker categories based on race and gender in the field of labor economics around the world. The initial purpose of this methodology is to divide the differences in wages between various groups, such as males and females, or white and non-white, into two parts. The first part concerned with the variations in the observable attributes of the two groups, such as education or experience levels. This part of the wage gap is known as the "explained part" and only accounts for a portion of the wage gap. The other portion of the gap, known as the "unexplained part," is caused by unequal incentives for different attributes between the two groups, for example, males and females with equal schooling levels may earn different rewards (Scorzafave and Pazello, 2007).

Castany et al. (2005) and Zhang (2014) used the Oaxaca decomposition to investigate the gap in Total Factor Productivity (TFP) between small and large enterprises. However, these studies did not address the issue of indeterminacy that arises when an estimated model contains multiple sets of dummy variables. In this study, we aim to examine the TFP gaps at the firm level while considering the indetermination issue and introducing a solution to address it. By employing this methodology, we can determine how much of the TFP gap between small and large firms can be attributed to differences in their characteristics or the returns associated with them.

3.1.4.1. *Total Factor Productivity (TFP) Decomposition Methodology.*

The decomposition methodology is described in this section. However, the following section explains the indeterminations issue and outline the solution. A firm's total factor productivity can be determined as follows (Islam et al., 2019):

$$Z_S = \beta_{S_0} + \sum_{n=1}^N \beta_{S_N} X_{S_N} + \varepsilon_S \quad (3.7)$$

Where Z_S is the mean $\ln$ (TFP) for a small firm, where X is a set of N noticeable parameters that can have an impact on the firm's productivity. ε_N is the error term. Replace the subscript "S" with "L". The equivalent of equation (3.7) for large firms is displayed in equation (3.8). below.

$$Z_L = \beta_{L_0} + \sum_{n=1}^N \beta_{L_N} X_{L_N} + \varepsilon_L \quad (3.8)$$

Under the assumption of $E(\varepsilon_S) = E(\varepsilon_L) = 0$

Taking the expectation of log TFP for small firms, equation (3.9) can be expressed as

$$\begin{aligned} E(Z_S) &= (\beta_{S_0} + \sum_n^N \beta_{S_N} X_{S_N} + \varepsilon_N) \\ &= \beta_{S_0} + \sum_{n=1}^N \beta_{S_N} E(X_{S_N}) \end{aligned} \quad (3.9)$$

Taking the expectation of log TFP for large firms, equation (3.9) can be expressed as:

$$\begin{aligned} E(Z_L) &= (\beta_{L_0} + \sum_{n=1}^N \beta_{L_N} X_{L_N} + \varepsilon_L) \\ &= \beta_{L_0} + \sum_{n=1}^N \beta_{L_N} E(X_{L_N}) \end{aligned} \quad (3.10)$$

The total factor productivity TFP gap (GA) can be expressed as $E(Z_S) - E(Z_L)$, the difference in TFP between small and large enterprises can be computed by subtracting equation (3.9) from equation (3.10), which is written as equation (3.11).

$$GA = \beta_{S_0} + \sum_{n=1}^N \beta_{S_N} E(X_{S_N}) - \beta_{L_0} - \sum_{n=1}^N \beta_{L_N} E(X_{L_N}) \quad (3.11)$$

We need to rearrange equation (3.12) by both adding and subtracting.

$\sum_{n=1}^N \beta_{S_N} E(X_{L_N})$, to obtain the productivity gap.

$$GA = \sum_{n=1}^N [E(X_{S_N}) - E(X_{L_N})] \beta_{S_N} + \beta_{S_0} - \beta_{L_0} + \sum_{n=1}^N [(\beta_{S_N} - \beta_{L_N}) E(X_{L_N})] \quad (3.12)$$

Where the explained or endowment effect is $\sum_{n=1}^N [E(X_{S_N}) - E(X_{L_N})] \beta_{S_N}$. However, the unexplained or coefficients effect is $\beta_{S_0} - \beta_{L_0} + \sum_{n=1}^N [(\beta_{S_N} - \beta_{L_N}) E(X_{L_N})]$. The unexplained part contains two parts the first one $(\beta_{S_0} - \beta_{L_0})$ reflects unexplained differences between large and small firms in terms of regression intercepts, which is likely due to unobservable factors. On the other hand, the second part. $(\sum_{n=1}^N [(\beta_{S_N} - \beta_{L_N}) E(X_{L_N})])$ refers to the variation in slope coefficients between companies of small and large sizes.

To perform the Oaxaca decomposition, a regression model is estimated in (3.7) for small firms, and (3.8) is also estimated for large firms, which links TFP with firm

characteristics and control variables as the first stage to obtain the coefficients of both size class samples. In the following step, the means of the independent variables are determined. Finally, using equation (3.12), both terms (endowments and coefficients) are computed. The ln (TFP) gap between the two kinds of firms under study is decomposed, as the following equation (3.13) illustrates.

$$TFP^S - TFP^L = (x^S - x^L)\beta^S + x^L(\beta^S - \beta^L) \quad (3.13)$$

On the left, the average ln (TFP) differential between large and small enterprises is depicted. The vector X is made up of a number of factors that may have an influence on firm's TFP, including an exporter dummy, sector technology level, wage rate, firm ages, the intensity of capital, debt to equity ratio, an innovation activity dummy as an indicator of research and development activity (R&D), as explained in equation (3.1). The vector β represents the coefficients of the aforementioned explanatory variables (Zhang, 2014).

Equation (3.13) can be explained with the help of an example innovation dummy. The first part of the equation reflects "the endowment effect," which is the impact of the variation in the mean value of the innovation dummy. The second part is the "return to innovation activity," which arises from a variation in the coefficients of the innovation dummy. It is possible that even when large and small businesses have equal endowments (i.e., the same proportion of innovation), they can still benefit differently from innovation, resulting in different coefficient estimates (Zhang, 2014).

3.1.4.2. *The Oaxaca Blinder Decomposition Faces the Identification Issue.*

The Oaxaca-Blinder decomposition is a statistical technique that can help us understand how individual variables contribute to the characteristics (endowment) and coefficients gaps. It is important to note, however, that the differential portion which is attributed to the model's dummy variables is dependent on the preference group selected, as demonstrated by Oaxaca and Ramson (1999). It's worth noting that this issue does not impact the overall percentage of the gap that is due to the "explained" and "unexplained" variables (Scorzafave and Pazello, 2007).

In this study, build on the research conducted by Oaxaca and Ransom (1999), the issue of the identification in Oaxaca-Blinder decomposition approach are handled. Specifically, we consider the case where separate TFP regressions are estimated for small and large firms,

and where the model includes both N continuous variables (x 's) and dummy variables (m 's), where $\sum_{j=1}^J m_{ij} = 1$ such that $\{i=S, L\}$ corresponding to a small and large firm. One example of such a dummy variable could be the innovation status of a firm (innovative and non-innovative). When estimating TFP equation for type i firms at the sample means, category m_{i1} is omitted and the results are given in the following equation number (3.14).

$$\hat{Z}_i = \hat{\beta}_{i0} + \sum_{j=2}^J \bar{m}_{ij} \hat{\delta}_{ij} + \sum_{n=1}^N \bar{x}_{in} \hat{\gamma}_{in} = \sum_{j=1}^J \bar{m}_{ij} \hat{\phi}_{ij} + \sum_{n=1}^N \bar{x}_{in} \hat{\gamma}_{in} \quad (3.14)$$

Where $\hat{Z}_i$ is the mean $\ln$ (TFP), the intercept is represented by $\hat{\beta}_{i0}$, $\hat{\delta}_{ij}$ is the predicted contribution for m_{ij} dummy variable, $\hat{\gamma}_{in}$ is a vector of predicted slope coefficients for the set of explanatory factors that form the n th variable, $\bar{x}_{in}$ is a vector of regressor average value for the set of explanatory variables that form the n th variable, $\hat{\delta}_{ij} = \hat{\phi}_{ij} - \hat{\phi}_{i1}$ and $\hat{\beta}_{i0} = \hat{\phi}_{i1}$. By following the methodology proposed by Oaxaca and Ramson (1999), the differences in mean total factor productivity were effectively break down, as demonstrated in equation (3.15) below (Scorzafave and Pazello, 2007).

$$\begin{aligned} & \bar{Z}_S - \bar{Z}_L = \\ & = (\hat{\beta}_{S0} - \hat{\beta}_{L0}) + \sum_{j=2}^J \bar{m}_{Lj} (\hat{\delta}_{Sj} - \hat{\delta}_{Lj}) + \sum_{n=1}^N \bar{x}_L \Delta \hat{\gamma}_n + \sum_{j=2}^J (\bar{m}_{Sj} - \bar{m}_{Lj}) \hat{\delta}_{Sj} + \\ & \sum_{n=1}^N \Delta \bar{x}_n \hat{\gamma}_{sn} \end{aligned} \quad (3.15)$$

Rearrange the above equation the mean total factor productivity difference or the Total Factor Productivity gap between small and large firms is presented below equation (3.16)

$$GA = \sum_{j=1}^J (\bar{m}_{Sj} - \bar{m}_{Lj}) \hat{\phi}_{Sj} + \sum_{n=1}^N \Delta \bar{x}_n \hat{\gamma}_{sn} + \sum_{j=2}^J \bar{m}_{Lj} (\hat{\phi}_{Sj} - \hat{\phi}_{Lj}) + \sum_{n=1}^N \bar{x}_{Ln} \Delta \hat{\gamma}_n \quad (3.16)$$

The first two terms signify the endowment effect, while the last two display the unexplained part of the return to coefficients.

Oaxaca and Ramson (1999, p156) assert that the overall explained and unexplained effect estimation remains consistent regardless of the reference group chosen or if the constant term is suppressed in the absence of a reference group. It is imperative to note that the variable d 's contribution to the return impact is quite adaptable according to the change of the chosen benchmark group. This is due to the fact that the intercept changes substantially depending on the omitted group chosen. Considering this when analyzing the data is

essential to ensure accurate and reliable results. For instance, if the last dummy variable is selected as the left-out reference group, it has an impact on the overall return effect and endowment effects. In this case, the “coefficient” effect would be $\sum_{j=1}^{J-1} \bar{m}_{Lj} (\hat{\sigma}_{Sj} - \hat{\sigma}_{Lj})$, Where $\hat{\sigma}_{ij} = \hat{\phi}_{ij} - \hat{\phi}_{iJ}$ (Scorzafave and Pazello, 2007).

In 1999, Oaxaca and Ramson conducted a study that revealed a solution to a common issue in the decomposition analysis. Specifically, when just a single set of dummy variables is included, the issue at hand could be overcome by taking into account $(\hat{\beta}_{S0} - \hat{\beta}_{L0})$ in the individual share of variable m to the coefficient effect. while, the aforementioned method cannot be applied if the estimated equation contains multiple sets of dummy variables, which is the case in this thesis

3.1.4.3. *The Solution to the Identification Problem.*

In the year 2005, Yun introduced a method for implementing the Oaxaca-Blinder decomposition that effectively addresses the challenges of indetermination. This approach involves the calculation of "normalized" formulas, which are formulated by mandating that the sum of the dummies' coefficients be zero (Yun. 2005a; Scorzafave and Pazello, 2007).

In order to demonstrate the method, we will be using the approach presented by Yun (2005b) In this scenario, a set of dummy variables (m's) have been assumed and N continuous variables (x's), just like the case of previous equation. However, we also have an additional set of dummy variables (r's). For the sake of simplicity, we will not be using the subscript i in this section.

$$Z = \beta + \left(\sum_{j=2}^J m_j \delta_j + \sum_{k=2}^K r_k \theta_k \right) + \sum_{n=1}^N x_n \phi_n + e \quad (3.17)$$

Equation (3.17) above was called a usual regression the reference groups are omitted Yun (2005b) introduced an alternate norm that included the reference group:

$$Z = \beta^* + \left(\sum_{j=1}^J m_j \delta_j^* + \sum_{k=1}^K r_k \theta_k^* \right) + \sum_{n=1}^N x_n \phi_n + e \quad (3.18)$$

Yun (2005b) demonstrated that when estimating an equation, excluding the first category of variable m, for instance, we are able to determine estimates. for δ_j that would be present if the group c has been left out. This is easily accomplished. by subtracting δ_c from δ_j , and the intercept changes from $\beta + \delta_1$ to $\beta + \delta_c$. However, adopting this averaging method

requires imposing that $\sum_{j=1}^J \delta_j^* = 0$ and $\sum_{k=1}^K \theta_k^* = 0$, as Suits (1984) states. He defines coefficients of the normalized equation as $\delta_j^* = \delta_j + m_\delta$ and $\theta_j^* = \theta_j + m_\theta$. Especially since there are no unique solutions to these constraints, he refines the challenge of obtaining normalized regressions as determining values of values m_δ and m_θ . it has been discovered that the values of these two variables are:

$$m_\delta = -\sum_{j=1}^J \delta_j / J$$

$$m_\theta = -\sum_{k=1}^K \theta_k / K$$

Where $\delta_1 = \theta_1 = 0$ in light of this, Yun (2005b) presents the “normalized equation”: (3.19) below.

$$Z = (\beta + \bar{\delta} + \bar{\theta}) + \left(\sum_{j=1}^J m_j (\delta_j - \bar{\delta}) + \sum_{k=1}^K r_k (\theta_k - \bar{\theta}) \right) + \sum_{n=1}^n x_n \phi_n + e \quad (3.19)$$

Where:

$$\bar{\delta} = \sum_{j=1}^J \delta_j / J, \text{ and } \bar{\theta} = \sum_{k=1}^K \theta_k / K \text{ and } \delta_1 = \theta_1 = 0$$

When Equation (3.18) is estimated independently for small firms subsample as well as their large counterparts, the Oaxaca decomposition method can be employed to analyze the total factor productivity equation. This method is not affected by the exclusion of the dummy variable's category variables, making it a reliable tool for analysis (Scorzafave and Pazello, 2007)

3.1.5. Employment Growth Rate of Survived and Closed Firms.

The main studies that examined the validity of Gibrat's law (of proportionate effect) focused on the firms that survived during their periods of analysis (Evans, 1987; Nurmi, 2004; Calvo, 2006). Since this methodology may be prone to sample selection bias, many of the studies applied a Tobit model.

On the other hand, the econometric technique used in this thesis to model employment growth rate seeks to take into account both closed and survived enterprises. So, the two-part model is best suited to achieve the thesis aim (Erhardt, 2017; Huber et al. 2016).

At the initial, the binary choice to survive or exit for a specific enterprise (i) in period (t) is described by the first part of the two-part model (Wooldridge, 2009; Erhardt, 2017).

$$\text{Let } U_{i,t} = \begin{cases} 1 & \text{for } EM_{i,t} > 0 \\ 0 & \text{for } EM_{i,t} = 0 \end{cases}$$

where:

$U_{i,t}$ is the response variable of time (t) for firm (i)

t : is the end of the analysis time.

Let " $EM_{i,t}$ " be the workforce number at a given time " t ".

Therefore, the survival rate (probit model) is:

$$P(U_{i,t} = 1 | X_i) = P(EM_{i,t} > 0 | X_i) = \Phi X_i \varphi \quad (3.20)$$

Φ : The given expression represents the cumulative distribution function of the standard normal distribution.

X_i : a set of regressors, including:

$EM_{i,2006}$: Number of employees in 2006.

$A_{i,2006}$: The age of firm in 2006. D_s : Sectors dummy at Nace-2-digit level, firm's size

φ : represents the vector of estimation coefficients.

The likelihood of a firm's exit can be calculated from its survival probability.:

$$P(U_{i,t} = 0 | X_i) = 1 - P(U_{i,t} = 1 | X_i) \quad (3.21)$$

The growth rate of employment is estimated by means of Ordinary Least Squares (OLS) in the second part of the two-part model. For surviving firms, the following regression is estimated:

$$E(G_{i,t}|X_i, EM_{i,t} = 1) = X\beta \quad (3.22)$$

For exiting firms:

$$E(G_{i,t}|X_i, EM_{i,t} = 0) = X\beta \quad (3.23)$$

β is a vector of coefficients, X is the same set of explanatory variables which include ($EM_{i,2006}$, $A_{i,2006}$, D_s) in the first part of the model.

Lastly, the results of the regressions from steps one equation (3.20) and two equation (3.22) of the two-part models are used to investigate the participation of firms across various sizes and ages to employment growth (conditional means) for exiting firms as well as the surviving ones.

$$E(EM_{i,t}|X_i) = P(EM_{i,t} > 0|X_i)E(G_{i,t}|X_i, EM_{i,t} = 1) + E(G_{i,t}|X_i, EM_{i,t} = 0)P(EM_{i,t} = 0|X_i) \quad (3.24)$$

3.2. The Data

The EIS Database the "Entrepreneur Information System" is used to create a firm-level dataset of the Turkish manufacturing industry from 2006 to 2020. EIS is confidential data; a protocol must be signed with the Ministry of Science, Industry, and Technology, and the data set can only be accessed at the ministry's study and research center. The General Primer of Production of the Ministry of Science, Industry, and Technology gathered data from eight separate sources at three distinct levels. for the EIS. Detailed description of the data set is available under Appendix-A.

The Business Register data can be obtained at the firm level. gives complete information on each firm's years of establishment, main activity codes at the NACE (Classification of Economic Activities in the European Community) with 4-digit classes, and ID number. The Social Security Institution provides detailed information about employees such as worker ID, age, number of working days, and daily wages. The Ministry of Finance provides comprehensive financial statements that offer detailed information about a firm's assets, liabilities, incomes, and expenses. The Ministry of Customs and Trade offers data at the firm level about firm ID and at the product level about (quantity, value, and product code) of exports/imports; this type of data is used to build a dummy variable representing firms' export/ import status, all firms also classified according to NACE at 4-digit. Technology levels at 4- digit classes are available for manufacturing firms. Detailed information about the technology level classification is available under Appendix-A.

3.2.1. The Data Cleaning Procedure

EIS is a database that has information on all Turkish enterprises. This dissertation utilizes all Turkish firms are listed in the Firm Registry Data provided by the Revenue Administration, which covers all manufacturing firms that submit comprehensive balance sheets and income statements to the Ministry of Finance. The number of observations in the population of all manufacturing firms whether they are obliged to provide their financial information or not, are shown in Table 1 below. The size of the sample ranges between 324,190 firms in 2006 to 542,747 in 2020.

Table 1*Number of the Turkish Manufacturing Firms between 2006-2020*

Year	Number of Firms
2006	324,190
2007	388,108
2008	405,890
2009	411,288
2010	420,245
2011	435,002
2012	453,791
2013	492,329
2014	501,229
2015	493,044
2016	485,266
2017	521,830
2018	514,095
2019	571,037
2020	542,747

Source: EIS, own calculations

The Firm Registry Data contains valuable information about a company's industry based on the NACE Rev. 2 Classification, as well as their location (province/city), the date of foundation, and beginning of activities for 2006 to 2020. The sector information is available at the 4-digit industrial level. However, it's important to note that industries can change over time due to firms switching to other sectors and data updates.

It is worth noting that all Turkish companies are included in the "Registry Data" provided by the Revenue Administration. This includes all types of businesses, whether they operate under fixed or small business tax regimes, and so on. Essentially, this compilation covers all enterprises that are subject to taxation in Turkey. The data includes many small self-employment enterprises that do not have any registered employees. During the first cleaning process, all observations of firms with no employees were dropped. Table 2 below provides a comprehensive overview of the number of manufacturing firms that operated between 2006 and 2020, classified under NACE-4 digits. Notably, the table accounts for businesses that either switched from or to the manufacturing sector during the study period.

Additionally, Table 2 illustrates the percentage of these firms in relation to the total number of companies within the manufacturing sector, as well as the total number of employees.

Table 2

The number of manufacturing firms (self-employed is dropped)

Year	Number of Firms	% Total Firms	Employment
2006	177,351	55%	2,536,395
2007	189,772	49%	2,712,029
2008	203,745	50%	2,820,474
2009	205,750	50%	2,652,262
2010	217,649	52%	2,894,567
2011	236,936	54%	3,203,968
2012	258,082	57%	3,528,045
2013	269,567	55%	3,716,294
2014	273,689	55%	3,883,838
2015	279,801	57%	4,079,455
2016	262,235	54%	3,990,594
2017	286,461	55%	4,156,181
2018	277,330	54%	4,216,410
2019	283,205	50%	3,855,423
2020	279,867	52%	4,207,253

Source: EIS, own calculations

In order to maintain consistency among industry samples, a crucial step in data cleaning was to use the recently available 4-digit industry sector reported by each firm (Akçigit et al., 2020). Table 3 summarizes the number of observations in Turkish manufacturing firms, wherein the last sector reported by each firm was considered the primary working sector for all available observations. This was done for firms that showed variation in their sectors during the sample period. Table 3 summarizes the percentage of total firms and their total employment (calculated as the annual average and converted into full-time equivalent). Finally, the last column presents the percentage of total formal employment in the Turkish manufacturing sector.

Throughout the analysis period, Table 3 displays that the percentage of manufacturing enterprises ranged between 41 percent and 47 percent of the sample. Although these firms make up less than half of all firms, they employ 89-92 percent of the total workforce. In 2006, there were 150,692 firms, which accounted for 46 percent of all registered manufacturing firms and employed 89 percent of formal employees in Turkey. In 2020, there

were 239,394 registered firms, accounting for 44 percent of all registered firms and employing 92 percent of the formal employment in Turkey.

Table 3

The number of firms and total employment the last 4-digit industry was used

Year	Number of Firms	% Total Firms	Employment	% Total Employment
2006	150,692	46%	2,264,791	89%
2007	160,988	41%	2,424,366	89%
2008	172,032	42%	2,519,616	89%
2009	171,931	42%	2,363,972	89%
2010	180,307	43%	2,585,575	89%
2011	195,099	45%	2,859,200	89%
2012	211,909	47%	3,149,691	89%
2013	220,876	45%	3,333,614	90%
2014	224,884	45%	3,502,467	90%
2015	231,221	47%	3,695,790	91%
2016	217,072	45%	3,631,768	91%
2017	233,185	45%	3,763,840	91%
2018	227,088	44%	3,835,932	91%
2019	240,926	42%	3,548,208	92%
2020	239,394	44%	3,881,301	92%

Source: EIS, own calculation.

As per EIS (2020), the Ministry of Finance holds financial information for specific categories of firms that have made purchases or sales above TL 160,000 or TL 220,000, respectively. During the second step of the data cleaning process, any observations that lacked balance sheets or income statement data were eliminated. Additionally, all observations from a particular year were dropped if the key variables used for empirical analysis had negative or missing values. The outcome of this second data-cleaning stage is reported in Table 4.

Table 4

Number of manufacturing firms and total employment after the second step of cleaning process

Year	Firm's Observations	% Total Firms	Employment	% Total Employment
2006	66,272	20%	1,733,226	68%
2007	73,154	19%	1,921,139	71%
2008	77,034	19%	2,003,930	71%
2009	76,596	19%	1,870,960	71%
2010	80,138	19%	2,104,696	73%
2011	85,363	20%	2,376,837	74%
2012	90,975	20%	2,612,138	74%
2013	95,230	19%	2,772,480	75%
2014	100,196	20%	2,966,157	76%
2015	105,596	21%	3,166,511	78%
2016	108,188	22%	3,179,298	80%
2017	112,065	21%	3,314,465	80%
2018	117,300	23%	3,448,078	82%
2019	116,766	20%	3,126,019	81%
2020	121,709	22%	3,407,743	81%

Source: EIS, own calculations.

Table 5 below presents an analysis of manufacturing companies from 2006 to 2020. The observations are from enterprises with an average number of employees equal to or greater than two after removing outliers. The selected sample represents approximately 16 to 20 percent of all firms in the Turkish manufacturing sector during the specified period. Notably, these businesses play a significant role in official employment in Turkey, estimated to range from 63 to 71 percent.

Table 5*Number of firms-with more than or equal two employees on average*

Year	Firm's Observations	% Total Firms	Employment	% Total Employment
2006	59,560	18%	1,620,693	64%
2007	65,114	17%	1,761,310	65%
2008	68,367	17%	1,837,168	65%
2009	67,435	16%	1,681,291	63%
2010	70,678	17%	1,906,267	66%
2011	75,186	17%	2,130,042	66%
2012	80,635	18%	2,318,042	66%
2013	85,997	17%	2,419,594	65%
2014	91,477	18%	2,634,555	68%
2015	96,076	19%	2,799,551	69%
2016	97,892	20%	2,818,826	71%
2017	100,653	19%	2,905,944	70%
2018	103,713	20%	3,010,937	71%
2019	100,028	18%	2,738,752	71%
2020	106,030	20%	2,767,054	66%

Source: EIS, own calculation

Turkey's manufacturing firms in various sectors have adopted four different levels of technology, categorized from low to high level a details information under APPENDIX-A. 2,862 observations of firms were discovered to be non-disclosing about their technology level. As a sector technology level is used as a dummy variable in the econometric estimation, these firms were excluded from the sample. The outcome of the thesis sample from 2006 to 2020 is presented in Table 6 below.

Table 6

The final sample after excluding the firms under unknown technology level

Year	Firm's Observations	% Total Firms	Employment	% Total Employment
2006	59,484	18%	1,619,403	64%
2007	65,011	17%	1,759,679	65%
2008	68,247	17%	1,834,941	65%
2009	67,300	16%	1,678,957	63%
2010	70,529	17%	1,903,489	66%
2011	75,015	17%	2,126,382	66%
2012	80,442	18%	2,314,138	66%
2013	85,675	17%	2,413,981	65%
2014	91,164	18%	2,630,441	68%
2015	95,771	19%	2,795,654	69%
2016	97,672	20%	2,816,120	71%
2017	100,487	19%	2,903,111	70%
2018	103,503	20%	3,004,631	71%
2019	99,838	18%	2,733,056	71%
2020	105,841	20%	2,759,653	66%

Source: EIS, own calculations.

EIS classifies firms into different size groups according to the NACE classification that depends on the number of employees. The following table explains these size groups.

Table 7

NACE classification of firm size depending on number of employees

Size Groups	Number of Employees
Micro Firm	0-9
Small Firm	10-49
Medium- Sized Firm	50-249
Large Firm	Greater than or equal to 250

Source: EIS website, [https:// gbs.sanayi.gov.tr](https://gbs.sanayi.gov.tr)

According to the size definition of this thesis, companies with more than 249 employees are considered large, while those with 2 to 249 employees are considered small. Our study differs from other studies, such as Castany et al. (2005), which focused on the factors contributing to the difference in the TFP index between small and large firms in the Spanish manufacturing sector. The difference is that they considered small firms with more than ten employees, while we included those with at least two employees. Their sample size

ranged from 523 firms in 1994 to 668 firms in 1998, out of which 35% and 25% were large firms with over 200 employees, respectively. On the other hand, our sample size changes from 59,484 firms in 2006 to 105,841 firms in 2020, with a small percentage of large firms having over 200 employees, at 1.98% and 2.40%, respectively.

3.3. Descriptive Statistics by Firm Size

This section presents a precise definition of the variables which are utilized in calculating total factor productivity. It also includes descriptive statistics that provide an overview of how these variables have evolved over the study period. Moreover, it introduces the variable used to examine the disparity in total factor productivity between small firms and their larger counterparts in the Oaxaca-Blinder decomposition. Lastly, it defines and introduces descriptive statistics for the primary variables employed to estimate employment growth using the Two-part model.

3.3.1. Definition of Variables Involved in Estimations of Production Function

The set of following variables are used to estimate the production function are output $y_{i,t}$, value added $v_{i,t}$, capital stock $k_{i,t}$, labor stock $n_{i,t}$, and the materials input $m_{i,t}$. As a measure of output previous literature used firm's revenue (sales) (Syverson, 2004; Hsieh and Klenow, 2009; Hann et al., 2020). $n_{i,t}$, is calculated as annual average converted into full-time equivalent. $k_{i,t}$ is measured as the value of depreciated tangible fixed assets (Hann et al., 2020).

The Social Security Institution provides, number of working days, and daily wages this information are used to calculate labor costs as the total wages paid to all employees within a year. As a measure of value-added the operating profit added to labor cost and the depreciation of fixed tangible assets. Materials $m_{i,t}$. is calculated by netting out total operating profits, labor cost, and depreciation of tangible assets from the output. (Hann et al., 2020).

To convert nominal values into real values, the two-digit sectoral PPI (Domestic Producer Price Index) for the manufacturing industry, PPI for capital goods and PPI for

intermediate goods, was obtained from Turkish statistical institute (TUIK) was used to get the sectoral deflator.

3.3.2. Description of Variables Used in Calculation TFP

This subsection provides an overview of the key variables that are pertinent to the calculation of TFP. We begin by presenting a descriptive analysis of the total sample. Subsequently, we examine whether there are any discernible differences in the results of subsamples of small and large firms.

The following Table 8 below, describes the development of the average values of firms' value-added, labor stock, capital stock, and intermediate inputs from 2006 to 2020 for the entire sample of firms. Additionally, it highlights the change over time of two relevant ratios: the capital-labor ratio, which represents the level of capitalization in Turkey's manufacturing industry, and the output-labor ratio, which measures labor productivity using both output and value-added. Tables 9 and 10 provide the same information but for small and large firm subsamples. The data in Tables 8 to 10 are expressed in millions of constant 2003 Turkish Lira, except for labor input, which is defined as the yearly average of employees converted to full-time equivalent.

Table 8*Average values of key factors involved into TFP estimation*

Year	Observations	Labor	Value added	Material	Capital	Capital/labor	Output / Labor	Value-added / Labor
2006	59484	27.22	11096.44	23678.29	7032.45	168.76	1187.29	201.71
2007	65011	27.07	10714.88	24473.36	7467.92	176.39	1206.90	202.11
2008	68247	26.89	11218.07	23737.22	7668.70	178.37	1131.96	200.08
2009	67300	24.95	10564.33	22228.44	7774.37	177.83	1122.93	208.81
2010	70529	26.99	11459.18	26248.54	8978.14	205.71	1240.49	210.11
2011	75015	28.35	12298.36	27910.11	9158.76	198.36	1332.54	211.37
2012	80442	28.77	11859.06	28561.16	9251.39	196.10	1351.58	210.05
2013	85675	28.18	12014.84	27534.86	9385.17	200.56	1365.53	221.21
2014	91164	28.85	12429.21	30200.62	10069.48	196.73	1265.09	219.20
2015	95771	29.19	13209.41	28713.58	9919.73	207.60	1267.37	225.24
2016	97672	28.83	13987.87	28760.31	10245.83	226.17	1308.62	244.26
2017	100487	28.89	14364.89	29758.52	10083.95	224.03	1330.51	241.13
2018	103503	29.03	14533.64	29076.75	9284.51	200.22	1297.09	231.28
2019	99838	27.37	14369.20	30807.70	9734.62	218.93	1435.06	250.35
2020	105841	26.07	15196.45	31628.89	9897.84	228.42	1581.21	263.29

Source: EIS, own calculations.

According to Table 8 above, the firms in the sample have, on average, increased their capital over the analysis period. However, this variable exhibits a cyclical behavior with declines in 2018 and some recovery in the following two years. Regarding firms' value-added productivity, it displays an increasing pattern except for a slowdown between 2008 and 2010. The labor stock variables also exhibit a similar pattern. The average annual number of employees (a full-time equivalent) increased slightly on average, with a significant decrease between 2008 and 2010. The improvement has been demonstrated until the 2013 slowdown, increased slightly between 2014 and 2018, and dropped again in the last two years. It has been observed that the usage of intermediate inputs has consistently mirrored the fluctuations in the business cycle.

The analysis of the ratios indicates a significant increase in labor productivity due to the process of capitalization. This increase is consistent with the evolution of production, labor, and capital. The capital-labor ratio has increased by more than 35 percent over the entire period, indicating a higher industry capitalization, which is expected to lead to higher production. The same trend was observed in the output-labor and value-added labor ratios, which are proxies for labor productivity. The level of productivity at the end of the period

increased by 33 and 31 percent, respectively. Notably, the increase in capital-labor ratio and labor productivity was more significant after 2013.

The production process factors of small and large enterprises were examined in the following analysis to see if there were any changes based on company size. The average values for both samples have been calculated and are shown in Tables 9 and 10, respectively. The study examines the evolution of the capital-labor ratio for small and large enterprises and discovers that smaller firms have lower levels of capital. As a result, small businesses tend to accelerate their capitalization process more than larger businesses. Large enterprises' capital-labor ratios were around double that of small firms by 2006. Despite a slightly better evolution for small enterprises, large firms still have more advantageous capitalization differences at the end of the period.

Table 9

Average values of key factors involved into TFP estimation small subsample

Year	Observations	Labor	Value added	Material	Capital	Capital/labor	Output / labor	Value-added / labor
2006	58670	18.33	4851.29	15189.63	3784.29	166.35	1181.70	196.36
2007	64137	18.41	4788.56	15948.76	4071.00	173.66	1201.57	197.07
2008	67364	18.40	4829.55	15130.60	4137.53	175.32	1124.57	194.74
2009	66466	17.42	4921.70	14420.34	4211.51	174.28	1114.59	203.31
2010	69551	18.43	5119.73	16074.43	4787.93	202.31	1233.21	204.39
2011	73905	19.03	5367.42	17208.71	4982.54	195.10	1325.31	205.66
2012	79231	19.34	5291.68	17649.68	5016.02	192.74	1344.95	204.64
2013	84402	18.94	5543.13	17269.96	5086.98	196.88	1359.21	215.66
2014	89743	18.99	5438.57	17115.12	5019.78	192.84	1255.99	213.25
2015	94240	18.90	5643.11	16690.55	5089.44	203.60	1257.99	218.90
2016	96088	18.35	5895.39	16893.91	5314.44	222.29	1299.47	237.60
2017	98829	18.11	5812.96	16741.50	5080.63	220.18	1319.29	233.94
2018	101767	17.81	5651.22	15631.91	4512.64	196.60	1284.52	223.98
2019	98238	16.76	5752.17	16259.36	4598.35	215.21	1421.72	243.48
2020	104281	16.12	6109.99	16816.97	4601.23	224.79	1569.07	255.74

Source: EIS, own calculation.

A steady increase in the output labor ratio throughout both subsamples has also been observed. It is logical to predict that more intensive capital usage will result in increased labor productivity. Higher labor productivity in large enterprises demonstrates this.

The research findings indicate that the labor stock variable exhibited a modest increase, on average, following the slowdown in 2009. However, a significant decrease was observed in 2013, which was followed by a substantial increase in large firms' subsample. Conversely, the subsamples of small firms indicate that the evolution of labor stock depicted a steady and significant decline after the 2013 slowdown until the end of the sample time.

Table 10

Average values of key factors involved into TFP estimation large subsample

Year	Observations	Labor	Value-added	Material	Capital	Capital/labor	Output / labor	Value-added / labor
2006	814	668.51	461222.84	635508.13	241147.97	342.41	1590.24	587.33
2007	874	662.61	445607.16	650036.38	256745.20	377.07	1598.20	571.94
2008	883	674.29	498597.88	680336.06	277060.97	411.24	1695.96	607.37
2009	834	624.89	460256.22	644498.69	291718.19	460.93	1787.40	647.19
2010	978	635.46	462292.66	749786.31	306967.84	447.18	1758.31	617.41
2011	1110	648.59	473767.41	740420.50	287216.16	415.17	1814.06	591.68
2012	1211	645.43	441537.00	742456.63	286355.31	415.85	1785.80	563.74
2013	1273	640.26	441099.28	708114.13	294362.50	444.54	1784.74	589.00
2014	1421	651.60	453922.34	856612.81	328982.41	442.74	1840.27	595.06
2015	1531	662.47	478949.59	768785.63	307245.84	453.88	1844.45	615.91
2016	1584	664.41	504891.03	748595.44	309391.91	461.01	1863.83	648.50
2017	1658	671.54	524122.72	805668.88	308318.59	453.03	1998.92	669.51
2018	1736	686.44	535235.06	817233.75	289018.81	412.76	2033.71	659.17
2019	1600	679.05	543444.50	924057.50	325095.19	447.24	2254.10	672.72
2020	1560	691.52	622597.06	1021758.50	363959.06	471.47	2392.41	768.00

Source: EIS, own calculation.

3.3.3. A Set of Variables for the Blinder-Oaxaca Decomposition

The study uses the natural logarithm of TFP as the dependent variable. Capital intensity, defined as the logarithm of the real capital stock per worker, and wage, defined as the logarithm of the average annual gross wage per worker, are used as regressors and control variables. The age of the firm variable is calculated using the establishment year and the operation date, based on the tax regime to which the firm belongs. The Innovation variable is a reliable proxy for research and development, as well as innovation. It is a binary variable

that takes on a value of 1 when a company has a positive ratio of intangible assets to total assets, and a value of 0 otherwise (Gonçalves & Martins , 2016). The study also examines international trade activities, by an exporter dummy, which take value 1 if a firm export at time t and a zero value otherwise. The debt-to-equity ratio is used to measure the financial constraint, which is the logarithmic value of the total liabilities to equity ratio (Camino-Mogro, 2022). A dummy variable of the technology level to which a firm's sector belongs, more details available under the APPENDIX-A section.

Table 11 compares the shares of large and small firms for various significant indicators. In 2006 and 2020, small-scale enterprises comprised about 98 percent of the total number of businesses. Despite being few in number, large firms controlled almost every other aspect of the economy. Large firms' contribution to the main economic indicators, such as value-added, employment, and revenue, exceeds more than half in both 2006 and 2020. However, the advantage of large businesses was further enhanced as their percentage of the total export value rose from 51 percent in 2006 to 59 percent in 2020.

Table 11

The share of large and small firms to main indicators

The Main Indicators	2006		2020	
	Small	Large	Small	Large
Total number of firms	(.98)	(.02)	(.98)	(.015)
Total output share	(.56)	(.44)	(.49)	(.51)
Total value-added share	(.43)	(.57)	(.40)	(.60)
Total export share	(.49)	(.51)	(.41)	(.59)
Total Revenue Share	(.39)	(.61)	(.45)	(.55)
Total number of employees share	(.66)	(.34)	(.61)	(.39)

Source: EIS, own calculation.

Table 12 below, compares small and large firms in 2006 and 2020 based on their main characteristics. In 2006 and 2020, small firms were less productive, younger, less capital intensive, and paid less wages than larger firms. The productivity-size gap was

approximately 2.257 in 2006 and 2.715 in 2020. Larger firms' productivity increased and their efficiency improved more, however the efficiency of small firms decreased these effects lead to, widen the productivity gap more. Table 12 also displays a decrease in the mean age of large firms from 17.16 years in 2006 to 16 years in 2020. However, the average age of small firms increases from 9 to 11 years.

According to Table 12, a value of 1 is given to the exporter dummy for positive exports and 0 for otherwise. The table also indicates a decline in the percentage of exporter firms for both small and large firms in 2020. However, Table 11 shows an increase in the rate of large enterprises in the total export value. This is because large exporter firms have exported goods and services worth much more in 2020 than in 2006. Moreover, Table 12 below demonstrates the debt-to-equity ratio of small and large firms, revealing that this ratio increased for both small and large firms in 2006 and 2020.

Table 12

A Comparison between the mean values of large and small firms

	2006		2020	
	Small	Large	Small	Large
Ln (TFP)	4.595	6.851	4.424	7.139
Capital Intensity	158	329	192	420
Ln (labor)	2.20	6.21	1.98	6.24
Ln (wage)	2.55	3.08	3.01	3.60
Ln (Total assets)	8.23	12.39	8.43	12.80
Age	9	17.16	11	16
Debit to Equity ratio	1.17	0.95	1.31	1.05
Exporter Dummy	0.22	0.93	0.17	0.92

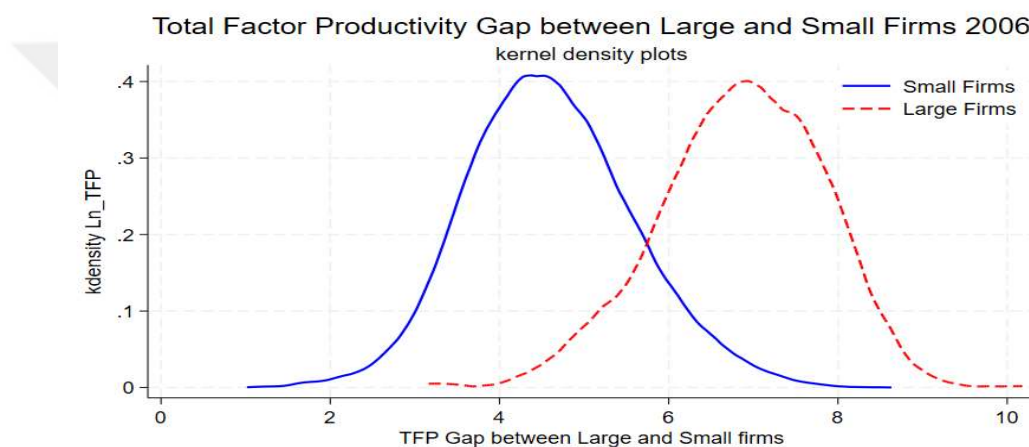
Source EIS, own calculations.

Two kernel density plots were created to compare productivity distribution in 2006 and 2020. Figures 1 and 2 show the kernel density of ln (TFP) for 2006 and 2020, respectively. In 2020, large firms experienced an improvement in their TFP, causing a

rightward shift in their curve, whereas small firms showed a decrease in their TFP, resulting in a leftward shift. Furthermore, the improvement seen in TFP for large firms was greater than the decrease observed in TFP for small firms. Consequently, the gap between TFP for large and small firms widened in 2020.

Figure 1

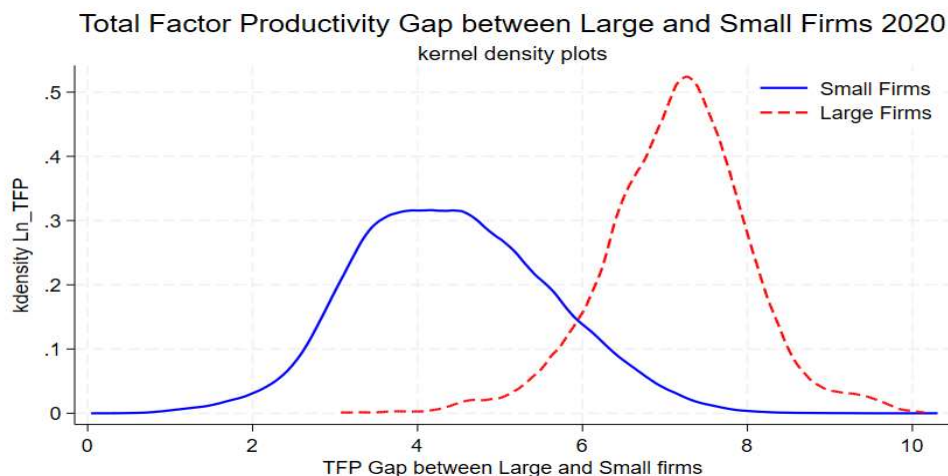
ln (TFP) distribution (Kernel density estimate 2006)



source: EIS, own calculations

Figure 2

ln (TFP) distribution (Kernel density estimate 2020)

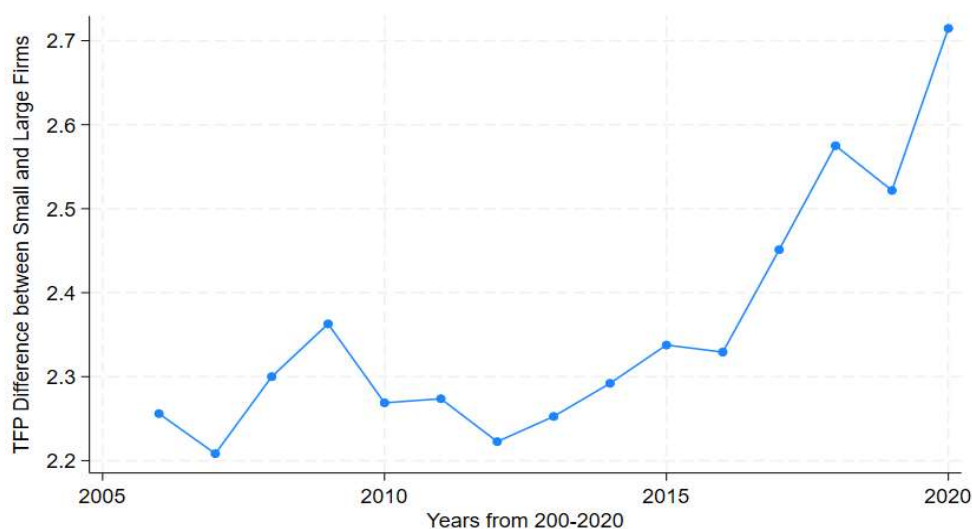


source: EIS, own calculations.

To gain a comprehensive understanding of the productivity gap between small and large firms, a regression for each year from 2006 to 2020 was conducted. Specifically, a regression of the natural logarithm of total factor productivity ($\ln(TFP)$) on a binary variable that denotes large enterprises was estimated. Figure 3 below illustrates the changes in productivity gap over time. The difference between large and small businesses productivity has been increasing, and it reached its highest point in 2020, according to the results.

Figure 3

The difference in TFP level between small businesses and their large counterparts (All Firms)



source: EIS, own calculations

In order to better understand the differences in productivity between small and large firms, it is crucial to analyze the main variables that may contribute to these differences. One such variable is capital intensity, which refers to the amount of capital a firm has invested in its operations. Another variable is the wage rate, which measures the level of skill and education among a firm's employees.

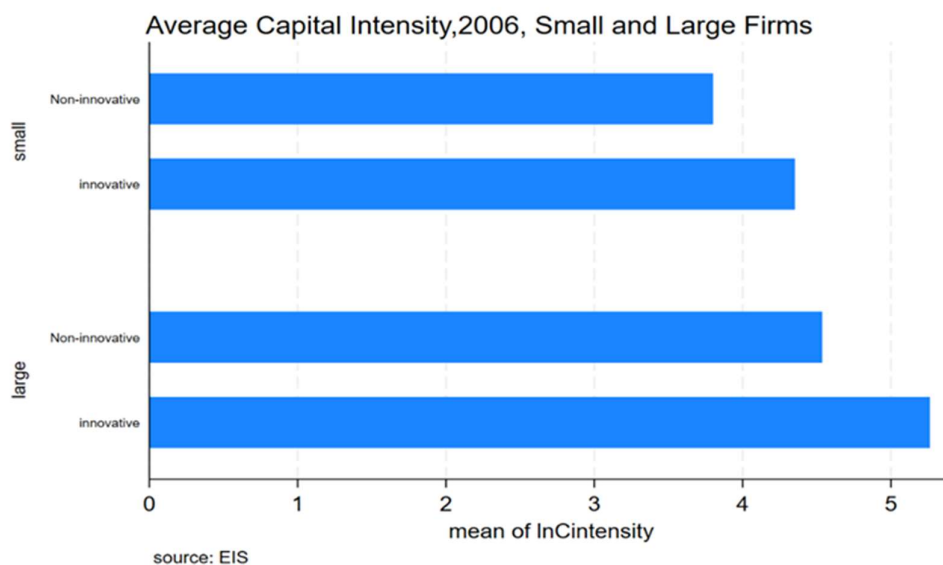
Figures 4 and 5 provide a visual representation of the differences in capital intensity across firms of different sizes and levels of innovation. The data suggests that larger innovative firms tend to be more capital-intensive than smaller innovative firms.

Additionally, Figure 4 shows that in 2006, the average capital intensity of large non-innovative firms was similar to that of small innovative firms.

On the other hand, Figure 5 below indicates that, on average, capital intensity increased for large innovative firms, while it declined for large non-innovative firms. Furthermore, the figure suggests that larger innovative firms were more capital-intensive than smaller innovative firms in 2020. However, there were no noticeable changes in the average distribution of capital intensity between innovative and non-innovative firms in 2020.

Figure 4

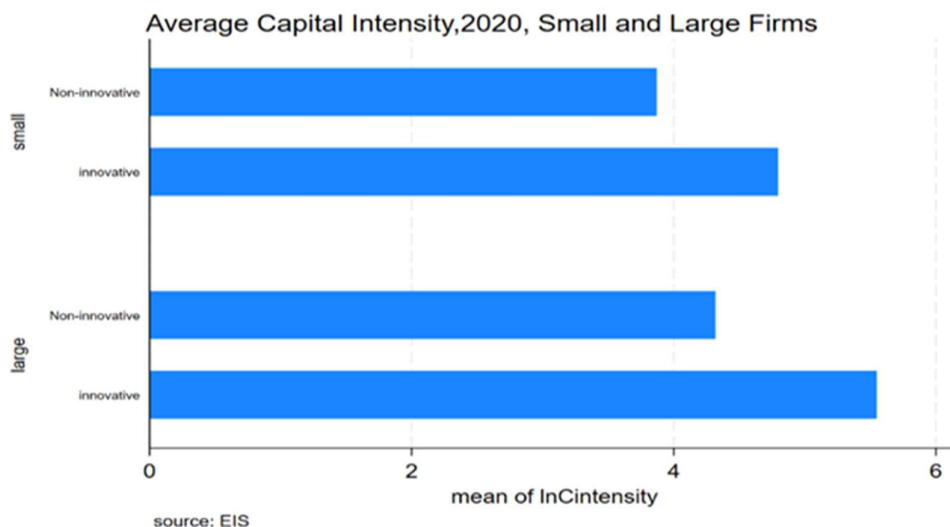
Distribution of capital intensity, by size, innovation status 2006



Source: EIS, own calculations.

Figure 5

Distribution of capital intensity, by size, innovation status 2020

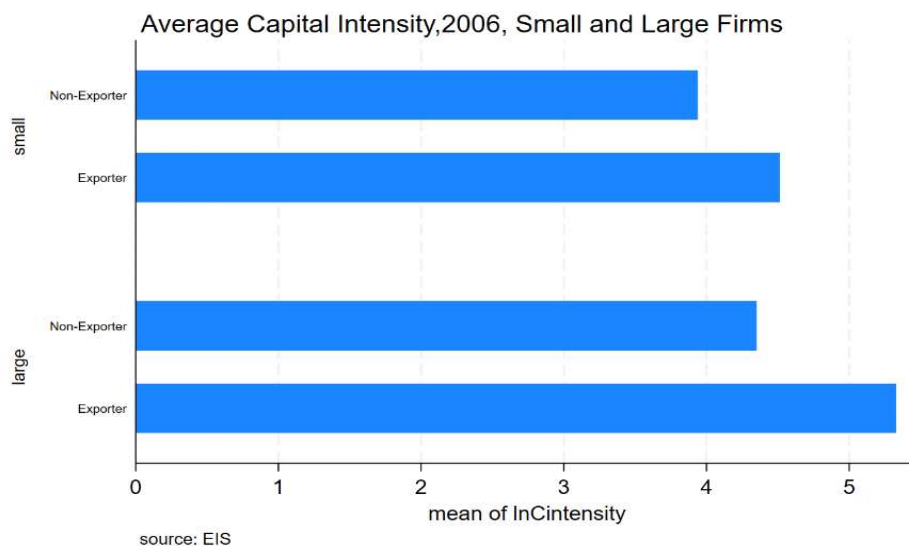


Source: EIS, own calculations.

In Turkey, manufacturing firms can be divided into two major categories based on their trading activities. A firm with a positive export value in a specific year is considered an exporter firm; otherwise, it is regarded as a non-exporter firm. A dummy variable was created to express a firm's trade activity. In 2006, a total of 814 firms were found, out of which 703 were large exporter firms, and the remaining 111 were non-exporter firms. However, there were only 13,585 small exporter firms out of 58,670 firms, which constituted about 23 percent of the total firms. Despite their relatively small number, these small exporter firms contributed 27 percent of the total value-added value. Moreover, these firms employed 31 percent of employees as full-time equivalents in 2006, while larger exporter firms, which represented only about 1 percent.

Figure 6

Distribution of capital intensity by size, export status 2006

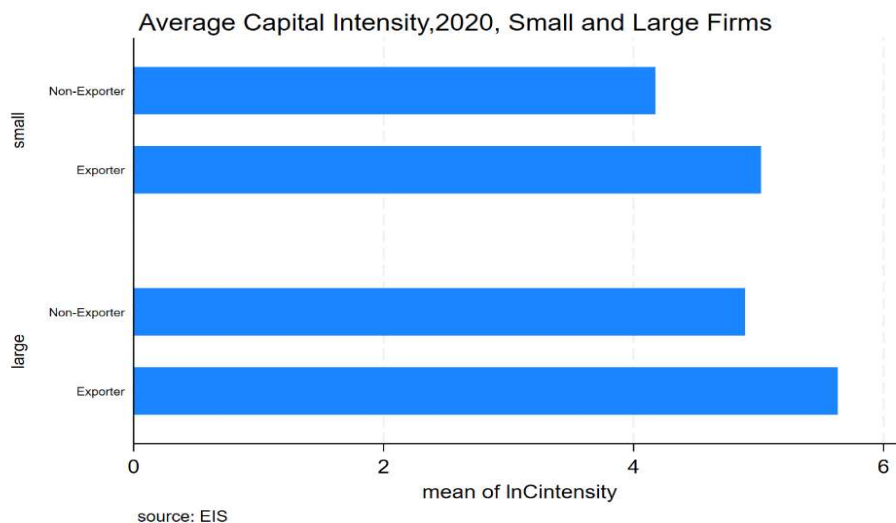


Source: EIS, own calculations.

The data presented in Figure 6 above indicates that large firms that engaged in international trade tend to use more capital than their smaller exporting counterparts. It is interesting to note that in 2006, the distribution of capital intensity for non-exporting large firms was similar to that of small exporting firms. However, in 2020 Figure 7 below clearly demonstrates that the capital intensity gap between small and large exporting firms still exists. It is noteworthy that both size groups of exporting firms exhibit greater capital intensity than non-exporting firms. During the period spanning 2006 to 2020, the average capital intensity of larger exporter firms demonstrated an increase, while small exporter firms remained unchanged. This analysis suggests that there has been no notable evolution in the situation of small exporter firms during this period, relative to their larger counterparts as Figure 7 reflects.

Figure 7

Distribution of capital intensity by size, export status 2020

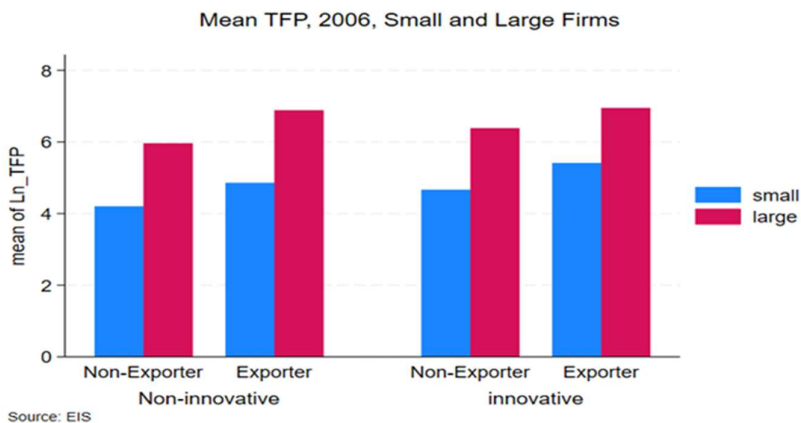


Source: EIS, own calculations.

The data presented in Figure 8 indicates that larger companies that engage in exporting and innovation activities exhibit higher levels of productivity compared to their smaller counterparts. Furthermore, it suggests that larger export firms, regardless of their innovation status, demonstrate greater productivity than smaller non-export firms, as observed in 2006.

Figure 8

Distributions of small and large firms by technology and trade 2006

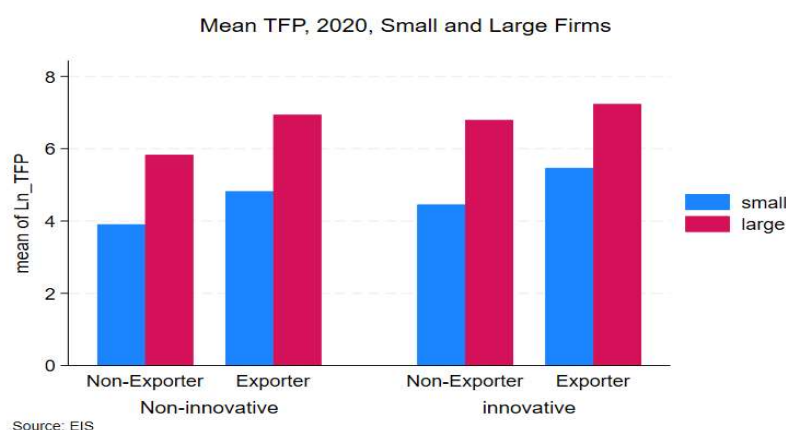


Source: EIS, own calculation.

The graphical representation of Figure 8 reveals that Total Factor Productivity (TFP) remained relatively equal between large exporter innovation and larger exporter non-innovation. Conversely, on average, TFP appears to be higher in large non-exporter innovation than in large non-exporter non-innovation in 2006. It is noteworthy that smaller firms with innovation activities exhibit more productivity than smaller firms without innovation activities. Moreover, small non-exporter innovation tends to be more productive than small non-exporter non-innovation, on average.

Figure 9

Distributions of small and large firms by technology and trade 2020



Source: EIS, own calculation.

The statistical data presented in Figure 9 suggests that in 2020, large innovation firms exhibited higher productivity levels compared to their small non-innovation counterparts, regardless of their export status. Furthermore, it reveals that larger innovation exporters are more productive than large innovation non-exporters, while small innovation exporters are more productive than small innovation non-exporters on average.

The graphical representation in Figure 9 shows that Total Factor Productivity (TFP) tends to be higher in small innovation non-exporter firms than in small non-innovation non-exporter firms. Additionally, TFP appears to be higher in large non-exporter innovation firms compared to large non-exporter non-innovation firms, as observed in 2006. It is worth noting that firms engaging in innovation activities tend to exhibit higher productivity levels,

particularly smaller ones. On average, small non-exporter innovation firms are more productive than small non-exporter non-innovation firms.

Table 13 displays the industry distribution of small firms in 2006 and 2020. This table presents the average industry share of firms and output. It aims to provide a clear overview of the contribution made by each industry at NACE 2-digit classification in terms of the number of enterprises and the total output generated. As showed in Table 13 below. Small businesses made up the majority of firms in all industries in 2006 and 2020, except for tobacco product manufacturing where they accounted for only about 70 percent of the industry in 2006. However, small firms faced disadvantages in industries such as basic pharmaceutical products and pharmaceutical preparations, computer, electronic, and optical products, electrical equipment manufacturing, and other transport equipment manufacturing, when it came to the share of output.

Table 13*Share of small Firms by industry*

		2006		2020	
		# of Firms	Output Share	# of Firms	Output Share
10	Food Product	0.98	0.55	0.98	0.50
11	Beverage Industry	0.98		0.96	0.36
12	Tobacco Products	0.71		0.93	
13	Textile Products	0.97	0.64	0.96	0.50
14	Wearing Products	0.97	0.68	0.98	0.63
15	Leather Products	0.99	0.82	0.99	0.82
16	Wood and corks	0.99		0.99	0.86
17	Paper products	0.99		0.97	0.50
18	Publishing printing	1.000		0.99	
19	Coke and refined Petroleum	1.000	1.000	0.97	
20	Chemical	0.99	0.69	0.98	0.54
21	Pharmaceuticals	0.83	0.17	0.88	0.23
22	Rubber and plastic	0.99	0.79	0.98	0.63
23	non-metallic mineral	0.97	0.63	0.98	0.62
24	Basic metal	0.97	0.49	0.96	0.35
25	Fabricated metal	0.99	0.82	0.99	0.70
26	Computer instruments	0.97		0.97	0.21
27	Electrical machinery	0.97	0.29	0.97	0.30
28	Other machinery	0.99	0.80	0.99	0.64
29	Motor vehicles trailers	0.96	0.26	0.95	0.29
30	Other transport equipment	0.95	0.52	0.94	0.24
31	Furniture build repair	0.99	0.63	0.99	0.72
32	Industries not classified	0.99	0.69	0.99	0.84
33	Installation of machine equip	0.99		0.99	0.69

Source: EIS, own calculation. note the blank lines were deleted by EIS staff for confidentiality

It was mentioned that Turkish manufacturing firms can be classified into two groups based on their trading activities: those that exporter and non-exporter Table 14 below, we can see the distribution of small and large firms based on their trade activities in 2006 and

2020, as well as the share of key variables such as number of employees, value-added, and real wages paid to employees.

Table 14

Large and small firms' distributions by trade activities in 2006, 2020

Size	Trade	% Firms	% Labor	% V. added	% Wages
Panel A: Large and small firms' distributions by trade activities 2006					
large	Exporter	0.01	0.30	0.54	0.44
	Non-Exporter	0.001	0.04	0.03	0.05
small	Exporter	0.23	0.31	0.27	0.27
	Non-Exporter	0.76	0.35	0.16	0.24
Panel B: Large and small firms' distributions by trade activities 2020					
large	Exporter	0.01	0.34	0.55	0.46
	Non-Exporter	0.003	0.05	0.05	0.07
small	Exporter	0.23	0.30	0.26	0.26
	Non-Exporter	0.78	0.31	0.14	0.21

Source: EIS, own calculations.

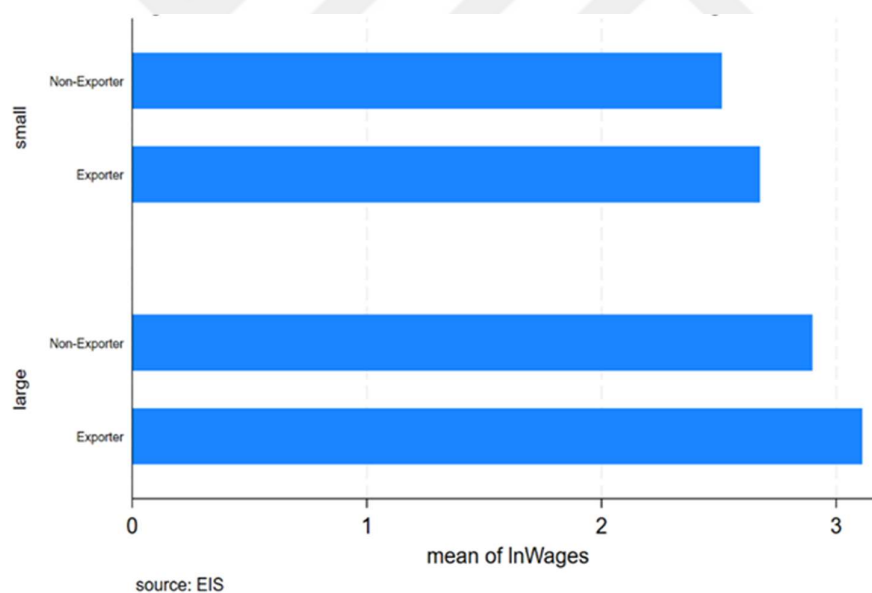
The following is an analysis of Table 14, which explains large exporter firms in-depth. These firms are defined as businesses that engage in export activities and accounted for the majority of large businesses in both 2006 and 2020. It is noteworthy that despite forming about 1 percent of the total number of firms annually, these firms play a significant role in the economy. This is evidenced by the fact that they employ over 30 percent of the overall workforce and contribute to more than 55 percent of the total value added of large firms. In contrast, small firms engaged in exporting activities comprised around 23 percent of the total small firms in both 2006 and 2020, but their employment share was less than 30 percent of the total workforce in each year.

Table 14 also explains small non-exporter firms, which are businesses that do not engage in trade activities during a specific period. These firms constituted a significant proportion of small businesses in both 2006 and 2020. In 2006, around 76 percent of all small firms did not engage in exporting, and these firms employed about 35 percent of the total workforce. However, by 2020, this proportion had increased to around 78 percent, and these small firms employed about 30 percent of the total workforce. Furthermore, their share of the total value added by small firms was around 26 percent for both years.

The following discussion analyzes the connection between firms' size, export status, and average wages they paid in 2006. Figure 10 clearly illustrates that, on average, firms that exported goods paid higher wages than those that did not export across all size distributions. Additionally, larger exporting firms paid higher salaries than smaller exporting firms. Furthermore, there was a notable difference between the average wages paid by large firms, depending on their export status. Specifically, larger exporting firms paid higher average wages than larger non-exporting firms. Conversely, the average wages paid to employees of small firms did not show a significant difference based on the firms' export status, as was the case with larger firms.

Figure 10

Average wage, size, export status 2006



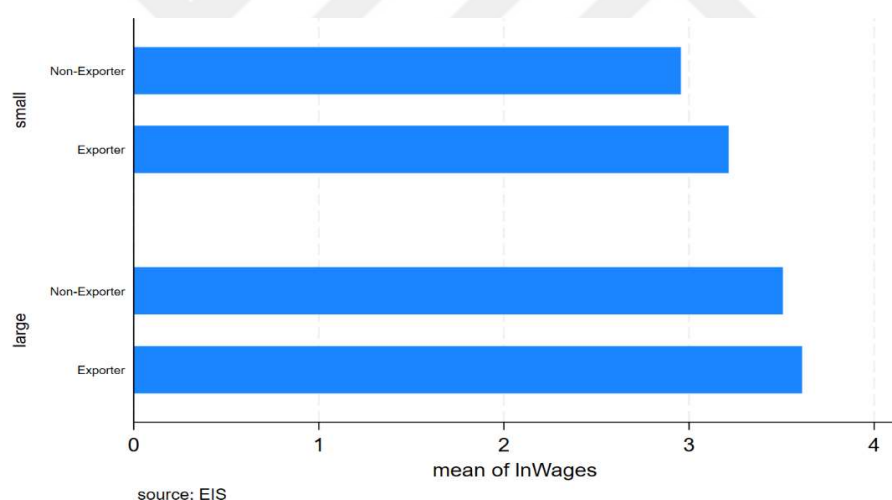
Source: EIS, own calculation.

In 2020, Figure 11 below analyzes the connection between the size of a firm, its export status, and the average wage paid to its employees. Figure 11 illustrates that, on average, exporter firms paid higher wages to their employees in comparison to non-exporter firms. This trend was observed across all size distributions, and the wage difference was also higher than what was paid in 2006.

Furthermore, the discussion of Figure 11 found that among exporter firms, larger firms paid higher wages on average to their employees compared to smaller firms. This trend was also more pronounced in 2020 than it was in 2006. Interestingly, it is also highlighted that there was a significant difference in the average wage paid by small firms depending on their export status. Specifically, the wages paid to employees of small exporting firms were higher than those paid by small non-exporting firms. However, this trend was not observed among large firms; Figure 11 reflects that the average wages paid to employees of large firms did not differ significantly depending on the firms' export status, unlike the trend observed in large firms in 2006.

Figure 11

Average wage, size, export status 2020



Source: EIS, own calculation.

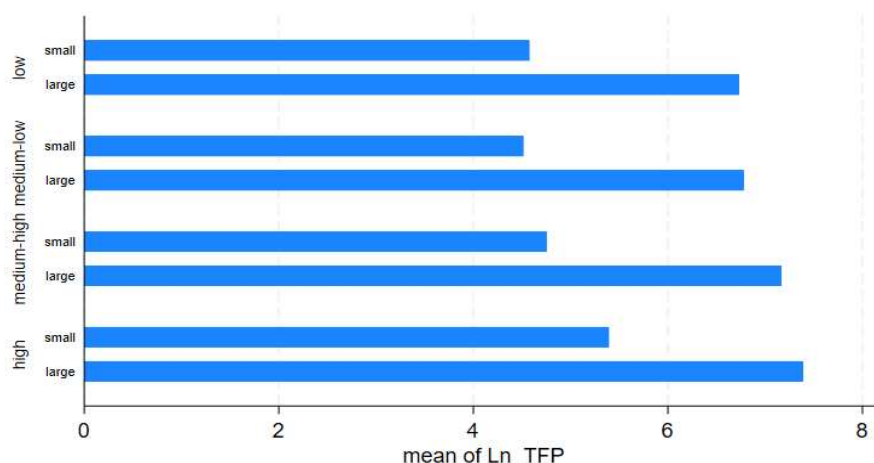
Turkish manufacturing firms in various sectors have adopted four different levels of technology, categorized from low to high. Table 15 below presents the distribution of these technology levels between 2006 and 2020. The share of firms with high-level technology remained unchanged during this period. However, the share of firms belonging to the medium-low technology levels has increased for both small and large firms between 2006 and 2020. According to Table 15, it is evident that nearly half of Turkish manufacturing firms have adopted low-level technology in 2006 and 2020.

Table 15*Technology level distribution of large and small firms*

	small		large	
	No. Firms	Share	No. Firms	Share
Panel A 2006				
Low Level	30,214	0.51	444	0.54
Medium- Low	17,505	0.30	182	0.22
Medium-High	10,434	0.18	155	0.19
High Level	517	0.01	33	0.04
Panel B: 2020				
Low Level	51,474	0.49	784	0.50
Medium- Low	34,398	0.33	393	0.25
Medium-High	17,412	0.17	326	0.21
High Level	997	0.01	57	0.04

source: EIS, own calculation.

The following is the analysis of total factor productivity, its distribution, and evolution by size and technological sectors of firms for the years 2006 and 2020, illustrated in Figures 12 and 13, respectively. As per Figure 12, large firms belonging to the high technology level were found to be more productive than their counterparts belonging to medium-high, medium-low, and low levels. Moreover, the findings suggest that large firms, regardless of the technology level, are more productive than small firms. Figure 12 also highlights that the TFP remained consistent across medium-high, medium-low, and low levels of technology in small firms during 2006.

Figure 12*Distribution of TFP by size, sectors technology level 2006*

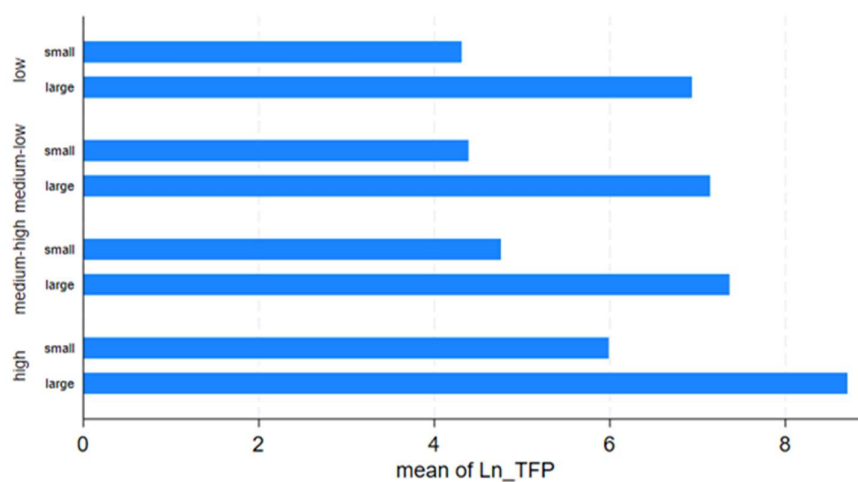
Source: EIS

Source: EIS, own calculation.

The data presented in Figure 13 provides a clear indication that firms with large-scale size and high technology levels tend to be more productive in comparison to their counterparts operating at medium-high, medium-low, and low technology levels. Additionally, the findings suggest that irrespective of their technology level, large firms continue to be more productive than smaller firms, as observed in 2006. The graphical representation in Figure 13 further demonstrates that the Total Factor Productivity (TFP) remained constant across medium-high, medium-low, and low technology levels in both small and large firms between 2006 and 2020. However, it is notable that both large and small firms with high technology levels experienced a significant increase in their TFP between the two years of analysis.

Figure 13

Distribution of TFP by size, sectors technology level 2020



Source: EIS

Source: EIS, own calculation.

3.3.4. The Sample and the Variables for Estimating Employment Growth Rate

To estimate the change in employment growth rate in 2020, we followed the firms that existed in 2006, resulting in an unbalanced panel dataset of 59,560 firms with 512,026 observations. Firms were classified into eight size groups based on their number of employees in 2006, as the following classification in Table 16 below.

Table 16

Size groups classification in 2006

Size Groups Classification in 2006	
Large2	$L > 250$
Large1	$100 < L \leq 250$
Medium	$50 < L \leq 100$
Small1	$20 < L \leq 50$
Small2	$10 < L \leq 20$
Micro1	$5 < L \leq 10$
Micro2	$2 < L \leq 5$
Micro3	$L = 2$
Where L is number of employees in 2006.	

Source EIS, depending on number of employees in 2006.

In 2006, the variable of firm age was determined by considering both the establishment year and the date of operations (i.e., the year in which each firm started its activities). Based on this age variable, firms were categorized into seven age groups, as explained in Table 17 below.

Table 17

Age groups classification in 2006

Age Group Classification in 2006	
Agegr1	$0 \leq \text{age2006} < 2$
Agegr2	$2 \leq \text{age2006} < 5$
Agegr3	$5 \leq \text{age2006} < 10$
Agegr4	$10 \leq \text{age2006} < 15$
Agegr5	$15 \leq \text{age2006} < 20$
Agegr6	$20 \leq \text{age2006} < 25$
Agegr7	$25 \leq \text{age2006}$

Source: EIS, depending on the establishment date and date of operation activities

The firm exit variable, used in this study, is defined based on Social Security records. Each year, 59,560 firms are tracked. If a firm stops reporting employee numbers the following year, it is considered an exit. As a result, 29,339 businesses are expected to continue operating until the end of the study period in 2020. However, 30,221 firms were not found in the Social Security records until 2020, indicating that they had exited business before 2020.

According to Table 18 below, the sample size for the businesses in question is relatively small. The average number of employees is approximately 37 and 20 for survived and exited firm, respectively, and the median, 25th percentile, and 50th percentile are all quite low, indicating that most of the businesses in the sample are small-scale. The skewness of the sample further confirms this fact, with only a few exceptions. Furthermore, the mean of surviving firms is twice as large as those that left the market, suggesting significant differences between the two groups.

When we compare the sizes of firms across different percentiles of their distributions, we can observe differences between them. For instance, if we consider the 50th and 75th percentiles (which represent the top 25 percent of firms with the highest number of employees), we can see notable variations in their sizes.

Table 18

Principal values of the sample (at the beginning of the study period)

Number of Employees in 2006	Survived	Exited
Mean	37.3	20
Median	10	5
Standard Deviation	185	73
Maximum	14094	6346
Minimum	2	2
Percentile 25	5	3
Percentile 50	10	7
Percentile 75	26	18
Percentile 95	126	66
Skewness	37.5	25
Number of Observations	29339	30221

Source EIS, own calculations.

3.3.4.1. *Descriptive Statistics of Firms That Existed in 2006.*

Based on the information provided in Table 19, it is evident that the manufacturing sector was predominantly dominated by small and medium-sized enterprises (SMEs) with less than 250 employees in 2006. SMEs accounted for over 98 percent of all firms. However, companies with more than 250 employees, although comprising only a minority, employed around 34 percent of the workforce. This highlights the crucial role played by larger employers in the sector.

Table 19

Distribution of firms and the total employment in 2006

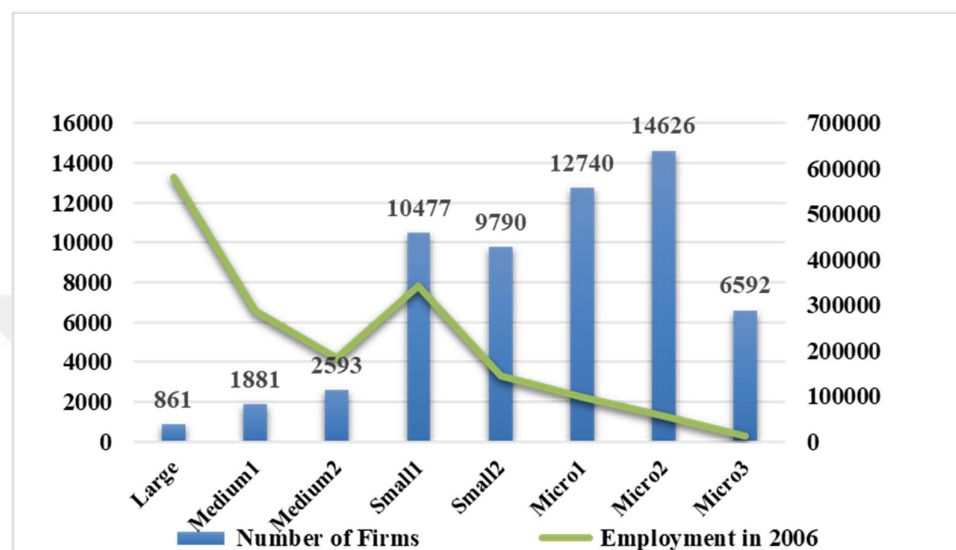
Size groups of firms in 2006	Number of firms	% Firms	Employment in 2006	% Employment
L > 250	861	0.01	5,804,77	0.34
100 < L ≤ 250	1,881	0.03	2,867,07	0.17
50 < L ≤ 100	2,593	0.04	183,902	0.11
20 < L ≤ 50	10,477	0.18	341,517	0.20
10 < L ≤ 20	9,790	0.16	144,032	0.08
5 < L ≤ 10	12,740	0.21	97,485	0.06
2 < L ≤ 5	14,626	0.24	56,756	0.03
L = 2	6,592	0.11	13,184	0.01
Total	59,560	%100	1,704,060	%100

Source EIS, own calculations.

The distribution of the number of employees among the eight size groups is shown in Figure 14. It is evident from the figure that the large firms' group, which had the minimum number of firms, employed the largest number of workers in 2006. The figure clearly indicates that the size of the firm is positively correlated with the number of employees, except for the fourth group (small1) that employed between twenty-one and fifty workers at most. Despite being a small group, it had the second-largest number of workers in the workforce in 2006, after the large group. According to the graph, the seventh and eighth size groups on the right side of the figure represent about 35 percent of Turkish manufacturing firms in 2006. However, despite their significant share of firms, these groups together only employed 0.04 percent of workers in 2006.

Figure 14

Number of firms and total employment by size groups in 2006



Source: EIS, own calculation.

Table 20 provides information on the number of businesses that were operational in 2020 as well as the ones that went out of business before that year. Out of a total of 59,560 firms, only 29,339 were still operating in 2020. The table highlights those micro-sized businesses had the highest exit rates, ranging from 50 to 63 percent, followed by small businesses with nine to fifty employees having exit rates varying between 45 to 47 percent.

Table 20

Number of firms in 2006, survived, and exited firms before 2020

Size groups of firms in 2006	Survived Firms	Exited Firms	% of Exited Firms
L > 250	676	185	0.21
100 < L ≤ 250	1,173	708	0.38
50 < L ≤ 100	1,419	1,174	0.45
20 < L ≤ 50	5,725	4,752	0.45
10 < L ≤ 20	5,216	4,574	0.47
5 < L ≤ 10	6,328	6,412	0.50
2 < L ≤ 5	6,334	8,292	0.57
L = 2	2,468	4,124	0.63
Total	29,339	30,221	0.51

Source: EIS, own calculations

3.3.4.2. *Descriptive Statistics of Firms that Exited the Market before 2020*

The data presented in Table 21 below indicates the number of businesses that left the market prior to 2020 and the corresponding employment figures. Out of a total of 59,560 businesses, 30,221 of them went out of business. The majority of job losses were observed in larger businesses. However, it should be noted that these larger businesses initially had a larger share of employment than smaller businesses, and the rate of employment change tends to be lower in larger firms than in smaller ones. Additionally, it is important to note that micro-sized businesses accounted for more than half of all job losses.

Table 21

Employment change in exited firms between 2006 and 2020

Size groups of firms in 2006	Number of firms	Total employment in 2006	Total employment in 2020	Employment change in exited firms
L > 250	185	111,150	0	-0.19
100 < L ≤ 250	708	106,254	0	-0.37
50 < L ≤ 100	1,174	823,83	0	-0.45
20 < L ≤ 50	4,752	154,200	0	-0.45
10 < L ≤ 20	4,574	672,41	0	-0.47
5 < L ≤ 10	6,412	48,890	0	-0.50
2 < L ≤ 5	8,292	31,950	0	-0.56
L = 2	4,124	8,242	0	-0.63
Total	30,221	610,316		

Source: EIS, own calculation.

3.3.4.3. *Descriptive Statistics of Firms that Survived until 2020*

The data presented in Table 22 highlights the changes in the employment rate in active firms till 2020. Out of the original 59,560 businesses, 29,339 are still operational. The number of employees has increased across micro, small, medium, and large firms. However, the most significant employment growth was observed in micro-sized businesses, followed by small and medium-sized firms. The data concludes that there is an inverse relationship between employment growth and firm size, which is evident from the figures in Table 22 below.

Table 22*Employment change in active firms between 2006 and 2020*

Size groups of firms in 2006	Number of firms	Total employment in 2006	Total employment in 2020	Employment change in survived firms
L > 250	676	469,327	620,236	0.26
100 < L ≤ 250	1,173	180,453	250,362	0.24
50 < L ≤ 100	1,419	101,519	157,306	0.30
20 < L ≤ 50	5,725	187,317	279,754	0.27
10 < L ≤ 20	5,216	76,791	120,276	0.30
5 < L ≤ 10	6,328	48,595	79,957	0.32
2 < L ≤ 5	6,334	24,806	50,805	0.46
L = 2	2,468	4,936	15,647	0.81
Total	29,339	1,093,744	1,574,343	

Source: EIS, own calculation.

The following table, Table 23, shows the difference in employment rates between businesses that were still operating in 2020 and those that had shut down before that. The data indicates that the size of a business has a negative correlation with its employment growth. Surprisingly, the majority of new employment opportunities were created by micro-sized businesses with only two employees. Furthermore, medium-sized businesses experienced a greater loss of jobs compared to their larger counterparts. Based on the results presented in Table 23, it can be inferred that business size has a significant impact on employment growth and job loss.

Table 23*Total Employment change in survived firms and exited firms*

Size groups of firms in 2006	Total Employment Change
L > 250	0.07
100 < L ≤ 250	-0.13
50 < L ≤ 100	-0.14
20 < L ≤ 50	-0.18
10 < L ≤ 20	-0.16
5 < L ≤ 10	-0.18
2 < L ≤ 5	-0.10
L = 2	0.19

Source: Employment change in survived plus employment change in Exited Firms

4. ECONOMETRICS ESTIMATIONS

The following sub sections provide a comprehensive overview of the estimation results obtained through the empirical models utilized in this thesis. The results have been presented in detail, highlighting the significant conclusions and findings that emerged from the research. The findings obtained through this research have significant implications for the field of study, and the results will be of great interest to the academic and business communities alike.

4.1. Static Blinder Oaxaca Decomposition Results

A regression model in (3.1) that connects TFP with firm characteristics and control variables is estimated as a first step in performing the Oaxaca-Blinder decomposition. In order to implement the Oaxaca-Blinder decomposition, we began by conducting four independent regressions of small and large enterprises in 2006 and 2020, with $\ln(\text{TFP})$ as the dependent variable. The regression results for these four samples are presented in Table 24. The second and third columns of Table 24 below show the regression findings for small and large businesses in 2006, while the third and fourth ones display the outcomes for small and large firms in 2020.

Table 24*Estimated coefficients usual TFP Eq. small and large firms*

Independent Variables	2006		2020	
	Small (1)	Large (2)	Small (3)	Large (4)
lnCintensity	0.058*** (0.00219)	0.222*** (0.0202)	0.043*** (0.00183)	0.216*** (0.014)
lnWages	0.763*** (0.0109)	0.817*** (0.0585)	0.930*** (0.0066)	0.823*** (0.0435)
lnAge	0.116*** (0.00367)	0.014*** (0.0346)	-0.012*** (0.0030)	-0.0165 (0.0221)
Debt/Equity ratio	-0.089*** (0.00390)	-0.259*** (0.0408)	-0.111*** (0.00284)	-0.127*** (0.0212)
Exporter dummy	0.544*** (0.0086)	0.271** (0.0762)	0.734*** (0.0075)	0.242*** (0.0538)
Innovation dummy	0.397*** (0.00691)	-0.102 (0.0883)	0.414*** (0.0063)	0.062 (0.0953)
Medium- Low	0.021*** (0.008)	0.024 (0.064)	0.075*** (0.0066)	0.042 (0.0434)
Medium –High	0.043*** (0.009)	-0.028 (0.0730)	0.142*** (0.0084)	0.088** (0.050)
High	0.271*** (0.037)	-0.296** (0.145)	0.395*** (0.0308)	0.393*** (0.1098)
2 digits industry dummies	Yes	Yes	Yes	Yes
provincial dummies	Yes	Yes	Yes	Yes
Constant	1.967*** (0.0293)	3.258*** (0.194)	1.164*** (0.0222)	2.862*** (0.187)
Observations	58,670	814	104,281	1,560
R-squared	0.297	0.462	0.370	0.443

*Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

The Table above, Table 24, presents the results of TFP regressions that were conducted for both large and small firms in 2006 and 2020. The analysis revealed that factors such as capital intensity, logarithmic wage, exporter status, and medium-low technology level positively impact a firm's productivity across all columns.

Based on the statistical analysis conducted and shown in Table 24, it can be observed that the coefficients of ln (wages), ln (Cintensity), and the exporter dummy are significant at a 1 percent significance level. The data suggests that for the exporter dummy and ln (Wage), small enterprises had higher coefficients than large firms in both 2006 and 2020. Regarding ln (Age), it can be concluded that a firm's age positively affected TFP in 2006 for firms of both sizes. However, the impact of age on TFP had a negative effect in 2020 for

small firms. Although it was negative in the large firms' sub-sample, too, it was not significantly different from zero.

Financial restrictions are represented by the debt-to-equity ratio (DTE). This ratio displays the financial stability of the company. In this regard, a rise in this ratio might lead to a decrease in TFP, as debt accumulation is a long-term consequence of hierarchical financing choices (Nucci et al., 2005).

Table 24, shown above, provides evidence that there is a negative relationship between DTE (Debit to Equity ratio) and the total factor productivity of firms. In all columns, this negative relationship is highly significant at a 1 percent significance level. In 2020, this negative relationship has worsened for small businesses. However, it has decreased for their larger counterparts.

The variable "innovation dummy" was used as a proxy for Research and Development (R&D) and significantly impacted the productivity of startups in 2006 and 2020. This impact was positive and highly significant, with a 1 percent significance level. However, it had an inverse effect on the productivity of large enterprises in 2006, but it was not significantly different from zero. In contrast, it positively impacted the productivity of large enterprises in 2020, but it was not significantly different from zero.

The technological level of the sector in which a firm operates is a critical variable that may affect the gap in Total Factor Productivity (TFP) between small and large enterprises from 2006 to 2020. Utilizing the statistics in Table 24, we can infer that for small firms in 2006 and 2020 operating in sectors with medium-High technology levels, technology has a positive and significant influence on TFP at the 1 percent significance level. Additionally, for large firms in 2020, technology has a significantly positive impact on productivity at the 5 percent significance level. However, for large firms in 2006 operating in similar sectors, the effect of technology on TFP was negative but not significantly different from zero.

Based on the data presented in Table 24, it is evident that small firms operating in sectors with a medium-low technology level experience a positive and statistically significant impact of technology level on TFP at a 1 percent significance level. This trend was observed in 2006 and 2020, but the coefficient of small firms in 2020 was greater than

that of 2006. Similarly, for large firms belonging to such sectors, the influence of technology level on TFP is positive but not statistically significant in both years.

Lastly according to the data presented in Table 24, it is clear that in 2006, small firms in high-technology sectors had a positive and significant effect on TFP, whereas large firms had a negative and statistically significant effect at a 5 percent level. However, in 2020, both small and large firms in high-technology sectors had a positive and significant impact on TFP at a 1 percent level. Nevertheless, the impact was larger for small firms compared to large firms.

4.2. The Solution to the Identification Problem.

If we apply equation (3.18) to small and large firms in 2006 and 2020 separately, we can utilize the Oaxaca decomposition technique to compute the TFP equation. This approach guarantees that the results are not impacted by the selection of the excluded category in the dummy variables.

This section uses Yun's (2005) solution to address the identification problem. Firstly, we estimated the normalized regressions for four subsamples: two for small and their larger counterparts in 2006 and the other two subsamples in 2020. Following this, we applied the Oaxaca decomposition technique.

In Table 25 below, we can see the results of the regression estimate equation (3.9). The dependent variable considered here is the mean $\ln$ (TFP), while the independent variables are capital intensity, annual gross wages per worker, firm age, and debt to equity ratio. All of these variables are in logarithmic form. In addition, there are dummies for innovation; (a value of 1 indicates that the proportion of fixed intangible assets to total assets was positive, while a value of 0 means that the ratio was zero). The table also includes dummies for export (exporter, non-exporter), and technology level (low level, medium-low, medium-high, high).

Table 24 above displays the results of the "usual" Total Factor Productivity (TFP) model regression without the reference group of dummy variables. The table includes four columns, with the first two showing data for small and large firms in 2006 and the other two showing data for 2020. On the other hand, Table 25 below presents "normalized" estimates for the same four columns. To avoid the indetermination problem in the Oaxaca

decomposition, the coefficients of each dummy variable category in Table 25 sum up to zero. By comparing the usual and normalized estimates, we can observe that the intercept and coefficients of the dummy variables change when the estimates are normalized.

Table 25

Estimated coefficients normalized TFP Eq. small and large firms

Independent Variables	2006		2020	
	Small (1)	Large (2)	Small (3)	Large (4)
lnCintensity	0.058*** (0.00219)	0.222*** (0.0202)	0.043*** (0.00183)	0.216*** (0.014)
lnWages	0.763*** (0.0109)	0.817*** (0.0585)	0.930*** (0.0066)	0.823*** (0.0435)
lnAge	0.116*** (0.00367)	0.014*** (0.0346)	-0.012*** (0.0030)	-0.0165 (0.0221)
Debt/Equity ratio	-0.089*** (0.00390)	-0.259*** (0.0408)	-0.111*** (0.00284)	-0.127*** (0.0212)
Exporter	0.272*** (0.00430)	0.136** (0.0381)	0.367*** (0.00377)	0.121 (0.0229)
Non-Exporter	- 0.272*** (0.00430)	- 0.136** (0.0381)	- 0.367*** (0.00377)	- 0.121 (0.0229)
Innovation1	- 0.198*** (0.0036)	0.051 (0.0441)	-0.207*** (0.00316)	-0.0309 (0.0476)
Innovation2	0.198*** (0.0036)	-0.051 (0.0441)	0.207*** (0.00316)	0.0309 (0.0476)
Low Level	-0.084*** (0.0101)	0.075 (0.0509)	-0.153*** (0.0085)	-0.131*** (0.0360)
Medium- Low	-0.063*** (0.0107)	0.099* (0.0583)	-0.078*** (0.0088)	-0.088*** (0.0389)
Medium –High	-0. 040*** (0.0111)	0.047 (0.0556)	-0.011 (0.0094)	-0.043 (0.0371)
High	0.188*** (0.0277)	-0.221** (0.1047)	0.242*** (0.0230)	0.263*** (0.0798)
2 digits industry dummies	Yes	Yes	Yes	Yes
provincial dummies	Yes	Yes	Yes	Yes
Constant	2.522*** (0.0325)	3.268*** (0.2118)	1.892*** (0.0258)	3.145*** (0.1948)
Observations	58,670	814	104,281	1,560
R-squared	0.297	0.462	0.370	0.443

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 26 below displays the mean values of the primary parameters that were used in the decomposition analysis. It comprises five columns. The first column lists the independent variables. The second and third columns show the mean values of the independent variables

used to estimate total factor productivity in 2006 for small and large firms respectively. Similarly, the fourth and fifth columns show the same information but for 2020.

Upon examining Table 26, it is evident that larger firms offered higher wages in both 2006 and 2020. Conversely, small firms were younger than large firms in both years. It was also observed that large firms were more capital-intensive than small firms in both 2006 and 2020. Additionally, it was noted that bigger companies had a higher proportion of fixed intangible assets in relation to their total assets that were greater than zero compared to smaller firms, indicating higher innovation levels. On the other hand, smaller firms had a higher debt-to-equity.

It has been observed that between 2006 and 2020, the share of exporter enterprises decreased for both small and large firms. On the other hand, in the same period, the share of large firms belonging to low, medium-high, and high levels of technology was higher as compared to small firms. However, the percentage of small firms belonging to the medium-low level of technology was higher than that of larger firms in both specified years.

Table 26

The mean values of the independent variables in 2006 and 2020

	2006		2020	
	Small	Large	Small	Large
Ln (Cintensity)	4.072	5.194	4.367	5.504
Ln (wages)	2.550	3.081	3.014	3.592
Ln (Age)	1.819	2.648	2.036	2.643
DTE ratio	1.169	0.945	1.312	1.054
Exporter	0.231	0.862	0.226	0.828
Non-Exporter	0.768	0.137	0.773	0.171
Innovation1	0.492	0.904	0.534	0.967
Innovation 0	0.507	0.095	0.465	0.032
Low level	0.514	0.544	0.493	0.502
Medium low	0.298	0.223	0.329	0.251
Medium high	0.177	0.190	0.166	0.208
High level	0.008	0.040	0.009	0.036

Source: EIS, regression results from Oaxaca Blinder decomposition.

4.2.1. The Detailed Decomposition

Table 27 and Table 28 below display the decomposition findings of the normalized equation for the years 2006 and 2020, respectively. As explained in the previous section, small firms have a lower average $\ln(\text{TFP})$ than large firms (with a log difference of 2.257 and 2.715) in 2006 and 2020, respectively.

There are two factors that cause TFP gaps - the endowment effect and the structural (coefficient) effect. The endowment impact relates to the factors that the firm experiences, while the structural effect is related to the returns that these attributes generate (Islam et al., 2019). For example, a firm's age contributes to the TFP gap through the endowment effect, since larger firms are, on average, older than smaller ones. Also, the return on a unit increase in firm age can vary for small and large firms, which is captured as a coefficient effect

Our estimation, conducted in 2006, revealed that almost half, 48.8 percent, of the differences in total factor productivity were explained by the characteristics or endowment effects. The remaining productivity gap of 51.2 percent was described by the return to coefficient or the structural effect. Furthermore, the independent variables also have a significant impact on the productivity gap through the structural and endowment effects. In the upcoming sections, we will discuss these factors in greater detail.

4.2.1.1. *Endowment Effect in 2006.*

In 2006, the endowment effect exerted a substantial impact on the productivity gap. The " $\ln(\text{Wage})$ " variable contributed the most to the difference between small and large firms, followed by the "exporter dummy" variable, innovation dummy, $\ln(\text{Age})$, capital intensity, the debt-equity ratio, and the technology level dummy variable. Below is Figure 15 illustrates the individual contributions of each factor towards the explained (characteristics effect) and unexplained (coefficient effect) factors.

Figure 15

The Detailed decomposition of explained, unexplained parts in 2006



Source: EIS, based on Oaxaca Blinder decomposition results

Small firms are less productive on average than big ones. Therefore, any factor that narrows the total factor productivity gap between them will benefit small firms. The findings for the endowment effect are presented in Column 2 of Table 27.

It is worth noting that trade activity and higher wages positively impact a firm's total factor productivity. However, small firms usually lag behind their larger counterparts in these two areas, as explained in Table 26. Consequently, the disparity in productivity between small and their larger counterparts increased by 18 percent (which is significant at the 1 percent level) due to differences in annual gross wages, as reflected by $\ln(\text{wages})$. Additionally, as mentioned earlier, the proportion of firms engaged in export activity is lower in small firms compared to large ones. The productivity of firms that export was significantly higher than those that did not. This created a productivity gap of 15.24 percentage points (significant at the 1 percent level) due to the difference in the number of firms involved in trade activity.

In this analysis, we examined the ratio of fixed Intangible assets to total assets and its impact on TFP. We use a dummy variable to represent a positive ratio value (1) and a zero value (0) for no ratio. Our study finds that a firm with a positive ratio has a positive impact on the $\ln$ (TFP). Additionally, based on the data in Table 27, we observe that larger firms tend to have more firms with innovation value equal to 1 than smaller firms. This led to an increase in the productivity gap of 7.24 percent between small and large firms in 2006 (significant at the 1 percent level).

It was mentioned in the previous section that as the age of a firm increases, its total factor productivity also increases. Additionally, larger firms tend to be older than startups. This means that the productivity gap between small and large firms widens by approximately 4.25 percent, which is a significant difference at a 1 percent level.

Upon thorough analysis of the regression results mentioned previously, it can be confidently concluded that the capital intensity factor had a significantly positive impact on TFP in the year 2006. According to the available data, larger corporations tend to have higher capital requirements as compared to their smaller counterparts. This translates to an approximate increase of 2.87 percent in the productivity gap between small and large firms due to the difference in their capital intensity ratio.

A deeper look at the debt-to-equity ratio (DTE) of the 2006 decomposition shows that DTE's contribution to the explained part is negative, which means that the overall difference would be even larger if the average DTE of small and large firms were the same. In other words, the DTE ratio has a negative impact on TFP, and smaller firms tend to have a higher DTE ratio than larger firms on average. By eliminating this DTE advantage, smaller firms would become even worse off, This would result in an increase in the productivity gap by about 0.88 percent, which is a significant difference at a 1 percent level.

Lastly, based on the regression results discussed earlier, it can be concluded that in 2006, a firm operating in a low-technology sector had a significant negative impact on TFP. Furthermore, the data suggests that this technology sector had a higher percentage of larger firms than smaller ones. therefore, the difference in productivity between small and large firms decreases by approximately 0.11 percent due to differences in the distribution of large and small firms in the low-level technology sector.

According to the regression results discussed earlier, it can be concluded that in 2006, a company operating in the medium-low technology sector significantly negatively impacted its Total Factor Productivity (TFP). Moreover, the data suggests that this particular technology sector had a higher proportion of smaller companies than larger ones. Therefore, the TFP-size gap widened by approximately 0.21 percent due to differences in the distribution of large and small firms in the medium -low-level technology sector.

Based on the regression results discussed in Table 25 above, it can be concluded that in 2006, firms operating in the medium-high technology sector had a significant negative impact on TFP. Moreover, the data suggests that this technology sector had a higher percentage of larger firms than smaller ones. Consequently, the disparity in productivity between firms of different size decreased by approximately 0.022 percent due to differences in the distribution of large and small firms in the medium-high-level technology sector.

Based on the previously discussed regression results, it can be concluded that a company operating in the high-level technology sector had a significantly positive impact on its Total Factor Productivity (TFP) in 2006. Additionally, the data indicates that the technology sector had a higher proportion of larger companies compared to start-ups. As a result, the differences in productivity between small and large firms widened by approximately 0.26 percent due to the differences in the distribution of large and small firms within the high-level technology sector.

4.2.1.2. *Coefficient (Structural) Effect in 2006*

The TFP-size gap can be widened or narrowed due to firms' returns to production factors or attributes. The role of these factors or attributes is called the return effect. By analyzing the variables that significantly contribute to this gap (at the 1 percent level or higher) through the return or coefficient effect, it is evident that the enormous contribution comes from differences in returns to capital intensity. This is followed by firms' age, innovation status, debt-to-equity ratio, exporter status, and technology level dummy. Among small and large firms, the productivity gap is affected by the level of technology a firm's sector belongs to, such as low level, medium-low level, medium to high, and high technology level. The individual contribution of each mentioned variable to the unexplained part or coefficient (structural) effect can be noticed in Figure 15 above.

The efficiency gap between small and large firms is significantly influenced by differences in returns to capital intensity and debt-to-equity ratios. The gap increased by 37.7 percent (significant at the 1 percent level) due to variations in returns to capital intensity. This implies that large firms with high capital-to-labor ratio features tend to experience a more significant increase in their TFP than start-ups. On the other hand, the gap decreased by 7.13 percent (significant at the 1 percent level) due to differences in returns to debt-to-equity ratios. This suggests that small firms tend to experience a lower diminishing return to debt-to-equity ratios than their larger counterparts.

Similarly, the results have shown that the Total Factor Productivity (TFP) variation was reduced by 8.9 percent (significant at the 1 percent level) due to differences in the returns to innovation. This implies that small firms that invest in innovation and research and development (R&D) activities experience a larger increase in TFP than large firms. Moreover, a comparison of the return to firms' age between small and large firms shows that the returns to age are greater in small firms, reducing the productivity gap by 11.9 percent (significant at the 1 percent level).

A significant reduction of 4.40 percent (significant at the 1 percent level) was observed in the difference in total factor productivity due to the difference in the export returns. This suggests that small firms experienced a greater increase in total factor productivity concerning export activity than their larger counterparts.

Lastly, the findings of the study revealed that when firms in a particular sector adopted a low level of technology, it resulted in a significant increase of 3.85 percent (significant at the 1 percent level) in the total factor productivity deficit between firms according to their sizes. This indicates that larger firms experienced a greater improvement in total factor productivity than their startup counterparts, given the low technology level.

Similarly, the study found that adopting a medium-low and medium-high level of technology resulted in a significant increase of 1.6 percent (significant at the 10 percent level) and 0.74 (significant at the 1 percent level) percent in the firms' efficiency disparity, respectively. However, if a firm in an industry adopted a high level of technology, the total factor productivity gap narrowed by 0.74 percent (significant at the 1 percent level) between large and small firms.

Table 27*Decomposition results (normalized equation) 2006*

	(1)	(2) Endowment effect	(3) Structural effect
Ln (TFP) of small Firms	4.595*** (0.00408)		
Ln (TFP) of Large Firms	6.852*** (0.0340)		
Difference (Small – Large)	-2.257*** (0.0342)		
explained	-1.101*** (0.0227)		
unexplained	-1.156*** (0.0285)		
Ln (Cintensity)		-0.0647*** (0.00371)	-0.851*** (0.106)
Ln (Wages)		-0.405*** (0.0158)	-0.167 (0.184)
Ln (Age)		-0.0961*** (0.00438)	0.270*** (0.0923)
Debt equity ratio		-0.0198*** (0.00220)	0.161*** (0.0391)
Exporter		-0.172*** (0.00429)	0.118*** (0.0331)
Non exporter		-0.172*** (0.00429)	-0.0188*** (0.00553)
Innovation 1		-0.0818*** (0.00256)	-0.0239*** (0.00497)
Innovation 2		-0.0818*** (0.00256)	0.226*** (0.0402)
low		0.00256* (0.00151)	-0.0869*** (0.0285)
Medium low		-0.00470*** (0.00123)	-0.0362*** (0.0135)
Medium high		0.000513 (0.000583)	-0.0167 (0.0109)
high		-0.00596*** (0.00157)	0.0166*** (0.00522)
Constant			-0.746***

*Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

4.2.1.3. *Endowment Effect in 2020*

In 2020, the endowment effect played a significant (significant at the 1 percent level) role in the productivity gap. This effect explained about 45.7 percent of the TFP gap the major contribution was due to the difference between small and large firms in the "ln (Wages)" variable. Following this variable, the "exporter dummy" variable, the, innovation status, capital intensity, and the debt-equity ratio also had a notable impact. Figure 16 below, illustrates the contributions of each variable to the explained or endowment (characteristics effect) and unexplained (coefficient effect) factors.

Figure 16

The Detailed decomposition of explained, unexplained parts in 2020



Source: EIS, based on Oaxaca Blinder decomposition results

Based on the analysis in Table 28 below, it is evident that smaller firms tend to be less productive than their larger counterparts. Thus, any factor that narrows the productivity differential between the two benefits small firms more than larger ones. The findings for the endowment effect are presented in Column 2 of Table 28 below.

It's worth noting that trade activity and higher wages have a positive impact on total factor productivity. However, small businesses tend to lag behind their larger counterparts

in both of these areas, as explained in Table 26. Consequently, the productivity differences between small and large firms widens by 19.8 percent (which is significant at the 1 percent level) because of differences in annual gross wages, as demonstrated by $\ln(\text{wages})$.

It has been observed that small firms tend to participate less in export activities than larger firms. It has also been noted that firms that engage in exporting have significantly higher productivity levels than those that do not. This leads to an increase in the productivity gap of 16.2 percent points, which is statistically significant at the 1 percent level. This gap is attributed to the difference in the number of firms participating in trade activities.

Based on the analysis of Table 25, it can be inferred that small companies experienced a significant increase in their total factor productivity (TFP) in 2020. This growth was mainly due to the innovation factor. Furthermore, the data indicates that larger firms tend to be more innovative than smaller ones. This suggests that the productivity deficit of small firms widened by approximately 6.6 percent, primarily due to differences in their R&D and innovation activities.

Based on the data presented in Table 25, it was found that a firm's total factor productivity decreases as it ages. Additionally, it was observed that larger firms tend to be older than startups. As a result, the productivity gap between small and large firms decreased by around 0.3 percent, which is considered a significant difference at a 1 percent level.

During the year 2020, the debt-to-equity (DTE) ratio had a negative impact on the total factor productivity (TFP). Smaller firms, on average, had a higher DTE ratio than larger firms, leading to a 1.05 percent increase in the productivity gap. This difference is significant at a 1 percent level. Additionally, the productivity gap increased by 1.8 percent due to variations in returns to capital intensity. However, the study discovered that adopting a medium-low or high level of technology resulted in a slight but significant (at the 1 percent level) increase of 0.22 percent and 0.24 percent, respectively, in the total factor productivity gap.

4.2.1.4. *Coefficients (Structural) Effect in 2020*

It has been found that the productivity gap is significantly (at the 1 percent level or higher) affected by certain variables in 2020 through the coefficient effect. These variables contribute to about 54.3 percent of the TFP gap. Figure 16 and Table 28 show that the major

factors responsible for this gap are differences in capital intensity, wage rate, exporter status, and innovation activity.

The impact of capital intensity on increasing total factor productivity is greater for small firms than for large ones. This difference is significant at the 1 percent level. Specifically, the productivity gap between small and large firms increased by 35 percent due to the return to capital intensity. This means that in 2020, large firms can benefit more from the return to capital intensity than small ones.

Comparing the returns to wages between small and large firms, we can see that wages generate greater returns in small firms, effectively decreasing the productivity gap by 14 percent (significant at the 1 percent level). This means that small businesses benefit more from the returns to wages, which helped them increase their total factor productivity (TFP) compared to larger firms in 2020.

According to the study, the gap in Total Factor Productivity (TFP) was reduced by 6 percent as a result of differences in the innovation dummy's returns. This suggests that small firms' innovation and research and development (R&D) activities are more closely related to a greater increase in TFP than those of larger firms.

Encouraging and supporting export activity in small firms can significantly increase their total factor productivity according to a study. The study found that the exporter dummy had a greater impact on increasing total factor productivity in small firms compared to large firms. This difference was significant at the 1 percent level. Specifically, the return to export activities decreased the productivity gap by 6 percent when comparing small and large firms. This implies that export activities can be used to reduce the productivity gap between small and large firms. Therefore, it is important to promote and support export activity in small firms to help them achieve greater productivity.

The detailed decomposition results in 2020 indicate that a significant portion of the structural impact is still undetermined. This is supported by the negative, large, and statistically significant value of the constant term in column 2 of Table 28 for structural effects.

Table 28*A details decomposition of the normalized equation in 2020*

	(1)	(2) Endowment effect	(3) Structural effect
Ln (TFP) of small Firms	4.424*** (0.00367)		
Ln (TFP) of Large Firms	7.139*** (0.0221)		
Difference (Small – Large)	-2.715*** (0.0224)		
explained	-1.240*** (0.0170)		
unexplained	-1.474*** (0.0188)		
Ln (Cintensity)		-0.0487*** (0.00250)	-0.958*** (0.0780)
Ln (Wages)		-0.538*** (0.0119)	0.384** (0.158)
Ln (Age)		0.00743*** (0.00189)	0.0113 (0.0590)
Debt equity ratio		-0.0285*** (0.00236)	0.0171 (0.0227)
Exporter		-0.221*** (0.00421)	0.204*** (0.0194)
Non exporter		-0.221*** (0.00421)	-0.0422*** (0.00462)
Innovation 1		-0.0895*** (0.00169)	-0.00575*** (0.00175)
Innovation 2		-0.0895*** (0.00169)	0.170*** (0.0462)
low		0.00137 (0.00195)	-0.0110 (0.0186)
Medium low		-0.00609*** (0.00111)	0.00270 (0.0101)
Medium high		0.000457 (0.000413)	0.00667 (0.00801)
high		-0.00653*** (0.00131)	-0.000756 (0.00304)
Constant			-1.253*** (0.197)

*Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Table 27 and Table 28 indicate that the aggregate effects of endowment and coefficients remain the same in size and standard error, regardless of whether we use the

usual or normalized estimates. Furthermore, the normalized equation has no effect on decomposition components associated with continuous variables.

4.3. Evidence that the Normalized Equation Solved the Identification Issue.

In Tables 36 and 37 in the APPENDIX B, specifically at the endowment columns (2) of Innovation, Export, and Technology Level; we can see that the normalized equation does not impact the effect of sets of dummy variables on the endowment. However, there is a change in the coefficient effects of Intercept, innovation, Export, and Technology levels, which is the focus of the identification problem in the detailed decomposition. Using a normalized equation resolves the long-standing identification or invariance issue in the detailed decomposition.

The effects of the coefficients vary significantly depending on whether we use the usual or normalized equation, emphasizing the significance of the technique used. As an example, in 2006 the traditional equation suggests that the dummy variables of the exporter, innovation, and technology level contribute to reducing the gap. However, the normalized regression shows that the effect of technology level results in an increase in the gap. Additionally, in the traditional equation, the exporter and innovation dummy variables have double the impact in reducing the total differential gap compared to the normalized equation.

In 2020, the traditional equation suggests that the use of dummy variables for exporter, innovation and technology levels can help reduce the gap. However, the normalized regression shows that the effect of technology level actually results in a slight increase in the gap, but the increase is insignificant. On the other hand, the traditional equation shows that the exporter dummies greatly reduced the total differential gap, while the innovation dummy variable had twice the effect in reducing the gap when compared to the normalized equation.

The impact of constant coefficients varies significantly depending on whether we use the traditional or normalized equation. In 2006 and 2020, the constant effect was larger when the standard equation was used, resulting in a 57 percent increase in the gap. This suggests that a significant portion of the structural impact remains unidentified. On the other hand, the normalized equation's coefficient effect of 33 percent increased the overall differential gap, indicating that the unknown structural effect is relatively smaller.

4.4. Estimation of Employment Growth Rate

The results of the Two-Part model regressions from steps one (3.20) and two (3.22) of the two-part model are used to investigate the contributions of businesses belonging to various size and age groups. to employment growth (conditional means) for exiting firms as well as the surviving ones. The STATA has been used in the analysis. “twopm” is not an original command in the program it’s a user-written command package.

4.4.1. Estimated Survival Probability

To estimate the likelihood of survival, the first part of the Two- part model calculates conditional survival probability. Table 29 displays the survival rates of firms in 2006 across eight size categories and seven age groups. It's clear from the statistics that older businesses had a greater chance of survival within a particular size group. The survival rate increases as we move horizontally from left to right. Moreover, for a given age, larger firms exhibit a higher survival rate.

Table 29

Surviving rate (1st of the Two-Part model by size and age groups) in 2006

Seven Age Groups based on Firms Ages in 2006

Size groups based on firm size in 2006	1	2	3	4	5	6	7
$L = 2$	0.36	0.37	0.39	0.40	0.42	0.43	0.39
$2 < L \leq 5$	0.40	0.43	0.46	0.49	0.52	0.54	0.53
$5 < L \leq 10$	0.44	0.47	0.51	0.55	0.59	0.62	0.64
$10 < L \leq 20$	0.46	0.50	0.54	0.59	0.63	0.67	0.71
$20 < L \leq 50$	0.49	0.51	0.56	0.62	0.67	0.71	0.76
$50 < L \leq 100$	0.49	0.52	0.57	0.63	0.69	0.74	0.80
$100 < L \leq 250$	0.47	0.54	0.57	0.65	0.71	0.76	0.83
$L > 250$	0.52	0.50	0.58	0.66	0.71	0.77	0.88

Source: EIS, The regression results of the Two-Part model.

4.4.2. Estimated Exiting Probability

The probability of firm's exit can be calculated from the probability of survival according to equation (3.21) Table 30 below presents the conditional probability of exit. For a given age, as a firm's size grows, the likelihood of its leaving lowers. Compared to younger firms, older businesses are less likely to leave the market at a given size.

Table 30

The conditional probability of exit

Seven Age Groups based on Firms Ages in 2006.

Size Groups based on Firm size in 2006	1	2	3	4	5	6	7
$L = 2$	0.64	0.63	0.61	0.60	0.58	0.57	0.61
$2 < L \leq 5$	0.60	0.57	0.54	0.51	0.48	0.46	0.47
$5 < L \leq 10$	0.56	0.53	0.49	0.45	0.41	0.38	0.36
$10 < L \leq 20$	0.54	0.50	0.46	0.41	0.37	0.33	0.29
$20 < L \leq 50$	0.51	0.49	0.44	0.38	0.33	0.29	0.24
$50 < L \leq 100$	0.51	0.48	0.43	0.37	0.31	0.26	0.20
$100 < L \leq 250$	0.53	0.46	0.43	0.35	0.29	0.24	0.17
$L > 250$	0.48	0.50	0.42	0.34	0.29	0.23	0.12

Source: EIS, the Regression Results of the Two-Part model.

4.4.3. The Second Part of the Two-Part Model (Growth of Survived Firms)

The average rate of growth that firms experience if they survive until the end of 2020 is presented in Table 31 below, which is the means of an ordinary Least Squares of survived firms up until 2020, it is remarkable that smaller and younger firms grow the most. The rate is decreasing with the firm's size for a given age. For a given size, it is inversely related to the firm's age. The findings are consistent with other studies, such as the findings of the (Hölzl, 2013) analysis; smaller firms exhibit lower survival rates. However, those firms that survived display higher growth rates compared to the larger ones.

Table 31*Conditional mean growth of survived firms*

Seven Age Groups based on Firms Ages in 2006.							
Size Groups based on Firm size in 2006	1	2	3	4	5	6	7
$L \leq 2$	3.11	3.06	2.96	2.85	2.74	2.62	2.27
$2 < L \leq 5$	1.72	1.67	1.57	1.46	1.35	1.23	0.83
$5 < L \leq 10$	1.36	1.31	1.21	1.10	0.99	0.87	0.53
$10 < L \leq 20$	1.32	1.26	1.17	1.06	0.94	0.83	0.52
$20 < L \leq 50$	1.50	1.44	1.35	1.24	1.12	1.01	0.68
$50 < L \leq 100$	1.27	1.22	1.13	1.01	0.90	0.79	0.50
$100 < L \leq 250$	1.29	1.25	1.15	1.03	0.92	0.81	0.53
$L > 250$	1.28	1.23	1.12	1.02	0.91	0.78	0.36

Source: EIS, the regression results of the Two-Part Model

4.4.4. The Conditional Mean Growth Rate of Exited Firms

Table 32 presents the conditional mean growth rate of exited firms, which is calculated by the means of OLS of exiting firms until 2020. entities that are smaller and younger in age exhibit a higher rate of exit when compared to their counterparts. According to Table 32 below, micro firms with two employees and aged around five years have the highest conditional mean growth of exit. Conversely, large firms with more than 250 employees tend to have a higher conditional mean growth of exit at age 26 (age group 7). Small firms in the third and fourth groups exhibit higher growth rates with age compared to larger firms. While the older large firms have higher growth rates than their younger counterparts (as seen in the seventh and eighth groups).

Table 32*Conditional mean growth of exiting Firms*

Seven Age Groups based on Firms Ages in 2006.							
Size Groups based on Firm size in 2006	1	2	3	4	5	6	7
$L = 2$	-0.90	-0.10	-1.10	-1.30	-1.50	-1.70	-1.80
$2 < L \leq 5$	-0.12	-0.23	-0.30	-0.95	-1.69	-2.28	-3.00
$5 < L \leq 10$	-0.71	-0.90	-0.96	-2.04	-2.29	-2.65	-5.29
$10 < L \leq 20$	-6.10	-5.10	-5.60	-4.70	-4.50	-4.20	-3.80
$20 < L \leq 50$	-8.20	-6.90	-6.80	-6.20	-6.10	-5.30	-5.60
$50 < L \leq 100$	-1.89	-1.65	-1.58	-1.56	-1.52	-1.46	-1.41
$100 < L \leq 250$	-5.21	-5.08	-4.86	-4.80	-4.80	-4.47	-4.43
$L > 250$	-7.96	-7.57	-6.76	-6.62	-6.28	-6.17	-5.59

Source: EIS, the Regression Results of the Two-Part model.

4.4.5. Estimated Surviving and Exiting Firms' Conditional Mean Growth Rates

Lastly, the results of the regressions from steps one equation (3.20) and two equation (3.22) of the two-part model are used to investigate the contribution of firms of different sizes and ages to employment growth (conditional means) for exiting firms as well as the surviving ones. The results in Table 31 conditional mean growth of survived multiplied by the results in Table 29, the results in Table 32 conditional mean growth of exited firms multiplied by the results in Table 30 to reach the results in Table 33 below, which is the equation number (3.24), the overall conditional mean of both exiting and surviving firms in the sample from 2006 to 2020. It is clear from Table 33 below that small firms with less or equal 10 employees grow the most especially at ages less than 10 years. Also, it's showing that the importance of taking the firm exit into account when analyzing employment generation for the coming periods. For medium-sized firms $50 < L \leq 100$ the overall conditional mean growth increases with age. Furthermore, accounting for firm exit reflects that most of the employment change occurs in firms that left the market before 2020.

Table 33*Surviving and exiting firms' conditional mean growth rates*

Seven Age Groups based on Firms Ages in 2006.							
Size Groups based on Firm size in 2006	1	2	3	4	5	6	7
$L=2$	0.55	1.06	0.48	0.38	0.27	0.18	-0.20
$2 < L \leq 5$	0.62	0.58	0.56	0.22	-0.12	-0.40	-0.98
$5 < L \leq 10$	0.20	0.14	0.16	-0.30	-0.36	-0.46	-1.56
$10 < L \leq 20$	-2.70	-1.92	-1.93	-1.32	-1.05	-0.82	-0.75
$20 < L \leq 50$	-3.47	-2.64	-2.23	-1.58	-1.30	-0.82	-0.85
$50 < L \leq 100$	-0.34	-0.15	-0.03	0.07	0.14	0.20	0.12
$100 < L \leq 250$	-2.17	-1.69	-1.44	-0.99	-0.74	-0.44	-0.33
$L > 250$	-3.11	-3.15	-2.15	-1.59	-1.15	-0.83	-0.35

Source: EIS, the Regression Results of the Two-Part model.

5. THE CONCLUSIONS

In 2006, there were 58,670 small firms and 814 large firms, according to firm-level data. The data revealed that small firms had a lower total factor productivity (TFP) than their larger counterparts by 2.257 log points. The Oaxaca-Blinder decomposition analysis showed that the TFP gap was almost equally contributed by the endowment effect and the structural effect. Most control variables significantly contributed to the productivity gap through the endowment and structural impact. These findings provide valuable insights into why small firms struggle to achieve the efficiency of larger firms.

Recent firm-level data from 2020 showed that there were 104,281 small firms and 1,560 large firms. The TFP of small firms was lower by 2.715 log points compared to large firms, and this productivity gap exists in both the total sample and subsamples. The Oaxaca-Blinder decomposition results revealed that the structural effect played a more significant role in the TFP gap than the endowment effect. Most control variables contributed significantly to the productivity gap through the endowment. However, $\ln(\text{wage})$, innovation, and the export dummy were found to decrease the gap. Still, a large portion of the structural effect remains unidentified, which could be explored in future research to understand the contributing factors better.

The result of the thesis has shown that supporting and promoting export activity in small firms can significantly increase their total factor productivity. The study found that the impact of exporting on increasing total factor productivity is greater in small firms compared to large firms. This suggests that export activities can be used to reduce the productivity gap between small and large firms. Higher wages are a sign of higher qualifications, and the study found that small firms can benefit more from the return to wage than large firms. This helps to reduce the gap between small and large firms, so it is important to support policies that incentivize investment in skills, encourage the use of skilled labor, promote specialized and efficient work, and increase training opportunities. Another important factor that can decrease the gap between small and large firms is the age of the firm. The study found that small firms benefit more from the return to age than large firms, which helps to narrow the gap. Therefore, it is crucial to support the creation of new young firms to reduce the gap in total factor productivity between small and large Turkish manufacturing firms. Innovation activities were also found to narrow the gap between large and small firms in total factor

productivity, so it is important to encourage investment in research and development and human capital in small firms.

The thesis examines the role of small and young firms in generating employment. The study used data from 59,560 firms with at least two employees, resulting in an unbalanced panel dataset of 512,026 observations. The firms were categorized into eight size groups based on their number of employees in 2006 and seven age groups.

The study did not consider the impact of new firms entering the market each year. However, it did consider the exit of firms from 2006 until 2020. A firm was considered to be exited one if it stopped reporting any number of employees in the following years until 2020. Accounting for firm exit in the estimation helps to determine whether the changes in total employment growth come from continuing firms or the firms that exited before 2020.

The study used the Two-part model to investigate the survival probability of the Turkish manufacturing industry from 2006 to 2020. The exit rate was also estimated. The second part of the Two-part model, which is the marginal conditional mean of the OLS for the firms, displayed the growth rate of both surviving and exiting firms. The study found that larger and older firms have a higher probability of survival. Still, small and young firms (specifically micro firms with two employees and ages less than two years) that survived showed a higher growth rate than the largest and mature firms. This finding is consistent with previous studies. The study also revealed that most employment change occurs in firms that left the market before 2020. Therefore, considering firm exit is crucial when analyzing employment generation for the coming periods

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APPENDIX A: DESCRIPTION OF EIS DATASET

EIS “Entrepreneur Information System” or GBS as Turkish term “GİRİŞİMCİ BİLGİ SİSTEMİ” is a comprehensive dataset containing all the registered firms in Turkey. the dataset was gathered from eight different sources the Table 8 below shows detailed information. It's worth mentioning that the dataset is available in the Turkish language and the translation is an own effort.

Table 34

Description of EIS dataset

Source	Coverage Period	Unit Measurment	Information
Ministry of Finance	2006-2020	Firm-Level	Partenr ID, Value of Purchased/ Sold Goods/ Services above 5000TL, Time of Transaction
Ministry of Finance ¹	2006-2020	Firm- Level	ID, Detailed Balance Sheet, Income Statment
Social Security Institute	2006-2020	Firm- Level	ID, Activity Code (NACE 4 Digit), Year of Establishment, Center's Location
Social Security Institute	2006-2020 2014-2020	Worker- Level	Firm's ID, Worker's ID, Age, Gender, Working Days, Daily Wages, Number of Employees at 1 st , 2 nd , 3 ^{3r} and 4 th Quarters. Occupation after 2014.
Ministry of Customs and Trade	2006- 2020	Firm- Level Product-Level	ID, Activity Code(2 Digit), Exports/ Imports(Quantity, Value and Product Code(GTİP, ISIC Rev.4 and BEC))
KOSGEB ²	2010-2020 2011- 2020	Firm- Level	ID, Amount of Support Recieved (2011), Amount of Loans Obtained (2010)
Turkish Patent and Trademark	2010-2020	Firm- Level	ID, Number of Design, Patents, Models and Brands ³ .
Turkish Statistical Institute	2006-2020	Firm- Level	ID, Activity Code (NACE 4 Digit), Location.
Ministry of Industry and Technology	2012-2020	Product- Level	ID, Actual Production Quantities, According to PRODTR ⁴
Scientific and Technological Research Council of Turkey	2008-2020	Firm- Level	ID, Amount of R&D Support Given to Startups.
¹ this information available for, firms that either make purchases for amounts above TL160000 or make sales for more than TL 220000. ² Small and Medium Enterprises Development Organization. ³ Model and Patent according to IPC (International Patent Classification), Design according to LOCARNO (International Industrial Design and Brands according to NICE (International Goods and Trademarks for Trademark Registration). ⁴ Industrial Product List in the European Community.			

Table 35*Manufacturing NACE -Rev 2.2 digit subsector.*

10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c

29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installment

The definition of the technology level of firms` sector

. TECH, TECHM, TECML, TECL are the

☐ TECH: High-level it takes value one if the firm belongs to one of the following sectors:

- o Manufacture of basic pharmaceutical products and pharmaceutical preparations
- o Manufacture of computer, electronic and optical products

☐ TECHM: Medium-high it takes value one if the firm belongs to one of the following sectors:

- o Manufacture of chemicals and chemical products.
- o Manufacture of electrical equipment.
- o Other Machinery Manufacturing
- o Manufacture of Transportation Equipment.
- o Manufacture of other transport equipment.

☐ TECML: Medium-low it takes value one if the firm belongs to one of the following sectors:

- o Manufacture of coke and refined petroleum products.

- o Manufacture of rubber and plastic products.
- o Manufacture of other non-metallic mineral products.
- o Manufacture of basic metals.
- o Manufacture of fabricated metal products, except machinery and equipment.
- o Installation of Machinery and Equipment
- ☐ TECL: Low-level it takes value one if the firm belongs to one of the following sectors:
 - o Manufacture of food products
 - o Manufacture of beverages.
 - o Manufacture of tobacco products.
 - o Manufacture of textiles.
 - o Manufacture of wearing apparel.
 - o Manufacture of leather and related products.
 - o Manufacture of Wood and Cork Products (not Furniture)
 - o Manufacture of paper and paper products.
 - o Publishing and Printing.
 - o Manufacture of furniture.

APPENDIX B: SUPPLEMENTARY MATERIALS

Table 36

the Total factor productivity size gap 2006

Explanatory Variables	Endowment effect		Coefficient effect			
	The amount	% of TFP Gap	Usual.	% of TFP Gap	Normalized	% of TFP Gap
Capital Intensity	-0.0647	2.9%	-0.851	37.7%	-0.851	37.7%
wage	-0.405	18%	-0.167	7.4%	-0.167	7.4%
Age	-0.0961	4.3%	0.270	-12%	0.270	-12%
DTE	-0.0198	0.87%	0.161	-7.13%	0.161	-7.13%
Export	-0.344	15.25%	0.235	-10.43%	0.0992	-4.39%
Innovation	-0.1636	7.24%	0.451	-19.98%	0.2021	-8.95%
Technology level	-0.0076	-0.0033%	0.036	-1.60%	-0.1232	5.45%
Constant			-1.29	57%	-0.746	33.05%
Total	-1.101	48.78%	1.156	51.22%	1.156	51.22%
Remark TFP Gap = -2.257						

Source: EIS, own calculations using Oaxaca Blinder decomposition results

Table 37
the Total factor productivity size gap 2020

Explanatory Variables	Endowment effect		Coefficient effect			
	The amount	% of TFP Gap	Usual.	% of TFP Gap	Normalized	% of TFP Gap
Capital intensity	-0.0487	1.79%	-0.958	35.28%	-0.958	35.28%
wage	-0.538	19.81%	0.384	-14.14%	0.384	-14.14%
Age	0.00743	-0.27%	0.0113	-0.42%	0.0113	-0.42%
DTE	-0.0285	1.05%	0.0171	-0.63%	0.0171	-0.63%
Export	-0.442	16.27%	0.408	-15.04%	0.1618	-5.95%
Innovation	-0.179	6.59%	0.340	-12.54%	0.1643	-6%
Technology level	-0.0108	0.40%	0.0228	-0.84%	-0.0024	0.088%
Constant			-1.697	62.5%	-1.253	46.15%
Total	-1.240	45.7%	-1.474	54.3%	-1.474	54.3%
Remark TFP Gap = -2.715						

Source: EIS, own calculations using Oaxaca Blinder decomposition results.