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**A CROSS-COUNTRY ANALYSIS ON THE EFFECTS OF GREEN ENERGY
INNOVATION ON MANUFACTURING PERFORMANCE: EVIDENCE
FROM OECD COUNTRIES**

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DECLARATION

I hereby declare that this master's thesis titled as "A Cross-Country Analysis on The Effects of Green Energy Innovation on Manufacturing Performance: Evidence from OECD Countries" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honour.

27/07/2020

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ABSTRACT

Master's Thesis

A Cross-Country Analysis on the Effects of Green Energy Innovation on Manufacturing Performance: Evidence From OECD Countries

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Green innovations contribute to environmental sustainability by minimizing environmental pollution, decreasing resource use, and increasing energy efficiency. Therefore, in order to achieve environmentally sustainable economic growth, it is vital to embed green innovations into industrial processes. Despite its importance, there are relatively small numbers of studies in the literature that empirically examine the effects of green innovations on manufacturing performance. Moreover, there is no consensus in the existing literature on whether green innovations positively or negatively affect manufacturing productivity. Therefore, this thesis aims to extend the empirical research on the effects of green innovations on manufacturing productivity. To this end, data on green innovation and manufacturing productivity for seventeen OECD countries over the period between 1990 and 2016 is analyzed. Both panel VECM/VAR and time series Autoregressive Distributed Lag (ARDL) methodologies are employed. Results of panel data analyses suggest that green innovations have in most cases a negative and statistically significant effect on manufacturing productivity. Moreover, according to results of the time

series analysis on data of individual countries, while for most countries the effect is insignificant, we found evidence on significant effects of green innovation on manufacturing productivity for Japan, Germany, Italy, and France.

Keywords: Green Energy Innovation, Manufacturing, Productivity, OECD Countries, VECM, VAR, ARDL



ÖZET

Yüksek Lisans Tezi

**Yeşil Enerji İnovasyonun İmalat Performansı Üzerine Etkilerinin Ülkeler Arası
Analizi: OECD Ülkelerinden Kanıtlar**

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Yeşil inovasyonlar, çevre kirliliğini en aza indirerek, kaynak kullanımını azaltarak ve enerji verimliliğini artırarak çevresel sürdürülebilirliğe katkıda bulunur. Bu nedenle, çevresel açıdan sürdürülebilir ekonomik büyüme sağlamak için yeşil yeniliklerin endüstriyel süreçlere yerleştirilmesi hayati önem taşımaktadır. Bu önemine rağmen, literatürde yeşil yeniliklerin imalat performansı üzerindeki etkilerini ampirik olarak analiz eden nispeten az sayıda çalışma bulunmaktadır. Ayrıca, mevcut literatürde yeşil inovasyonların imalat üretkenliğini olumlu ya da olumsuz etkileyip etkilemediği konusunda fikir birliği yoktur. Bu nedenle, bu tez yeşil yeniliklerin imalat üretkenliği üzerindeki etkileri üzerine ampirik araştırmayı genişletmeyi amaçlamaktadır. Bu amaçla, 1990-2016 yılları arasında 17 OECD ülkesi için yeşil yenilik ve üretim verimliliği hakkında veriler analiz edilmiştir. Hem panel VECM / VAR hem de zaman serileri Otoregresif Dağıtılmış Gecikme (ARDL) yöntemleri kullanılmıştır. Panel veri analizlerinin sonuçları yeşil yeniliklerin çoğu durumda imalat verimliliği üzerinde olumsuz ve istatistiksel olarak anlamlı bir

etkiye sahip olduğunu göstermektedir. Ayrıca, zaman serisi analizinin sonuçlarına göre, çoğu ülke için etkisi önemsiz iken, yeşil yeniliğin üretim verimliliği üzerinde Japonya, Almanya, İtalya ve Fransa için önemli etkileri olduğuna dair kanıtlar bulduk.

Anahtar Kelimeler: Yeşil Enerji İnovasyonu, İmalat, Üretkenlik, OECD Ülkeleri, VECM, VAR, ARDL



**A CROSS-COUNTRY ANALYSIS ON THE EFFECTS OF GREEN ENERGY
INNOVATION ON MANUFACTURING PERFORMANCE: EVIDENCE
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ABBREVIATIONS

ADF	Augmented Dickey- Fuller
AR	Autoregressive Models
ARDL	Autoregressive Distributed Lag
ECT	Error Correction Term
EE	Energy Efficiency
EI	Environmental Innovation
EOP	End-of-Pipe
EPS	Environmental Policy Stringency
GE	Green Energy
IC	Industrial Competitiveness
IEA	International Energy Agency
I (0)	Integrated of order zero
I (1)	Integrated of order one
I (2)	Integrated of order two
IPS	Im-Pesaran-Shin
LLC	Levin-Lin-Chu
MFP	Multifactor Productivity
OECD	Organisation for Economic Co-operation and Development
RE	Renewable Energy
VAR	Vector Autoregression
VECM	Vector Error Correction Model

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INTRODUCTION

Increasing economic activities, such as industrial production, cause severe damage to the global environment (Stavropoulos et al., 2018: 1378). The channel through which industrial processes affect the environment is ever-increasing energy consumption, mostly in the form of greenhouse gas (GHG) emitting fossil fuels. In today's world, many scientists, economists, and policy-makers are trying to deal with the adverse effects of increasing GHG emissions, which are the main drivers of the recent global climate change (Yang et al., 2012: 514). These attempts have resulted in several international climate change initiatives and agreements such as the Kyoto Protocol in 1997 and the Paris Agreement in 2015. Within the context of these initiatives, many countries have started to adopt environment-friendly policies and regulations, which eventually promoted green innovation within the industrial sectors.

The developed nations built the foundations of the Kyoto Protocol upon the purpose of bringing the greenhouse gas emissions back to the levels of the 1990s. Although the Kyoto Protocol is turned out to be a failure, it has played an essential role in reshaping carbon emission reduction strategies and in promoting green Technologies to change the global warming trends. However, it is clear that the effect of the Kyoto Protocol is not the same across each nation. (Hashmi and Alam, 2019: 1100). Due to its failure, many nations came together to sign the Paris agreement, which aimed to keep the global average temperature rise well below pre-industrial levels of 2°C. This agreement was one of the best alternatives to understand a country's climate performance until 2020 (Wang et al., 2019: 611).

Environmental problems are complex topics that mostly arise due to market failures in various economic activities. Negative externalities created by economic activities lead to the exploitation of natural resources and indirectly cause environmental degradation. In other words, these economic activities add external costs to society through pollution. In line with their interests, individuals would overexploit the environment even more due to the lack of regulations. For this reason, governments need to enact environmental regulations in order to limit environmental externalities, to achieve green growth and to maintain environmental equality (Stavropoulos et al., 2018: 1378-1379).

Spulber (1989: 37) describes regulations as “general rules or specific actions imposed by administrative agencies that interfere directly with the market allocation mechanism or indirectly by altering consumer and firm demand and supply decisions.” The direct effect of regulation is observed in the firms’ and industries’ production levels because of the changes in the cost structure. Yet, this could also trigger innovative activities in the industry. For instance, as a result of such regulations, firms’ production levels are directly affected due to changes in the cost structure, to which firms respond by investing in R&D and possibly by innovating. Although environmental policies and regulations bring compliance costs to regulated firms, regulations could encourage innovations which improve the product quality and/or reduce production costs. As a result of the innovation, an increase in productivity is expected. This idea that the innovations triggered by the environmental regulations would have productivity benefits is now known as the Porter Hypothesis (Porter and van der Linde, 1995). Hence, in a case when the triggered innovations are in harmony with the costs of regulations, the firms’ efficiency will rise (Wang et al., 2019: 612).

Porter's hypotheses are classified as in three main groups, namely *weak*, *strong*, and *narrow*. The weak Porter Hypothesis implies that environmental regulations could encourage innovation. Hence according to the weak Porter Hypothesis, environmental regulations positively affect the innovative activities of the firm. Strong Porter Hypothesis, on the other hand, suggests that well-prepared environmental regulations would also increase industrial productivity through promoting innovation to balance additional regulation costs. According to the last group of the classification, namely "narrow", several kinds of environmental regulations would encourage innovation, which is related to the impacts of various environmental policies (e.g., market-based instruments and regulatory regulation). This version of the Porter hypothesis confirms that “flexible environmental regulations, such as market-based instruments, are found to be productivity growth friendly and to increase firms’ incentives to innovate, compared to prescriptive regulation, such as the command-and-control policy” (Jaffe and Palmer, 1997: 610; Wang et al., 2019: 612).

Whether or not environmental regulations cause a rise in industrial productivity, it is almost certain that they lead to innovations towards environmentally friendly technologies. In this regard, Rubashkina et al. (2015) studied strong and weak versions of the Porter hypotheses in their work based on the manufacturing industry of 17 European countries between 1997 and 2009. While they observed the positive effect of environmental regulations on innovation, they found no evidence on productivity. Hence his work supports the weak version of the Porter hypothesis. In parallel, De Vries and Withagen (2005) analyzed a positive relationship between environmental rigidity and innovation. They found evidence for the weak version of the Porter hypothesis. In addition, Lee et al. (2011) underlined that the government interference in the form of technology-compelling regulation leads firms to invest in technological innovation. Lanoie et al. (2011) studied different variants of the Porter hypothesis in their study, depending on 7 OECD countries. While they found significant and influential results for the weak version, they could not achieve significant evidence towards a strong version. Van Leeuwen and Mohnen (2017) analyzed the validity of the Porter Hypotheses based on Dutch data. According to their empirical results, environmental regulations have a direct and significant contribution to green innovations. In other words, while the existence of the weak Porter Hypothesis is mostly supported by the literature, the evidence in the literature towards the strong Porter Hypothesis is quite mixed. Hence, obviously, there is no consensus in the literature that green innovation leads to productivity.

Since the link between green innovation and industrial performance is very complicated, this thesis tries to contribute to the literature in this regard. Therefore, firstly, the definition and drivers of green innovation are given. Then, the effects of green innovation on productivity are examined. Then various empirical analyses are conducted on an unbalanced dataset of 17 OECD countries for the period 1990 – 2016. Multi-factor productivity is employed as an indicator to estimate the industrial performance due to the fact that it can be easily interpreted and is available for many countries in the world. On the other hand, environmental patents and green R&D expenditures are also used as a proxy for green innovation. OECD countries are preferred for the examination of this relationship. OECD countries have a large share in the industrial area and a substantial effect on the world economy. For these

reasons, it can be concluded that these countries could represent global results. Besides, researching the green innovations of OECD countries can make significant contributions to other countries. For this reason, three models are established for analyzing this relationship and the results are given for these three models. Panel analysis is used primarily for the analysis of this section. Accordingly, Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), Fisher-ADF, and Fisher-PP unit root tests are performed to determine the stability. Pedroni, Kao, and Johansen cointegration tests will be applied for analyzing the long-term relationship. It is established with the Vector Error Correction Model (VECM) and Vector Autoregression (VAR) model according to the existence of long-term relationships, and the Granger causality test is used for causality analysis. After the panel data methodology, time series analysis is used to further assess the result for each country. Short and long-term dynamics are examined with the Autoregressive Distributed Lag (ARDL) methodology.

The thesis is organized in the following way. In Chapter 1, the background and literature are examined. In this section, especially, the effects of the Porter hypothesis and the answer to the question of how green innovation emerged were discussed. In Chapter 2, the data set, methodology and empirical results are given. Finally, in the last section, general results and some policy implications are proposed.

CHAPTER ONE

BACKGROUND AND LITERATURE

1.1. DEFINITION OF GREEN INNOVATION

Although the term innovation has appeared in the early fifteenth century, its first modern interpretation was based on the writings of Joseph Schumpeter in the 1930s. “In 1934, Schumpeter added a definition of innovation or development, as *new combinations* of new or existing knowledge, resources, equipment, and other factors” (Shah et al., 2014: 3). According to Schumpeter, the notions of innovation and invention should be discriminated from each other. Inventions can implement anywhere and without a commercialization intention, while innovations are the process by which new ideas are produced and transformed into commercial practice (Shah et al., 2014).

Innovation is crucial since it generally leads to new business creation, which stimulates economic development or growth. While businesses benefit from this situation with increasing profits, the overall net effect of innovation is the growth in the national and global economy. Since Schumpeter (1934), various economists underlined that economic growth, which could not solely be explained by the traditional inputs such as capital and labor, might be attributed to increasing technological progress (see Solow, 1956; Barro and Sala-i-Martin, 2004; Acemoglu, 2009; Aghion and Howitt 2009, among others). Romer (1990) stated that the long-term growth model driven by the accumulation of knowledge can be seen as an equilibrium model of endogenous technological change. Several models used innovation as a proxy for technological progress in explaining economic growth dynamics. Verspagen (2005) mentioned that technological and organizational innovations are responsible for growth. Segerstrom (1991) showed that innovation subsidies obviously support economic growth. Hasan and Tucci (2010) underlined that innovations have a positive impact on economic growth by controlling innovation with patent data.

OECD (2005: 46) defines innovation as “the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or new organizational method in business, practices, workplace organization

or external relations.” Malerba (2002) also emphasizes that innovation should be seen as an interactive and collective process among various actors. In the innovative process, firms also engaged with universities, research centers, government agencies, financial institutions, and similar companies. According to Krugman (1979: 259), “innovation is the process by which new products are created.” Besides, Krugman (1979) divides the countries into two groups: innovative North and non-innovative South. He suggests that innovation activities are generally generated in the Northern hemisphere in the first stage, and are extended to the South after a certain lag. The delays in the acceptance of new technologies are what caused an increase in trade. In addition, he underlines that technical innovation is even more significant than it seems in conventional models. Developed countries must continuously innovate not only to grow but also to protect and sustain their real income (Krugman, 1979). Audretsch and Feldman (1996) state that innovation depends on new economic knowledge. They focus on spillovers of economic information among firms and suggest that these the spillovers have an important role in increasing returns and ultimately economic growth. Moreover, it is widely accepted that innovation should create value and competitive advantage for the innovator (Munodawafa and Johl, 2019). In general, it is seen that the definition and effects of innovation are very wide and important extensively in the literature.

There are also several definitions of green innovation in the literature. First of all, it can be observed that the terms green innovation, environmental innovation, and eco-innovation are used quite interchangeably.

By referring to Kemp and Pearson (2007: 7), OECD (2005) defines eco-innovation as:

the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organisation (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives.

Compared to the definition of eco-innovation, Oltra and Saint-Jean (2009: 567) describe environmental innovation as “innovations that consist of new or modified processes, practices, systems, and products which benefit the environment and so contribute to environmental sustainability.”

To define the notion of *green innovation*, Chen et al. (2006: 534) said that “hardware or software innovation that is related to green products or processes, including the innovation in technologies that are involved in energy-saving, pollution-prevention, waste recycling, green product designs, or corporate environmental management.”

To summarize, regarding the three concepts mentioned above, they contain very small differences in their definition. They review a similar issue in content and can often be employed interchangeably (Tietze et al., 2011). Therefore, throughout the thesis, I only use the term green innovation in order to avoid confusion.

The definition of green innovation is generally relevant for increasing the environmental performance of innovators. After the innovation, positive environmental effects should be observed in economic activities. (Kemp and Pearson, 2007). Related to this, Porter and van der Linde (2000: 33- 34) state that

Properly designed environmental standards can trigger innovations that lower the total cost of a product or improve its value. Such innovations allow companies to use a range of inputs more productively—from raw materials to energy to labor—thus offsetting the costs of improving environmental impact and ending the stalemate. Ultimately, this enhanced resource productivity makes companies more competitive, not less.

As a result, it can also create a positive impact on economic performance. Hence, a clear definition of green innovation requires explaining these effects explicitly (Kemp and Pearson, 2007: 5).

Moreover, green innovations may not necessarily cause an absolute decline in environmental harm often due to having a *rebound effect* during enhanced expenditure (Oltra, 2008: 2). The rebound effect which is generally known as Jevons paradox named after Jevons (1866) can be explained as follows; if a technology is replaced with a more environmentally friendly type, environmental damage is possible to decrease but in the event of extra capacity or use environmental damage may rise. Therefore, green innovation cannot be identified from the point of absolute environmental effect, but it can be identified regarding alternative technologies. Furthermore, to determine whether an innovation is a green innovation, the relevant criterion is the use of innovation, which will lead to the reduction of environmental harm compared to alternatives (Kemp and Pearson, 2007).

The extensive meaning of green innovation can have an effect on the concept of eco-industry. Eurostat and OECD define eco industries as “activities which

produce goods and services to measure, prevent, limit, minimize or correct environmental damage to water, air and soil, as well as problems related to waste, noise and eco-systems. This includes technologies, products and services that reduce environmental risk and minimize pollution and resources” (Ernst and Young, 2006: 8).

1.2. ORIGINS OF GREEN INNOVATION

The concept of green innovation can be extended to the notion of *appropriate technology* or *intermediate technology* proposed by Ernst F. Schumacher in the 1960s. The focus of this concept is to draw attention to minimize resource consumption and decreased environmental degradation (Hazarika and Zhang, 2019).

By the late 1960s, the link between sustainability and innovation began to attract the attention from the academia (Pansera, 2011). A significant contribution was made to the sustainability debate with the report entitled *Limits to Growth*, which was prepared by the Roman Club in 1972. In this report, the authors argued that economic growth could not continue infinitely due to the planet has limited carrying capacity (Meadows et al, 1972). At this point, to see how the notion of green innovation has evolved and to understand it better, O' Riordan's environmental discourse (from being techno-centric to ecocentric) can be explored. Techno-centrists believed in developing market-oriented technology development that would help sustainable development. “Scholars of the *neo-classical economics school* viewed technology as the solution for all sorts of environmental inadequacies and supported ecological modernization” (Hazarika and Zhang, 2019: 66). However, Solow, who is one of the key figures of the *neo-classical school*, remarked that technological progress could balance the boundaries of the natural environment through capital accumulation and rose productivity (Hazarika and Zhang, 2019). This has been criticized a lot, but it was crucial to trigger two main branches about the sustainability debate: Environmental Economics that focus on the environmental externality concept and Ecological Economics that focus on the economic system and nature. Consequently, there has been increasing interest in innovation studies and approaches to sustainability over the past three decades. For this reason, the concept

of innovation is essential in debates on sustainability and is generally suggested as a fundamental tool to drive the transition to a sustainable society (Pansera, 2011).

The notion of green innovation is also connected to the notion of sustainable development. Van Dieren et al., (1995: 88) state that

the first use of phrase 'sustainable development' in widely published document can be traced back to the 1980 'World Conservation Strategy' prepared by the three leading environmental agencies: former IUCN (now World Conservation Union), the United Nations Environment Program (UNEP) and The World Wildlife Fund (WWF).

Dresner (as cited in Pansera, 2011: 130) states that "the concept was first used in 1980 by the International Union for the Conservation of Nature and Natural Resources in their World Conservation Strategy Report." Despite this information, the concept of sustainability has not become a clear concept until today.

Ecocentrism view proposes to correct imbalances between humans and nature through advanced information and knowledge. The United Nations World Environment and Development Commission published the famous Brundtland Report report entitled *Our Common Future* in 1987, where there was a clear definition of the concept of the sustainable development. According to this report, technological innovations should be developed to reduce environmental impacts. Thanks to the United Nation's (UN) Brundtland Report, the thought of sustainable development has expanded all over the world. The main idea underlying Sustainable Development is that socio-technological changes can extend the boundaries of environmental restrictions (Pansera, 2011). The Brundtland report is accepted as eco-centric but lends towards being more tech-centric (Hazarika and Zhang, 2019). The Brundtland Report decomposes environmentalism into two different currents. It creates a more apparent distinction: "cult of wilderness" appertaining to the protection' wild nature, and "the gospel of eco-efficiency" to improve energy and material use efficiency (Martinez, 2002: 40-43).

Besides, the eco-centric school has attached importance to the use of technology that minimizes resource consumption. Raising energy efficiency is one of the most critical issues of this school. By moving the discourse of ecocentrism forward, ideas about transformative changes such as the application of renewable energy at a larger scale and the reduction of environmental footprint have emerged. It is emphasized the environmental performance of innovation analyzed by

evolutionary theory. Moreover, government intervention is an essential factor in ensuring sustainability (Hazarika and Zhang, 2019). At this point, Porter and Linde argued that “properly designed environmental standards can trigger innovation that may partially or more than fully offset the costs of complying with them” (Porter and van der Linde, 1995: 98).

Thus, the green innovation term was born in this theoretical process based on the positivist belief in technology (Pansera, 2011). After a while, it was noticed that green innovations formed external costs, in smaller amounts, in both innovation and diffusion phase. It was pointed out that this problem, which is named the double externality problem in green innovations, requires government intervention. For this reason, green innovations have been criticized even more for not being able to cope with social and institutional dimensions. In this context, Rennings (2000) also offered organizational, social, and institutional green innovation concepts.

1.3. DRIVERS OF GREEN INNOVATION

Studies that have been carried out in the scope of innovation and environmental economics mainly aim to identify the drivers affecting green innovation (Kesidou and Demirel, 2012). In the context of green innovation, Bleischwitz et al., (2009: 27) states that “drivers are generally understood as specific and evident agents or factors leading to increased or reduced pressure on the environment.” At this point, the purpose is to examine potential mechanisms to provide new information about the driving forces of green innovation and explain various kinds of green innovation. In this context, both neoclassical and environmental approaches are included to identify potential factors affecting green innovation decisions (Triguero et al., 2013). In the late 1990s, empirical analysis began to appear on the driving forces of green innovations. Many researchers employed research to determine both the environmental impact of firm' activities and environmental management strategies. Besides, several companies have used in green innovation activities for many different reasons (Sanni, 2018).

In a broad sense, drivers of green innovation can be classified in three groups namely demand-side, supply-side and environmental policy related as in Table 1.

This classification concerns the environmental policy and institutional framework of technological push and demand-pull factors. There seems to be a consensus among the researchers that demand factors have a more significant role in the diffusion stage, while technology push elements are particularly significant during the first stage of constructing a new product. When evaluated in general, market pull factors and technology push factors are defined as the major driving forces of innovation in traditional innovation. However, it should also regard the impact of environmental policy and other institutional factors (Horbach, 2008; Triguero et al., 2013).

Table 1: Drivers of Green Innovation

Supply Side	◦Technological Capabilities ◦Appropriation Problem and Market Characteristics
Demand Side	◦ (Excepted)Market Demand ◦Social Awareness of The Need for Clean Product: Environmental Consiousness and Preferences for Environmentally Friendly Product
Institutiona and Political Influnces	◦Environmental Policy ◦Institutional Structure

Source: Harbach (2008)

Considering the studies carried out in the field of innovation, especially the demand factors were emphasized in the production of green innovation. According to studies that impact on manufacturing companies within the context of technological and organizational capacities are thought to play an essential role in promoting green innovations (Kesidou and Demirel, 2012). Moreover, Sanni (2018) mentions the importance of environmental regulations and policies as the drivers of green innovation for manufacturing firms.

In the next part of the thesis, various factors of the existing green innovation theory are used to define the drivers of green innovation.

1.3.1. Supply Side Drivers

Green innovations generate “products and services which cause positive (or less negative) externalities on environment compared to alternative production processes” (Triguero et al., 2013: 27). Innovation literature dealing with green innovations has indicated rising investments in green innovation are motivated at the firm level according to their technological capacities. Therefore, technological capabilities are the main drivers of green innovations (Kesidou and Demirel, 2012; Triguero et al., 2013). Horbach (2008: 164) states that “these capabilities comprise the physical and knowledge capital stock of a firm to develop new products and processes.” If a firm has advanced innovation capabilities, that firm can further innovate in the future. “In particular, those firms that build organisational capabilities and practices such as source reduction, recycling, pollution prevention, and green product design are more likely to invest” in green innovation (Kesidou and Demirel, 2012: 863).

Empirical evidence has confirmed that the technological capabilities and knowledge stocks are necessary for the evolution and spread of green innovation (Sanni, 2018). Based on an empirical study on German firm-level panel, Horbach (2008) underlined that increasing technological capabilities through R&D activities, positively affect green innovations. Based on this, Kammerer (2009: 2287) states that the concept of green capabilities as “firm's knowledge of environmental issues relevant to its business and procedures implemented to act and react on these issues”, is important internal factors for firms. Furthermore, companies' skills, knowledge, and connections with other companies have an important role in the improvement of the green innovation process. Besides, some authors state that external networking is a crucial factor that could increase the firms' tendency to innovate only if the firm exhibits an in-house R&D capacity to be able to internalize the external knowledge (Sanni, 2018; Triguero et al., 2013).

According to Sanni (2018: 306), “knowledge is one of the basic ingredients for innovative activities which are often specific to sectors and firms.” Moreover, Rennings and Rammer (2009) suggested that the source of knowledge capital for innovation came from a variety of sources, such as suppliers, competitors,

universities, public research institutes, scientific publications, and industry associations. Furthermore, the sources of knowledge have a variety of effects on the firm's tendency to recognize green innovation and on different green innovation portfolios. To illustrate, although many of the comprehensive interactions are beneficial for the firm, internalizing comprehensive acquired knowledge can be difficult (Sanni, 2018).

Generally, technological and managerial capabilities increase green and non-green innovation process. For this reason, all assets such as knowledge, skills, and connections with other companies that enable companies to make process innovations should be considered. In particular, “the availability of environmentally concerned/trained human resources (managers and employees)” essential in the development or advancement of green innovation processes (Triguero et al., 2013: 27). In addition, technical information obtained from external sources such as suppliers, universities or independent users also plays an important role.

According to Del Rio (2005), green technologies that contribute to sustainability are generally accepted by firms and are useful in the diffusion process. The green innovation process is generally grouped into two technologies. These are clean technologies and end-of-pipe (EOP) technologies. Del Rio (2005) defines the EOP technologies as “are devices or plants added at the end of the production process with the aim to transform primary emissions into substances easier to handle.” The author also represents cleaner technologies as “are change in production processes that reduce the quantity of wastes and pollutants generated in the production process or during the whole life cycle of the product.” Both technologies include capital expenditure. “While EOP (incremental) probably does not guarantee a reduction of production costs per unit, clean technologies (radical) can improve the efficiency of production process by reducing the consumption of materials and energy improving the firm's productivity and competitiveness” (Triguero et al., 2013: 27). In other words, when the cost increase arising from the adoption of clean technologies is balanced with the increase in revenues, the productivity and competitiveness of firms increase. However, the same situation cannot be thought of for EOP technologies (Del Rio, 2005).

Cost-saving methods, such as usage of materials and energy, are also significant elements in order to interpret the green innovation process. Applying the green innovation process often requires additional investments, but it often raises green productivity. The primary origins of this green productivity are the decrease in required inputs (such as energy and materials). Therefore, the cost-saving advantages of green innovation processes and recycling (EOP technologies and cleaner) activities are important in this process. Despite the significance of the supply side, these environmentally friendly processes are directly relevant to the company's image and reputation. Additionally, the adoption of environmentally friendly processes is generally a prerequisite for green product innovations (Triguero et al., 2013).

1.3.2. Demand Side Drivers

When looking at the innovation literature, theoretical studies focus on the significance of demand-pull elements for innovations. It is seen that both producers and consumers are involved in the innovation process. For this reason, innovations are now considered as an interactive and cumulative process that evaluates technology's push and market pull as a whole (Kesidou and Demirel, 2012). There have been studies demonstrating that demand-pull factors are essential in supporting green innovation. Horbach (2008) shows that demand is a significant determinant for green innovations in German manufacturing companies. Wagner (2007) also mentions the significance of interaction with stakeholders for green innovation. He shows that collaboration with concerned environmental stakeholders plays an essential role in the production of innovative green products using data on German manufacturing firms.

Studies are showing that demand-side elements are crucial determinants of green innovation. Green et al. (1994) stated that companies are trying to raise their market share by launching green products. Moreover, demand-pull factors- are encouraged or strengthened by environmental regulations such as taxes and subsidies- which can influence the customers' internal and external motivation (Sanni, 2018). The government also supports green innovations using *green*

purchasing plans, and there is an increase. “Overall, this evidence pinpoints that demand factors and in particular, calls for corporate responsibility and consumer demand for environmentally friendly products and processes, will affect the decision of the firm to invest” in green innovation (Kesidou and Demirel, 2012: 863).

Demand from consumers, public procurements, other firms, and exports are essential in the diffusion of green products. At this point, environmental awareness, which can be interpreted as an environmentally oriented demand-pull effect of consumers and companies, is an important variable for the diffusion of green innovations and green products (Horbach, 2008). “From a public choice perspective, the environmental awareness of the population becomes even more important because environmentally sensitive citizens may put more pressure on governments to pass stricter environmental regulations” (Horbach, 2016: 4).

However, environmentally friendly products should be noticed by consumers. This issue is linked to the firms' image, and reputations depend on green products (Triguero et al., 2013). Green labels allow companies to use their environmental performance. At this point, firms use marketing strategies by diversifying their products to achieve a competitive advantage (Rennings, 2000). Using the green image will raise the benefits since it leads to increases in sales or the price of products. If the consciousness of consumers and stakeholders about green products is increased by using green labels, an expectable rise in market demand can be observed. This may enhance green product innovation in both *old* and *new* products. Firms try to produce and offer greener products not only to become different from other companies but also to gain market share. Moreover, Triguero et al. (2013) underlined that the expectation to extend its market share with new *green* products is the most critical factor in explaining the implementation of green product innovations.

1.3.3. Environmental Policy Influences

There is not much consensus on the definition of regulation. Nevertheless, generally speaking, regulation is a sustained and focused control applied by the government on activities valued by a society (Sanni, 2018). The reason for choosing

this definition is its suitability for green innovation discussions. There may not be a clear market incentive in order to enhance new products that do not damage the environment since the required cost for green innovations is high. Hence, (environmental) policy measures and institutional determinants could play a crucial role in achieving green innovations (Horbach, 2016). Most of the studies in the environmental economics literature have mentioned the effectiveness of different policy measures, namely regulations and market-based instruments, to restrict the firms' pollution activities (see for instance, Kesidou and Demirel, 2012). In many empirical studies, regulations have been recognized as an essential driver of green innovation and effect on innovations are generally identified as the *regulatory push/pull effect* (Rennings, 2000: 330). Therefore, imposing environmental regulations is an important way to encourage green innovations (Brunnermeier and Cohen, 2003).

In empirical studies, it can be seen that green innovations increase as more stringent environmental regulations increase. It is also underlined that the country's level of development has important place in the rigidity of environmental regulations. Green innovations react to national or local regulations, which mean that environmental regulations can be expected to be tight to encourage green innovations. In another point of view, higher levels of environmental tightness can enhance green innovation in less innovative companies that adopt green innovations to reduce production costs. On the other hand, more innovative companies may not react to environmental tightness, as they already comply with the new regulations. However, these companies can also increase their green innovation investments due to strategic reasons (such as market advantage). To summarize, according to these results, it can be seen that the tighter regulations do not influence green innovation companies' investments in the same way (Kesidou and Demirel, 2012).

In addition, there are opposed opinions on the role of environmental regulation on firm's performance. When a firm meets strict environmental regulations, it is thought that there will be increase costs that the firm will incur, hence reduce its competitiveness and efficiency. In other words, firms will need to redistribute available labor and capital resources. As a result, firms' ability to compete at the national and international levels can be prevented (Sanni, 2018).

Porter and van der Linde (1995, as cited in Sanni, 2018: 305) underlines that “appropriately designed environmental regulations have the ability to promote environmentally-friendly innovation and in the process create win-win opportunities which result in increased productivity and a greener environment.” Porter initially tested this hypothesis. In the literature, there are three versions of the Porter Hypotheses. Jaffe and Palmer (1997) underline the weak version of the Porter hypothesis that regulations will only encourage particular kinds of innovation and the strong version of the Porter hypothesis will increase firm competitiveness and productivity. Finally, the narrow version of the Porter hypothesis is not clear on empirical implications regarding existing regulations. The famous Porter hypothesis (Porter and van der Linde, 1995) assumes that the pollution will be reduced and profits will be increased. In addition, the Porter hypothesis mainly depends on the evolutionary innovation theory. This theory states that firms use basic rules for innovation behavior owing to the significant uncertainties regarding the achievement of R&D (Horbach, 2008). Therefore, innovation activities are not the result of an optimization process. As a result, the idea underlying the Porter hypothesis is the *win-win* situation. In other words, “regulations can force firms to invest in environmental research and development in order to cut down the costs of complying with environmental regulation standards” (Kesidou and Demirel, 2012: 864). As a result of green innovation companies would experience decreases in the manufacturing costs and would enter to new markets for green products. For this reason, regulations may be the only way to move towards green technologies (Kesidou and Demirel, 2012).

1.4. LITERATURE

1.4.1. Literature on the Impact of Environmental Regulation on Innovation and Productivity: Porter Hypotheses

There are many studies on environmental regulation in the literature. Many of these studies are based on the Porter hypotheses and on the effects of environmental regulations on both innovation and productivity.

In studies examining the relationship between environmental regulations and productivity, there is evidence that environmental regulations increase productivity. Stavropoulos et al. (2018) try to demonstrate the effects of environmental regulations on industrial competitiveness (IC) for China and suggest that there exists a U-shaped relation between the two. According to this result, the traditional hypothesis shows that when the regulations are lax, it fits the situation first; afterward the critical point, Porter's Hypothesis kicks in. Therefore, they say that only strict regulations that exceed the critical level can have a positive impact on the IC. Despite this effect, China's development is still unstable. For this reason, Stavropoulos et al. (2018) suggest that the Chinese government should adopt market-based instruments. They also advocate that the long-term influence is positive as long as the regulations are properly designed. According to them, the government should implement stringent environmental regulations. Wang et al. (2019) examines the impacts of environmental policy tightness on green productivity growth in industry sectors based on OECD countries. The study examines the strictness of environmental regulation the growth of green productivity by applying the Slack Based Model-Directional Distance Function (SBM-DDF) approach on a panel of 24 OECD countries between 2004 and 2010. Environmental Policy Stringency (EPS) analysis of the study shows that the level of general regulation became stricter in 2012 than in 1990, and there were important differences among countries. Efficiency change is the primary cause of green productivity growth in OECD countries. There is a positive relationship between environmental regulations and green productivity growth. Hence there is evidence for the strong version of the Porter hypothesis. This effect is observed if the environmental tightness level is below a certain level (lower than 3.08). Otherwise, the relationship reverses. They also underline that environmental regulations are useful mechanisms to encourage green growth in OECD countries. Yang et al. (2012) examine whether strict environmental regulations cause more R&D and support Taiwan's productivity depending on panel data for the country's manufacturing industries between 1997 and 2003. They confirm that there is a significant positive relation between pollution abatement fees and R&D expenditure. They say that the indirect impacts of higher strict environmental regulations on productivity need to be examined in more detail. It also shows that environmental

R&D contributes substantially to manufacturing production. Nevertheless, the efficiency impact of induced R&D is less effective than normal R&D. Yang et al. (2012) that a win-win condition can only be achieved if there are well-prepared environmental regulations as a result of the study.

In some of the studies on the impacts of environmental regulations on productivity and R&D, no significant relationship was found. For example; Yuan and Xiang (2018) analyzed the effect of environmental regulation on industrial innovation inputs and outputs in the 2003-2014 periods, using the expanded Crépon-Duguet-Maire (CDM) model in Chinese manufacturing industries. By examining the effects of environmental regulation on various innovation outputs of the manufacturing industry, they reveal that the Chinese manufacturing industry's innovation behavior has changed in response to environmental regulations. They analyze the presence of a long-term relationship with the Cointegration Test. It reveals that environmental regulation prevents patent output, and thus the *weak* version of the Porter hypothesis is not supported. The study enhances the *strong* version of the Porter hypothesis. In the short term, environmental regulations support productivity in the manufacturing industry, except green total factor productivity (GTFP). Moreover, environmental regulations only increase energy efficiency whereas preventing labor productivity in the long run. Kneller and Manderson (2012) conducted the drivers of innovation activity in a panel study on 25 manufacturing industries in the United Kingdom between 2000 and 2006 using generalized moments method (GMM). They found that environmental R&D and investment in environmental capital is further encouraged by pollution abatement pressures. Hence, Kneller and Manderson (2012) have found an indication of the Porter Hypotheses' presence. Accordingly, they state the requirements of environmental regulations for the industry's innovation activities. Nevertheless, environmental compliance costs have no positive influence on total R&D or total capital accumulation. In other respects, they said that environmental capital expenses do not crowd out other capital expenses, and may complement them.

In addition, Hashmi and Alam (2019) investigated the impact of both environmental regulation and innovation on carbon emission between 1999 and 2014 for OECD countries. They tested the effects of environmental regulations and

environmentally friendly technologies with the GMM model in their studies. This analysis made in 29 OECD countries found that a 1% rise in environmental patents decreased CO₂ emissions by 0.017% and confirmed that a 1% rise in environmental tax income per person reduces CO₂ emissions by 0.03%. They advocate the importance of regulations and environmental technology on reducing CO₂ emissions. Hashmi and Alam (2019) also underlined that adopting *green technology* instead of *environmental technology* is an important factor in reducing carbon emissions. Therefore, OECD countries can regulate clean production conditions for firms in order to innovate on green technologies.

1.4.2. Literature on Impact of Green Innovation on Productivity

Although the literature generally concentrates on the relationship between innovation and productivity, not much consideration has been paid to green energy innovations, their impacts, and the relationship between green innovation and productivity or economic performance. However, in recent empirical studies, green innovations have become an important topic. For this reason, this literature can help to answer the debated questions about whether productivity or economic performance will increase by making green innovations.

Aldieri et al. (2019) examined the effects of environmental innovations on productivity in 85 regions of Russia between 2010 and 2015. To measure the clean innovation, they assessed the share of organizations that are primarily concerned with environmental innovation and decreasing the footprint of CO₂. The results of their work show that clean innovations have a lower efficiency than dirty ones due to the high compliance costs. Nevertheless, in the long run, they observed that clean innovations have been shown to increase productivity in Russian regions. The authors suggest that policymakers can apply opportunity taxes to increase effective environmental performance. Moreover, they also stated that direct and indirect subsidies could have positive impacts on the economic system in general to encourage the founding of innovation in clean technology. Lee and Min (2015) analyzed the effects of green R&D investment on environmental and financial performance on eco-innovation. The study is carried out in Japanese manufacturing

firms for the period 2001- 2010. The impact of R&D, especially green R&D investments, on environmental and financial performance, was examined. Green R&D was used to measure environmental performance. The results reveal that the firms' green R&D investment reduced carbon emissions and increased its firm value. In other words, they mention that there is a negative correlation between green R&D investment and carbon emissions and green R&D investment is positively associated with firm-level financial performance. They also emphasized that green R&D investment provides environmental performance and financial performance. Küçükoğlu and Pınar (2015) try to examine the impacts of green innovation on environmentally sensitive firm performance. Based on the records of the Istanbul Chamber of Industry, a survey was conducted for the top 500 firms in order to observed the relationship between green innovation and environmentally friendly firm performance. Correlation and regression analyses were employed with the data obtained from the survey study. Accordingly, they found a meaningful relation between green innovation and environmentally friendly firm performance. They also underline that green innovations have an effect on both a firm's environmental performance and competitive advantage. According to the results obtained in this context, the impact of green innovation on environmental performance is higher than its competitive advantage. Besides, they suggest that green innovation activities are the most suitable possible in ISO 14001 certified firms. Bai et al. (2019) investigate the effects of government R&D subsidies on green innovation of energy-intensive firms. Their work was analyzed according to the Heckman two-step approach in China's energy-intensive firms between 2010 and 2015. According to the results of their work, factors such as innovation inputs, income, tax level are the main determinants affecting energy-intensive companies receiving government R&D subsidies. Besides, their results explain that government R&D subsidies significantly promote not only green innovation of state-owned businesses but also non-state businesses. “The green innovation tendency of the subsidized state-owned enterprises and the subsidized non-state-owned enterprises has increased by 105.92% and 84.14%, respectively, and the green innovation performance has increased by 90.88% and 51.81%, respectively” (Bai et al. 2019: 828). In addition, they argue that government R&D subsidies encourage green innovation, especially in energy-

intensive firms and the government must inject abundant R&D subsidies to energy-intensive firms in order to achieve green development in China. Moreover, Bai et al. (2019) underline that green innovation provided by government R&D subsidies is more effective in SMEs and state-owned enterprises. Feng and Chen (2018) studied the impact of environmental regulation on both green innovation and industrial development for 30 provinces in China between 2007 and 2015. They stated that environmental regulation and green innovation are the most important points for realizing the green transition of industrial development. They provided an analysis of this relationship by applying the Spatial Durbin Model (SDM). According to the results, the six regions of China exhibit a better improvement in green industrial development. The effect of various types of environmental regulation on industrial development varies across regions. Under environmental regulation restrictions, there is a positive relationship between environmental regulations and industrial green development. For these reasons, Feng and Chen emphasize that the government should implement environmental policy, and these policies can be determined differently in different regions of China. In addition, they also point out that more comprehensive projects are needed to promote businesses to maintain green product innovation. Brunel (2019) claims that environmental policies encourage domestic economies. To analyze this, he observed 31 OECD countries between 1988 and 2003. In the first step, Brunel observes that renewable energy policies caused a 30% rise in the patent application and some of them produce by domestic inventors. In the second step, he observed that the domestic production for export developed after the technology acceptance and this was more evident especially for the wind industry. The evidence implies that renewable policies in the OECD promote the economy during manufacturing. Stucki (2019) investigated the relationship between the energy costs of a firm and the efficiency effects of investments in green energy technologies in the light of firm-based data of Austria, Germany and Switzerland. The focus of his work is energy-saving technology and energy use technology from renewable sources. He analyzed with OLS method in the 2012-2014 period. Different results have been observed for companies with different energy costs. The impacts of investment in green energy technologies on productivity are positive, ineffective and negative, respectively, for companies with

high, medium and low energy costs. This impact is positive for 19% of companies with the highest energy costs. For this reason, Stucki stated that government interventions are also needed for companies with high energy costs. Stucki also emphasizes that subsidies can be more effective for companies with average energy costs and regulations that enhance their investments in green energy technologies may be appropriate for companies with high energy costs. Moreover, he suggests that the group most distant from those political interventions should be the companies with the lowest energy costs. Brunnermeier and Cohen (2003) explore the relationship between environmental innovation and pollution abatement pressures. They conducted their analysis for 46 US manufacturing industries between 1983 and 1992 by using a panel dataset. They said that the rise in pollution abatement expenditures caused a significant rise in environmental innovation. According to them, these outcomes are compatible with previously limited empirical proof on patents and the innovation process formulated by Schumpeter. They also mentioned that industries having high PACE may push firms in that industry to investigate more environmental patents.

In contrast the above-mentioned studies, some empirical studies have not observed a significant and positive correlation. For instance, Marin (2014) investigates the determinants of environmental innovations and their efficiency in Italian manufacturing companies in the period 2000-2007. The author uses the CDM model, which defines innovation patterns consistent with expectations. There is evidence of an essential bias in environmental innovation for polluting firms. According to his results, environmental innovations have a significantly lower return than non-environmental innovations. This result is a possible proof of avoiding environmental innovations despite of non-environmental innovations. Kruse (2016) observed the effects of innovation in green energy (GE) technologies on companies' economic performance and compared the effects of GE innovation and non-GE innovation. GE innovations are examined innovation under two titles, Renewable Energy Sources (RES) and Energy Efficiency (EE) technologies. In his work, there was a panel dataset consisting of 8,619 patent companies which were 968 GE patents in 22 European countries between 2003 and 2010. Kruse finds that there is a negative relationship between firms' economic performance and GE technologies.

Furthermore, non-GE technologies have a positive impact on firms' economic performance. Also, according to his results, he reveals that the negative impacts on firm performance are more evident for RES than EE technologies. Besides, the negative effect of GE innovation on performance has been more reliable with the larger time lag among them. On the other hand, he said that GE innovation's marginal costs have diminished and the demand for GE innovation has grown in the progress of time. In addition, Kruse thinks that contributes existing literature by finding solutions on how innovation in GE technologies affects the economic performance of companies and underlines that the policy intervention aimed at increasing the private returns of GE innovation will be an argument to promote socially beneficial green growth. Soltman et al. (2015) examined the relation between green inventions and performance in the manufacturing industry. They found a U-shaped relationship between the intensity of green inventions and performance. Hence, they conclude that the relationship is negative for industries with a low level of green innovation stock and only industries with an extensive accumulation of green inventions are possible to present a positive impact on their performance.

To summarize, the literature so far does not have a consensus on whether or not the green innovation positively affect industrial performance. This thesis aims at contributing to the literature by re-assessing the impacts of green innovation on productivity. As explained in the upcoming chapters I use a panel dataset on 17 OECD countries over the period of 1990-2016 to test the hypothesis that green innovations positively affect the industrial productivity.

CHAPTER TWO

DATA, METHODOLOGY AND EMPIRICAL FINDINGS

2.1. DATA

Since the primary aim of this thesis to evaluate the relationship between green innovation and productivity, it is important to clearly explain how these two variables are measured before the details of the modeling approach employed.

First of all “productivity is efficiency in production: how much output is obtained from a given set of inputs. As such, it is typically expressed as an output–input ratio” (Syverson, 2011: 329). Even though there is no discussion about this general concept, it is revealed that productivity has neither a unique purpose nor a single measure considering the various literature and resources related to it. While there are several methods to measure productivity, the research question and the data availability would be the main drivers behind the actual choice of measurement method. When it comes to industrial productivity the literature generally uses. Two types of productivity measures, namely single-factor productivity and multifactor productivity (OECD, 2001). “Single-factor productivity is a synonym for partial productivity measure. It relates output to one particular type of input” (OECD, Stat.-Portal, 2001). On the other hand, “the multifactor productivity (MFP) relates a change in output to several types of inputs” (OECD, 2001: 124). “Multifactor productivity measurement helps disentangle the direct growth contributions of labour, capital, intermediate inputs and technology. This is an important tool for reviewing past growth patterns and for assessing the potential for future economic growth.” The MFP measurement highlights the importance of productivity change that promotes output growth (OECD, 2001: 20). Hence, this thesis uses the MFP as the dependent variable¹.

MFP indicates the overall efficiency of the production process when all the inputs are considered together (OECD, 2020). According to OECD (2020), “growth

¹ The dataset used to measure manufacturing performance in this periods, is not available. There is too much missing data in some periods. In addition, the correlation between manufacturing productivity and multifactor productivity variables are very high. That's why multifactor productivity is used as a proxy to control manufacturing performance.

in MFP is measured as a residual, i.e. that part of GDP growth that cannot be explained by changes in labour and capital inputs. In simple terms therefore, if labour and capital inputs remained unchanged between two periods, any changes in output would reflect changes in MFP.”

Fundamental data on multi-factor productivity comes from the Organisation for Economic Co-operation and Development Database (OECD).

This dataset provides comparable rates of change of Multi-factor Productivity for the total economy, computed as the difference between the rate of change of output and the rate of change of total inputs; shares of compensation of labour input and of capital inputs in total costs for the total economy measured at current prices and total inputs calculated as volume indices of combined labour and capital inputs for the total economy (OECD, Stat., 2013).

This indicator is measured as an index with 2010 as the base year (2010=100). According to OECD, Stat., (2013), “the indices have been constructed as weighted averages of the rate of change of total hours worked and the rate of change of capital services. Cost shares of inputs averaged over the two periods under consideration serve as weights.”

The second variable of interest is the green innovation, which is defined in the previous section. Considering the literature, two proxies are used to control for green innovation: the number of environmental patents and green R&D expenditures as a share of GDP. These two proxies are later used in two different models as independent variables.

Environmental patents data are compiled from the OECD’s Database.

In collaboration with the Directorate for Science, Technology and Innovation, has developed patent-based innovation indicators that are suitable for tracking developments in environment-related technologies. The indicators allow the assessment of countries' and firms' innovative performance as well as the design of governments' environmental and innovation policies. The patent statistics presented here are constructed using data extracted from the Worldwide Patent Statistical Database (PATSTAT) of the European Patent Office (EPO) using algorithms developed by the OECD (OECD, Stat., 2019).

The relevant patent documents are defined as environmental technologies (ENV-TECH) and have been specially developed for this purpose.

Data characteristics are presented by three kinds of patent-based proxies. These are indicators of technology development, international collaboration in technology development and technology diffusion. The indicator of technology development was examined for this study. According to OECD, Stat. (2019), this indicator is “number of inventions (simple patent families) developed by country's

inventors, independent of the jurisdictions where patent protection is sought (i.e. all known patent families worldwide are considered).”

The unit of patent data is provided in numbers. Fractional counts are computed based on the country of residence of the inventor (s). For example, for the patent that lists an inventor from two different countries, each country will receive the number 0.5 in order to prevent double-counting. Also, the size of the patent family relates to the value of the invention: “family size 1 and greater (i.e. all patent priorities) will yield figures based on all available data worldwide, including many low-value inventions” (OECD, Stat., 2019). Therefore, *1 and greater* was selected which includes all environmental patents as family size.

Data on R&D expenditures moreover is obtained from OECD but the source of the data is provided as the International Energy Agency (IEA). “Energy RD&D covers research, development and demonstration related to the production, storage, transportation, distribution and rational use of all forms of energy.” All of IEA's RD&D data focus on providing energy, transporting energy, using energy, and increasing energy efficiency (IEA Report, 2011: 16).

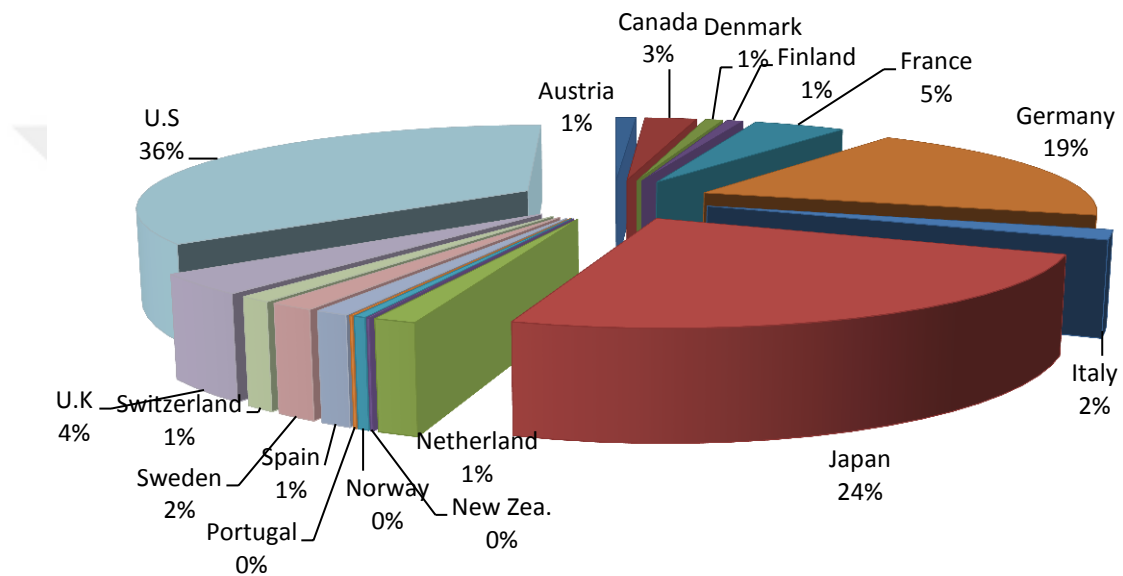
This includes all RD&D programmes that concern one of the following seven main branches of energy-related developments, as collected by the IEA, which are: (i) energy efficiency; (ii) fossil fuels (oil, gas and coal); (iii) renewables; (iv) nuclear fission and fusion; (v) hydrogen and fuel cells; (vi) other power and storage techniques; and (vii) other cross-cutting technologies or research (IEA Report, 2011:17).

As mentioned above, energy R&D expenditures are grouped under seven topics. Two of these could be considered as green R&D expenditures: Renewable Energy (RE) expenditure and Energy Efficiency (EE) expenditure. Hence in this thesis, these two will serve as a Proxy for green energy R&D expenditures.

According to IEA (2019), “the energy technology RD&D budgets database includes data on budgets in national currencies (in nominal and real prices), in USD (at latest year prices and exchange rates), in USD (at latest year prices and PPP) and in Euro (at latest year prices and exchange rates).” USD (last year prices and exchange rates) was chosen as the data. This dataset has been converted from the current prices in national currencies to US dollars at constant 2019 prices using GDP deflators and the 2019 exchange rate.

This thesis uses a panel dataset on the above-mentioned variables for 17 OECD countries over the period between 1990 and 2016.² Unfortunately, due to restrictions on the data availability only OECD countries could be included in the final data set. Moreover, since in several OECD countries there has been a lot of missing data, only 17 OECD countries could be selected.

Figure 1: The share of each country in cumulative environmental patents of 17 OECD countries over the period 1990-2016



In Figure 1, the ratio of each country in total cumulative environmental patents generated within 17 OECD countries from 1990 to 2016 is given. While the USA, Japan, and Germany seem to have largest proportions, there are much lower rates in other countries. Moreover, when all countries considered together, environmental patents constitute only 8% of total patents.

² The countries are (sorted by country code): Austria (AT), Canada(CA), Denmark (DK), Finland (FI), France (FR), Germany (DE), Italy (IT), Japan (JP), Netherlands (NL), New Zealand (NZ), Norway (NO), Portugal (PT), Spain (ES), Sweden (SE), Switzerland(CH), United Kingdom (GB) and United States(US).

Figure 2: The share of each country in cumulative Renewable Energy R&D expenditures of 17 OECD countries over the period 1990-2016

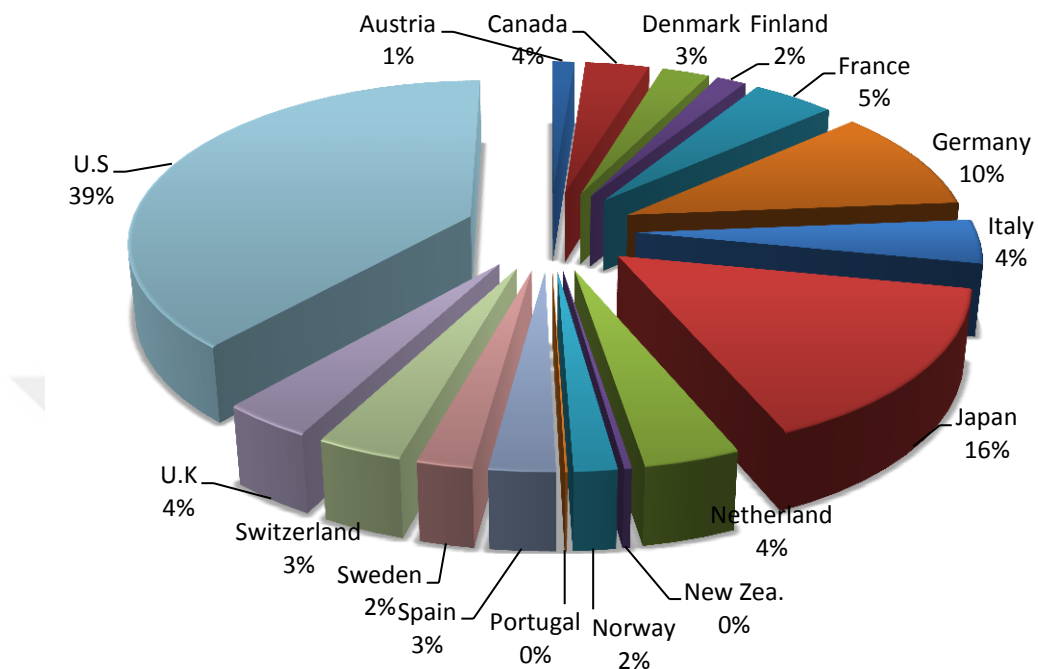
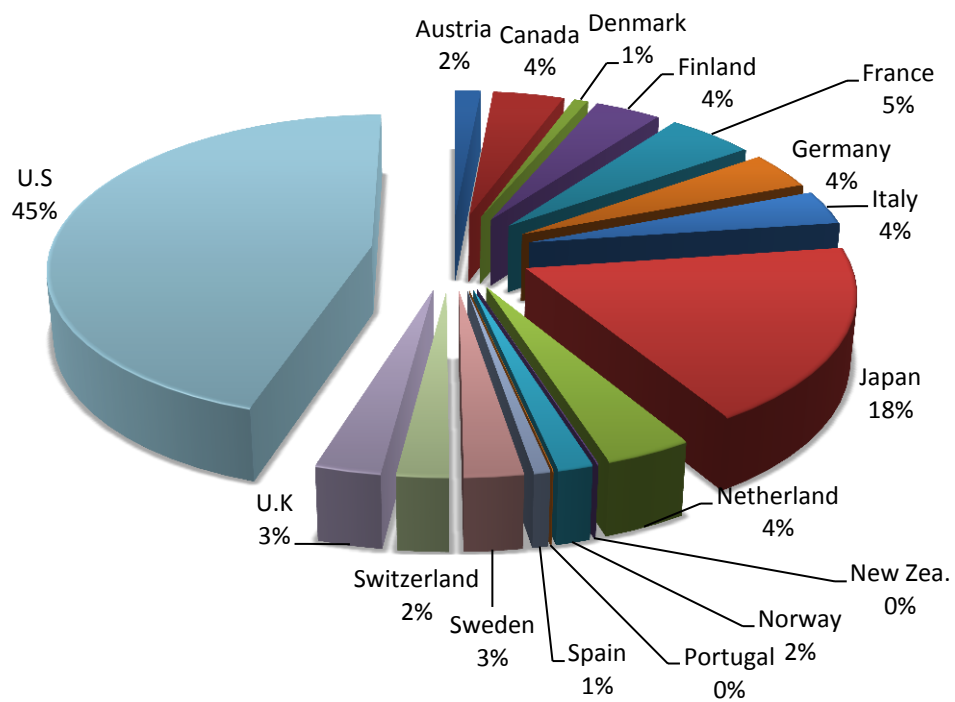


Figure 3: The share of each country in cumulative Energy Efficiency R&D expenditures of 17 OECD countries over the period 1990-2016



Figures 2 and 3 show the share of each country in cumulative green R&D expenditures (renewable energy and energy efficiency) made by 17 OECD countries from 1990 to 2016. According to both figures the USA ranks top in green R&D expenditures with the shares of 39% and 45% in renewable energy and energy efficiency R&D expenditures, respectively. Moreover, Japan ranks second in both R&D expenditure by constituting 16% of all renewable R&D expenditures and 18% of all efficiency R&D expenditures. While Germany ranks third in renewable R&D, France has the largest third share in efficiency R&D. When all the figures are considered four out of 17 OECD countries, namely the USA, Japan, Germany and France, are most environmentally innovative.

Table 2: The descriptive statistics of variables

Variable	Mean	Max	Min	Std.dev.	Observation
Multi-factor Productivity (<i>MFP</i>)	97.04085	109.1930	73.18133	6.112944	446
Environmental Related Patent (<i>env_pat</i>)	1572.131	16613.48	1.000000	2919.103	446
Energy Efficiency R&D (<i>R&D_eff</i>)	112.6978	2409.923	0.000000	235.2971	446
Renewable Energy R&D (<i>R&D_renew</i>)	99.12647	2502.962	0.330000	210.1129	446

Table 2 summarizes the descriptive statistics of the variables in the final data set. As can be seen, the standard deviations of environmental patent data are quite high. Therefore, in the empirical applications, two conversions have been used: (1) the natural logarithm of environmental patent $\ln(env_pat)$ and (2) the proportion of environmental patents to all patents (*share_pat*). Moreover, two green R&D variables are also used in natural logarithms namely $\ln(R\&D_renew)$ and $\ln(R\&D_eff)$, due to the high standard deviations like environmental patent data. As a result, the logarithmic form was employed for all variables in the equations.

2.2. METHODOLOGY

Using the above mentioned data set, this thesis examines the relationship between green innovation and industrial productivity for OECD countries employing both panel data analyses and individual country time-series analyses. This subsection describes the methodologies employed for both cases.

2.2.1. Panel Data Analyses

To investigate the relationship between productivity and green innovation this thesis employs the following panel data methods: Cointegration Test, Vector Error Correction Model (VECM), Vector Autoregression Model (VAR) and Granger Causality Test. First of all unit root tests will be implemented in order to determine the stationarity of data and then cointegration test will be applied to analyze the long-term relationship between the variables of interest. According to the existence of a long-term relationship, VECM or VAR model will be utilized. Finally, Granger causality test will be used to determine the direction of the causal relationship.

Panel data sets with relatively large time dimensions could exhibit usual time series problems such as non-stationarity. Therefore it is necessary to examine whether the series is stationary over time. Hence, in this thesis following unit root tests are performed to check stationarity:

LLC (Levin-Lin-Chu), IPS (Im-Pesaran-Shin), Fisher-ADF and Fisher-PP to determine the stability of variables, and also ensure the robustness of the test. Among them, the LLC test is a method with the same unit root, however, the IPS, Fisher-ADF and Fisher-PP are the test methods with different unit root. The null hypothesis of four tests are the unit root. Unit root test equation include the constants and time trends (Yuan and Xiang, 2018:899).

Variables that contain unit roots at level can be related in the long term. Cointegration tests are used to test this relationship. In precondition of the panel cointegration test, the variables should not be stationary at the level, and all variables should be stationary state at first difference (Sarıkovanlık et al., 2019). Two or more series having a common stochastic trend are cointegrated, that is, they must be stationary at the same level (Stock and Watson, 2011). Pedroni (1995, 1999), Kao (1999), and Johansen (1988, 1990) cointegration tests will be applied to examine the long-term relationship between variables in the series.

If there is a long term relationship between variables, the error correction model will be used. Taking the difference of the series causes loss in the long term in order to make stationary to series. For this reason, these imbalances try to be eliminated by using VECM. If there is cointegration between the variables at the same level, the causality relationship will be determined with the VECM (Sarıkovanlık et al., 2019).

Furthermore, $\ln(MFP)$ vs. $\ln(env_pat)$, $\ln(MFP)$ vs. $(share_pat)$ and $\ln(MFP)$ vs. both green R&D variables ($\ln(R\&D_renew)$ and $\ln(R\&D_eff)$) equations will be used as Model 1, Model 2 and Model 3, respectively.

VECM of long-run relationship for these three models could be formulated as follows:

Model 1: $\ln(MFP)$ vs. $\ln(env_pat)$

$$\Delta \ln MFP_{i,t} = \beta_{10} + \sum_{i=1}^m \beta_{1i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \gamma_{1i} \Delta \ln env_pat_{t-i} + \alpha_1 ECT_{t-1} + \varepsilon_{1i} \quad (1)$$

$$\Delta \ln env_pat_{i,t} = \beta_{20} + \sum_{i=1}^m \beta_{2i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \gamma_{2i} \Delta \ln env_pat_{t-i} + \alpha_2 ECT_{t-1} + \varepsilon_{2i} \quad (2)$$

Model 2: $\ln(MFP)$ vs. $(share_pat)$

$$\Delta \ln MFP_{i,t} = \delta_{10} + \sum_{i=1}^m \delta_{1i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \rho_{1i} \Delta share_pat_{t-i} + \vartheta_1 ECT_{t-1} + \varepsilon_{1i} \quad (3)$$

$$\Delta share_pat_{i,t} = \delta_{20} + \sum_{i=1}^m \delta_{2i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \rho_{2i} \Delta share_pat_{t-i} + \vartheta_2 ECT_{t-1} + \varepsilon_{2i} \quad (4)$$

Model 3: $\ln(MFP)$ vs. $\ln(R\&D_renew)$ and $\ln(R\&D_eff)$

$$\Delta \ln MFP_{i,t} = \varphi_{10} + \sum_{i=1}^m \varphi_{1i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{1i} \Delta \ln R\&D_renew_{t-i} + \sum_{i=1}^m \tau_{1i} \Delta \ln R\&D_eff_{t-i} + \mu_1 ECT_{t-1} + \varepsilon_{1i} \quad (5)$$

$$\Delta \ln R\&D_renew_{i,t} = \varphi_{20} + \sum_{i=1}^m \varphi_{2i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{2i} \Delta \ln R\&D_renew_{t-i} + \sum_{i=1}^m \tau_{2i} \Delta \ln R\&D_EFF_{t-i} + \mu_2 ECT_{t-1} + \varepsilon_{2i} \quad (6)$$

$$\Delta \ln R\&D_eff_{i,t} = \varphi_{30} + \sum_{i=1}^m \varphi_{3i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{3i} \Delta \ln R\&D_renew_{t-i} + \sum_{i=1}^m \tau_{3i} \Delta \ln R\&D_eff_{t-i} + \mu_3 ECT_{t-1} + \varepsilon_{3i} \quad (7)$$

where, $\ln(MFP)$ is the natural logarithm of multifactor productivity, $\ln(env_pat)$ and $share_pat$ denote the natural logarithm of environmental patents and the share of environmental patents in total patents, respectively, $\ln(R\&D_renew)$ and $\ln(R\&D_eff)$ represents renewable energy R&D and energy efficiency R&D, respectively and finally $\varepsilon_{i,t}$ is the error term.

Single-equation models may be insufficient to explain some events in economic studies. In such circumstances, the Vector Autoregressive Model is often used to explain these events. VAR model, which was developed by Sims (1980), generalizes single variable Autoregressive Models (AR) (Sarıkovanlık et al., 2019). VAR models are the system of equations where each endogenous variable in an equation system contains the lagged values of both its own and other variables in the system (Sevüktekin and Nargeleçekenler, 2017). It helps to predict many variables with a single model (Stock and Watson, 2011).

VAR models have several advantages compared to structural models of simultaneous equations. Firstly, it is not necessary to determine whether the variables are exogenous as all of the variables are treated endogenously. This is a very important advantage since all equations in the system are defined for structural models to be predictable for simultaneous equations. Secondly, another advantage of the VAR model is its flexibility and ease of generalization. Finally, “VARs allow the value of a variable to depend on more than just its own lags or combinations of white noise terms, so VARs are more flexible than univariate AR models.” Therefore, VAR models can offer a very rich structure (Brooks, 2008: 291).

Due to all these benefits, we used the VAR model in our study to determine the relationship between the variables. To create the VAR model, the series must be stationary and the appropriate lag length must be determined (Sevüktekin and Nargeleçekenler, 2017: 496).

If there is no long term relationship between variables, the VAR model will be established as follows:

Model 1: $\ln(MFP)$ vs. $\ln(env_pat)$

$$\ln MFP_{i,t} = \beta_{10} + \sum_{i=1}^m \beta_{1i} \ln MFP_{t-i} + \sum_{i=1}^m \gamma_{1i} \ln env_pat_{t-i} + \varepsilon_{1i} \quad (8)$$

$$\ln env_pat_{i,t} = \beta_{20} + \sum_{i=1}^m \beta_{2i} \ln MFP_{t-i} + \sum_{i=1}^m \gamma_{2i} \ln env_pat_{t-i} + \varepsilon_{2i} \quad (9)$$

Model 2: $\ln(MFP)$ vs. $(share_pat)$

$$\ln MFP_{i,t} = \delta_{10} + \sum_{i=1}^m \delta_{1i} \ln MFP_{t-i} + \sum_{i=1}^m \rho_{1i} share_pat_{t-i} + \varepsilon_{1i} \quad (10)$$

$$share_pat_{i,t} = \delta_{20} + \sum_{i=1}^m \delta_{2i} \ln MFP_{t-i} + \sum_{i=1}^m \rho_{2i} share_pat_{t-i} + \varepsilon_{2i} \quad (11)$$

Model 3: $\ln(MFP)$ vs. $\ln(R\&D_renew)$ and $\ln(R\&D_eff)$

$$\ln MFP_{i,t} = \varphi_{10} + \sum_{i=1}^m \varphi_{1i} \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{1i} \ln R\&D_renew_{t-i} + \sum_{i=1}^m \tau_{1i} \ln R\&D_eff_{t-i} + \varepsilon_{1i} \quad (12)$$

$$\begin{aligned} \ln R\&D_renew_{i,t} &= \varphi_{20} + \sum_{i=1}^m \varphi_{2i} \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{2i} R\&D_renew_{t-i} + \\ &\sum_{i=1}^m \tau_{2i} \ln R\&D_eff_{t-i} + \varepsilon_{2i} \end{aligned} \quad (13)$$

$$\begin{aligned} \ln R\&D_eff_{i,t} &= \varphi_{30} + \sum_{i=1}^m \varphi_{3i} \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{3i} \ln R\&D_renew_{t-i} + \\ &\sum_{i=1}^m \tau_{3i} \ln R\&D_eff_{t-i} + \varepsilon_{3i} \end{aligned} \quad (14)$$

If there is no cointegration between the variables at the same level, the causality relationship will be determined with the VAR model (Sarikovanliket al., 2019). Wald test or Granger Causality test was used for causality analysis. The Granger causality test is applied to determine the aspect of the causality of the relationship between the two variables and was developed by Granger (1969). In addition, Wald test is used to investigate whether the two variables affect the dependent variable in the equation. We used the Wald test in our analysis to determine the direction of the causality of the relationship between the two variables. The following model may use to examine the causality relation between the variables.

2.2.2. Time Series Analyses

Given the fact that some of the countries in our dataset are way more innovative than others, it would be valuable to shed more light on the issue by analyzing individual countries' time series data. To this end, ARDL bounds testing approach of cointegration is used in this thesis.

In classical cointegration tests, variables must be integrated to the same level. This is a constraint for cointegration tests (Esen et al., 2012). However, Pesaran et al. (1996) suggested the ARDL approach, which allows testing the relationship between different degrees of integrated variables (Bahmani-Oskooee ve Ng, 2002). This approach will allow testing the cointegration relationship if the variables are only I (0), only I (1), or a combination of these two states (Görüş and Türköz, 2016). This approach, developed by Pesaran and Pesaran (1997), Pesaran and Smith (1998), Pesaran and Shin (1999) and Pesaran et al. (2001), has become frequently used in cointegration analysis (Esen et al., 2012).

“The ARDL cointegration approach has numerous advantages in comparison with other cointegration methods such as Engle and Granger, Johansen, and Johansen and Juselius.” Firstly, all variables in the system do not need to have the same integration degree. Second, the samples are small and some of the regressors are an effective predictor, even if they are endogenous. Third, it enables that the variables may have various optimal lags. Finally, it uses a single reduced form equation. Nevertheless, if any of the variables are I (2), the critical bounds ensured are not valid. Variables are considered as I (0) or I (1). For this reason, the unit root of all variables is examined before the ARDL bound testing is estimated. Augmented Dickey- Fuller (ADF) test is preferred for testing unit roots (Acaravci and Ozturk, 2010: 5414-5415).

Acaravci and Ozturk (2010: 5414) underline that “basically, the ARDL bounds testing approach of cointegration involves two steps for estimating long-run relationship. The first step is to investigate the existence of long-run relationship among all variables in the equation.”

The ARDL model for a long-run relationship between productivity and environmental patent, productivity and share patent, productivity and green R&D will be presented as follows:

$$\Delta \ln MFP_t = C_1 + \sum_{i=1}^m \beta_{1i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \gamma_{1i} \Delta \ln env_pat_{t-i} + \phi_1 \ln MFP_{t-1} + \phi_2 \ln env_pat_{t-1} + \varepsilon_{1t} \quad (15)$$

$$\Delta \ln MFP_{i,t} = \partial_1 + \sum_{i=1}^m \delta_{1i} \Delta \ln MFP_{t-1} + \sum_{i=1}^m \rho_{1i} \Delta share_pat_{t-i} + \pi_1 \ln MFP_{t-1} + \pi_2 share_pat_{t-1} + \varepsilon_{1t} \quad (16)$$

$$\Delta \ln MFP_t = \omega_1 + \sum_{i=1}^m \varphi_{1i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{1i} \Delta \ln R\&D_renew_{t-i} + \sum_{i=1}^m \tau_{1i} \Delta \ln R\&D_eff_{t-i} + \rho_1 \ln MFP_{t-1} + \rho_2 \ln R\&D_renew_{t-1} + \rho_3 \ln R\&D_eff_{t-1} + \varepsilon_{1t} \quad (17)$$

“The second step is to estimate the following long-run and short-run models that are represented in Equations (18) to (23) if there is evidence of long-run relationships (cointegration) between these variables” (Acaravci and Ozturk, 2010: 5415).

For long-run:

$$\ln MFP_t = C_3 + \sum_{i=1}^m \beta_{3i} \ln MFP_{t-i} + \sum_{i=1}^m \gamma_{3i} \ln env_pat_{t-i} + \varepsilon_{3t} \quad (18)$$

$$\ln MFP_t = \partial_3 + \sum_{i=1}^m \delta_{3i} \ln MFP_{t-1} + \sum_{i=1}^m \rho_{3i} share_pat_{t-i} + \varepsilon_{3t} \quad (19)$$

$$\ln MFP_t = \omega_3 + \sum_{i=1}^m \varphi_{3i} \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{3i} \ln R\&D_renew_{t-i} + \sum_{i=1}^m \tau_{3i} \ln R\&D_eff_{t-i} + \varepsilon_{3t} \quad (20)$$

For short-run:

$$\Delta \ln MFP_t = C_2 + \sum_{i=1}^m \beta_{2i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \gamma_{2i} \Delta \ln env_pat_{t-i} + \in ECT_{t-1} + \varepsilon_{2t} \quad (21)$$

$$\Delta \ln MFP_t = \partial_2 + \sum_{i=1}^m \delta_{2i} \Delta \ln MFP_{t-1} + \sum_{i=1}^m \rho_{2i} \Delta share_pat_{t-i} + \in ECT_{t-1} + \varepsilon_{2t} \quad (22)$$

$$\Delta \ln MFP_t = \omega_2 + \sum_{i=1}^m \varphi_{2i} \Delta \ln MFP_{t-i} + \sum_{i=1}^m \sigma_{2i} \Delta \ln R\&D_renew_{t-i} + \sum_{i=1}^m \tau_{2i} \Delta \ln R\&D_eff_{t-i} + \in ECT_{t-1} + \varepsilon_{2t} \quad (23)$$

In the short term equation, the error correction term added to the model. This term is a delayed value of the residuals from which the long-term relationship is obtained in the model. The coefficient of this variable indicates how much of an

imbalance happening in the short term will be adjusted in the long term. At the same time, the expectation is that the sign of this coefficient should be negative and significant (Esen et al., 2012).

2.3. EMPIRICAL FINDINGS

2.3.1. Results of Panel Data Analyses

Table 3: Panel Unit Root Test Result

Regressors	Levin, Lin& Chu		Paseran and Shin		Fisher ADF		Fisher PP	
	Level	1st differences	Level	1st differences	Level	1st differences	Level	1st differences
lnMFP	-1.13	-11.54***	0.76	-11.61***	35.94	187.24***	26.66	224.81***
lnenv_pat	7.25	-5.33***	2.34	-7.29***	33.43	135.52***	14.17	240.98***
share_pat	-1.40*	-11.13***	-3.8***	-11.89***	61.82***	186.02***	33.22	235.62***
lnR&D_eff	-0.55	-15.77***	-1.60*	-14.67***	47.77*	242.35***	75.08***	300.96***
lnR&D_renew	0.24	-15.29***	-2.4***	-14.55***	60.69***	240.86***	50.50**	324.50***

Notes: ***, **and * are 1%, %5 and %10 significance levels, respectively.

Unit root test results are presented in Table 3. LLC (Levin-Lin-Chu), IPS (Im-Pesaran-Shin), Fisher-ADF and Fisher-PP tests were used to test the evidence of unit root. The results of the unit-root tests on both natural forms and logarithmic forms of all variables can be seen in Appendix 1. According to Table 3, although different panel unit root tests reveal different conclusions for the levels of variables, all variables are certainly stationary once they are first-differenced. For instance, $\ln(MFP)$ and $\ln(env_pat)$ variables contain unit root at a level according to LLC, IPS, ADF and PP unit root tests. When the first difference of $\ln(MFP)$ and $\ln(env_pat)$ is taken, it is stationary at a 1% significance level in all unit root tests. While the $share_pat$ variable contains unit root at a level according to LLC and

Fisher PP unit root tests, it is stationary at the level according to IPS and ADF unit root tests. When the first difference of *share_pat* is taken, it is stationary at a 1% significance level in all unit root tests. While $\ln(R\&D_eff)$ variable contains unit root at the level according to LLC, IPS and Fisher ADF unit root tests; in Fisher PP unit root tests it is stationary at the level. When the first difference of $\ln(R\&D_eff)$ is taken, it is stationary at a 1% significance level in all unit root tests. Finally, while the $\ln(R\&D_renew)$ variable contains unit root at a level according to LLC unit root test; in IPS, Fisher ADF and Fisher PP unit root tests, it is stationary at the level. When the first difference of $\ln(R\&D_renew)$ is taken, it is stationary at a 1% significance level in all unit root tests.

After the evaluation of stationarity of variables the next step is to determine whether there consists a long-term relationship between variables. To this end, this thesis uses most frequently employed cointegration tests, such as Pedroni's, Kao's, and Johansen-Fisher tests. Appropriate lag lengths that solve the autocorrelation problem have been determined via Akeika Information Criteria and are provided in the Appendix 2.

Table 4 provides results on different cointegration tests conducted on different three pairs of variables in three models mentioned above.

Firstly, for Model 1, according to the Kao test, evidence of cointegration can be found between the variables analyzed. Two different Fisher statistics (i.e trace test and max-eigen value test) were acquired in the Johansen Cointegration test. Accordingly, the hypotheses are given respectively as, no cointegration equation could be written, at most one cointegration equation could be written, at most two different cointegration equations could be written. In the Johansen cointegration test, it is seen that probability value is less than 0.05 for none. At this stage, H_0 of no cointegration is rejected. Therefore, it is concluded that there exists cointegration. For at most 1, the probability value in trace and max tests appears to be less than 0.05 in trace and max-eigen tests. As a result, it can be concluded that there is a long-term relationship between variables and cointegration equations can be written. Pedroni cointegration test includes in-group statistics (panel statistics) and intergroup statistics. Panel statistics are the in-group statistics that allow homogeneity. Intergroup statistics are statistics that allow heterogeneity. As seen in Table 4, Panel

PP, panel ADF, and Group ADF statistics are significant at 1% and 5%. The null hypothesis that there is no cointegration can not be rejected since 7 out of 11 statistics that make up both panel and group statistics are not significant at 95% confidence level. Hence, for Model 1, two out of three cointegration tests indicate the evidence of long-term relationship between the variables. Therefore, causality for Model 1 will be examined with VECM since there is cointegration between variables of the same level.³

Table 4: Results of the Cointegration tests on Model 1, Model 2 and Model 3

Test	Model 1		Model 2		Model 3	
Kao Test (t-stat)	-1.93**		-3.07***		-3.27***	
Johansen Fisher Test	Trace	Max-Eigen	Trace	Max-Eigen	Trace	Max-Eigen
None	151.7***	109.8***	145.3***	105.4***	109.3***	91.41***
At most 1	118.1*	118.1***	112.7***	112.7***	49.10**	34.29
At most 2					69.33***	69.33***
Pedroni Test	t-stat	weighted	t-stat	weighted	t-stat	weighted
Panel v	0.53	1.54*	-2.39	-2.10	-2.24	0.98
Panel rho	-0.58	-1.39*	1.24	1.00	0.43	0.66
Panel PP	-1.20	-1.77**	-0.63	-0.54	-1.10	0.14
Panel ADF	-3.50***	-2.78***	-2.77***	-1.83**	-0.28	0.27
Grouprho	0.15			2.56		1.59
Group PP	-1.21			-0.14		-1.01
Group ADF	-2.79***			-1.71**		-0.90

Notes: ***, ** and * are 1%, 5 % and 10 % significance levels, respectively.
Used user specified: 3 for lag length, Barlett Kernel method and Newey-West method for Bandwith selection.

Secondly, the long-term relationship will be examined between $\ln(MFP)$ and $share_pat$ (Model 2). The results are given as follows:

³ According to the the Pedroni test, panel VAR model should be utilized to analyze causality for all models. Results of Panel VAR models for all three models are provided in Appendix 4.

It is observed that there is a long-term relationship between the variables at 1% in Kao test results. Johansen-Fisher Panel cointegration rejects the null hypothesis at a 1% significance level in both the maximum eigenvalue and the trace test. This indicates that there are stable and long-term relationships between the variables. Pedroni cointegration test exhibits that Panel ADF and Group ADF statistics are significant at 1% and 5%. Except for 3 of 11 test statistics, other test statistics demonstrate that there is no cointegration. Like Model 1, 2 of the 3 cointegration tests point out the existence of a long-term relationship in Model 2. Due to the existence of cointegration relations, VECM modeling can be performed and then causality can be analyzed (Table 4).

Thirdly, the long-term relationship between $\ln(MFP)$ and two green R&D variables ($\ln(R\&D_{renew})$ and $\ln(R\&D_{eff})$) will be tested (Model 3). In the Kao test, the null hypothesis of no cointegration is rejected at %5 significance level. In the Johansen-Fisher Panel cointegration test, maximum eigenvalue and trace critical values are used. According to the results, the null hypothesis, which indicates there is no cointegration, is rejected at a 1% significance level in both the maximum eigenvalue and the trace test. In other words, according to both Kao's and Johansen-Fisher's test results, there is a long term relationship between $\ln(MFP)$ and green R&D. When the Pedroni test results were examined, it was observed that the probability values were greater than 0.05 in all test statistics. There is no long-term evidence relationship between the variables by considering the Pedroni test. When all cointegration tests are evaluated, it can be concluded that there is a long-term relationship in this equation, as in other equations (Table 4).

To summarize, according to the results, causality analysis will be created with VECM for all three models.

Table 5 provides panel VECM results for Model 1. It is seen that the error correction term (ECT) is negative and statistically significant in the model where $\ln(MFP)$ is dependent variable. Therefore, deviations among the series that move together in long run, disappear in the short term and the series are returning to the long-term equilibrium value again. This situation shows that both the long term analysis results are reliable and there is a causality relationship from independent variables to dependent variables. According to the model, when there is a deviation

from balance, approximately 10% of deviations are corrected and the next period these imbalances decrease and hence the system reaches to equilibrium.

Moreover, the short-run dynamics are captured through the individual coefficients of the difference term. According to this, the coefficient of the lagged productivity variable, appears to be positive and statistically significant in both first and third lags. While the first lag of environmental patents is negative and statistically insignificant; second lag has a statistically significant and negative effect with a coefficient of -0.007 in the short-term.

Table 5: VECM Test Result (for Model 1)

Independent Variables	Dependent Variable	
	$\Delta \ln \text{MFP}$	$\Delta \ln \text{env_pat}$
$\Delta \ln \text{MFP}(-1)$	0.1071** (0.04)	0.1225 (0.73)
$\Delta \ln \text{MFP}(-2)$	-0.0677 (0.04)	0.9392 (0.73)
$\Delta \ln \text{MFP}(-3)$	0.0972** (0.04)	-0.6459 (0.69)
$\Delta \ln \text{env_pat}(-1)$	-0.0049 (0.00)	-0.2348 (0.05)***
$\Delta \ln \text{env_pat}(-2)$	-0.0070** (0.00)	0.09450* (0.05)
$\Delta \ln \text{env_pat}(-3)$	-0.0037 (0.00)	-0.0123 (0.04)
ECT	-0.1069*** (0.01)	-0.1254 (0.18)
C	0.0057*** (0.00)	0.0544*** (0.01)

Notes: ***, ** and * are 1%, 5 % and 10 % significance levels, respectively.
Standard errors in ()

When the cointegration relationship exists, there must be at least one directional causality relationship between the variables. However, cointegration analysis does not provide information about the direction and degree of causality between the variables. After the model was established, the short and long-term causality relationship was tested with the Wald test and the Error Correction Term (ECT) variable. Furthermore, the direction and degree of causality relationship have

been determined. The Wald test shows a short-term causal relationship, while ECT examines the long-term causal relationship.

Table 6: Granger Causality Test (for Model 1)

Short-run (or weak) causalities		
	$\Delta \ln MFP$	$\Delta \ln env_pat$
$\Delta \ln MFP$	—	1.60
$\Delta \ln env_pat$	5.44*	—
Long-run causalities (α_i , $i=1, 2$ in eqn 1,2)		
$\ln env_pat \rightarrow \ln MFP$	0.10(0.01)***	
$\ln MFP \rightarrow \ln env_pat$	-0.12(0.18)	

Notes: *** and * are 1% and 10 % significance levels, respectively.
values are Chi-sq for short run & standard errors in () and values are coefficient for short run.

Granger Causality test results for Model 1 are presented in Table 6, a causality test was established to examine the short-term causality of the $\ln(env_pat)$ variable on $\ln(MFP)$. The null hypothesis where the coefficients of lags of $\ln(env_pat)$ are all equal to zero is tested. According to the table, the statistical value is significant at 10%. In other words, it is seen that there is causality from $\ln(env_pat)$ to $\ln(MFP)$ at 10%. When the short term causality of the $\ln(MFP)$ variable is examined on $\ln(env_pat)$, no causality has been found. As a result, a one-way causality relationship was observed in the short term. In the long-term causality analysis results, it shows the one-way long-term causality from $\ln(env_pat)$ to $\ln(MFP)$ at a 1% significance level. Panel causality analysis results can be summarized as follows for both the short and long term; there is a one-way ($\ln(env_pat) \rightarrow \ln(MFP)$) causal relationship between productivity and environmental patents both in the short run and the long run.

Table 7: VECM Result (for Model 2)

Independent Variables	Dependent Variable	
	$\Delta \ln MFP$	$\Delta share_pat$
$\Delta \ln MFP (-1)$	0.1105 ** (0.04)	-0.0847 (0.05)
$\Delta \ln MFP (-2)$	-0.0682 (0.04)	0.0739 (0.05)
$\Delta \ln MFP (-3)$	0.0983 ** (0.04)	-0.0373 (0.05)
$\Delta share_pat (-1)$	-0.0821* (0.04)	-0.2335*** (0.05)
$\Delta share_pat (-2)$	-0.1057 ** (0.04)	0.1372*** (0.05)
$\Delta share_pat (-3)$	-0.0590 (0.03)	-0.0857* (0.04)
ECT	-0.1028 *** (0.01)	0.0441*** (0.01)
C	0.0050 *** (0.00)	0.0015 * (0.00)

Notes: ***, ** and * are 1%, 5 % and 10 % significance levels, respectively.
Standard errors in ()

Panel VECM estimation results for Model 2 is represented in Table 7. The results suggest that productivity is significantly and positively affected by its first and third lag. Besides, coefficient of first and second lag of *share_pat* is significant and negative. Hence, while productivity is positively affected by its own lag, it is negatively affected by *share_pat*. A 1 unit increase in *share_pat* (hence 1% increase in the share of environmental patents in total patents) decreases productivity by 0.0821 % and 0.1057% in first and second lags, respectively. The other short-run coefficients in this equation, where productivity is the dependent variable, are not significant. In the *share_pat* regression, the effects of the one lag of *share_pat* and the third lag of *share_pat* are significantly negative, but the impact of the second lag of *share_pat* is significantly positive. The other short-run coefficients, where *share_pat* is the dependent variable, are not significant. Furthermore, it is observed that the error correction term coefficient (ECT) is negative and statistically significant in the model where $\ln(MFP)$ is dependent variable.

Table 8: Granger Causality Test Result (for Model 2)

Short-run (or weak) causalities		
	$\Delta \ln MFP$	$\Delta share_pat$
$\Delta \ln MFP$	—	3.77
$\Delta share_pat$	8.56**	—
Long-run causalities (ϑ_i , $i=1, 2$ in eqn 3, 4)		
$share_pat \rightarrow \ln MFP$	-0.10 (0.01)***	
$\ln MFP \rightarrow share_pat$	0.04 (0.01)	

Notes: *** and ** are 1% and 5 % significance levels, respectively.
 values are Chi-sq for short run & standard errors in () and values are coefficient for short run.

Granger Causality test results for Model 2 are presented in Table 8. According to this, *share_pat* granger cause $\ln(MFP)$ unidirectional at the 5% significance level. That's why, it can be seen that there is a short-run causality running from *share_pat* to productivity at 5%. In the long-term causality analysis results, it shows the one-way long-term causality from *share_pat* to $\ln(MFP)$ at a 1% significance level.

Table 9: VECM Result (for Model 3)

Independent Variables	Dependent Variable		
	$\Delta \ln \text{MFP}$	$\Delta \ln \text{R\&D_eff}$	$\Delta \ln \text{R\&D_renew}$
$\Delta \ln \text{MFP} (-1)$	0.1115** (0.04)	-3.3416* (2.02)	-2.9427** (1.40)
$\Delta \ln \text{R\&D_eff} (-1)$	-0.0019* (0.00)	-0.0905* (0.05)	0.0372 (0.03)
$\Delta \ln \text{R\&D_renew} (-1)$	0.0020 (0.00)	0.0836 (0.07)	-0.2681*** (0.05)
ECT	-0.0773*** (0.00)	0.7635** (0.38)	-0.1517 (0.26)
C	0.0048*** (0.00)	0.0594* (0.03)	0.0740*** (0.02)

Notes: ***, ** and * are 1%, 5 % and 10 % significance levels, respectively.
Standard errors in ()

Panel VECM estimation results for Model 3 is represented in Table 9. According to Table 9, the results show that productivity is significantly and positively affected by its lag. Furthermore, first lag of $\ln(\text{R\&D_eff})$ is significant and negative. A 1 unit increase in $\ln(\text{R\&D_eff})$ decrease productivity by 0.0019 %. When $\ln(\text{R\&D_renew})$ was evaluated, first lag of $\ln(\text{R\&D_renew})$ is insignificant. In the model where $\ln(\text{R\&D_eff})$ is dependent variable, first lag of productivity and first lag of $\ln(\text{R\&D_eff})$ are statistically significant but negative. In the model where $\ln(\text{R\&D_renew})$ is dependent variable, first lag of productivity and the first lag of $\ln(\text{R\&D_renew})$ are statistically significant but negative again.

Table 10: Granger Causality Test Result (for Model 3)

Short-run (or weak) causalities			
	$\Delta \ln MFP$	$\Delta \ln R\&D_eff$	$\Delta \ln R\&D_renew$
$\Delta \ln MFP$	—	2.71*	4.41**
$\Delta \ln R\&D_eff$	2.85*	—	1.12
$\Delta \ln R\&D_renew$	1.60	1.28	—
Long-run causalities (μ_i , $i= 1, 2, 3$ in eqn 5, 6, 7)			
$\ln R\&D_eff$ and $\ln R\&D_renew \rightarrow \ln MFP$	-0.07 (0.00)***		
$\ln MFP \rightarrow \ln R\&D_eff$	0.76(0.38)**		
$\ln MFP \rightarrow \ln R\&D_renew$	-0.15(0.26)		

Notes: ***,** and *are 1%, 5% and 10 % significance levels, respectively.
values are Chi-sq for short run & standard errors in () and values are coefficient for short run.

Table 10 provides causality results for Model 3. The statistical value is significant at 10% for $\ln(R\&D_eff)$. These results are shown that there is a causality relationship from $\ln(R\&D_eff)$ to $\ln(MFP)$ at 10%. Furthermore, causality has been found from $\ln(MFP)$ to $\ln(R\&D_eff)$ at 10%. In other words, it observed that there is a bidirectional causality relationship between $\ln(MFP)$ and $\ln(R\&D_eff)$ at 10% in the short run. Besides, $\ln(MFP)$ granger cause $\ln(R\&D_renew)$ at the 5% significance level. When considering long-run causality, it is found that the evidence of causality from both $\ln(R\&D_eff)$ and $\ln(R\&D_renew)$ to $\ln(MFP)$ at a 1%.

According to the results of all three models, it can be said that the effect of green innovation on manufacturing productivity in OECD countries is negative. On the other hand, there are some previous studies in the literature suggesting positive effects. For instance, Aldieri et al. (2019) indicate that green innovations have a positive effect on the productivity of Russian regions. Lee and Min (2015) emphasized that green R&D investment is positively related to companies' financial performance. Küçükoğlu and Pınar (2015) underline that green innovation has a positive impact on both a company's environmental performance and competitive advantage. Nevertheless, in contrast to these studies, Marin (2014) says that

environmental innovations provide lower returns than non-environmental innovations. Kruse (2016) finds that GE innovations have a negative effect on firms' economic performance, and innovation in non-GE technologies positively affects firms' economic performance. Soltman et al. found that there is a U-shaped relationship between the intensity of green inventions and performance, and the rising level of green invention has a negative influence on performance for most industries.

In summary, considering the definition of green innovations it is expected to observe a beneficial impact on the environment. On the other hand there is no consensus in the literature about the effects of these innovations on productivity and several studies reveal mixed results. Policies that limit the environmental by-products of firms are expected to cause a reduction in productivity. This decline in productivity can be reduced by environmental innovations, but not entirely.

According to the results of this thesis, it is seen that proxy variables measuring green innovation has a significant but negative effect on productivity for all three models. Although, at first sight, this seems to be a counterintuitive result, it may be due to the proxy variables to measure green-innovation, namely patents and R&D expenditures. First of all, using patent data arises some limitations. For instance, according to Kemp and Pearson (2007: 21), patents cover only a part of innovation process. The tendency to use patents in order to proxy innovations varies considerably across industries and technologies. Especially when evaluating green innovations, these innovations are underrepresented. Besides, while these data consider only the 'new to the market' innovations, the 'new to the firm' innovations are ignored. Secondly, the impact of environmental regulations and policy interventions must also be considered. Since the Kyoto Protocol in 1997, many countries have begun to conduct more environmentally friendly policies and regulations, and as a result, have attempted to cope with climate change by promoting green innovation and reducing emissions. As a result of these regulations, the production decisions and cost structures of firms or industries are directly affected. As the Porter Hypothesis has stated, firms' productivity will increase when triggered innovations can offset regulations' compliance costs (Porter and Van der Linde, 1995). According to Marin and Lotti (2017), cost savings with green

innovations can not be adequate in order to offset both the compliance costs of new regulations and innovation costs. This may reduce productivity. According to Soltmann et al., (2015: 459), “it is unlikely that green innovation will proceed without policy interventions to a level where green technologies would replace environmentally unfriendly technologies in due time.” Thirdly, it should be noted for what purpose green innovations are applied. Rexhauser and Rammer (2013) stated in their study that while cost-reducing innovations to reduce energy and material input have a positive impact on firms' profitability, environmental regulatory innovations that do not increase resource efficiency and aim to reduce environmental pressures, have a negative impact on profitability. In other words, when we evaluate the negative effect of our results, it can be assumed that green innovations may have been made to reduce environmental pressures for these countries. Finally, the impact of technological innovation capacity or technological innovation of firms on productivity is remarkable. According to Noci and Verganti (1999), firms must employ technological investments in order to enhance green products. In other words, it requires changing, at least in the firm's resource base. This can create a cost for the firms. According to Soltman et al., (2015), there are also costs associated with technological changes (such as hiring new employees, constitute new departments). All of these carry a high technical risk for firms. That's why firms may not be willing to bear these costs. In other words, it may not be possible to be competitive for firms in the first stage, where the costs are high. This can significantly reduce the performance of firms or an industry.

2.3.2. Results of Individual Time Series Analyses

When panel data results are evaluated in general, it is seen that although there is causality from green innovation to productivity, the effect is significantly negative. While this result may be interpreted as green innovation leading to more cost than benefit in OECD countries, time series analyses on individual countries would be used to check the robustness of the results across countries. Due to the fact that four countries in our dataset, namely, the USA, Japan, Germany and France, are leading in green innovations, it would be expected to observe different results for different countries. For this reason, in this section cross-country analysis is conducted to analyze this effect in more detail. To this end, the ARDL methodology on individual time series data of 17 countries covering the period from 1990 to 2016 is employed to assess the impact of green innovation on productivity. In the first step, the ADF unit root test was performed. In the second step, the long-term relationships between the variables were tested by using the ARDL bounds testing approach of cointegration. Accordingly, countries that are related in the long term are identified. Finally, long-term and short-term models are estimated for these countries.

Table 11: Unit root test results

	ADF(levels)	ADF(1st differences)		ADF(levels)	ADF(1st differences)	
<i>Austria</i>			<i>New Zea.</i>			
lnMFP	-2.07 c+t	-3.22** c	lnMFP	-2.87 c+t	-4.78*** c	
lnenv_pat	-2.99 c+t	-6.98*** c	lnenv_pat	-2.07 c+t	-6.62*** c	
share_pat	-3.11 c+t	-6.83*** c	share_pat	-2.03 c+t	-2.22 c	-6.59*** c
lnR&D_eff	-1.74 c+t	-5.12*** c	lnR&D_eff	-3.35* c+t	-4.02*** c	
lnR&D_renew	-2.68 c+t	-3.90*** c	lnR&D_renew	-1.01 c+t	-4.17*** c	
<i>Canada</i>			<i>Norway</i>			
lnMFP	-1.95 c+t	-3.88*** c	lnMFP	-2.13 c+t	-2.04 c	-4.39*** c
lnenv_pat	2.67 c+t	0.34 c	lnenv_pat	-2.06 c+t	-2.20 c	-14.6*** c
share_pat	-2.77 c+t	-4.93*** c	share_pat	-2.10 c+t	-4.56*** c	
lnR&D_eff	-4.18** c+t		lnR&D_eff	-1.76 c+t	-1.41 c	-5.66*** c
lnR&D_renew	-2.38 c+t	-2.16 c	lnR&D_renew	-1.38 c+t	-4.16*** c	
<i>Denmark</i>			<i>Portugal</i>			
lnMFP	-2.71 c+t	-4.27*** c	lnMFP	-3.82** c+t		
lnenv_pat	-1.53 c+t	-5.28*** c	lnenv_pat	-4.15*** c+t		
share_pat	-2.20 c+t	-4.51*** c	share_pat	-3.23 c+t	-11.9*** c	
lnR&D_eff	-2.78 c+t	-5.20*** c	lnR&D_eff	-2.50 c+t	-5.21*** c	
lnR&D_renew	-2.18 c+t	-5.46*** c	lnR&D_renew	-2.65 c+t	-7.60*** c	
<i>Finland</i>			<i>Spain</i>			
lnMFP	-0.72 c+t	-3.96*** c	lnMFP	-3.33* c+t	-2.20 c	-3.86*** c
lnenv_pat	-3.03c+t	-5.56*** c	lnenv_pat	-0.15 c+t	-2.46 c	-9.21*** c
share_pat	-1.94 c+t	-6.69*** c	share_pat	-3.50* c+t	-2.59 c	-7.64*** c
lnR&D_eff	-3.39* c+t	-3.12** c	lnR&D_eff	-2.65 c+t	-8.09*** c	
lnR&D_renew	-2.33 c+t	-6.51*** c	lnR&D_renew	-2.15 c+t	-4.82*** c	
<i>France</i>			<i>Sweden</i>			
lnMFP	-0.69 c+t	-3.84*** c	lnMFP	-1.17 c+t	-4.06*** c	
lnenv_pat	0.94 c+t	-3.31** c	lnenv_pat	-3.89** c+t		
share_pat	-3.28* c+t	-3.31** c	share_pat	-3.43* c+t	-3.94*** c	
lnR&D_eff	-2.66 c+t	-4.49*** c	lnR&D_eff	-3.08 c+t	-2.30 c	-4.73*** c
lnR&D_renew	-2.31 c+t	-4.51*** c	lnR&D_renew	-4.32** c+t		
<i>Germany</i>			<i>Switzerland</i>			
lnMFP	-2.57 c+t	-5.07*** c	lnMFP	-2.63 c+t	-4.41*** c	
lnenv_pat	-2.05 c+t	-3.08** c	lnenv_pat	-2.70 c+t	-2.07 c	-12.80*** c
share_pat	-2.70 c+t	-3.40** c	share_pat	-3.44* c+t	-1.67 c	-11.16*** c
lnR&D_eff	-2.06 c+t	-5.02*** c	lnR&D_eff	0.06 c+t	-1.07 c	-3.67** c
lnR&D_renew	-1.59 c+t	-5.44*** c	lnR&D_renew	-0.15 c+t	-4.17*** c	
<i>Italy</i>			<i>U.K</i>			
lnMFP	-1.77 c+t	-3.39** c	lnMFP	-0.19 c+t	-3.53** c	
lnenv_pat	-1.61 c+t	-1.31 c	lnenv_pat	0.42 c+t	-2.66* c	-4.24*** c
share_pat	-2.36 c+t	-4.85*** c	share_pat	-2.87 c+t	-2.22 c	-4.98*** c
lnR&D_eff	-2.09 c+t	-5.82*** c	lnR&D_eff	-1.67 c+t	-2.78* c	-5.36*** c
lnR&D_renew	-2.70 c+t	-4.11*** c	lnR&D_renew	-3.74** c+t		
<i>Japan</i>			<i>U.S</i>			
lnMFP	-3.04 c+t	-5.83*** c	lnMFP	-0.12 c+t	-4.165*** c	
lnenv_pat	0.70 c+t	-0.82 c	lnenv_pat	0.48 c+t	-3.40** c	
share_pat	-3.45* c+t	-3.42** c	share_pat	-3.38* c+t	-1.73	-4.05*** c
lnR&D_eff	-1.17 c+t	-7.02*** c	lnR&D_eff	-2.92 c+t	-5.01*** c	
lnR&D_renew	-3.22 c+t	0.09 c	lnR&D_renew	-2.42 c+t	-7.27*** c	
<i>Netherland</i>						
lnMFP	-0.72 c+t	-4.29*** c				
lnenv_pat	-0.85 c+t	-1.60 c				
share_pat	-3.40 c+t	-2.12 c				
lnR&D_eff	-3.93** c+t					
lnR&D_renew	-2.56 c+t	-3.76** c				

Notes: ***, **and * are 1%, %5 and %10 significance levels, respectively.

Model c + t involves an intercept and trend; model c only involves intercept in Dickey-Fuller regressions.

The results presented on Table 11 suggest that the $\ln(MFP)$ variable is $I(2)$ for Norway and Spain. Since the $\ln(MFP)$ variable is the dependent variable for three models, these two countries are completely dropped from the ARDL analysis. Moreover the $\ln(env_pat)$ variable is $I(2)$ for Canada, Italy, Japan, the Netherlands, Switzerland, and the UK, the $share_pat$ is $I(2)$ for the Netherlands, New Zealand, Switzerland, England and the USA and finally $\ln(R\&D_eff)$ and $\ln(R\&D_renew)$ variables are $I(2)$ for Japan, Sweden, Switzerland, and U.K. Since ARDL methodology requires $I(0)$ or $I(1)$ series the mentioned countries are dropped from the corresponding models. Therefore, it can be confidently applied the ARDL methodology with other countries. Moreover, the unit-root test results on both natural forms and logarithmic forms of all variables can be found in Appendix 5 for all countries.

After the unit root test was performed, the appropriate lag length was determined according to the AIC and SBC criteria in order to estimate the ARDL model. Besides, various diagnostic tests, which indicate no evidence of serial correlation and heteroskedasticity, were applied to establish the ARDL model. Boundary test, which is based on F-statistics, tests that the null hypothesis of there is no cointegration. If the calculated bounds F-test is above the upper critical level, the null hypothesis is rejected, indicating evidence towards cointegration. If the calculated F statistic is below the upper critical value, the null hypothesis can not be rejected, indicating evidence towards no cointegration. According to results on cointegration test depicted on Table 12, the bounds F-test for cointegration for Model 1 provides evidence of a long-term relationship between productivity and environmental patents in U.S and France at 1% significance level; in Germany, New Zealand and Portugal at 5% significance level; in Austria and Finland at 10% significance level. On the other hand, there is no evidence of long-term relationships for Model 1 for other countries. For Model 2, it is seen that there is a long-term relationship between productivity and $share_pat$ in France at a 1% significance level; in Germany and Portugal at a 5% significance level and in Austria, Canada, Finland, Italy, Japan and Sweden at a 10% significance level. For Model 3, a long-term relationship was found between productivity and twogreen R&D variables in

the U.S at 1%; in France, Germany, Italy and Portugal at 5%; in Austria and Finland at 10%.

Table 12: Bounds F-test for cointegration and ARDL model selection for individual countries

		MODEL 1		MODEL 2		MODEL 3	
Countries	Periods	Model	F	Model	F	Model	F
Austria	1990-2016	(1,0)	3.86*	(1,0)	4.23*	(1,0,1)	3.81*
Canada	1990-2016	N/A	N/A	(1,0)	4.12*	(1,0,0)	2.99
Denmark	1990-2016	(1,0)	2.73	(1,0)	2.72	(1,2,2)	3.68
Finland	1990-2016	(1,0)	4.05*	(1,0)	4.01*	(1,0,1)	3.73*
France	1990-2016	(1,1)	7.07***	(1,1)	8.61***	(1,1,1)	5.12**
Germany	1990-2016	(1,0)	5.49**	(1,2)	5.32**	(1,1,0)	6.25**
Italy	1990-2016	N/A	N/A	(1,0)	3.85*	(1,0,1)	5.18**
Japan	1990-2016	N/A	N/A	(1,1)	3.95*	N/A	N/A
Netherland	1990-2016	N/A	N/A	N/A	N/A	(1,1,0)	2.29
New Zea.	1990-2016	(1,0)	5.16**	N/A	N/A	(1,0,1)	0.79
Norway	1990-2016	N/A	N/A	N/A	N/A	N/A	N/A
Portugal	1990-2016	(1,0)	6.39**	(1,2)	5.48**	(1,0,0)	5.12**
Spain	1990-2016	N/A	N/A	N/A	N/A	N/A	N/A
Sweden	1990-2016	(1,1)	2.94	(1,1)	4.43*	N/A	N/A
Switzerland	1990-2016	N/A	N/A	N/A	N/A	N/A	N/A
U.K	1990-2016	N/A	N/A	N/A	N/A	N/A	N/A
U.S	1990-2016	(1,0)	10.84***	N/A	N/A	(1,0,0)	8.45***
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
Critical values at 1%		6.027	6.76	6.027	6.76	5.155	6.265
Critical values at 5%		4.094	4.663	4.094	4.663	3.538	4.428
Critical values at 10%		3.303	3.797	3.303	3.797	2.915	3.695

Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
F is the ARDL cointegration test. The critical values are seen as the lower I(0) and upper I(1) bounds

ARDL estimates for Model 1 are represented on Table 13. The long-run elasticity estimates of productivity concerning environmental patents are expected to be positive, i.e. $\beta_1 > 0$ which means that environmental patent positively affects the productivity. According to the results on Table 13, this is the case only for New Zealand as the coefficient of $\ln(env_pat)$ is positive and significant at 1%. Moreover, it is observed that the long-term coefficient is quite small such that a 1% increase in $\ln(env_pat)$ causes only 0.0475% increase $\ln(MFP)$. In addition, results are insignificant for other countries in the long run. All the coefficients of predicted ECTs are also negative and statistically significant at a 1% confidence level, which means that the model's error correction mechanism applies. When short-term elasticity estimates are evaluated, it is seen that the significant effects are observed only in New Zealand and France. The effect $\ln(env_pat)$ on $\ln(MFP)$ is positive and statistically significant at %1 in New Zealand. On the other hand, $\ln(env_pat)$ negatively affects $\ln(MFP)$ at %5 significance level in France, yet the first lag of $\ln(env_pat)$ is statistically significant and positive. Therefore, expected positive effect is observed in the first lag of $\ln(env_pat)$ for France.

Table 13: Estimated coefficients from ARDL models (Model 1)

Regressors	Austria	Finland	France	Germany	New Zealand	Portugal	U.S
long run							
lnenv_pat	-0.03 (-0.13)	-1.53 (-0.15)	0.18 (1.13)	0.08 (1.33)	0.04 (5.05)*	-0.00 (-0.38)	-0.45 (-0.04)
constant	4.80*** (3.50)	13.79 (0.23)	3.18*** (2.51)	3.86*** (6.46)	4.43*** (134.28)	4.60*** (371.18)	9.63 (0.09)
ECT(-1)	-0.10*** (-3.60)	-0.01*** (-3.63)	0.05*** (4.81)	-0.15*** (-4.23)	-0.47*** (-4.10)	-0.46*** (-4.56)	-0.00*** (-5.94)
short run							
lnMFP(-1)	0.89*** (6.79)	0.98*** (15.82)	1.05*** (15.45)	0.84*** (8.16)	0.52*** (4.02)	0.53*** (4.12)	0.99*** (7.50)
lnenv_pat	-0.003 (-0.16)	-0.01 (-1.03)	-0.03** (-2.15)	0.01 (0.75)	0.02*** (2.98)	-0.0007 (-0.40)	-0.003 (-0.17)
lnenv_pat (-1)			0.02* (1.78)				
constant	0.48 (0.95)	0.15 (0.71)	-0.16 (-0.59)	0.58* (1.71)	2.10*** (3.63)	2.15*** (3.66)	0.0822 (0.20)
ARDL	(1,0)	(1,0)	(1,1)	(1,0)	(1,0)	(1,0)	(1,0)
R ²	0.93	0.96	0.97	0.95	0.84	0.46	0.99
RSS	0.0017	0.0107	0.0014	0.0034	0.0051	0.0018	0.0015
LM	0.6702 [0.7070]	0.8612 [0.8736]	0.9007 [0.9117]	0.0737 [0.0954]	0.2583 [0.2979]	0.3609 [0.4243]	0.8509 [0.8642]
HET	0.8498 [0.8698]	0.8262 [0.8435]	0.5536 [0.5965]	0.2893 [0.3157]	0.1718 [0.1874]	0.8744 [0.8875]	0.2390 [0.2615]

Notes: Notes: ***, ** and * are 1%, 5% and 10% significance levels, respectively.

(1) represent to one lag of variables; t-statistics in (); p-values are in []

RSS is the residual sum of squares; LM and HET refer to serial correlation and heteroskedasticity, respectively.

Results on Model 2 are presented on Table 14. Similarly, the long-run elasticity estimates of productivity with respect to *share_pat* are expected to be positive, $\rho_1 > 0$. As mentioned above, this indicates that an increase in *share_pat* leads to a rise in the productivity. According to this, the expected results are completely seen in Japan. It can be seen that the effect of *share_pat* in Japan is positive and significant at a 5% significance level. The coefficient is quite large such that a 1% increase in *share_pat* leads to a 1.84% increase in productivity. Furthermore, Italy is statistically significant at a 5% significance level but negative. Other countries are statistically insignificant in the long-run. ECT terms are also

negative and statistically significant at 1%, except France. In the short-term, it observed that one lag of *share_pat* is statistically significant and positive in Japan at a 5% significance level. Meanwhile *share_pat* is significant at 1% and negative, one lag of *share_pat* is significant and positive in France and Sweden. Besides, two lag of *share_pat* is positive and significant at 10% in Germany (Table 14).

Table 14: Estimated coefficients from ARDL models (Model 2)

Regressors	Austria	Canada	Finland	France	Germany	Italy	Japan	Portugal	Sweden
long run									
share_pat	-1.34 (-0.61)	- 5.05 (-0.36)	-4.81 (-0.54)	16.82 (0.25)	1.76 (1.48)	-1.19** (-2.70)	1.84** (2.59)	-0.32 (-1.57)	-17.95 (-0.21)
constant	4.78*** (17.73)	5.18*** (3.59)	5.17*** (5.30)	2.47 (0.28)	4.47*** (32.79)	4.71*** (141.24)	4.45*** (73.59)	4.63*** (210.82)	7.06 (0.62)
ECT(-1)	-0.09*** (-3.77)	-0.03*** (-3.66)	-0.03*** (-3.61)	0.01*** (5.30)	-0.11*** (-4.19)	-0.25*** (-3.54)	-0.15*** (-3.59)	-0.40*** (-4.25)	-0.00*** (-3.81)
short run									
lnMFP(-1)	0.90*** (14.43)	0.96*** (18.85)	0.96*** (21.84)	1.01*** (23.39)	0.88*** (14.18)	0.74*** (8.16)	0.84*** (1137)	0.59*** (4.43)	0.99*** (24.09)
share_pat	-0.12 (-0.82)	-0.15 (-0.78)	-0.19 (-0.99)	-0.66*** (-3.02)	0.77 (1.09)	-0.30*** (-3.01)	-0.36 (-1.32)	0.06 (1.22)	-0.95*** (-3.39)
share_pat (-1)				0.49** (2.44)	-1.95 (-1.57)		0.65** (2.12)	-0.06 (-1.44)	0.78*** (2.88)
share_pat (-2)					1.38* (1.98)			-0.13*** (-3.32)	
constant	0.45 (1.64)	0.15 (0.69)	0.20 (1.07)	-0.02 (-0.12)	0.49* (1.82)	1.18*** (2.77)	0.67* (2.05)	1.89*** (3.10)	0.06 (0.38)
ARDL	(1,0)	(1,0)	(1,0)	(1,1)	(1,2)	(1,0)	(1,1)	(1,2)	(1,1)
R ²	0.93	0.96	0.96	0.97	0.95	0.84	0.94	0.64	0.96
RSS	0.0017	0.0021	0.0108	0.0012	0.0028	0.0028	0.0025	0.0010	0.0044
LM	0.6264 [0.6672]	0.4600 [0.4993]	0.8375 [0.8520]	0.8812 [0.8944]	0.0142 [0.0236]	0.8149 [0.8313]	0.3617 [0.4429]	0.0613 [0.1027]	0.7362 [0.7646]
HET	0.8168 [0.8405]	0.3470 [0.3766]	0.8256 [0.8430]	0.5068 [0.5497]	0.0172 [0.0083]	0.6673 [0.6952]	0.0030 [0.0006]	0.0516 [0.0424]	0.1017

Notes: Notes: *** , ** and * are 1%, %5 and %10 significance levels, respectively.

(1) represent to one lag of variables; t-statistics in ();p-values are in []

RSS is the residual sum of squares; LM and HET refer to serial corelation and heteroskedasticity, respectively.

For Model 3 under the long-run analysis, elasticity estimates of both $\ln(R\&D_{eff})$ and $\ln(R\&D_{renew})$ are expected to be positive, $\tau_1 > 0$ and $\sigma_1 > 0$. This means that an increase in green R&D expenditures results in an increase in productivity. It can be seen that $\ln(R\&D_{eff})$ is positive at a 1% significance level, but $\ln(R\&D_{renew})$ is negative in Germany at 10%. In other words, a 1% increase in $\ln(R\&D_{renew})$ causes a 0.12% decrease in $\ln(MFP)$ while 1% increase in $\ln(R\&D_{eff})$ leads to 0.09% enhance in $\ln(MFP)$. Results also show that $\ln(R\&D_{eff})$ and $\ln(R\&D_{renew})$ are negative and statistically significant in Italy. Remarkably, $\ln(R\&D_{renew})$ is positive and significant in Finland at 1%. Besides, long-run coefficients are insignificant for other countries. Considering the countries where ARDL is applied for Model 3, the ECT term is negative and significant at a 1%. Under short-term elasticity estimates, one lag of $\ln(R\&D_{eff})$ is a significant 5% significance level and positive, while $\ln(R\&D_{eff})$ is negative and insignificant in Germany. Although the first lag of $\ln(R\&D_{renew})$ is significant 5% significance level and negative, $\ln(R\&D_{renew})$ is positive and statistically insignificant in Italy. Moreover, $\ln(R\&D_{eff})$ is significant at the 10% significance level but negative in Italy. When France is evaluated, only the first lag of $\ln(R\&D_{eff})$ is significant at 5% but negative (Table 15).

Besides, serial correlation and heteroscedasticity tests required for ARDL model estimation were also examined. The null hypothesis is that there is no heteroscedasticity and no serial correlation. According to the results of LM and HET, there is no serial correlation and heteroscedasticity problem for any country in tables 13 and 15. According to Table 14, both LM and HET problems occurred only for Germany.

Table 15: Estimated coefficients from ARDL models (Model 3)

Regressors	Austria	Finland	France	Germany	Italy	Portugal	U.S
long run							
lnR&D_eff	-0.08 (-0.84)	-0.08 (-1.21)	-0.21 (-0.54)	0.09*** (2.89)	-0.02* (-1.92)	-0.004 (-1.43)	0.46 (0.41)
lnR&D_renew	0.12 (1.03)	0.13*** (2.89)	0.13 (0.63)	-0.12* (-1.88)	-0.04*** (-3.47)	0.002 (0.48)	-0.42 (-0.38)
constant	4.53*** (16.69)	4.50*** (19.97)	5.06*** (4.63)	4.93*** (19.97)	4.92*** (77.23)	4.59*** (991.71)	4.58* (2.02)
ECT(-1)	-0.10*** (-4.27)	-0.16*** (-4.12)	-0.03*** (-4.85)	-0.16*** (-5.34)	-0.46*** (-4.93)	-0.57*** (-4.84)	-0.01*** (-6.19)
short run							
lnMFP(-1)	0.89*** (8.08)	0.83*** (9.72)	0.96*** (13.12)	0.83*** (11.95)	0.53*** (4.89)	0.42*** (3.19)	0.98*** (31.48)
lnR&D_eff	-0.009 (-1.30)	-0.01 (-1.46)	0.006 (0.93)	-0.004 (-0.51)	-0.009* (-1.82)	-0.002 (-1.33)	0.007 (0.84)
lnR&D_eff (-1)			-0.01** (-2.28)	0.01** (2.55)			
lnR&D_renew	-0.005 (-0.41)	0.02 (1.70)	-0.006 (-0.80)	-0.02 (-1.54)	0.003 (0.31)	0.001 (0.49)	-0.006 (-1.07)
lnR&D_renew (-1)	0.01 (1.49)		0.01 (1.52)		-0.02** (-2.70)		
constant	0.48 (1.01)	0.72*** (2.00)	0.20 (0.61)	0.836** (2.47)	2.30*** (4.36)	2.62*** (4.23)	0.07 (0.54)
ARDL	(1,0,1)	(1,0,0)	(1,1,1)	(1,1,0)	(1,0,1)	(1,0,0)	(1,0,0)
R ²	0.94	0.96	0.97	0.96	0.87	0.49	0.99
RSS	0.0014	0.0098	0.0013	0.0026	0.0016	0.0017	0.0014
LM	0.9047 [0.9216]	0.7673 [0.7925]	0.4337 [0.5064]	0.0614 [0.1007]	0.0392 [0.0679]	0.2529 [0.3060]	0.8007 [0.8416]
HET	0.1556 [0.1685]	0.7245 [0.7599]	0.5378 [0.5992]	0.0481 [0.0390]	0.1162 [0.1183]	0.9194 [0.9335]	0.5793 [0.6217]

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.

(1) represent to one lag of variables; t-statistics in ();p-values are in []

RSS is the residual sum of squares; LM and HET refer to serial corelation and heteroskedasticity, respectively.

When the results of all models are compared, it is seen that the effect of green innovation on manufacturing performance is more significant in only a few countries.⁴ For instance, the results of model 2 and model 3 for *Italy* suggest that there is a significant but negative effect of green innovation on productivity. Hence, there is no evidence that green innovations cause a rise in industrial productivity in Italy. This finding is to certain extent consistent with the previous literature. For instance, Cainelli et al. (2011) observed that the impacts of environmental innovation on firms' turnover and productivity are negative after analyzing data on 773 Italian firms. Similarly, Marin (2014) evaluated drivers and productivity effects of environmental innovation and observed that environmental innovations do not have an essential impact on the performance of the Italian companies. Marin and Lotti (2017), on the other hand, have observed positive influence of "eco-innovations" on returns of Italian manufacturing firms though they suggest that these returns are lower than that of non-eco innovations create particularly for the firms in more polluting subsectors. Ghisetti and Quatraro (2017) examined the effects of Italian regions' environmental innovations on environmental performance. Contrary to previous studies, according to their results, it has been observed that innovations in the environmental field increase the overall environmental performance.

In line with the results of these empirical studies and our thesis, Marin (2014) underlined that this situation is more pronounced when polluting firms are considered. There may be lower returns due to expenses and limited financing support for R&D in green technologies. This can be seen as a possible result of insignificant effects of environmental innovations. Marin and Lotti (2017), moreover, highlighted that the public return of environmental innovations is positive, but the private return of environmental innovations is uncertain. This is based on the Porter Hypothesis that stringent environmental regulations can trigger productivity and encourage innovation that helps improve competitiveness. In other words, strict environmental regulations enable cleaner technologies to be adopted and

⁴ All results here are based solely on the ARDL results above. However, these results do not contain control variables. For this reason, several control variables were also added by considering the literature. The results with control variables for these selected countries are presented in Appendix 6. As can be seen in Appendix 6, results are mostly robust, i.e., we do not observe notable changes in the significance and sign of the variables.

environmental innovations to be efficient. Cost savings that will occur with environmental innovations can compensate for the compliance costs brought by environmental regulations and the costs of innovation. On the other hand, it may be thought that environmental regulations may cause higher costs (such as failure to meet compliance costs) for polluting firms and this may reduce the effect of cost savings. As a result, compliance costs may not balance cost savings. In this case, it can be concluded that the concentration of polluting firms for Italy can be high and can reduce the effectiveness of strict environmental regulations (due to compliance costs). This may be another reason for avoiding environmental innovations.

In addition, Cainelli et al. (2011) state that the negative impact is obvious in the short to medium term and could be offset by higher benefits in terms of higher value-added in the long term. Besides, negative effects on environmental performance can be achieved through 'economic' innovation strategies (cost reduction, value-added enhancement). According to the authors, the only strategy that pays off at this point is to adopt innovation and investment. According to Marin (2014: 315), the “possible positive effects of policy-induced environmental innovations on competitiveness (and possibly measured productivity)” may occur in the medium and long term, based on “early-mover advantages of eco-innovators and on the creation of new markets for *green* technologies.” According to Ghisetti and Quatraro (2017), particularly efficient policies should ensure the required incentives for the formation of green technologies. They state that tight environmental regulations can also originate new markets for polluting firms. For these to be successful, policymakers should implement supply-side policies between suppliers and users, reduce information asymmetries and ensure appropriate coordination. According to Colombelli et al., (2014), incentives for local creation of green technologies should be analyzed correctly. On the other hand, it may be inefficient and unsuccessful in pushing local agents into new activities that are far from their competencies.

The expected positive effect observed at the first lag in models for **France, Sweden, and Japan**. As mentioned previously, this situation can be based on the Porter hypothesis. In other words, it can be said that compliance costs brought by environmental regulations can be compensated after the first year by cost-savings.

Also, Pinget et al. (2015) investigated the barriers to environmental innovation for French manufacturing firms. They examined the collected barrier to environmental innovation in three groups: cost, knowledge and the market. “First, cost barriers reflect a firm’s difficulties in financing its innovation projects.” “Second, knowledge barriers pertain to limited access to information about technology and skilled labor” (Pinget et al., 2015: 138). Environmental Innovations' require specialized knowledge and information to explore new environmental technologies. Third, barriers to market, technology push and demand-pull can restrict innovative activities. Galia and Legros (2004) examining the barriers to innovation for French manufacturing firms, underlined that the economic risk of companies, lack of skilled personnel, innovation costs, lack of sensitivity to customers and lack of information about technologies are important obstacles for innovation activities. According to Pinget et al. (2015), firms facing stronger barriers seem to more likely to innovate. Thus, it can be said that these countries can overcome these barriers to green innovations after a certain lag.

According to our results, it was found that the impact was significant after certain lag for **Germany**. Within Germany’s context, Rexhauser and Rammer (2013) examined the effects of different types of environmental innovation on firm profits based on German firm-level data. They investigated whether environmental innovations are regulation-induced or voluntary. In parallel to their results, environmental innovations that do not provide resource efficiency may reduce environmental pressure for firms. (e.g., lower SO₂ emissions by investing in end-of-pipe scrubber technology). Besides, environmental innovations that increase energy or material use may also change the firm's production process. According to their view based on the Porter hypothesis, the innovations that decrease the environmental pressure and increase the efficiency of material and energy use will not only result in lower emission, but will also decrease the firm's unit costs. In this case, with the decline of costs, the regulation's compliance costs can be balanced. As a result, they point out that the performance impacts of green innovations depend on how the innovation changes the firm’s production process. In other words, for what purpose environmental innovation is made is important. Considering our empirical results for Germany, it can be said that the green innovation is used for its purpose; that is, it is aimed at increasing efficiency rather than pressure. Brunel (2019) investigated the

impact of policies on innovation and the impact of this innovation on manufacturing production in 31 OECD countries between 1988 and 2003. According to Brunel, when technology is patented and developed within the country, the industrial output increases. On the other hand, if the technology is imported from abroad, environmental policies can potentially have little influence on manufacturing output. Their results show that renewable energy policies cause a 30 percent raise in patent application, but some of them are developed by domestic inventors. As an innovative economy, domestic inventors in countries such as Germany, Japan and the USA respond to these policies. The positive effect this thesis finds for Germany could also be attributed to the fact that Germany is a successful innovator in green energy technologies. Finally, Stucki (2019) examined the impact of investments in green energy technologies on productivity with firm-level data from Austria, Germany and Switzerland. Different results were observed for companies with low, medium and high energy costs. “While the productivity effects of investment in green energy technologies turn out to be significantly positive for firms with high energy costs, no significant effects are found for firms with medium energy costs, and the effects are even significantly negative for firms with low energy costs” (Stucki, 2019: 553). According to Stucki (2019), increasing energy efficiency is an essential driver for the dispersion of green energy technologies. In line with this suggestion, we found that that energy efficiency R&D expenditure positively affects productivity both in the short and long term in Germany.

CONCLUSION

The industrial sector has an essential place in the economy. However, environmental damages caused by consumed energy in the industrial sector bring climate change with it. Therefore, many countries try to eliminate this problem by conducting environment friendly policies and by promoting green energy innovations. For these reasons, the concept of green innovation has become an important issue and the need for green innovations has gradually risen over recent years. The countries' incentives to invest in green innovations are primarily attributed to the performance impact of those innovations. The aim of this thesis is to examine the effect of green energy innovations made by countries on their manufacturing performance.

The impact of green energy innovation on manufacturing performance was analyzed in the light of data based on productivity and green innovations, which includes 17 OECD countries and a period of 27 years between 1990 and 2016. While multi-factor productivity was used as a proxy to measure manufacturing performance, both environmental patents and green R&D expenditures were used to control green innovation. The effect of green innovation on productivity was examined with the panel VECM and VAR methodologies using three different models across which independent variables change. According to the results of the analysis, it was observed that green innovations have a significant but negative effect on productivity for all three models. This also rejects our hypothesis that green innovations positively affect productivity.

As the panel data methodologies suggest a negative effect of green innovations, it is important to shed more light on the issue by answering for which individual countries the results are robust. To this end, the effect of green innovations on productivity was further analyzed for each country using the ARDL method. In the light of these results, both the long and short-term expected positive effects were observed for New Zealand and Japan. For France, expected positive effect was generally found on its first lag in the short run. In the same way, a positive effect was observed for Sweden and Germany after a certain lag. Moreover, this impact for Germany came from energy efficiency R&D in the long run. In other words, the impact on productivity was more pronounced for energy efficiency R&D

expenditures in Germany. Finally, Italy also drew attention due to the fact that it has a negative effect on productivity in both the long and short term. Moreover, these findings generally show that the negative relationship between green innovation and productivity weakened with a more time lag. Considering the ratio of environmental patents and green R&D expenditures, Japan, Germany and the USA which especially innovative economies, have a large share. The results were as expected for Japan. Although there is a high rate in Germany, the effects were not obvious. No significant results have been found for the USA.

These results are also crucial in terms of policy implications. Without a doubt, green innovations are meant to solve certain environmental problems. For this to happen there are some conditions. Firstly, market incentives would not be enough to generate sufficient innovations hence government intervention would be needed to promote these green innovations. In this case, in line with Porter Hypotheses, strict environmental regulations can lead green innovations which would eventually increase productivity. However, the important point is to determine the structure of regulations. For instance, many countries apply different levels of rigidity to different sectors and companies regarding their energy consumption and pollution amounts. Secondly, innovation strategies such as cost reduction, added value, reducing environmental pressures or providing competitive advantage, need to be determined correctly. It will be realized that the purpose of green innovation is of great importance. For example, green innovations to gain a competitive advantage can result in positive returns. Thirdly, the creation of new and more attractive markets for green innovations could increase the effectiveness of green innovations. Last but not the least implementing green innovations to improve resource efficiency can positively affect countries' manufacturing sector performance.

This thesis also has some contributions to the literature. First of all, there are not many studies on the topic and existing studies reveal mixed results hence this thesis further elaborates on the effects of green innovations on manufacturing performance by creating three different models. Secondly, along with panel data methodologies, it is revealed which countries perform better in terms of green innovations and manufacturing performance with cross-country analyzes. Therefore, these reviews can be an example for similar studies. Despite these contributions,

future work using firm-level data could reveal more evidence towards the effects of green innovations. Such a firm-level micro data set could lead to more precise estimates on the effects of green innovations on the productivity of different firms operating in different manufacturing subsectors.



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APPENDICES

APPENDIX 1: Unit Root Table (Panel Analysis - for all variables)

Appendix Table 1. 1: Unit Root Table (Panel Analysis)

Regressors	Levin		Paseran		Fisher ADF		Fisher PP	
	Level	1st differences	Level	1st differences	Level	1st differences	Level	1st differences
MFP	-1.13	-11.54***	0.76	-11.61***	35.94	187.24***	26.66	224.81***
lnMFP	-0.79	-11.49***	1.47	-11.53***	29.16	185.76***	27.06	220.39***
env_pat	3.67	-3.45***	-2.54***	-5.74***	53.96**	105.30***	13.53	192.30***
lnenv_pat	7.25	-5.33***	2.34	-7.29***	33.43	135.52***	14.17	240.98***
share_pat	-1.40*	-11.13***	-3.82***	-11.89***	61.82***	186.02***	33.22	235.62***
R&D_eff	-1.34	-13.75***	-0.60	-12.51***	52.578	216.21***	42.61	287.40***
lnR&D_eff	-0.55	-15.77***	-1.60*	-14.67***	47.77*	242.35***	75.08***	300.96***
R&D_renew	0.21	-17.85***	-1.40*	-17.52***	54.35**	286.13***	53.06**	566.06***
ln R&D_renew	0.24	-15.29***	-2.45***	-14.55***	60.69***	240.86***	50.5**	324.50***

Notes: ***, ** and * are 1%, 5% and 10% significance levels, respectively.

APPENDIX 2: Lag Length Selection

(* indicates lag order selected by the criterion)

$\ln(MFP) - \ln(env_pat)$

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-138.2568	NA	0.007131	0.732412	0.753028	0.740590
1	1222.944	2701.077	5.96e-06	-6.354798	-6.292948	-6.330263
2	1242.051	37.71610*	5.51e-06	-6.433688	-6.33060*	-6.39279*
3	1246.343	8.427409	5.50e-06*	-6.43521*	-6.29089	-6.377966
4	1249.799	6.747890	5.51e-06	-6.432368	-6.246821	-6.358765

$\ln(MFP) - share_pat$

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1414.037	NA	2.15e-06	-7.373562	-7.352945	-7.365384
1	2216.355	1592.066	3.33e-08	-11.54232	-11.48047	-11.51779
2	2235.772	38.32841	3.07e-08	-11.62283	-11.51975*	-11.58194
3	2247.640	23.30115*	2.95e-08	-11.66392	-11.51960	-11.60667*
4	2251.698	7.925380	2.95e-08*	-11.66422*	-11.47867	-11.59062

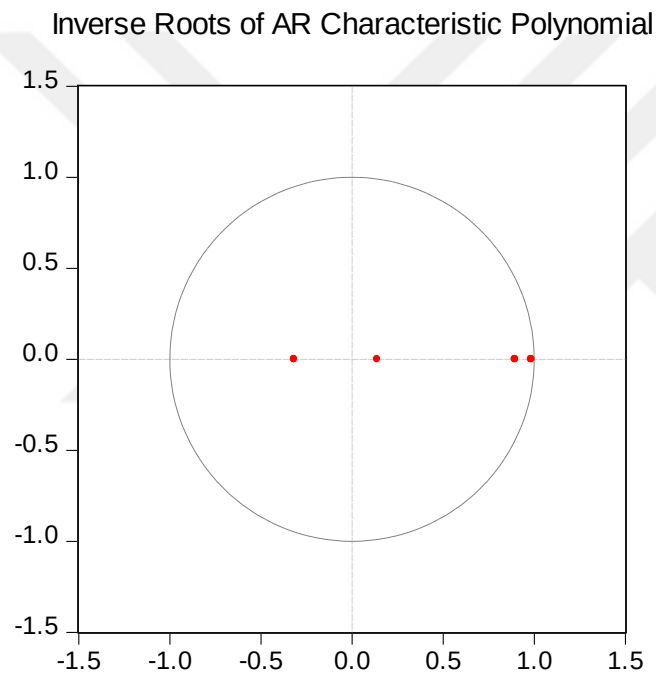
$\ln(MFP) - \ln(green_R\&D)$

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-571.6245	NA	0.005019	3.219185	3.251771	3.232146
1	632.5430	2381.351	6.21e-06	-3.476431	-3.346087*	-3.424588*
2	648.0162	30.33960	5.98e-06	-3.512696	-3.284593	-3.421969
3	657.5130	18.46156	5.97e-06*	-3.515479*	-3.189619	-3.385870
4	666.3317	16.99514*	5.97e-06	-3.514463	-3.090845	-3.345972

APPENDIX 3: Serial Correlation and AR Root

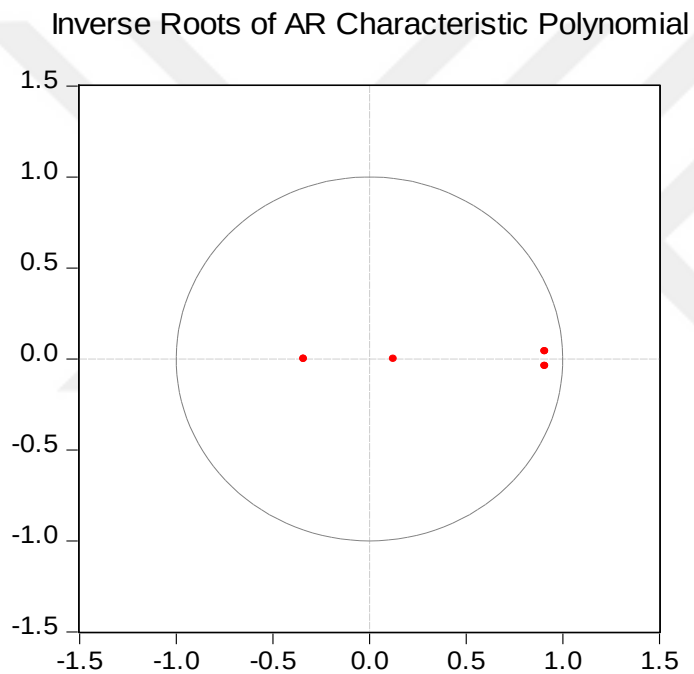
$\ln(MFP) - \ln(env_pat)$

Lags	LM-Stat	Prob
1	13.09587	0.0108
2	9.495288	0.0498
3	7.892877	0.0956
4	9.489485	0.0500



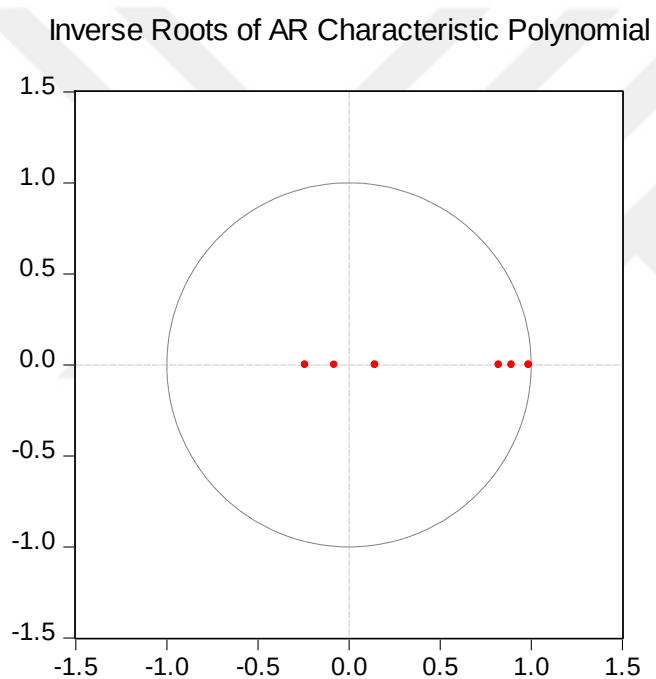
$\ln(MFP)$ - *share_pat*

Lags	LM-Stat	Prob
1	16.99539	0.0019
2	13.53992	0.0089
3	5.773866	0.2167
4	4.522573	0.3399



$\ln(MFP) - \ln(green_R\&D)$

Lags	LM-Stat	Prob
1	9.304486	0.4097
2	20.48374	0.0152
3	11.60472	0.2365
4	30.77067	0.0003



APPENDIX 4: Hausman Test and Panel VAR / Wald Test

Appendix 4. 1: Hausman Test

For Model 1

$\ln(MFP) \rightarrow \ln(env_pat)$

Hausman Test			H_0 : Random Effect Model H_1 : Fixed Effect Model
Cross-section random	Chi-Sq. Stat	Prob	
	10.5983	0.1016	

$\ln(env_pat) \rightarrow \ln(MFP)$

Hausman Test			H_0 : Random Effect Model H_1 : Fixed Effect Model
Cross-section random	Chi-Sq. Stat	Prob	
	5.748223	0.4520	

For Model 2

$\ln(MFP) \rightarrow share_pat$

Hausman Test			H_0 : Random Effect Model H_1 : Fixed Effect Model
Cross-section random	Chi-Sq. Stat	Prob	
	13.796741	0.0320	

$share_pat \rightarrow \ln(MFP)$

Hausman Test			H_0 : Random Effect Model H_1 : Fixed Effect Model
Cross-section random	Chi-Sq. Stat	Prob	
	3.280967	0.7728	

For Model 3 $\ln(MFP) \rightarrow \ln(R\&D_eff), \ln(R\&D_renew)$

Hausman Test			H_0 : Random Effect Model H_1 : Fixed Effect Model
Cross-section random	Chi-Sq. Stat	Prob	
	16.587082	0.0009	

 $\ln(R\&D_eff) \rightarrow \ln(MFP), \ln(R\&D_renew)$

Hausman Test			H_0 : Random Effect Model H_1 : Fixed Effect Model
Cross-section random	Chi-Sq. Stat	Prob	
	3.063587	0.3819	

 $\ln(R\&D_renew) \rightarrow \ln(MFP), \ln(R\&D_eff)$

Hausman Test			H_0 : Random Effect Model H_1 : Fixed Effect Model
Cross-section random	Chi-Sq. Stat	Prob	
	5.480249	0.1398	

Appendix 4. 2: Panel VAR and Wald Test

According to the results of Pedroni Test, VAR model should be utilized to conduct causality analyses. The VAR model was estimated by taking the first difference of the variables and Wald test was performed for causality. To make an accurate prediction of the VAR model, the optimal lag length must be determined. Furthermore, the maximum lag length was chosen as four and according to this, the convenient lag length was determined (Appendix: 2). The location of inverse roots of the AR characteristic polynomial for model also revealed that the model does not have any problems in terms of stationary. Whether there is a serial correlation in the residuals of the estimated VAR model was tested with the Lagrange multiplier (LM) test (Appendix: 3). Before the Panel VAR model was created, the Hausman test was performed to determine which fixed or random-effects model was suitable and the VAR model was established (Appendix: 4).

Appendix Table 4.2.1: Panel VAR (For Model 1)

	$\Delta \ln \text{MFP}$	$\Delta \ln \text{env_pat}$
$\Delta \ln \text{MFP} (-1)$	0.186(3.65)***	0.215(0.29)
$\Delta \ln \text{MFP} (-2)$	-0.008(-0.17)	1.008(1.37)
$\Delta \ln \text{MFP} (-3)$	0.144(2.93)	-0.590(-0.83)
$\Delta \ln \text{env_pat}(-1)$	-0.004(-1.37)	-0.234(-4.54)***
$\Delta \ln \text{env_pat}(-2)$	-0.006(-1.74)*	0.095(1.74)*
$\Delta \ln \text{env_pat}(-3)$	-0.003(-1.03)	-0.012(-0.24)
C	0.004(4.87)***	0.053(3.96)***
R^2	0.07	0.09
F	4.76	6.36

Notes: ***, ** and * are 1%, 5 % and 10 % significance levels, respectively.
Standard errors in ()

For Model 1, the appropriate lag length was found as three and AR root have been checked. It was determined that the random effects were suitable for Model 1.

Similar to VECM, the results have shown negative and significant at the second lag. While the first lag of environmental patents is negative and statistically insignificant, the second lag has a statistically significant and negative effect with a coefficient of -0.006 (Appendix Table 4.2.1). In contrast to VECM, no causality was observed according to the causality analysis for Model 1 (Appendix Table 4.2.2).

Appendix Table 4.2.2: Wald Test (For Model 1)

Wald Test		$\Delta \ln MFP$	$\Delta \ln env_pat$
$\Delta \ln MFP$	Chi-sq		0.3555
$\Delta \ln env_pat$	Chi-sq	0.9297	

For Model 2, the appropriate lag length was found as three. According to the Hausman test, fixed effects were suitable for Model 2. In Appendix Table 4.2.3, in the model where the $\ln(MFP)$ variable is the dependent variable, *share_pat* variable has a statistically significant but negative effect. According to Appendix Table 4.2.4, it is found causality relationship from *share_pat* to $\ln(MFP)$ at the 5% significance level. In short, the results are very similar to VECM for Model 2.

Appendix Table 4.2.3: Panel VAR (For Model 2)

	$\Delta \ln MFP$	$\Delta share_pat$
$\Delta \ln MFP$ (-1)	0.151 (2.95)***	-0.007(-1.15)
$\Delta \ln MFP$ (-2)	-0.044 (-0.87)	0.004(0.68)
$\Delta \ln MFP$ (-3)	0.124 (2.53)**	-0.007(-1.26)
$\Delta share_pat$ (-1)	-0.799 (-1.96)*	-0.242(-4.68)***
$\Delta share_pat$ (-2)	-1.214(-2.88)***	0.057(1.07)
$\Delta share_pat$ (-3)	-0.682(-1.93)*	-0.142(-3.18)***
C	0.437(5.37)***	0.022(2.20)**
R ²	0.07	0.13
F	5.19	9.48

Notes: ***, ** and * are 1%, 5 % and 10 % significance levels, respectively.
Standard errors in ()

Appendix Table 4.2.4: Wald Test (For Model 2)

Wald Test		$\Delta \ln MFP$	$\Delta share_pat$
$\Delta \ln MFP$	Chi-sq		2.9154
$\Delta share_pat$	Chi-sq	14.0040**	

For Model 3, the appropriate lag length was found as one. Results differ from the VECM analysis. In Appendix Table 4.2.5, in the model where the $\ln(MFP)$ variable is the dependent variable, the first lag of $\ln(R\&D_eff)$ and $\ln(R\&D_renew)$ are insignificant. In parallel, no causality has been found from both $\ln(R\&D_eff)$ and $\ln(R\&D_renew)$ to $\ln(MFP)$.

Appendix Table 4.2.5: Panel VAR (For Model 3)

	$\Delta \ln \text{MFP}$	$\Delta \ln \text{R\&D}_{\text{eff}}$	$\Delta \ln \text{R\&D}_{\text{renew}}$
$\Delta \ln \text{MFP} (-1)$	0.119(2.40)***	-0.041(-1.95)*	-0.029(-2.02)**
$\Delta \ln \text{R\&D}_{\text{eff}} (-1)$	-0.183(-1.51)	-0.093(-1.79)*	0.039(1.11)
$\Delta \ln \text{R\&D}_{\text{renew}} (-1)$	0.074(0.42)	0.093(1.24)	-0.272(-5.28)***
C	0.459 (6.49)***	0.061(2.01)**	0.073(3.48)***
R^2	0.07	0.01	0.07
F	1.65	2.47	10.84

Notes: ***, ** and * are 1%, 5 % and 10 % significance levels, respectively.
Standard errors in ()

Appendix Table 4.2.6: Wald Test (For Model 3)

Wald Test		$\Delta \ln \text{MFP}$	$\Delta \ln \text{R\&D}_{\text{eff}}$	$\Delta \ln \text{R\&D}_{\text{renew}}$
$\Delta \ln \text{MFP}$	Chi-sq		3.8244***	4.0889**
$\Delta \ln \text{R\&D}_{\text{eff}}$	Chi-sq	2.3078		1.2432
$\Delta \ln \text{R\&D}_{\text{renew}}$	Chi-sq	0.1813	1.5541	

APPENDIX 5: Unit Root Table (Cross Country Analysis)

Appendix Table 5: Unit Root Table (Cross Country Analysis)

	ADF(level)	ADF(1st differences)		ADF(level)	ADF(1st differences)	
Austria			New Zea.			
MFP	-2.04 c+t	-3.23** c	MFP	-2.98 c+t	-4.90*** c	
lnMFP	-2.07 c+t	-3.22** c	lnMFP	-2.87 c+t	-4.78*** c	
env_pat	-3.08 c+t	-7.22*** c	env_pat	-1.45c+t	-0.81 c	-9.12*** c
lnenv_pat	-2.99 c+t	-6.98*** c	lnenv_pat	-2.07c+t	-6.62*** c	
share_pat	-3.11 c+t	-6.83*** c	share_pat	-2.03 c+t	-2.22 c	-6.59*** c
R&D_eff	-1.86 c+t	-3.40** c	R&D_eff	-2.98c+t	-3.81*** c	
lnR&D_eff	-1.74 c+t	-5.12*** c	lnR&D_eff	-3.35* c+t	-4.02*** c	
R&D_renew	-2.07 c+t	-4.79*** c	R&D_renew	-1.33 c+t	-3.90*** c	
ln R&D_renew	-2.68 c+t	-3.90*** c	ln R&D_renew	-1.01 c+t	-4.17*** c	
Canada			Norway			
MFP	-1.92 c+t	-3.90*** c	MFP	-2.09 c+t	-2.00 c	-4.34*** c
lnMFP	-1.95 c+t	-3.88*** c	lnMFP	-2.13 c+t	-2.04 c	-4.39*** c
env_pat	0.27 c+t	-3.65** c	env_pat	-4.31** c+t		
lnenv_pat	2.67 c+t	0.34 c	lnenv_pat	-2.06 c+t	-2.20 c	-14.62*** c
share_pat	-2.77 c+t	-4.93*** c	share_pat	-2.10 c+t	-4.56*** c	
R&D_eff	-3.76** c+t		R&D_eff	2.63 c+t	2.01 c	0.80 c
lnR&D_eff	-4.18** c+t		lnR&D_eff	-1.76 c+t	-1.41 c	-5.66*** c
R&D_renew	-1.16 c+t	-4.59*** c	R&D_renew	-2.43 c+t	-4.1*** c	
ln R&D_renew	-2.38 c+t	-2.16 c	ln R&D_renew	-1.38 c+t	-4.16*** c	
Denmark			Portugal			
MFP	-2.71 c+t	-4.24*** c	MFP	-3.75** c+t		
lnMFP	-2.71 c+t	-4.27*** c	lnMFP	-3.82** c+t		
env_pat	-3.06 c+t	-4.24*** c	env_pat	-3.39* c+t	-7.29*** c	
lnenv_pat	-1.53 c+t	-5.28*** c	lnenv_pat	-4.15*** c+t		
share_pat	-2.20 c+t	-4.51*** c	share_pat	-3.23 c+t	-11.99*** c	
R&D_eff	-2.61 c+t	-3.96*** c	R&D_eff	-3.55* c+t	-5.51*** c	
lnR&D_eff	-2.78 c+t	-5.20*** c	lnR&D_eff	-2.50 c+t	-5.21*** c	
R&D_renew	-3.12 c+t	-6.59*** c	R&D_renew	-1.69 c+t	-5.07*** c	
ln R&D_renew	-2.18 c+t	-5.46*** c	ln R&D_renew	-2.65 c+t	-7.60*** c	
Finland			Spain			
MFP	-0.85 c+t	-4.09*** c	MFP	-3.3520* c+t	-2.1977 c	-3.8478*** c
lnMFP	-0.72 c+t	-3.96*** c	lnMFP	-3.33* c+t	-2.20 c	-3.86*** c
env_pat	-2.58 c+t	-4.68*** c	env_pat	-3.21 c+t	-1.91 c	-8.84*** c
lnenv_pat	-3.03 c+t	-5.56*** c	lnenv_pat	-0.15 c+t	-2.46 c	-9.21*** c
share_pat	-1.94 c+t	-6.69*** c	share_pat	-3.50* c+t	-2.59 c	-7.64*** c
R&D_eff	-2.95 c+t	-5.69*** c	R&D_eff	-3.32* c+t	-8.73*** c	
lnR&D_eff	-3.39* c+t	-3.12** c	lnR&D_eff	-2.65 c+t	-8.09*** c	
R&D_renew	-3.51* c+t	-9.05*** c	R&D_renew	-2.49 c+t	-5.26*** c	
ln R&D_renew	-2.33 c+t	-6.51*** c	ln R&D_renew	-2.15 c+t	-4.82*** c	
France			Sweden			
MFP	-0.72 c+t	-3.85*** c	MFP	-1.29 c+t	-4.04*** c	
lnMFP	-0.69 c+t	-3.84*** c	lnMFP	-1.17 c+t	-4.06*** c	
env_pat	-2.86 c+t	-1.57 c	env_pat	-5.68*** c+t		
lnenv_pat	0.94 c+t	-3.31** c	lnenv_pat	-3.89** c+t		
share_pat	-3.28* c+t	-3.31** c	share_pat	-3.43* c+t	-3.94*** c	

R&D_eff	-2.01 c+t	-3.88*** c	R&D_eff	-3.18 c+t	-5.45*** c	
lnR&D_eff	-2.66 c+t	-4.49*** c	lnR&D_eff	-3.08 c+t	-2.30 c	-4.73*** c
R&D_renew	-1.92 c+t	-7.14*** c	R&D_renew	-3.57* c+t	-5.12*** c	
ln R&D_renew	-2.31 c+t	-4.51*** c	ln R&D_renew	-4.32** c+t		

Germany

MFP	-2.75 c+t	-5.21*** c			
lnMFP	-2.57 c+t	-5.07*** c			
env_pat	-3.23 c+t	-3.06** c			
lnenv_pat	-2.05 c+t	-3.08** c			
share_pat	-2.70 c+t	-3.40** c			
R&D_eff	-1.88 c+t	-2.93* c	-5.33*** c		
lnR&D_eff	-2.06 c+t	-5.02*** c			
R&D_renew	-2.05 c+t	-2.48 c	-9.82*** c		
ln R&D_renew	-1.59 c+t	-5.44*** c			

Switzerland

MFP	-2.68 c+t	-4.41*** c			
lnMFP	-2.63 c+t	-4.41*** c			
env_pat	-3.23 c+t	-1.52 c	-11.28*** c		
lnenv_pat	-2.70 c+t	-2.07 c	-12.80*** c		
share_pat	-3.44* c+t	-1.67 c	-11.16*** c		
R&D_eff	0.53 c+t	0.19 c	-3.61** c		
lnR&D_eff	0.06 c+t	-1.07 c	-3.67** c		
R&D_renew	0.96 c+t	-3.83*** c			
ln R&D_renew	-0.15 c+t	-4.17*** c			

Italy

MFP	-1.77 c+t	-3.39** c			
lnMFP	-1.77 c+t	-3.39** c			
env_pat	-2.81 c+t	-2.26 c	-5.88*** c		
lnenv_pat	-1.61 c+t	-1.31 c	-8.88*** c		
share_pat	-2.36 c+t	-4.85*** c			
R&D_eff	-2.70 c+t	-6.66*** c			
lnR&D_eff	-2.09 c+t	-5.82*** c			
R&D_renew	-2.20 c+t	-3.58** c			
ln R&D_renew	-2.70 c+t	-4.11*** c			

U.K

MFP	-0.23 c+t	-3.61** c			
lnMFP	-0.19 c+t	-3.53*** c			
env_pat	-1.84 c+t	-1.75 c	-5.35*** c		
lnenv_pat	0.42 c+t	-2.66* c	-4.24*** c		
share_pat	-2.87 c+t	-2.22 c	-4.98*** c		
R&D_eff	-2.42 c+t	-4.21*** c			
lnR&D_eff	-1.67 c+t	-2.78* c	-5.36***		
R&D_renew	-3.29* c+t	-6.59*** c			
ln R&D_renew	-3.74** c+t				

Japan

MFP	-3.06 c+t	-5.84*** c			
lnMFP	-3.04 c+t	-5.83*** c			
env_pat	0.70 c+t	-2.01 c	-5.51*** c		
lnenv_pat	-3.45* c+t	-0.82 c	-4.95*** c		
share_pat	-1.95 c+t	-3.42** c			
R&D_eff	-1.17 c+t	-3.74*** c			
lnR&D_eff	2.32 c+t	-7.02*** c			
R&D_renew	-3.22 c+t	1.80 c	-6.57*** c		
ln R&D_renew	-2.52 c+t	0.09 c	-6.04*** c		

U.S

MFP	-0.29 c+t	-4.05*** c			
lnMFP	-0.12 c+t	-4.16*** c			
env_pat	-2.44 c+t	-2.882* c	-7.96*** c		
lnenv_pat	0.48 c+t	-3.40** c			
share_pat	-3.38* c+t	-1.73	-4.05*** c		
R&D_eff	-3.51* c+t	-5.02*** c			
lnR&D_eff	-2.92 c+t	-5.01*** c			
R&D_renew	-3.31* c+t	-7.54*** c			
ln R&D_renew	-2.42 c+t	-7.27*** c			

Netherland

MFP	-0.76 c+t	-4.34*** c			
lnMFP	-0.72 c+t	-4.29*** c			
env_pat	-2.78 c+t	-1.89 c	-10.82*** c		
lnenv_pat	-0.85 c+t	-1.60 c	-15.31*** c		
share_pat	-3.40 c+t	-2.12 c	-13.84*** c		
R&D_eff	-3.74** c+t				
lnR&D_eff	-3.93** c+t				
R&D_renew	-2.50 c+t	-3.75** c			
ln R&D_renew	-2.56 c+t	-3.76** c			

Notes: ***, **and * are 1%, %5 and %10 significance levels, respectively.

Model c + t involves an intercept and trend; model c only involves intercept in Dickey-Fuller regressions.

APPENDIX 6: Control Variables

In order to evaluate the relationship between green innovation and productivity, some control variables were added to the model considering the literature. These are total research and development expenditure as % of GDP, gross capital formation as a % of GDP, GDP per capita as current US\$, CO₂ emissions per capita in metric tons, primary energy intensity level in MJ/\$2011 PPP GDP and Environmental Policy Stringency Index (EPS). While fundamental data on EPS come from the OECD, others are compiled from the World Bank. GDP per capita, CO₂ emissions, energy intensity, and EPS variables were also used in logarithms form. Moreover, $\ln_{energy}$, $\ln_{gdp}$, $\ln_{eps}$, and $\ln_{co_2}$ represent, respectively, logarithms form of energy intensity, GDP per capita, Environmental Policy Stringency Index and CO₂ emissions. Furthermore, $gross_ca$ and $r\&d_exp$ denote, respectively, gross capital formation and research and development expenditure.

The results suggest that the $\ln_{co_2}$ variable is I (2) for Italy and France, $\ln_{energy}$ and $r\&d$ expenditure variables are I (2) for Japan. Therefore, the mentioned variables were dropped from the corresponding countries model.

APPENDIX 6. 1: ITALY

Appendix Table 6.1.1: Estimated coefficients from ARDL models (Model 2)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
long run							
share_pat	-1.19** (-2.70)	-1.65* (-1.85)	-1.01 (-1.01)	-2.03** (-2.29)	-1.32** (-2.25)	-0.83** (-2.50)	-0.43 (-1.36)
constant	4.71*** (141.24)	5.08*** (9.90)	4.97*** (6.12)	4.72*** (125.23)	4.79*** (27.18)	4.72*** (92.01)	5.08*** (19.93)
ECT(-1)	-0.25*** (-3.54)	-0.22*** (-3.58)	-0.23*** (-3.50)	-0.25*** (-3.85)	-0.23*** (-3.53)	-0.67*** (-4.08)	-0.84*** (-5.30)
short run							
lnMFP(-1)	0.74*** (8.16)	0.77*** (7.70)	0.76*** (7.26)	0.744*** (8.07)	0.76*** (7.67)	0.32* (1.75)	0.15 (0.77)
share_pat	-0.30*** (-3.01)	-0.36*** (-2.89)	-0.23 (-1.15)	-0.51*** (-0.51)	-0.30*** (-3.00)	-0.07 (-0.26)	-0.37 (-1.36)
share_pat (-1)						-0.49 (-1.34)	
lnenergy		-0.06 (-0.89)					-0.23 (-1.70)
lngdp			-0.006 (-0.34)				-0.008 (-0.30)
lneps				0.01 (1.43)			-0.008 (-0.51)
gross_cap					-0.00 (-0.50)		0.006** (2.51)
r&d_exp						-0.02 (-0.45)	-0.09 (-1.11)
constant	1.18*** (2.77)	1.12** (2.50)	1.16** (2.65)	1.20** (2.80)	1.11** (0.02)	3.19*** (3.64)	4.28*** (4.40)
ARDL	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)	(1,1)	(1,0)
R ²	0.84	0.84	0.84	0.84	0.84	0.89	0.93
RSS	0.0028	0.0027	0.0028	0.0026	0.0028	0.0014	0.0009
LM	0.8149	0.9801	0.9368	0.9599	0.9507	0.5316	0.5926
HET	0.6673	0.5573	0.8382	0.9325	0.7245	0.8561	0.9688

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
(1) represent to one lag of variables; t-statistics in ().

Appendix Table 6.1.2: Estimated coefficients from ARDL models (Model 3)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
long run							
lnR&D_eff	-0.02* (-1.92)	-0.02* (-1.89)	-0.02* (-1.94)	-0.02* (-2.09)	-0.02* (-2.10)	-0.01** (-2.53)	-0.02** (-2.40)
lnR&D_renew	-0.04*** (-3.47)	-0.05** (-2.71)	-0.03* (-1.86)	-0.05*** (-3.01)	-0.06*** (-3.44)	-0.02** (-2.67)	-0.01 (-1.27)
constant	4.92*** (77.23)	5.07*** (19.22)	5.22*** (19.13)	4.96*** (56.53)	5.12*** (32.17)	4.90*** (170.42)	5.50*** (18.85)
ECT(-1)	-0.46*** (-4.93)	-0.45*** (-4.82)	-0.43*** (-5.18)	-0.48*** (-4.89)	-0.41*** (-5.55)	-0.78*** (-6.00)	-0.69*** (-7.70)
short run							
lnMFP(-1)	0.53*** (4.89)	0.54*** (4.50)	0.56*** (5.15)	0.51*** (4.53)	0.58*** (5.50)	0.21 (1.37)	0.30 (1.77)
lnR&D_eff	-0.009* (-1.82)	-0.01* (-1.86)	-0.009* (-1.85)	-0.01* (-2.00)	-0.01* (-2.05)	-0.01** (-2.73)	-0.01*** (-3.65)
lnR&D_renew	0.003 (0.31)	0.001 (0.16)	0.008 (0.78)	-0.0003 (-0.03)	0.005 (0.58)	-0.003 (-0.42)	0.005 (0.54)
lnR&D_renew (-1)	-0.02** (-2.70)	-0.02** (-2.66)	-0.02** (-2.42)	-0.02** (-2.75)	-0.03*** (-3.33)	-0.01* (-2.10)	-0.01 (-1.66)
lnenergy		-0.04 (-0.64)					-0.20* (-2.08)
lngdp			-0.01 (-1.29)				-0.007 (-0.28)
lneps				0.008 (0.87)			0.02 (1.23)
gross_cap					-0.002* (-1.80)		0.0009 (0.34)
r&d_exp						-0.06** (-2.52)	-0.17** (-3.13)
constant	2.30*** (4.36)	2.31*** (4.11)	2.28*** (4.41)	2.39*** (4.32)	2.14*** (4.26)	3.83*** (4.96)	3.81*** (4.55)
ARDL	(1,0,1)	(1,0,1)	(1,0,1)	(1,0,1)	(1,0,1)	(1,0,1)	(1,0,1)
R ²	0.87	0.87	0.88	0.88	0.89	0.94	0.97
RSS	0.0016	0.0016	0.0015	0.0015	0.0013	0.0006	0.0002
LM	0.0392	0.0374	0.1363	0.0173	0.3043	0.1654	0.2161
HET	0.1162	0.1470	0.1948	0.1086	0.1956	0.4443	0.2332

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
 (1) represent to one lag of variables; t-statistics in ().

APPENDIX 6. 2: JAPAN

Appendix Table 6.2.1: Estimated coefficients from ARDL models (Model 2)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
long run						
share_pat	1.84** (2.59)	1.67*** (7.90)	1.60 (1.50)	-0.93 (-0.98)	0.68 (1.00)	1.87 (1.57)
constant	4.45*** (73.59)	1.66*** (3.46)	3.84* (1.97)	4.57*** (75.87)	4.72*** (31.66)	1.44 (0.93)
ECT(-1)	-0.15*** (-3.59)	-0.30*** (-8.16)	-0.14** (-2.17)	-0.23** (-2.79)	-0.25** (-2.67)	-0.30*** (-6.67)
short run						
lnMFP(-1)	0.84*** (1137)	0.37*** (2.98)	0.85*** (10.74)	0.49** (2.30)	0.74*** (6.83)	0.24 (1.42)
lnMFP(-2)		0.31** (2.65)		0.26 (1.34)		0.44** (2.50)
share_pat	-0.36 (-1.32)	0.51*** (4.92)	-0.39 (-1.34)	-0.21 (-1.12)	-0.61* (-1.86)	1.17** (2.58)
share_pat (-1)	0.65** (2.12)		0.62* (0.06)		0.78** (2.48)	-0.60 (-1.17)
lnco		0.38*** (7.61)				0.46*** (5.60)
lngdp			0.008 (0.33)			-0.01 (-0.86)
lneps				0.04** (2.81)		0.01 (0.63)
gross_ca					-0.001 (-1.33)	0.001 (1.09)
constant	0.67* (2.05)	0.50** (2.21)	0.55 (1.11)	1.06** (2.32)	1.22** (2.34)	0.43 (0.72)
ARDL	(1,1)	(2,0)	(1,1)	(2,0)	(1,1)	(2,1)
R ²	0.94	0.97	0.94	0.94	0.95	0.98
RSS	0.0025	0.0006	0.0025	0.0020	0.0023	0.0005
LM	0.3617	0.0234	0.3204	0.2320	0.1169	0.0901
HET	0.0030	0.1077	0.0063	0.0020	0.0066	0.6131

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
(1) represent to one lag of variables; t-statistics in ().

APPENDIX 6. 3: FRANCE

Appendix Table 6.3.1: Estimated coefficients from ARDL models (Model 1)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
long run							
lnenv_pat	0.18 (1.13)	-4.05 (-0.09)	0.14 (0.80)	-6.62 (-0.02)	0.16 (1.11)	-0.02 (-0.31)	-0.07 (-0.95)
constant	3.18*** (2.51)	68.51 (0.09)	2.12 (0.47)	50.04 (0.02)	3.16** (2.54)	5.71*** (4.86)	7.08*** (3.67)
ECT(-1)	0.05*** (4.81)	-0.005*** (-3.63)	0.04*** (2.91)	-0.002*** (-4.96)	0.05*** (2.94)	-0.10*** (-3.76)	-0.26** (-2.66)
short run							
lnMFP(-1)	1.05*** (15.45)	0.99*** (15.59)	1.04*** (14.98)	0.99*** (8.90)	1.05*** (14.71)	0.89*** (8.91)	0.73*** (5.28)
lnenv_pat	-0.03** (-2.15)	-0.02*** (-2.88)	-0.03 (-1.45)	-0.04** (-2.56)	-0.03** (-2.11)	-0.04** (-2.52)	-0.01 (-1.06)
lnenv_pat (-1)	0.02* (1.78)		0.02 (1.52)	0.02* (1.72)	0.02* (1.76)	0.03** (2.38)	
lnenergy		-0.12** (-2.41)					-0.11 (-1.11)
lngdp			-0.006 (-0.32)				-0.02 (-0.82)
lneps				0.01 (0.83)			0.02 (1.30)
gross_ca					-0.0003 (-0.21)		2.68 (0.006)
r&d_exp						-0.04 (-1.29)	-0.04 (-0.81)
constant	-0.16 (-0.59)	0.39 (1.26)	-0.10 (-0.30)	0.12 (0.23)	-0.17 (-0.60)	0.61 (1.32)	1.84** (2.33)
ARDL	(1,1)	(1,0)	(1,1)	(1,1)	(1,1)	(1,1)	(1,0)
R ²	0.97	0.97	0.97	0.97	0.97	0.94	0.95
RSS	0.0014	0.0013	0.0014	0.0081	0.0084	0.0009	0.0008
LM	0.9007	0.9137	0.8127	0.6191	0.8255	0.7901	0.7424
HET	0.5536	0.1421	0.7661	0.4651	0.6968	0.6174	0.1691

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
(1) represent to one lag of variables; t-statistics in ().

Appendix Table 6.3.2: Estimated coefficients from ARDL models (Model 2)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
long run							
share_pat	16.82 (0.25)	-7.13 (-0.73)	21.60 (0.14)	-3.51 (-0.89)	25.98 (0.14)	-0.67 (-0.38)	-1.09 (-0.74)
constant	2.47 (0.28)	7.96** (2.17)	3.41 (0.17)	4.86 (12.17)	2.34 (0.16)	5.67*** (5.59)	7.09 (2.19)
ECT(-1)	0.01*** (5.30)	-0.04*** (-3.13)	0.008*** (3.11)	-0.08*** (-5.63)	0.006*** (3.14)	-0.08*** (-3.54)	-0.18* (-1.81)
short run							
lnMFP(-1)	1.01*** (23.39)	0.95*** (13.75)	1.00*** (18.95)	0.91*** (8.05)	1.00*** (21.30)	0.91*** (11.61)	0.81*** (4.64)
share_pat	-0.66*** (-3.02)	-0.76*** (-3.22)	-0.67** (-2.47)	-0.85*** (-3.71)	-0.67*** (-2.96)	-0.67** (-2.82)	-0.67* (-1.97)
share_pat (-1)	0.49** (2.44)	0.42 (1.55)	0.49** (2.36)	0.56** (2.36)	0.50** (2.39)	0.61** (2.52)	0.47 (1.26)
lnenergy		-0.07 (-1.34)					-0.06 (-0.71)
lngdp			0.001 (0.06)				-0.01 (-0.69)
lneps				0.01 (1.06)			0.01 (0.93)
gross_ca					0.0003 (0.20)		-0.001 (-0.25)
r&d_exp						-0.03 (-1.16)	-0.05 (-0.97)
constant	-0.02 (-0.12)	0.36 (0.92)	-0.02 (-0.13)	0.40 (0.78)	-0.01 (-0.07)	0.48 (1.24)	1.30 (1.47)
ARDL	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)
R ²	0.97	0.97	0.97	0.98	0.97	0.94	0.96
RSS	0.0012	0.0010	0.0012	0.0010	0.0012	0.0009	0.0006
LM	0.8812	0.9463	0.8967	0.5775	0.9229	0.5246	0.7075
HET	0.5068	0.2986	0.6516	0.5087	0.6591	0.4827	0.2736

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
(1) represent to one lag of variables; t-statistics in ().

Appendix Table 6.3.3: Estimated coefficients from ARDL models (Model 3)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
long run							
lnR&D_eff	-0.21 (-0.54)	0.04 (0.30)	-0.22 (-0.48)	-0.079 (-0.78)	-0.22 (-0.58)	-0.02 (-0.71)	0.05* (1.94)
lnR&D_renew	0.13 (0.63)	-0.24 (-0.57)	0.14 (0.54)	0.03 (0.38)	0.13 (0.67)	0.04 (1.22)	-0.05 (-1.26)
constant	5.06*** (4.63)	9.13 (1.38)	5.48 (1.00)	4.77*** (18.27)	4.40*** (5.47)	5.00*** (18.08)	6.61*** (5.56)
ECT(-1)	-0.03*** (-4.85)	-0.05*** (-3.80)	-0.03*** (-3.33)	-0.10*** (-4.83)	-0.04*** (-3.51)	-0.27*** (-3.15)	-0.35*** (-4.41)
short run							
lnMFP(-1)	0.96*** (13.12)	0.94*** (13.26)	0.96*** (11.85)	0.89*** (8.55)	0.95*** (12.93)	0.72*** (3.48)	0.64*** (3.72)
lnR&D_eff	0.006 (0.93)	0.01 (1.55)	0.006 (0.90)	0.007 (1.05)	0.006 (0.87)	0.007 (0.92)	0.02** (2.84)
lnR&D_eff (-1)	-0.01** (-2.28)	-0.009* (-2.06)	-0.01* (-1.97)	-0.01** (-2.36)	-0.01** (-2.36)	-0.01* (-1.89)	
lnR&D_renew	-0.006 (-0.80)	-0.01 (-1.42)	-0.006 (-0.77)	-0.009 (-1.05)	-0.007 (-0.94)	-0.004 (-0.50)	-0.02* (-2.04)
lnR&D_renew (-1)	0.01 (1.52)		0.01 (1.43)	0.01 (1.50)	0.01 (1.66)	0.01 (1.63)	
lnenegy		-0.12** (-2.14)					-0.07 (0.31)
lngdp			-0.001 (-0.09)				-0.06*** (-3.57)
lneps				0.01 (0.85)			0.02 (1.74)
gross_ca					0.001 (0.78)		0.004 (1.14)
r&d_exp						-0.05 (-1.18)	-0.01 (-0.22)
constant	0.20 (0.61)	0.46 (1.34)	0.20 (0.60)	0.49 (1.03)	0.18 (0.56)	1.38 (1.37)	2.37** (2.56)
ARDL	(1,1,1)	(1,1,0)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,0,0)
R ²	0.97	0.97	0.97	0.97	0.97	0.94	0.96
RSS	0.0013	0.0080	0.0013	0.0012	0.0013	0.0010	0.0006
LM	0.4337	0.5308	0.4570	0.3536	0.2671	0.0191	0.9144
HET	0.5378	0.2006	0.5204	0.6566	0.4245	0.6615	0.1573

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
(1) represent to one lag of variables; t-statistics in ().

APPENDIX 6. 4: GERMANY

Appendix Table 6.4.1: Estimated coefficients from ARDL models (Model 1)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
long run								
lnenv_pat	0.08 (1.33)	0.42 (1.13)	-0.002 (-0.03)	0.08 (0.77)	0.06 (0.84)	0.35 (0.51)	0.006 (0.06)	-0.04 (-1.10)
constant	3.86*** (6.46)	-3.03 (-0.37)	5.11*** (4.76)	3.82*** (0.77)	3.98*** (6.87)	-0.03 (-0.002)	4.28*** (6.97)	4.34** (2.51)
ECT(-1)	-0.15*** (-4.23)	-0.13*** (-3.24)	-0.27** (-2.72)	-0.15** (-2.14)	-0.21*** (-2.95)	-0.04** (-2.46)	-0.25 (-1.73)	-0.74*** (-6.74)
short run								
lnMFP(-1)	0.84*** (8.16)	0.86*** (7.09)	0.72*** (5.95)	0.84*** (7.98)	0.78*** (6.68)	0.95*** (8.00)	0.74*** (4.15)	0.10 (0.68)
lnMFP(-2)								0.14 (1.00)
lnenv_pat	0.01 (0.75)	0.05** (2.20)	-0.0007 (-0.03)	0.01 (0.58)	0.01 (0.67)	0.01 (0.92)	0.001 (0.06)	0.09** (2.48)
lnenv_pat (-1)								-0.12** (-2.35)
lnco2		0.23* (1.88)						0.55*** (6.13)
lnenegy			-0.08 (-1.34)					-0.63*** (-5.67)
lngdp				0.001 (0.05)				0.01 (0.11)
lneps					0.01 (0.61)			0.09*** (3.91)
gross_ca						0.003 (1.64)		-1.69 (-0.39)
r&d_exp							0.02 (0.83)	-0.03 (-0.87)
constant	0.58* (1.71)	-0.40 (-0.53)	1.39** (2.32)	0.58 (1.61)	0.86* (2.06)	-0.001 (-0.002)	1.10 (1.47)	3.24** (2.32)
ARDL	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)	(2,1)
R ²	0.95	0.95	0.95	0.95	0.95	0.95	0.89	0.98
RSS	0.0034	0.0027	0.0030	0.0034	0.0032	0.0031	0.0031	0.0002
LM	0.0737	0.0226	0.1667	0.0731	0.0651	0.5631	0.0467	0.0136
HET	0.2893	0.0177	0.2419	0.4658	0.5311	0.1046	0.5351	0.1892

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.
(1) represent to one lag of variables; t-statistics in ().

Appendix Table 6.4.2: Estimated coefficients from ARDL models (Model 2)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
long run								
share_pat	1.76 (1.48)	3.63 (0.40)	-1.07** (-2.39)	3.44 (0.76)	0.60 (0.56)	-2.183 (-0.19)	-0.61 (-0.59)	-0.61** (-2.81)
constant	4.47*** (32.79)	2.60 (0.30)	5.43*** (37.03)	5.81 (1.67)	4.42*** (57.03)	7.71 (0.79)	4.27 (30.41)	4.47 (12.40)
ECT(-1)	-0.11*** (-4.19)	-0.07* (-1.76)	-0.42*** (-3.59)	-0.09* (-1.95)	-0.20** (-2.56)	0.02** (2.25)	-0.27* (-1.86)	-1.10*** (-5.31)
short run								
lnMFP(-1)	0.88*** (14.18)	0.92*** (6.35)	0.57*** (4.47)	0.90*** (12.23)	0.79*** (7.07)	1.02*** (11.71)	0.72*** (4.12)	-0.26 (-1.12)
lnMFP(-2)								0.15 (1.12)
share_pat	0.77 (1.09)	0.80 (1.05)	-0.45* (-1.95)	0.99 (1.16)	0.68 (0.93)	0.05 (0.34)	-0.16 (-0.60)	0.72 (1.71)
share_pat (-1)	-1.95 (-1.57)	-1.84 (-1.34)		-2.24 (-1.60)	-1.93 (-1.51)			-1.40** (-2.36)
share_pat (-2)	1.38* (1.98)	1.30 (1.68)		1.56* (1.94)	1.36* (1.90)			
lnco2		0.05 (0.38)						0.60*** (5.53)
lnenegy			-0.20** (-2.69)					-0.71*** (-4.72)
lngdp				-0.01 (-0.48)				-0.004 (-0.23)
lneps					0.02 (0.89)			0.05 (1.75)
gross_ca						0.003 (1.56)		-0.003 (-0.87)
r&d_exp							0.04 (1.22)	-0.02 (-0.61)
constant	0.49* (1.82)	0.18 (0.19)	2.28 (3.19)	0.54* (1.84)	0.89 (1.81)	-0.19 (-0.43)	1.16 (1.56)	4.96* (3.70)
ARDL	(1,2)	(1,2)	(1,0)	(1,0)	(1,2)	(1,0)	(1,0)	(2,1)
R ²	0.95	0.94	0.96	0.95	0.95	0.95	0.89	0.98
RSS	0.0028	0.0027	0.0025	0.0027	0.0026	0.0032	0.0030	0.0027
LM	0.0142	0.0035	0.2666	0.0121	0.0138	0.1397	0.0350	0.0351
HET	0.0172	0.0236	0.0209	0.0219	0.0369	0.0495	0.2542	0.1680

Notes: Notes: *** , ** and * are 1%, %5 and %10 significance levels, respectively.
(1) represent to one lag of variables; t-statistics in ().

Appendix Table 6.4.3: Estimated coefficients from ARDL models (Model 3)

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
long run								
lnR&D_eff	0.09*** (2.89)	0.27 (0.44)	0.01 (1.00)	0.08* (2.06)	0.07* (1.77)	0.29 (0.82)	0.04 (0.62)	0.008 (0.71)
lnR&D_renew	-0.12* (-1.88)	-0.31 (-0.48)	-0.06** (-2.76)	-0.12* (-1.83)	-0.10 (-1.68)	-0.43 (-0.78)	-0.08 (-0.75)	-0.03* (-2.11)
constant	4.93*** (19.97)	1.03 (0.08)	5.49*** (39.70)	4.66*** (4.16)	4.84*** (19.23)	4.31*** (3.68)	4.64*** (8.14)	4.27*** (7.83)
ECT(-1)	-0.16*** (-5.34)	-0.05** (-2.65)	-0.51*** (-3.71)	-0.17** (-2.62)	-0.20*** (-3.12)	-0.06*** (-3.25)	-0.22* (-1.80)	-0.79*** (-7.08)
short run								
lnMFP(-1)	0.83*** (11.95)	0.94*** (6.91)	0.48*** (3.04)	0.82*** (10.24)	0.79*** (8.38)	0.93*** (11.14)	0.77*** (4.00)	0.20 (1.11)
lnR&D_eff	-0.004 (-0.51)	-0.003 (-0.43)	-0.003 (-0.48)	-0.004 (-0.54)	-0.003 (-0.44)	-0.0006 (-0.07)	-0.007 (-0.65)	0.006 (0.78)
lnR&D_eff (-1)	0.01** (2.55)	0.01** (2.33)	0.012 (1.58)	0.01** (2.50)	0.01** (2.18)	0.01** (2.67)	0.01* (1.92)	
lnR&D_renew	-0.02 (-1.54)	-0.01 (-1.21)	-0.03** (-2.37)	-0.02 (-1.52)	-0.02 (-1.51)	-0.02* (-2.00)	-0.01 (-0.83)	-0.03** (-2.45)
lnco2		0.10 (0.97)						0.39*** (4.21)
lnenegy			-0.21** (-2.31)					-0.42*** (-3.46)
lngdp				0.004 (0.23)				-0.0007 (-0.03)
lneps					0.01 (0.55)			0.11*** (3.54)
gross_ca						0.004* (1.99)		0.004 (1.31)
r&d_exp							0.02 (0.38)	-0.02 (-0.65)
constant	0.836** (2.47)	0.06 (0.06)	2.80*** (3.09)	0.83** (2.40)	0.99** (2.23)	0.27 (0.63)	1.02 (1.25)	3.39*** (3.36)
ARDL	(1,1,0)	(1,1,0)	(1,1,0)	(1,1,0)	(1,1,0)	(1,1,0)	(1,1,0)	(1,0,0)
R ²	0.96	0.96	0.97	0.95	0.96	0.97	0.91	0.98
RSS	0.0026	0.0024	0.0020	0.0026	0.0025	0.0021	0.0024	0.0003
LM	0.0614	0.8827	0.5381	0.9239	0.8590	0.6128	0.8655	0.0001
HET	0.0481	0.0550	0.0500	0.0467	0.0674	0.0582	0.1412	0.1580

Notes: Notes: ***, ** and * are 1%, %5 and %10 significance levels, respectively.

(1) represent to one lag of variables; t-statistics in ().