THREE ESSAYS ON INNOVATION: FIRMS' RESPONSES TO TRADE SHOCKS, GOVERNMENT POLICIES, AND LABOR MARKET DYNAMICS IN KOREA

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ABSTRACT

Recent, prolonged low growth has made innovation-driven economic growth essential for many countries, especially in high-technology sectors such as semiconductors. Research and development (R&D) is the primary engine of this innovation, and firms in countries such as South Korea (hereafter Korea) and the United States now contribute more than 80 percent of total national R&D.

With this in mind, this study pursues three interrelated objectives. First, it examines how external shocks spur or hinder firm-level innovation. Second, it investigates how government policy can be designed to encourage private sector R&D. Third, it traces how the R&D-driven innovation affects employment, the central mechanism through which its effects reach the wider economy. This study is based on three empirical essays that use financial statement panel data for Korean listed firms. By connecting external shocks, policy design, and employment outcomes, this study aims to provide insights for policies that promote active firm innovation, and to clarify the labor market dynamics that accompany the pursuit of innovation.

The first chapter examines the impact of the 2019 Korea-Japan trade dispute on Korean firms, focusing on their innovation responses. Affected firms are classified into two groups: user-side firms that rely on Japanese export-controlled chemicals for semiconductors, displays, and rechargeable batteries, and producer-side firms that can substitute those chemicals domestically. Both groups increased R&D expenditures in response to the shock, with some producer-side firms increasing patent applications. However, user-side firms faced higher costs, while producer-side firms benefited from productivity gains. This contrast suggests that supply chain diversification and domestic production substitution created opportunities for producer-side firms, while imposing higher costs on user-side firms due to production inefficiencies.

The second chapter investigates the policy effects of a new R&D tax credit system implemented in Korea since 2011. The system classifies eligible firms from two to three groups: Small Medium Enterprises (SMEs), non-SMEs, and newly medium-sized firms from previously non-SMEs, to align tax incentives with actual firm classifications. It raised the tax credit rate for medium-sized firms from 6 percent to 15 percent. Although, this study finds no clear evidence that the reform had a significant effect, firm heterogeneity does matter. Medium-sized firms with a higher intangible asset-to-capital ratio show a larger increase in R&D spending. Within the treatment group, the policy had clearly boosted R&D in high-tech firms and in firms with below average R&D intensity and poor financial conditions, suggesting that it eased financial constraints.

The third chapter examines how firms' innovation activity, measured by R&D expenditures, is reshaping the Korean labor market. The key findings are as follows. First, R&D investment is generally associated with increased employment. This effect is especially strong in high-tech manufacturing, where longer R&D duration further amplifies it. Second, higher R&D investment tends to reduce the share of non-regular workers. In high-tech services, it is also associated with a decline in the share of female workers. Third, while the overall impact on average salaries is modest, there is a significant increase in high-tech conglomerates. These results highlight the skill-biased nature of R&D and labor force heterogeneity. As a result, the benefits tend to be disproportionately concentrated among regular employees. Thus, R&D-driven innovation may create high-quality jobs but also exacerbate labor market inequalities.

Taken together, the essays demonstrate how external shocks or intentional government policy can trigger firms' innovation activities, and how employment channels transmit both the benefits and the strains of firm-level R&D to the broader economy, thereby providing guidance for policies that seek sustainable and inclusive growth.

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CHAPTER 1
FIRM’S INNOVATION RESPONSE TO ADVERSE TRADE SHOCKS

1.1 Introduction

In today's global economy, where international trade is closely linked through value chains, it is intuitive to expect that adverse trade shocks can significantly affect the growth trajectories of national economies. A key question, however, is how individual economic agents, particularly firms at the core of industrial production, respond to such shocks. While firms can adjust various decision variables such as prices or output, this study focuses on innovation as the primary response mechanism. Specifically, it examines the impact of the Korea-Japan trade dispute, which began in July 2019, on firms' innovation efforts and on their productivity, profitability, and cost as reflected in financial statement data. This focus is particularly relevant because the industries most affected by the dispute-semiconductors, displays, and rechargeable batteries-are high-tech sectors that have played a central role in driving Korea's recent economic growth. In addition, this study examines the responses of Korean producers that compete directly with Japanese firms whose products were subject to export restrictions.

In this paper, I approached the industries or companies under investigation by dividing them into two broad categories. I grouped semiconductors, displays, and rechargeable batteries, which use Japanese export-controlled items as intermediates, and the chemical industry, which produces these materials. Looking at the impact on the user side, as expected, the impact of the shock led to an increase in costs, which could lead to a decline in productivity and profitability, but firms tried to innovate more by increasing R&D expenditures. Furthermore, the producer-side effects show that firms increased their innovation efforts, such as R&D expenditures and patent applications. In addition, productivity is positively affected. When the control group was narrowed down using Propensity score matching (PSM), the results were even more evident.

This study contributes to the understanding of the Korea-Japan trade dispute by taking a more disaggregated approach than previous research, which has primarily focused on industry-level analysis. By using firm-level financial statement data, this paper accounts for firm heterogeneity and employs multiple variables to examine how firms on both the user and producer sides have performed and how their innovation responses have evolved in the aftermath of the dispute.

1.2 Background

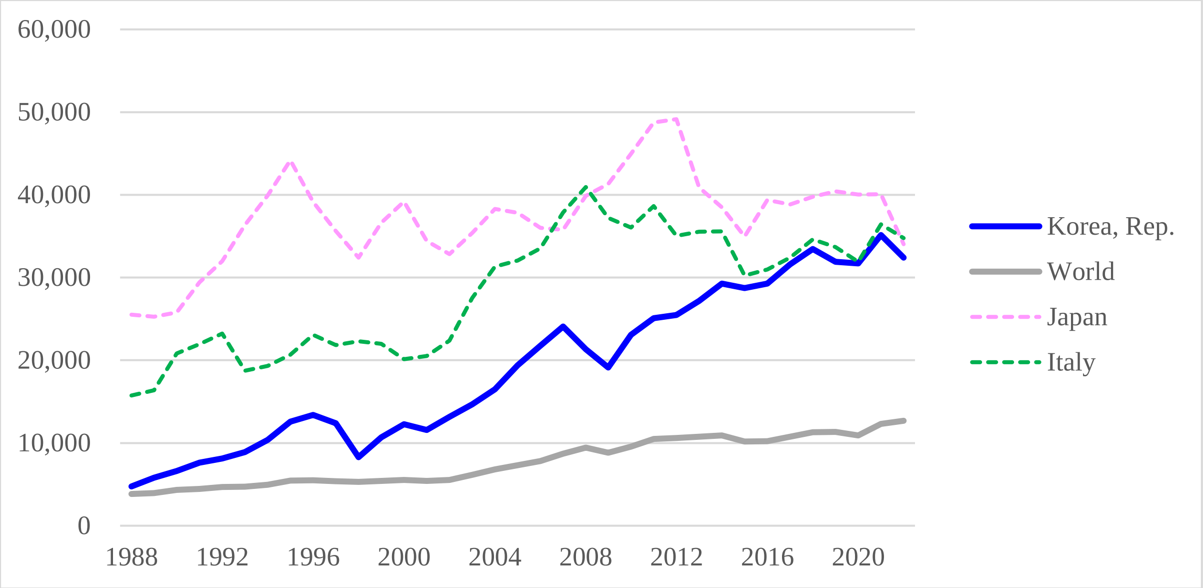
1.2.1 Korea's growth path and semiconductor industry

Korea can be seen as a prime example of the new trade theory supported by empirical evidence. By pursuing an export-led strategy and restructuring its industrial structure, particularly focusing on high-tech industries, Korea has achieved rapid economic growth relative to the world and relative to countries with similar GDP per capita levels by 2022 (Figure 1.1). The trend since the global financial crisis, especially since 2008, shows this even more clearly.

One striking feature of Table 1.1 is that semiconductors account for a significant share of Korea's trade structure. Even without considering the fierce competition among governments to promote the semiconductor industry in recent years, semiconductors have historically been a core industry, accounting for 20% of Korea's exports and equipment investment.

Figure 1.1.

Trends in GDP per capita (current USD)



Source: World Bank (WB)

Table 1.1.

Trends in Korea's major export and import items (USD million)

		1988		2006		2024	
Export	1	Clothing	8,449	Semiconductor	33,236	Semiconductor	141,920
	2	Furniture	3,801	Car	32,924	Car	70,782
	3	Video equipment	3,520	Wireless communication device	27,033	Petroleum products	50,326
		Total	60,696	Total	325,465	Total	683,609
Import	1	Crude oil	3,688	Crude oil	55,959	Crude oil	85,334
	2	Semiconductor	3,202	Semiconductor	26,382	Semiconductor	72,216
	3	Aircraft and parts	1,806	Natural gas	11,931	Natural gas	29,272
		Total	51,811	Total	309,383	Total	631,767

Source: Korea Customs Service

In the present day, high technology industries are deeply embedded within global value chains. A prime example is the semiconductor industry, which features a highly complex and globally fragmented value chain encompassing stages such as design, manufacturing (wafer fabrication or foundry), assembly, testing, and packaging. The semiconductor supply chain is characterized by high geographical concentration, with key production hubs located in a few Asian economies, notably Korea and Taiwan. To elaborate further, high-end semiconductors are typically based on core source technologies and design processes that originate in the United States. The manufacturing stage, which requires highly advanced technological capabilities, is largely undertaken in Korea and Taiwan. Meanwhile, the production of essential materials and equipment is distributed across Japan, China, and European countries such as the Netherlands. In particular, Japan holds a competitive edge in the production of specialized chemicals and semiconductor manufacturing equipment, both of which are critical inputs for semiconductor fabrication. In this context, it can be said that industries based on the global value chain, such as the semiconductor industry, are inherently vulnerable to geopolitical tensions between countries.

1.2.2 Trade dispute between Korea and Japan

Based on the sensitive historical background of conflicting interests between Korea and Japan, in July 2019, Japan imposed strict controls on the export of three key chemicals[1] used in chip manufacturing. It also removed Korea from its export "white list[2]" as trade tensions escalated. These measures mean, first, that three materials required for the manufacture of

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[1] Photoresists, hydrogen fluoride etching gas and fluorinated polyimide

[2] A list of countries with preferential trade status, if excluded, may require exporters to obtain special licenses when shipping a wide range of building materials, chemicals, and electronic goods. (Inagaki, Song & White. (2019, August 1). Japan cuts S Korea from export 'white list' as trade tensions rise. Financial Times. https://www.ft.com/content/71d09ea2-b4cd-11e9-8cb2-799a3a8cf37b)

semiconductors and displays will be subject to individual licenses instead of the previous comprehensive license system. Second, the exclusion of Korea from the whitelist means that key materials needed by other industries will also be subject to individual licensing under the Japanese government's decision, even if they are non-strategic materials.

However, as of July 2023, Korea has been reinstated to the Japanese government's white list following efforts by the leaders of two countries to restore bilateral relations[3]. Despite recent restoration of relationships, the Korea-Japan trade dispute highlighted the vulnerabilities inherent in highly concentrated and specialized supply chains, where disruptions in one area can have significant repercussions (Haramboure, A. et al., 2023).

To understand how important the three chemical products that Japan imposed export controls on are to Korea's semiconductor and display industries, we can look at the import status in 2019 using HS codes that cover the three products. From Table 1.2, it is obvious that Japan accounts for a significant share of Korea's imports of key materials for semiconductor and display production. Meanwhile, according to the Ministry of Trade, Industry and Energy of Korea, there are limitations in accurately calculating the import volume changes of the three items except for hydrogen fluoride based on HS codes. Even though they are the same product in terms of HS code, whether they are strategic materials subject to export control or not depends on the differences in detailed technical specifications.[4] Therefore, I will focus on

[3] THE ASSOCIATED PRESS (2023, June 28). Japan to reinstate South Korea as preferred trade nation from July 21 as two sides improve ties. The Asahi Shimbun. https://www.asahi.com/ajw/articles/14943308

[4] It is known that the HS code can identify polyimide films (for OLED panels) and resists for semiconductor manufacturing. However, it cannot distinguish fluorinated polyimide (for flexible displays) and photoresists (some of the short wavelength and next generation resists such as EUV resists), which were subject to export controls.

hydrogen fluoride, which exactly matches the export control item and HS code, and examine the changes in the amounts that Korea imported from January 2017 to July 2024 (Figure 1.2).

Table 1.2.

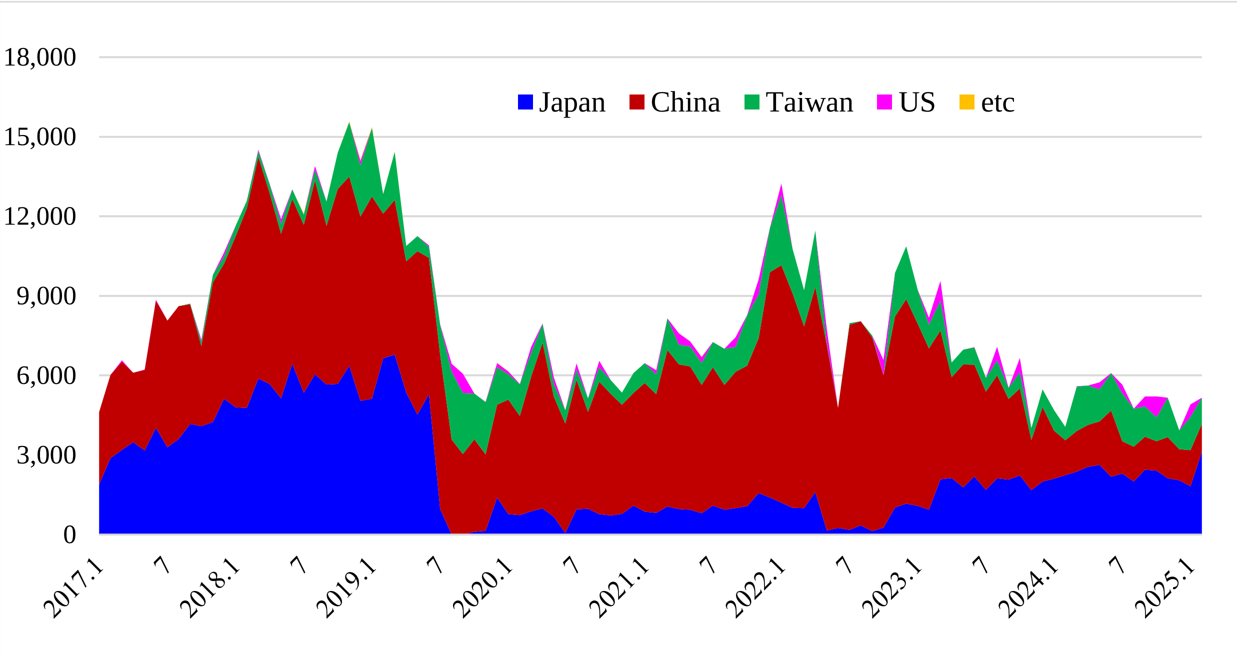
Imports of semiconductor materials (Jan-May 2019) (USD thousand, %)

Resists			Hydrogen fluoride etching gas			Polyimides film		
Countries	Imports	%	Countries	Imports	%	Countries	Imports	%
Total	112,663	100.0	Total	64,786	100.0	Total	12,964	100.0
Japan	**103,516**	**91.9**	China	30,025	46.3	**Japan**	**12,142**	**93.7**
U.S.	8,325	7.4	**Japan**	**28,436**	**43.9**	Taiwan	508	3.9
Belgium	486	0.4	Taiwan	6,276	9.7	China	180	1.4
Taiwan	259	0.2	India	35	0.1	U.S.	76	0.6

Source: Korea International Trade Association (KITA)

Figure 1.2.

Korea's hydrogen fluoride etching gas imports (USD Thousand)

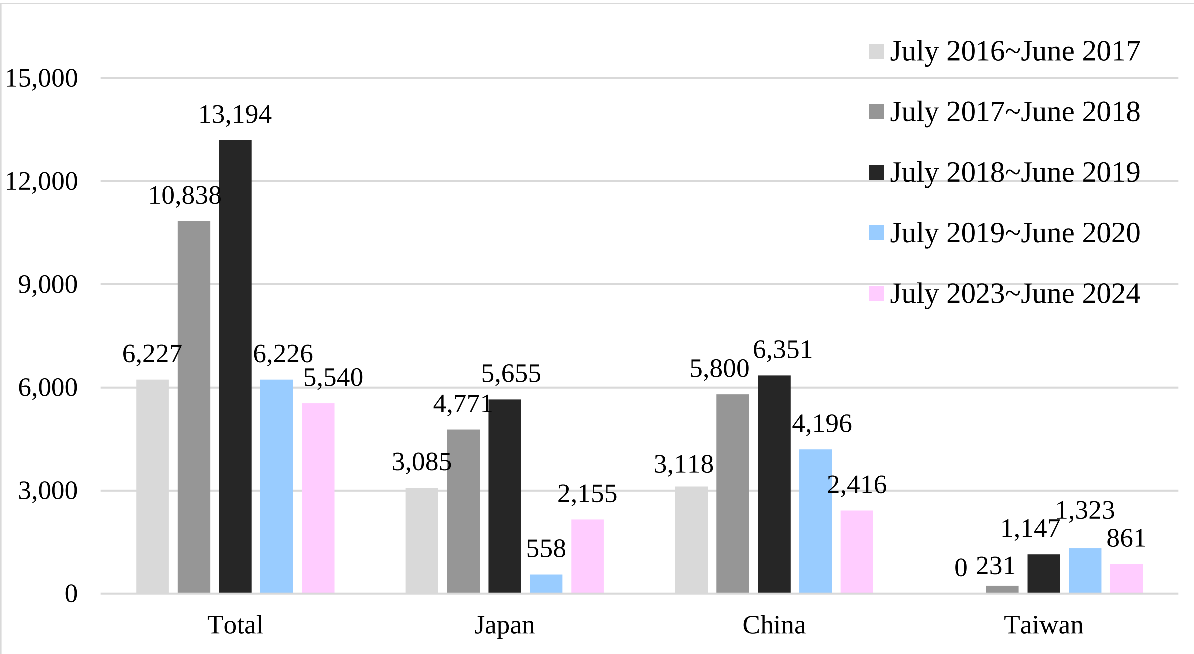


Source: Korea International Trade Association (KITA)

Figure 1.2 shows three main features. First, it can be seen that imports of hydrogen fluoride from Japan dropped sharply after Japan imposed export restrictions from July 2019. Second, if we look at whether there was a substitution of importing countries, we can see that imports from Taiwan increased in particular right after July 2019. Third, even considering possible external factors such as the semiconductor boom in 2018, the sharp decline in total imports after July 2019 indicates that the impact of Japan's export restrictions was significant. A comparison of average monthly hydrogen fluoride imports for each year since July 2016 shows a sharp decline in imports from Japan after July 2019. Since July 2023, when export controls were reinstated, imports from Japan have increased, but at lower levels than in previous years, and overall imports have been slow to recover (Figure 1.3).

Figure 1.3.

Average monthly Korea's hydrogen fluoride etching gas imports (USD Thousand)



Source: Korea International Trade Association (KITA)

As noted above, the three chemicals subject to export controls were essential materials for semiconductor production, which is very important to Korea. Therefore, significant negative impacts were expected. At that time, the Korean government and firms made efforts to secure alternative supply chains for key materials, and to promote domestic production to cope with similar situations in the future. Therefore, this study aims to examine how Korean firms responded to the negative trade shock resulting from Japan's export controls by promoting innovation through increased R&D investment, patent applications to secure and develop technologies, and the subsequent outcomes in terms of productivity and profitability.

1.3 Literature Review

The literature review in this paper is divided into two main parts. First, this section reviews studies that examine the impact of trade shocks on the innovation efforts of individual firms. Second, it also provides a review of the literature on the impact of the Korea-Japan trade dispute, which serves as the starting point for this study.

Bloom et al. (2016) argue that import competition can stimulate innovation. Using data on European firms, they find that increased import competition from China led to higher innovation, as measured by patenting, along with improvements in total factor productivity, IT adoption, R&D expenditures, and management practices. Their analysis distinguishes between within firm effects and intra industry reallocation. These findings build on models of firm heterogeneity (Melitz, 2003; Melitz and Redding, 2015) and extend them by demonstrating that trade shocks can enhance within firm productivity. Bloom et al. (2013) further support this argument by showing that lower input costs from trade reduce adjustment frictions, thereby encouraging innovation. Similarly, Bernard et al. (2010) show that trade liberalization leads firms to shift toward more productive product lines, reinforcing the importance of internal restructuring in innovation dynamics.

In contrast, Autor et al. (2020) offer a more skeptical view. Analyzing United States firms, they find that rising import competition, particularly from China, reduces sales, profitability, research and development spending, and patent output. Their findings align with the inverted U-shaped relationship between competition and innovation proposed by Aghion et al. (2005), in which moderate competition encourages innovation, but excessive competition suppresses it due to reduced returns and heightened risk. Likewise, Hombert and Matray (2018) find that import competition adversely affects firm performance, especially in terms of sales growth and profitability. However, these negative effects are significantly weaker among firms that invest heavily in R&D. They highlight product differentiation, measured using the Text based Network Industry Classification (TNIC), as a key mechanism through which R&D cushions the impact of trade shocks. In summary, while the effects of import competition on innovation may vary depending on context and intensity, many studies suggest that negative trade shocks can stimulate innovation either through within firm responses or inter firm reallocation mechanisms.

Several studies have examined the impact of the Korea Japan trade dispute, particularly from the perspective of global value chains, highlighting the economic costs arising from the vulnerability of tightly interlinked production relationships. From the production side, Kim (2021) argues that key sectors in Korea face supply constraints, which may lead to production cuts unless immediate substitutes are found. The author assumes a 10 percent decline in gross output for Korea's semiconductor and display sectors as a direct consequence of Japan's export controls. Shin and Balistreri (2022), using a computable general equilibrium model, estimate welfare losses for both Korea (0.144 percent, or 1.0 billion USD) and Japan (0.013 percent, or 346 million USD), driven by sectoral output changes in both countries and Korea’s attempt at trade diversion.

Goodman et al. (2019) suggest that the dispute incentivized Korean chipmakers to reduce long term dependence on Japanese suppliers not only for controlled chemicals but across the broader semiconductor value chain. The study also notes that Japanese chemical producers faced risks of losing access to Korea's growing semiconductor market. Makioka and Zhang (2024) show that Korean firms responded by diversifying their sourcing of restricted inputs, turning to countries such as Belgium, the United States, and Taiwan. They also report negative spillover effects on Korean imports of semiconductor equipment. The authors argue that the dispute illustrates the limited effectiveness of unilateral export controls in a globally interconnected economy, as firms adapt through alternative sourcing and production strategies. Meanwhile, Ahn et al. (2022) highlight that the dispute escalated beyond manufacturing to services, as evidenced by Korean consumer boycotts of travel to Japan, indicating wider economic costs for both countries.

Notably, some studies point out that Korean firms mitigated the impact by securing alternative suppliers, thereby minimizing the disruption. In line with the research question of this study, this study aims to examine how the Korea-Japan trade dispute affected Korean firms. In particular, I test whether such cost pressures led to increased innovation efforts at the firm level, as suggested by the existing literature.

1.4 Data and methodology

1.4.1 Empirical strategy

To evaluate the outcomes of Korean firms' innovation activities in response to Japanese export restrictions, this study employs a Difference-in-Differences (DID) approach. The empirical analysis is divided into two categories: industries that use the export-controlled chemicals and those capable of producing these materials domestically. On the user side, the treatment group consists of firms in the semiconductor, display, and rechargeable battery industries, which were considered the most vulnerable due to their high dependence on Japanese imports. The control group comprises firms in the wireless communication equipment industry, whose R&D expenditure trends are comparable to those of the treated industries. Firms within the treated sectors whose products are not directly related to the restricted materials were excluded from the treatment group and reclassified as part of the control group. On the producer side, 17 firms identified as likely beneficiaries of the shift from imported to domestically produced materials were selected as the treatment group, while other firms in the same industry were assigned to the control group.

For both user and producer side, I also employed Propensity Score Matching (PSM) to narrow the control groups. On the user side, there were seven companies that were expected to be directly affected by Japan's export controls. Therefore, I applied PSM to narrow down the control group for further analysis by selecting these seven firms as the treatment group. On the producer side, PSM was also used to narrow down the control group by selecting firms with similar characteristics to the 17 treated firms.

The model equations in this study can be represented by the following one. This is for both industries that use and produce the three chemicals mentioned above in Korea.

$$Y_{it} = \beta_0 + \beta_1 After_t + \beta_2 (After \times Treatment)_{it} + \delta Control_{it} + u_i + v_t + \gamma_i \times Trend_t + e_{it}$$

$$(Y_{it} : (1)\ R\&D_{it},\ (2)\ Patent_{it},\ (3)\ Productivity_{it},\ (4)\ Profit_{it},\ (5)\ Cost_{it})$$

Regarding the dependent variable, $R\&D_{it}$ is the R&D expenditure of each firm by year, $Patent_{it}$ is the number of patent applications filed annually with the Korean Intellectual Property

Office (KIPO) by each firms, $Productivity_{it}$ is the value added per employee, which is considered an indicator of labor productivity in financial statements. Meanwhile, $Profit_{it}$ refers to earnings before interest, taxes, depreciation, and amortization (EBITDA[5]). $Cost_{it}$ is the cost of goods sold[6] which includes the direct cost incurred in the production of any goods such as material cost. Assuming that Japan's export restrictions caused cost increases through production inefficiencies, this variable is applied solely to the user side.

For independent variables, $After_t$ is a time dummy variable that equals one for years following the enforcement of Japanese export controls and zero for years prior 2019. $(After \times Treatment)_{it}$ is an interaction term that captures the differential effect of the treatment from 2019. The treatment dummy variable is defined based on the Korean Standard Industrial Classification (KSIC): firms in the semiconductor, display, and rechargeable battery industries are assigned a value of one, while firms in the wireless communication equipment industry and those within the treated industries that are not directly affected by the export-controlled materials are assigned a value of zero. Additionally, on the producer side, the 17 firms capable of manufacturing the export-controlled chemicals are assigned a value of one, while all other firms in the chemical industry are assigned a value of zero.

As control variables, I include R&D intensity (measured as the ratio of R&D expenditures to revenue), the number of employees, revenue, labor cost per employee (user side), cost to revenue (producer side) and the debt-to-equity ratio, all of which help account for firm size and financial conditions. I also include firm fixed effects (u_i) and time fixed effects

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5 Since EBITDA casts aside costs such as taxes, interest, and depreciation, it can yield a clearer picture of the money-generating performance compared to net income.

6 Cost of Goods Sold (COGS) = Beginning Inventory + Purchases − Ending Inventory

(v_t). In particular, the introduction of a specific linear time trend for individual firms ($\gamma_i \times Trend_t$) is a means to address unobserved heterogeneity. e_{it} stands for error term.

1.4.2 Data

The firm-level data are based on publicly available financial statements from 2010 through 2023. It is collected from the Korea Listed Company Association (KLCA) database, which includes financial statements of publicly listed firms and other individual firms that are subject to external audit under the law[7]. However, this study focuses exclusively on listed companies, as their financial data are more readily accessible and allow for consistent and reliable analysis. Listed firms are also more likely to be directly affected by external shocks such as fluctuations in stock prices following Japan's export restrictions, and their innovation activities are closely monitored and valued by the capital market.

Based on the KSIC, the final sample excludes firms with missing data (for example, those without reported R&D expenditures) and firms listed after 2019. The resulting number of sample firms and the summary statistics are presented in Tables 1.3, 1.4, and 1.5.

Table 1.3.

Number of sample firms

User side	Semiconductor, Display and Rechargeable battery (direct impact expected) 53	Semiconductor, Display and Rechargeable battery (others) & Wireless communication apparatuses 75
Producer side	Estimated Beneficiaries 17	Others in Chemical industry 214

[7] ACT ON EXTERNAL AUDIT OF STOCK COMPANIES, Etc

Table 1.4.

Summary statistics: user side (model 1)

Variables	Mean	SD	Min	Max	Obs	Format
R&D expenditure	15.382	1.965	7.326	23.765	1,372	Log
Patent	1.788	1.910	0	9.010	1,538	Log
Value added per employee	8.258	0.211	0	9.115	1,660	Log
EBITDA	14.329	0.506	0	17.909	1,657	Log
Cost	11.307	1.805	5.635	18.843	1,652	Log
R&D intensity	7.674	11.334	0.006	239.067	1,368	Percent
Employee	21.009	102.661	0	1,212.04	1,660	100 employees
Revenue	24.691	150.492	0	2,118.675	1,673	KRW 100 billion
Labor cost per employee	24.440	24.403	0	281.23	1,660	KRW million
Debt to equity	90.775	128.919	0	2,723.11	1,660	Number

Table 1.5.

Summary statistics: producer side (model 2)

Variables	Mean	SD	Min	Max	Obs	Format
R&D expenditure	14.843	1.740	4.007	20.794	2,155	Log
Patent	1.552	1.384	0	8.140	2,671	Log
Value added per employee	6.965	0.196	0.001	7.867	2,857	Log
EBITDA	13.550	0. 303	0.049	15.422	2,856	Log
R&D ratio	4.772	8.708	0	211.28	2,155	Percent
Employee	4.289	13.263	0	201.62	2,857	100 employees
Revenue	4.998	20.228	0.003	438.636	2,908	KRW 100 billion
Cost to revenue	0.790	0.201	0	5.577	2,908	Number
Debt to equity	133.717	2,162.371	0	115,158.8	2,857	Number

1.5 Empirical results

1.5.1 User side (Model 1)

Turning now to the validation of the common trend assumption, which is a key premise of the DID approach. To test the common trend assumption, I follow the method used by Ahn et al. (2022). For empirical analysis, the equation is similar to what has been discussed previously. *Trend* is the time period from 2010 to 2018, and the interaction term $(Trend \times Treatment)_{it}$ can be represented as the product of trend and an industry dummy variable. Table 1.6 shows the results, and all coefficients of the interaction terms are insignificant, indicating that the common trend assumption is satisfied.

$$Y_{it} = \beta_0 + \beta_1 Trend_t + \beta_2 (Trend \times Treatment)_{it} + \delta Control_{it} + u_i + v_t + \gamma_i \times Trend_t + e_{it}$$

$$(Y_{it} : (1)\ R\&D_{it},\ (2)\ Patent_{it},\ (3)\ Productivity_{it},\ (4)\ Profit_{it},\ (5)\ Cost_{it})$$

Table 1.6.

Common trend assumption (2010-2018)

	R&D (log)	Patent (log)	Value added per employee (log)	EBITDA (log)	Cost (log)
	(1)	(2)	(3)	(4)	(5)
Trend	-0.267 (0.421)	-0.284 (0.308)	-0.191*** (0.061)	-0.985** (0.471)	3.290*** (0.318)
Trend × Treatment	0.020 (0.033)	-0.016 (0.030)	-0.001 (0.001)	-0.001 (0.002)	0.008 (0.018)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	879	866	879	879	873
R^2	0.099	0.067	0.183	0.544	0.256

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, labor cost per employee, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

From the user side perspective, disruptions in the import of essential materials caused by the trade dispute are likely to affect the production processes of the firms involved. To assess the impact on firms' innovation efforts, I analyze changes in individual firms' R&D expenditures and patent applications. As shown in Table 1.7, the coefficient on R&D expenditure with the interaction term $(After \times Treatment)_{it}$ is positive, indicating that Japan's export restrictions increased user firms' R&D spending. Specifically, Column (2) shows that firms in the semiconductor, display, and rechargeable battery industries increased their R&D expenditures by 35.6% relative to the control firms after the trade shock. In contrast, the coefficient on patent applications is negative but not statistically significant. However, column (5) shows that the elasticity of R&D expenditures with respect to patent applications is around 0.16, suggesting that increased R&D investment is positively associated with innovation output.

On the other hand, the interaction term coefficient for value added per worker, a proxy for firm productivity, in Table 1.8 is statistically insignificant. Turning to the impact on firm profitability, it is observed that the coefficient of the interaction term in Column (4) of Table 1.8 is negative, but statistically insignificant. As expected, the external shock from Japanese export controls led to a 23.2% increase in firms' costs. This suggests a reasonable possibility that the export restrictions increased firms' production costs and consequently worsened their profitability, even though the estimated coefficient for profitability remains statistically insignificant.

In sum, while Japanese export controls may have increased firms' innovation efforts on the user side, they also appear to have had negative effects on costs and may have reduced profitability by increasing production expenses, for example through disruptions to processes previously optimized for specific inputs.

Table 1.7.

Effect on R&D expenditure and patent application

	R&D expenditure (log)		Patent application (log)		
	(1)	(2)	(3)	(4)	(5)
After	0.018 (0.318)	0.211 (0.270)	-1.000*** (0.217)	-0.886*** (0.248)	-
After × Treatment	0.397** (0.173)	0.356** (0.149)	-0.054 (0.123)	0.010 (0.131)	-
R&D expenditure (log)	-	-	-	-	0.163*** (0.034)
R&D intensity	-	0.024** (0.011)	-	0.004*** (0.001)	0.001 (0.002)
Employee	-	0.009* (0.005)	-	0.005* (0.003)	-
Revenue	-	-0.001 (0.001)	-	-0.001 (0.001)	-
Labor cost per employee	-	-0.007*** (0.003)	-	-0.001 (0.003)	-
Debt to equity	-	-0.000 (0.000)	-	-0.001** (0.000)	-
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,372	1,366	1,538	1,346	1,348
R^2	0.046	0.152	0.125	0.169	0.185

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, labor cost per employee, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.8.

Effect on productivity, profit and cost

	Value added per employee (log)		EBITDA (log)		Cost (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
After	-0.049** (0.020)	0.012 (0.020)	-0.123 (0.181)	0.037 (0.028)	-0.426* (0.222)	0.423** (0.213)
After × Treatment	0.043 (0.038)	0.030 (0.025)	-0.040 (0.059)	-0.008 (0.015)	0.394*** (0.116)	0.232** (0.116)
R&D intensity	-	-0.001 (0.001)	-	-0.000* (0.000)	-	-0.015*** (0.005)
Employee	-	-0.000 (0.000)	-	0.002 (0.002)	-	0.001 (0.003)
Revenue	-	0.000 (0.000)	-	0.001*** (0.000)	-	0.002 (0.002)
Labor cost per employee	-	-0.001 (0.001)	-	-0.000 (0.000)	-	-0.012*** (0.004)
Debt to equity	-	-0.000 (0.000)	-	-0.000 (0.000)	-	0.000 (0.000)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,660	1,366	1,657	1,366	1,652	1,356
R^2	0.011	0.016	0.010	0.327	0.057	0.226

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, labor cost per employee, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

This study employs PSM to mitigate selection bias in the construction of the control group and to minimize pre-treatment differences between the treatment and control groups. As the control group is drawn from the wireless communication equipment industry with R&D trends comparable to those of the treatment industries, the cost-to-revenue ratio is used as a matching variable to reflect firms' cost structure. A balance test confirmed that no significant differences existed between the treatment and control groups before the intervention ($After_t$ = 0).

The corresponding Table 1.9 presents these results, demonstrating that the key findings remain consistent with the prior analysis. Compared to the results presented in Table 1.7, following Japan's export restrictions, user firms in the treatment group increased their R&D expenditures by approximately 39.0 percent relative to the control group. As a result of redefining the control group using PSM, the coefficient on the interaction term for R&D expenditure increased from 0.356 to 0.390. This result can be interpreted as indicating that Japan's export controls more strongly increased R&D activities among user-side firms.

Regarding costs, an important dependent variable in the user side analysis, the coefficient of the interaction term is 0.226 and statistically significant. However, this effect is relatively smaller and less robust than in previous results, with significance at the 10 percent level, indicating weaker statistical evidence. Nonetheless, the coefficient's magnitude remains nearly identical, suggesting a degree of consistency. As in earlier findings, the coefficients for patents, productivity, and profitability remain statistically insignificant. These consistent patterns across multiple model specifications support the robustness and reliability of the user side empirical results.

Table 1.9.

Results of PSM

	R&D (log)	Patent (log)	Value added per employee (log)	EBITDA (log)	Cost (log)
	(1)	(2)	(3)	(4)	(5)
After	0.180 (0.281)	-0.861*** (0.250)	0.015 (0.022)	0.039 (0.029)	0.427* (0.217)
After × Treatment	0.390** (0.154)	-0.006 (0.132)	0.031 (0.026)	-0.009 (0.015)	0.226* (0.117)
R&D intensity	0.023** (0.011)	0.004*** (0.001)	-0.001 (0.001)	-0.000* (0.000)	-0.015*** (0.005)
Employee	0.009* (0.005)	0.005* (0.003)	-0.000 (0.000)	0.002 (0.002)	0.001 (0.003)
Revenue	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.000)	0.001*** (0.000)	0.002 (0.002)
Labor cost per employee	-0.006 (0.004)	-0.001 (0.003)	-0.001 (0.001)	-0.000 (0.000)	-0.013*** (0.004)
Debt to equity	-0.000 (0.000)	-0.001** (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,299	1,305	1,325	1,325	1,325
R^2	0.149	0.168	0.017	0.327	0.227

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, labor cost per employee, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

1.5.2 Producer side (Model 2)

The verification of the common trend assumption is the same as for the user side. The results of the following model are shown in Table 1.10. Since all of the coefficients on the interaction terms are insignificant, we can conclude that the common trend assumption is satisfied.

Table 1.10.

Common trend assumption (2010-2018)

	R&D (log)	Patent (log)	Value added per employee (log)	EBITDA (log)
	(1)	(2)	(3)	(4)
Trend	0.030 (0.027)	-0.007 (0.020)	0.000 (0.002)	-0.002 (0.004)
Trend × Treatment	0.019 (0.024)	-0.027 (0.035)	-0.001 (0.003)	-0.035 (0.037)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,313	1,307	1,313	1,313
R^2	0.092	0.040	0.231	0.021

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, the cost to revenue ratio, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

Next, this section examines the impact of the external shock on Korean firms producing chemicals affected by Japanese export controls, i.e., the producer side. In this context, the trade dispute prompted Korean user-side firms to shift their supply chains from Japanese suppliers to domestic Korean firms. This shift was further supported by government initiatives to promote local production of the restricted materials to replace Japanese materials. Thus, the export restrictions can be interpreted as a positive external shock for these manufacturing firms. As shown in Figure 1.2, the import level of hydrogen fluoride did not recover after 2023, suggesting that some of the input supply may have been redirected to domestic producers. Table 1.5 presents summary statistics for these firms. So now, I'd like to look at the effect on the innovation efforts of producer firms.

According to Table 1.11, the coefficient on R&D expenditures is positive and statistically significant at the individual firm level. Specifically, it indicates that Korean firms producing chemicals affected by trade disputes increased their R&D expenditures by nearly 20.7 percent in response.

However, when examining changes in patent applications, no statistically significant overall effect was observed, similar to the findings on the user side. To explore this further, the 17 firms in the treatment group were divided into two subsets. Based on the average log of patent applications[8] over the study period, the firms were divided into the top 15% and the middle 65%. Of these, nine firms were in the top 15%, while the remaining eight firms were in the middle 65%. Analyzing these two groups separately, the coefficients of the interaction terms were positive in both cases. In particular, the middle 65% group showed a statistically significant 25.6 percent increase in patent applications. This suggests that firms initially positioned in the relatively lower range of patenting activity responded more strongly to the trade shock than firms that already had higher levels of patenting activity. Given that the coefficients on the time dummy variables were significantly negative, these results suggest that Japan's export restrictions served as a significant catalyst for Korean firms to actively increase their patenting efforts despite an overall downward trend.

[8] Firms were grouped into quantiles based on the average value of the logarithm of patent applications over the study period for each individual firm. Notably, none of the 17 treatment firms were in the bottom 20%. Therefore, the firms were distributed among the remaining top 80% of the sample.

Table 1.11.

Effect on R&D Expenditure and Patent applications

	R&D (log)		Patent (log)			
			Total		Middle 65%	Top 15%
	(1)	(2)	(3)	(4)	(5)	(6)
After	-0.221 (0.571)	-0.289 (0.683)	-0.113 (0.085)	0.097 (0.062)	-0.754*** (0.243)	-0.915* (0.490)
After × Treatment	0.302* (0.166)	0.207* (0.139)	0.085 (0.107)	0.068 (0.117)	0.256** (0.127)	0.118 (0.217)
R&D intensity	-	0.028*** (0.003)	-	0.005* (0.003)	0.006* (0.003)	0.012 (0.019)
Employee	-	0.053*** (0.006)	-	0.031*** (0.010)	0.134** (0.054)	0.021*** (0.006)
Revenue	-	-0.002 (0.002)	-	-0.004*** (0.002)	0.002 (0.028)	-0.004** (0.002)
Cost to revenue	-	-0.435** (0.193)	-	0.158 (0.233)	-0.012 (0.317)	1.039 (0.627)
Debt to equity	-	0.000 (0.000)	-	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.003)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,155	2,145	2,671	2,124	1,355	360
R^2	0.023	0.118	0.057	0.099	0.119	0.327

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, the cost to revenue ratio, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

In terms of the effect on productivity, unlike in model 1, the results show a clearly significant increase in value added per worker. According to column (2) of Table 1.12, productivity among firms in the treatment group increased by 5.8 percent relative to the control group following the Japanese export restrictions. This finding may be associated with the earlier observed increase in innovation efforts. On the other hand, as was the case on the user side, no statistically significant effects were observed with respect to profitability (Table 1.12).

Table 1.12.

Effect on Productivity and Profit

	Value added per employee (log)		EBITDA (log)	
	(1)	(2)	(3)	(4)
After	-0.102*** (0.017)	0.003 (0.020)	-0.014 (0.013)	-0.009 (0.012)
After × Treatment	0.014 (0.020)	0.058** (0.022)	0.146 (0.134)	0.149 (0.117)
R&D intensity	-	-0.000 (0.001)	-	-0.001 (0.001)
Employee	-	-0.002* (0.001)	-	0.004 (0.003)
Revenue	-	0.001*** (0.000)	-	0.003 (0.002)
Cost to revenue	-	-0.313*** (0.069)	-	-0.187*** (0.071)
Debt to equity	-	-0.001*** (0.000)	-	-0.000 (0.000)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,857	2,145	2,856	2,145
R^2	0.016	0.472	0.011	0.032

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, the cost to revenue ratio, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

In the following section, as in the user-side analysis, PSM was reapplied on the producer side to verify the DID results. In order to take into account both cost-related and financial structure aspects, the matching variables included cost to employees, interest coverage ratio, and debt-to-equity ratio. The results of the balance test confirmed that there were no statistically significant differences between the treatment and control groups before 2019. Table 1.13 shows that the results for the four dependent variables are consistent with those presented earlier. First, with respect to the effect on R&D expenditures, the coefficient on the interaction term increases to 0.290, indicating a larger effect compared to the previous results. Moreover, the statistical significance of this effect also increased. Specifically, R&D expenditures of domestic producer-side firms affected by the trade dispute increased by about 29.0 percent relative to the control group. In addition, the coefficient on the cost-to-revenue ratio became more pronounced. A one percentage point increase in this ratio is associated with a 68.7 percent decrease in R&D spending, highlighting a trade-off between revenue-related costs and investment in R&D.

With respect to patent applications, no statistically significant relationship is observed overall. As in the previous analysis, the 17 firms in the treatment group are divided into two subgroups and reassigned to the corresponding full sample population. Again, the treated firms in the middle 65 percent group show a 31.7 percent increase in post-trade dispute patent applications. Although the interaction term for the top 15 percent group is not statistically significant, its positive sign suggests that efforts to increase innovation through patenting activity were also present in this group.

In terms of productivity, as measured by value added per capita, the trade dispute led to a 5.6 percent increase in productivity for firms in the treatment group (Table 1.14). Although this effect is somewhat smaller than the 5.8 percent observed earlier, it is consistent with the earlier findings. Finally, in terms of profitability, the results after applying PSM continue to show no statistically significant effect. This may reflect the considerable heterogeneity across firms. Nevertheless, the interaction term is positive, suggesting that the Japan-Korea trade dispute may have served as a form of positive trade shock for producer firms in Korea.

Table 1.13.

Results of PSM: R&D expenditure and Patent applications

	R&D (log)		Patent (log)			
				Total	Middle 65%	Top 15%
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.451** (0.181)	0.270 (0.168)	-0.926*** (0.085)	-0.876*** (0.062)	-1.047*** (0.334)	-0.923 (0.594)
After × Treatment	0.412** (0.192)	0.290** (0.146)	0.085 (0.116)	0.114 (0.127)	0.317** (0.146)	0.183 (0.268)
R&D intensity	-	0.022*** (0.006)	-	0.005* (0.003)	0.005* (0.003)	0.008 (0.016)
Employee	-	0.057*** (0.016)	-	0.030*** (0.009)	0.132** (0.065)	0.024*** (0.007)
Revenue	-	-0.003 (0.002)	-	-0.004*** (0.001)	-0.004 (0.028)	-0.005*** (0.002)
Cost to revenue	-	-0.687** (0.325)	-	0.269 (0.272)	-0.010 (0.350)	1.684** (0.659)
Debt to equity	-	0.000 (0.000)	-	0.000 (0.000)	0.000 (0.000)	-0.001 (0.003)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,239	1,235	1,649	1,414	886	261
R^2	0.025	0.121	0.077	0.124	0.150	0.332

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, the cost to revenue ratio, and the debt to equity ratio. The top 9 firms in the treatment group (17 firms) are in the top 15% group. The remaining 8 firms are in the middle 65%.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.14.

Results of PSM: Productivity and Profit

	Value added per employee (log)		EBITDA (log)	
	(1)	(2)	(3)	(4)
After	-0.081*** (0.028)	0.045** (0.019)	-0.011 (0.018)	-0.003 (0.013)
After × Treatment	0.029 (0.023)	0.056** (0.025)	0.150 (0.135)	0.150 (0.117)
R&D intensity	-	0.001 (0.001)	-	-0.001 (0.002)
Employee	-	-0.001 (0.001)	-	0.005 (0.004)
Revenue	-	0.001*** (0.000)	-	0.004 (0.003)
Cost to revenue	-	-0.304*** (0.077)	-	-0.156** (0.077)
Debt to equity	-	-0.001*** (0.000)	-	-0.000 (0.000)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,643	1,328	1,642	1,328
R^2	0.009	0.605	0.015	0.039

Notes: Standard errors are clustered at the firm level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include R&D intensity, number of employees, total revenue, the cost to revenue ratio, and the debt to equity ratio.

*** p<0.01, ** p<0.05, * p<0.1

1.6 Conclusion

Beyond the negative trade impact, Japan's 2019 export restrictions were a political and economic shock to Korea. Since then, political and economic resources in Korea have been devoted to improving its persistent trade deficit with Japan. Aside from the political sensitivity, I started this study because I thought it would be a very good research topic to examine firms' efforts to increase innovation in response to negative trade shocks, which is similar to the topic studied in leading papers.

I divided industries or firms that use Japanese export-controlled items as intermediates (semiconductors, displays and rechargeable battery) and industries that produce these materials (chemicals) to examine how firms' innovation activities were affected. On the user side, firms responded to the shock by increasing R&D expenditure in an effort to enhance innovation. However, as expected, the shock also led to higher costs, which may have contributed to a decline in profitability. On the producer side, the impact was somewhat different. Seventeen firms that were capable of substituting Japanese export-controlled materials increased their innovation efforts, including higher R&D expenditure and greater patenting activity. In addition, these firms experienced improvements in productivity.

Taken together, the results reveal some negative effects of the trade shock, particularly in the form of increased costs. However, firms on both the user and producer sides responded by intensifying their innovation activities to adapt to the disruption. Although I was unable to directly assess the effectiveness of government efforts to support localization as a substitute for Japanese materials, there is some observable evidence of such responses among the seventeen firms. 24

Of course, this study has its limitations. To account for the possibility that errors may be correlated across observations, standard errors were clustered at the firm level. Nevertheless, it is possible that the pandemic-induced industry-wide boom in the treatment group had a positive impact on R&D spending and other financial indicators. Moreover, in response to Japan's export restrictions, the Korean government expanded its R&D subsidies to over KRW 2 trillion per year. Given this, the results of the study would be more robust if the effect of government policy could be separated from the observed increase in firms' R&D expenditures. However, a clear limitation is the unavailability of firm-level data on R&D subsidy amounts, which makes it difficult to estimate the effect of government support accurately. Nevertheless, given that the main recipients of government-led R&D programs in Korea are public research institutes or government-funded agencies, and that only 27.8 percent of the recipients in 2022 were private firms-most of which were unlisted small and medium-sized enterprises-it can be reasonably assumed that the firms in the treatment group are all listed and thus unlikely to have received substantial direct R&D funding from the government. Moreover, even if some of the firms in the treatment group did benefit from such funding, previous studies have consistently found evidence of a crowding in effect of government R&D support on firms' R&D spending (Guellec et al., 1997; Hussinger, 2008; Szücs, 2020). Therefore, the possibility that private firms independently increased their R&D efforts cannot be ruled out.

In addition, since patent applications do not typically reflect short-term innovation outcomes, further analysis should take into account the time lag between the trade shock and its potential effect on patenting behavior. For producer-side firms, it would also be important to examine changes in actual production levels. With respect to productivity measures, future research should consider supplementing the analysis with estimates of total factor productivity (TFP) to provide a more comprehensive assessment.

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CHAPTER 2

FIRM HETEROGENEITY AND THE EFFECTIVENESS OF R&D TAX POLICY

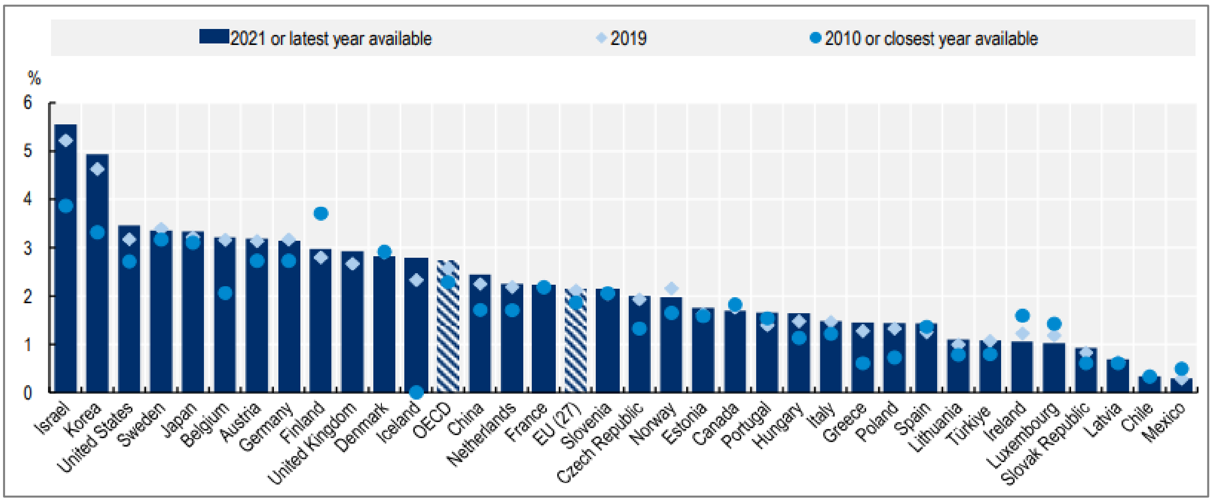
2.1 Introduction

According to modern economic growth theories, represented by endogenous growth theory, technological progress within the economy is essential for sustained economic growth. Romer (1986) was the first to model the idea that knowledge increases marginal productivity in long-run growth. In addition, Romer (1990) argued that technological progress in long-run economic growth models is endogenously determined by firms' profit-maximizing R&D investments. Aghion & Howitt (1990) considered creative innovation, where new innovations replace old technologies, as the driving force of long-run economic growth, and believed that R&D and human capital accumulation are necessary for this process. Grossman & Helpman (1993) also proposed innovation as the driver of economic growth and suggested that international trade can increase competition and increase firms' access to new ideas and technologies, thus promoting innovation.

In particular, the growth of the working-age population has stagnated in many countries into the 2010s due to population aging, leading to a decline in the potential growth rate in developed countries. As endogenous growth theory suggests, technological development remains essential to sustain economic growth. Furthermore, the presence of knowledge spillovers can generate market failures and lead to a supply level that is lower than the optimal for the economy as a whole. Governments worldwide are currently using this spillover effect to justify various policies aimed at fostering technological innovation in firms to promote economic growth under low-growth conditions. R&D tax credits are among the most widely used tools to stimulate innovation in many countries.

Figure 2.1.

R&D intensity: Gross domestic expenditure on R&D as a percentage of GDP



Source: OECD Science, Technology and Innovation Outlook 2023

As shown in Figure 2.1, Korea has the second highest ratio of R&D expenditure to GDP after Israel. This underscores the proactive nature of the Korean economy in promoting innovation through R&D, making research on Korea's R&D tax credit system highly relevant. Furthermore, the Korean government launched a new R&D tax credit in 2011, providing a better tax incentive for firms of different sizes. The tax system was organized into three brackets[9] instead of two, to better reflect the actual size structure of firms.

This paper focuses on two main research questions regarding the new R&D tax credit scheme implemented in 2011. First, did the tax reform effectively incentivize increased R&D expenditures, considering the varying sizes of firms? Second, for Middle Market Enterprises

9 (Before) two groups: (1) SMEs, (2) Non-SMEs
(After) three groups: (1) SMEs, (2) MMEs, (3) Conglomerates

(MMEs), how did firm heterogeneity influence the impact of the tax reform? To address these questions, I conduct an empirical analysis using firm-level data from listed Korean companies and review relevant literature. I also establish two control groups-SMEs and conglomerates-since their R&D tax credit rates remained unchanged between 2008 and 2013. Using a Difference-in-Differences (DID) approach, the analysis reveals no significant increase in R&D expenditures among MMEs, a result that diverges somewhat from findings in related literature.

Firm heterogeneity can potentially limit the effectiveness of tax policy. This paper examines how R&D expenditure responses to the new tax policy differ across firms within the treatment group (MMEs). Since R&D expenditure is a key input for intangible assets[10], the initial analysis explores how variations in the intangible assets-to-capital ratio influence the policy effect. The findings show that a one-unit increase in this ratio, following the new tax reform, corresponds to a 12.4% increase in R&D expenditure. Further analysis, controlling for industry differences, reveals that MMEs in the high-tech[11] sector experienced a 28.4% increase in R&D expenditures post-policy implementation. However, no significant effects were observed based on the firms' manufacturing status or export activities.

I also investigate financial condition variables from the existing literature, including the debt-to-equity ratio, EBITDA-to-financial-cost ratio[12], borrowings-to-asset ratio, the Kaplan-Zingales (KZ) index[13], and the Hadlock-Pierce (HP) index[14]. These variables were

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[10] Intangible asset: goodwill, intellectual property (IP), copyrights, patents, etc.

[11] OECD high-tech classification: Electronics, Aerospace, and Pharmaceuticals are classified as high-tech due to their high R&D spending.

[12] Unlike the other four variables, the EBITDA-to-financial-cost ratio indicates the ability of a firm to secure internal financing.

[13] The Kaplan-Zingales index quantifies a firm's dependence on external financing using financial variables. Higher KZ index values indicate that a company is more financially constrained and more dependent on external financing.

[14] The Hadlock-Pierce index primarily relies on firm size and age, with the assumption that smaller and younger

divided into "poor" and "non-poor" groups using criteria commonly accepted in capital markets. The analysis indicates that firms with poor financial conditions-excluding those evaluated by the EBITDA-to-financial-cost ratio and HP index-tended to increase R&D expenditures after the policy was implemented, particularly if their R&D expenditure-to-revenue ratio was below average. However, the overall impact of poor financial conditions on the treatment group was not significant, as listed companies generally have stronger financial conditions and better access to external financing compared to unlisted firms. This result highlights heterogeneity within the treatment group and suggests that the R&D tax credit was more effective for firms with below-average R&D spending and limited access to external capital.

Additionally, I employ a parametric Regression Discontinuity Design (RDD) methodology to analyze the policy effect using asset cutoffs between SMEs, MMEs, and conglomerates, which reflect Korea's firm classification system based on asset size. The results indicate that when the analysis is restricted to firms near the asset cutoff, the policy implementation led to a substantial increase in R&D expenditure-145.1% and 198.5%-for firms in the treatment group compared to SMEs and conglomerates. This suggests that the policy effect differs by firm size, even within the treatment group.

This paper makes a significant contribution to the literature by emphasizing firm heterogeneity within the quasi-experimental context of R&D tax credits. Unlike Lee (2018), who focused solely on MMEs and examined R&D expenditure variations between listed and unlisted MMEs, this paper uses two control groups comprising SMEs and conglomerates with unchanged tax credit rates. The RDD shows that policy effects become more pronounced when

firms are more likely to face financial constraints.

the size difference between the control and treatment groups is minimal. The institutional framework of Korea related to the 2011 tax policy reform will be discussed in the next section.

2.4 Institutional Background

2.2.1 R&D tax policy reform in Korea

First and foremost, Korea implemented a major reform of its R&D tax credits in 2011. Initially, only SMEs and non-SMEs were eligible for the tax credit, but a new bracket was created for Middle Market Enterprise (MMEs). Basically, Korea's corporate policy has focused on developing SMEs in order to restructure the economic structure, which is heavily weighted toward major companies, and diversify the business ecosystem by providing policy support such as tax, budget, and finance to SMEs. However, the purpose of this tax reform was to incentivize small and medium-sized enterprises to grow on their own to avoid the perverse effect of making SMEs reluctant to grow beyond a certain threshold.

Table 2.1

General research and workforce development credit rate

	2007	2008-10		2011-13	2014-23
SMEs	15%	25%	SMEs	25%	25%
Non-SMEs	6% (max)	6% (max)	**MMEs**	**15%**	**15%**
			Others (conglomerates)	6% (max)	4 → 3 →2% (max)

Source: Restriction of Special Taxation Act (Korea)

The R&D tax credit rates by company size are summarized in the Table 2.1. To briefly explain the history of Korea's R&D tax credit system since 2007: Initially, SMEs had a basic tax credit rate of 15%, which increased to 25% in 2008. For non-SMEs, the maximum credit rate was 6%, up from a basic rate of 3%. In 2011, a major policy reform reclassified MMEs as distinct from non-SME, establishing a basic tax credit rate of 15% for MMEs, up from the previous rate of 6%. Prior to 2011, tax credit rates were only differentiated between SMEs and non-SMEs. However, starting in 2011, the system was restructured into three brackets to better align with the actual size distribution of firms. As a result, under the new R&D tax credit regime, MMEs benefited from a distinct 15% rate, separate from conglomerates.

2.2.3 Firm size structure in Korea

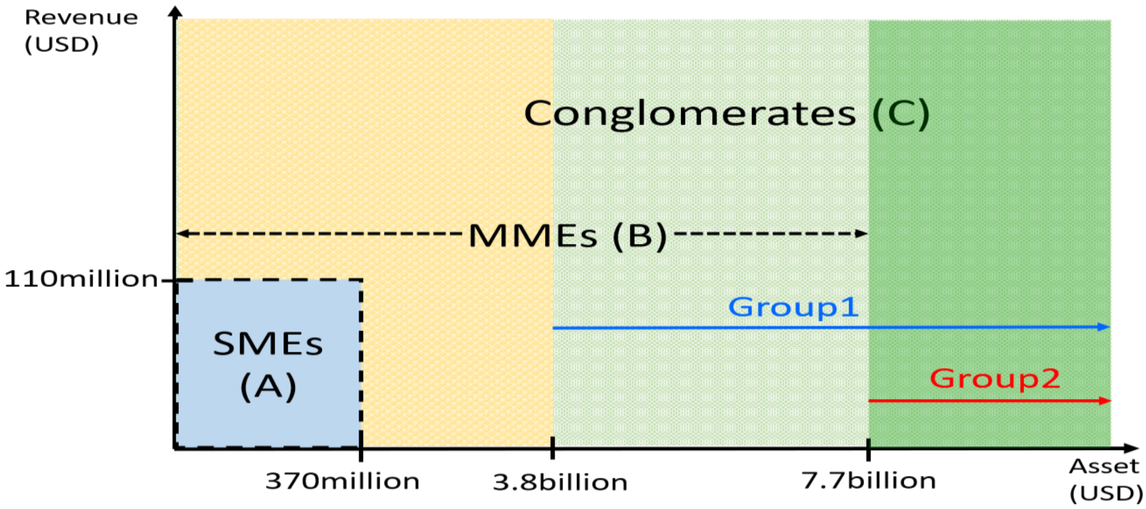
The 2011 reform of Korea's R&D tax credit system was notable for further refining the tax law's classification of firms by size, making it more relevant to real-world business structures. To provide some context, let's examine how the Korean government classifies firms. Businesses are categorized into SMEs, MMEs, and conglomerates, with revenue and asset size being the main criteria. Figure 2.2 below illustrates this classification based on revenue and asset size. The concepts of Group 1 and Group 2[15] were introduced to prevent the excessive concentration of economic power in conglomerates, with firms in Group 2 being the widely recognized "Chaebol."

[15] The Korea Fair Trade Commission designates business groups with total assets of KRW 5 trillion or more as " Business groups subject to disclosure." Among these, groups with total assets equal to or greater than 0.5% of the GDP (10.4 trillion KRW as of 2024) are designated as "Business groups subject to limitations on cross shareholding".

- *Business groups subject to disclosure*: Subject to obligations such as disclosing important matters for unlisted companies, obtaining board approval and disclosure for large internal transactions, disclosing the status of the business group, and reporting share ownership status. Additionally, providing unfair benefits to related parties is prohibited.
- *Business groups subject to limitations on cross shareholding*: In addition to the regulations for Business groups subject to disclosure, they are subject to further restrictions, including prohibitions on cross-shareholding, circular shareholding, and debt guarantees, as well as limits on voting rights of financial and insurance subsidiaries within the group.

Figure 2.2

Firm size structure by revenue and asset in Korea



First, let's take a look at SMEs: The criteria for determining whether a firm is an SME is based on the law. There are some differences depending on the industry, but the average revenue over a three-year period should not exceed a maximum of $110 million (KRW 150 billion), and the asset size should not exceed USD 370 million (KRW 500 billion). In addition, the firm must not be part of a business group subject to disclosure (Group 1) with group total assets exceeding USD 3.8 billion (KRW 5 trillion). Next, MMEs must not be part of a business group subject to limitations on cross shareholding (Group 2) whose group total assets exceed 0.5% of Korea's GDP in the relevant year, or USD 7.7 billion (KRW 10.4 trillion) in 2024. MMEs also must exceed the SME threshold, either in terms of revenue or by having assets over KRW 500 billion, to qualify as MMEs. Finally, conglomerates are classified as a large enterprise if it is part of a Group 2, or if Group 2 holds more than 30% ownership and is the majority investor.

To summarize, SMEs must meet specific size criteria to be eligible for government support policies. However, if a firm belongs to Group 2, it cannot be classified as an SME even if it meets the size requirements. Furthermore, MMEs and conglomerates are categorized based on the size of the business group they belong to, rather than the size of a single enterprise. This means that some MMEs analyzed in this paper may meet the SME size threshold in terms of either revenue or assets, and in some cases, they may even be larger than certain conglomerates.

2.3 Literature review

This section provides a broad review of the existing literature on the relationship between tax policy and business R&D expenditures. The review is divided into three main parts. First, I examine how tax incentives for R&D affect firms' responses. Second, consistent with the focus of this study, I explore how firm-level heterogeneity affects the effectiveness of tax policy, focusing in particular on firms' financial conditions. Finally, I review studies that have specifically examined the 2011 reform of Korea's R&D tax policy, which is the main policy change analyzed in this study.

Bloom et al. (2002) analyze tax policy and R&D spending across nine OECD countries from 1979 to 1997. They find that tax changes significantly affect R&D levels, with an estimated short-run elasticity of just over 0.2 and a long-run elasticity approaching one. Rao (2016) uses confidential U.S. tax return data and finds that a 10 percent reduction in the user cost of R&D increases R&D intensity by 19.8 percent in the short run. Long-run effects are more modest due to adjustment costs. Agrawal et al. (2020) examine Canada's SRED program and show that refundable tax credits substantially raise R&D spending among small firms with little or no tax liability. A 10 percent reduction in user cost leads to a 17 percent increase in R&D investment. Dechezleprêtre et al. (2016) study a 2008 UK policy change using regression discontinuity design. They find that tax relief increases R&D expenditures and innovation outputs such as patents and patent citations, with the effects being stronger for small and young firms. Spillover effects are also observed in technologically related firms.

Next, regarding how firm heterogeneity affects the effectiveness of tax policy, most existing studies focus on financial constraints. Hall (2002) explores R&D financing, highlighting that internal sources like cash flow are the main funding channel for R&D, particularly for small and young firms. External financing plays a limited role due to high risk and information asymmetry. Hall et al. (2016) find that financial constraints significantly reduce R&D investment in European firms, especially in technology-intensive sectors and among smaller firms. Patent applications can help alleviate financing constraints by serving as a signal of innovative capacity and quality. Hall and Lerner (2010) argue that small and new firms face high capital costs, which are only partially offset by venture capital. Large firms prefer internal financing and actively manage cash flows to fund R&D. Venture capital remains a limited solution, especially in markets lacking robust public equity exit options. Brown et al. (2012) also show that financing constraints hinder R&D investment, particularly for small and young firms. Cash flow is a critical determinant, as constrained firms rely heavily on internal funds for innovation activities.

Finally, I review research that examines the impact of the 2011 tax reform in Korea, the main policy change analyzed in this study, on R&D expenditures. However, there is a noticeable lack of studies that focus directly on this reform. One exception is Lee (2018), who analyzes how a firm's ability to access external financing affects the effectiveness of the R&D tax credit. The study finds that when external financing is costly, firms are less able to increase R&D investment. Focusing on the introduction of a new R&D tax credit for medium-sized firms in Korea in 2011, the paper shows that listed firms, which have better access to external capital markets, increased R&D more than unlisted firms. However, this analysis relies on the assumption that unlisted firms have weaker financial conditions and does not consider the responses of SMEs or conglomerates, which, unlike MMEs, did not experience a change in the tax credit rate.

To summarize the literature, first, R&D tax credits have been shown to have a positive impact on increasing firms' R&D investment. Second, and related to my core research question, firms' financial condition acts as a negative constraint on their R&D investment decisions.

2.4. Empirical Results

2.4.1 Methodology

To evaluate the effects of Korea's R&D tax credit reform (implemented in 2011), I adopted the Difference in Difference (DID). The model equations for this study are as follows.

$$R\&D_{it} = \beta_0 + \beta_1 After_t + \beta_2 Treat_{it} + \beta_3 (After \times Treat)_{it} + \delta Control_{it} + u_i + v_t + \gamma_i \times Trend_t + e_{it}$$

Regarding the variable settings, to better capture the tax reform shock, I set the log transformed annual R&D expenditures as the dependent variable ($R\&D_{it}$). $Treat_{it}$ term denotes the treatment group, i.e., MMEs. Firms belonging to MMEs take the value of 1, while firms belonging to SMEs or conglomerates take the value of 0. $After_t$ term, which refers to the implementation status, takes the value of 1 from 2011 to 2013 and 0 from 2008 to 2010. This takes into account that the tax law change took place at the end of 2010, but the implementation of the reform started on January 1, 2011. As additional control variables, I include employees, assets, capital, intangible assets, and revenues. I also include year (v_t), firm fixed effects (u_i) and firm-specific linear time trend ($\gamma_i \times Trend_t$). e_{it} stands for error term.

To control for the impact of firms' heterogeneity I employ the Difference-in-Difference-in-Differences (DDD) methodology as shown in the following equation. Regarding firm heterogeneity, I use the ratio of intangible assets to capital as a continuous variable. Next, the KSIC industry classification codes were used to categorize the industry sector to which a firm belongs in the high-tech industry. Finally, in assessing a firm's financial condition, commonly accepted criteria in the capital market were used to identify whether a firm is in a poor or risky financial state.

$$\begin{aligned} R\&D_{it} = {} & \beta_0 + \beta_1 After_t + \beta_2 Treat_{it} + \beta_3 Heterogeneity_{it} + \beta_4 (After \times Treat)_{it} \\ & + \beta_5 (After \times Heterogeneity)_{it} + \beta_6 (Treat \times Heterogeneity)_{it} \\ & + \beta_7 (After \times Treat \times Heterogeneity)_{it} + \delta Control_{it} + u_i + v_t + \gamma_i \times Trend_t + e_{it} \end{aligned}$$

($Heterogeneity_{it}$: (1) $Intangible\ asset_{it}$, (2) $Industry_i$, (3) $Financial\ constraint_{it}$)

As noted earlier in studies of the impact of individual firms' financial conditions on the effectiveness of the R&D tax credit system, firms' sources of R&D funding can be divided into internal and external funds. As in Hall (2002)'s research, internal funds are cash flows generated from a firm's operations, while external funds are closely related to borrowing or raising equity through the capital markets by going public. Therefore, taking this into account, I used the following variables. A debt-to-equity ratio exceeding 200% was assigned a value of one. An EBITDA[16]-to-financial cost ratio of 1 or less was also given a value of one. Similarly, a borrowings-to-asset ratio exceeding 60% was assigned a value of one. The KZ index[17] and HP index[18], which are quantifiable measures of financial constraint, indicate poorer financial

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16 Earnings before interest, taxes, depreciation, and amortization (EBITDA) is a measure of profitability and is calculated by adding interest, taxes, depreciation and amortization expenses to net income.

17 KZ Index = -1.001909 * Cash flows / K + 0.2826389 * Q + 3.139193 * Debt / Total capital - 39.3678 * Dividends / K - 1.314759 * Cash / K (Q: Tobin's Q / K: Property, Plant, and Equipment from the previous period)

18 HP = -0.737 * Size + 0.043 * Size^2 - 0.040 * Age (Size: the natural log of inflation-adjusted total assets / Age: the number of years the firm has been listed on Compustat)

conditions with higher values. A value of one is assigned to firms in the top 10%. This top 10% threshold was determined based on the distribution of observations across the other financial variables. Specifically, a value of one is assigned to financially constrained firms in order to examine how firm-level heterogeneity in financial conditions, combined with the effects of the policy reform, influences individual firms' R&D expenditures.

2.4.2 Data description

The firm-level data were collected from the Korea Listed Company Association (KLCA) database, which includes financial statements of individual companies that are subject to external audit under the law (sales of more than KRW 10 billion and more than 100 employees) in addition to publicly listed companies. However, only listed companies were analyzed in this study because they are considered to be directly affected by factors such as stock prices in response to the tax reform, and their innovation efforts are evaluated in the capital market.

Table 2.2

Number of firms by year

Year	SMEs	new	exit	MMEs	new	exit	Conglomerates	new	exit	Total
2008	814	-	-	**466**	-	-	159	-	-	1,439
2009	869	108	53	**421**	**56**	**101**	173	18	4	1,463
2010	842	48	75	**441**	**72**	**52**	196	27	4	1,479
2011	713	33	162	**569**	**161**	**33**	213	18	1	1,495
2012	735	146	124	**667**	**151**	**53**	217	13	9	1,619
2013	738	75	72	**730**	**90**	**27**	211	7	13	1,679

Regarding the sample, the total number of firms, including SMEs, MMEs, and conglomerates, is 1,495 in 2011 (Table 2.2). Notably, the trends in the number of SME exits and MME entries appear to be similar, suggesting that movement between the two categories is relatively active within the firm classification system. However, these numbers exclude cases where firms could not be classified due to missing data in the firm classification. The analysis period is from 2008 to 2013. The numbers by firm classification are shown in Table 2.2. Table 2.3 summarizes the model's panel data.

Table 2.3

Summary statistics

Variables	Mean	SD	Min	Max	Obs	Format
R&D expenditure	14.398	1.826	4.868	23.308	6,757	Log
R&D to revenue ratio	4.917	17.157	0	670.36	6,757	Percent
Intangible asset[19] to capital ratio	1.519	26.184	0	2,035	10,725	Number
Employee	8.597	37.846	0.01	1,019.7	8,539	Number (Hundreds)
Asset	10.633	71.153	0	2,036.808	10,991	KRW 100 billion
Capital	2.471	17.442	0	573.597	10,991	KRW 100 billion
Intangible asset[19]	0.164	1.327	0	36.710	10,785	KRW 100 billion
Revenue	6.841	39.422	0	1,583.721	10,991	KRW 100 billion
High-tech	0.350	0.477	0	1	7,053	Number
Debt to equity	125.950	317.817	0	12,842.42	10,335	Percent
EBITDA to financial cost	7,577.422	239,047.1	-178,856.9	14,040,287	10,307	Number
Borrowings to asset	22.738	22.494	0	1,214.56	10,335	Number
KZ index	78.734	12,052.75	-133,072.7	1,104,231	10,278	Number
HP index	-2.738	0.570	-3.294	1.481	10,893	Number

[19] 86 outlier observations with negative values were excluded from the analysis.

2.4.3 Results

2.4.3.1 Difference-in-Differences (DID)

Table 2.4 presents the results using the DID. According to this, the R&D tax credit reform favorable to MMEs does not clearly demonstrate the expected policy effect. So, I incoporated individual firms' heterogeneity by employing DDD as shown in Table 2.5.

Table 2.4

Effect on R&D expenditures (DID)

	R&D expenditures (log)	
	(1) Control: SMEs	(2) Control: Conglomerates
After	-1.157 (45.366)	-2.579 (55.273)
Treatment	-0.007 (0.053)	0.012 (0.207)
After × Treatment	-0.020 (0.059)	0.010 (0.108)
Obs.	5,661	3,073
R-squared	0.008	0.002

Notes: Standard errors are clustered at the firm level. All specifications include year, firm and firm-specific linear time trend fixed effects. Control variables include employee, asset, capital, intangible asset, revenue.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5

Effect on R&D expenditures (DDD)

	R&D expenditures (log)			
	(1) Control: SMEs	(2) Control: Conglomerates	(3) Control: SMEs	(4) Control: Conglomerates
After× Treatment × Intangible asset ratio	0.069* (0.039)	0.195*** (0.075)	-	-
After× Treatment × High-tech	-	-	-0.035 (0.125)	0.142 (0.226)
Obs.	5,624	3,031	4,218	2,122
R-squared	0.014	0.006	0.008	0.005

Notes: Standard errors are clustered at the firm level. All specifications include year, firm and firm-specific linear time trend fixed effects. Control variables include employee, asset, capital, intangible asset, revenue.
*** p<0.01, ** p<0.05, * p<0.1

First, considering that R&D expenditure is a major source of a firm's intangible assets, intangible assets were incorporated into the model, and the coefficient of the triple interaction term was examined within the DDD methodology. As a result, the policy effect is clearly observed in the form of increased R&D expenditure. Specifically, for treatment firms, a 10 percentage point increase in the intangible asset ratio after the 2011 tax reform leads to a 0.68 percent increase in R&D spending relative to SMEs, and a 1.9 percent increase relative to conglomerates (Table 2.5). Then, the policy effect in high-tech industries, which have a higher share of R&D expenditures, is analyzed. However, unlike the case of intangibles, the DDD analysis did not find significant results for high-tech industries.

Next, I examine the impact of financial conditions, which has been a focus of much existing literature. Table 2.6 presents the results when SMEs are used as the control group, and Table 2.7 shows the results when conglomerates are used as the control group. The DDD analysis incorporating financial conditions did not yield significant results.

Table 2.6

Effect on R&D expenditures (DDD, control group: SMEs)

	R&D expenditures (log)				
	Debt to equity (1)	EBITDA to financial cost (2)	Borrowings to asset (3)	KZ index (4)	HP index (5)
After × Treatment × Financial condition	0.184 (0.205)	-0.022 (0.125)	0.533 (0.476)	0.019 (0.232)	-
Obs.	5,661	5,661	5,661	5,630	-
R-squared	0.010	0.009	0.010	0.007	-

Notes: HP index results were omitted due to a lack of observations. Standard errors are clustered at the firm level. All specifications include year, firm and firm-specific linear time trend fixed effects. Control variables include employee, asset, capital, intangible asset, revenue.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7

Effect on R&D expenditures (DDD, control group: conglomerates)

	R&D expenditures (log)				
	Debt to Equity (1)	EBITDA to Financial cost (2)	Borrowings to Asset (3)	KZ index (4)	HP index (5)
After × Treatment × Financial condition	0.292 (0.267)	-0.175 (0.206)	-0.579 (0.826)	0.112 (0.292)	0.008 (0.303)
Obs.	3,073	3,073	3,073	3,042	3,051
R-squared	0.008	0.006	0.008	0.005	0.004

Notes: Standard errors are clustered at the firm level. All specifications include year, firm and firm-specific linear time trend fixed effects. Control variables include employee, asset, capital, intangible asset, revenue.
*** p<0.01, ** p<0.05, * p<0.1

To more clearly demonstrate the policy effect, it is necessary to examine how individual MMEs within the treatment group respond in terms of R&D expenditures. Similar to the previous DDD analysis, I analyze the policy effect based on firm heterogeneity, including intangible assets, industry, and financial conditions in the following equation.

$$R\&D_{it} = \beta_0 + \beta_1 After_t + \beta_2 Heterogeneity_{it} + \beta_3 (After \times Heterogeneity)_{it} + \delta Control_{it} + u_i + v_t + \gamma_i \times Trend_t + e_{it}$$

Tables 2.8 and 2.9 present the policy effects within the treatment group. In summary, following the tax reform, R&D expenditure increased by 1.24% with a 10 percentage points higher ratio of intangible assets, and MMEs in high-tech industries saw a 28.4% increase in R&D expenditure compared to those not in high-tech sectors. However, unlike in the high-tech industry, the tax reform did not have a significant effect on manufacturing and export firms.

Meanwhile, the impact of financial constraints becomes even more pronounced within the treatment group. Existing literature commonly suggests that R&D expenditure is marked by uncertainty and risk, which poses challenges for securing external financing. Of the five financial condition variables I have introduced, all except the EBITDA-to-financial-cost ratio reflect a firm's access to external financing. As shown in Table 2.9, firms with below average R&D intensity and poor financial conditions-indicated by the debt-to-equity ratio, borrowings-to-asset ratio, and KZ index-experienced increased R&D expenditures after the tax reform. This suggests that the increase in the R&D tax credit rate for MMEs has helped alleviate funding constraints for firms with limited access to external financing especially for low R&D spending firms. It can be inferred that firms with above-average R&D expenditures tend to smooth[20] their R&D investments, making them less responsive to tax policy compared to firms with below-average R&D expenditures.

Table 2.8

Effect on R&D expenditures, within the treatment group

	R&D expenditures (log)			
	Intangible asset (1)	High-tech (2)	Manufacturing (3)	Export (4)
After × Intangible asset ratio	0.124** (0.050)	-	-	-
After × Industry	-	0.284** (0.126)	0.068 (0.153)	-0.150 (0.114)
Obs.	2,270	1,701	2,191	2,273
R-squared	0.016	0.018	0.014	0.016

Notes: Standard errors are clustered at the firm level. All specifications include year, firm and firm-specific linear time trend fixed effects. Control variables include employee, asset, capital, intangible asset, revenue.
*** p<0.01, ** p<0.05, * p<0.1

[20] R&D smoothing refers to firms' efforts to maintain a relatively stable and consistent level of R&D spending over time, even in the face of fluctuations in their financial resources or external economic conditions. This behavior stems from the recognition that R&D activities involve significant adjustment costs, primarily related to the specialized and often firm-specific nature of the human capital involved in R&D

Table 2.9

Effect on R&D expenditures, within the treatment group & below avg. R&D intensity

	R&D expenditures (log)				
	Debt to equity	EBITDA to financial cost	Borrowings to asset	KZ index	HP index
	(1)	(2)	(3)	(4)	(5)
After × Financial condition	0.320**	0.051	0.832*	0.673***	0.186
	(0.142)	(0.125)	(0.448)	(0.258)	(0.263)
Obs.	1,131	1,131	1,131	1,119	1,119
R-squared	0.036	0.021	0.040	0.020	0.008

Notes: All specifications include year, firm and firm-specific linear time trend fixed effects. Control variables include employee, asset, capital, intangible asset, revenue.
*** p<0.01, ** p<0.05, * p<0.1

2.4.3.2 Regression Discontinuity Design (RDD)

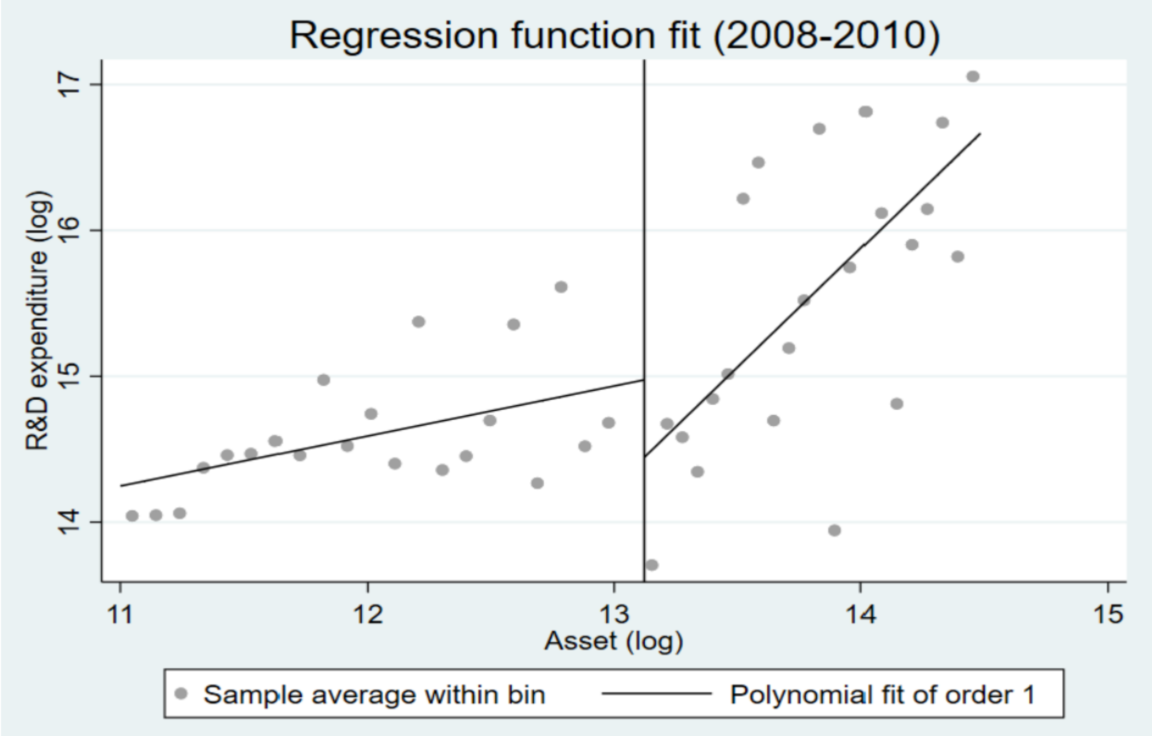
From this point on, since asset size is one of the criteria for classifying firms, I employ an RDD to examine how R&D expenditures change around the cutoff. To ensure analytical rigor, I clearly distinguish between the treatment and control groups on either side of the cutoff. This distinction is important because under the Korean firm classification system, some MMEs or conglomerates may have asset sizes comparable to those of SMEs below the cutoff.

Figure 2.4 clearly illustrates the policy effect. Observations around the cutoff are continuous during the period from 2008 to 2010, while a clear discontinuity appears only after 2011, when the differential tax credit rates were introduced. A notable decline in R&D expenditures is observed as firm size crosses the cutoff. In contrast, as shown in Figure 2.3, there is a clear discontinuity at the cutoff before and after the tax reform, which is consistent with the difference in R&D tax credit rates applied to SMEs and MMEs.

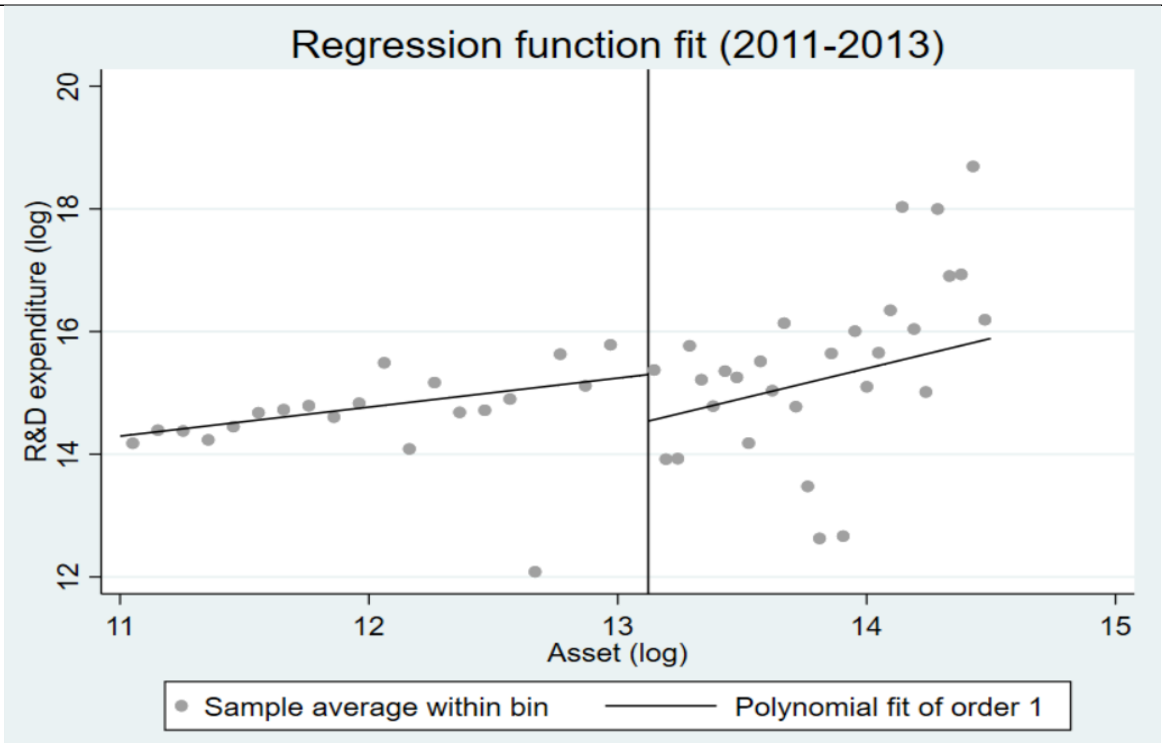
Figure 2.3

RDD (cutoff: asset (log) = 13.122 (KRW 150 billion), control group: SMEs)

2008-2010



2011-2013

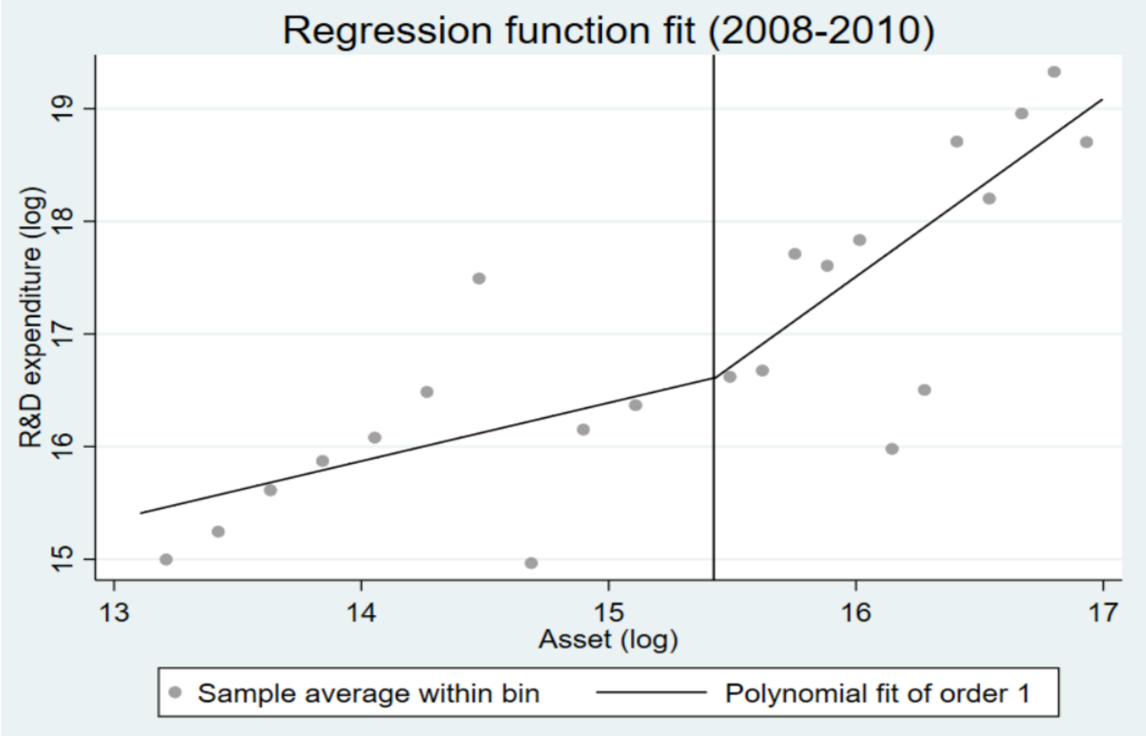


Notes: This analysis focuses on firms with 11 < asset (log) ≤ 14.4, where SMEs only (control group) lie below the cutoff and MMEs only (treatment group) lie above, with observations below asset (log) = 12 excluded as outliers. No SMEs exceed the cutoff in Korean classification

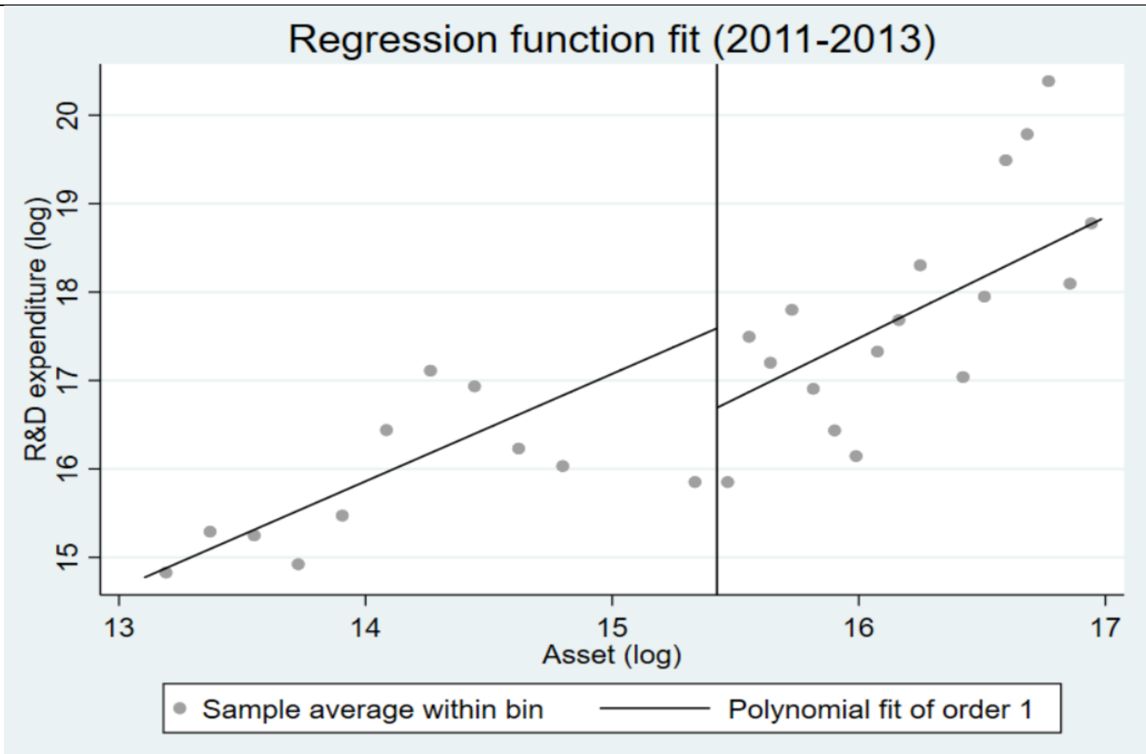
Figure 2.4

RDD (cutoff: asset (log) = 15.425 (KRW 5 trillion), control group: conglomerates)

2008-2010



2011-2013



Notes: This analysis focuses on firms with 13.1 < asset (log) ≤ 17, where MMEs only (treatment group) lie below the cutoff and conglomerates only (control group) lie above, with observations below asset (log) = 11.5 excluded as outliers. No MMEs exceed the cutoff in the data.

In order to clearly identify policy effects near the cutoff, I redefined the treatment and control groups based on a specific asset range around the cutoff to ensure that the two groups were not mixed. This classification follows the same approach used to produce Figures 2.3 and 2.4 presented earlier. Using the parametric RDD methodology, I then examined whether there was an increase in R&D expenditure before and after the policy implementation. As shown by the After× Treatment interaction term in Table 2.10, the results confirm a clear effect of the tax reform. Although the limited sample size may have caused the coefficients to be somewhat inflated, the significant positive coefficient warrants attention. Furthermore, the negative coefficient of the triple interaction term After× Treatment × Asset(log) involving asset size indicates that the positive impact of the policy diminishes as asset size increases. In other words, MMEs near the cutoff are similar to the control group in terms of asset size, and when restricted to this subset, the policy implementation positively influences R&D expenditure. The triple interaction term further reveals that the R&D response is more substantial for smaller firms within the MME group, implying heterogeneity in policy effectiveness by firm size.

Table 2.10

Parametric RDD

	R&D expenditures (log)	
	(1) Control: SMEs	(2) Control: Conglomerates
After× Treatment	12.553** (5.514)	16.469** (6.619)
After× Treatment × Asset(log)	-0.943** (0.413)	-1.142** (0.455)
Obs.	970	574
R-squared	0.039	0.026

Notes: Asset size is controlled as: (1) 12.4 < asset (log) < 13.9, (2) 14.0 < asset (log) < 18.0. Standard errors are clustered at the firm level. All specifications include year, firm and firm-specific linear time trend fixed effects. Control variables include employee, asset, capital, intangible asset, revenue.

*** p<0.01, ** p<0.05, * p<0.1

2.5 Conclusion

This paper examines the impact of the 2011 R&D tax credit reform, creating a quasi-experimental setting and exploiting unique datasets to estimate the effects of the policy. I analyze the impact of this tax policy on the R&D expenditures of medium-sized enterprises (MMEs) over the period from 2008 to 2013, using SMEs and conglomerates - whose R&D tax credit rates remained unchanged - as control groups. Contrary to existing research suggesting that R&D tax credits increase R&D spending by lowering the user cost of R&D investment, no significant policy effect was observed.

However, controlling for firm heterogeneity, the analysis reveals a clear tax reform effect for firms with a higher ratio of intangibles to capital and for firms in high-tech industries. In addition, the 2011 tax reform seemed to alleviate financing constraints for firms with below-average R&D expenditure-to-revenue ratios. Furthermore, using a regression discontinuity design (RDD) based on asset-based firm classification criteria, the results show an increase in R&D expenditures for MMEs with asset sizes comparable to the control group. These results suggest that accounting for the heterogeneity of beneficiaries can lead to more effective policy design and better expected outcomes for specific tax policies.

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CHAPTER 3

THE IMPACT OF FIRMS' R&D ACTIVITIES ON LABOR MARKET IN KOREA

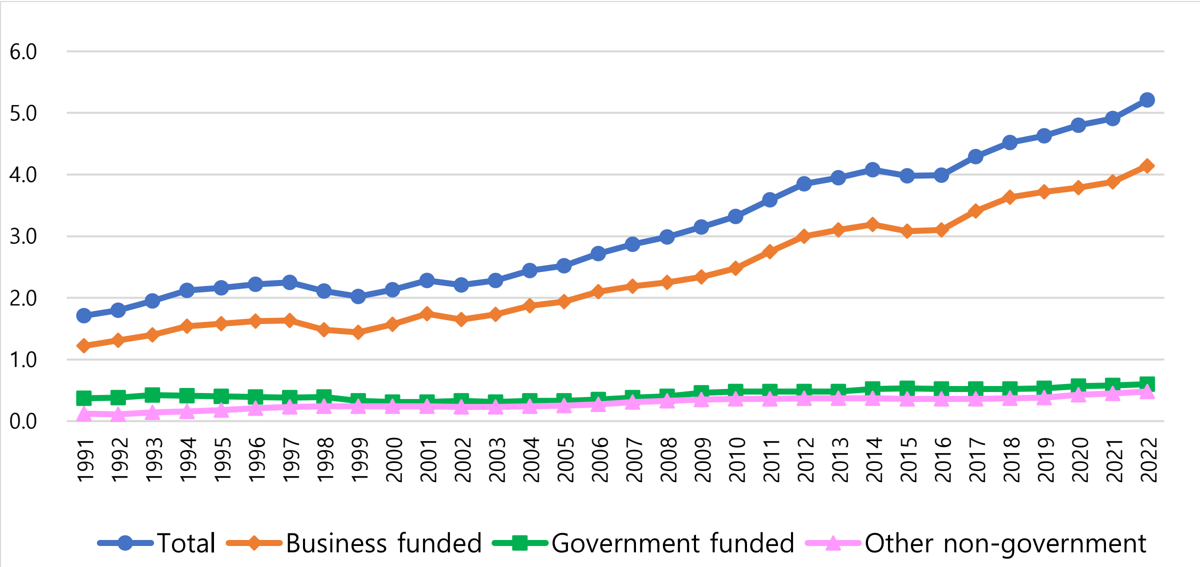
3.1 Introduction

The relationship between technological advancements and employment has been a subject of ongoing debate among economists and policymakers. The rapid pace of technological change in recent decades, characterized by automation, artificial intelligence (AI), and digital transformation, has intensified concerns about potential job displacement and the future of work. Since population decline has emerged as the top policy priority in major developed countries and East Asia, digitalization, a topic left by Covid-19, has become a challenge for not only businesses but also individual countries to survive and achieve sustainable growth. It can be said that governments and businesses around the world are competing to accelerate technological development and focusing on preparing various support measures to encourage this.

Among the tools for promoting technological development, R&D spending stands out as pivotal. Business R&D activities not only enhance firm and industry productivity but also stimulate further innovation across the economy through spillover effects. In Korea, as in the United States, private firms account for 80% of the country's total R&D expenditures, highlighting the key role of the private sector in driving R&D and the need to focus on their decision-making processes (Figure 1, 2). Given that the private sector leads the trend in both R&D spending and employment, its influence is significant.

Figure 3.1

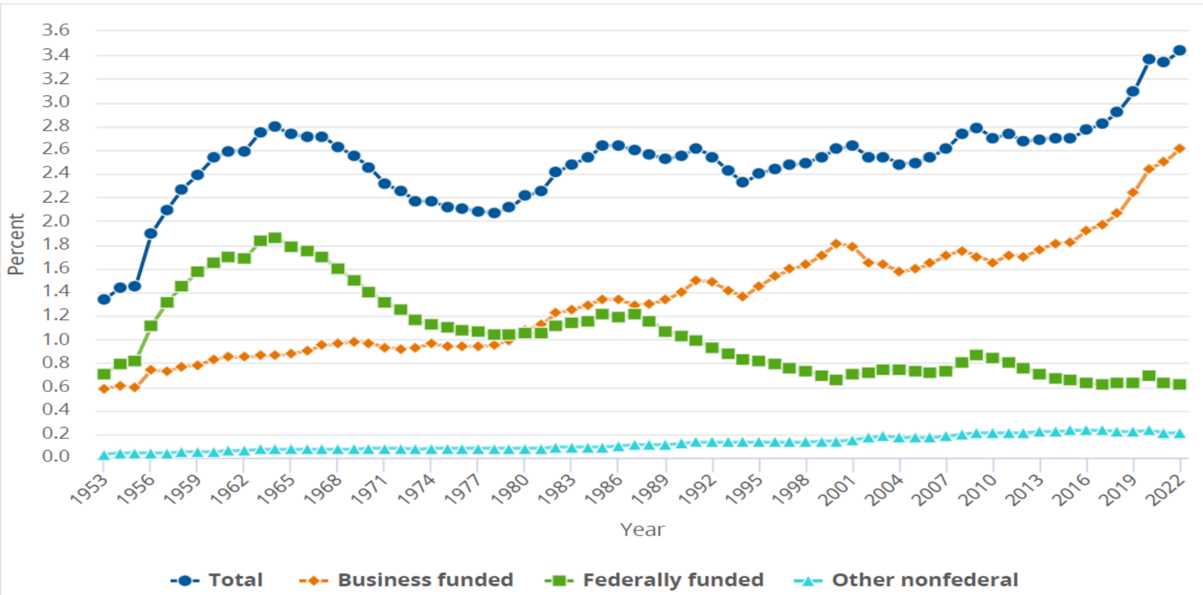
Korea R&D as % of GDP by Funding Source (1991-2022)



Source: Korea Institute of Science $ Technology Evaluation and Planning (KISTEP)

Figure 3.2

U.S. R&D as % of GDP by Funding Source (1953-2022)



Source: National Science Foundation, National Patterns of R&D Resources

On the other hand, the direction of change in employment, which is a key outcome variable in the labor market, is based on the decision-making of individual firms and can be said to be a major independent variable that determines the direction of government policy. The amount of employment in the labor market is a result of growth, but it is also a key variable in determining macroeconomic policy because it is a major source of income for individuals or households and is directly linked to consumption levels, which are key macroeconomic variables. At the same time, maintaining employment stability is directly linked to welfare policies because it ensures stability in personal or household income. This is especially true in countries where income support for the unemployed is a basic welfare policy. Therefore, at this point, it is necessary to look again at the impact of technological progress on employment.

According to the new classical economic theory, if R&D enhances firm productivity (Griliches, 2007), it is expected to positively impact employment by increasing labor demand, which stems from higher product demand. However, existing research, such as Acemoglu and Autor (2011), suggests that technological progress can also exacerbate job polarization, widening the wage gap between workers with different skill levels and impacting employment unevenly across skill level. This complexity makes it challenging to predict the overall effects on employment with certainty. Based on existing theories, the mechanisms through which technological progress influences the labor market have been well established. While the impact may vary depending on the nature of technological advancement, it generally follows two primary paths: product innovation and process innovation (Van Reenen, 1997). Product innovation, characterized by the development of new products, increases labor demand as firms experience higher demand for their goods and services. In contrast, process innovation, often associated with automation, replaces existing labor by introducing advanced machinery and technologies into production processes. Additionally, technological progress affects employment through three key channels: the displacement effect, the productivity effect, and the reinstatement effect (Acemoglu & Restrepo, 2019).

Therefore, this paper investigates the impact of R&D spending on the labor market by examining how individual firms' R&D expenditures affect employment-related decisions, using firm-level financial statement data from Korea. This study seeks to address two main questions. The first is whether increased innovation by firms leads to benefits for workers, such as higher employment or wages. The second is how increased R&D spending affects the composition of employment in the labor market, particularly the balance between regular and non-regular employment.

Building on these questions, I first examine the impact of R&D on the employment of individual firms, which serve as the primary agents of job creation, as R&D represents a key means of promoting innovation at the individual firm level. This question is particularly relevant in the context of Korea, where employment related laws and institutions, such as strict employment protection legislation, are known to be rigid. As a result, firms may face high adjustment costs when expanding their workforce (Van Long and Siebert, 1983; Pissarides, 1999). Even in a context where labor demand is inherently sticky and path dependent, this study seeks to determine whether R&D can lead to employment growth. If such a positive relationship is confirmed, it would strengthen the justification for various government R&D support policies, complementing the traditional argument based on spillover effects. In addition, my second research question is how an increase in R&D affects job insecurity and wage disparities in the labor market. Major disparities in the labor market can become social problems through income disparities, so alleviating them is a major policy task for governments. In view of this, this study will examine the effects on the ratio of non-regular employees, the ratio of female workers, and annual salary per employee as the main dependent variables to observe the unintended consequences that R&D may cause in the labor market.

This research is based on the entire financial data of listed firms in Korea from 2010 to 2023. The total R&D expenditure provided by the financial statements of individual companies covers about 96% of the R&D expenditure by private companies officially announced by the Korean government. Therefore, analysis based on this data is meaningful in terms of reliability.

The main results of the study are as follows. First, the impact of an increase in R&D spending on the total employment of individual firms was positive. For a more multifaceted analysis, the manufacturing industry was divided into high-tech, medium-tech, and low-tech based on the level of technology. To carry out this analysis, the OECD classification was employed. Furthermore, within the high-tech sector, conglomerates and non-conglomerates were distinguished. Additionally, for the manufacturing industry, the R&D duration was adopted to compare the results of existing studies on the effects of technological progress on employment. In other words, this study examined the effects of R&D intensity (measured as the ratio of R&D expenditures to revenue) on employment by taking into account not only the intensity of R&D but also the duration of maintaining or increasing it. As a result, the longer the persistence of R&D spending in the high-tech industry, the more pronounced the positive effect on employment. Meanwhile, considering that technological progress affects not only the manufacturing industry but also the service industry, the so-called high-tech service industry was also divided into a separate category from the overall service industry using the OECD classification criteria. In this regard, it was found that the employment increased significantly as the R&D intensity increased in the overall high-tech service industry and in the non-conglomerates high-tech service industry.

On the other hand, the proportion of non-regular workers has decreased due to the technology-biased nature of R&D. This was also observed for the entire industry, and the extent to which the proportion of non-regular workers decreased in the high-tech industry was more pronounced. In addition, the proportion of female workers did not show a significant direction in terms of overall R&D growth, but it did show an increase in high-tech conglomerates and a decrease in non-conglomerate high-tech service industries. Finally, in contrast to the impact on employment, no significant impact was observed on annual salary per capita.

This research makes three major contributions to the existing literature. First, in verifying the employment effects of R&D, I have considered the size of the firm in addition to the industry classification based on the level of technology. This is especially meaningful in Korea, where conglomerates are preferred workplaces in terms of job stability and wage gap, and in the sense of how many good jobs they can create. Secondly, this study considered the duration of time that R&D spending continues at a certain level or above, taking into account not only the intensity of R&D but also the nature of technological development. Hall (1993) suggests that the long-term nature of R&D and the fact that much of a firm's knowledge capital is tied up in its R&D workforce make it difficult for even large firms to quickly adjust their R&D expenditures. This study examines the effects of R&D expenditure on employment by breaking down the period of time over which R&D expenditure actually has a lasting effect, as opposed to previous studies that assumed the stability of R&D expenditure. Finally, to determine the impact on the labor market as a whole, I looked at the effects on the ratio of non-regular workers, the ratio of female workers, and wages, in addition to simply analyzing the effects on total employment. This is to determine whether labor market disparities, such as wage gaps and job instability, are expanding due to R&D expenditures.

The remainder of this paper is organized as follows. It provides an overview of the Korean labor market and reviews the existing research. It then introduces the data and methodology. It then presents the main findings and draws conclusions from them.

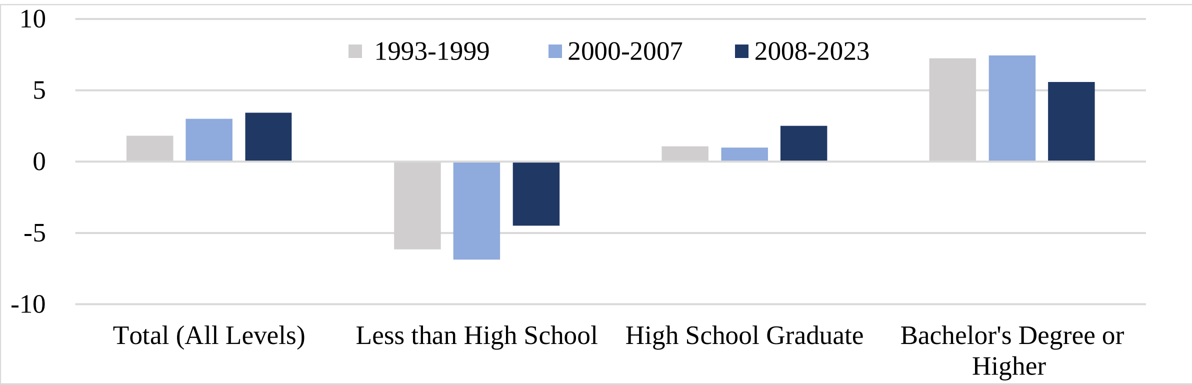
3.2 Background: Korea's labor market

First, the main features of the Korean labor market will be examined. It is well known that Korea has experienced high economic growth through an export expansion strategy since the 1960s. Meanwhile, in the process of sustaining economic growth based on the expansion of international trade, the industrial structure has advanced from the light industry to the advanced heavy and chemical industries and the electronics industry. As a result, the demand for labor in Korea has continued to grow in terms of quantity. Alongside the transformation of the industrial structure, labor demand, as a derived demand for goods, has also increased rapidly, particularly in the form of demand for highly educated workers (Figure 3.3). This shift has contributed to a rise in the demand for high wage workers as well (Figure 3.4).

On the other hand, the disparities in the labor market have been expanding during Korea's economic growth and are considered to be the top priority policy issue to be addressed. First, the wage gap by educational level, which is directly related to the changes in labor demand discussed earlier, can be pointed out. As shown in Figures 3.5 and 3.6, the wage gap between workers by educational level is continuously expanding as labor demand increases, mainly for highly educated and highly skilled workers.

Figure 3.3

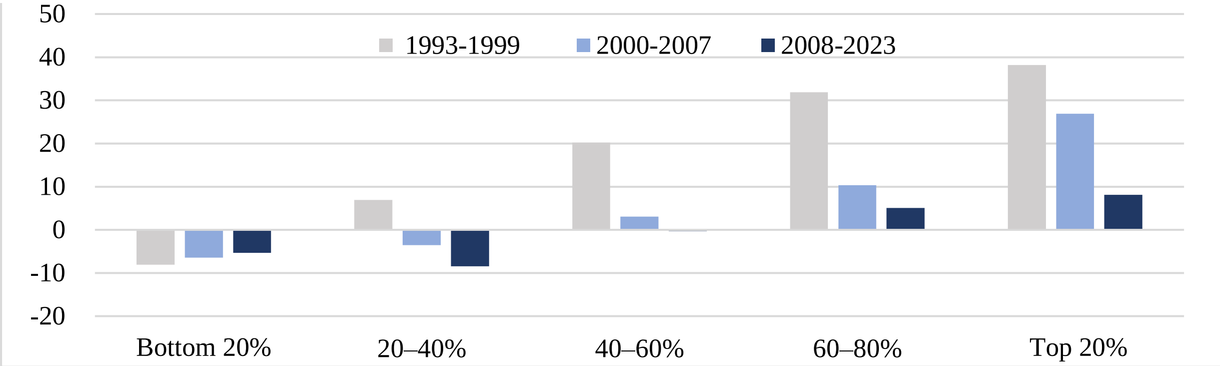
Average annual worker growth by education level in Korea (1993-2023)



Source: Ministry of Employment and Labor

Figure 3.4

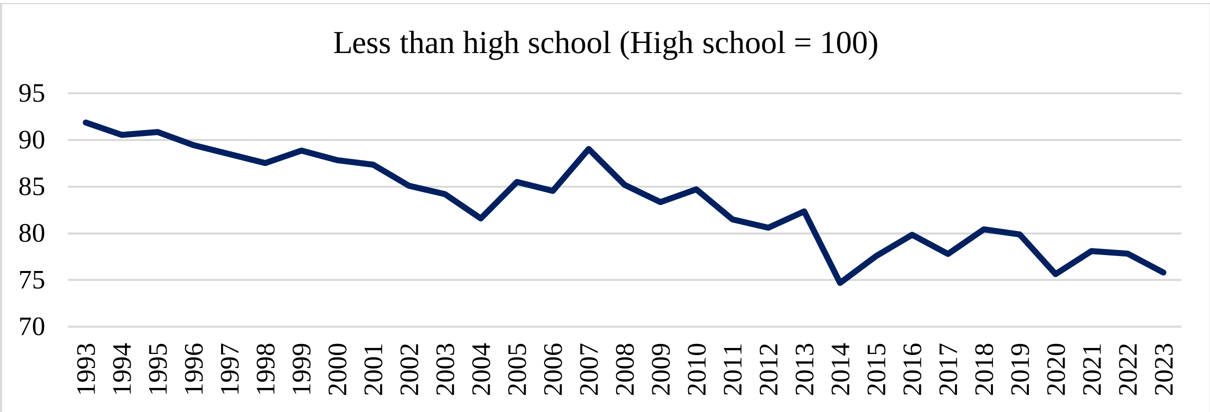
Employment growth by wage quintile (annual avg., 1993-2023)



Notes: Quintile classification based on 2004 wage distribution. Adapted from Ministry of Employment and Labor

Figure 3.5

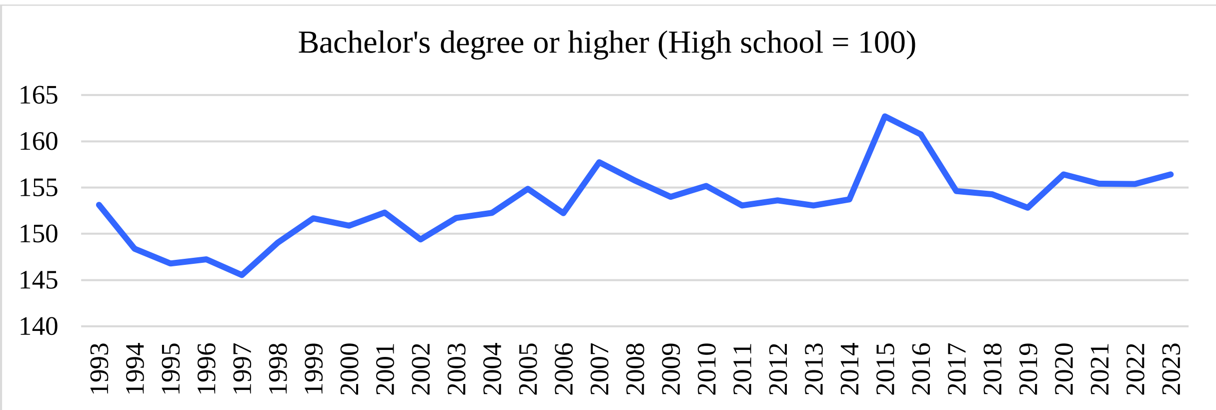
Wage differentials by education level



Source: Ministry of Employment and Labor

Figure 3.6

Wage differentials by education level

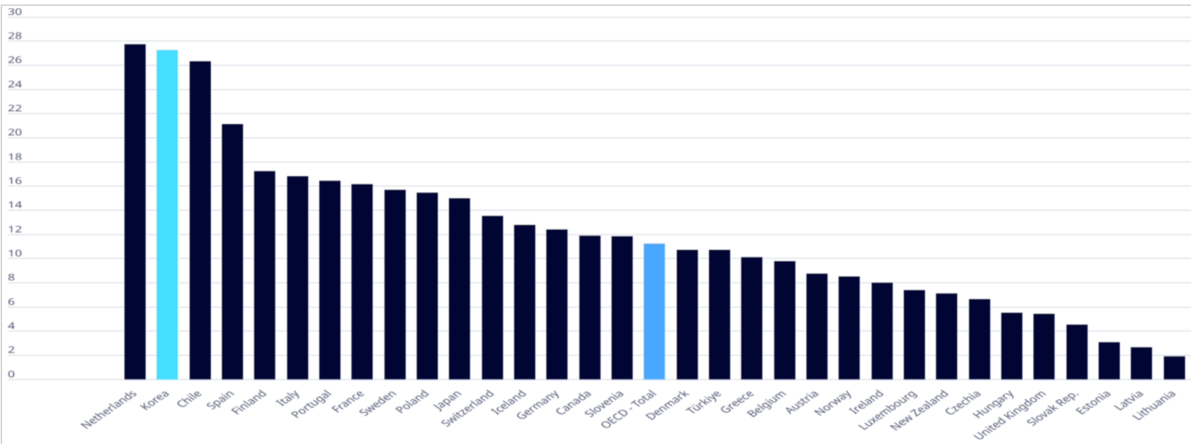


Source: Ministry of Employment and Labor

Next, there is the gap between regular and non-regular workers, represented by the term dichotomy of the labor market, and the gap between workers in conglomerates and small and medium-sized enterprises (SMEs). This is informed by the dual labor market theory proposed in the 1970s (Doeringer and Piore, 1971, 2020) and the segmented labor market theory (Cain, 1976). According to these theories, the labor market is divided into two main sectors: the Primary sector, characterized by stable employment, good working conditions, and opportunities for advancement, and the Secondary sector, characterized by low-skilled jobs, poor working conditions, low wages, and limited job security. The OECD (2013) found that labor market duality is unusually high in Korea, reflected in one of the highest shares of temporary employment among OECD countries. In 2022, the share of temporary workers was 11.25% on average in the OECD and 27.28% in Korea, the second highest after the Netherlands (Figure 3.7). As of August 2023[21], there were 8.1 million non-regular workers in Korea, accounting for 37% of the 22 million total number of salaried workers. Monthly average wages are only 54% of those of regular workers.

Figure 3.7

Temporary employment (% of Total, 2022)



Source: OECD

[21] Non-regular employment statistics 2023, Korea Labor Institute (KLI)

According to existing studies, the labor market has a dual structure, consisting of a primary market, where high wages and better employment conditions are guaranteed, and a secondary market, characterized by lower wages and poorer working conditions. However, to explain this dual structure in practice, Korea classifies workers as regular and non-regular, while the OECD categorizes them as permanent and temporary. To provide a brief overview of this concept, the OECD (2018) defines non-regular workers in Korea as encompassing three distinct categories of salaried workers: non-permanent workers, part-time workers, and non-typical workers[22]. Meanwhile, the OECD defines the dual structure of the labor market based on the distinction between permanent and temporary workers. Accordingly, this classification captures only a part of non-regular workers in Korea. Nevertheless, it is undeniable that the dual structure of the Korean labor market is particularly pronounced when viewed in an international context.

As Table 3.1 shows, the gap between regular and non-regular workers in Korea is quite large. The differences in average monthly wages and education levels between regular and non-regular employees are significant, and non-regular workers tend to be employed by smaller businesses. In contrast, regular employees are more likely to work for large conglomerates, while non-regular employees are concentrated in SMEs. In Korea, the distinction between conglomerates and SMEs is directly linked to income disparities, welfare benefits, and job stability. This is evident in the differences in average job tenure and the coverage rates of social insurance and severance pay, as shown at the bottom of Table 1. The divide between regular and non-regular employment also exacerbates socio-economic gaps, including disparities

[22] (1) Non-permanent workers: Workers engaged on a temporary or fixed-term basis. (2) Part-time workers: Workers with 35 or fewer regular working hours per week. (3) Non-typical workers, who include daily workers, contractors (either engaged for a specific task or paid on commission), temporary work agency workers, domestic workers and other such categories of workers with only loose or spurious ties to the job-giver.

between conglomerates and SMEs, and contributes to social fragmentation and deepening inequality. Moreover, the high dismissal rate of non-regular employees hinders skill accumulation, which may lead to a long-term decline in economic productivity. The dual structure of the Korean labor market has been identified as a key issue in efforts to enhance equality and rationalize the labor market to support economic growth.

Table 3.1

Comparison of regular and non-regular workers in Korea (August. 2023)

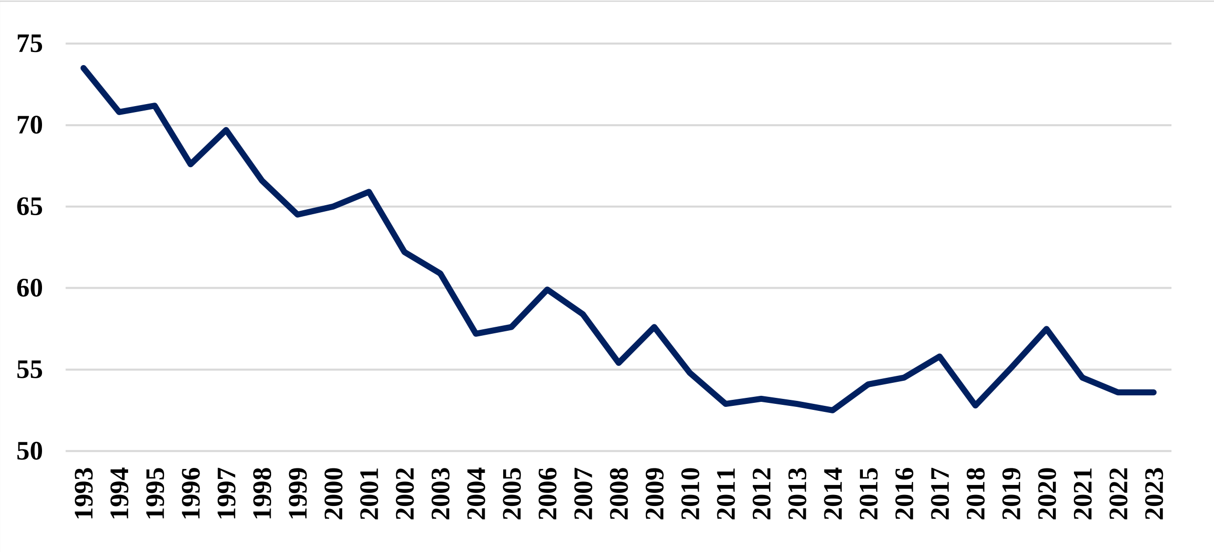
	Regular	Non-regular
Wage (monthly average)	100.0	54.0
Sex (%)		
- Male	60.5	43.8
- Female	39.5	56.2
Education (%)		
- High School or Below	34.3	62.7
- University or Above	48.3	25.6
Business size (employee, %)		
- 1-4	43.8	56.2
- 5-9	54.3	45.7
- 10-29	60.5	39.5
- 30-99	67.9	32.1
- 100-299	78.8	21.2
- 300 or More	84.2	15.8
Tenure (month)	97.8	32.0
Social Insurance		
- National pension (%)	88.0	38.4
- Employment insurance (%)	81.8	53.5
- National health insurance (%)	94.3	52.6
Severance Pay (%)	94.5	45.3

Notes: For regular workers, enrollment in the national pension, national health insurance is legally mandatory. However, the above table only includes workplace subscribers. Employment insurance is also mandatory for regular employees. However, those with separate occupational pensions, such as military personnel and public officials, as well as high-income professionals like lawyers and doctors, may be exempt from enrollment. Adapted from Non-Regular Employment Statistics 2023, Korea Labor Institute (KLI)

Meanwhile, the wage gap between regular and non-regular employees is directly linked to the gap between conglomerates and SMEs. This is because conglomerates have a high proportion of regular employees, while SMEs have a high proportion of non-regular employees. As shown in Figure 3.8, the salary gap between conglomerates and SMEs is large, and the gap is continuing to widen.

Figure 3.8

Annual average salary ratio of SMEs to conglomerates in Korea



Source: Ministry of Employment and Labor

In Korea, stable jobs and work-life balance are perceived as having a positive impact on marriage and childbearing[23]. Against this backdrop, conglomerates with relatively child-friendly work environments tend to be preferred over SMEs. As a result, jobs in conglomerates are perceived as decent jobs by job seekers in Korea. For this reason, the Korean government has identified reducing the labor market gap as a key policy task as part of its efforts to fundamentally address the low fertility rate[24].

[23] Presidential Committee on Ageing Society and Population Policy (2024, May 3). Survey on Perception of Marriage, Childbirth, and Parenting 2024

[24] Presidential Committee on Ageing Society and Population Policy (2024, June 19), Korean Policies to

As discussed above, the labor market in Korea has shown a development path in which the rewards are allocated differentially while the quantity is expanding. In particular, Korea's focus on employment flexibility during the economic recovery following the 1997 foreign exchange crisis led to a significant increase in the proportion of non-regular workers (KDI, 2009). Deepening labor market disparities may exacerbate social inequality, increase wage inequality and job insecurity, and reduce overall economic productivity (BOK, 2016). In the Korean case, the labor market dichotomy is not only limited to labor market issues, but is also closely related to product market oligopoly and vertical subcontracting relationships among firms. This is the result of complex causes, including the productivity and profit gap between conglomerates and SMEs, and the blind spots in labor market institutions and labor protection laws in the low-wage labor market (BOK, 2018).

However, this study does not focus on the causes of the labor market duality, but rather on the impact of firms' R&D decisions on this phenomenon when considering it as a policy issue to be addressed. The significance of this study lies in estimating how the impact of R&D, or technological progress, on individual firms' decision-making will combine with the impact of these characteristics on the labor market.

3.3 Literature Review

This section reviews key studies examining the relationship between technological progress, R&D investment, and labor market dynamics, focusing on employment effects, wage inequality, and firm-level innovation outcomes.

Reverse the Decline in the Fertility

3.3.1 Theoretical framework: Technology’s impact on employment

Economic theories on technological advancements and employment emphasize the dual forces of job displacement and job creation. Several key models provide insights into the mechanisms by which technology affects labor markets.

The OECD Employment Outlook 2019 highlights technological progress as a key force driving labor market transformation, alongside globalization and demographic shifts. While automation threatens some jobs, overall employment remains resilient due to job transformation and adaptation. However, labor markets are polarizing, with high-skilled jobs growing while middle-skilled roles decline (OECD, 2019).

The Asian Development Outlook (ADO) 2018 examines technology’s dual impact on jobs in Asia, balancing productivity gains with displacement risks (Asian Development Bank, 2018). While automation threatens routine jobs, rising demand and industry growth are expected to offset job losses. The transition to a digital economy requires higher cognitive and digital skills, putting low-skilled workers at risk. artificial intelligence (AI), robotics, and internet of things (IoT) could drive economic prosperity but also endanger over 50% of jobs in some Asian economies. Automation reduces routine employment but creates new opportunities in nonroutine, information and communication technology (ICT)-intensive roles, driving wage growth in tech-complementary jobs.

Next, the channels through which technological advancement affects employment can be divided into two categories. First, Acemoglu and Restrepo’s task-based models provide critical theoretical foundations for understanding how technology affects labor demand. They develop a task-based model distinguishing between automation’s displacement effect (reducing labor demand) and new task creation’s reinstatement effect (increasing labor demand). Their research highlights that the net employment effect of technology depends on whether automation effects outweigh reinstatement effects (Acemoglu & Restrepo, 2019). They are also examining how demographic shifts, such as aging populations, influence the adoption of robots and their subsequent impact on employment and wages (Acemoglu & Restrepo, 2020, 2022), their study suggests that regions with aging populations may be more susceptible to automation-driven job displacement. Next, Van Reenen (1997) suggest that innovation impacts labor demand differently depending on whether it is product innovation or process innovation. The author differentiates between product innovation, which increases labor demand, and process innovation, which reduces labor demand, particularly for low-skilled workers.

3.3.2 R&D investment and employment growth

The relationship between technological advancement and employment growth is complex, varying across sectors, regions, and firm sizes. While empirical studies generally find that R&D investment fosters job creation, sectoral disparities remain.

Bogliacino and Pianta (2010) finds that technology adoption correlates with higher employment growth, though effects vary by firm size, with larger firms experiencing greater employment gains. Bogliacino et al. (2012) also examines data from 15 European countries across 25 manufacturing and service sectors and found that R&D expenditures, particularly those associated with product innovation, had a significant positive effect on job creation.

Harrison et al. (2014) suggest a dynamic panel study differentiates between innovation inputs (R&D spending) and outputs (new products/processes), revealing that employment effects vary by sector and depend on firms' ability to translate R&D investment into productive innovation. Research by Coad and Rao (2011) finds that previous research may have underestimated the total employment gains from innovation using a firm-specific "innovativeness index" based on patents and R&D expenditure histories. A study of Japanese industry sectors (2002–2017) finds a statistically significant positive effect of R&D investment on job creation, particularly in the manufacturing sector and industries with high routine intensity. Findings support the idea that innovation compensates for potential job losses due to technological advancements (Shah et al., 2024).

3.3.3 The impact of technology on labor market inequality

Technological progress affects workers unevenly, often leading to labor market polarization by reshaping wage distribution and employment composition. These advancements tend to reinforce labor market disparities, disproportionately benefiting high-skilled workers and large firms while limiting opportunities for low-skilled and temporary workers. This section synthesizes key researches on the impact of technological change on labor market inequality, emphasizing firm heterogeneity, skill-biased technological change, and innovation-driven income disparities.

Van Reenen (1997) shows that process innovation disproportionately affects low-skilled jobs, exacerbating labor market segmentation. Autor et al. (2003) and Acemoglu and Autor (2011) highlight how innovation can lead to structural shifts in the labor market, where routine-intensive jobs in the secondary sector are increasingly replaced by automation, further reinforcing labor market disparities.

Allen (2001) provides direct evidence linking technological change to shifts in the wage structure. The study examines R&D intensity, high-tech capital investment, capital-labor ratio growth, and total factor productivity, finding that rising R&D expenditures and capital-labor ratio growth are associated with widening wage gaps by education level. It further highlights that R&D has the greatest impact on wage growth among college graduates.

Acemoglu (2002), Holm, J. R. et al. (2020) emphasizes the role of skill-biased technological change (SBTC), demonstrating that technological advancements disproportionately benefit skilled workers, increasing demand for their labor and raising wage inequality. Aghion et al. (2019) establish a positive correlation between innovation and top income inequality, suggesting a causal relationship where innovation increases top income shares. Cortes et al. (2023) confirm that SBTC significantly contributes to rising wage disparities across firms, reinforcing inequality between establishments. Card et al. (2018) further highlight the role of firm-specific factors such as productivity in shaping wage inequality, showing that more productive firms offer higher wages and attract higher-skilled workers, leading to persistent wage gaps.

The reviewed literature underscores the complex relationship between technological change, R&D investment, and employment. R&D investment stimulates employment, though its impact varies by sector and firm size. While R&D investment fosters job creation and productivity growth, it also alters the composition of employment by reinforcing skill-biased technological change. Automation and digitalization contribute to rising wage inequality, favoring workers with specialized skills while stagnating wages for low-skilled labor. These findings provide the foundation for analyzing the impact of R&D spending on employment in the Korean labor market.

3.4 Empirical Strategy

3.4.1 Estimating R&D effect on outcomes

As explained above, this study investigates the impact of R&D expenditures on firms' employment-related decisions using financial statement data from publicly traded companies.

This dataset includes firm-level annual R&D expenditures as well as detailed employment data disaggregated by total employment, employment type (regular vs. non-regular), and gender.

From a methodological perspective, this study applies a firm and year fixed effects model to control for firm-specific and year-specific heterogeneities. In addition, to account for differences in growth trajectories across firms, firm-specific linear time trends are included to capture unobserved firm-level trends over time. The empirical model is specified as follows.

$$Y_{it} = \beta_0 + \beta_1\, R\&D\ group_{it} + \delta Control_{it} + u_i + v_t + \gamma_i \times Trend_t + e_{it}$$

$$(Y_{it}\text{: (1) } Total\ employee_{it}\text{, (2) } Ratio\ of\ non\text{-}regular\ workers_{it}\text{,}$$

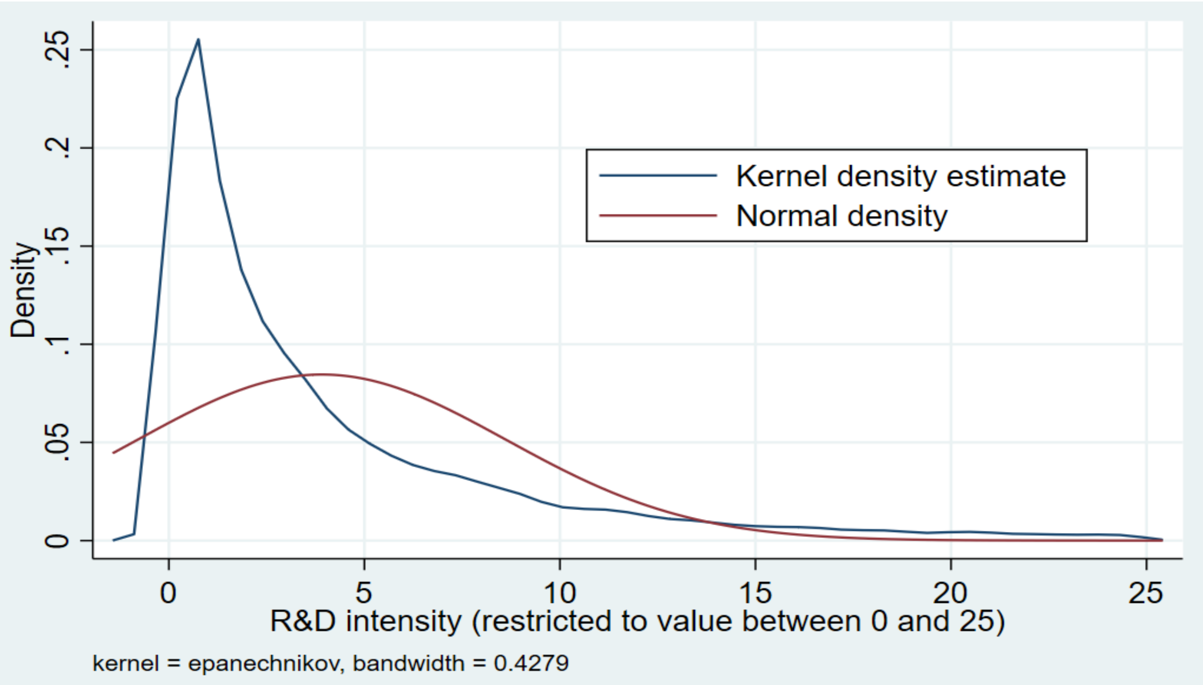
$$\text{(3) } Ratio\ of\ female\ workers_{it}\text{, (4) } Yearly\ salary\ per\ capita_{it})$$

Regarding the dependent variable, this study uses four key variables to assess the impact of R&D expenditures on firm-level employment and labor market outcomes. These include total employment, the ratio of non-regular workers to total employment, the ratio of female workers to total employment, and annual per capita salary. By analyzing these variables, this research seeks to determine whether R&D expenditures have a greater impact on employment or wages, and to assess whether R&D contribute to widening labor market disparities. (1) $Total\ employee_{it}$ represents the total number of employees in firm *i* in year *t*. (2) $Ratio\ of\ non\text{-}regular\ workers_{it}$ is defined as the ratio of non-regular workers relative to the total workforce of each firm in year *t*. (3) $Ratio\ of\ female\ workers_{it}$ represents the ratio of female workers relative to the total employees of each firm in year *t*. (4) $Yearly\ salary\ per\ capita_{it}$ denotes the average annual salary per employee in firm *i* in year *t*.

The independent variable, $R\&D\ group_{it}$, is defined as the ratio of R&D expenditures to total sales, commonly referred to as R&D intensity. Given the potential nonlinearity in the relationship between R&D intensity and the dependent variables, as well as the asymmetric distribution of R&D intensity (Figure 3.9), the firms are categorized into three dummy-coded groups based on R&D intensity. The bottom 20 percent group (assigned a value of 0) includes firms with R&D intensity of 0.53 percent or lower; the middle 40 percent group (value of 1) comprises firms between the 20th and 60th percentiles, with the 60th percentile closely matching the overall average of approximately 3.5 percent; and the top 40 percent group (value of 2) consists of firms with R&D intensity above the 60th percentile.

Figure 3.9

Kernel density of R&D intensity



To conduct a sector-specific analysis of R&D effects, this study adopts the OECD (2016) industry classification, dividing manufacturing and service industries into high-tech and non-high-tech sectors[25]. Given the significant influence of conglomerates in Korea's economy,

[25] OECD high-tech classification: (manufacturing) electronics, aerospace, pharmaceuticals
(services) scientific R&D, S/W publishing, IT and information services

high-tech manufacturing and service industries are further categorized into conglomerates and non-conglomerates to examine heterogeneous R&D effects. Moreover, within the manufacturing sector, non-high-tech industries are subdivided into low-tech and medium-tech[26] industries to provide a more detailed assessment of R&D effects.

Table 3.2

Movers & Stayers: Transitions between R&D groups

		Current group 0	Current group 1	Current group 2	Total
Lagged Group	0	3,206	**<u>446</u>**	**<u>48</u>**	3,700
	1	**<u>548</u>**	6,468	**<u>683</u>**	7,699
	2	**<u>58</u>**	**<u>800</u>**	6,883	7,741
Total		3,812	7,714	7,614	19,140

The top 40% group was intentionally defined with a broader range to facilitate dynamic tracking of firms shifting between R&D intensity groups based on fluctuations in their R&D spending. This approach allows for a more effective analysis of how changes in R&D spending affect labor market outcomes. As shown in Table 3.2, a total of 2,583 observations have transitions between groups. Given that the number of observations with both current and

[26] (1) Low-tech: food products, beverages, tobacco, textiles, wearing apparel, leather and related products, wood and products of wood and cork, paper and paper products, printing and reproduction of recorded media, coke and refined petroleum products, furniture. & two firms with extreme values of R&D intensity were identified and excluded as outliers to ensure robustness of the analysis.

(2) Mid-tech: industries classified as neither high-tech nor low-tech within the manufacturing sector, such as the automobile and chemical industries.

previous year data on R&D intensity is 19,140[27], the proportion of transitioning observations is 13.5%, which is considered appropriate for the analysis.

As control variables, enterprise value (EV), which reflects market capitalization, sales, capital stock, and borrowing dependence were selected to account for firm size and financial conditions. I include firm fixed effects (u_i) and time fixed effects (v_t). e_{it} stands for error term.

3.4.2 Data

In this research, I utilize the financial statement data of publicly listed firms from 2010 to 2023. The analysis period begins in 2010 to exclude the effects of the 2008 global financial crisis and subsequent policy responses.

Tables 3.3 and 3.4 present summary statistics of key variables, categorized by sector in accordance with the analytical framework of this study. Since the OECD (2016) industry classification is based on R&D intensity, it is evident that high-tech sectors exhibit higher R&D intensity. Additionally, non-conglomerates tend to have higher R&D intensity than conglomerates, likely due to their smaller revenue base and more active R&D expenditures relative to their size. Furthermore, the overall ratio of non-regular employees appears to be lower than the national average in Korea. This trend is likely explained by the fact that the dataset covers listed firms, which generally have stronger financial conditions, larger and more stable employment structures, and greater pressure to maintain regular employment rather than increasing reliance on non-regular workers.

[27] From the total of 30,463 observations, cases with missing R&D intensity were excluded, including cases where R&D intensity was not available for the first year of the analysis period (due to lack of prior year data). As a result, the number of observations for which both current and previous year R&D intensity was available was reduced to 19,140.

Table 3.3

Summary statistics (manufacturing)

Mean and standard deviation	Total	Manuf.	High-tech All	High-tech Conglo.	High-tech Non-conglo.	Non high-tech
R&D intensity (%)	12.6 (72.7)	9.7 (60.2)	20.9 (96.4)	6.3 (5.9)	21.7 (99.0)	3.0 (11.8)
Total employee	791.9 (3,673.5)	785.3 (4,239.4)	897.1 (5,787.8)	12,337.3 (22,889.7)	288.2 (384.0)	724.2 (3,076.9)
Ratio of non-regular employees (%)	4.6 (9.8)	3.2 (7.4)	2.9 (7.4)	4.8 (7.4)	2.8 (7.4)	3.4 (7.4)
Ratio of female employees (%)	24.1 (17.6)	20.5 (15.8)	26.2 (14.2)	21.1 (12.7)	26.5 (14.2)	17.4 (15.8)
Salary (log) (yearly, per capita)	10.8 (0.4)	10.8 (0.3)	10.7 (0.3)	11.1 (0.3)	10.7 (0.3)	10.8 (0.3)

Table 3.4

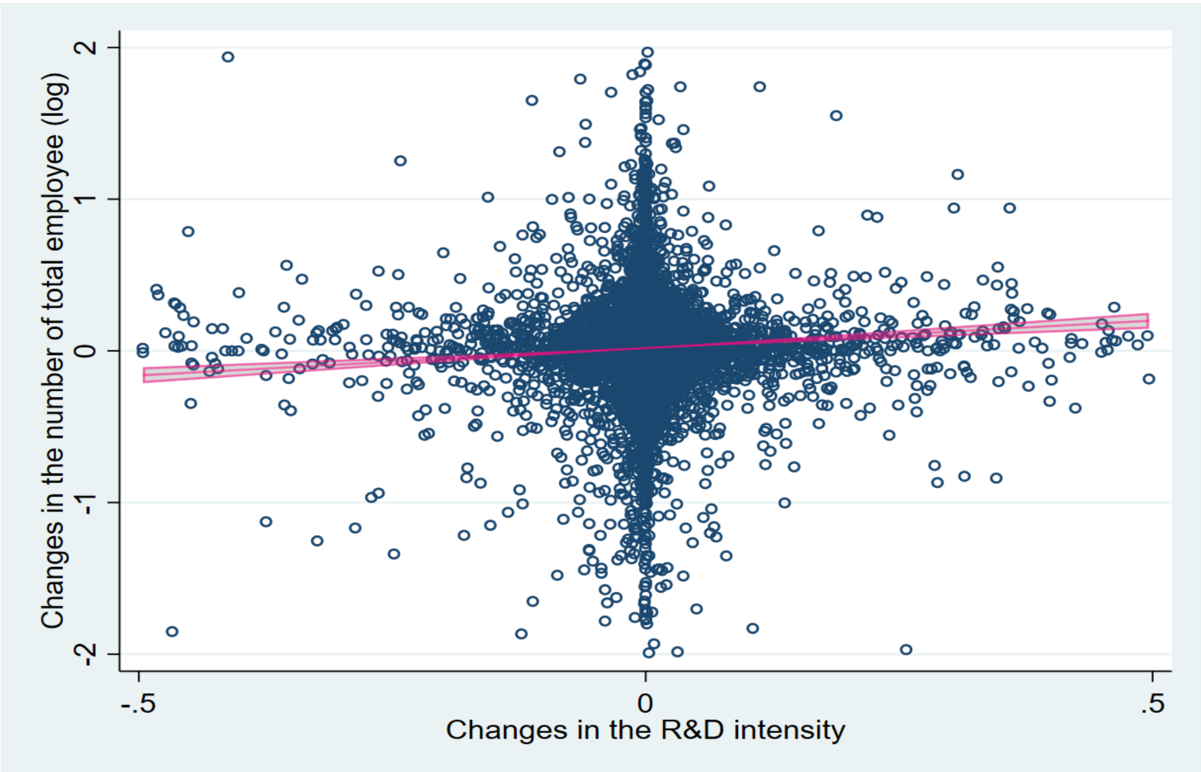
Summary statistics (services)

Mean and standard deviation	Total	Services	High-tech All	High-tech Conglo.	High-tech Non-conglo.	Non high-tech
R&D intensity (%)	12.6 (72.7)	21.5 (101.0)	47.2 (154.5)	21.2 (71.8)	48.6 (157.7)	4.6 (23.1)
Total employee	791.9 (3,673.5)	786.3 (2,430.3)	409.8 (1,276.3)	3,080.6 (4,124.1)	237.0 (385.5)	943.1 (2,757.9)
Ratio of non-regular employees (%)	4.6 (9.8)	6.3 (11.5)	4.7 (9.6)	6.0 (7.8)	4.6 (9.7)	7.0 (12.2)
Ratio of female employees (%)	24.1 (17.6)	31.9 (18.5)	32.2 (17.2)	36.0 (20.7)	32.0 (16.9)	31.7 (19.0)
Salary (log) (yearly, per capita)	10.8 (0.4)	10.8 (0.4)	10.8 (0.3)	11.0 (0.5)	10.7 (0.3)	10.9 (0.5)

Given that the primary focus of this study is to examine the impact of R&D expenditures on employment growth, the relationship between changes in R&D spending and total employment over the full time period is visualized in Figures 3.10, 3.11, and 3.12[28]. The pink regression line in the graphs represents the estimated relationship between the two variables, showing a weakly positive association within a limited range. This trend is particularly pronounced in the high-tech services sector. Additionally, the ratio of average annual salary per employee in SMEs relative to conglomerates within this dataset closely aligns with the official statistics reported by the Korean government, confirming the robustness of the data trends (Figure 3.13).

Figure 3.10

R&D intensity vs. employment growth (total industry)



[28] In all three graphs, the range of R&D intensity is restricted to -0.5 to 0.5, which limits the generalizability of the findings.

Figure 3.11

R&D intensity vs. employment growth (high-tech manufacturing)

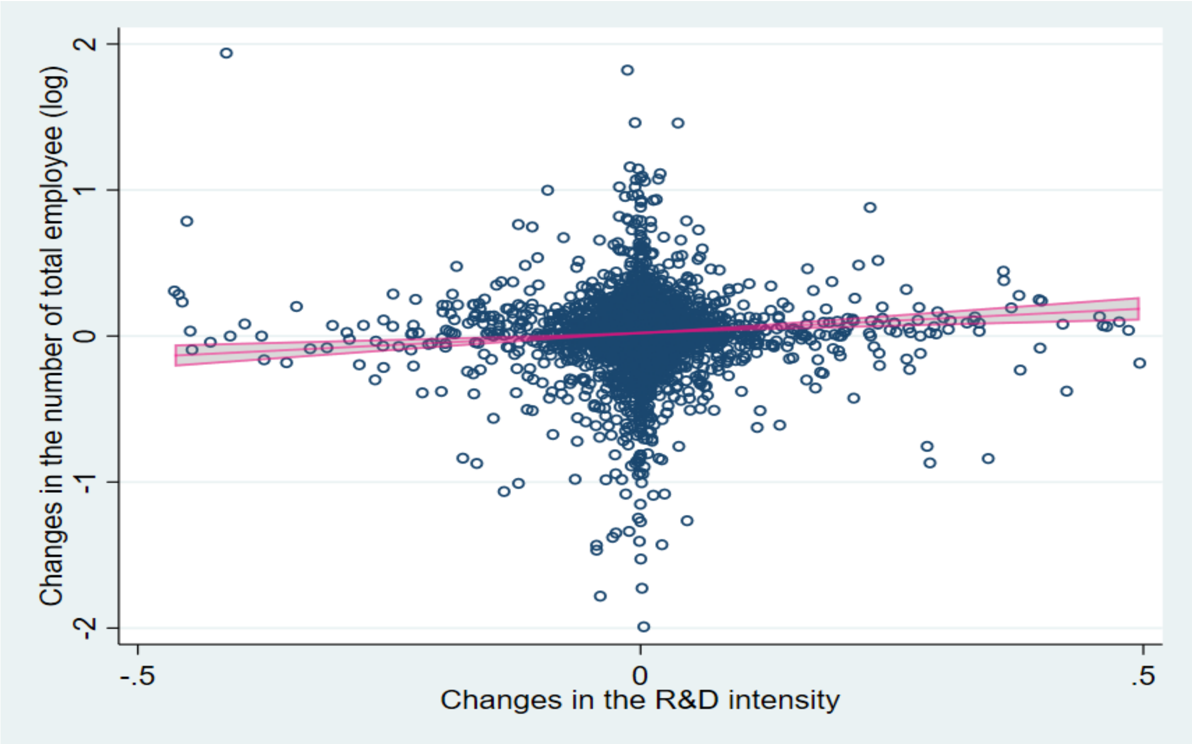


Figure 3.12

R&D intensity vs. employment growth (high-tech services)

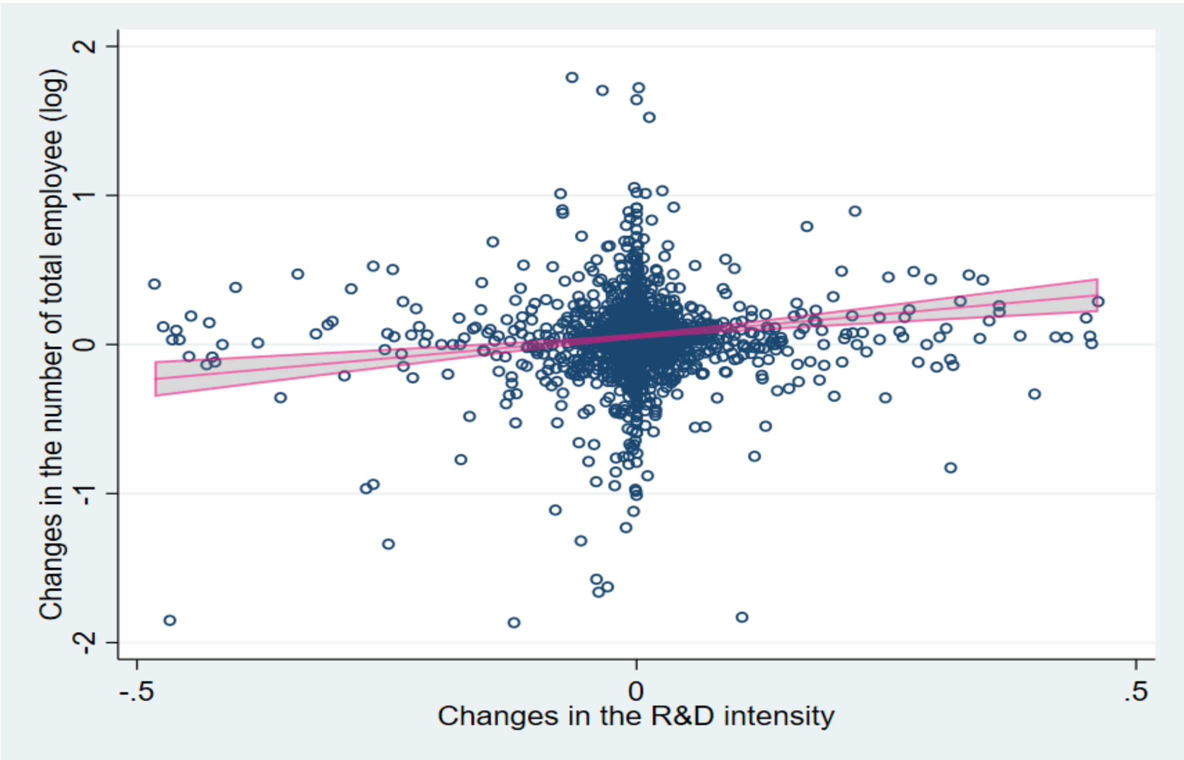
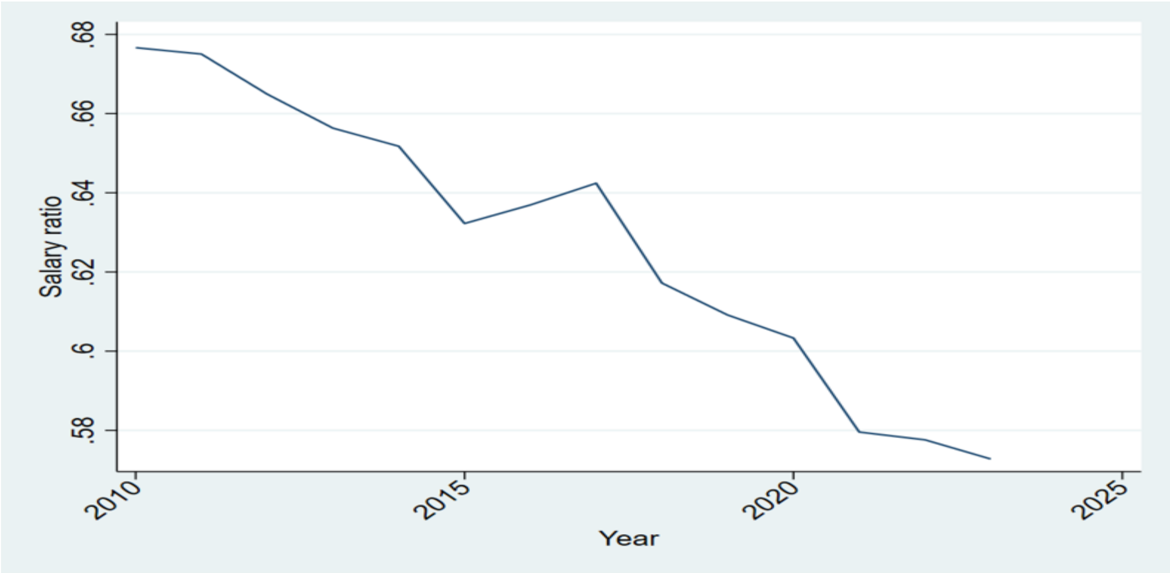


Figure 3.13

Annual average salary ratio of SMEs to conglomerates in data



3.5 Results

3.5.1 Employment

First, the impact of R&D expenditure growth on employment is analyzed as follows. For the total industry, firms in the middle 40% of R&D intensity show a statistically significant positive association with the logarithm of total employees, corresponding to an increase of 4.8 percent, while firms in the top 40% exhibit an even stronger positive association of an 8.8 percent increase compared to when they were in the bottom 20% (Table 3.5).

When analyzed by sector, the employment growth effect is not clearly observed in high-tech manufacturing, except for firms in the top 40% R&D intensity group, which show a 10 percent increase. A further breakdown of high-tech manufacturing into conglomerates and non-conglomerates yields similar results, with no significant employment effect observed. However, in the non-high-tech manufacturing sector, firms in the middle 40% R&D intensity group show a statistically significant positive association with employment of a 6.0 percent increase, while those in the top 40% R&D intensity group exhibit a 6.8 percent increase.

Table 3.5

Effect on employment in high-tech manufacturing

	Employee (log)				
	Total industry	High-tech manufacturing			Non high-tech
		All	Conglo.	Non-conglo.	
	(1)	(2)	(3)	(4)	(5)
R&D group					
- Middle 40%	0.048** (0.024)	0.038 (0.038)	0.155 (0.116)	0.081 (0.065)	0.060*** (0.023)
- Top 40%	0.088*** (0.031)	0.100* (0.042)	0.078 (0.071)	0.172 (0.084)	0.068*** (0.025)
Yearly salary per capita (log)	-0.377*** (0.087)	-0.217 (0.151)	-0.022 (0.186)	-0.301 (0.129)	-0.268*** (0.090)
Enterprise value	-0.003 (0.003)	0.001 (0.002)	-0.000 (0.000)	0.002 (0.016)	0.003 (0.005)
Sales	0.062** (0.024)	0.022* (0.011)	0.008 (0.004)	1.402* (0.519)	0.030* (0.017)
Capital	-0.005 (0.015)	-0.009 (0.011)	0.001 (0.001)	4.150* (1.535)	0.062 (0.038)
Borrowing ratio	0.001 (0.001)	0.003* (0.001)	-0.001 (0.003)	0.001 (0.001)	0.001 (0.001)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	21,382	5,680	296	5,384	9,538
R^2	0.061	0.037	0.181	0.293	0.072

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

To further examine the stronger employment effects in the non-high-tech manufacturing sector, firms within the manufacturing industry were classified into three groups based on OECD (2016) technology classification (Table 3.6): low-tech, mid-tech, and high-tech. The results indicate that in the mid-tech manufacturing sector, firms in the middle 40% R&D intensity group exhibit a 7.1 percent increase, while those in the top 40% R&D intensity group show a 6.0 percent increase, suggesting a notable employment effect. Meanwhile, in the manufacturing sector as a whole, the results show that employment increases by 5.9 percent and 9.1 percent, respectively, compared to when firms are in the bottom 20 percent group.

Table 3.6

Effect on employment in manufacturing by tech level

	Employee (log)			
	(1) Total manuf.	(2) High-tech	(3) Mid-tech	(4) Low-tech
R&D group				
- Middle 40%	0.059*** (0.021)	0.038 (0.038)	0.071*** (0.024)	-0.031 (0.040)
- Top 40%	0.091*** (0.022)	0.100* (0.042)	0.060** (0.026)	0.204 (0.177)
Yearly salary per capita (log)	-0.253*** (0.074)	-0.217 (0.151)	-0.205** (0.089)	-0.454** (0.182)
Enterprise value	-0.003 (0.003)	0.001 (0.002)	0.002 (0.006)	0.045 (0.033)
Sales	0.036** (0.013)	0.022* (0.011)	0.033 (0.024)	0.015 (0.010)
Capital	0.003 (0.015)	-0.009 (0.011)	0.057 (0.040)	0.088** (0.036)
Borrowing ratio	0.002 (0.001)	0.003* (0.001)	-0.000 (0.001)	0.008* (0.004)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	15,218	5,680	7,887	1,624
R^2	0.045	0.037	0.074	0.134

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Several factors may account for these findings. The high-tech sector is inherently skill-intensive, and even at moderate levels of R&D intensity, investment in R&D may primarily benefit high-skilled workers, resulting in limited overall employment growth. In contrast, the mid-tech sector has a different skill composition, where moderate R&D investment may drive broader job creation across various skill levels. Additionally, sector-specific factors such as market dynamics, production processes, and innovation pathways may influence the extent to which R&D expenditures translate into employment growth. Lastly, in the low-tech manufacturing sector, after excluding firms identified as outliers[29], no significant employment increase was observed.

In contrast, an analysis of the services sector (Table 3.7) shows a different pattern than in manufacturing. High-tech services firms in the middle 40% R&D intensity group show a statistically significant positive association with employment, with an increase of 10.8 percent, while firms in the top 40% show an even stronger positive effect, with an increase of 17.1 percent. This positive association is pronounced for high-tech services firms that are not conglomerates (column 4).

This trend may be explained by the fact that, unlike in manufacturing, R&D activities in high-tech services, particularly those related to new service development, tend to generate a reinstatement effect (creation of new tasks) and spillover effect during the adoption of new technology. The expansion of labor demand in this sector is more pronounced due to the nature of high-tech services, where R&D-driven innovations such as the development and implementation of new software, information technology (IT) solutions necessitate a larger workforce to support both technological innovation and service delivery.

[29] Firms in the food industry that maintain an R&D intensity exceeding 10% consistently.

Table 3.7

Effect on employment in high-tech services

	Employee (log)				
	Total services	High-tech services			Non high-tech services
		All	Conglo	Non-conglo.	
	(1)	(2)	(3).	(4)	(5)
R&D group					
- Middle 40%	0.047 (0.033)	0.108** (0.024)	-0.064 (0.030)	0.101*** (0.017)	0.014 (0.047)
- Top 40%	0.106* (0.062)	0.171** (0.032)	0.146 (0.096)	0.160*** (0.021)	0.091 (0.098)
Yearly salary per capita (log)	-0.530*** (0.172)	-0.029 (0.048)	-0.421 (0.391)	-0.037 (0.060)	-0.703*** (0.219)
Enterprise value	0.026 (0.015)	-0.010 (0.012)	0.006 (0.005)	-0.026 (0.026)	0.032 (0.037)
Sales	0.084** (0.038)	0.529 (0.243)	0.433*** (0.053)	0.077 (0.403)	0.084** (0.033)
Capital	0.321*** (0.114)	0.019 (0.449)	-0.656 (0.290)	1.148** (0.285)	0.291** (0.119)
Borrowing ratio	0.001 (0.002)	-0.003** (0.001)	0.005 (0.012)	-0.004** (0.001)	0.007* (0.004)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	5,613	2,217	117	2,100	3,396
R^2	0.153	0.099	0.378	0.111	0.203

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

3.5.2 Employment: R&D persistence duration

The lack of statistically significant results regarding the impact of increased R&D expenditures in the high-tech sector presents a deviation from previous research findings. To explore this further, R&D persistence duration is introduced. This approach aims to capture differences between firms that consistently invest in R&D over multiple years and those that do not. The analytical model for this examination is as follows. R&D persistence is defined as a dummy variable indicating whether a firm's R&D intensity has increased or remained stable compared to the previous year[30]. The R&D persistence duration is categorized into three groups based on the length of sustained R&D persistence: short (1–3 years), medium (4–7 years), and long (8 years or more).

$$Y_{it} = \beta_0 + \beta_1 \, R\&D\ group_{it} + \beta_2 R\&D\ duration_{it} + \beta_3 (R\&D\ group \times R\&D\ duration)_{it}$$
$$+ \delta Control_{it} + u_i + v_t + \gamma_i \times Trend_t + e_{it}$$

(Y_{it}: (1) *Total employee*$_{it}$, (2) *Ratio of non-regular workers*$_{it}$,
(3) *Ratio of female workers*$_{it}$, (4) *Yearly salary per capita*$_{it}$)

By analyzing the coefficients of the interaction term $(R\&D\ group \times R\&D\ duration)_{it}$, this study examines the combined effect of R&D intensity and R&D persistence duration to assess how sustained R&D expenditures influence labor market outcomes. Incorporating persistence duration provides a more nuanced understanding of the relationship between R&D and employment by accounting for the temporal aspect of R&D.

For high-tech firms with high R&D intensity, maintaining this intensity over an extended period is significantly associated with increased employment (Table 3.8). Specifically, among firms in the top 40% R&D intensity group, the interaction term coefficient for medium duration is 0.419, while for longer duration, it rises substantially to 1.118, indicating a strong positive impact on employment. This implies that firms in the high technology sector that belong to the top 40% group and maintain R&D investment for more than eight years experience up to a 112 percent increase in employment compared to when they were in the

[30] Increase: a transition in the R&D group from 0→1, 0→2, or 1→2 / Stable: cases where 1→1 or 2→2
Cases with 0→0 transitions were set as the reference group and assigned a value of 0 for persistence.
Cases with a decrease (such as 2 to 1) were also assigned a value of 0 for persistence.

bottom 20% group. In contrast, in the low-tech sector, the coefficient appears negative, suggesting that R&D investment may have a stronger labor-substituting effect.

Table 3.8

Effect of R&D persistence duration on employment by tech level

	Employee (log)		
	(1) High-tech	(2) Mid-tech	(3) Low-tech
R&D group			
- Middle 40%	-0.128 (0.122)	0.063 (0.045)	0.011 (0.047)
- Top 40%	-0.296** (0.069)	0.017 (0.065)	0.332 (0.268)
R&D duration			
- Short (1-3 yrs)	0.098 (0.272)	-0.010 (0.066)	-0.195 (0.119)
-Medium (4-7 yrs)	-0.146 (0.237)	0.101 (0.128)	-0.096 (0.104)
-Long (8 or more yrs)	-0.739** (0.130)	0.074 (0.131)	-0.402** (0.167)
R&D group × R&D duration			
- Middle 40% × Short	-0.104 (0.241)	0.051 (0.059)	0.057 (0.109)
- Middle 40% × Medium	0.160 (0.166)	-0.038 (0.101)	-0.178** (0.056)
- Middle 40% × Long	0.798*** (0.092)	-0.016 (0.092)	0.021 (0.151)
- Top 40% × Short	-0.019 (0.210)	0.068 (0.071)	0.059 (0.202)
- Top 40% × Medium	0.419** (0.106)	0.013 (0.112)	-0.307 (0.217)
- Top 40% × Long	1.118*** (0.082)	0.013 (0.133)	-0.157 (0.233)
Firm FE	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*
Observations	5,680	7,887	1,624
R^2	0.072	0.077	0.161

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects. The control variables include yearly salary per capita (log), enterprise value, sales, capital, borrowing ratio.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.9 presents the estimated combined marginal effects of R&D intensity on firms' employment, conditional on the duration of R&D engagement. These figures represent the average effects of R&D spending, calculated on the basis of the estimates in Table 3.8. In the high-tech sector (column 1), both the middle 40% and top 40% R&D intensity groups exhibit an initial reduction in labor dependence in the short term. However, as R&D investment continues over a longer duration, firms significantly increase labor input, amplifying the positive employment effect. In particular, firms in the top 40% group experience up to an 82.2 percent increase in employment compared to when they were in the bottom 20% group as the duration of R&D engagement extends.

Table 3.9

Marginal effect of R&D intensity at different persistence duration

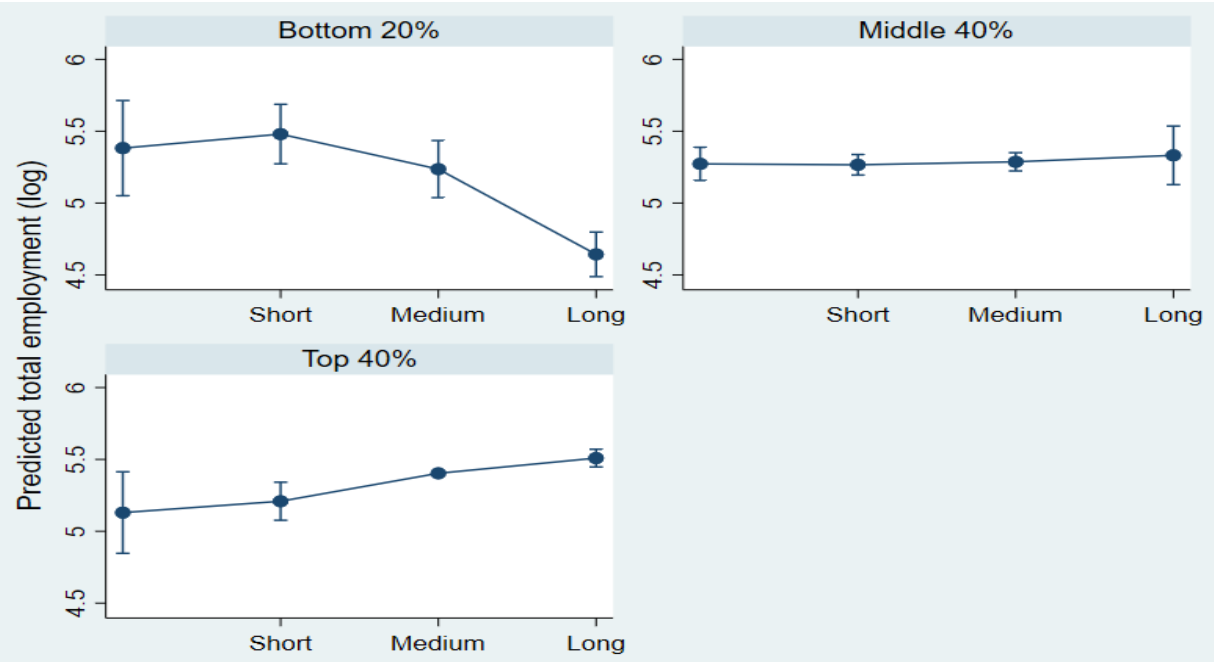
	Employee (log)		
	(1) High-tech	(2) Mid-tech	(3) Low-tech
R&D group: Middle 40%			
- at Short (1-3 yrs)	-0.232* (0.132)	0.114* (0.060)	0.068 (0.112)
- at Medium (4-7 yrs)	0.032 (0.084)	0.024 (0.071)	-0.167** (0.071)
- at Long (8 or more yrs)	0.670*** (0.177)	0.047 (0.079)	-0.032 (0.129)
R&D group: Top 40%			
- at Short (1-3 yrs)	-0.315** (0.145)	0.085 (0.063)	0.390 (0.254)
- at Medium (4-7 yrs)	0.123 (0.087)	0.030 (0.069)	0.024 (0.133)
- at Long (8 or more yrs)	0.822*** (0.127)	0.030 (0.101)	0.175 (0.260)
Observations	5,680	7,887	1,624

Notes: Reference group is bottom 20% R&D intensity. *** p<0.01, ** p<0.05, * p<0.1

Additionally, when visualizing the effect of R&D persistence duration on firm-level employment projections by R&D intensity group in the high-tech manufacturing sector (Figure 3.14), it becomes evident that firms with higher R&D intensity and longer R&D persistence experience the strongest employment growth effects. In contrast, for firms in the bottom 20% R&D intensity group, prolonged R&D persistence appears to reduce employment, suggesting that, in this group, R&D investment primarily substitutes labor rather than creating jobs as the duration increases.

Figure 3.14

Effect of R&D duration on employment by R&D group in high-tech



These findings suggest that short-term R&D involvement may not lead to immediate employment growth and may even be associated with a decline, possibly due to upfront costs or strategic reallocation of resources. However, firms that sustain R&D investment over longer periods achieve significantly higher levels of employment. This pattern is consistent with the conventional view that technological progress may initially reduce labor dependence, but ultimately generate innovation-driven growth that offsets labor substitution effects and leads to long-term employment gains. Overall, these results underscore the importance of considering both R&D intensity and persistence when assessing the employment effects of R&D investment.

3.5.3 Ratio of non-regular employees

This analysis indicates that higher R&D intensity is generally associated with a lower ratio of non-regular employees, particularly across the overall industry and within the high-tech sector.

In Table 3.10, firms in the middle 40% R&D intensity group exhibit a statistically significant decrease of 0.565 percentage points in the ratio of non-regular employees compared to being in the bottom 20% group. This suggests that, relative to periods when firms were in the bottom 20% R&D intensity group, being in the medium intensity group is associated with employing a lower proportion of nonregular workers across the total industry. Similarly, firms in the top 40% R&D intensity group display a statistically significant decrease of 0.982 percentage points, indicating that firms with high R&D intensity have a significantly lower ratio of non-regular employees. This trend is even more pronounced in the high-tech sector. Firms in the middle 40% R&D intensity group within this sector have a decrease by 0.777 percentage points, while those in the top 40% R&D intensity group exhibit a lager decrease of 1.739 percentage points in the ratio of non-regular employees.

These findings strongly suggest that in high-tech industries, higher R&D intensity is associated with a lower proportion of non-regular workers. When further distinguishing between conglomerates and non-conglomerates within the high-tech sector, the effect remains particularly notable among non-conglomerate firms. Specifically, firms in the middle 40% and top 40% R&D intensity groups among non-conglomerates show a decrease of 0.673 percentage points and 1.552 percentage points, respectively.

Table 3.10

Effect on non-regular employment ratio in high-tech manufacturing

	Ratio of non-regular employees to total employees (%)				
	Total industry	High-tech manufacturing			Non high-tech
		All	Conglo.	Non-conglo.	
	(1)	(2)	(3)	(4)	(5)
R&D group					
- Middle 40%	-0.565*	-0.777**	-0.879	-0.673*	0.086
	(0.301)	(0.210)	(0.491)	(0.220)	(0.218)
- Top 40%	-0.982**	-1.739**	-6.546*	-1.552**	0.021
	(0.465)	(0.372)	(2.576)	(0.337)	(0.437)
Yearly salary per capita (log)	-4.318***	-3.038***	-7.999	-2.951***	-4.328***
	(0.745)	(0.247)	(4.089)	(0.235)	(1.087)
Enterprise value	0.015	-0.007*	-0.012	-0.134	0.016
	(0.019)	(0.003)	(0.006)	(0.103)	(0.022)
Sales	0.165***	0.154***	0.174**	0.839	0.066
	(0.055)	(0.020)	(0.048)	(0.463)	(0.056)
Capital	-0.238**	-0.085***	-0.118*	13.852	-0.416**
	(0.114)	(0.014)	(0.039)	(7.943)	(0.180)
Borrowing ratio	-0.011*	-0.003	0.018	-0.010*	-0.012
	(0.006)	(0.006)	(0.023)	(0.004)	(0.008)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	21,382	5,680	296	5,384	9,538
R^2	0.030	0.020	0.150	0.027	0.027

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

However, the impact appears less pronounced or statistically insignificant in the non-high-tech sector and certain segments of the service sector. While some negative coefficients are observed in high-tech and non-high-tech services, they are generally not statistically significant, with a few exceptions. Notably, in Table 3.11, the top 40% R&D intensity group in high-tech services among non-conglomerates shows a decrease of 2.986 percentage points, indicating a substantial reduction in the ratio of non-regular employees in this specific category.

Table 3.11
Effect on non-regular employment ratio in high-tech services

	Ratio of non-regular employees to total employees (%)				
		High-tech services			
	Total industry (1)	All (2)	Conglo. (3)	Non-conglo. (4)	Non high-tech services (5)
R&D group					
- Middle 40%	-0.565* (0.301)	-1.858 (1.257)	0.686 (0.529)	-2.406 (1.344)	-0.464 (0.613)
- Top 40%	-0.982** (0.465)	-2.487 (1.140)	-0.515 (1.038)	-2.986* (1.142)	-0.291 (1.126)
Yearly salary per capita (log)	-4.318*** (0.745)	-4.633 (2.057)	-5.912 (3.441)	-4.673 (2.138)	-3.758** (1.514)
Enterprise value	0.015 (0.019)	0.043** (0.010)	0.017 (0.123)	-0.001 (0.048)	0.080 (0.159)
Sales	0.165*** (0.055)	-0.609 (0.263)	3.989*** (0.635)	-0.964* (0.378)	0.521** (0.221)
Capital	-0.238** (0.114)	-0.344 (0.256)	-11.499 (7.858)	0.438 (0.592)	-1.197** (0.570)
Borrowing ratio	-0.011* (0.006)	0.015 (0.009)	0.161*** (0.023)	0.015 (0.009)	-0.043*** (0.013)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	21,382	2,217	117	2,100	3,396
R^2	0.030	0.062	0.178	0.066	0.034

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

3.5.4 Ratio of female employees

The impact of R&D on the proportion of female employees varies significantly across sectors. In the high-tech manufacturing sector, particularly within conglomerates, higher R&D intensity is associated with an increased share of female employees. Conversely, in the high-tech services sector, greater R&D intensity correlates with a lower proportion of female workers.

In the high-tech sector (Table 3.12), firms in the middle 40% R&D intensity group exhibit a positive and statistically significant effect on the ratio of female employees, with an increase of 1.250 percentage points compared to being in the bottom 20% group. However, for being in the top 40% R&D intensity group, the coefficient is not statistically significant. Within high-tech conglomerates, both the middle 40% and top 40% R&D intensity groups demonstrate a statistically significant increase in the proportion of female employees. Specifically, the middle 40% R&D intensity group reports an increase of 3.716 percentage points, while the top 40% R&D intensity group records an increase of 5.503 percentage points.

In contrast, in the high-tech services sector (Table 3.13), increased R&D intensity is associated with a decline in the proportion of female employees. Firms in the middle 40% R&D intensity group exhibit a decrease of 1.209 percentage points, while those in the top 40% R&D intensity group show an even strong decrease of 1.577 percentage points. The negative relationship between R&D intensity and female employment is particularly pronounced among non-conglomerate high-tech service firms.

These findings underscore the sector-specific nature of the relationship between R&D intensity and female employment. While increased R&D investment in high-tech manufacturing, particularly within conglomerates, appears to support greater female workforce participation, the opposite effect is observed in high-tech services, particularly among non-conglomerate firms. The underlying causes of this divergence may include skill biased technological change, which tends to favor male dominated fields such as STEM, as well as the nature of R&D activities within these industries. In other words, the service sector among non-conglomerates reflects the characteristics of STEM fields. In contrast, the manufacturing sector, particularly among conglomerates, has actively increased the employment of skilled women despite this structural tendency.

Table 3.12

Effect on female employment ratio in high-tech manufacturing

	Ratio of female employees to total employees (%)				
		High-tech manufacturing			
	Total industry	All	Conglo.	Non-conglo.	Non high-tech
	(1)	(2)	(3)	(4)	(5)
R&D group					
- Middle 40%	-0.129 (0.244)	1.250* (0.484)	3.716** (0.903)	0.889 (0.392)	-0.130 (0.264)
- Top 40%	-0.578 (0.351)	0.377 (0.505)	5.503** (1.718)	-0.075 (0.522)	-0.102 (0.266)
Yearly salary per capita (log)	-4.824*** (0.781)	-6.755** (1.511)	-2.341 (2.505)	-6.975** (1.381)	-4.631*** (1.090)
Enterprise value	0.033 (0.023)	0.002 (0.006)	-0.001 (0.002)	0.502* (0.181)	0.065* (0.038)
Sales	-0.098 (0.062)	0.059 (0.071)	-0.001 (0.026)	-1.189 (0.827)	-0.086 (0.073)
Capital	-0.155 (0.097)	-0.105 (0.090)	0.031 (0.047)	9.115*** (1.236)	-0.152 (0.253)
Borrowing ratio	0.000 (0.005)	0.005 (0.006)	-0.102 (0.077)	0.005 (0.008)	0.003 (0.008)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	21,382	5,680	296	5,384	9,538
R^2	0.052	0.054	0.189	0.063	0.031

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.13

Effect on female employment ratio in high-tech services

	Ratio of female employees to total employees (%)				
		High-tech services			
	Total industry	All	Conglo.	Non-conglo.	Non high-tech services
	(1)	(2)	(3)	(4)	(5)
R&D group					
- Middle 40%	-0.129 (0.244)	-1.209** (0.253)	0.011 (0.629)	-1.280** (0.266)	0.106 (0.480)
- Top 40%	-0.578 (0.351)	-1.577*** (0.240)	-0.934 (1.049)	-1.591*** (0.206)	-0.622 (1.052)
Yearly salary per capita (log)	-4.824*** (0.781)	-4.235** (0.954)	-5.548 (4.213)	-4.269** (1.086)	-4.354*** (0.819)
Enterprise value	0.033 (0.023)	0.011 (0.060)	0.091 (0.069)	0.077 (0.253)	0.067 (0.123)
Sales	-0.098 (0.062)	1.772 (2.008)	-0.273 (0.494)	1.373 (2.949)	0.034 (0.158)
Capital	-0.155 (0.097)	-7.687 (4.883)	1.198 (3.793)	-9.972** (2.776)	-1.694*** (0.572)
Borrowing ratio	0.000 (0.005)	0.005 (0.007)	-0.070 (0.075)	0.005 (0.007)	-0.042** (0.018)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	21,382	2,217	117	2,100	3,396
R^2	0.052	0.175	0.604	0.169	0.105

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

3.5.5 Yearly salary per capita

In general, higher R&D intensity is associated with increased average salaries, particularly in the high-tech manufacturing sector and among conglomerates. However, in certain sectors, such as non-conglomerate high-tech services with medium R&D intensity, a statistically significant negative relationship is observed.

For the total industry, firms in the top 40% R&D intensity group exhibit an increase of 1.8 percent, whereas being in the middle 40% R&D intensity group do not show a statistically significant effect (Table 3.14). This suggests that firms with high R&D intensity in the total industry tend to offer slightly higher average salaries compared to be in the bottom 20% R&D intensity group. Within the high-tech sector, firms in the middle 40% R&D intensity group report an increase of 4.3 percent on salary. However, for firms in the top 40% R&D intensity group, the coefficient is not statistically significant. Among high-tech conglomerates, firms in the middle 40% R&D intensity group exhibit an increase of 3.3 percent, while those in the top 40% R&D intensity group report an increase of 3.2 percent. Conversely, within high-tech non-conglomerates, the coefficients for both the middle 40% and top 40% R&D intensity groups are not statistically significant, indicating that increased R&D intensity does not have a meaningful effect on wages in these firms. Meanwhile, R&D intensity does not have a significant impact on salaries within the high-tech services sector (Table 3.15). In contrast, within non-conglomerate high-tech service firms, the middle 40% R&D intensity group reports a decrease of 1.7 percent on salary. This suggests that in non-conglomerate high-tech services, medium R&D intensity may have an adverse effect on average salaries.

These findings underscore the sector-specific nature of the relationship between R&D intensity and wages, indicating that while high-tech conglomerates experience higher salaries with increased R&D investment, the impact is less pronounced or even negative in certain non-conglomerate service sectors. Given these results, there is a possibility that R&D expenditures may contribute to widening the wage gap between SMEs and conglomerates, further reinforcing disparities in the labor market.

Table 3.14

Effect on salary in high-tech manufacturing

	Yearly salary per capita (log)				
	Total industry	High-tech manufacturing			Non high-tech
		All	Conglo.	Non-conglo.	
	(1)	(2)	(3)	(4)	(5)
R&D group					
- Middle 40%	0.006 (0.008)	0.043* (0.016)	0.033*** (0.003)	0.045 (0.020)	0.003 (0.008)
- Top 40%	0.018* (0.010)	0.053 (0.027)	0.032** (0.010)	0.060 (0.030)	0.008 (0.011)
Enterprise value	0.002 (0.001)	0.000 (0.000)	0.000 (0.000)	0.003 (0.009)	0.002* (0.001)
Sales	0.004* (0.002)	0.007 (0.004)	0.006 (0.003)	0.146* (0.052)	-0.000 (0.003)
Capital	-0.007 (0.004)	-0.004 (0.004)	-0.002 (0.001)	-0.106 (0.101)	-0.011** (0.005)
Borrowing ratio	-0.001*** (0.000)	-0.001*** (0.000)	-0.004** (0.001)	-0.001** (0.000)	-0.001*** (0.000)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	21,382	5,680	296	5,384	9,538
R^2	0.435	0.450	0.682	0.442	0.517

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.15

Effect on salary in high-tech services

	Yearly salary per capita (log)				
	Total industry	High-tech services			Non high-tech services
		All	Conglo.	Non-conglo.	
	(1)	(2)	(3)	(4)	(5)
R&D group					
- Middle 40%	0.006 (0.008)	-0.010 (0.009)	0.025 (0.022)	-0.017* (0.007)	-0.011 (0.018)
- Top 40%	0.018* (0.010)	-0.008 (0.019)	0.017 (0.080)	-0.016 (0.019)	0.023 (0.021)
Enterprise value	0.033 (0.023)	0.011 (0.060)	0.091 (0.069)	0.077 (0.253)	0.067 (0.123)
Sales	-0.098 (0.062)	1.772 (2.008)	-0.273 (0.494)	1.373 (2.949)	0.034 (0.158)
Capital	-0.155 (0.097)	-7.687 (4.883)	1.198 (3.793)	-9.972** (2.776)	-1.694*** (0.572)
Borrowing ratio	0.000 (0.005)	0.005 (0.007)	-0.070 (0.075)	0.005 (0.007)	-0.042** (0.018)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	21,382	2,217	117	2,100	3,396
R^2	0.435	0.388	0.674	0.372	0.366

Notes: Reference group is bottom 20% R&D intensity. Standard errors are clustered at the industry level. Firm specific linear time trends are included in addition to firm & year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

3.6 Conclusion

This study investigates whether firms' R&D activities in Korea contribute to employment growth and examines how these effects vary across sectors, with a particular focus on job security and labor market disparities. It provides empirical evidence on the nuanced and sector-specific impact of firms' R&D activities on the Korean labor market. The results indicate that R&D expenditures influence various labor market outcomes, though the magnitude and direction of these effects differ by industry and firm characteristics.

The impact of R&D investment on labor market outcomes varies significantly across sectors. Differences between high-tech and non-high-tech industries, as well as between manufacturing and services within the high-tech sector, play a critical role in shaping these effects. R&D investment is generally linked to employment growth and a reduction in non-regular employment, suggesting potential job stability benefits in high-tech industries. When considering R&D persistence duration, the relationship between R&D intensity and employment in the high-tech sector becomes more pronounced. However, the effects on gender composition and salary structures are more complex while high-tech manufacturing is associated with a higher proportion of female employees, high-tech services exhibit the opposite trend. Moreover, the wage benefits of R&D are concentrated within conglomerates, whereas smaller firms, particularly in high-tech services, do not experience comparable wage gains.

While this study lacks detailed data on the educational distribution of individual employees and the specific nature of R&D activities, necessitating further research to address these limitations, its findings should be interpreted with caution and not immediately generalized. However, the observed reduction in the ratio of non-regular employees associated with increased R&D investment suggests that the skill-biased nature of R&D

disproportionately benefits regular employees. This asymmetric distribution of benefits may widen the gap between regular and non-regular workers, reinforcing labor market segmentation.

Moreover, considering that conglomerates in high-tech manufacturing experience salary increases associated with higher R&D expenditures, there is a potential risk that R&D investment could further exacerbate existing disparities in the Korean labor market, particularly the gaps between conglomerates and SMEs, as well as between regular and non-regular employment. These findings underscore the need for a differentiated policy approach that accounts for firm- and industry-level heterogeneity. Specifically, government policies supporting firm R&D expenditures must incorporate measures to mitigate the unintended consequences of skill-biased technological change and address its implications for labor market inequality.

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