EFFECT OF INNOVATION ON WAGES, PROFITS, AND LABOR TURNOVER IN TURKISH MANUFACTURING

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ABSTRACT

EFFECT OF INNOVATION ON WAGES, PROFITS, AND LABOR TURNOVER IN TURKISH MANUFACTURING

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Innovations are among the main factors that influence long-term economic growth and affect important economic indicators such as profits and wages. Changes in profits and wages, in turn, determine the distribution of income in a society. This thesis analyzes the effects of innovation on wages, profits, and labor turnover. Changes in wages after innovations for high-wage, median-wage, and low-wage earners and male and female workers are first considered. Subsequently, changes in profits and labor productivity after innovations are explored. Finally, changes in both labor turnover rates and labor turnover wages, or the wages of new hires and leavers (both voluntary and involuntary), are analyzed. Data from the Entrepreneurship Information System (EIS) covering the population of Turkish manufacturing firms from 2006 to 2020 are used for these purposes. Patent applications and R&D activities are used as proxies for innovations. The results show that wages and profits increase after innovative activities, but high-wage and male workers benefit more than low-wage and female workers. After innovations, within-firm wage differentials increase. Innovations' effects on labor turnover rates and wages are weak and ambiguous.

Keywords: Innovation, wages, profits, labor turnover

ÖZ

TÜRK İMALAT SANAYİİNDE İNOVASYONUN ÜCRETLERE, KÂRLARA VE İŞGÜCÜ DEVRİNE ETKİSİ

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Yenilikler, uzun vadeli ekonomik büyümeyi etkileyen ve kâr ve ücretler gibi önemli ekonomik göstergeleri etkileyen ana faktörler arasındadır. Kâr ve ücretlerdeki değişiklikler de bir toplumdaki gelir dağılımını belirler. Bu tezde, yeniliğin ücretler, kârlar ve işgücü devri üzerindeki etkileri analiz edilmiştir. Yeniliklerden sonra yüksek ücretli, orta ücretli ve düşük ücretli çalışanlar ile erkek ve kadın çalışanlar için yapılan ücretlerdeki değişiklikler öncelikle dikkate alınmıştır. Daha sonra, yeniliklerden sonra kâr ve emek verimliliğindeki değişiklikleri araştırılmıştır. Son olarak hem işgücü devir oranlarındaki yani işe giren ve işten çıkan oranı (hem gönüllü hem de gönülsüz) hem de işgücü devir ücretlerindeki değişiklikler analiz edilmiştir. Bu amaçlar için, 2006'dan 2020'ye kadar Türkiye'deki imalat firmalarının nüfusunu kapsayan Girişimcilik Bilgi Sistemi'nden (GBS) alınan veriler kullanılmıştır. Patent başvuruları ve Ar-Ge faaliyetleri yenilikler için gösterge olarak kullanılmıştır. Sonuçlarımıza göre, yenilikçi faaliyetlerden sonra ücretlerin ve kârların arttığı, ancak yüksek ücretli ve erkek çalışanların düşük ücretli ve kadın çalışanlardan daha fazla fayda sağladığı görülmektedir. Yeniliklerden sonra firma içi ücret farklılıkları artmaktadır. Yeniliklerin işgücü devir hızı ve ücretler üzerindeki etkileri zayıf ve belirsizdir.

Anahtar Kelimeler: Yenilik, ücretler, kârlar, işgücü devri

To Working Class

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CHAPTER 1

INTRODUCTION

Innovation[1] is one of the most important factors for long-term economic growth. It provides benefits to society by creating new markets and increasing productivity. Innovation also increases the competitiveness of firms and enables them to earn extra profits. Firms that innovate grow faster and prove to be more efficient than other firms.[2]

While innovations bring considerable benefits, the question of how those benefits are shared among employees, innovative firms, and other firms is of critical importance. While innovative firms may benefit through higher profits, other firms may benefit through labor turnover (Lhuillery, 2011), affecting innovative firms' accumulation of human capital. Employees may benefit from productivity through higher wages (Herman, 2020). The distribution of innovation's benefits across society is influenced by wage and spillover effects, which could have significant implications for inclusive growth.

The main research question of this work is the effect of innovations on wages, profits, and labor turnover in Turkish manufacturing in the period of 2006-2020. We formulate our hypotheses as follows:

1. Innovations increase average wages.

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[1] "An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)" (OECD, 2018).

[2] For the effects of innovations, see Atalay et al. (2013), Clark and Guy (1998), and Geroski, Machin, and Reenen (1993).

2. The impact of innovations on wages is higher for high-wage earners than low-wage earners.
3. The impact of innovations on wages is higher for male workers than female workers.
4. Innovations increase labor productivity[3] and profits.
5. Innovations increase the rate of new hires and decrease the rate of leavers.
6. Innovations increase the wage rates of new hires and the wage rates of leavers.

In the first part of the study, the impact of innovations on wages is examined because wages are essential in terms of income distribution, which means that there is also a social dimension to innovations. Wage increases do not occur at the same rate for all wage earners; on the contrary, highly skilled workers benefit more than less skilled workers (Aghion et al., 2018). This affects within-firm wage differentials. Similarly, wage rate changes after innovation are not the same for men and women. The wage increase for male workers is higher than that for female workers. Thus, innovations increase the gender pay gap. This study was undertaken with the aim of addressing the following questions: how does innovation affect wages, how much does it affect low-wage and high-wage workers, and how does it affect gender-based wage differentials?

In the second part of the study, we consider the effect of innovations on productivity and profits. Labor productivity increases after innovation (Wakelin, 2001), which positively affects profits. Income increases after innovation also raise the question of how the rises in income differ between employees and employers. The answer to that question is sought in this study.

In the final part, we investigate the effects of innovations on turnover rates (new hires and leavers) and the wage rates of new hires and leavers. Profits increase after innovation, affecting the rates of new hires positively and the rates of leavers negatively. Furthermore, employers may increase wages to keep employees in their firms while other firms offer high wages. Therefore, the wage rates of new hires and leavers may increase after innovation. The following questions are addressed in this regard: how do labor turnover rates change after innovation, and how do innovations affect the wage rates of labor turnover?

[3] Value added per employee.

Data from the Entrepreneurship Information System (EIS) of the Turkish Ministry of Industry and Technology are used in this study. That system includes the Social Security Institution dataset (employee-level information), the Revenue Administration dataset (firm-level balance sheet and income statement data), and the Turkish Patent and Trademark Office dataset (patent applications).

We use the data on all registered Turkish manufacturing firms and workers working in those firms. The data cover the period from 2006 to 2020. We match these tree datasets by using the variable of firm ID. To investigate labor turnover rates and average wages of new hires and leavers, we use the worker ID variable, which is available for the 2012-2020 period.

Innovations are proxied by patent applications and R&D activities. We further limit the sample to firms that began applying for patents and engaging in R&D after 2009 in order to create a sample in which some firms switch from "non-innovative" to "innovative" states. We employ the coarsened exact matching (CEM) method (for a description of this method, see Iacus, King, & Porro, 2021) to create two balanced control groups, one for patent applications and one for R&D activities. We use the difference-in-differences (DiD) method as suggested by Wooldridge (2021) to estimate the effect of innovative activities.

According to the OECD (2012), the proportion of innovative firms in developing countries is lower than that in developed countries, and studies on innovations are less often carried out in developing countries. However, this subject is important regarding innovation and industrial policy design in developing countries. This thesis will contribute to the literature in that direction.

The remainder of the thesis is organized as follows: After this introduction, the literature is summarized in Chapter 2. Chapter 3 provides details on the data and descriptive statistics. The methodology is explained in Chapter 4. Chapter 5 presents the results and Chapter 6 summarizes the main findings and conclusions.

CHAPTER 2

LITERATURE REVIEW

Innovation is the main driver of long-run economic growth and welfare. In this study, we explore the effects of innovation on wages, profits, and labor turnover for the manufacturing sector in Turkey between the years 2006 and 2020.

This work is related to previous studies focusing on the impacts of innovations on wages. Many previous studies have addressed the average wages in developed countries. Chennells and Van Reenen (1999) analyzed the effects of technological progress on skills, wages, and employment using micro-econometric data. The results of their analysis suggested that innovation is biased toward skilled labor and the correlation between innovation and wages is strongly positive; that is, as innovations increase, wages increase. Van Reenen (1996) utilized panel data of British firms between 1945 and 1983 to identify the effect of technological improvements on wages. Compared to non-innovative firms, it was evident that the average wages of innovative firms were higher. However, it was also stated that rival inventions frequently caused wages to decline. Toivanen and Väänänen (2008) used US patent data with inventors linked to Finnish employer-employee data to examine the impacts of patenting on wages. They demonstrated that, depending on the quality of the patent, different percentage increases occurred in earnings. Innovations led to an increase in average wages.

While the studies mentioned above focused on the effects of innovations on average wages, more recent studies have analyzed their impact on the distribution of wages using matched employee-employer data. For example, Aghion et al. (2019) examined the relationship between wages and R&D expenditures using matched employee-employer data from the UK. Their analysis showed that more R&D-intensive firms paid higher wages on average and particular workers in some low-skilled occupations received significant benefits. They used fixed effects model to estimate the effects of innovation on low-skill and high-skill occupations and used two-way fixed effects method to check the robustness.

Merging individual income, employer and plant characteristics, patenting, and IQ data obtained from Finland in 1988 to 2012, Aghion et al. (2018) observed that the effect of inventions on both innovators and their stakeholders or coworkers were positive within the same firm. The estimation results showed substantial earning increases for inventors. Additionally, non-inventing coworkers and entrepreneurs also benefited from those inventions, and these gains were long-lasting for all groups. These researchers used CEM with one-to-one matching and applied a conditional DiD method.

Akcigit, Grigsby, and Nicholas (2017) used state-level and country-level aggregate data together with US patent data from 1880 to 1940. They reported a link between long-term economic growth and patented inventions, and that finding was consistent with the fact that technological improvements increase the inequality between skilled and unskilled labor. Using Spanish manufacturing firm data, Martínez-Ros (2001) examined the change in real wages when firms made innovations, arguing that innovation causes wage increases. At the same time, it has been shown that workers' bargaining power positively affects wage increases (Ballot, Fakhfakh, and Taymaz, 2006). The largest salary increase in such cases is seen for incumbent employees. Pianta and Tancioni (2008) noted that wages rise with inventions and those wages grow more quickly when innovation spending is higher. They used two European innovation surveys offering data from 1994-1996 and 1998-2000 at country and industry levels. Most wage growth was found to come from highly skilled labor, researchers, and technicians. Patent applications and R&D activities increased average wages and affected wage distributions.

The impact of innovation differs between skilled and unskilled labor in developed countries. At the same time, the effects of those variations may be greater between male and female workers. Kline et al. (2019) used US patent applications, US business tax records, and US worker tax records to explore how labor compensation is affected by patent-induced shocks. According to the results of that study, employees in the top half of the earnings distribution are disproportionately affected by the earnings effects of patent allowances. Patent benefits also widen the gender pay gap. In contrast to how less responsive female workers' earnings are to patent decisions, male workers' earnings increase significantly in response to patent allowances. Considering another aspect, Erdil, Cetin, and Findik (2008) analyzed panel data from 13 developed countries for the manufacturing industry in 1980-1998 to determine whether there was any effect of technological development on gender-based differences in wages. Their results indicated that technological developments diminished male-female worker wage differences, reducing the gender pay gap. As a result, however, it was concluded that male and female workers do not benefit from such increases equally. While some studies state the opposite, some have suggested that wage increases for male workers are higher than those for female workers. While some studies indicate a decrease in the gender pay gap after innovation, others have suggested an increase in that gap.

When firms introduce innovations, productivity rises (Arvanitis, 2006; Long et al., 2017) and income increases. This rise in income is possibly shared between employers and workers, and the critical question here is how the division of the increased income is shared between employers and employees and there is no much emphasis on that. Previous studies have emphasized that there is a positive relationship between innovation and profit (Pianta & Tancioni, 2008; Kline et al., 2018; d'Andria et al., 2021). Cefis and Ciccarelli (2005) used panel data of UK manufacturing firms from 1988-1992. They investigated the impact of innovation on firm profitability and found a positive relationship between those variables. Analyzing 38 manufacturing and service sectors of 8 European countries for two periods between 1994-2006, Bogliacino and Pianta (2012) researched the ability of innovations to increase profits. It was demonstrated that innovations increased profits (Maliranta et al., 2009).

A further important question regards the relationship between innovation and labor turnover. A series of studies have indicated that knowledge spillovers are frequently caused by high labor turnover among firms (Maliranta et al., 2009; Song et al., 2013; Almedia & Kogut, 1999; Lenzi, 2013; Lenger & Taymaz, 2005). Knowledge spillover increases productivity and encourages innovative activities (Feldman, 1999; Nadiri, 1993). The majority of prior research primarily concentrated on how labor turnover affects innovation with little attention paid to how innovation influences labor turnover. Eriksson et al. (2014) used survey data from Chinese enterprises in five high-technology industries to highlight the connection between workers' mobility, human resource management practices, and innovation. According to that study, innovative firms experience greater rates of technical labor turnover than non-innovative firms. This indicates that labor turnover has a favorable effect on a firm's capacity for innovation. The authors claimed that the study's findings confirmed the theory that new hires bring new ideas to the workplace.

Recent studies have also analyzed the relationship between labor turnover and innovation in developed countries. Kaiser et al. (2015) used population data of Danish firms active in R&D from 1999-2004. The dataset contained the patent applications of those Danish firms with matched employer-employee registry data. They analyzed the impact of labor turnover on the patenting activities of the firms and argued that mobility causes knowledge spillover between firms while the inflow of workers increases innovative activities. Using the same Danish dataset, Ejsing et al. (2013) demonstrated that new hires contributed to innovative activities more than long-term employees. The hiring of researchers from universities also contributed significantly to innovative activities. Conducting a survey in Germany, Hoisl (2007) collected data to investigate the causality between inventor productivity and inventor mobility. She found that mobile inventors were more productive compared to non-mobile inventors, and mobility increased inventor productivity. Braunerhjelm, Ding, and Thulin (2020) utilized Sweden's unique matched employer-employee data and firm-level patent application data. They examined the link between labor turnover and firm innovation output, which was measured by firm patent applications. They found a positive and strongly significant relationship between them, and when the workers came from innovative firms, the effects were shown to be strongest. In addition, due to the learning-by-diaspora effect, firms received only limited benefits from the knowledge of lost workers. Using a sample of European R&D investing firms, Rahko (2016) analyzed the impact of inventor mobility on firm-level innovation performance. The estimation results suggested that inventor mobility increased future innovation activity and led to knowledge spillover. On the contrary, some studies have indicated that labor turnover negatively impacts innovations at firm level (Pieroni & Pompei, 2007; Abbasi & Hollman, 2000). The literature on the relationship between labor turnover and innovation is less consistent. While some articles claim the reverse, past studies have found that labor turnover affects innovation positively.

There have not been many studies conducted on this subject in developing countries. One of the few examples is the study of Castillo et al. (2013). They analyzed the effect of an innovation program to evaluate innovation's impact on employment and wages. They claimed that the Argentinean Support Program increased innovation in small and medium-sized businesses, raising wages and increasing employment. In that research, they applied propensity score matching and the DiD method. Crillo (2014) utilized Chile's firm-level panel data from 2007 to 2009 for the manufacturing, agriculture, mining, and construction sectors. She analyzed innovation's impact on wages across professional categories. The analysis results suggested that product innovations increased salaries for all professional categories, such as managers, clerks, and skilled employees, but not for unskilled manual work. According to the literature, equal wage increases do not occur among employees. While highly skilled workers benefit more from innovation, less skilled workers benefit less. Utilizing matched employer-employee data from Estonia, Masso and Vahter (2020) analyzed the effects of innovation on wages and the gender pay gap. According to their estimation results, innovation increased the wages of both male and female workers; however, female workers earned 3-5 percentage points less than male workers after wage increases due to innovation. In a more recent study, Mbaye, Tani, and Okara (2022) explored the effects of labor mobility on innovation using firm-level and country-level data for Africa obtained from the World Bank, the World Trade Organization, and the United Nations. Compared to the rest of the world, short-term labor mobility in African firms positively affects innovation. These studies in developing countries show that innovations increase wages, but the increases are different across worker groups and genders, and labor turnover affects innovation positively.

When we look at the literature for the Turkish case, there are no studies addressing innovation's effects on wages, profits, and labor turnover, mainly because of the absence of data. Related studies for Turkey can be summarized as follows. Karabulut (2015) investigated the impact of innovation strategies on firm performance among manufacturing sectors in İstanbul. She showed that Turkish manufacturing firms' innovation strategies helped them boost their financial performances. Additionally, innovative approaches helped these businesses enhance their performance regarding customers, internal business processes, and learning and growth. Atalay et al. (2013) utilized a survey administered to the top-level managers of 113 firms operating in the automotive supplier industry in Turkey as of the year 2011. The estimation results suggested that innovation affects firms' performances positively and significantly. Using a survey administered to 150 high-tech firms in İstanbul, Ankara, and Antalya, Dogan et al. (2020) examined the links between knowledge sharing, innovation, and firm performance. They concluded that innovation speed and quality impacted the firms' operational and financial performances and that knowledge sharing also had a positive effect on firm performance. Meschi, Taymaz, and Vivarelli (2016) analyzed the impact of globalization and technological changes on the employment and wages of skilled and unskilled workers. The data used in their analysis came from the Turkish Statistical Institute's Annual Manufacturing Industry Survey, which contained data on all manufacturing sectors in Turkey from 1992 to 2001. The results of the estimations suggested that skill-biased technological change and skill-enhancing trade increased the pay gap between skilled and unskilled labor and employment. Taken together, these studies indicate that innovations increase firm performance and affect wage distributions in Turkey.

Few studies in Turkey have used EIS data in their analyses. Akgunduz et al. (2019) carried out a descriptive analysis of job mobility for different sectors between 2012 and 2016 in Turkey. Among their results, they found that employees moving to higher positions were most likely to be young and male. More than half of the job mobility occurred in the direction of more successful, larger, and more productive firms. There was considerable job mobility in the manufacturing and trade-transportation sectors. Akcigit et al. (2020) used the same dataset to analyze competition and business dynamism for manufacturing sectors in Turkey in 2006-2016. Their findings suggested that, up until 2012, the Turkish manufacturing sector's business dynamism was comparatively stable and even growing, but after 2012 it started to decline. Labor turnover in large and productive firms was found to be higher and manufacturing firms in Turkey were described as relatively stable.

As evolutionist-Schumpeterian economists have argued since the 1980s, innovations are important for long-term economic growth (for a pioneering study, see Nelson &

Winter, 1984). Innovations have uneven effects on wages and profitability. High-wage workers benefit more than low-wage workers, and male workers are positively affected more than female workers. Moreover, labor turnovers affect innovations positively.

We can explain these effects with theories such as skill-biased technological change, wage bargaining models, and gender and occupational discrimination theories. Skill-biased technological changes lead to increasing pay gaps between skilled and unskilled labor with the impact of technology (Berman, Bound, & Griliches, 1994). After innovation, wages change in favor of skilled labor. Wage bargaining models suggest that a wage is the weighted average of the reservation wage (the outside wage) and labor productivity, where the weights are the bargaining powers of workers and the firm (Ballot, Fakhfakh, & Taymaz, 2006). Wage bargaining models can explain wage increases after innovation, while gender discrimination theories can explain the gender pay gap increase after innovation.[4] These theories could not be tested in this thesis because of data limitations. Instead, we empirically look at the impact of innovations on profits, wages, and labor turnover in the Turkish manufacturing industry.

The links between innovations, wages, profits, and labor turnover rates have been studied more often in developed countries. The present work is the first study to analyze innovation effects on labor turnover in Turkey. The EIS data allow us to follow all individual registered workers employed in manufacturing industries. In addition, this is the first study to use population data from the manufacturing sector to estimate the impact of innovation on different wage percentiles, gender pay gaps, and profits.

[4] For further information about discrimination theories, see Antonji and Black (1999) and Anker (1997).

CHAPTER 3

MODEL, DATA AND DESCRIPTIVE STATISTICS

3.1. Model and Hypotheses

The impact of innovations on wages, profits, and labor turnover in Turkish manufacturing from 2006 to 2020 is the main topic of this study. The first hypothesis states that innovations increase average wages. After innovation, labor productivity increases and, as a result, wages also increase. Moreover, the bargaining power and reservation wages of employees may also increase because their (tacit) knowledge increases after innovation. Therefore, according to wage bargaining models, their wages will be raised.

The second hypothesis of this study is that innovations have a more significant effect on earnings for high-wage workers than for low-wage workers. The wage increases of low-wage earners are usually less than those of high-wage earners (Akcigit et al., 2017; Jones & Kim, 2018). The reason for this is that the bargaining power of highly skilled workers is higher than that of less skilled workers. This increases wage inequality among workers and negatively affects income distribution.

The third hypothesis is that innovations positively affect the wages of both male and female workers but favor male workers. The labor market discrimination theory and occupational segregation theory can explain the hypothesis. Discrimination theory in the labor market explains the persistence of pay differences with the role of non-labor-market factors (Huang, 1999). Occupational segregation theory addresses the unequal distribution of workers across and within occupations with different wages and possibilities for promotion based on gender. Innovative firms in manufacturing sectors are more likely to employ male workers, which may affect gender pay gaps. Female labor ratio is around 20% in manufacturing.

Fourth, it is hypothesized that innovations increase labor productivity and profits, and the income of the capital owner increases as well. If workers' earnings rise at the same rate, there will be a neutral effect on income distribution. If the rate of the wage increase is less than that of the profit, the income distribution will be distorted.

Fifth, it is hypothesized that new hire rates increase and leaver rates decrease after innovations. This is because, as a firm grows, it employs new employees, and since the firm is profitable and wages rise, the proportion of employees who are leaving decreases. Conversely, if innovation increases productivity too much, leavers may increase. In addition, employees with increased knowledge as a result of innovation can go to other firms, which can increase the leaver rate. Since there is no information about the reason for leaving in our dataset, we are not able to separate these effects.

Finally, it is hypothesized that innovations increase the wage rates of new hires and the wage rates of leavers. There is a difference, however, in the wages of new hires and leavers because workers who leave innovative firms enter other firms for higher wages. The wages of those who leave will increase because innovative firms may pay higher wages to avoid losing their employees. However, these wage changes are more applicable for highly skilled workers. There is no information about education level in our dataset to follow highly skilled workers, so we cannot separate these effects.

Variables such as wages, profits, and labor turnover affect the probability of innovations. Therefore, there is a bidirectional causality between innovations and these variables. In this study, we only examine the effects of innovations on wages, profits, and labor turnover.

3.2. Data

This study is based on EIS data accessed through the Turkish Ministry of Industry and Technology to analyze the effects of innovation. The Ministry collects data on economic activities from various administrative sources and assigns unique codes for firms and employees so that different databases can be matched together using those unique keys. The dataset contains information on the registered and operating population of Turkish firms, excluding firms in the public and financial sectors, and it covers all employees working in these firms. The overall dataset includes data from the Ministry of Trade (bilateral trade relations), the Social Security Institution (employees' information and wage payments), the Revenue Administration (balance sheets, income statements, and R&D costs), the Turkish Patent and Trademark Office (patent, trademark, and utility model applications), and the Small and Medium Enterprises Development and Support Administration (SME support recipients).

The primary dataset in this study comes from the Social Security Institution and it contains employee-level data regarding the wages of employees whose social security contributions are paid. There is also information on workers' ages and genders, numbers of days worked, firms in which they worked, and the sectors of the firms. These employee-level data are available for 2006-2019 at quarterly frequency and for the years after 2019 at monthly frequency. For the years before 2012, registration numbers of workers are not available, so we could not follow workers before 2006. Therefore, we analyze the effects of innovation on the rates of new hires and leavers and wages of new hires and leavers in the period of 2012-2020. We use the wage data from this employee dataset.

The second dataset is from the Revenue Administration, which comprises firm-level data. The following variables are available in this dataset: balance sheet, income statement, sector code (4-digit, NACE Rev. 2), geographical location, province, exports, imports, number of employees, wage bill, and year of establishment. The firm-level data cover the years of 2006 to 2020 with annual frequency. In the present study, we use the balance sheet, income statement, sector code, firm size (number of employees), wage bill, exports, and R&D expenditures.

In addition, we use patent application data from the Turkish Patent and Trademark Agency. These data include information on the patent applications of firms. The manufacturing sectors account for the highest share of patent applications and R&D activities; for that reason, we analyze manufacturing sectors. We merge these three datasets at the firm level.

The Social Security Administration in Turkey determines the maximum (ceiling) and minimum (floor) amounts of covered earnings subject to social security contributions. The minimum amount is equal to the (gross) minimum wage, whereas the maximum has been equal to 7.5 times the minimum wage since 2017; previously, it was 6.5 times.

Since the social security data provide information on covered earnings, we can observe changes in wages as long as they are within this range. It is important to note that the number of workers above the ceiling is rather small, meaning that the vast majority of employees are paid under the imposed ceiling and the wage data used in this study are not distorted.

There were 459,600 firms in the manufacturing sector in 2020 (Table 3.1). Among the manufacturing firms, we include those taxed on a balance sheet basis since we need balance sheet and income statement data to calculate value added and profits. There were 216,503 firms whose balance sheets were available in 2020. We exclude firms that were not operating continuously for a certain period. Many firms in the dataset show on-and-off patterns, appearing in the dataset for a few years, then going missing and reappearing again a few years later. After eliminating those, 156,646 firms were left. As our examination of wages requires data from firms with at least one employee, we also exclude firms that do not employ anyone and we find that 135,113 firms have at least one employee.

Table 3.1: Number of firms, 2020

		Number of firms
All firms		459600
In the scope of balance sheet		216503
Continuous firms		156646
Having at least one employee		135113
	Patent applicants	851
	R&D performers	3022
Balanced panel firms		32274
	Patent applicants	429
	R&D performers	1470
Treatment and control groups		
	Patent applicants	1095
	R&D performers	2010
Patent applicant and R&D performer		399

Source: Author's calculations based on the EIS dataset[5]

[5] Unless otherwise stated, all data presented in this thesis were calculated from the EIS dataset by the author.

We use patent applications and R&D activities as proxies for innovation. If a firm applies for a patent or starts to conduct R&D activities, we call this firm "innovative." The dataset is available for the years of 2006-2020. To calculate the value added, we use the years' beginning and ending values of stocks, which are provided in the balance sheets. Since there are no stock values for the beginning of 2006, we cannot calculate the value added for 2006. The data from 2007 to 2008 (2 years) are used to create a sample in which no firm undertook any innovative activities and we use the firms that engaged in patent application/R&D activities after 2009. In short, we use the data for 14 years, from 2007 to 2020. In order to exclude the effects of firm entry and exit, we prepare balanced panel data that include only those firms that operated in all years in the dataset (2007-2020), with 32,274 firms for the balanced dataset (see Table 3.1). The number of observations we have is 32,274 × 14 = 451,836.[6]

After 2012, the registration numbers of workers become available in the dataset, allowing us to follow workers and identify labor turnover. To perform the labor turnover analysis, we use the data from 2012-2020. Data from before 2012 are used to create a sample with no innovative activities. For labor turnover estimations, we use 9 years of data (2012-2020).

We use two different methods in our impact analysis. In the first method, we create a control group of non-innovative firms that are "similar" to the innovative firms in terms of firm size, firm age, capital intensity, exporting status, and being in the same sector. In the second analysis, we compare the firms that engage in innovation and all balanced panel firms that have been operating for 14 years.

3.3. Descriptive Statistics

This section provides the relevant descriptive statistics for visualizing the differences between patent applicants, R&D performers, and non-innovative firms.

[6] For further information about data cleaning, see the Appendices.

3.3.1. Unbalanced Panel Data

This subsection presents the data on all "continuous" manufacturing firms, i.e., this dataset includes those firms that entered or exited from the manufacturing industry during the period under investigation.

Table 3.2 shows the number of firms, sizes, relative firm sizes, and relative wage rates in the dataset. We compare all manufacturing firms with the innovative firms (patent applicants/R&D performers). The number of all firms increased from 88,500 to 156,646 between 2006 and 2020. In the years of 2006-2008, the number of patent applicants was very small, but after 2009 it started to increase. There were two major policy changes in this period.[7]

The number of firms submitting patent applications and conducting R&D activities were 850 and 3022, respectively, in 2020. The number of R&D performers was 2063 in 2006; with the exception of a few years, it increased continuously until 2020. On average, the number of R&D performers is about 2% of all firms, and the number of patent applicants is approximately 0.4% of all firms after 2009. The number of firms making both patent applications and R&D activities was 399 in 2020 (see Table 3.1). These figures show that about 60% of patent applicants did not perform any R&D activities, i.e., a large number of innovations were generated by non-R&D activities, and not all R&D activities end with patent applications, partly for reasons of secrecy, but they may still generate knowledge. Therefore, by using two different measures of innovation, we are able to analyze the effects of different types of innovative activities.

The relative size columns show innovative firms' sizes with respect to the average firm in manufacturing. We use the number of employees as a proxy for firm size. The average number of employees in a manufacturing firm is 22. The number of employees among patent applicants is, on average, 20 times higher than the numbers for other

[7] Major policy changes in the period of 2006-2020 were as follows: First, Law No. 5746 in 2008 granted firms high income-tax-withholding support and allowed firms to write R&D expenditures as expenses (Akcomak et al., 2020). Second, Law No. 4691 ("Technology Development Zones Law") in 2011 was intended to increase the circulation of knowledge in technoparks via encouraging the establishment of technoparks in universities or research centers, thus enabling firms to be a part of innovative activities. This law also introduced financial advantages (Akcomak et al., 2020).

firms. The size of the firms active in R&D is 11 time larger than the others. There is a substantial size difference between innovative and non-innovative firms.

The average median wage of innovative firms is higher than that of other manufacturing firms. The wage difference was 90% for patent applicants and 60% for R&D performers in 2006. However, these differences decreased to 30-50% in 2020. In other words, the employees of patent applicants and R&D performers were then paid 30-50% higher wages than others. As predicted, those who work in firms active in R&D and patent applications earn higher wages than the average manufacturing worker. Differences in wages could be explained by employee characteristics (education, skills, experience, gender, etc.) and/or firm characteristics (size, technology, market power, etc.). In the following section, we determine whether a part of these differences can be explained by innovativeness by using DiD methodology.

Table 3.2: Number of firms, firm sizes, relative firm sizes, and relative wages

	Number of firms			Size	Relative firm size[8]		Relative wage rate[9]	
Years	All firms	Patent applicants	R&D performers	All firms	Patent applicants	R&D performers	Patent applicants	R&D performers
2006	88500	15	2063	22	14.5	9.3	1.9	1.6
2007	103167	67	2308	21	37.0	9.8	1.7	1.6
2008	108880	24	2410	21	24.5	9.7	1.5	1.6
2009	110770	271	2401	19	21.5	10.3	1.7	1.6
2010	112015	396	2370	21	18.3	10.5	1.7	1.6
2011	116104	453	2455	22	17.9	10.5	1.7	1.5
2012	120923	533	2521	23	16.9	10.3	1.6	1.5
2013	126226	570	2606	23	16.6	10.7	1.6	1.5
2014	133241	592	2698	23	19.1	10.6	1.6	1.5
2015	140402	602	2755	23	21.8	11.3	1.6	1.5
2016	146898	643	2814	22	22.3	12.1	1.5	1.4
2017	150104	690	2847	23	22.8	12.9	1.5	1.4
2018	163809	830	3041	21	22.8	13.5	1.5	1.4
2019	169773	875	3152	19	23.1	14.2	1.5	1.4
2020	156646	851	3022	20	25.4	14.2	1.5	1.3

[8] Relative firm size is the ratio of the number of employees in firms with patent applications/R&D activities to the number of employees in all manufacturing firms.

[9] Relative wage rate is the ratio of the median wage of firms with patent applications/R&D activities to the median wage of all manufacturing firms.

We create a within-firm wage differential measure by dividing the 90th percentile wage by the 10th percentile wage. This difference is about 2 for all manufacturing firms on average, as shown in Table 3.3. This means that when we sort the wages of workers in a firm from highest to lowest, the highest 10th percentile of workers earn 2 times more than the lowest 10th percentile of workers. On average, the within-firm wage differential for patent applicants is about 3, and this differential is 2.8 for the R&D performers. Thus, the difference is higher for innovative firms. This shows a difference between innovative firms and the average manufacturing firms.

Table 3.3: Wage differentials, 2006-2020

	Within-firm wage differentials[10]		
Years	All firms	Patent applicants	R&D performers
2006	1.98	3.57	2.63
2007	2.01	3.42	2.64
2008	2.08	3.12	2.87
2009	2.10	3.10	2.87
2010	2.08	2.94	2.83
2011	2.10	2.86	2.88
2012	2.09	2.78	2.80
2013	2.15	2.88	2.86
2014	2.17	2.74	2.76
2015	2.24	2.73	2.87
2016	2.09	2.83	2.75
2017	2.14	2.76	2.77
2018	2.14	2.81	2.72
2019	2.05	2.72	2.59
2020	2.16	2.95	2.79

Table 3.4 shows the new hire and leaver rates between 2012 and 2020. The rates of new hires and leavers are computed from December to December. A December 2012 employee who is no longer employed at the same firm in December 2013 is considered to have left the firm, while a December 2013 employee who did not work for the same firm in December 2012 is considered to have entered the firm. In this dataset, the jobs of some employees are changing frequently. When an employee switches jobs more frequently than twice annually, that employee is not taken into consideration while

[10] Within-firm wage differential: 90th percentile wage divided by 10th percentile wage.

calculating rates of new hires and leavers because it is likely that they are either employed temporarily or working with a temporary employment agency.

As shown in Table 3.4, while the new hire rate is 32% in average manufacturing firms, 30% of the employees leave their firms in a year. The difference between new hires and leavers equals the employment growth in these firms. Except for the years of 2018 and 2019, there was employment growth in these manufacturing firms because the rate of new hires was higher than the rate of leavers. We can observe the impact of the pandemic in 2020 on the rate of new hires, which is very low compared to other years.

For patent applicants, the leaver rate is about 18% and the new hire rate is about 20%. For R&D performers, approximately 20% of employees leave their firm in a year, and about 23% of employees in R&D performers enter the firm in a year. The labor turnover rate is relatively low in innovative firms. This may be due to the sustained loyalties of the innovative firms' employees. This sustained loyalty may contribute to low labor turnover. Furthermore, innovative firm's sizes are larger than those of other firms, which could be another reason for low turnover (see Even & Macpherson, 1996). Low new hire and leaver rates could help the accumulation of firm-specific knowledge and technology in innovative firms.

Table 3.4: New hire and leaver rates, 2012-2020

	Leaver rates			New hire rates		
Years	All firms	Patent applicants	R&D performers	All firms	Patent applicants	R&D performers
2012	0.298	0.182	0.206	-	-	-
2013	0.309	0.200	0.217	0.322	0.209	0.244
2014	0.302	0.193	0.209	0.325	0.243	0.250
2015	0.292	0.180	0.206	0.330	0.241	0.269
2016	0.272	0.172	0.195	0.284	0.189	0.208
2017	0.289	0.199	0.210	0.308	0.201	0.227
2018	0.305	0.186	0.230	0.262	0.170	0.193
2019	0.228	0.120	0.138	0.277	0.165	0.188
2020	-	-	-	0.110	0.071	0.080

Table 3.5 shows the wages of leavers and new hires in innovative firms relative to other firms. The leavers' wage rate in firms with patent applications is 8% higher than those of others while it is 7% higher for R&D performers on average. The new hires'

wage rate is 10% higher for firms with patent applications and 9% higher for firms active in R&D. These high new hire and leaver wages show that innovative firms hire more skilled labor than other firms, and their leavers are also more skilled than those of other firms.

Table 3.5: The relative wage rates of new hires and leavers

Years	The relative wage rate of leavers		The relative wage rate of new hires	
	Patent applicants	R&D performers	Patent applicants	R&D performers
2013	1.09	1.08	1.11	1.10
2014	1.09	1.08	1.11	1.10
2015	1.07	1.08	1.10	1.11
2016	1.08	1.06	1.11	1.08
2017	1.08	1.06	1.09	1.08
2018	1.06	1.06	1.10	1.08
2019	1.09	1.06	1.11	1.08
2020	1.07	1.07	1.09	1.08

Table 3.6 shows the relative labor productivity of patent applicants and R&D performers with respect to all manufacturing firms. The labor productivity of patent applicants is 2 times higher than that of all manufacturing firms and it is 1.7 times higher for the R&D performers on average. This productivity increase may lead to higher profits in innovative firms.

Table 3.6: Relative labor productivity of innovative firms compared to all manufacturing

	Relative labor productivity	
Years	Patent applicants	R&D performers
2007	2.2	1.8
2008	1.6	1.9
2009	2.1	1.7
2010	2.2	1.7
2011	2.2	1.7
2012	2.0	1.7
2013	2.0	1.7
2014	1.9	1.7
2015	2.1	1.7
2016	1.9	1.6
2017	2.0	1.6
2018	2.1	1.7
2019	1.9	1.6
2020	1.8	1.6

3.3.2. Balanced Panel Data

We use the dataset of firms operating in all years from 2007 to 2020 (14 years) and the number of observations is 32,274. Since these are "balanced panel data," they do not include entering and exiting firms. Rather, they include the "successful" firms that could survive for 14 years, whether they innovated or not.

We use two different methods while working with this dataset. First, we form treatment groups and compare them with all balanced panel firms for 14 years. Second, we compare a treatment group with a similar control group created using CEM. However, we will first consider some descriptive statistics for the balanced panel of 32,274 firms.

The annual number of patent applicants in the balanced panel dataset is about 300, while there are about 1300 R&D performers. Table 3.7 shows that the number of employees in balanced panel manufacturing firms is approximately 60. On average, the number of employees in firms with patent applications is 14 times higher than the number in balanced panel firms, and the number in R&D performers is 7 times higher. The average firm size in the balanced panel is relatively large compared to all manufacturing firms. Furthermore, the sizes of innovative firms (patent applicants/R&D performers) in the balanced panel are larger than those of other firms in the balanced panel.

The relative median wage of innovative manufacturing firms is about 40-50% higher compared to firms in the balanced panel. For patent applicants, the relative wage difference decreases from 60% to 40%, and the decrease for R&D performers is from 50% to 20%. The wage difference among firms in the balanced panel is smaller than that of average manufacturing firms (see Table 2) because, in this sample, we have firms operating for 14 years, which are more successful than average manufacturing firms.

Table 3.7: Number of firms, sizes, relative firm sizes, and relative wage rates of firms in the balanced panel

Year	Number of firms		Size	Relative firm size		Relative wage rate	
	Patent applicants	R&D performers	Balanced panel firms	Patent applicants	R&D performers	Patent applicants	R&D performers
2007	41	1240	42	29.1	7.5	1.6	1.5
2008	17	1295	43	14.6	7.1	1.3	1.4
2009	158	1289	41	14.6	7.2	1.6	1.5
2010	235	1288	45	11.8	7.4	1.5	1.4
2011	268	1309	49	11.9	7.2	1.5	1.4
2012	270	1340	52	12.7	7.0	1.5	1.4
2013	288	1342	54	12.9	7.2	1.5	1.4
2014	316	1356	56	13.0	7.0	1.5	1.4
2015	317	1354	59	13.9	7.2	1.5	1.3
2016	316	1361	59	14.9	7.6	1.4	1.3
2017	355	1384	61	13.9	7.8	1.4	1.3
2018	396	1428	62	13.7	7.9	1.5	1.3
2019	398	1486	56	14.3	8.1	1.4	1.3
2020	429	1470	56	15.6	8.5	1.4	1.2

The leaver and new hire rate is about 25%. However, this rate is 18% for patent applicants and 20% for R&D performers (see Table 3.8). There is growth in the firms.

Table 3.8: New hire-leaver rates of firms in the balanced panel, patent applicants, and R&D performers

	Labor turnover rate for firms in the balanced panel					
	All firms in the balanced panel		Patent applicants		R&D performers	
Years	Leaver rate	New hire rate	Leaver rate	New hire rate	Leaver rate	New hire rate
2013	0.25	0.29	0.16	0.20	0.18	0.24
2014	0.26	0.29	0.16	0.23	0.20	0.24
2015	0.25	0.30	0.16	0.23	0.18	0.26
2016	0.25	0.25	0.16	0.18	0.18	0.20
2017	0.22	0.26	0.15	0.19	0.17	0.21
2018	0.24	0.22	0.17	0.16	0.19	0.18
2019	0.30	0.22	0.19	0.15	0.23	0.17
2020	0.06	0.09	0.03	0.06	0.04	0.07

Table 3.9 shows the labor productivity of innovative firms in the balanced panel compared to all firms in the balanced panel. This sample's productivity difference is smaller because almost all of the firms are large. Patent applicants are 70% more productive than all successful firms, and this value is 50% for firms active in R&D. There is a difference between innovative and non-innovative manufacturing firms.

Table 3.9: Relative labor productivity of innovative firms in the balanced panel compared to all firms in the balanced panel

	Relative labor productivity of firms in the balanced panel	
Years	Patent applicants	R&D performers
2007	1.9	1.6
2008	1.2	1.6
2009	2.1	1.5
2010	1.9	1.5
2011	1.8	1.5
2012	1.7	1.5
2013	1.7	1.5
2014	1.6	1.4
2015	1.8	1.5
2016	1.7	1.4
2017	1.7	1.4
2018	1.7	1.4
2019	1.7	1.4
2020	1.6	1.4

3.3.3. Control Groups

We observe substantial differences in the variables of interest between innovative and non-innovative firms. These differences do not necessarily imply any causation, so we use the DiD method to determine whether innovation (patent applications/R&D activities) causes changes in these variables. We need treatment (innovative firms) and control (non-innovative firms) groups to implement this method. We include all innovative firms in the treatment group, and then, for each treated (innovative) firm, we select a non-innovative but otherwise "similar" firm for the control group. These "similar" firms are found by applying CEM.[11]

Table 3.10 shows the innovation cohorts between 2009 and 2020. While the total number of patent applicants is 1095, the total number of R&D active firms is 2010. Each innovation cohort has 90 firms with patent applications and 170 in R&D activities on average.

The variables for the year 2008 used in the selection of the control group firms are as follows: the firm's size, the firm's age, the sector code (NACE Rev. 2, 2-digit level), capital intensity, and export status. The two groups are similar in terms of these variables. We have in total 2190 observations to investigate patent applications and 4022 observations to investigate R&D activities after balancing the data. We have in total 1095 innovative firms and 1095 similar firms to compare in the control group. There are also 2010 firms engaged in R&D activities.

[11] Methods such as propensity score matching are also widely used to establish control groups. The CEM algorithm involves reducing the imbalance in covariates across the treatment and control groups, so it is able to more accurately estimate causal effects, and the covariates' empirical distributions are similar between the treated and control groups (Blackwell, Iacus, King, & Porro, 2009). In addition, CEM can achieve lower levels of bias, imbalance, and model dependence (King & Nielsen, 2019).

Table 3.10: Number of firms in innovation cohorts

Cohort	Patent applicants	R&D performers
2009	75	224
2010	107	201
2011	113	196
2012	90	200
2013	91	163
2014	88	177
2015	87	162
2016	88	157
2017	82	149
2018	102	154
2019	77	135
2020	95	92
Total	1095	2010

Table 3.11 shows the firm size of the control group, relative firm size, and relative wage rate. The number of employees in the control group for patent applicants is about 1000 and that for R&D performers is about 300 on average. The sizes of the patent applicants are about 2 times larger than those of the control group, while R&D performers' sizes are about 1.5 times larger. The relative firm sizes are very close to each other in 2007 and 2008, because the control group was created according to 2008 data, but this difference widens over time.

Table 3.11: Firm sizes, relative firm sizes, and relative wage rates of the control

	Firm size of control group		Relative firm size		Relative wage rate	
Years	Patent applicants	R&D performers	Patent applicants	R&D performers	Patent applicants	R&D performers
2007	657	181	1.1	1.1	1.00	1.01
2008	828	222	1.1	1.1	1.01	1.01
2009	760	197	1.2	1.2	1.01	1.01
2010	915	245	1.4	1.3	1.01	1.01
2011	1087	291	1.6	1.4	1.01	1.01
2012	1202	333	1.7	1.5	1.01	1.01
2013	1263	339	1.8	1.7	1.01	1.01
2014	1303	360	1.9	1.8	1.01	1.01
2015	1435	390	2.2	1.9	1.01	1.02
2016	1300	347	2.4	2.1	1.01	1.01
2017	1252	326	2.6	2.2	1.01	1.01
2018	1148	315	2.9	2.3	1.01	1.01
2019	812	216	3.1	2.5	1.01	1.01
2020	833	213	3.2	2.7	1.01	1.01

The average median wages for patent applicants and control firms are almost the same. The difference is 1%. For R&D performers, the wage difference is similar. That is to say, the control group and innovative group contain similar firms. Compared to average manufacturing firms and firms in the balanced panel, the sizes and wages of control group firms are more similar to those of the innovative firms.

When we compare innovative firms with all other firms, we find that the difference between them is very large, but this difference is less in the balanced dataset. Also, in the control group, this difference is very small. One of the reasons for this is that innovative firms are already large firms. Therefore, when we use the firms in the balanced panel (the set of "successful" firms) in a comparison with innovative firms, the difference becomes smaller because more successful firms are larger. Consequently, in order to measure the effect of innovation, the effects of such factors must be controlled.

CHAPTER 4

METHODOLOGY

4.1. Difference in Differences and Coarsened Exact Matching

This study aims to determine the impact of innovation on profits, wages, and labor turnover. We apply the DiD estimator to measure the outcomes of patent applications and R&D activities. For this purpose, we make use of two-way fixed effects (TWFE) model as described by Wooldridge (2021). Before we apply the model, we form a treatment group and use the CEM method to balance the observations. In this section, the methods employed in this study will be described.

Callaway & Sant'Anna (2021) stated that one of the most widely utilized research strategies for assessing the causal impacts of policy changes is the DiD. In the standard DiD setup, there are two groups and two periods: one group is the treated group and the other is the comparison group. No unit receives treatment during the first period, and during the second period, some units receive treatment (the treated group) while others do not (the comparison group). The parallel trends assumption, which states that the average outcomes for the treatment and comparison groups should follow a parallel path over time, is one of the key assumptions of the DiD. If the assumption is true, it is possible to estimate the average treatment effect for the treated group. To measure the average treatment effect, it is necessary to compare the average change in outcomes for the comparison group and the treatment group. We apply the staggered DiD model because our data contain firms that innovated in multiple time periods. Staggered DiD means that once units start receiving treatment, they continue receiving treatment; that is to say, the treatment experience is not forgotten by the units (Callaway & Sant'Anna, 2021).

If this assumption holds, the average treatment effect for the treated subpopulation can be estimated by comparing the average change in outcomes experienced by the treated group to the average change in outcomes experienced by the comparison group.

To use this method, we need non-treated observations before the treatment period for the treated and non-treated groups. We need at least 1 year of observations before the treatment, and we choose firms that started to conduct innovative activities (treatment) in or after 2009. We have observations after treatment for the treated and non-treated units. We then take the difference of the counterfactual and treated groups to find the treatment effect. We observe only the outcome of the treated group and impose the common trend assumption to estimate the counterfactual outcome.

The DiD measures the difference between the treatment and counterfactual units for each year after treatment. The coefficients of the years' dummy variables provide the estimation of this difference. The average treatment effect on the treated group (ATT) is obtained as a result of this method or, in other words, the average of the difference between realized and counterfactual outcomes.

We use cohorts for these estimations. A cohort is made up of firms that innovate (start conducting R&D or apply for patents) in the same year. A balanced control group is created by using the CEM method for all cohorts.

4.2. Coarsened Exact Matching (CEM)

CEM uses a nonparametric approach to control for the confounding impact of pretreatment control variables in observational data (Iacus et al., 2011). According to Blackwell et al. (2009), the CEM method improves causal effect estimation by minimizing variables' imbalances between treated and control groups. The CEM method generates similar empirical distributions of the covariates between treated and control groups.

The CEM method has some advantages compared to other matching methods. CEM is less sensitive to measurement error than other matching methods, and while other methods increase the imbalance in many circumstances, CEM does not increase imbalance (Iacus, 2012). CEM also eliminates bias. Smaller CEM-matched datasets frequently reduce significant heterogeneity, producing causal estimates with lower variances. In other words, CEM can attain lower levels of bias, imbalance, and model dependence (King & Nielsen, 2019).

4.3. Two-Way Fixed Effects Model

Fixed effects models are widely used for estimating treatment effects. If the effects are heterogenous for different cohorts and/or over treatment time, the ATT may be estimated with negative weights. For this reason, the estimated value of the coefficient of the treatment variable could be negative although all ATT values are positive (de Chaisemartin & D'Haultfœuille, 2020). To deal with this problem, we use the TWFE model proposed by Wooldridge. The advantages of using the TWFE method are that it allows the possibility to control for heterogeneities in treatment effects across treatment intensity, calendar time, and covariates and to test the null hypothesis for anticipation and parallel trend assumptions (Wooldridge, 2021). Furthermore, it is an efficient method.

There is bidirectional causality between innovation and wages, profits, and labor turnover. In this study, we look at the effect of innovation on these variables. The method used under the no-anticipation and common trend assumptions is not affected by this bidirectional causality or innovation being endogenous, because all explanatory variables in the model that we use are exogenous.

In the model, we observe firms from the 1st year to time T $(t = 1, \ldots, T)$. If the firm undertakes its first patent application or R&D activities at time q $(1 < q < T)$, knowing that it has not innovated before $(t = 1, \ldots, q - 1)$, we assume that the effect of innovation at time q continues until time T $(t \geq q)$. We presume staggered entry for innovative activities (i.e., patent applications and R&D activities).

The cohort dummy d_q ($d_q = 1$ for firms treated first at time q) defines the cohort of firms treated at time q. $z_t(q)$ is the outcome variable, and it is observed at time q and continues until time T $(t \geq q)$. For never-treated firms, the potential outcome variable for these firms is indicated by $z_t(\infty)$ at time t.

The treatment effect (innovative activities) at time s $(s \geq q)$ is the difference between the outcome of under-treatment and no-treatment cases:

[1] $te_t(s) = z_t(s) - z_t(\infty), s = q, \ldots, T$

q is the first treatment year; before q, there are no treated firms in the sample. *z(1)* denotes the observed treatment case and *z(0)* denotes the no-treatment case, which is unobserved.

The innovation effect is the difference between the wage an innovating firm pays and the wage it would have paid if the firm had not innovated. For example, a firm submits a patent application in the 4th year and pays a certain wage in the 5th year. If the firm had not engaged in innovative activities, it would have paid a different wage in the 5th year. The difference between these two wages is the treatment effect.

We can observe only the treatment case; the no-treatment case is not observed for the innovative firms. To find treatment effects, we need to know these two outcomes, but we cannot observe the counterfactual outcome. The counterfactual is estimated under certain assumptions. We can estimate ATT for all cohorts of treated firms as follows:

[2] $\tau_{st} = E[te_t(s)|d_s = 1], s = q, \ldots, T; t = s, \ldots, T$

For example, when s is equal to 3, we select the set of firms treated at time 3. Before the treatment, we can observe 2 untreated years of this set of firms ($q = 3$, $s \geq 3$).

We have two main assumptions in estimating the ATT values:

A1. No-anticipation assumption: For treatment indicator d and treatment cohorts, s=q, ..., T:

[3a] $E[z_t(s) - z_t(\infty)|d] = 0, t < s$

According to the no-anticipation assumption, there is no distinction between treated and non-treated firms before treatment. We assume, for instance, that there will be a wage increase in treated firms after treatment. However, this effect can start before innovative. Workers are already doing the research before obtaining a patent, and the competence and/or knowledge of the workers may increase due to innovative activities before applying for a patent. In such a case, firms can increase their wages before applying for a patent. This effect is called the anticipation effect. We control for the anticipation effect and common trend assumption together.

A2. Common trend assumption: For the treatment cohort dummies d_q, …, d_T:

[4a] $E\left[z_t(\infty) - z_1(\infty) | d_q, \dots, d_T\right] = E[z_t(\infty) - z_1(\infty)], t = 2, \dots, T$

The second assumption is the common trend assumption. According to the common trend assumption, if the treated firms had not received treatment, the outcome variables for treated and untreated firms would have changed similarly. For example, labor turnover in treated and non-treated firms moves in parallel when they are not treated. Under this assumption, we can compare two outcomes: the non-treatment cases of treated and non-treated firms.

The trend of the outcome variable may depend on some variables (the x vector is a vector of covariates). If it depends on covariates x, we can write the following two assumptions conditional on the covariates:

[3b] $E[z_t(s) - z_t(\infty) | d_r = 1, x] = 0, t < s$

[4b] $E[z_t(\infty) - z_1(\infty) | d, x] = E[z_t(\infty) - z_1(\infty) | x], t = 2, \dots, T$

We can relax the common trend assumption even in the case of staggered treatment since we have access to covariates that allow treatment effects to vary.[12] Therefore, the common trend assumption is quite flexible.

Thus, the expected outcome given d and x can be expressed as follows:

[5] $E(z_t | d, x) = E[z_t(\infty) | d, x] + d_q \tau_{qt}(x) + \dots + d_T \tau_{Tt}(x)$

d_q, …, d_T are cohort dummies, and they are mutually exclusive because of the nature of cohort dummies. Those dummies will be equal to 1 for treated firms and 0 for untreated firms. $\tau_{qt} + \dots + \tau_{Tt}$ shows the cohort-time specific ATTs. The expected value of the outcome variable for untreated firms is $E(z_t \mid d,x)$ at time t.

[12] For more details, see Wooldridge (2021).

The ATT values can be reliably and effectively estimated using the fixed effects estimator of the following equation, as demonstrated by Wooldridge (2021), assuming a linear expectation function:

$$[6] z_{it} = \alpha_i + \sum_{t=2}^{T} \theta_t T_t + \sum_{t=2}^{T} (T_t x_i) \pi_t + \sum_{s=q}^{T} \sum_{r=s}^{T} \tau_{st} (w_{it} d_{is} T_t) + \sum_{s=1}^{T} \sum_{r=s}^{T} (w_{it} d_{is} T_t \dot{x_{is}}) \rho_{st}$$

In this equation, z_{it} is the outcome variable, and i represents firms and t time. T represents time dummies. Thus, we control for time and firm-level effects. We introduce a time-varying treatment dummy, w, to capture the treatment effect. x is the vector of covariates that affects the trend; d is a cohort dummy ($d_{is} = 1$ if firm i belongs to cohort s), and the vector of covariates around the within-cohort mean is $\dot{x}$. α_i is a unit-specific effect.

In Equation 6, the estimated value of τ_{st} is equal to the average treatment effect for cohort s at time t where $s = q, \ldots, T$ and $t = s, \ldots, T$. Directly applying this model, we get $(T - q + 1)(T - q + 2)/2$, the number of coefficients for the treatment effect. When the model with a full set of interactions is estimated, we get a large number of coefficients, and it is difficult to explain all of the coefficients. In addition, the number of observations for each treatment becomes low, so the standard error increases. Since we are interested in how treatment effects change over time, we set the following restriction:

$$[7] \quad \tau_{st} = \tau_{t-s}, s = q, \ldots, T; t = s, \ldots, T$$

Equation 7 states that the average treatment effect τ_{st} depends on the time after treatment. When $t = s + 1$, τ_1 indicates the average treatment effect 1 year after innovative activity.

CHAPTER 5

RESULTS

5.1. CEM Estimations

We use CEM to balance the control and treatment groups by using the 2008 values of the following variables: number of employees (in log form), age of the firm (in log form), capital intensity, export status, and sector code (NACE Rev. 2, 2-digit level). In other words, we match the firms using these variables and form the control group.

Table 5.1. CEM matching results for wages and profits

	Number of patent applicants		Number of R&D performers	
	Control group	Treatment group	Control group	Treatment group
All	28760	1179	27666	2273
Matched	1075	1075	2079	2079
Unmatched	27685	104	25587	194

Table 5.1 shows the CEM matching results. There are 1179 patent applicants. While 1075 patent applicants are matched, 104 of them are not. We create a control group (not patent applicants) from 28760 firms, and 1075 firms are selected for the control group. As a result of the matching, we have 1075 firms in the treatment and control groups.

For R&D performance, there are 2273 R&D performers and 2079 them are matched. We create a control group (not R&D performers) from 27666 firms and 2079 of them are matched. We have 2079 firms to estimate the effect of R&D activity. The imbalance tables for the CEM method are provided in Appendices 1 and 2.

To estimate the effects on labor turnover, we create control groups using the same variables, but with variables for 2012, not 2008.

Table 5.2: CEM matching results for labor turnover

	Patent applicants		R&D performers	
	Control group	Treatment group	Control group	Treatment group
All	28053	673	27441	1285
Matched	647	647	1236	1236
Unmatched	27406	26	26205	49

We create the control group from 28053 firms and the treatment group (patent applicants) from 673 firms (see Table 5.2), and 647 firms are matched in the control and treatment groups.

For R&D performers, there are 1285 firms in the treatment group and 27441 firms in the control group. After the matching, 1236 firms remain for the treatment and control groups. After matching, the imbalance decreases and balanced matching groups are created. The balance tables are provided in Appendices 3 and 4.

5.2. No-anticipation Effect Test

We observe the effect of treatment after 2009 ($t = 2009, \ldots, 2020$) on wages and profits and after 2012 on labor turnover changes. There were no treated firms in the sample before those years. We leave 2 years before the treatment to check the common trend assumption and no-anticipation effect. The common trend and no-anticipation assumptions cannot be tested separately. If the no-anticipation effect is rejected, the common trend assumption and/or the no-anticipation assumption is/are not satisfied. However, if the test is not rejected, both assumptions are satisfied.

We test the anticipation effect/common trend assumption using robust Wald statistics for all outcome variables and choose the longest period relevant for a variable. For example, if the anticipation times for the 10th, 50th, and 90th percentile wages are 0, 1, and 3 years, respectively, we use 3 years for all wages. If there is an anticipation effect, we drop those observations for the period of the anticipation effect. For example, if there are 2 years of anticipation effects, we are not using these 2 years of observations before treatment in the estimation. After the assumption is satisfied, we estimate the difference between treated and untreated firms, conditional on the covariates.

Table 5.3. Anticipation Period

	Anticipation time	
Variables	Patent applicants	R&D performers
10 percentile wage	3	3
50 percentile wage	3	3
90 percentile wage	3	3
Male wage	3	3
Female wage	3	3
Profit	1	3
Value added	0	3
Leaver wage	0	0
New hire wage	0	0
Leaver rate	0	0
New hire rate	0	0

Table 5.3 shows the anticipation time for all variables that we choose. The anticipation times of the 10th, 50th, and 90th percentiles and of male and female wages are 3 for patent applicants and R&D performers. It seems that either innovative firms are increasing their employees' wages 3 years before the innovations or they have a different trend than non-innovators during these years.

Anticipation time for labor productivity (value added) and profit is 3 for R&D performers. In other words, labor productivity and profit increased 3 years before R&D was conducted. For other variables, the effect of innovation is observed immediately after application (anticipation time is 0).

5.3. Estimation Result of Control Groups and Firms in the Balanced Panel

We present the estimation results of the DiD and show the effect of innovations. First, we estimate the control group together with the treatment group, and then we estimate the same model for the firms in the balanced panel. There should not be much difference between the two estimation results because the TWFE model takes into account differences between innovators and non-innovators.

We create two control groups, one for patent applicants and the other for R&D performers, using the same set of variables. Under the restrictions of Equation 7, we estimate Equation 6 to find treatment effects (τ_{st}) by the fixed effects estimator (Wooldridge, 2021) using the fixest package in R. There are 12 estimates for wage and profit outcomes and 8 for labor turnover outcomes.

The following outcome variables are used: wages at the 10th, 50th, and 90th percentiles (in log form); wages for male and female employees (in log form); firm output per employee (in log form); value added per employee (labor productivity) (in log form); and operating profit margin (operating profit/net sales). Moreover, we make use of the rates of new hires and leavers and the wages of new hires and leavers (in log form). The export dummy, capital intensity, firm size (in log form), and firm age (in log form) are covariates in the DiD model.

Figures 5.1-5.20 present the estimation results. A circle on a line indicates that that estimate is statistically significant at the 5% level. Figures labeled “Control Group” show ATTs over the treatment duration as estimated using the CEM control groups, whereas the “Balanced Panel” figures present estimation results based on the firms in the balanced panel. Time 0 is the innovation year (patent application or first R&D activity).

Figure 5.1 presents the estimation results for treated firms that make patent applications compared to the firms in the control group that are not patent applicants. The treatment effect of patent applicants compared to firms in the balanced panel operating between 2007 and 2020 (14 years) is represented in Figure 5.2. Estimation results are similar between the groups.

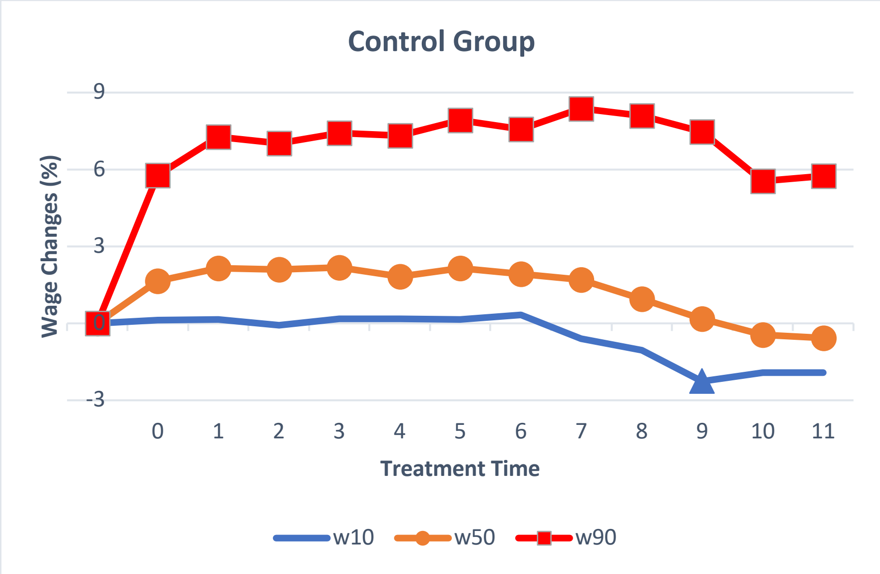

Figure 5.1: Effects of patent applications on wages for the control group

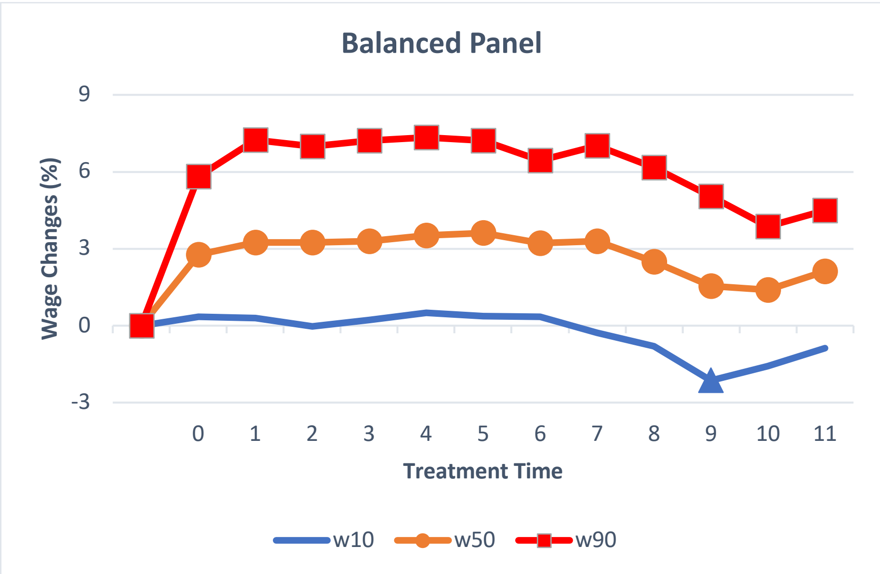

Figure 5.2: Effects of patent applications on wages for firms in the balanced panel

Low-wage earners (10th percentile, w10) have no change in wages after innovation. On the other hand, the increase of median wages (w50) is stable at about 2-3% when compared to wages of workers who work in non-innovative firms. The wages of the high-wage earners (w90) rise quickly, reaching an increase of 8%. Workers do not equally share the benefits of innovation. The figure shows that within-firm wage differentials increase after patent applications.

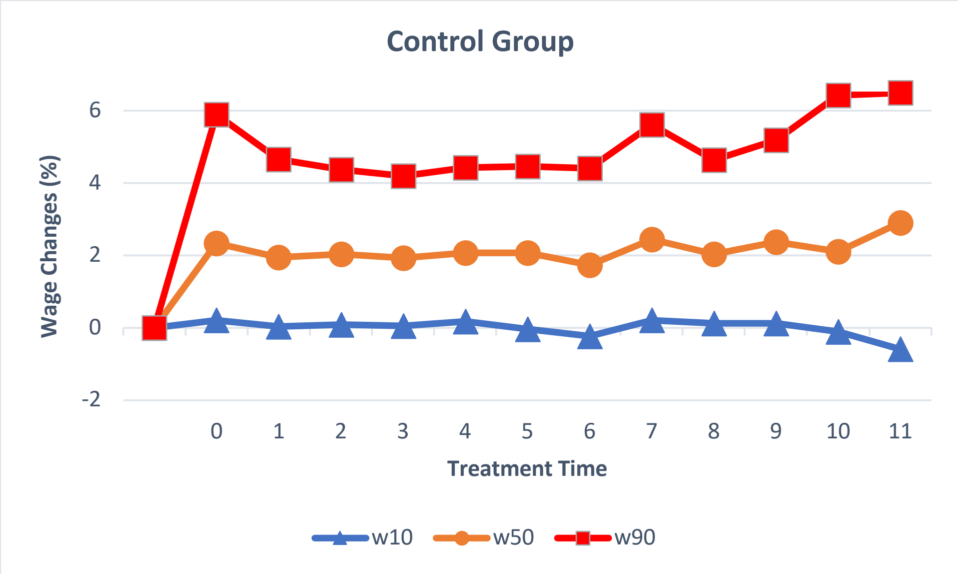

Figure 5.3: Effects of R&D activities on wages for the control group

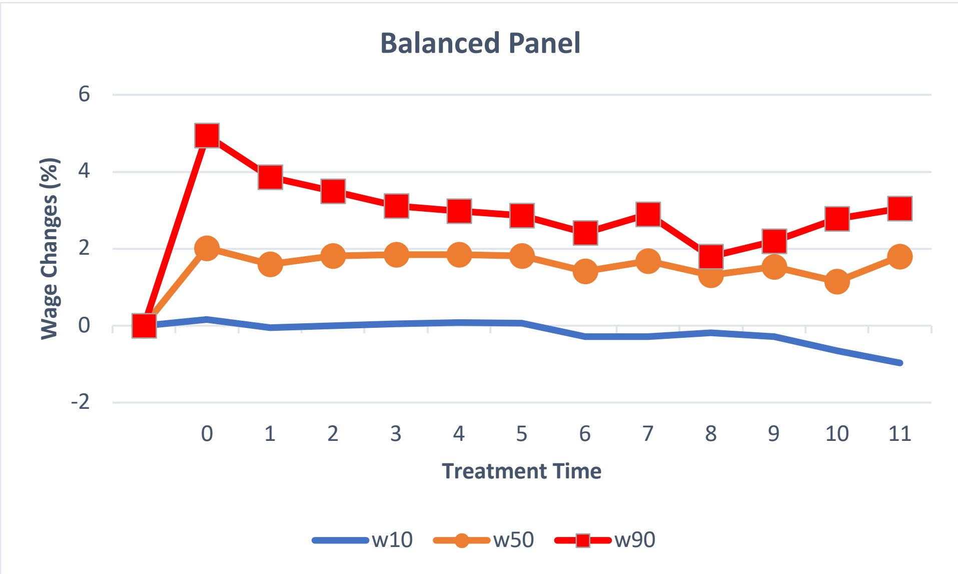

Figure 5.4: Effects of R&D activities on wages for firms in the balanced panel

Wage increases among R&D performers are similar to those of the patent applicants. There are no wage changes among low-wage (lowest 10th percentile) earners (Figure 5.3). Median-wage and high-wage earners benefit more than low-wage earners. The wage increase for median-wage earners is about 2%. The wage increase for high-wage earners (highest 10th percentile) in firms engaged in R&D is 4-6%. There is also an increase in within-firm wage differentials among R&D performers. In other words, innovations (patent applications/R&D activities) increase within-firm wage differentials.

Nash wage bargaining models can explain the rise in salaries after innovation (i.e., patent applications and R&D activities). These models show that the wage rate is a weighted average of the labor productivity and the reservation wage (Ballot, Fakhfakh, and Taymaz, 2006). The reservation wage is the minimum wage at which a worker is willing to accept a job, and it depends on the qualifications of the workers. After innovation, the wage rate increases due to an increase in reservation wage and/or an increase in the bargaining power of the workers and/or a rise in labor productivity. Our estimation results show that labor productivity increases after innovation. If high-wage workers are involved in the innovation process, their reservation wages may increase because of human capital accumulation. Moreover, the bargaining power of these workers may also increase if a part of the new knowledge is tacit and embodied in these workers.

To summarize, high-wage earners benefit more than low-wage earners because of high reservation wages, high bargaining power, and high labor productivity. These effects seem to be weaker for median-wage earners. It seems that low-wage earners do not have any bargaining power; therefore, their earnings do not increase and they remain at the (legally enforced) minimum wage level.

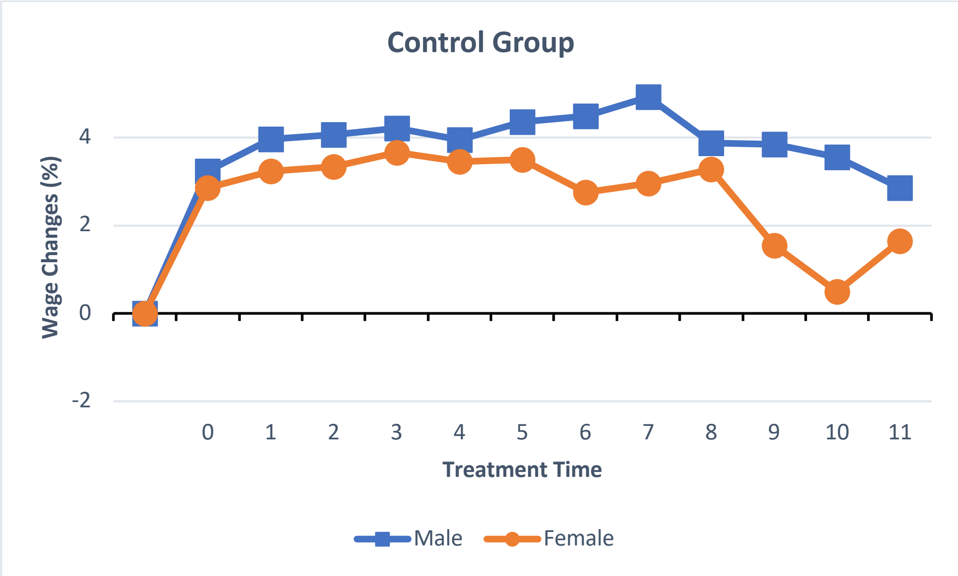

Figure 5.5: Effects of patent applications on men's and women's average wages for the control group

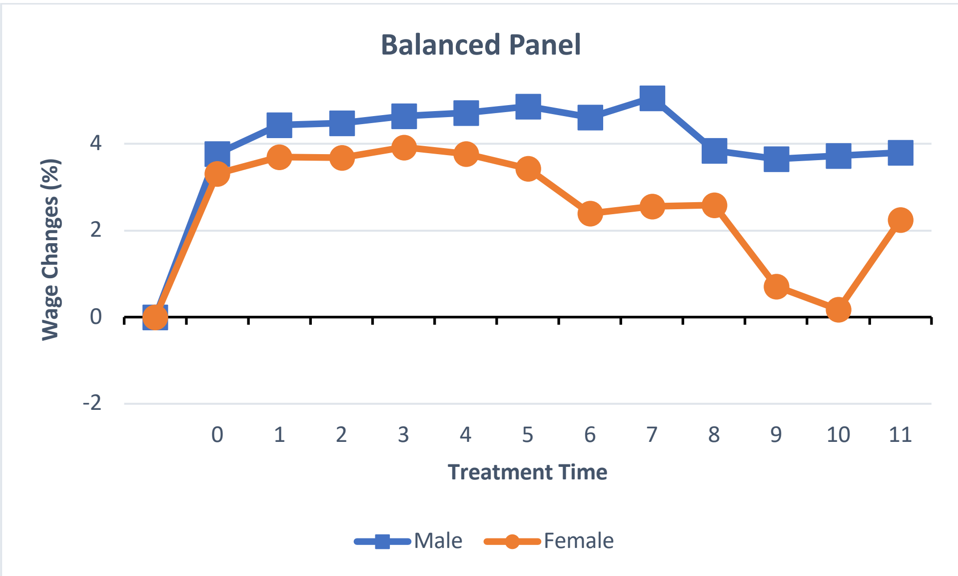

Figure 5.6: Effects of patent applications on men's and women's average wages for firms in the balanced panel

Regarding gender-based wage differentials, there is an increase in the wages of male and female workers after patent applications (Figures 5.5 and 5.6), but the maximum wage increase is about 5% for male workers 7 years after the beginning of the patent applications and only about 3% for female workers. After patent applications, wage differences between men and women are likely to increase.

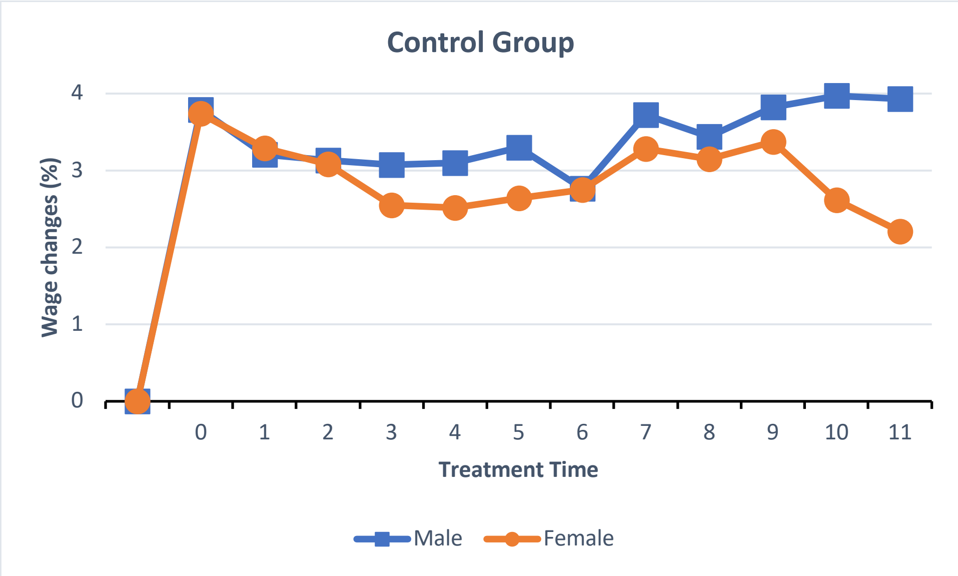

Figure 5.7: Effects of R&D activities on men's and women's average wages for the control group

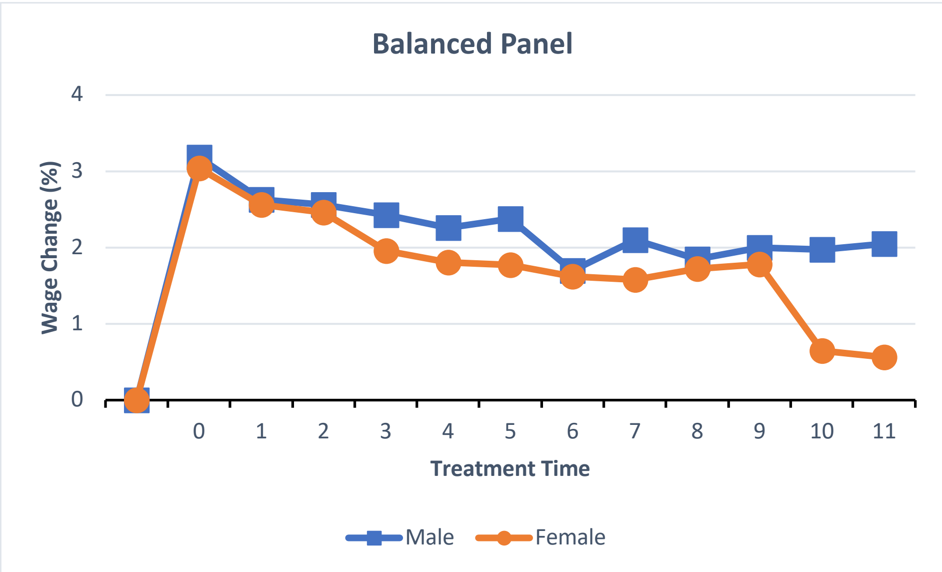

Figure 5.8: Effects of R&D activities on men's and women's average wages for firms in the balanced panel

For R&D performers, male-female wage differences increase over time after innovation. While male workers' wages increase between 3% and 4%, female workers' wage increases are about 3% (see Figures 5.7 and 5.8). After patent applications or R&D activities, the gender pay gap widens.

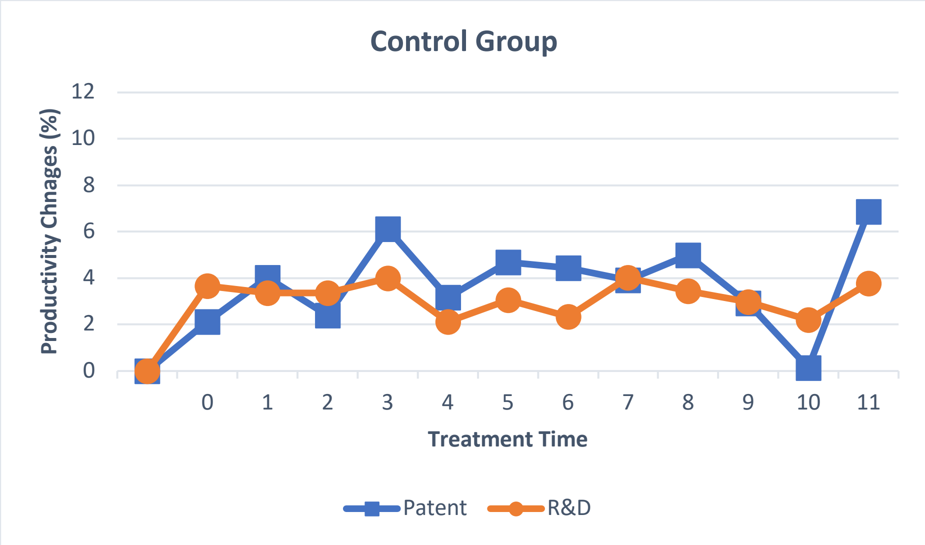

Figure 5.9: Effects of patent applications and R&D activities on labor productivity for the control group

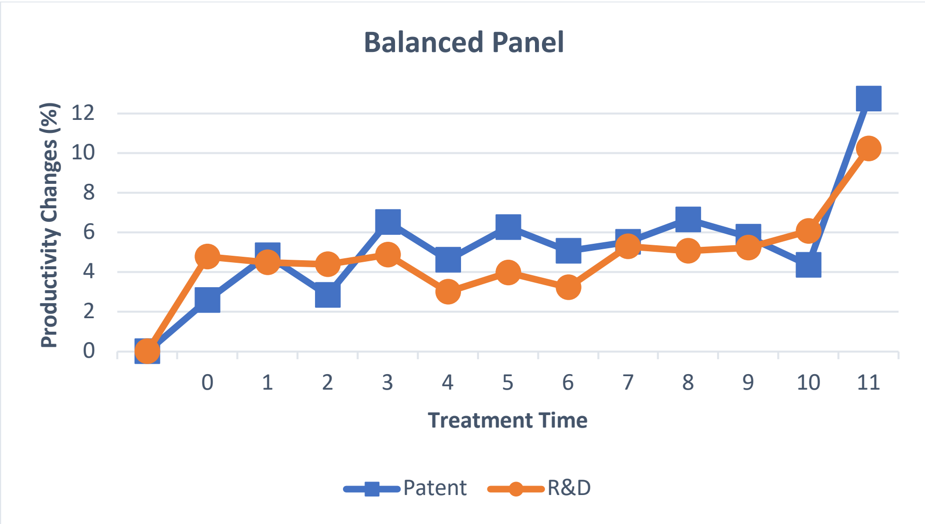

Figure 5.10: Effects of patent applications and R&D activities on labor productivity for firms in the balanced panel

Figure 5.9 shows the treatment effect of firms performing R&D and submitting patent applications on labor productivity (value added per employee). The increase in labor productivity for patent applicants is between 2% and 6%, although there are some fluctuations in labor productivity over time. Labor productivity among R&D performers is about 2-4% higher than that of non-performers. As a result of increased productivity, the profits of the innovative firms increase because the share of wages in labor productivity is about 30% in innovative firms.

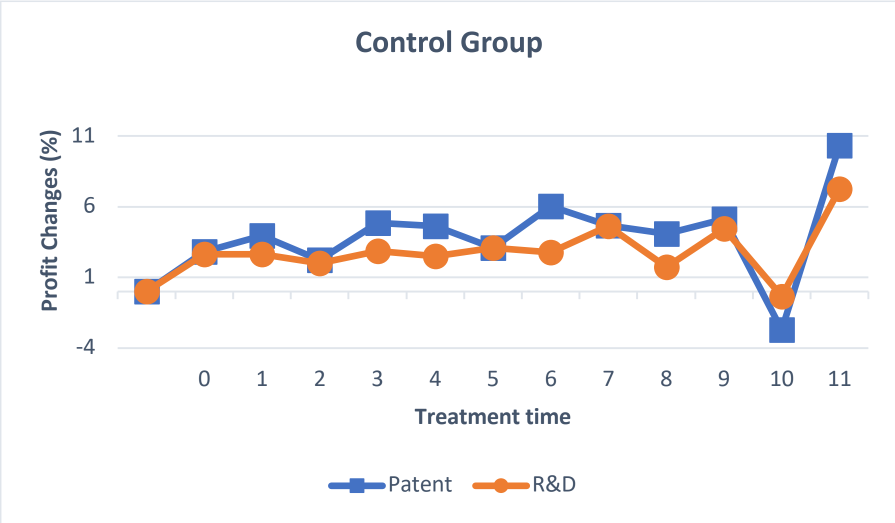

Figure 5.11: Effects of patent applications and R&D activities on firms' profit margin for the control group[13]

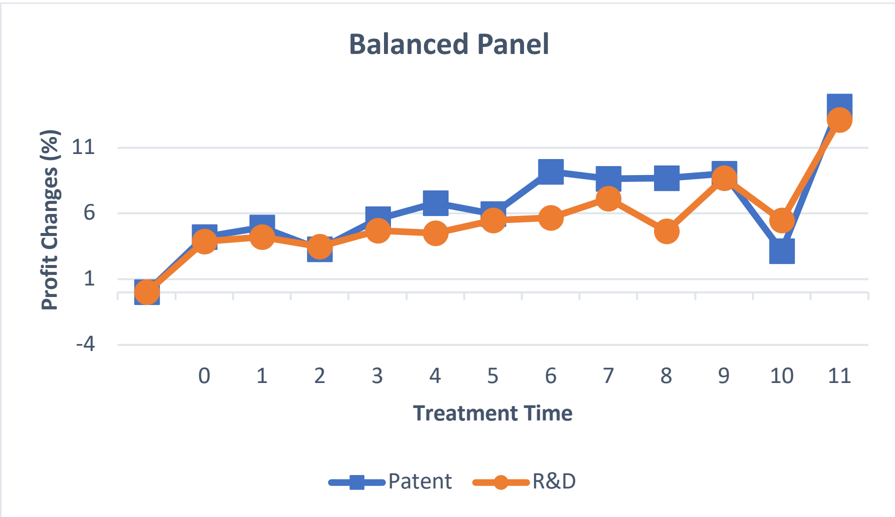

Figure 5.12: Effects of patent applications and R&D activities on firms' profit margin for firms in the balanced panel

Figure 5.11 shows the effect of innovation on operating profit margin (operating profit/net sales). For patent applicants, the operating profit margin continuously increases during the considered period, except for the 10th year. After 5 years of innovation, the profit margin is about 8%. Like patent applicants, the operating profit margin also increases after innovation among R&D performers. The profit is between

[13] The number of observations decreases as the treatment time increases, so the estimations are not precise, having high standard errors, and the estimation values may fluctuate.

4% and 8%. The profit of the patent applicants rises more than that of R&D performers. When we compare employees' earnings with employers' earnings, employers benefit more, and firms become more profitable after innovation.

Figure 5.13: Effects of patent applications on the rates of new hires and leavers for the control group

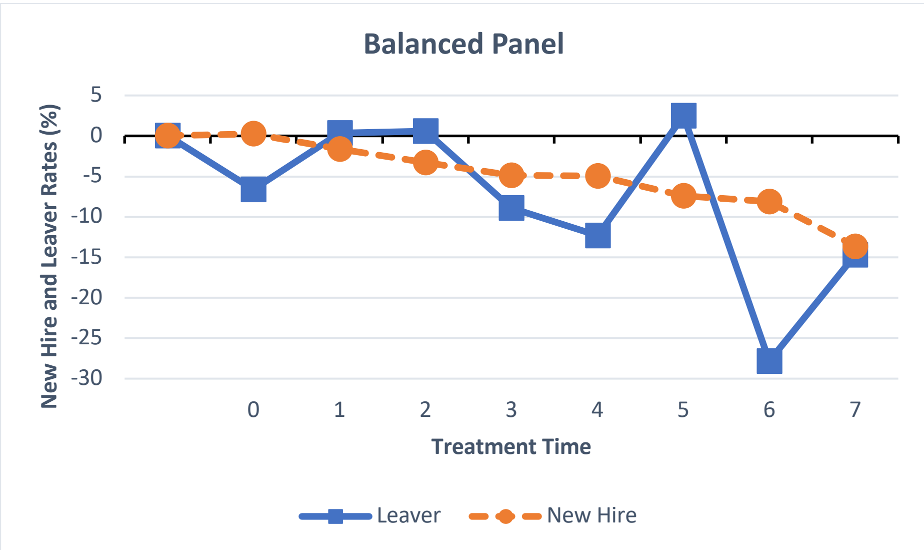

Figure 5.14: Effects of patent applications on the rates of new hires and leavers for firms in the balanced panel

Knowledge diffusion between firms mostly occurs through labor turnover. Figure 5.13 shows the treatment effects of patent applications on rates of new hires and leavers. The estimation results show that the rates of leavers fluctuate between 16% and -6%.

Five years after the beginning of patent applications, rates of leavers are decreasing. New hire rates fall over time after innovation (statistically significant in 1 year). However, these estimation results are insignificant.

Figure 5.15: Effects of R&D activities on the rates of new hires and leavers for the control group

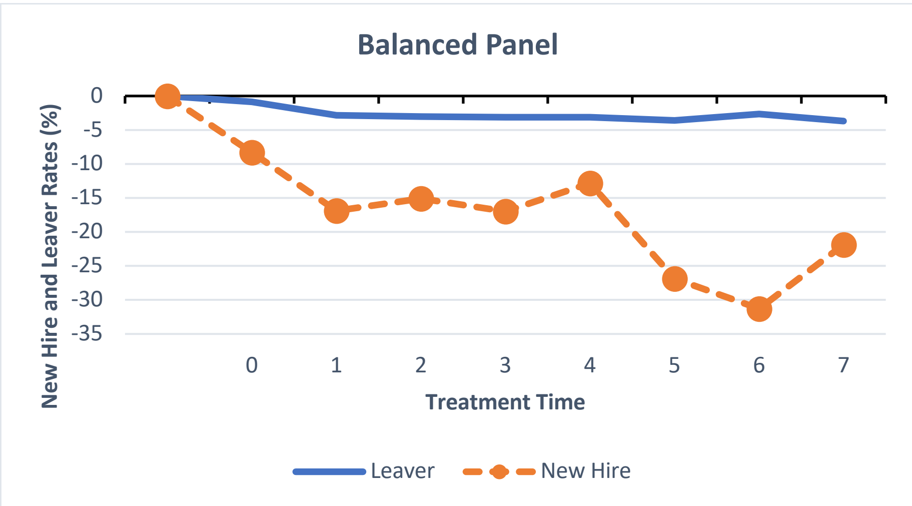

Figure 5.16: Effects of R&D activities on the rates of new hires and leavers for firms in the balanced panel

Leaver rates increase after R&D activities. The rates of new hires decrease over time and the decrease is about 2% (Figure 5.15). The increase in the rates of leavers and decrease in the rates of new hires are not statistically significant (statistically significant in 3 years).

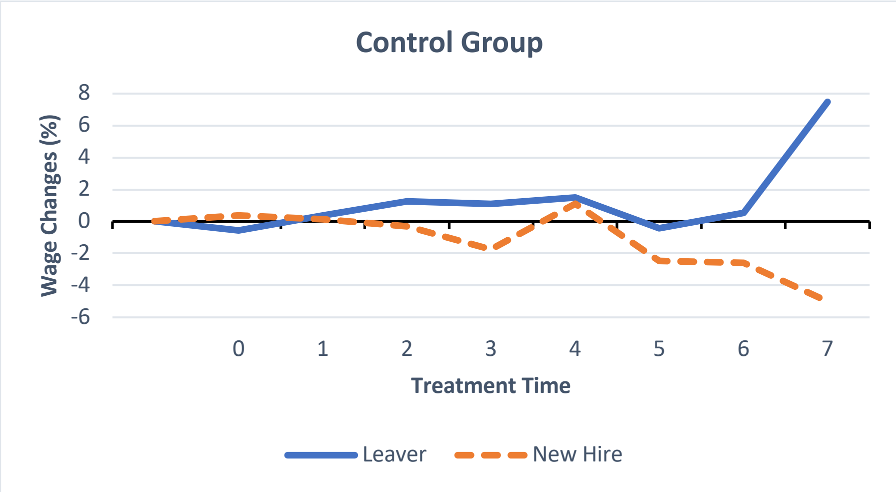

Figure 5.17: Effects of patent applications on the wage rates of new hires and leavers for the control group

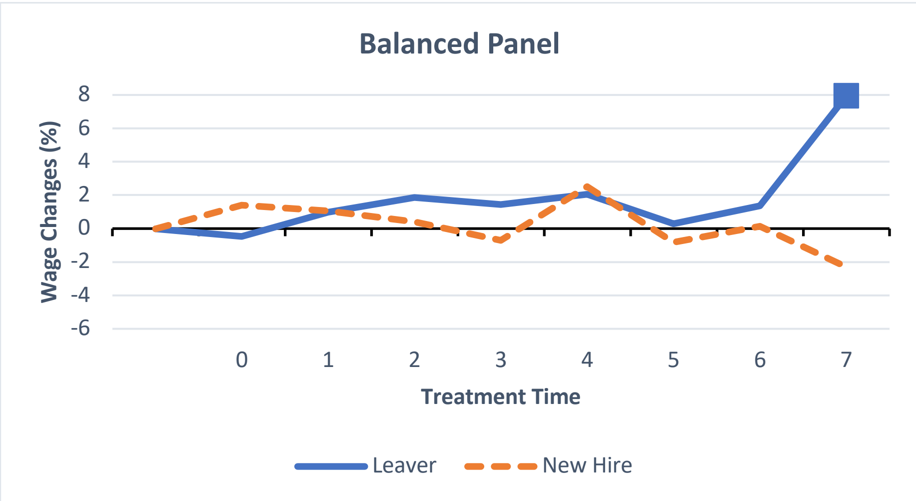

Figure 5.18: Effects of patent applications on the wage rates of new hires and leavers for firms in the balanced panel

We look at the average earnings of new hires and leavers to understand their qualifications. Figure 5.17 shows the treatment effect of patent applications on the wage rates of new hires and leavers. Even though the estimation results are not statistically significant, the increase in the wage rates of the leavers is about 0.5%. There are fluctuations in the wage rates of new hires, which is also insignificant. After patent applications, the wage rate of new hires decreases, and this decrease is about 1.5%. After innovation, it appears that patent applicants hire workers at lower wages and the leaver wages of the workers increase.

Figure 5.19: Effects of R&D activities on the wage rates of new hires and leavers for the control group

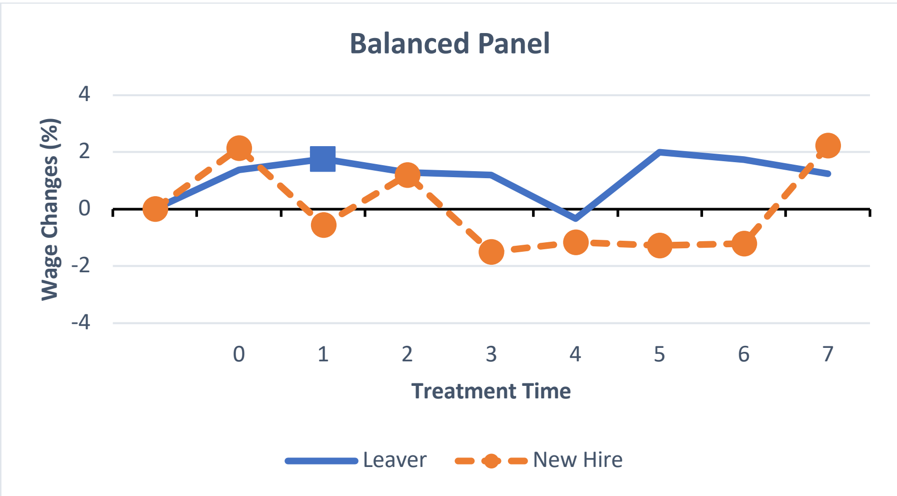

Figure 5.20: Effects of R&D activities on the wage rates of new hires and leavers for firms in the balanced panel

There are no significant changes in the wage rates of leavers in R&D performers after R&D activities (Figure 5.19). Except for the 4th year after innovation, the increase in the wage rates of leavers is about 1% (Figure 5.19). The increases in the wage rates of new hires are not statistically significant and they fluctuate over time. Fluctuations are between 2.5% and -2.5% (statistically significant in only 2 years).

Firms that innovate are generally larger and pay their employees higher wages. When we create a control group, the size of the control group is the same as that of the treatment group. Wages are also getting closer between the groups. In other words, we are comparing firms that are similar to each other. This is not a requirement for the Wooldridge method. However, we use the control group to compare the results for two different groups (control group and balanced panel) to check the robustness of our findings.

Innovation leads to an increase in wages, profits, and labor productivity. Within-firm wage differentials and gender pay gaps increase after patent applications/R&D activities. Because employers benefit more than employees, income distributions are worsened. The innovation effect on the rates of labor turnover of leavers and new hires and their wages are weak and ambiguous.

CHAPTER 6

CONCLUSIONS

This study has investigated the impact of innovation (patent applications/R&D activities) on workers' wages, firms' profits, and labor turnover. We utilized the DiD setup and used data on the population of Turkish manufacturing firms operating during the period of 2006-2020. We found that profits and labor productivity significantly increase after innovation. Additionally, while the innovation's impact on low-wage workers is negligible and statistically not significant, median-wage and high-wage workers are affected positively and significantly. Wage increases for high-wage workers are higher than those for other workers and so within-firm wage differentials increase after innovative activities. Moreover, gender-based wage disparities also widen to some extent as a result of men's earnings increasing more than women's.

Innovation's impacts on new hire and leaver rates and wages of new hires and leavers are ambiguous and weak. Changes in leaver rates are insignificant and increasing for both patent applicants and R&D performers. New hire rates are significant for some years, and they are decreasing for innovative firms. In addition, the wages of leavers are increasing while the wages of new hires decrease; however, these effects are not significant. For R&D performers firms, new hires' and leavers' wages are not changing much and there are fluctuations for both. New hires' wage changes are significant for only 2 years.

The estimation results suggest that there could be discrepancies between R&D performers and patent applicants in the Turkish manufacturing industry. Although R&D activities and patent applications are frequently employed in empirical studies as proxies for innovation, further research is required to understand the distinctions between patent applicants and R&D performers.

The Wooldridge method gave the same result whether we use a control group or not. If we use the necessary covariates and if the assumptions are valid, using a control group is not essential in the Wooldridge method.

The results of this study show that although innovation has significant benefits for the society, these benefits are not distributed equally. At least in the short and medium terms, inequality in income distribution may increase after innovation.

The findings furthermore suggest that policymakers should implement support programs that promote innovative activities that contribute to economic development. Support programs may involve subsidies for R&D expenditures and inputs and outputs of innovations in firms; therefore, the risks of innovators will decrease. Technoparks should also be supported to increase interactions between researchers and firms to increase innovative activities. Similarly to the German Energiwende, policymakers should support innovative activities at different degrees of maturity with experimentation, implementation, and exploitation (Edler & Fagerberg, 2017).

While innovation benefits society, it increases the inequality between highly skilled and less skilled workers. In order to cope with income inequality, policymakers need to adjust their policy tools. More public spending should be allocated to higher education to ensure an increase in human capital as the basis for innovative activities. This will make it possible for technology and knowledge advancements to decrease the inequality of opportunity. The share of highly skilled labor will increase and the percentage of the population benefiting from innovation will increase.

In addition to these long-term and medium-term plans, further wage premiums should be applied to workers who receive low wages in the short term. Redistributive tax and transfer policies should be implemented to raise the wages of low-skilled labor, which can be financed by a labor income tax.

Innovations cause gender pay gaps, and policymakers should promote gender equality in paid work to overcome this problem. More appropriate training and education should be provided, and quotas for female workers should be implemented for female workers to be hired in different occupations and to increase the equality of opportunity.

Equal-pay legislation should be applied for the same work positions to increase average wages.

Although we used data on the population of manufacturing firms in Turkey, the number of patent applicants and R&D performers was not sufficient to estimate cohort-time effects. Therefore, we restricted the model so that only time effects were estimated. In spite of this restriction, some of the estimates, and especially those on labor turnover, suffered from high variance. Finally, since there were no data on employee characteristics (education, experience, etc.), it was not possible to control for those factors.

In this thesis, it has been assumed that once a firm innovates, its impact continues (i.e., the staggered intervention assumption). We have not considered different patterns of innovation, such as firms that continuously innovate by applying for patents in subsequent years or continuing R&D projects. These effects may be important so that they should be considered in future research. In addition, the joint effects of patenting and R&D were not evaluated here. Complementarities between different types of innovation need to be analyzed.

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APPENDICES

A. CEM ESTIMATION RESULTS

Appendix 1

The imbalance tables for patent applicants in 2008 are presented in this section.

Table A1. Patent applicants, L1 and LCS

	Multivariate Imbalance Measure: L1	Percentage of Local Common Support: LCS
Before matching	0.597	19.9%
After matching	0.420	41.1%

After matching the treatment and control groups, the multivariate imbalance measure (L1) is decreased from 0.597 to 0.420 and the percentage of local common support (LCS) is increased from 19.9% to 41.1% (Table A1).

Table A2. Patent applicants, before matching

	Univariate Imbalance Measures: Before Matching							
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	-1.19	(diff)	3.2E-01	-1.39	-1.01	-1.17	-1.47	0.93
Firm age (in log)	0.01	(diff)	5.3E-02	0	-0.13	-0.07	-0.05	0
NACE-2	-2.30	(diff)	2.5E-01	0	-4	-3	-1	0
Export dummy	-0.36	(diff)	3.6E-01	0	0	-1	0	0
Capital intensity	-0.70	(diff)	5.6E-17	-11.76	-0.75	-0.64	-0.57	2.59

Table A3. Patent applicants, after matching

Univariate Imbalance Measures: After Matching								
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	-0.05	(diff)	0	-0.29	0	-0.05	-0.03	-0.08
Firm age (in log)	0	(diff)	0	0	0	-0.07	0	0
NACE-2	-0.04	(diff)	0.04	0	0	0	0	0
Export dummy	0	(diff)	0	0	0	0	0	0
Capital intensity	-0.04	(diff)	0.04	0.11	-0.03	-0.05	0.00	0.24

Tables A2 and A3 show the parts of the distribution in which there may be more imbalance and balance for the treatment group (patent applicants) and control group.

Appendix 2

The imbalance tables for R&D performers in 2008 are presented in this section.

Table A4. R&D performers, L1 and LCS

	Multivariate Imbalance Measure: L1	Percentage of local common support: LCS
Before matching	0.646	18.1%
After matching	0.380	48.0%

After matching the treatment and control groups, the multivariate imbalance measure (L1) is decreased from 0.646 to 0.380 and the percentage of local common support (LCS) is increased from 18.1% to 48.0% (Table A4).

Table A5. R&D performers, before matching

Univariate Imbalance Measures: Before Matching								
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	-1.19	(diff)	0.32	-1.39	-1.01	-1.17	-1.47	0.93
Firm age (in log)	0.01	(diff)	0.05	0	-0.13	-0.07	-0.05	0
NACE-2	-2.30	(diff)	0.25	0	-4	-3	-1	0
Export dummy	-0.36	(diff)	0.36	0	0	-1	0	0
Capital intensity	-0.70	(diff)	0.18	-11.76	-0.75	-0.64	-0.57	2.59

Table A6. R&D performers, after matching

Univariate Imbalance Measures: After Matching								
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	0.04	(diff)	0	0	0.11	0.05	0.09	-0.11
Firm age (in log)	-0.02	(diff)	0	0	0	0	0.05	0
NACE-2	0	(diff)	0.01	0	0	0	0	0
Export dummy	0	(diff)	0	0	0	0	0	0
Capital intensity	0.03	(diff)	0.03	0.34	0.01	0.01	0.02	0.00

Tables A5 and A6 show the parts of the distribution in which there may be more imbalance and balance for the treatment group (R&D performers) and control group.

Appendix 3

The imbalance tables for patent applicants in 2012 are presented in this section.

Table A7. Patent applicants, labor turnover, L1 and LCS

	Multivariate Imbalance Measure: L1	Percentage of local common support: LCS
Before matching	0.610	15.0%
After matching	0.036	93.8%

After matching the treatment and control groups, the multivariate imbalance measure (L1) is decreased from 0.610 to 0.036 and the percentage of local common support (LCS) is increased from 15.0% to 93.8% (Table A7).

Table A8. Patent applicants before matching, labor turnover

Univariate Imbalance Measures: Before Matching								
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	-1.25	(diff)	3.5E-01	-0.69	-1.08	-1.25	-1.56	0.09
Firm age (in log)	0.04	(diff)	4.3E-02	0	-0.09	0	0.043	0
NACE-2	-2.05	(diff)	2.4E-01	0	-4	-3	-1	0
Export dummy	-0.37	(diff)	3.7E-01	0	0	-1	0	0
Capital intensity	-0.71	(diff)	1.1E-16	-13.08	-0.82	-0.66	-0.49	4.34

Table A9. Patent applicants after matching, labor turnover

Univariate Imbalance Measures: After Matching								
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	-0.05	(diff)	0	0	-0.07	-0.08	-0.07	-0.12
Firm age (in log)	-0.02	(diff)	0	0	-0.09	0	0	0
NACE-2	-0.03	(diff)	0.01	0	0	0	0	0
Export dummy	0	(diff)	0	0	0	0	0	0
Capital intensity	-0.10	(diff)	0	-0.41	-0.08	-0.13	-0.15	0.41

Tables A8 and A9 show the parts of the distribution in which there may be more imbalance and balance for the treatment group (patent applicants) and control group.

Appendix 4

The imbalance tables for R&D performers in 2012 are presented in this section.

Table A10. R&D performers, labor turnover, L1 and LCS

	Multivariate Imbalance Measure: L1	Percentage of local common support: LCS
Before matching	0.610	15.0%
After matching	0.057	94.1%

After matching the treatment and control groups, the multivariate imbalance measure (L1) is decreased from 0.610 to 0.057 and the percentage of local common support (LCS) is increased from 15.0% to 94.1% (Table A10).

Table A11. R&D performers before matching, labor turnover

Univariate Imbalance Measures: Before Matching								
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	-1.25	(diff)	3.5E-01	-0.69	-1.08	-1.25	-1.56	0.09
Firm age (in log)	0.04	(diff)	4.3E-02	0	-0.09	0	0.04	0
NACE-2	-2.05	(diff)	2.4E-01	0	-4	-3	-1	0
Export dummy	-0.37	(diff)	3.7E-01	0	0	-1	0	0
Capital intensity	-0.71	(diff)	1.1E-16	-13.08	-0.82	-0.66	-0.49	4.34

Table A12. R&D performers after matching, labor turnover

Univariate Imbalance Measures: After Matching								
	Statistic	Type	L1	min	25%	50%	75%	max
Employment (in log)	-0.04	(diff)	0	0	-0.02	-0.03	-0.01	0.01
Firm age (in log)	0.01	(diff)	0	0	0	0	0	0
NACE-2	-0.02	(diff)	0.03	0	0	0	0	0
Export dummy	0	(diff)	0	0	0	0	0	0
Capital intensity	-0.10	(diff)	0	-1.10	-0.02	-0.14	-0.10	-0.10

Tables A11 and A12 show the parts of the distribution in which there may be more imbalance and balance for the treatment group (R&D performers) and control group.

B. DATA MANIPULATION

Entrepreneurship data

When wages are zero, we made NA. We drop duplicated manufacturing id.

Balance sheet data – Firm level data

We drop non-manufacturing firms. We drop NA years. When net sales are smaller than zero, we made NA.

Wage data – Employee level data

If monthly earnings are smaller than zero, we drop those workers. When the monthly workday is smaller than 1, we set the workday as 10. Some workers are younger than 15, and we set it as 15. If the ages are NA, we set it as 30. We drop the NA wages. When gender is NA, we put it as male.

New hire-leaver data – Employee level data

We use only 12th month in employee data. We drop NA worker id and NA years. We drop duplicated data.

Balance sheet data

If financial fixed assets, intangible fixed assets, plants machinery and equipment, accumulated amortization, accumulated depreciation are smaller than zero, we made NA. When the cost of R&D is NA, we made it zero, and we put R&D dummy if the cost of R&D is bigger than zero. If export share is NA, we make them zero. When sales net is 0, firm may not share balance sheet, so we drop them. We drop firms that have entered and exited for more than one year. We make negative output and input as NA.

Merged firm and employee level data

We drop firm which did not employ anyone 2006 year. If the number of employments is NA, we make zero. We drop NA median-wage. We make zero when the women's work ratio is smaller than zero. Cost R&D /sales net is bigger than 1, and we made it equal to zero. The logarithm of wage of women new hire and leaver, leaver and new hire rate, women leaver and new hire rate, if profit margins smaller than -10, we made as -10. If the logarithm of total output divided by employment and capital intensity is minus infinity, we make NA. When the new hire and leaver wage logarithm is infinity, we make NA.

C. TURKISH SUMMARY / TÜRKÇE ÖZET

Yenilik, uzun vadeli ekonomik büyüme için en önemli faktörlerden biridir. Yeni pazarlar yaratarak ve verimliliği artırarak topluma fayda sağlar. Yenilik aynı zamanda firmaların rekabet gücünü arttırır ve ekstra kâr elde etmelerini sağlar. Yenilik yapan firmalar daha hızlı büyür ve diğer firmalardan daha verimli olduklarını kanıtlarlar.

Yenilikler önemli faydalar sağlarken, bu faydaların çalışanlar, yenilikçi firmalar ve diğer firmalar arasında nasıl paylaşıldığı sorusu kritik bir öneme sahiptir. Yenilikçi firmalar daha yüksek kârlarla fayda sağlayabilirken, diğer firmalar işgücü devri yoluyla fayda sağlayabilir (Lhuillery, 2011), bu da yenilikçi firmaların insan sermayesi birikimini etkiler. Çalışanlar da daha yüksek ücretler yoluyla verimlilikten yararlanabilir (Herman, 2020). Yeniliklerin faydalarının toplum genelinde dağılımı ücret ve yayılma etkilerinden etkilenir, bu durumun da kapsayıcı büyüme için önemli etkileri olabilir.

Bu çalışmanın temel araştırma sorusu, 2006-2020 döneminde Türk imalatında yeniliklerin ücretler, kârlar ve işgücü devir hızı üzerindeki etkisidir. Bu çalışmadaki hipotezlerimizi şu şekilde formüle ediyoruz:

1. Yenilikler ortalama ücretleri artırır.
2. Yeniliklerin ücretler üzerindeki etkisi, yüksek ücretlilerde düşük ücretlilere göre daha fazladır.
3. Yeniliklerin ücretler üzerindeki etkisi erkek işçilerde kadın işçilere göre daha fazladır.
4. Yenilikler, emek verimliliğini ve kârı artırır.
5. Yenilikler, yeni işe alım oranını arttırır ve işten ayrılma oranını düşürür.
6. Yenilikler, yeni işe alınanların ücret oranlarını ve işten ayrılanların ücret oranlarını artırmaktadır.

Çalışmanın ilk bölümünde, ücretlerin gelir dağılımı açısından elzem olması dolayısıyla yeniliklerin sosyal bir boyutu da olduğu için yeniliklerin ücretler üzerindeki etkisi incelenmektedir. Ücret artışları tüm ücretliler için aynı oranda gerçekleşmez; aksine, yüksek vasıflı işçiler, daha az vasıflı işçilerden daha fazla fayda sağlar (Aghion vd., 2018). Bu, firma içi ücret farklılıklarını etkiler. Benzer şekilde, yenilik sonrası ücret oranı değişiklikleri kadın ve erkek için aynı değildir. Erkek işçilerin ücret artışı, kadın işçilere göre daha yüksektir. Böylece yenilikler, cinsiyetler arasındaki ücret farkını artırıyor. Bu çalışma, yenilik ücretleri nasıl etkiler, düşük ücretli ve yüksek ücretli çalışanları nasıl etkiler ve cinsiyete dayalı ücret farklılıklarını nasıl etkiler, soruları cevaplanıyor.

Bu çalışmada T.C. Sanayi ve Teknoloji Bakanlığı'nın Girişimcilik Bilgi Sistemi (GBS) verileri kullanılmıştır. Bu sistem, Sosyal Güvenlik Kurumu veri setini (çalışan düzeyindeki verileri), Gelir İdaresi Başkanlığı veri setini (firma düzeyinde bilanço ve gelir tablosu verileri) ve Türk Patent ve Marka Kurumu veri setini (patent başvuruları) içermektedir.

Kayıtlı tüm Türk imalat firmaları ve bu firmalarda çalışan işçiler hakkındaki verileri kullanıyoruz. Veriler 2006'dan 2020'ye kadar olan dönemi kapsamaktadır. Bu üç veri kümesini firma numarası değişkenini kullanarak eşleştiriyoruz. İşgücü devir hızlarını ve yeni işe alınanların ve işten ayrılanların ortalama ücretlerini araştırmak için 2012-2020 dönemi için mevcut olan çalışan sicil numarası değişkenini kullanıyoruz.

Yenilikler, patent başvuruları ve Ar-Ge faaliyetleri ile temsil edilmektedir. Ayrıca örneklemi, bazı firmaların “yenilikçi olmayan” durumdan “yenilikçi” duruma geçtiği bir örnek oluşturmak için 2009'dan sonra patent başvurusunda bulunan ve Ar-Ge'ye giren firmalarla sınırlandırıyoruz. Biri patent başvuruları ve diğeri Ar-Ge faaliyetleri için olmak üzere iki dengeli kontrol grubu oluşturmak için kabalaştırılmış tam eşleştirme (CEM) yöntemini kullanıyoruz (bu yöntemin açıklaması için bkz. Iacus, King & Porro, 2021). Yenilikçi faaliyetlerin etkisini tahmin etmek için Wooldridge (2021) tarafından önerilen farkların farkı (DiD) yöntemini kullanıyoruz.

OECD'ye (2012) göre, gelişmekte olan ülkelerde yenilikçi firmaların oranı gelişmiş ülkelere göre daha düşüktür ve gelişmekte olan ülkelerde yeniliklerle ilgili çalışmalar daha az yapılmaktadır. Ancak bu konu, gelişmekte olan ülkelerde yenilik ve sanayi politikası tasarımı açısından önemlidir. Bu tez bu yönde literatüre katkı sağlayacaktır.

Literatürdeki çalışmalara bakacak olursak daha önceki birçok çalışma gelişmiş ülkelerdeki ortalama ücretleri ele almıştır. Yapılan çalışmaların sonucuna göre yenilikler ortalama ücretlerin artmasına neden olur (Chennells & Van Reenen, 1999; Toivanen & Väänänen, 2008).

Yukarıda bahsedilen çalışmalar, yeniliklerin ortalama ücretler üzerindeki etkilerine odaklanırken, daha yakın tarihli çalışmalar, eşleşen çalışan-işveren verilerini kullanarak bunların ücretlerin dağılımı üzerindeki etkilerini analiz etmiştir (Aghion vd., 2019; Aghion vd., 2018; Akcigit vd., 2017; Martínez-Ros, 2001). Patent başvuruları ve Ar-Ge faaliyetleri ortalama ücretleri artırdı ve ücret dağılımlarını etkiledi.

Yeniliğin etkisi, gelişmiş ülkelerde vasıflı ve vasıfsız işgücü arasında farklılık göstermektedir. Aynı zamanda, bu etkiler erkek ve kadın işçiler arasında da farklı olabilir. Bazı çalışmalar yenilikten sonra cinsiyetler arası ücret farkının azaldığını gösterirken (Erdil vd., 2008), diğerleri bu farkta bir artış olduğunu göstermiştir (Kline vd., 2019).

Firmalar yenilikleri yaptıklarında verimlilikleri (Arvanitis, 2006; Long vd., 2017) ve gelirleri artar. Gelirdeki bu artış muhtemelen işverenler ve işçiler arasında paylaşılıyor ve buradaki kritik soru, artan gelirin işverenler ve işçiler arasında nasıl paylaşıldığıdır. Önceki çalışmalarda da yenilik ve kâr arasında pozitif bir ilişki olduğunu vurgulamıştır (Pianta ve Tancioni, 2008; Kline vd., 2018; d'Andria vd., 2021).

Bir başka önemli soru da yenilik ve işgücü devri arasındaki ilişkiyle ilgilidir. Bir dizi çalışma, bilgi yayılmalarının sıklıkla firmalar arasındaki yüksek işgücü devir hızından kaynaklandığını göstermiştir (Maliranta vd., 2009; Song vd., 2013; Almedia & Kogut, 1999; Lenzi, 2013; Lenger & Taymaz, 2005). Bu bilgi yayılımı üretkenliği artırır ve yenilikçi faaliyetleri teşvik eder (Feldman, 1999; Nadiri, 1993). Fakat önceki araştırmaların çoğu, öncelikle işgücü devrinin yeniliği nasıl etkilediğine odaklandı ve yeniliğin işgücü devrini nasıl etkilediğine çok az çalışıldı. İşgücü devri ve yenilik arasındaki ilişkiye ilişkin literatür de daha az tutarlıdır. Bazı makaleler bunun tersini iddia ederken (Rahko, 2016; Pieroni vd., 2007; Abbasi vd., 2000), geçmiş araştırmalar işgücü devir hızının yeniliği olumlu yönde etkilediğini bulmuştur (Kaiser vd., 2015; Ejsing vd., 2013; Hoisl, 2007; Braunerhjelm vd., 2020).

Gelişmekte olan ülkelerde bu konuda çok fazla çalışma yapılmamıştır ve yapılan kısıtlı sayıdaki çalışmalar da yeniliklerin ücretleri artırdığını, ancak artışların işçi grupları ve cinsiyetler arasında farklı olduğunu ve işgücü devir hızının yeniliği olumlu etkilediğini göstermektedir (Castillo vd.,2013; Crillo, 2014; Estonia vd., 2020; Mbaye vd., 2022).

Türkiye örneği için literatüre baktığımızda, esas olarak veri eksikliğinden dolayı yeniliğin ücretler, kârlar ve işgücü devri üzerindeki etkilerini ele alan herhangi bir çalışma bulunmamaktadır. Yapılan çalışmalar da yeniliklerin firma performansını artırdığını ve Türkiye'de ücret dağılımlarını etkilediğini göstermektedir (Atalay vd., 2013; Dogan vd., 2020; Meschi vd., 2016).

Evrimci-Schumpeterci iktisatçıların 1980'lerden beri tartıştıkları gibi, yenilikler uzun vadeli ekonomik büyüme için önemlidir (öncü bir çalışma için bkz. Nelson & Winter, 1984). Yeniliklerin ücretler ve kârlılık üzerinde eşit olmayan etkileri vardır. Yüksek ücretli işçiler, düşük ücretli işçilerden daha fazla fayda sağlıyor ve erkek işçiler, kadın işçilerden daha fazla olumlu etkileniyor. Ayrıca, işgücü devirleri yenilikleri olumlu yönde etkiler.

Bu etkileri beceriye dayalı teknolojik değişim, ücret pazarlık modelleri, cinsiyet ve mesleki ayrımcılık teorileri gibi teorilerle açıklayabiliriz. Beceriye dayalı teknolojik değişimler, teknolojinin etkisiyle vasıflı ve vasıfsız işgücü arasında artan ücret farklarına yol açmaktadır (Berman, Bound & Griliches, 1994). Yenilikten sonra ücretler vasıflı işgücü lehine değişmektedir. Ücret pazarlık modellerine göre, ücret rezervasyon ücretinin ve verimliliğin ağırlıklı ortalaması olduğunu öne sürer (Ballot, Fakhfakh ve Taymaz, 2006). Ücret pazarlığı modelleri yenilik sonrası ücret artışlarını açıklayabilirken, cinsiyet ayrımcılığı teorileri yenilik sonrası cinsiyete dayalı ücret farkı artışını açıklayabilir. Bu teoriler, veri sınırlamaları nedeniyle bu tezde test edilememiştir. Bunun yerine, Türkiye imalat sanayindeki yeniliklerin kârlar, ücretler ve işgücü devir hızı üzerindeki etkisine ampirik olarak bakıyoruz.

Yenilikler, ücretler, kârlar ve işgücü devir oranları arasındaki bağlantılar gelişmiş ülkelerde daha sık incelenmiştir. Bu çalışma, Türkiye'de yeniliğin işgücü devri üzerindeki etkilerini analiz eden ilk çalışmadır. GBS verileri, imalat sanayiinde istihdam edilen tüm kayıtlı işçileri takip etmemizi sağlar. Ayrıca bu çalışma, yeniliğin farklı ücret yüzdeleri, cinsiyete dayalı ücret farkları ve kârlar üzerindeki etkisini tahmin etmek için imalat sektöründen nüfus verilerini kullanan ilk çalışmadır.

Bu çalışmadaki birincil veri seti Sosyal Güvenlik Kurumu'ndan gelmekte olup, sosyal güvenlik primi ödenen çalışanların ücretlerine ilişkin çalışan düzeyindeki verileri içermektedir. Ayrıca çalışanların yaş ve cinsiyetleri, çalışılan gün sayıları, çalıştıkları firmalar ve firmaların sektörleri hakkında da bilgiler bulunmaktadır. Bu çalışan düzeyindeki veriler, 2006-2019 için üç aylık sıklıkta ve 2019'dan sonraki yıllar için aylık sıklıkta mevcuttur. 2012'den önceki yıllar için çalışan sicil numaraları olmadığı için 2006'dan önce çalışanları takip edemedik. Bu nedenle yeniliğin yeni işe alınan ve ayrılanların oranları ile yeni işe alınan ve ayrılanların ücretleri üzerindeki etkilerini 2012-2020 yılları için analiz ediyoruz. Bu çalışan veri setindeki ücret verilerini kullanıyoruz.

Firma düzeyindeki verileri içeren ikinci veri seti, Gelir İdaresi'nden alınmıştır. Bu veri setinde şu değişkenler mevcuttur: bilanço, gelir tablosu, sektör kodu (4 haneli, NACE Rev. 2), coğrafi konum, il, ihracat, ithalat, çalışan sayısı, ücret faturası ve kuruluş yılı. Firma düzeyindeki veriler yıllık olarak paylaşılmakta ve 2006 ile 2020 yıllarını kapsamaktadır. Bu çalışmada bilanço, gelir tablosu, sektör kodu, firma büyüklüğü (çalışan sayısı), ücret faturası, ihracat ve Ar-Ge harcamaları kullanılmıştır.

Ayrıca Türk Patent ve Marka Kurumu'ndan alınan patent başvuru verilerini kullanıyoruz. Bu veriler firmaların patent başvurularına ilişkin bilgileri içermektedir. İmalat sanayideki sektörler, patent başvuruları ve Ar-Ge faaliyetlerinde en yüksek paya sahiptir, bu nedenle imalat sektörlerini analiz ediyoruz. Bu üç veri setini firma düzeyinde birleştiriyoruz.

Kısaca temel betimleyici istatistiklere bakacak olursak, Tablo 3.2, veri setindeki firma sayıları, büyüklükleri, göreli firma büyüklükleri ve göreli ücret oranlarını göstermektedir. Tüm imalat sanayi firmalarını yenilikçi firmalarla (patent başvurusu yapanlar/Ar-Ge yapanlar) karşılaştırıyoruz. 2006-2020 yılları arasında tüm firma sayısı 88.500'den 156.646'ya yükseldi. 2006-2008 yıllarında patent başvuru sayısı çok azdı ancak 2009'dan sonra artmaya başladı. Bu dönemde olan politika değişikliğinden etkilenmiş olabilir.

2020 yılında patent başvurusu yapan ve Ar-Ge faaliyeti yürüten firma sayısı sırasıyla 850 ve 3022 idi. 2006 yılında Ar-Ge yapan firma sayısı 2063 ve birkaç yıl hariç 2020 yılına kadar sürekli artış göstermiştir. Ortalama olarak Ar-Ge yapanların sayısı tüm firmaların yaklaşık %2'si, patent başvurularının sayısı ise 2009 yılından sonra tüm firmaların yaklaşık %0,4'ü kadardır. 2020 yılında hem patent başvurusu hem de Ar-Ge faaliyeti yapan firma 399 tanedir (bkz. Tablo 3.1). Bu rakamlar, patent başvuru sahiplerinin yaklaşık %60'ının herhangi bir Ar-Ge faaliyeti gerçekleştirmediğini, yani çok sayıda yeniliğin Ar-Ge dışı faaliyetler tarafından üretildiğini ve kısmen gizlilik nedenleriyle tüm Ar-Ge faaliyetlerinin patent başvurularıyla bitmediğini, ancak bu durumda yine de bilgi üretebilir. Bu nedenle, iki farklı yenilik ölçüsü kullanarak, farklı türdeki yenilik faaliyetlerin etkilerini analiz edebiliyoruz.

Göreceli firma büyüklüğü sütunları, imalattaki ortalama firmaya göre yenilikçi firmaların büyüklüklerini göstermektedir. Firma büyüklüğü için çalışan sayısını gösterge olarak kullanıyoruz. Bir imalat firmasında ortalama çalışan sayısı 22'dir. Patent başvurusu yapan firmalardaki çalışan sayısı, diğer firmalara göre ortalama 20 kat fazladır. Ar-Ge'de faaliyet gösteren firmaların büyüklüğü diğerlerine göre 11 kat daha büyüktür. Yani yenilikçi ve yenilikçi olmayan firmalar arasında önemli bir farkı var.

Yenilikçi firmaların ortalama medyan ücreti, diğer imalat firmalarından daha yüksektir. Ortalama imalat sanayi firmalarına göre, 2006'da patent başvurusu yapan firmalar çalışanlarına %90, Ar-Ge yapan çalışanlarına %60 daha çok ücret ödenmektedir. Ancak bu farklar 2020'de %30-50'ye düştü. Tahmin edildiği gibi, Ar-Ge ve patent başvurularında faaliyet gösteren firmalarda çalışanlar, ortalama imalat işçisinden daha yüksek ücret alıyor. Ücretlerdeki farklılıklar çalışan özellikleri (eğitim, beceriler, deneyim, cinsiyet vb.) ve/veya firma özellikleri (büyüklük, teknoloji, pazar gücü vb.) ile açıklanabilir. Bir sonraki bölümde, bu farklılıkların bir kısmının yenilikçilikle açıklanıp açıklanamayacağını DiD metodunu kullanarak belirliyoruz.

Patent başvurularının ve Ar-Ge faaliyetlerinin sonuçlarını ölçmek için DiD metodunu kullanıyoruz. Bu amaçla Wooldridge (2021) tarafından açıklanan çift yönlü sabit etkiler (TWFE) modelinden yararlanılmıştır. Modeli uygulamadan önce bir deney grubu oluşturuyoruz ve gözlemleri dengelemek için CEM yöntemini kullanıyoruz.

Bu yöntemi kullanmak için yenilik yapan (treatment) ve yapmayan gruplar için yenilik yapılmadan önce yenilik yapmamış gözlemlere ihtiyacımız var. Yenilik öncesi en az 1 yıllık gözleme ihtiyacımız var ve 2009 yılı ve sonrasında yenilik faaliyetlerine başlayan firmaları seçiyoruz. Daha sonra yenilik etkisini bulmak için karşı olgusal ve yenilik yapan grupların farkını alırız. Yalnızca yenilik yapan grubun sonucunu gözlemleriz ve karşı olgusal sonucu tahmin etmek için ortak eğilim varsayımını uygularız.

DiD metodu, yenilikten sonraki her yıl için yenilik ve karşı olgusal birimler arasındaki farkı ölçer. Yılların kukla değişkenlerinin katsayıları bu farkın tahminini sağlar. Politika uygulanan grup üzerindeki ortalama politika etkisi (ATT) bu yöntemin bir sonucu olarak elde edilir veya başka bir deyişle, gerçekleşen ve karşı olgusal sonuçlar arasındaki farkın ortalamasıdır.

ATT değerlerini tahmin ederken iki ana varsayımımız var:

A1. Öngörülememe varsayımı: Politika etkisini (yenilik) d ve kohortları $s=q,\ldots,T$ göstermektedir:

[3b] $E[z_t(s) - z_t(\infty)|d_r = 1, x] = 0, t < s$

Öngörmeme varsayımına göre, politika öncesi politika uygulanan ve uygulanmayan firmalar arasında bir ayrım yoktur. Örneğin, politika uygulanan firmalarda politikadan sonra ücret artışı olacağını varsayıyoruz. Ancak bu etki politikadan önce başlayabilir. İşçiler zaten patent almadan önce araştırma yapıyorlar ve patent başvurusu öncesindeki yenilikçi faaliyetler nedeniyle çalışanların yetkinlikleri ve/veya bilgileri artabilir. Böyle bir durumda firmalar patent başvurusu yapmadan önce ücretlerini arttırabilmektedir. Buna öngörme etkisi denir.

A1. Paralel trend varsayımı: $d_q, \ldots, d_T$ politika kukla değişkenleridir:

[4b] $E[z_t(\infty) - z_1(\infty)|d, x] = E[z_t(\infty) - z_1(\infty)|x], t = 2, \ldots, T$

İkinci varsayım, paralel trend varsayımıdır. Ortak eğilim varsayımına göre, politika uygulanan firmalara politika uygulanmamış olsaydı, politika uygulanan ve uygulanmayan firmalar için sonuç değişkenleri benzer şekilde değişecekti. Örneğin, politika uygulanan ve uygulanmayan firmalardaki işgücü devri, politika uygulanmadığında paralel olarak hareket eder. Bu varsayım altında, iki sonucu karşılaştırabiliriz, politika uygulanan ve uygulanmayan firmaların politika uygulanmama durumlarını.

Sonuç değişkeninin eğilimi bazı değişkenlere bağlı olabilir (x vektörü bir ortak değişken vektörüdür). x ortak değişkenlerine bağlıysa, ortak değişkenlere bağlı olarak yukarıdaki şekilde iki varsayımı yazabiliriz.

ATT değerleri, doğrusal bir beklenti fonksiyonu varsayarak, Wooldridge (2021) tarafından gösterildiği gibi, aşağıdaki denklemin sabit etkiler tahmincisi kullanılarak güvenilir ve etkili bir şekilde tahmin edilebilir:

$$[6] z_{it} = \alpha_i + \sum_{t=2}^{T} \theta_t T_t + \sum_{t=2}^{T} (T_t x_i) \pi_t + \sum_{s=q}^{T} \sum_{r=s}^{T} \tau_{st} (w_{it} d_{is} T_t) + \sum_{s=1}^{T} \sum_{r=s}^{T} (w_{it} d_{is} T_t \dot{x}_{is}) \rho_{st}$$

Bu denklemde, z_{it} sonuç değişkenidir ve *i* firmaları ve *t* zamanı temsil eder. *T* zaman kukla değişkenlerini temsil eder. Böylece zaman ve firma düzeyindeki etkileri kontrol ederiz. Politika etkisini yakalamak için zamanla değişen bir politika kukla değişkeni olan *w*'yi kullanıyoruz. *x,* trendi etkileyen ortak değişkenlerin vektörüdür; *d* bir kohort kuklasıdır (firma *i* kohort *s*'ye aitse d_{is} = 1) ve kohort içi ortalama etrafındaki ortak değişkenlerin vektörü $\dot{x}$'dir. α_I de birime özgü bir etki değişkenini göstermektedir.

Denklem 6'da, τ_{st}'nin tahmini değeri, $s = q, \ldots, T$ *ve* $t = s, \ldots, T$ olmak üzere *t* zamanında kohort *s* için ortalama politika etkisine eşittir. Bu modeli doğrudan uygulayarak, *(T − q + 1)(T − q + 2)/2* kadar politika etkisi için katsayı sayısı elde ederiz. Tam etkileşimli model tahmin edildiğinde çok sayıda katsayı elde edilir ve tüm katsayıları açıklamak zordur. Ek olarak, her bir deney grubu için gözlem sayısı azalır, dolayısıyla standart hata artar. Politika etkilerinin zaman içinde nasıl değiştiğiyle ilgilendiğimiz için aşağıdaki kısıtlamayı belirledik:

$$[7] \quad \tau_{st} = \tau_{t-s}, s = q, \ldots, T; t = s, \ldots, T$$

Denklem 7, ortalama politika etkisinin τ_{st} ‘nin politikadan sonraki zamana bağlı olduğunu belirtir. $t = s + 1$ olduğunda, τ_1 yenilikçi aktiviteden 1 yıl sonra ortalama yenilik etkisini gösterir.

Tahminleri yapmadan önce aşağıdaki değişkenlerin 2008 yılındaki değerlerini kullanarak kontrol ve deney (treatment) gruplarını dengelemek için CEM’i kullanıyoruz: çalışan sayısı (log formunda), firma yaşı (log formunda), sermaye yoğunluğu, ihracat durumu ve sektör kodu (NACE Rev. 2, 2 basamaklı seviye). Yani bu değişkenleri kullanan firmaları eşleştirip kontrol grubunu oluşturuyoruz.

Politikanın 2009'dan sonra (t = 2009, …, 2020) ücretler ve kârlar üzerindeki ve 2012'den sonra işgücü devir değişiklikleri üzerindeki etkisini gözlemliyoruz. O yıllardan önce örneklemde politika uygulanmış firma yoktu. Paralel trend varsayımını ve öngörülememe etkisini kontrol etmek için 2 yıl hiç politika uygulanmamış firmaları tutuyoruz. Paralel trend ve öngörülememe etkisi varsayımları ayrı ayrı test edilemez. Öngörülememe etkisi reddedilirse, paralel trend varsayımı ve/veya öngörülememe etkisi varsayımı karşılanmaz. Ancak test reddedilmezse her iki varsayım da karşılanır. Tüm sonuç değişkenleri için sağlam Wald istatistiklerini kullanarak öngörülme etkisi/paralel trend varsayımını test ediyoruz ve bir değişkenle ilgili en uzun süreyi seçiyoruz.

Tahmin sonuçlarına gelecek olursak, önce kontrol grubunu deney grubuyla birlikte tahmin ediyoruz ve ardından aynı modeli dengeli paneldeki firmalar için tahmin ediyoruz. İki tahmin sonucu arasında çok fazla fark olmamalıdır çünkü TWFE modeli yenilik yapanlar ve yenilik yapmayanlar arasındaki farklılıkları hesaba katmaktadır.

Aynı değişken setini kullanarak, biri patent başvuru sahipleri ve diğeri Ar-Ge uygulayıcıları için olmak üzere iki kontrol grubu oluşturuyoruz. Denklem 7'nin kısıtlamaları altında, R'dan “fixest” paketi kullanarak sabit etkiler modeli (Wooldridge, 2021) ile politika etkilerini (τ_{st}) bulmak için Denklem 6'yı tahmin ediyoruz. Ücret ve kâr sonuçları için 12 ve işgücü devir sonuçları için 8 tahmin var.

Yeniliğin aşağıdaki değişkenler üzerine etkisi inceledik: 10., 50. ve 90. yüzdelik dilimlerdeki ücretler (log formunda); erkek ve kadın çalışanlar için ücretler (log formunda); çalışan başına firma çıktısı (log formunda); çalışan başına katma değer (çalışan üretkenliği) (log formunda); ve faaliyet kâr marjı (faaliyet kârı/net satışlar). Ayrıca, yeni işe alınanların ve ayrılanların oranlarını ve yeni işe alınanların ve ayrılanların ücretlerini (log formunda) kullanıyoruz. İhracat kuklası, sermaye yoğunluğu, firma boyutu (log formunda) ve firma yaşı (log formunda) DiD yönteminde ortak değişkenlerdir.

Tahmin sonuçlarına gelecek olursak, Şekil 5.1 patent başvurusunda bulunan işlem görmüş firmalar ile kontrol grubundaki patent başvurusunda bulunmayan firmalara kıyasla tahmin sonuçlarını göstermektedir. 2007 ve 2020 yılları arasında (14 yıl) faaliyet gösteren patent başvuru sahiplerinin dengeli paneldeki firmalara göre etkisi Şekil 5.2'de gösterilmektedir. Tahmin sonuçları gruplar arasında benzerdir.

Düşük ücretlilerin (yüzde 10'luk dilim, w10) yenilik sonrasında ücretlerinde herhangi bir değişiklik olmadı. Öte yandan, medyan ücretlerdeki (w50) artış, yenilikçi olmayan firmalarda çalışan işçilerin ücretlerine göre yaklaşık %2-3 oranındadır. Yüksek maaşlıların (w90) ücretleri hızla yükselerek %8'lik bir artışa ulaşıyor. Çalışanlar, yeniliklerin faydalarını eşit olarak paylaşmıyorlar. Şekil 5.1 ve 5.2, patent başvurularından sonra firma içi ücret farklılıklarının arttığını göstermekteriyor.

Ar-Ge çalışanları arasındaki ücret artışları, patent başvurusu yapan firma çalışanlarına benzer. Düşük ücretli (en düşük yüzde 10'luk dilim) çalışanlar arasında ücret değişikliği yoktur (Şekil 5.3). Ortalama ücretli ve yüksek ücretli çalışanlar, düşük ücretlilerden daha fazla yararlanır. Ortalama ücretli çalışanlar için ücret artışı yaklaşık %2'dir. Ar-Ge yapan firmalarda yüksek ücretlilerin (en yüksek yüzde 10'luk) ücret artışı %4-6'dır. Ar-Ge yapan firmalarda firma içi ücret farklılıklarında da bir artış var. Diğer bir deyişle, yenilikler (patent başvuruları/Ar-Ge faaliyetleri) firma içi ücret farklılıklarını artırmaktadır.

Nash ücret pazarlığı modelleri, yenilik (yani patent başvuruları ve Ar-Ge faaliyetleri) sonrası maaşlardaki artışı açıklayabilir. Bu modeller, ücret oranının emek üretkenliği ve rezervasyon ücretinin ağırlıklı ortalaması olduğunu göstermektedir (Ballot, Fakhfakh, and Taymaz, 2006). Rezervasyon ücreti, bir işçinin bir işi kabul etmek istediği asgari ücrettir ve işçilerin niteliklerine bağlıdır. Yenilikten sonra, rezervasyon ücretindeki artış ve/veya işçilerin pazarlık gücündeki artış ve/veya emek verimliliğindeki artış nedeniyle ücret oranı yükselir. Tahmin sonuçlarımız yenilikten sonra emek verimliliğinin arttığını göstermektedir. Yüksek ücretli işçiler yenilik sürecine dahil olursa, beşerî sermaye birikimi nedeniyle rezervasyon ücretleri artabilir. Ayrıca, yeni bilginin bir kısmı zımnidir ve bu bilgi işçilerdedir, bu bilgi işçilerin pazarlık gücü de arttırır.

Özetlemek gerekirse, yüksek ücretliler, yüksek rezervasyon ücretleri, yüksek pazarlık gücü ve yüksek emek verimliliği nedeniyle düşük ücretlilere göre yeniliklerden daha fazla fayda sağlıyor. Bu etkiler, medyan ücretliler için daha zayıf görünmektedir. Düşük ücretlilerin pazarlık gücü yok gibi görünüyor; dolayısıyla kazançları artmaz ve (yasal olarak uygulanan) asgari ücret düzeyinde kalırlar.

Cinsiyete bağlı ücret farklılıklarına ilişkin olarak, patent başvuruları sonrasında kadın ve erkek işçilerin ücretlerinde artış görülmektedir (Şekil 5.5 ve 5.6), ancak patent başvurularının başlamasından 7 yıl sonra erkek işçiler için maksimum ücret artışı yaklaşık %5 civarındadır ve kadın işçiler için sadece yaklaşık %3. Patent başvurularından sonra kadın ve erkek arasındaki ücret farklılıklarının artması muhtemeldir.

Ar-Ge yapanlar için, yenilikten sonra zaman içinde erkek-kadın ücret farklılıkları artar. Erkek işçilerin ücretleri %3 ile %4 arasında artarken, kadın işçilerin ücret artışları yaklaşık %3'tür (bkz. Şekil 5.7 ve 5.8). Patent başvuruları veya Ar-Ge faaliyetleri sonrasında cinsiyetler arası ücret farkı açılmaktadır.

Şekil 5.9, Ar-Ge yapan ve patent başvurusu yapan firmaların işgücü verimliliği (çalışan başına katma değer) üzerindeki etkisini göstermektedir. Patent başvuru sahipleri için emek verimliliğindeki artış, zaman içinde emek verimliliğinde bazı dalgalanmalar olmasına rağmen %2 ile %6 arasındadır. Ar-Ge yapanlar arasında emek verimliliği, çalışmayanlara göre yaklaşık %2-4 daha yüksektir. Artan verimlilik sonucunda, yenilikçi firmalarda ücretlerin işgücü verimliliği içindeki payı %30 civarında olduğu için yenilikçi firmaların kârları artmaktadır.

Şekil 5.11, yeniliklerin faaliyet kâr marjı üzerindeki etkisini göstermektedir (faaliyet kârı/net satışlar). Patent başvuru sahipleri için işletme kâr marjı, 10. yıl hariç, dikkate alınan dönem boyunca sürekli olarak artar. 5 yıllık yenilikten sonra, kâr marjı yaklaşık %8'dir. Patent başvuru sahipleri gibi, Ar-Ge faaliyetleri yürütenler arasında yenilikten sonra faaliyet kâr marjı da artar. Kâr %4 ile %8 arasındadır. Patent başvuru sahiplerinin kârı, Ar-Ge yapanların kârından daha fazla artıyor. Çalışanların kazançları ile işverenlerin kazançlarını karşılaştırdığımızda, işverenler daha fazla fayda sağlıyor ve yenilikten sonra firmalar daha kârlı hale geliyor.

Firmalar arasında bilgi yayılımı çoğunlukla işgücü devri yoluyla gerçekleşir. Şekil 5.13, patent başvurularının yeni işe alınanlar ve işten ayrılanların oranları üzerindeki etkilerini göstermektedir. Tahmin sonuçları, ayrılanların oranlarının %16 ile %6 arasında dalgalandığını göstermektedir. Patent başvurularının başlamasından beş yıl sonra işten çıkma oranları azalmaktadır. Yeni işe alım oranları, yenilikten sonra zamanla düşer (1 yılda istatistiksel olarak anlamlıdır). Ancak, bu tahmin sonuçlar anlamsızdır. R&D faaliyetleri yürüten firmalar için de benzer sonuçlar çıkmıştır (Şekil 15). Ayrıca işten ayrılma ve işe girme maaş oranları için yapılan tahminler de anlamsız çıkmıştır ve sonuçları Şekil 17 ve 19 gösterilmektedir.

Yenilik yapan firmalar genellikle daha büyüktür ve çalışanlarına daha yüksek ücret öderler. Bir kontrol grubu oluşturduğumuzda, kontrol grubunun büyüklüğü deney grubununkiyle aynıdır. Gruplar arasında ücretler de yakınlaşıyor. Başka bir deyişle, birbirine benzeyen firmaları karşılaştırıyoruz. Bu, Wooldridge yöntemi için bir gereklilik değildir. Ancak, bulgularımızın sağlamlığını kontrol etmek için iki farklı grubun (kontrol grubu ve dengeli panel grubu) sonuçlarını karşılaştırmak için kontrol grubunu kullanıyoruz.

Yenilik, ücretlerin, kârların ve emek üretkenliğinin artmasına yol açar. Patent başvuruları/Ar-Ge faaliyetleri sonrasında firma içi ücret farklılıkları ve cinsiyete dayalı ücret farklılıkları artmaktadır. İşverenler çalışanlardan daha fazla fayda sağladığı için gelir dağılımları daha da kötüleşiyor. Ayrılanların ve yeni işe alınanların işgücü devir oranları ve ücretleri üzerindeki yenilik etkisi zayıf ve belirsizdir.

Bu çalışma, yeniliğin (patent başvuruları/Ar-Ge faaliyetleri) işçi ücretleri, firmaların kârları ve işgücü devri üzerindeki etkisini araştırmıştır. DiD yöntemini kullandık ve 2006-2020 döneminde faaliyet gösteren Türkiye'deki imalat firmalarının popülasyon verilerini kullandık. Yenilikten sonra kârların ve emek verimliliğinin önemli ölçüde arttığını bulduk. Ayrıca, yeniliğin düşük ücretli çalışanlar üzerindeki etkisi ihmal edilebilir düzeyde ve istatistiksel olarak anlamlı değilken, medyan ücretli ve yüksek ücretli çalışanlar olumlu ve önemli ölçüde etkilenmektedir. Yüksek ücretli çalışanlar için ücret artışları diğer çalışanlara göre daha yüksektir ve bu nedenle yenilikçi faaliyetlerden sonra firma içi ücret farklılıkları artmaktadır. Ayrıca, erkeklerin kazançlarının kadınlardan daha fazla artması sonucunda cinsiyete dayalı ücret eşitsizlikleri de bir dereceye kadar büyümektedir.

Yeniliğin yeni işe alınan ve ayrılanların oranları ile yeni işe alınanların ve ayrılanların ücretleri üzerindeki etkileri belirsiz ve zayıftır. Ayrılma oranlarındaki değişiklikler önemsizdir ve hem patent başvuru sahipleri hem de Ar-Ge çalışanları için artmaktadır. Yeni işe alım oranları bazı yıllar için anlamlıdır ve yenilik yapan firmalar için azalmaktadır. Ayrıca, yeni işe alınanların ücretleri düşerken, işten ayrılanların ücretleri artmakta; ancak, bu etkiler önemli değildir. Ar-Ge yapan firmalar için yeni işe alınanların ve ayrılanların ücretleri çok fazla değişmiyor ve her ikisi için de dalgalanmalar var. Yeni işe alınanların ücret değişiklikleri sadece 2 yıl için önemlidir.

Tahmin sonuçları, Türkiye’deki imalat sanayinde Ar-Ge yapanlar ile patent başvuru sahipleri arasında farklılıklar olabileceğini göstermektedir. Ar-Ge faaliyetleri ve patent başvuruları, ampirik çalışmalarda yeniliğin göstergeleri olarak sıklıkla kullanılmasına rağmen, patent başvuru sahipleri ile Ar-Ge uygulayıcıları arasındaki farkları anlamak için daha fazla araştırmaya ihtiyaç vardır.

Kontrol grubu kullansak da kullanmasak da Wooldridge yöntemi aynı sonucu verdi. Gerekli ortak değişkenleri kullanırsak ve varsayımlar geçerliyse, Wooldridge yönteminde bir kontrol grubu kullanmak şart değildir.

Bu çalışmanın sonuçları, yeniliğin toplum için önemli faydaları olmasına rağmen, bu faydaların eşit olarak dağıtılmadığını göstermektedir. En azından kısa ve orta vadede, yenilik sonrası gelir dağılımındaki eşitsizlik artabilir.

Bulgular ayrıca, politika yapıcıların ekonomik kalkınmaya katkıda bulunan, yenilikçi faaliyetleri teşvik eden destek programları uygulaması gerektiğini göstermektedir. Destek programları, Ar-Ge harcamaları için sübvansiyonları ve firmalardaki yeniliklerin girdi ve çıktılarını içerebilir; bu nedenle, yenilikçilerin riskleri azalacaktır. Teknoparklar, yenilikçi faaliyetleri artırmak için araştırmacılar ve firmalar arasındaki etkileşimi artırmak için de desteklenmelidir. Alman Energiwende'ye benzer şekilde, politika yapıcılar farklı olgunluk derecelerinde yenilikçi faaliyetleri deneme, uygulama ve yararlanma yoluyla desteklemelidir (Edler & Fagerberg, 2017).

Yenilik topluma fayda sağlarken, yüksek vasıflı ve daha az vasıflı işçiler arasındaki eşitsizliği artırır. Gelir eşitsizliği ile baş edebilmek için politika yapıcıların politika araçlarını ayarlamaları gerekmektedir. Yenilikçi faaliyetlerin temeli olarak beşerî sermayede bir artış sağlamak için yükseköğretime daha fazla kamu harcaması tahsis edilmelidir. Bu, teknoloji ve bilgi ilerlemelerinin fırsat eşitsizliğini azaltmasını mümkün kılacaktır. Nitelikli işgücünün payı artacak ve yenilikten yararlanan nüfusun yüzdesi artacaktır.

Bu uzun ve orta vadeli planlara ek olarak, kısa vadede düşük ücret alan işçilere ek ücret primleri uygulanmalıdır. Gelir vergisi ile finanse edilebilecek düşük vasıflı emeğin ücretlerini yükseltmek için yeniden dağıtım vergisi ve transfer politikaları uygulanmalıdır.

Yenilikler cinsiyetler arası ücret farklarına neden oluyor ve politika yapıcılar bu sorunun üstesinden gelmek için ücretli işlerde cinsiyet eşitliğini teşvik etmelidir. Kadın işçilerin farklı mesleklerde istihdam edilmeleri ve fırsat eşitliğinin artırılması için daha uygun eğitim ve öğretim verilmeli, kadın işçi kotaları uygulanmalıdır. Ortalama ücretlerin yükseltilmesi için aynı iş pozisyonları için eşit ücret mevzuatı uygulanmalıdır.

Türkiye'deki imalat firmalarının nüfusuna ilişkin verileri kullanmamıza rağmen, patent başvurusu yapanların ve Ar-Ge yapanların sayısı kohort-zaman etkilerini tahmin etmek için yeterli değildi. Bu nedenle, modeli yalnızca zaman etkileri tahmin edilecek şekilde kısıtladık. Bu kısıtlamaya rağmen, bazı tahminler, özellikle de işgücü devri ile ilgili olanlar, yüksek varyanstan zarar gördü. Son olarak, çalışan özelliklerine (eğitim, deneyim vb.) ilişkin herhangi bir veri bulunmadığından, bu faktörlerin kontrol edilmesi mümkün olmamıştır.

Bu tezde, bir firma bir kez yenilik yaptığında etkisinin devam ettiği varsayılmıştır (yani, aşamalı deney varsayımı). Sonraki yıllarda patent başvurusunda bulunarak sürekli yenilik yapan veya Ar-Ge projelerine devam eden firmalar gibi farklı yenilik kalıplarını dikkate almadık. Bu etkilerin gelecekteki araştırmalarda dikkate alınması önemli olabilir. Ayrıca patent ve Ar-Ge'nin ortak etkileri burada değerlendirilmemiştir. Farklı yenilik türleri arasındaki tamamlayıcılıkların analiz edilmesi gerekir.

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