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Contents

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Introduction

International trade was first emphasized in the Mercantilism theory in the sixteenth century, then in the absolute advantage introduced by Adam Smith and the comparative advantage suggested by David Ricardo. Along with the improvement in the theory of trade over time, the contributions of trading activities to the development of the economy are increasingly highlighted. However, the path of international trade has not always been smooth. Throughout history, trade has witnessed periods of significant expansion, accelerated by technological advancements. Notably, international trade has experienced remarkable growth, thanks to the wave of globalization in the 1980s (e.g, technology revolution). Besides, international trade also experienced a sharp decrease due to wars, economic crises (e.g, global financial crisis in 2008), and diseases (e.g, Covid 19).

The determinants of trade have been explored widely in the literature. According to the gravity equation model first applied in international trade by Tinbergen (1962), trading between two countries is proportional to the economic size and inversely proportional to the distance between these countries. In empirical findings, the determinants of international trade include GDP, trade costs, trade policy, exchange rates, participation in Free Trade Agreements (FTAs), geographic distance between partners, foreign direct investment (FDI), and innovation. While the determinants of export quality are GDP, credit constraints, imported input, FDI, R&D investment, and innovation. Among the various determinants of trade in general and export quality in particular, the relationship with innovation has also been examined from multiple perspectives, and the findings from the current studies are heterogeneous. Besides, the research exploring the impact of export quality on innovation outputs is still lacking. Regarding innovation, many governments have implemented various subsidy programs to stimulate R&D and innovation. However, the causal effect of subsidies on different types of innovation needs more investigation. Thus, this is the motivation for me to conduct the thesis covering the topics of international trade and innovation to fill the existing three gaps in the literature: (1) the overall effect of patents on export performance; (2) the bidirectional relationship between export quality and patent intensity, and the moderating role of institutions on this nexus; and (3) the causal effect of funding from the Horizon 2020 program[1] on European firms' innovation activities.

Over the past two decades, the nexus between patents and export performance has been

[1]The European research and innovation funding program from 2014 to 2020 to accelerate innovation activities, competitiveness, and economic growth.

widely investigated, and the existing findings are heterogeneous based on the types of data and econometric methods used. To investigate the overall effect of patents on export performance, in the first chapter, I use the most prominent tool - Meta-analysis based on the results of the empirical studies. To have a broad view of this relationship, I extract the estimates from 42 empirical studies containing 536 estimates during the span from 2005 to 2025 and then apply Meta-analysis to obtain the overall true effect of patents on export activities.

A crucial factor to enhance trading activities these days lies in the quality rather than the quantity of products sold. Many scholars examine the determinants of export quality. Existing literature often points to factors such as GDP, credit constraints, imported inputs, FDI, and R&D investment as influences. However, the specific and potentially pivotal role of innovation as a direct driver of export quality has been overlooked and warrants more investigation. Especially, only one study (Cai & Wu, 2024) investigated the impact of export quality on innovation outputs, and the results are heterogeneous depending on different types of innovation outputs (patents for inventions, utility model patents, and design patents). Hence, in the second chapter, the two-way relationship between export quality and patent intensity is examined using the three-dimensional panel data of 89 countries from 1999 to 2014 with a Simultaneous Equations Model (SEM), along with Two-Stage Least Squares (2SLS) and Three-Stage Least Squares (3SLS) estimation methods. Besides, this bidirectional relationship is also checked under different subsamples, e.g., different types of countries, levels of technology, levels of export dependence, and export quality levels. Furthermore, I introduce different interaction terms between institutions (government stability, control of corruption, law and order, and bureaucracy quality) and export quality, and between institutions and patent intensity in the SEM to explore the moderation effect of institutional quality on the bidirectional nexus between export quality and patent intensity. Finally, a theoretical model that extends the foundational work on firm heterogeneity by Melitz (2003) and Kugler and Verhoogen (2012) is built. The theoretical model provides insight to first understand how a firm's choices between enhancing quality and increasing patenting are two sides of the same coin, and second, to confirm the findings from the empirical analysis. The key contribution is to endogenize product quality by introducing a technology cost associated with R&D investment, where higher R&D investment leads to higher quality. I further link innovation to intellectual property by modeling the number of patents a firm secures as an increasing function of its R&D investment. The model is designed to analyze the bidirectional relationships between patent intensity and export quality, conditional on a country's given level of institutional quality.

Innovation is crucial for enhancing product quality. However, due to different reasons, e.g., knowledge spillovers (Arrow, 1972; R. R. Nelson, 1959) and financial constraints (Hall & Lerner, 2010), firms cannot conduct innovative activities. The government is an important actor that can remedy these situations by introducing subsidies to support firms. The impact of government subsidies is examined widely in the literature. However, only three studies explored the impact of the Horizon 2020 program on firms' performance, including investment and cite-weighted patents (Santoleri et al., 2024), employment, total assets and revenue (Mitra & Niakaros, 2023), and tangible assets, intangible assets, turnover, employment, patent stock/dummy (Mulier & Samarin, 2021). No studies examine the causal effect of Horizon 2020 on different types of innovation. Thus, this is the incentive for conducting the third chapter to examine the causal effect of the Horizon 2020 program on the innovation of European firms. First, based on the similar model developed in the second chapter, I endogenize a firm's innovation represented in product quality by introducing a technology cost associated with R&D investment and the subsidy from the Horizon 2020 program. The model is static, but I believe that this model can serve as a good starting point to explore the impact of Horizon 2020 on firms' innovation, since Horizon 2020 is a short-run program starting from 2014 to 2020. Production occurs as a sequence: at the beginning of the period, firms receive an initial budget (B) and they choose the innovation level that maximizes their profit subject to their budget constraint; at the end of the period, the profit is realized and earned by firms. I apply the Lagrange method to solve the firm's profit maximization problem. The First Order Condition (FOC) allows me to explain the impact of subsidy on a firm's R&D investment with two different cases. Then, continuing from this step, I solve the FOC to obtain the optimal innovation, which depends on the Horizon 2020 funding. This helps to directly analyze how this subsidy shapes the firm's innovation activities. Second, using firm-level data from the Community Innovation Survey (CIS) adopted from the Eurostat and applying the Difference-in-difference (DiD) estimation with repeated cross-section with multiple periods and time heterogeneity, I estimate the causal effect of Horizon 2020 on firms' innovation, including product innovation, process innovation, organizational innovation, marketing innovation, and expenditure on innovation. This is one of the important contributions of this chapter to the literature since no prior studies have investigated the impact of subsidies on different types of innovation.

The structure of the thesis is as follows: Chapter 1 discovers *The Impact of Patents on Export Performance: A Meta-Analysis*. *Export Quality and Patent Intensity: A Bidirectional Relationship Moderating by Institutional Quality* is explored in Chapter 2. Finally, Chapter 3 unearths the *Innovation Activities of European Firms under Horizon 2020*.

Chapter 1

The Impact of Patents on Export Performance: A Meta-Analysis

Over the past two decades, hundreds of studies have investigated the impact of patents on trade activities, with results varying widely across data types, methodologies, and countries. This paper seeks to systematically explore the true effect of patents on exports. Our meta-analysis includes 536 estimates from 42 empirical studies conducted between 2005 and 2025. I employ a mixed-effects multilevel model to uncover the genuine effect. The findings reveal that the average effect of patents on export performance is: (i) positive across the entire sample, as well as in country-level data, sector-level data, firm-level data, and developed countries data studies; (ii) after controlling for moderators, the genuine effect remains positive for all studies, country-level data, and firm-level data subsamples, but is insignificant in the other subsamples; (iii) the moderators influence the effect-size estimates in a heterogeneous manner.

1.1 Introduction

Since the 1980s, the wave of globalization has fostered growth in international trade. Trading activities play an important role in the development of a country (Cao & Wang, 2017; Sun & Heshmati, 2010). The determinants of exports are thus investigated broadly in the literature. They are trade policy, trade cost, exchange rate, geographic distance, and Free Trade Agreements (FTAs). Foreign direct investment (FDI) and economic growth are also important determinants of trade (Dritsakis & Stamatiou, 2017). Among the several different determinants of trade, the relationship with innovation has been examined from different perspectives. Specifically, the positive impact of innovation on export performance is discovered by D'Angelo (2012), Golovko and Valentini (2011), A. N. Nguyen et al. (2008), and Tavassoli (2018); F. Wu et al. (2020) found a negative impact of innovation on export; while Edeh et al. (2020) show a negative nexus between product innovation and export, but a positive relationship between process and marketing innovation and export performance.

Patents are a key output of innovation, and numerous studies have explored the relationship between innovation, as measured by patent applications, and export activities. The findings are heterogeneous, varying based on factors such as data type, econometric methods, and the time span covered in the studies. Specifically, several studies using firm-level data report a positive impact of patents on exports, including Bhattacharyya et al. (2024), Chadha (2009), Dosi et al. (2015), Rodríguez and Rodríguez (2005), and L. Wu et al. (2022). A similar result is also found in studies using country-level data (Bierut & Kuziemska-Pawlak, 2017; Meo & Usmani, 2014; Ohm & Penickova, 2023). On the other hand, a negative impact of patents on export performance is identified in Alshubiri and Al Ani (2024), Banerji and Suri (2017), and Ghorbal et al. (2021). Additionally, several studies uncover a non-linear relationship between patents and trade (Bai & Oh, 2024; Mac An Bhaird & Curran, 2016; Nam & An, 2017; Orviská et al., 2019) suggest that the impact of patents on exports is positive and significant for large enterprises, while it appears insignificant for small and medium-sized enterprises (SMEs). Johnson and Van Wagoner (2021) argue that, at the aggregate level, imports drive innovation, which in turn leads to increased exports; however, at the industry level, the relationship is more complex, with innovation influencing both imports and exports. The existing studies display the heterogeneous impact of patents on export performance. Thus, it is necessary to conduct a literature review on this topic to discover the reasons for this discrepancy in the current findings.

Meta-analysis is a powerful tool for synthesizing evidence across multiple studies. There is a wide range of research using the meta-analysis approach to examine the innovation topic, particularly, the impact of open innovation on innovation output (T. P. T. Nguyen et al., 2021), the relationship between internationalization and innovation (S. Wu & Fan, 2024), impact of innovation on export performance (Bıçakcıoğlu-Peynirci et al., 2020; Panda & Sharma, 2023). In these studies, the authors use different measures of innovation, such as technological innovation, organizational innovation, innovation capabilities, innovation resources, and innovation performance in (Bıçakcıoğlu-Peynirci et al., 2020); and R&D, patent, innovation outcome, innovation capabilities, and technological effort in (Panda & Sharma, 2023). The positive overall effect of internationalization on innovation is discovered in S. Wu and Fan (2024). Innovation has a positive true effect on exports is also found in Bıçakcıoğlu-Peynirci et al. (2020). While Panda and Sharma (2023) prove that developed countries' domestic innovation accelerates exports; however, innovation does not enhance exports of developing countries. However, to the best of our knowledge, there is no meta-analysis tackling the impact of patents on export performance.

Thus, this study aims to fill this gap and provide a comprehensive synthesis of the evidence showing the relationship between patents and export activities. Based on the literature regarding Meta-analysis, I conduct this study in the following steps. First, the publication bias is evaluated by different methods (Funnel plot, FAT/PET, and PEESE); second, the weighted average effects from adequately-powered (WAAP) is conducted to address the issue of studies with low statistical power, which may lead to biased or misleading effect size estimates; third, to select the suitable moderators in the meta-regression model, the weighted-average least squares (WALS) is applied; finally, the mixed-effects multilevel model is employed to estimate meta-regression. This method provides more consistent results compared to other methods.

The paper uses the data obtained from 42 empirical studies containing 536 estimates during the span from 2005 to 2025. Besides estimating all the studies in the data, I divide the studies into country-level data, sector-level data, firm-level data, and the data for firms in developed, developing, and mixed countries (studies using data from developed and developing countries) to investigate the heterogeneity in the true effect and the influence of moderators on this effect-size estimate for each specific subsample. The findings suggest that there is a genuine positive patent effect on exports for the whole sample and four subsamples: country-level data, sector-level data, firm-level data, and developed countries data. After controlling for moderating variables, this positive result remains for the whole sample, country-level data, and firm-level data. In the other samples (sector-level data and developed countries), these findings turn out to be insignificant. The moderators help to explain the heterogeneity in the findings of the primary studies significantly.

The structure of the paper is as follows: Section 1.2 is the Literature Review, representing the historical view of innovation and patents, and the nexus between patents and exports. The Meta-Analysis and Studies' Selection for the research are provided in Section 1.3. Section 1.4 discusses the Average Effect and Publication Bias before jumping to the Meta-Regression Analysis in Section 1.5. Finally, the Conclusion is in Section 1.6.

1.2 Literature Review

1.2.1 The Overview of Innovation and Patents

Innovation in the understanding of economists has changed over time, namely *"Economists first understood it as process innovation, then as technological change, then as innovation, and now as innovation in a very broad sense"* (Vernardakis, 2016, p.91).

Classical economics, particularly Adam Smith, viewed innovation as new production methods driven by learning (doing, using, scientific) (Smith, 1937). Joseph Schumpeter later formalized innovation as the implementation of new resource combinations leading to new products, processes, markets, supply sources, or organizational forms, driven by entrepreneurs (Schumpeter, 1954). The Oslo Manual defines innovation as a significantly new or improved product or process made available or brought into use. It identifies four types: product, process, marketing, and organizational (OECD, 2018). Innovation can be categorized into technological (product/process) and non-technological (organizational/managerial) (Ortigueira-Sánchez et al., 2022). Regarding the measurement of innovation, Rogers (1998) categorizes innovation measures into input indicators (e.g., R&D, new technology acquisition) and output indicators (e.g., new product introductions, sales from innovation, intellectual property, firm performance).

Due to "*The value and cost of individual patents vary enormously within and across in-*

dustries. Many inventions are not patented. And in some industries, like electronics, there is considerable speculation that the patent system is being bypassed to a greater extent than in the past. Some types of technologies are more likely to be patented than others." (Mansfield, 1984, p.462), patenting activities vary across industries. Scherer (1983) noted that in highly concentrated and capital-intensive industries, firms are incentivized to invest in patents as a strategy to elevate entry barriers for potential competitors. Using the data from 100 US manufacturing firms, Mansfield (1986) shows that patents significantly enhance the innovation rate of the pharmaceuticals and chemicals industries, but this impact is trivial in most other industries investigated in the study[1].

Although "*patents are a flawed measure (of innovative output), particularly since not all new innovations are patented, and since patents differ greatly in their economic impact*" (Pakes & Griliches, 1980, p.378), patents are still regarded as one of the most significant forms of intellectual property and a key indicator of innovation. According to Griliches (1990), patents offer three main advantages: (1) they are closely linked to inventive activities, (2) they provide objectivity, as they are granted by independent patent offices, and (3) data on patents are widely available across different countries, years, and fields of innovation. Moreover, patents serve two essential economic functions: they provide legal protection for knowledge capital and disclose detailed specifications of innovations (Fung, 2005). Patents protect novel inventions and grant firms or individuals exclusive rights to exploit their intellectual property for a limited period. This exclusivity can influence trade dynamics by driving export growth and facilitating technology transfer. The impact of patents on exports is explored in detail below.

1.2.2 The Nexus between Patents and Exports

A wide range of studies investigates the relationship between innovation and international trade. The findings are controversial depending on the different measures of innovation and trading activities, and different types of data and econometric approaches used.

Patents are a key output of innovation, and many studies have explored the relationship between innovation, measured by patent applications, and export activity, generally finding a positive connection. Specifically, Rodríguez and Rodríguez (2005) used data from Spanish manufacturing firms, Dosi et al. (2015) analyzed data from Italian firms, Spuldaro et al. (2021) examined 140 manufacturing firms from Brazil, Russia, India, and China between 2008 and 2012, Liu Y. (2022) used the data from Chinese state-owned enterprises (SOEs), and L. Wu et al. (2022) focused on Chinese manufacturing firms from 1998 to 2007, all demonstrating the positive impact of patents on export performance. Additionally, several studies examining Indian pharmaceutical firms over different periods have also found a positive relationship between patents and pharmaceutical exports (Bhattacharyya et al., 2024; Chadha, 2009; Tyagi & Nauriyal, 2017; Tyagi et al., 2014). On the contrary, Banerji and Suri (2019) prove that total patents do not affect but their lagged negatively affect export intensity of Indian

[1] primary metals, electrical equipment, instruments, office equipment, motor vehicles, rubber, and textiles.

pharmaceutical firms. Further evidence exploiting firm-level data, for instance, Chalioti et al. (2020) use Greek firms' data to show a positive impact of patent applications on export sales, and Zucoloto et al. (2017) prove a positive relationship between invention patents and export of manufacturing firms in Brazil. Using French data within firm-product-country destinations, De Rassenfosse et al. (2022) examine the relationship between international patent protection and trade. Their results show that patents in a destination country are positively associated with export quantities. In a recent analysis, Pulido-López and López-Salazar (2025) explore the nexus between internationalization measured by export propensity and intellectual capital components for the Colombian manufacturing sector. The findings suggest a positive impact of innovation, measured by patents on export.

Several studies use state, sector, or industry-level data to explore a similar nexus. For example, using the data from 25 sectors and 9 countries, Montobbio and Rampa (2005) show a positive impact of the share of patents on exports for the high-tech sector, while no significant impact is found for medium or low-tech ones. Vlčková and Stuchlíková (2021) investigate the relationship between patents and export activities at the state level in Germany and found that patent applications positively affect exports but negatively affect exports to GDP. Using the data on 14 manufacturing industries in 16 OECD countries, Lamperti et al. (2020) prove a positive impact of the share of national industry patent applications over the sum of the industry's patent applications on the country's exports in the industry over the total industry's export.

Besides, country-level data is also widely used to discover the nexus between patents and export activities. The number of patent applications does not affect absolute exports (Neuhäusler & Frietsch, 2013). The positive relationship between patents and exports has been demonstrated in several studies using data from European countries. Notable examples include 47 European countries covering the period from 1996 to 2011 (Meo & Usmani, 2014), Central and Eastern European (CEE) countries (Bierut & Kuziemska-Pawlak, 2017), 28 EU member states from 2008 to 2019 (Ohm & Penickova, 2023), 28 countries in Europe along with 11 CEE economies (Kittová et al., 2023), and China (Kittová & Družbacká, 2023). Other studies have explored similar relationships using diverse countries' datasets. For instance, Verheyen (2015) analyzed 27 countries from 1980 to 2011, Frietsch et al. (2014) focused on technology fields in selected countries, and Kabaklarli and Üçler (2018) examined selected OECD countries between 1989 and 2015. Additionally, Malik et al. (2021) analyzed data from 101 countries over 21 years, while Tadevosyan (2023) studied 67 countries from 1993 to 2020, and Hoan and My (2022) focused on Vietnam's ICT exports to EU countries from 2000 to 2019. Konya et al. (2021) used data from six fast-growing emerging economies (Brazil, Russia, India, China, South Africa, and Turkey) spanning the period from 1996 to 2017. Ashari and Blind (2024) analyzed data from 32 countries covering the period from 1995 to 2019 to examine the impact of hydrogen innovation on international hydrogen trade. The findings from these studies suggest that export performance is positively correlated with the number of patents. The most recent study, by Islam et al. (2025), investigates the relationship between recyclable materials export, employment, and technological innovation in Europe from 2000 to 2021. The results prove a positive impact of industrial patents on recyclable material exports.

The non-linear relationship between patents and trade is demonstrated by Nam and An (2017), who explored the link between patents and internationalization, measured by exports, using data from 47 Korean healthcare firms over a seven-year period from 2008 to 2014. Wagner (2006), employing quantile regression and a rich cross-sectional data set from German manufacturing plants, found that patents are not significant at the lower end of the conditional distribution of exports relative to sales. Similar findings are reported in the studies by Mac An Bhaird and Curran (2016) and Orviská et al. (2019). Specifically, Orviská et al. (2019), using data from 61 countries over 20 years and applying Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) methods, found that, after controlling for academic publications and GDP, the relationship between patents and high-tech exports is insignificant. Similarly, Mac An Bhaird and Curran (2016), using firm-level data from Irish SMEs and Quasi-maximum likelihood models, investigated the relationship between patent income and export intensity. The results indicated that patent income only influences export intensity in the Cloglog model, while there are no significant effects in the Logit, Probit, and Loglog models. Using the data from the Indian pharmaceutical industry, Banerji and Suri (2017) shows that total patents granted do not Granger-cause pharmaceutical exports. Additionally, when using the Autoregressive Distributed Lags (ARDL) model to examine the determinants of pharmaceutical exports, the results confirm that patents do not affect, but their lag does have a negative impact on export performance. Applying the prominent gravity equation model with bilateral trade data, Palangkaraya et al. (2017) indicated that exporters are deterred from doing export activities to the countries with a higher number of patents.

To sum up, the relationship between patents and export performance varies across studies, influenced by factors such as the type of country, firm, and sector. In particular, the impact is positive and significant for large enterprises, while it appears insignificant for small and medium-sized enterprises (SMEs) (Bai & Oh, 2024). Additionally, patents are positively associated with exports in developing countries but have a negative effect in developed countries (Alshubiri & Al Ani, 2024). The quality of patents negatively impacts export activities in developed countries, though this effect is not significant in developing countries (Bhat & Momaya, 2020). Bayraktutan and Bıdırdı (2018) and Kunze (2016) highlight the critical role of innovation for both imports and exports, although this relationship is not consistent across sectors. At the aggregate level, the literature suggests that imports drive innovation, which in turn leads to increased exports, but at the industry level, the causality is more complex, with innovation influencing both imports and exports (Johnson & Van Wagoner, 2021). Furthermore, the time frame used in studies can impact the findings. Specifically, Ghorbal et al. (2021) find that both foreign and non-foreign patents positively affect trade in the short term, but in the long term, only non-foreign patents negatively impact trade. Similar to the time frame, the effect of patents on export performance is also changing for different sectors.

Namely, the innovation quantity, measured by the number of patents, does not affect export values in the aerospace industry, as found in the study of Caliari et al. (2023). Miremadi and Mardukh (2024) used the country-level data to explore the nexus between the knowledge dimensions of the innovation system and renewable equipment export and renewable electricity generation, and found that renewable patents do not affect renewable energy equipment export.

The summary of the impact of patents on exports is provided in Table 1.1.

Table 1.1: The impact of patents on export performance

Author(s)	**Findings**	**Sign of impact**
Islam et al. (2025)	There is a positive impact of industrial patents on recyclable material exports.	positive
Pulido-López and López-Salazar (2025)	The relationship between innovation and export propensity of the Colombian manufacturing sector is positive.	positive
Alshubiri and Al Ani (2024)	Patents are positively associated with exports in developing countries but have a negative effect in developed countries.	mixed
Ashari and Blind (2024)	Patenting accelerates hydrogen exports.	positive
Bai and Oh (2024)	Overseas patent applications positively affect the total export of large enterprises, but this impact is insignificant in the case of SMEs.	mixed
Bhattacharyya et al. (2024)	Granting of patents shows a significant and positive impact on pharmaceutical exports.	positive
Miremadi and Mardukh (2024)	Renewable patents do not affect renewable energy equipment export.	insignificant
Caliari et al. (2023)	The innovation system quantity, measured by the number of patents, does not affect export values in the aerospace industry.	insignificant
Kittová et al. (2023)	The number of patent applications per million inhabitants in the economy positively affects domestic value added in exports per capita.	positive
Kittová and Družbacká (2023)	The number of patents by residents per million inhabitants positively affects the domestic value added share on gross export.	positive
Ma et al. (2023)	Utility model patent quality significantly enhances enterprises' export domestic value-added rate.	positive
Ohm and Penickova (2023)	EPO per million inhabitants and export volumes per million inhabitants have a positive correlation.	positive
Tadevosyan (2023)	Patents have a positive impact on export and Grange causes an increase in export.	positive
De Rassenfosse et al. (2022)	Patents in destination country enhance the export quantities.	positive
Hoan and My (2022)	The number of patents registered in Vietnam contributes to increased high-tech exports.	positive
Liu Y. (2022)	The impact of innovation competence on firms' exports is positive.	positive
L. Wu et al. (2022)	Technological innovation, measured by patents, has a positive effect on exports.	positive

Table 1.1: The impact of patents on export performance (cont.)

Author(s)	Findings	Sign of impact
Ghorbal et al. (2021)	Foreign patents and non-foreign patents positively affect trade in the short run but only non-foreign patents negatively affect trade in the long run.	mixed
Konya et al. (2021)	Economic growth, FDI, patents, and trade deficit are determinants of high-tech exports.	positive
Johnson and Van Wagoner (2021)	While the literature generally assumes imports drive innovation, which in turn boosts exports at a national level, the relationship is more complex within specific industries. In these cases, imports, exports, and innovation can all influence each other.	mixed
Malik et al. (2021)	The national absorptive capacity measured by patents per capita positively affects high-tech exports.	positive
Spuldaro et al. (2021)	Domestic and foreign patents positively affect export intensity.	positive
Vlčková and Stuchlíková (2021)	Patent applications positively affect exports but negatively affects exports to GDP	mixed
Bhat and Momaya (2020)	Patent quality negatively affects the export performance of developed countries and no significant results are found in developing countries.	mixed
Chalioti et al. (2020)	Patent applications positively affects export sales.	positive
Lamperti et al. (2020)	The share of national industry patents applications over the sum of the industry's patents applications is positively associated with the country's exports in the industry over the total industry's export.	positive
Banerji and Suri (2019)	Total patents do not affect but its lagged negatively affect export intensity.	mixed
Orviská et al. (2019)	The effect of patents on high technology exports is insignificant when controlling for academic publications and GDP.	insignificant
Bayraktutan and Bıdırdı (2018)	The impact of patents on high-tech exports can be positive, negative, or insignificant depending on the countries considered.	mixed
Kabaklarli and Üçler (2018)	The increase in patent applications plays a decisive role in upgrading selected OECD countries' high-tech exports.	positive
Banerji and Suri (2017)	Patents do not affect, but its lag does harm export performance.	mixed
Bierut and Kuziemska-Pawlak (2017)	Patent applications significantly and positively impact export performance.	positive
Nam and An (2017)	There is a non-linear relationship between patents and internationalization measured by exports.	non-linear
Palangkaraya et al. (2017)	Being refused a patent has a negative impact on trade.	negative
Tyagi and Nauriyal (2017)	Higher patent count is an important determinant of firm-level export performance.	positive
Zucoloto et al. (2017)	Invention patents positively influence exports of Brazilian manufacturing firms.	positive
Kunze (2016)	Innovation measured by patents is a significant determinant for imports and exports; however, this relationship is not significant in every sector.	mixed
Mac An Bhaird and Curran (2016)	Patent income does not significantly impact export intensity.	insignificant
Dosi et al. (2015)	At the micro level in most sectors patents correlate positively both with the probability of being an exporter and with the capacity to acquire and to increase exports.	positive
Verheyen (2015)	Patents affect export demand positively.	positive

Table 1.1: The impact of patents on export performance (cont.)

Author(s)	Findings	Sign of impact
Frietsch et al. (2014)	Export is positively associated with the number of patent applications.	positive
Meo and Usmani (2014)	There is a positive correlation between patents and high-tech exports.	positive
Tyagi et al. (2014)	Lagged total patents affect exports positively.	positive
W.-C. Chen (2013)	Patents positively affect both extensive and intensive margins.	positive
Neuhäusler and Frietsch (2013)	The number of patent applications does not affect absolute exports.	insignificant
Chadha (2009)	Foreign patent rights has a positive impact on exports.	positive
Tikkanen (2008)	Number of innovations, measured by the number of patent applications, is positively correlated with exports.	positive
Wagner (2006)	Patents do not matter at the very lower end of the conditional distribution of export over sales.	insignificant
Blind and Jungmittag (2005)	The primary reason for Germany's export achievements is its ability to innovate.	positive
Montobbio and Rampa (2005)	There is a positive impact of the share of patents on exports for high-tech sector but no impact is found for medium and low-tech ones.	mixed
Rodríguez and Rodríguez (2005)	Patents positively and significantly affect both the decision to export and the export intensity.	positive

1.3 Meta-Analysis and Studies' Selection

This paper reviews the prior analyses of the relationship between patent applications and export performance using the Meta-analysis technique, which *"provides a more formal and objective process on reviewing empirical literature. It employs conventional statistical methods and criteria to summarize and evaluate empirical economics"* (Stanley, 2001, p.147-148). This technique uses statistical methods to summarize and analyze the empirical results. Besides, it allows us to compare the differences in empirical results and identify the sources of heterogeneity. Specifically, the heterogeneity in the effect sizes reported in the primary studies is explained by estimating the standard regression model (from Stanley and Jarrell (2005)) as follows:

$$b_j = \alpha + \sum_{k=1}^{K} \alpha_k Z_{kj} + e_j \qquad (j = 1, 2, ..., L) \tag{1.1}$$

Where b_j: the reported estimate of the phenomenon α. In the context of this analysis, b_j is the reported estimate of the impact of patents on export performance. Z_{kj}: K meta-independent variables measuring relevant characteristics of empirical studies; α_k: the meta-regression coefficients; and e_j is the error term. Equation (1.1) evaluates how the studies' characteristics affect the estimation of the effect sizes.

To select the studies for the meta-analysis, in the first stage, I adopt the three strategies outlined in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method: identification, screening, and inclusion, which is shown in Figure 1.1. We conduct searches within the article title, abstract, and keywords in Scopus and searches within all fields in Web of Science using the keywords *"Patents"* and *"Export"* to identify relevant papers for analysis. Scopus retrieved 835 papers, while Web of Science retrieved 228[2]. After removing non-English papers; non-article types (such as conference papers and proceedings); non-economics, econometrics, and finance, business, management and accounting, and social sciences areas; and papers before 2005, we obtain 350 papers from Scopus[3] and 130 from Web of Science[4]. After removing duplicates, we obtain 389 papers. Screening the abstracts of these papers and excluding 200 papers that only cover either patents or exports. After scanning and skimming 189 papers, 132 papers that did not examine the impact of patents on exports (patents and exports act as the independent variables or papers explore the impact of exports on patents), and did not include empirical approaches were excluded. 57 full-text articles were assessed for eligibility after excluding papers that did not provide the necessary information to support the meta-analysis. Ultimately, 42 papers met the criteria for analysis, as shown in Table 1.2.

According to Aguinis et al. (2011) and Geyskens et al. (2009), there are two types of effect sizes in management: correlation coefficients and standardized mean differences. However, in finance and economics, the marginal effects obtained from regression models are more pivotal in the views of researchers (Stanley & Doucouliagos, 2012). Following Neves et al. (2021) and Ugur (2014), this analysis uses the partial correlation coefficient (PCC) as an effect size, which is calculated as follows:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \tag{1.2}$$

$$SE_i = \sqrt{(1 - PCC_i^2)/df_i} \tag{1.3}$$

Where SE_i is the standard error of the PCC in study i, t_i denotes the t-statistic correlated with each coefficient in the study i, and df_i represents the degree of freedom in the respective estimation.

There are a total of 536 estimates, of which 437 are positive and 99 are negative. The coefficient showing the impact of patents on export performance ranges from -13.66 (Malik et al., 2021) to 267 (Ohm & Penickova, 2023). Of these, 331 estimates are derived from data from developed countries, while 87 estimates come from developing countries, and 80 from mixed-country (studies using data from developed and developing countries) data. Additionally, 256 estimates are based on country-level data, 31 estimates are based on sector-level data, and 249 are derived from firm-level data. The majority of studies utilize panel data, with 468 estimates obtained from this approach. The main characteristics of primary studies are provided in detail in Table 1.3.

[2]Data is retrieved on 14th May 2025.

[3]Excluding 63 non-English papers, 221 non-article papers, 154 papers not in economics, econometrics, and finance areas, and 47 papers before 2005.

[4]Excluding 1 non-English paper, 52 non-article papers, 32 papers not in the economics; business, management and accounting, and social sciences areas, and 13 papers before 2005.

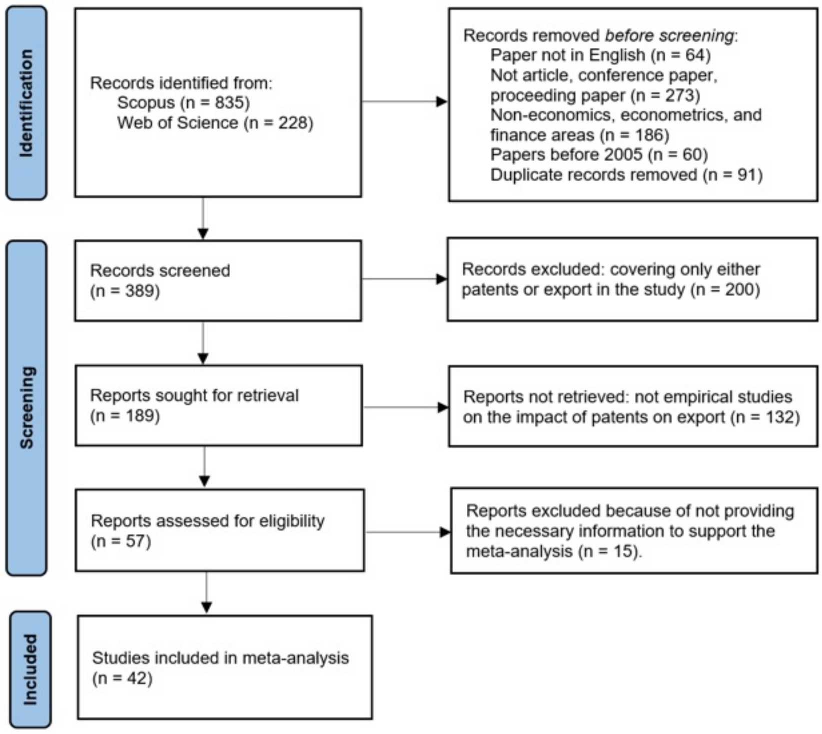


Figure 1.1: PRISMA Flowchart for the Selection Process

Table 1.2: Studies selection for Meta-analysis

Author(s)	Title	Journal
Islam et al. (2025)	Recycling through technology diffusion for circular economy in Europe: A decomposed assessment	Technological Forecasting and Social Change
Pulido-López and López-Salazar (2025)	Business internationalization and intellectual capital components: the case of the Colombian manufacturing sector exports	Journal of Intellectual Capital
Alshubiri and Al Ani (2024)	Do intellectual property rights promote foreign direct investment inflows and technological exports in developing and developed countries?	Foresight
Ashari and Blind (2024)	The effects of hydrogen research and innovation on international hydrogen trade	Energy policy
Bai and Oh (2024)	Export effects of overseas patent applications by Korean SMEs	Economics of Innovation and New Technology
Bhattacharyya et al. (2024)	Pharmaceutical exports and patents in India - a systems approach	Indian growth and development review
Miremadi and Mardukh (2024)	Catching-up in renewable energies: the role of knowledge dimensions in sectoral innovation systems	Innovation and Development
Caliari et al. (2023)	Global value chains and sectoral innovation systems: An analysis of the aerospace industry	Structural Change and Economic Dynamics
Kittová et al. (2023)	Determinants of domestic value added in exports of the EU countries	Acta Oeconomica
Kittová and Družbacká (2023)	Developments in the field of innovations in China and Chinese exports	Ekonomski Pregled
Ohm and Penickova (2023)	Internationalization process, innovation, and export volumes of the EU member states	Transformations in Business and Economics
Tadevosyan (2023)	Innovations and international competitiveness: Country-level evidence	Economics & Sociology

Table 1.2: Studies selection for Meta-analysis (cont.)

Author(s)	Title	Journal
De Rassenfosse et al. (2022)	International patent protection and trade: Transaction-level evidence?	European Economic Review
Liu Y. (2022)	The Effects of Exports, FDI, and Innovation Competence on the Efficiency and Profitability of Privatized SOEs in China	Journal of Global Business and Trade
L. Wu et al. (2022)	The importance of institutional and financial resources for export performance associated with technological innovation	Technological Forecasting and Social Change
Johnson and Van Wagoner (2021)	The Chicken or the Egg: Causality Between Trade and Innovation	Journal of Industry Competition & Trade
Malik et al. (2021)	The transformation of national patents for high-technology exports: Moderating effects of national cultures	International Business Review
Spuldaro et al. (2021)	The effect of innovation on the financial performance and export intensity of firms in emerging countries	International Journal of Business Innovation and Research
Vlčková and Stuchlíková (2021)	Patents, exports and technological specialization at the state level in Germany	Acta Universitatis Carolinae, Geographica
Bhat and Momaya (2020)	Innovation capabilities, market characteristics and export performance of EMNEs from India	European Business Review
Chalioti et al. (2020)	Innovation, patents and trade: A firm-level analysis	Canadian Journal of Economics
Lamperti et al. (2020)	Does the position in the inter-sectoral knowledge space affect the international competitiveness of industries?	Economics of Innovation and New Technology
Banerji and Suri (2019)	Impact of R&D Intensity, Patents and Regulatory Filings on Export Intensity of Indian Pharmaceutical Industry	Indian Journal of Pharmaceutical Education and Research
Orviská et al. (2019)	From academic publications and patents to the technological development of the economy: Short and long run causalities	Quality Innovation Prosperity
Bayraktutan and Bıdırdı (2018)	Innovation and High-Tech Exports in Developed and Developing Countries	Journal of International Commerce Economics and Policy
Kabaklarli and Üçler (2018)	High-technology exports and economic growth: Panel data analysis for selected OECD countries	Forum Scientiae Oeconomia
Banerji and Suri (2017)	Patents, R&D expenditure, regulatory filings and exports in Indian pharmaceutical industry	Journal of Intellectual Property Rights
Bierut and Kuziemska-Pawlak (2017)	Competitiveness and Export Performance of CEE Countries	Eastern European Economics
Nam and An (2017)	Patent, R&D and internationalization for Korean healthcare industry	Technological Forecasting and Social Change
Zucoloto et al. (2017)	Technological appropriability and export performance of Brazilian firms	African Journal of Science Technology Innovation & Development
Kunze (2016)	Empirical analysis of innovation and trade in Europe: A gravity model approach	International Journal of Trade and Global Markets
Mac An Bhaird and Curran (2016)	Sectoral differences in determinants of export intensity	Journal of Business Economics and Management
Dosi et al. (2015)	Technology and costs in international competitiveness: From countries and sectors to firms	Research policy

Table 1.2: Studies selection for Meta-analysis (cont.)

Author(s)	Title	Journal
Frietsch et al. (2014)	Patent indicators for macroeconomic growth - The value of patents estimated by export volume	Technovation
Tyagi et al. (2014)	Innovations in Indian drug and pharmaceutical industry: Have they impacted exports?	Journal of Intellectual Property Rights
W.-C. Chen (2013)	The extensive and intensive margins of exports: The role of innovation	World Economy
Neuhäusler and Frietsch (2013)	Patent families as macro level patent value indicators: applying weights to account for market differences	Scientometrics
Chadha (2009)	Product Cycles, Innovation, and Exports: A Study of Indian Pharmaceuticals	World Development
Wagner (2006)	Export intensity and plant characteristics: What can we learn from quantile regression?	Review of world economics
Blind and Jungmittag (2005)	Trade and the impact of innovations and standards: the case of Germany and the UK	Applied Economics
Montobbio and Rampa (2005)	The impact of technology and structural change on export performance in nine developing countries	World Development
Rodríguez and Rodríguez (2005)	Technology and export behaviour: A resource-based view approach	International Business Review

Table 1.3: Main characteristics of primary studies

Author(s)	NE	PCC	SEPCC	Type of countries	Data level	Estimation method	Measure of export	Measure of patent
Islam et al. (2025)	12	0.2916	0.0396	Developed	Country	OLS, Quantile	Export value	Patent count
Pulido-López and López-Salazar (2025)	2	0.0216	0.0115	Developing	Firm	Logit	Export dummy	Patent dummy
Alshubiri and Al Ani (2024)	6	0.2221	0.0635	Mixed	Country	OLS, FE, RE, GLS, FMOLS, DOLS	Export value	Patent count
Ashari and Blind (2024)	16	0.0359	0.0192	Developed	Country	OLS, FE, PPML	Export value	Patent count
Bai and Oh (2024)	16	0.4077	0.1375	Developed	Firm	OLS, FE, GMM	Export value	Patent count
Bhattacharyya et al. (2024)	5	0.0852	0.0298	Developing	Industry	3SLS	Export value	Patent count
Miremadi and Mardukh (2024)	4	0.1458	0.0923	Mixed	Country	OLS	Export value	Patent count/citation
Caliari et al. (2023)	12	0.0149	0.0530	Mixed	Country	FE	Export value	Patent count
Kittová et al. (2023)	4	0.2693	0.0742	Developed	Country	FE, RE	Export value	Patent count
Kittová and Družbacká (2023)	2	0.2366	0.0893	Developing	Country	FE	Export value	Patent count
Ohm and Penickova (2023)	3	0.3909	0.1477	Developed	Country	OLS	Export value	Patent count
Tadevosyan (2023)	1	0.0608	0.0231	Developed	Country	RE	Export value	Patent count
De Rassenfosse et al. (2022)	17	0.0033	0.0009	Mixed	Firm	OLS	Export value	Patent dummy

Table 1.3: Main characteristics of primary studies (cont.)

Author(s)	NE	PCC	SEPCC	Type of countries	Data level	Estimation method	Measure of export	Measure of patent
Liu Y. (2022)	1	0.0239	0.0096	Developing	Firm	SEM	Export value	Patent count
L. Wu et al. (2022)	28	0.0054	0.0016	Developing	Firm	Probit, IV-Probit, 2SLS	Export value/dummy	Patent count
Johnson and Van Wagoner (2021)	5	0.0836	0.0463	Developed	Country	SUR	Export value	Patent count
Malik et al. (2021)	14	0.0071	0.0257	Mixed	Country	FE, RE	Export value	Patent count
Spuldaro et al. (2021)	8	0.2232	0.0367	Developing	Firm	OLS	Export value	Patent count
Vlčková and Stuchlíková (2021)	3	0.6204	0.2025	Developed	State	OLS	Export value	Patent count
Bhat and Momaya (2020)	6	0.0778	0.0843	Developing	Firm	FE, RE	Export value	Patent citation
Chalioti et al. (2020)	20	0.0353	0.0042	Developed	Firm	OLS	Export value	Patent dummy
Lamperti et al. (2020)	16	0.0718	0.0189	Developed	Industry	OLS, GMM	Export value	Patent count
Banerji and Suri (2019)	2	−0.6593	0.3235	Developing	Industry	ARDL	Export value	Patent count
Orviská et al. (2019)	23	0.0175	0.0311	Mixed	Country	FMOLS, DOLS, VECM	Export value	Patent count
Bayraktutan and Bıdırdı (2018)	30	0.4192	0.2100	Mixed	Country	FMOLS, VECM	Export value	Patent count
Kabaklarli and Üçler (2018)	2	0.1312	0.0513	Developed	Country	PMG	Export value	Patent count
Banerji and Suri (2017)	2	-0.5656	0.2904	Developing	Firm	ARDL	Export value	Patent count
Bierut and Kuziemska-Pawlak (2017)	66	0.1732	0.0535	Developed	Country	FE, GLS, LSDV	Export value	Patent count
Nam and An (2017)	12	-0.0493	0.0586	Developed	Firm	FE, RE, GLS	Export value	Patent count
Zucoloto et al. (2017)	9	0.0918	0.0248	Developing	Firm	OLS, FE, Logit	Export value/dummy	Patent dummy
Kunze (2016)	25	0.0238	0.0153	Developed	Country	OLS	Export value	Patent count
Mac An Bhaird and Curran (2016)	12	0.0313	0.1030	Developed	Firm	Probit, Logit, Loglog, Cloglog	Export value	Patent dummy
Dosi et al. (2015)	57	0.0364	0.0112	Developed	Firm	ARDL, GMM	Export value	Patent dummy
Frietsch et al. (2014)	7	0.2601	0.0103	Developed	Country	OLS, FE, GMM	Export value	Patent count
Tyagi et al. (2014)	1	0.0595	0.2882	Developing	Industry	OLS	Export value	Patent count
W.-C. Chen (2013)	1	0.0450	0.0063	Mixed	Country	OLS	Export value	Patent citation
Neuhäusler and Frietsch (2013)	14	0.0127	0.0131	Developed	Country	FE	Export value	Patent count
Chadha (2009)	2	0.0450	0.0218	Developing	Firm	GMM	Export value	Patent count

Table 1.3: Main characteristics of primary studies (cont.)

Author(s)	NE	PCC	SEPCC	Type of countries	Data level	Estimation method	Measure of export	Measure of patent
Wagner (2006)	6	0.1358	0.0467	Developed	Firm	OLS	Export value	Patent dummy
Blind and Jungmittag (2005)	7	0.0717	0.0484	Developed	Country	OLS	Export value	Patent count
Montobbio and Rampa (2005)	4	0.1636	0.0994	Developing	Sector	OLS	Export value	Patent count
Rodríguez and Rodríguez (2005)	8	0.0731	0.0285	Developed	Firm	Logit, Tobit	Export value/dummy	Patent count/dummy

NE: the number of estimates; **PCC**: the average of the partial correlation coefficients; **SEPCC**: the average of the standard errors of the partial correlation coefficients; **OLS**: Ordinary Least Squares; **FMOLS**: Full Modified Ordinary Least Squares; **DOLS**: Dynamic Ordinary Least Squares; **GLS**: Generalized Least Squares; **2SLS**: Two-Stage Least Squares; **3SLS**: Three-Stage Least Squares; **RE**: Random effect; **FE**: Fixed effect; **GMM**: Generalized Method of Moment; **IV**: instrumental variables; **PPML**: Poisson Pseudo Maximum Likelihood; **SUR**: Seemingly Unrelated Regression; **ARDL**: Autoregressive Distributed Lag; **VECM**: Vector Error Correction Model; **LSDV**: Least Square Dummy Variable; **PMG**: Pooled Mean Group.

1.4 Average Effect and Publication Bias

To conduct a meta-analysis, it is essential to assess publication bias. The simplest method is using a funnel plot, which displays the distribution of effect sizes. Specifically, the funnel plot is a scatter plot that represents the relationship between effect size on the horizontal axis and precision, measured as the inverse of the standard error estimate, on the vertical axis (Neves et al., 2016). A symmetric distribution of effect sizes around the average true effect indicates no publication bias (Benos & Zotou, 2014). In contrast, an asymmetrical distribution suggests the presence of publication bias (Stanley, 2005). Figure 1.2 presents the funnel plots for the estimated impact of patents on export performance, including data from all studies, country-level data studies, sector-level data studies, and firm-level data studies. The visual inspection of these funnel plots suggests a positive average impact of patents on exports. However, in all three plots, the effect size estimates are asymmetrically distributed toward the right side, indicating the presence of publication bias. The funnel plots for the data from developed, developing, and mixed countries are provided in Figure A1, Appendix A. These plots also represent the existence of publication bias.

However, funnel graphs are based on the assumption that there is a single underlying *true effect* consistent across all studies. This assumption might be reasonable for experimental research, but not for empirical economic studies. According to Egger et al. (1997), with the existence of publication bias, the effect size depends on the standard error (SE_i), which is shown in Equation (1.4). The effect size is correlated with its respective standard error if there is publication bias. If there is no publication bias, the effect size will vary around β (Stanley, 2005). Thus, to test for publication bias, it is plausible to estimate the regression in Equation (1.4).

$$r_i = \alpha + \beta SE_{ri} + \epsilon_i \tag{1.4}$$

r_i denotes the estimate of the impact of patents on exports, α is the true effect of the relationship between patents and export, β is the strength of publication bias, SE_{ri} is the standard error of r_i, and ϵ_i is normal distribution term.

A heteroscedasticity problem arises in the above regression. This problem is solved by dividing both sides of Equation (1.4) by SE_{ri}. The new regression model will become the following:

$$t_i = \alpha(1/SE_{ri}) + \beta + \varepsilon_i \tag{1.5}$$

Where $t_i = \mathit{coefficient}_i/SE_i$ denotes the t-statistic associated with the coefficient reported in the primary studies. $1/SE_{ri}$ is the precision, $\varepsilon_i = \epsilon_i/SE_i$. The Funnel asymmetry test (FAT) is one of the most common tests used to test the funnel plot using Weighted Least Squares (WLS) regression. The null hypothesis of this test is that $\beta = 0$, which indicates no publication bias. According to C. Doucouliagos and Stanley (2013) and H. Doucouliagos and Stanley (2009), $|\beta| \geq 1$ indicates a substantial publication bias, while $|\beta| \geq 2$ shows a severe publication bias. The precision effect test (PET) checks the null hypothesis: $\alpha = 0$. The rejection of the null hypothesis indicates a genuine non-zero true effect after correcting for publication bias.

Andrews and Kasy (2019) suggests that interpreting α as the average effect between studies might be flawed, since the conditional expectation of the effect size across studies is not necessarily linear with respect to the standard error (or precision). They proposed a non-parametric method of correcting for publication selection. However, Moreno et al. (2012) and Stanley and Doucouliagos (2014) pointed out that the non-linear method outweighs the linear one when the effect size exists, namely, the result from PET rejects the null. The non-linear Egger model and its WLS are as follows:

$$r_i = \gamma + \varphi SE_{ri}^2 + \theta_i \tag{1.6}$$

$$t_i = \gamma(1/SE_{ri}) + \varphi SE_{ri} + \vartheta_i \tag{1.7}$$

Equation (1.7) is the Precision Effect Estimate with Standard Error (PEESE) test, which is conducted to obtain the estimate of the overall effect after the PET rejects the null hypothesis (Alinaghi & Reed, 2018). The procedure for conducting FAT, PET, and PEESE is shown in Figure A2, Appendix A.

We estimate Equation (1.5) and Equation (1.7) using hierarchical models (HLM) as the result of estimation using OLS can be biased due to the statistical dependence problem. This problem is attributed to the correlation between observations from the same study since they share the same data, and procedure of estimation (J. P. Nelson & Kennedy, 2009). According to Stanley (2001), one of the solutions for this problem is to choose only one estimation from each study. Since the number of studies in this analysis is pretty small, it is implausible to fulfill this option. Another way to tackle this issue is to employ the hierarchical models (HLM), which are used by Afonso et al. (2020), Havranek and Irsova (2011), Neves and Sequeira (2018), Neves et al. (2021), and Ugur et al. (2016, 2020). The advantage of HLM is that it considers the observations of each study as a cluster. In other words, each study represents a cluster. HLM outweighs OLS in terms of allowing the estimation of coefficients when there is heterogeneity between studies (Katahira, 2016). The typical HLM is as follows:

$$Y_{ij} = (\delta_0 + \omega_{0j}) + (\delta_1 + \omega_{1j})X_{ij} + \mu_{ij} \tag{1.8}$$

Where i and j denote the observation and group, respectively. δ_0 is the fixed-effect intercept and δ_1 shows fixed-effect slope. ω_{0j} and ω_{1j} have a normal distribution with zero mean and constant variance. They represent group-specific random intercept and group-specific random slope, respectively. According to Ugur et al. (2020), HLM is considered random-slopes-only model when $\omega_{0j} = 0$, and random-intercepts-only model when $\omega_{1j} = 0$.

Table 1.4 summarizes the FAT/PET analysis (Equation (1.5)) and the PEESE correction (Equation (1.7)). Panel A's results confirm a positive true impact of patents on exports in most cases, except for developing and mixed countries. Publication bias exists in all studies, firm-level data studies, developed countries, and developing countries subsamples, but the results are insignificant in country-level, sector-level, or mixed country data subsamples. After removing outliers[5] (results in Panel B), the precision coefficients remain significant and positive in all studies and four subsamples as the abovementioned. Interestingly, the coefficient becomes larger in the case of all studies, firm-level data studies, and developed countries. Panel C and Panel D provide the results after applying the PEESE correction with outliers and without outliers, respectively. In Panel C, the average impact of patents on exports remains consistent for the whole sample, firm-level data, and developed countries. However, this correction renders the precision coefficients for country-level and sector-level data studies insignificant. Panel D's results further reinforce the positive and significant impact of patents on export performance for the full sample, firm-level data studies, and the developed countries subsample.

Another issue in meta-analysis is the adequate power of the evidence base, and what would the average effect size be when only adequately powered effect-size estimates are used. According to Ioannidis et al. (2017), adequate power in social scientific research is conventionally defined as 80% or higher. The authors suggested the rule of the relationship between the genuine effect and the standard error, which satisfies Equation (1.9). The estimates that satisfy this inequality are the most informative and less biased.

$$\left|\gamma\right|/SE_i \geq 2.8 \quad \text{or} \quad SE_i \leq \left|\gamma\right|/2.8 \tag{1.9}$$

γ is obtained from the results of PEESE in Table 1.4. The percentage of adequately-powered evidence in the sample is calculated by dividing the number of adequately-powered effect-size estimates by the total number of estimates in the relevant sample. Lastly, the weighted average of the adequately-powered evidence (WAAP) is computed as the weighted average of effect-size estimates that meet the power threshold, using $1/SE^2$ as the analytical weights.

[5]Followed by Havranek and Irsova (2011), the outliers are defined by the Hadi's multivariate outlier detection method, using the `hadimvo` command in STATA.

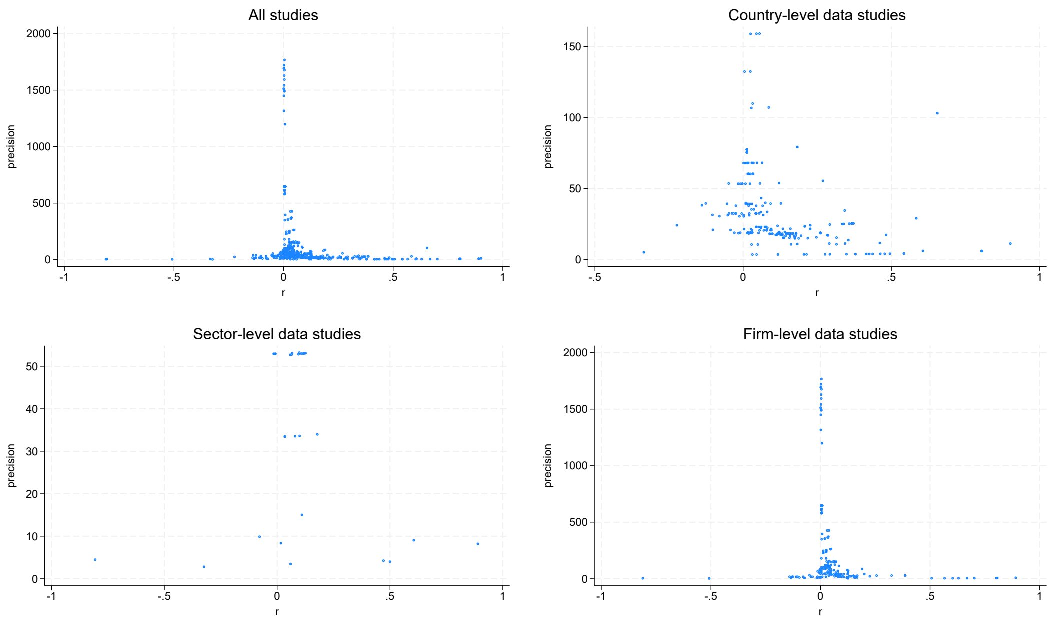


Figure 1.2: Funnel plot of publication bias in published studies

Table 1.5 presents the WAAP effect and the proportion of adequately powered studies for the three samples in the meta-analysis of the whole sample and the other four subsamples[6]. The powers are quite low in both the whole samples and the other four subsamples, ranging from 8% to 28%. However, as indicated by Ioannidis et al. (2017), there are around 20% of the empirical economics fields does not contain an adequately-powered estimate. The WAAP effects for all studies and subsamples are positive and significant in both Panel A (with outliers) and Panel B (without outliers). Similar to the results from FAT/PET and PEESE, the WAAP effects in the case of no outliers are larger than those with outliers. The findings point out that the average true effect of patents on export performance based on the adequately-powered evidence is much larger, especially after excluding the outliers from the samples.

[6]The other two subsamples: sector-level data studies and developing countries do not have any observations, which meet the requirement of Equation (1.9).

Table 1.4: Test of publication bias and corrected patents effect

Dependent variables: t	All studies	Country-level data studies	Sector-level data studies	Firm-level data studies	Developed countries	Developing countries	Mixed countries
Panel A - FAT/PET							
Precision	0.004**	0.051**	0.058*	0.004***	0.004***	0.003	0.071
	(0.002)	(0.026)	(0.001)	(0.001)	(0.001)	(0.003)	(0.049)
Constant	2.766***	1.768	0.828	2.106***	2.617***	1.998***	0.961
	(0.700)	(1.538)	(1.086)	(0.731)	(0.532)	(0.657)	(3.943)
Obs/Studies	493/42	256/20	31/6	206/16	326/21	87/15	80/8
Log restricted-likelihood	−1450.525	−804.241	−77.326	−520.642	−794.106	−199.454	−294.111
Wald test	5.68**	3.92**	3.73*	12.04***	12.94***	0.81	2.08
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	0.437	0.000	0.000	0.000	0.000
Panel B - FAT/PET excluding outliers							
Precision	0.038***	0.051**	0.043*	0.031***	0.027***	0.016	0.071
	(0.011)	(0.026)	(0.024)	(0.008)	(0.007)	(0.021)	(0.049)
Constant	1.705**	1.768	1.534	1.282**	1.887***	2.162***	0.961
	(0.785)	(1.538)	(0.998)	(0.627)	(0.510)	(0.789)	(3.943)
Obs/Studies	426/40	256/20	30/6	140/14	289/20	57/14	80/8
Log restricted-likelihood	−1264.452	−804.241	−73.650	−340.717	−668.927	−138.954	−294.111
Wald test	11.02***	1.76	3.18*	16.36***	14.38***	0.58	2.08
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	1.000	0.000	0.000	0.010	0.000
Panel C - PEESE							
Precision	0.004**	0.044	0.009	0.004***	0.004***	−0.0003	0.044
	(0.002)	(0.028)	(0.060)	(0.001)	(0.001)	(0.003)	(0.070)
Standard error	−10.367*	−7.426	−11.905	−6.532	−6.003	−12.806***	−75.350
	(5.575)	(3.749)	(11.454)	(5.452)	(4.319)	(3.978)	(156.925)
Obs/Studies	493/42	256/20	31/6	206/16	326/21	87/15	80/8
Log restricted-likelihood	−1446.184	−800.643	73.440	−517.350	−790.759	−193.139	−288.053
Wald test	9.14**	4.19	4.14	13.33***	14.92***	11.40***	1.98
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	0.332	0.000	0.000	0.000	0.000
Panel D - PEESE excluding outliers							
Precision	0.034***	0.044	0.009	0.032***	0.026***	−0.024	0.044
	(0.013)	(0.028)	(0.045)	(0.009)	(0.008)	(0.024)	(0.070)
Standard error	−4.190	−7.426	−8.973	0.522	−0.482	−14.791***	−75.350
	(6.185)	(12.110)	(9.767)	(5.349)	(4.184)	(5.259)	(156.925)
Obs/Studies	426/40	256/20	30/6	140/14	289/20	57/14	80/8
Log likelihood	−1261.482	−800.643	−70.053	−338.119	−666.572	−132.717	−288.053
Wald test	11.40***	4.19	3.85	16.16***	14.33***	25.43***	1.98
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	0.4917	0.000	0.000	0.019	0.000

Standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
These results are derived from a mixed-effect multilevel model using restricted maximum likelihood, using the *xtmixed* command in STATA.

Table 1.5: Weighted average effects from adequately-powered (WAAP) evidence

	All studies	Country-level data studies	Firm-level data studies	Developed countries	Mixed countries
Panel A - With outliers					
WAAP effect	4.444***	7.579**	4.444***	4.444***	13.210**
	(0.577)	(2.800)	(0.577)	(0.577)	(5.410)
Observations	15	43	15	15	12
Adequately powered (%)	12	17	28	18	15
Panel B - Excluding outliers					
WAAP effect	6.759***	7.579**	4.990***	5.832***	13.210**
	(1.315)	(2.800)	(0.556)	(0.672)	(5.410)
Observations	51	43	36	22	12
Adequately powered (%)	12	17	26	8	15

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Adequately powered (%) = (Number of adequately-powered estimates / all observations in sample) × 100

1.5 Meta-Regression Analysis

To examine the factors causing the differences in the effect sizes, a multivariate meta-regression is estimated. The effect size is the dependent variable and is regressed on the moderator variables, which are enacted from the studies selected in Section 1.4. The multivariate meta-regression is as Equation (1.10).

$$t_{ij} = \beta + \alpha(1/SE_{ij}) + \gamma_k X_k(1/SE_{ij}) + \gamma_l Z_l + \varepsilon_{ij} \tag{1.10}$$

X_k and Z_l are the dummy moderators and continuous moderators, respectively. The dummy moderators are divided by standard error. All the moderators and their summary statistics are provided in Table 1.6. The moderators are divided into three groups: Publication characteristics, data characteristics, and estimation characteristics. Since there is no theoretical instruction for the moderators' selection, followed Neves et al. (2021) and Ugur et al. (2020), the weighted-average least squares (WALS) that combines ideas from Bayesian and frequentist methods to model averaging (De Luca & Magnus, 2011; Magnus et al., 2010) is applied. According to Havránek (2015) and Iršová and Havránek (2013), WALS is more efficient than Bayesian model averaging (BMA) in terms of computation time. The dependent variable in WALS is the precision; all the moderators are auxiliary covariates. Follow De Luca and Magnus (2011), the selected moderators possess the t-statistic in WALS greater than one in absolute value. The results of WALS are provided in Table A1, Appendix A. Based on the results, 12 out of 19 moderators are selected.

As a robustness check, Disdier and Head (2008) and H. Doucouliagos and Laroche (2009) recommend using OLS with clustered robust standard errors. However, OLS treats each estimate with equal weight, which can lead to overrepresentation of studies that report multiple estimates. In contrast, the mixed-effects multilevel model assigns equal weight to studies when there is high heterogeneity between them (Rabe-Hesketh & Skrondal, 2008). We present results from the mixed-effects multilevel model since this approach provides more reliable estimates than OLS.

Table 1.7 presents the meta-regression results for all studies and the six subsamples: country-level data studies, sector-level data studies, firm-level data studies, developed countries, developing countries, and mixed countries. The results are separated into two panels: Panel A with outliers and Panel B without outliers. The result indicates no impact of patents on export performance in most of the samples, except for the case of country-level data studies, where there is a positive true effect. After extracting the outliers, I found a positive true effect of patents on export performance in all studies, country-level data studies, and firm-level data studies. The other cases are insignificant, indicating that the overall impact of patents on exports is also insignificant when controlling for the moderating variables. However, most of the moderators are significantly associated with the effect-size estimates reported in the primary studies. The marginal effect of patents on exports, conditional on the moderators, can be calculated as the sum of all significant coefficients, excluding the constant term, which captures the residual selection bias (Ugur, 2014). Thus, the marginal effect of patents on exports is -0.979[7] for sector-level data, -0.262 for developed countries, -0.133 for developing countries, and -1.699 for mixed countries.

Regarding the moderators of data characteristics, in the whole sample, I find that the true effect of patents on export performance is lower in high-tech exports, but stronger in studies using the number of patents. While the true effect is more pronounced in studies using a dynamic econometric approach, the impact of patents on exports is more adverse when studies employ the OLS, FE, and instrumented estimation methods. For the case of country-level data studies, the coefficient of the Q1 journal is positive and significant. This means that the impact of patents on the export of country-level data studies is stronger in the Q1 journal. The moderators related to estimation characteristics: OLS, FE, and instrumented, are similar to the case of all studies. However, the true effect is weaker in studies employing the MLE method. For firm-level data studies, there exists a negative coefficient for the Q1 journal, using the FE method, but a positive coefficient for manufacturing, suggesting that manufacturing firms experience a stronger true effect of patents on export activities. I also regress Equation (1.10) with OLS, and provide the results in Table A3, Appendix A. The findings from OLS are almost in line with those from the mixed-effects multilevel model.

The results with all the moderators are in Table A2, Appendix A. Regarding Panel A, after controlling for moderators, no impact of patents on export performance is found in all studies, country-level data studies, firm-level data studies, and developed countries. However, the true effect of patents on exports for the industry-level data studies is found to be significantly negative. Besides, a positive true effect is proven in the case of developing and mixed countries. After extracting the outliers, a positive true effect of patents on export performance is explored in all studies and mixed countries. The other cases become insignificant, indicating that the overall impact of patents on exports is also insignificant when controlling for the moderating variables.

[7] $-0.979 = -0.535 - 0.444$

Table 1.6: Variables and summary statistics (All the dummy moderators are divided by SE_{ri})

Variable	**Type**	**Measure**	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
t	Count	t-statistic of primary studies	535	3.018	5.121	-5.421	67.561
Precision	Count	Inverse of standard error of the partial correlation coefficient	493	131.730	292.306	2.596	1767.103
Publication characteristics							
Ncitat	Count	Log of number of citations	536	3.474	1.576	0	6.317
Year	Count	log of (Year of publication - 2005)	536	2.534	0.577	0	3.045
Q1Journal	Dummy	1 if the paper is published in the first quarter Journal	493	108.786	295.739	0	1767.103
Data characteristics							
Nob	Count	Log of number of observations	494	7.456	2.810	2.565	16.988
Country	Dummy	1 if the paper uses country-level data	493	19.399	26.987	0	159.177
Firm	Dummy	1 if the paper uses firm-level data	493	111.969	298.583	0	1767.103
High-tech export	Dummy	1 if the paper uses high-tech export as the dependent variable	493	2.685	9.264	0	39.591
Manufacturing	Dummy	1 if the paper uses manufacturing export as the dependent variable	493	50.378	145.999	0	646.777
Pharma	Dummy	1 if the paper uses pharmaceutical export as the dependent variable	493	1.122	5.264	0	45.788
Dpatent	Dummy	1 if the paper uses dummy as a measure for patent	493	74.699	273.009	0	1767.103
Cpatent	Dummy	1 if the paper uses the number of patent applications as a measure for patent	493	55.874	139.359	0	646.777
Export	Dummy	1 if the paper uses the export value as a measure for export performance	493	115.134	284.846	0	1767.103
Panel	Dummy	1 if the paper uses panel data	493	129.689	293.106	0	1767.103
Estimation characteristics							
OLS	Dummy	1 if the paper uses OLS in the estimation	493	67.491	267.010	0	1767.103
FE	Dummy	1 if the paper uses FE in the estimation	493	7.601	19.273	0	132.493
RE	Dummy	1 if the paper uses RE in the estimation	493	0.907	5.327	0	43.335
Instrumented	Dummy	1 if the paper uses 2SLS, 3SLS, IV or GMM in the estimation	493	38.402	142.596	0	646.777
Dynamic	Dummy	1 if the paper uses ARDL, VECM, FMOLS or DOLS in the estimation	493	4.216	16.786	0	246.321
MLE	Dummy	1 if the paper uses Probit, Logit, Tobit, Loglog or Cloglog in the estimation	493	8.337	61.027	0	1198.421

Table 1.7: Estimation of Meta-regression Analysis

Dependent variable: t	All studies	Country-level data studies	Sector-level data studies	Firm-level data studies	Developed countries	Developing countries	Mixed countries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A - With outliers							
Publication characteristics							
Q1Journal	-0.017^{*}	0.133^{**}	-0.529^{***}	-0.022^{***}	-0.017^{***}	-0.180^{**}	0.152
	(0.009)	(0.056)	(0.171)	(0.005)	(0.005)	(0.072)	(0.673)
Data characteristics							
Country	−0.113				−0.003	0.343^{*}	-
	(0.145)				(0.028)	(0.187)	
Firm	−0.150				-	0.118	-
	(0.143)					(0.128)	
High-tech export	-0.147^{**}	−0.090	-	-	−0.004	-	0.405
	(0.071)	(0.089)			(0.125)		(0.863)
Manufacturing	0.030^{***}	−0.153	-	0.028^{***}	0.029^{***}	0.104^{*}	1.172
	(0.007)	(0.210)		(0.004)	(0.004)	(0.063)	(1.508)
Pharma	−0.094	-	-0.438^{***}	−0.042	−0.189	0.106	-
	(0.089)		(0.169)	(0.047)	(0.120)	(0.112)	
Cpatent	0.091^{***}	0.072	-	0.007	0.001	−0.024	0.296
	(0.019)	(0.046)		(0.019)	(0.021)	(0.047)	(0.192)
Estimation characteristics							
OLS	−0.002	-0.248^{***}	1.031^{***}	0.015^{***}	0.016^{***}	0.173^{*}	-0.437^{***}
	(0.007)	(0.035)	(0.355)	(0.004)	(0.004)	(0.102)	(0.059)
FE	-0.096^{***}	-0.236^{***}	1.032^{***}	−0.023	0.013	0.077	-0.369^{***}
	(0.017)	(0.027)	(0.356)	(0.024)	(0.016)	(0.101)	(0.049)
Instrumented	-0.122^{***}	-0.358^{***}	0.920^{**}	−0.020	-0.055^{***}	0.141	-0.480^{***}
	(0.019)	(0.045)	(0.356)	(0.019)	(0.020)	(0.114)	(0.064)
Dynamic	0.089^{***}	−0.155	-	0.002	0.037^{*}	−0.107	0.056
	(0.022)	(0.098)		(0.020)	(0.020)	(0.123)	(0.909)
MLE	0.002	-0.079^{**}	-	0.018^{***}	0.019^{***}	0.130	-0.413^{***}
	(0.007)	(0.034)		(0.004)	(0.004)	(0.106)	(0.094)
Precision	0.171	0.150^{*}	−0.416	0.009	0.003	−0.153	0.571
	(0.143)	(0.081)	(0.435)	(0.006)	(0.006)	(0.211)	(0.736)
Constant	0.919	0.927	0.702	1.811^{***}	2.632^{***}	0.392	-34.929^{**}
	(0.803)	(1.569)	(0.756)	(0.569)	(0.601)	(0.838)	(15.259)
Obs/Studies	493/42	256/20	31/6	206/16	326/21	87/15	80/8
Log restricted-likelihood	−1445.787	−766.986	−69.209	−508.033	−773.967	−210.913	−272.504
Wald test	99.64^{***}	141.75^{***}	75.67^{***}	141.15^{***}	152.91^{***}	28.16^{***}	99.3^{***}
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	1.000	0.000	0.000	0.019	0.002
Panel B - Without outliers							
Publication characteristics							
Q1Journal	0.019	0.133^{**}	-0.535^{***}	-0.063^{***}	0.016	-0.133^{**}	0.152
	(0.029)	(0.056)	(0.174)	(0.021)	(0.021)	(0.060)	(0.673)
Data characteristics							
Country	−0.202				−0.002	0.747	-
	(0.147)				(0.027)	(0.562)	
Firm	−0.218				-	0.629	-
	(0.142)					(0.577)	
High-tech export	-0.152^{**}	−0.090	-	-	0.002	-	0.405
	(0.073)	(0.089)			(0.118)		(0.863)
Manufacturing	−0.051	−0.153	-	0.044^{**}	−0.028	0.078	1.172
	(0.035)	(0.210)		(0.022)	(0.025)	(0.054)	(1.508)
Pharma	−0.125	-	-0.444^{**}	−0.068	-0.214^{*}	0.047	-
	(0.089)		(0.172)	(0.041)	(0.110)	(0.126)	
Cpatent	0.050^{**}	0.072	-	0.020	−0.035	−0.003	0.296
	(0.025)	(0.046)		(0.020)	(0.027)	(0.040)	(0.192)

Table 1.7: Estimation of Meta-regression Analysis (cont.)

Dependent variable: t	All studies	Country-level data studies	Sector-level data studies	Firm-level data studies	Developed countries	Developing countries	Mixed countries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation characteristics							
OLS	-0.039^{***}	-0.248^{***}	0.731	0.008	0.010	0.124	-0.437^{***}
	(0.013)	(0.035)	(0.645)	(0.008)	(0.007)	(0.118)	(0.059)
FE	-0.111^{***}	-0.236^{***}	0.732	-0.048^{*}	0.002	0.037	-0.369^{***}
	(0.019)	(0.027)	(0.645)	(0.025)	(0.017)	(0.118)	(0.049)
Instrumented	-0.173^{***}	-0.358^{***}	0.620	0.026	-0.064^{***}	0.650	-0.480^{***}
	(0.027)	(0.045)	(0.645)	(0.042)	(0.020)	(0.578)	(0.064)
Dynamic	0.107^{***}	-0.155	-	-0.063	0.032	-0.014	0.056
	(0.032)	(0.098)		(0.044)	(0.022)	(0.136)	(0.909)
MLE	-0.011	-0.079^{**}	-	0.012	0.016^{**}	0.087	-0.413^{***}
	(0.012)	(0.034)		(0.008)	(0.007)	(0.127)	(0.094)
Precision	0.278^{*}	0.150^{*}	-0.108	0.034^{**}	0.022	-0.659	0.571
	(0.144)	(0.081)	(0.704)	(0.013)	(0.015)	(0.596)	(0.736)
Constant	1.629^{*}	0.927	0.638	1.823^{***}	2.809^{***}	1.693^{**}	-34.929^{**}
	(0.871)	(1.569)	(0.776)	(0.537)	(0.601)	(0.817)	(15.259)
Obs/Studies	426/40	256/20	30/6	140/14	289/20	57/14	80/8
Log restricted-likelihood	-1262.943	-766.986	-66.986	-356.083	-681.590	-148.548	-272.504
Wald test	83.07^{***}	141.75^{***}	58.05^{***}	53.61^{***}	58.01^{***}	34.71^{***}	99.32^{***}
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	1.000	0.034	0.000	1.000	0.002

Cluster robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. (-) indicates the coefficient is omitted due to collinearity. Results are estimated using the mixed-effects multilevel model.

1.6 Conclusion

In conclusion, this study is the first meta-analysis that provides a comprehensive analysis of the relationship between patents and export activities, filling a gap in the existing meta-analytic literature. By synthesizing evidence from 42 empirical studies spanning from 2005 to 2025, I uncover important insights into the true effect of patents on export performance.

This study addresses key methodological issues, such as publication bias, by applying various techniques (Funnel plot, FAT/PET, and PEESE). I also tackle the problem of low statistical power in studies through the use of the Weighted Average Effects from Adequately-Powered (WAAP), ensuring a more accurate estimate of the true effect. The WALS routine is adopted to select the most suitable moderators to add to the meta-regression. Additionally, both OLS with standard error clustered with studies and the mixed-effects multilevel model are employed in this meta-regression analysis. Among the two methods, the mixed-effects multilevel model provides more consistent and reliable results.

Not only examining the genuine effect for the entire sample, but this impact is also investigated for six subsamples: country-level data studies, sector-level data studies, firm-level data studies, studies on developed countries, studies on developing countries, and studies on mixed countries. The findings indicate a genuine positive effect across all five samples (all studies, country-level data studies, sector-level data studies, firm-level data studies, and studies on developed countries). After controlling for moderating variables, this effect remains positive and significant for all studies, country-level data studies, and firm-level data studies. However, the effect turns insignificant for sector-level data studies and studies from developed countries. Furthermore, the study highlights the importance of considering moderators and the role of study design in understanding the impact of patents on export performance. The findings contribute to a more nuanced understanding of the complex relationship between patents and trade, offering valuable insights for policymakers (e.g., the true effect is lesser in the case of high-tech exports and stronger for manufacturing firms) and researchers (e.g,. the true effect is more pronounced in the studies using dynamic econometric models, but this impact is lesser in papers employing OLS, FE, instrumented variables, and MLE).

Although this study offers a comprehensive understanding of the impact of patents on export performance and provides an explanation for the heterogeneity in the findings of empirical primary studies, it has several limitations. First, the analysis is limited to published studies written in English. Second, some empirical studies were excluded due to the lack of necessary information required to calculate the effect size, which may affect the robustness of the results.

Chapter 2

Export Quality and Patent Intensity: A Bidirectional Relationship Moderated by Institutional Quality

Innovation and export quality are widely regarded as twin engines of economic growth. This paper challenges the notion of a simple synergistic relationship, investigating a potential strategic trade-off between them. First, I analyze the two-way relationship between export quality and patent intensity using the data from 89 countries, covering the export quality index for 4-digit SITC products and 4-digit International Patent Classification (IPC) from 1999 to 2014. The analysis employs a Simultaneous Equation Model (SEM) with Two-Stage Least Squares (2SLS) and Three-Stage Least Squares (3SLS) approaches. The results indicate a surprising and significant negative impact in both directions. This bidirectional negative linkage holds across various country subsamples, including different types of countries (OECD and non-OECD), levels of income, technological levels, export dependence levels, and export quality levels. Crucially, I find that the quality of institutions plays a moderating role: stronger institutions not only foster higher export quality and patenting directly but also buffer the negative relationship between them. Then, a theoretical model is built to show how a firm's choices between enhancing quality and increasing patenting are two sides of the same coin.

2.1 Introduction

International trade plays an important role in the process of development of a country (Cao & Wang, 2017; Sun & Heshmati, 2010). During the 1990s, international trade increased significantly due to lower costs, especially due to improvements in Information and Communication Technology (ICT) (Luong & Nguyen, 2021; Xing, 2018). However, trade flows also slowed down following the years of the global financial crisis and, more recently, because of the COVID-19 pandemic.

Studies about export determinants are quite wide, including those focused on the role of foreign direct investment (FDI) (Dritsakis & Stamatiou, 2017), trade policy, trade cost, exchange rate, geographic distance, bilateral and multilateral Free Trade Agreements (FTAs) (Anderson & Yotov, 2016; Dadakas et al., 2020; Doan & Xing, 2018; Mukwaya, 2019). Among the several different determinants of trade, the relationship with innovation has also been examined from different perspectives. Specifically, the impact of innovation on export at the firm level is proven in the analyses of D'Angelo (2012), Edeh et al. (2020), Golovko and Valentini (2011), A. N. Nguyen et al. (2008), Tavassoli (2018), and F. Wu et al. (2020). Patent applications boost exports in the particular countries where they are filed (Bai & Oh, 2024). Several studies investigated and pointed out the positive relationship between patent reform and export (Ivus, 2010; Ivus & Park, 2019; Maskus & Yang, 2013), for example, in China, strengthening Intellectual Property Rights (IPRs) accelerates import (Awokuse & Yin, 2010), the enhancement of trading partners' IPRs stimulates intra-industry trade in the UK (Hasim et al., 2018), and Australian bilateral trade (Salim et al., 2014). However, a wide literature has evidenced that there is a two-way relationship between export and innovation (Girma et al., 2008).

While research on related areas like export diversification has progressed, the determinants of export quality remain comparatively underexplored. Existing literature often points to factors such as GDP, credit constraints, imported inputs, FDI, and R&D investment as influences. However, amidst this scarcity, the specific and potentially pivotal role of innovation as a direct driver of export quality has been notably overlooked and warrants more dedicated investigation. There is only a small number of papers taking into consideration the relationship between innovation and export quality. According to H. Zhang and Yang (2016) and Song et al. (2021), the improvement of product quality plays an important role in achieving export upgrading. Innovative activities are essential to improving the quality of products. In fact, the relationship between innovation and export quality is proven by Akcigit et al. (2018) and Sampson (2016). A positive effect of green innovation on export quality is shown by Chai (2023). The reverse causality is discovered in a recent analysis of Cai and Wu (2024), which investigates the impact of export quality on innovation output, that is, invention patents and utility model patents, using firm-level data from China. However, the literature has yet to analyze the bidirectional relationship between export quality and patent intensity specifically, leaving this dynamic as an open and crucial question for understanding national competitiveness.

The institutional environment in which firms operate can fundamentally alter their strategic calculations. The literature confirms that strong institutions directly boost trade (Levchenko, 2007), export quality (Faruq, 2011; Lin et al., 2021), and innovation (Donges et al., 2023; Tebaldi & Elmslie, 2013). Furthermore, institutions positively moderate the nexus between technological innovation and trade openness of the G20 economies (Zhuang et al., 2021), the relationship between innovation and export of SMEs in developing countries (Hashmi et al., 2022), and the nexus between technology adoption and the export performance of 49 African countries (Sakyi et al., 2023). However, the moderating role of institutions in shaping the specific relationship between export quality and patent intensity remains a critical gap. We therefore hypothesize that institutional quality acts as a key moderator, buffering the bidirectional nexus between export quality and patent intensity.

To test the bidirectional relationship and the moderating role of the institutions, I employ a Simultaneous Equations Model (SEM), estimated with 2SLS and 3SLS. The analysis uses a three-dimensional panel dataset covering 89 countries from 1999 to 2014. Export quality is defined by following Henn et al. (2020), where the trade price of a product from exporter to importer is a function of unobserved quality, the exporter's income per capita, and the distance between the exporter and the importer. Patent intensity is measured as the number of patents per unit of export value. The results suggest a negative two-way relationship between export quality and patent intensity. The findings from different types of countries, levels of technology, levels of export dependence, and export quality also support the benchmark estimates. The quality of institutions not only positively affects export quality and patent intensity, but it also shows the positive moderating effects on the reciprocal relationship between export quality and patent intensity. To get robust results, the model is re-estimated with a different measurement of export quality, following the method of Fan, Li, and Yeaple (2015) and Khandelwal et al. (2013). The results remain confirmed after conducting several robustness checks.

Besides, I develop a theoretical framework that extends the seminal heterogeneous firm models of Kugler and Verhoogen (2012) and Melitz (2003). By introducing R&D investment as a choice that simultaneously enhances quality and generates patents, the model provides a clear micro-foundation illustrating that quality enhancement and patent intensity are two facets of a single, integrated strategy. This framework allows us to derive testable hypotheses about the reciprocal nature of the export quality and patent intensity nexus.

This study contributes to the literature on innovation and international trade in four key ways. First, a simple theoretical model that articulates the reciprocal relationship between export quality and patent intensity is proposed. The framework, derived from a firm's profit maximization problem, treats institutional quality as a contextual parameter. The model's central insight is that a firm's strategic decisions on quality upgrading and patenting activities are fundamentally intertwined, representing two facets of a single, integrated strategy. Second, instead of using the number of patents as an outcome of innovation, I measure patent intensity as a ratio of the number of patents (at 4-digit IPC) per export value (at 4-digit SITC). This new measure is more insightful and informative in explaining the level of innovation of firms/sectors than the number of patents. Specifically, the increase in the number of patents implies (1) more patents due to more firms or sectors, (2) the existing firms conduct more innovation and apply additional patents while the number of firms is unchanged. Patent intensity can address the second mechanism. Third, the study of the relationship is done using three-dimensional panel data with a large sample of countries not considered before. Besides, the main relationships are investigated with different subsamples, namely, different types of countries (OECD and non-OECD), levels of income, levels of technology, levels of export dependence, and levels of export quality. Finally, the role of institutional quality is introduced, particularly its moderating effect on the two-way relationship between export quality and patent intensity by interacting export quality and patent intensity with each of the following institutions: government stability, corruption, law and order, and bureaucracy quality, which are mostly used in the literature.

The structure of the paper is as follows: Section 2.2 provides the Literature Review before jumping to Data and Methodology in Section 2.3. Empirical Analysis is discussed in Section 2.4. After that, the Theoretical Framework is conducted in Section 2.5. Finally, the Conclusion is in Section 2.6.

2.2 Literature Review

2.2.1 Determinants of export quality

As mentioned in the recent trade theories, the increase in trade is driven more by the new products rather than the rise in quantity (Amiti & Freund, 2010; Broda & Weinstein, 2006; Funke & Ruhwedel, 2001; Hummels & Klenow, 2005). The improvements in the quality of products play an important role in achieving export upgrading (Song et al., 2021; H. Zhang & Yang, 2016). The products are now manufactured meticulously and upgraded to meet the high demand of domestic and foreign customers. The literature has evidenced many determinants of export quality, such as GDP, credit constraints, imported input, FDI, R&D investment, and innovation. Specifically, high-income countries tend to export higher-quality products compared to low-income ones (Falvey, 1981; Falvey & Kierzkowski, 1987; Hummels & Klenow, 2005; Mora, 2002; Schott, 2004). The possible explanation is that higher-quality products contain factor endowments such as physical capital, which only high-income countries can possess. Moreover, the production of high-quality products requires more skillful workers. Countries with a greater stock of human capital export higher-quality products (Schott, 2004). A further determinant is credit constraints, which shows a negative impact on quality upgrading (Fan, Lai, & Li, 2015). An analogous result is found by Ciani and Bartoli (2020), which indicates that exporting firms have fewer incentives to upgrade their product quality when their credit score worsens. Besides, export product quality is promoted by imported input (Bas & Strauss-Kahn, 2015; Xu & Mao, 2018), R&D investment, and FDI (Amighini & Sanfilippo, 2014; Aw et al., 2008; Faruq, 2010).

Technological innovation is also a determinant of export quality (Flam & Helpman, 1987). The authors suggested a model in which countries in the North export high-quality products while countries in the South export low-quality ones. They found that the Northern countries would enhance their product quality once the Southern countries increased their technological progress. Innovative activities are blatantly essential to improving the quality of products. Indeed, employing the prominent gravity equation model in international trade with the data from 60 exporting countries and 57 importing countries from 1995 to 2000, Cipollina et al.

(2016) pointed out the positive nexus between innovation and export quality. The authors also show that this impact hinges on the level of technology intensity and economic growth of exporting countries. Various analyses use Chinese firm-level data to tackle the relationship between innovation and export quality[1]. Rahman et al. (2022) found that technological innovation unidirectionally causes export quality. Firms' export product quality is enhanced under the intervention of smart cities, namely, the quality of manufactured products is improved with the support of innovative cities (Yang et al., 2023). In a recent study, Pang et al. (2024) show that export quality is promoted by the high- and new-technology enterprise (HNTE) program[2] by improving firms' innovation ability.

Institutional quality plays a crucial role in enhancing export quality beyond its direct impact on exporting activities. Henisz (2000), Mauro (1995), Méon and Sekkat (2005), and Mo (2001) demonstrate that better institutional frameworks foster investment by reducing business environment uncertainty, thereby influencing export quality. Employing the export data from 58 countries to the US in 1996, Faruq (2011) suggests that improvements in export quality are linked to stronger institutional frameworks, characterized by lower corruption, higher bureaucratic efficiency, and stronger property rights protection. Rule of law, government effectiveness, and political stability are positively associated with export upgrading measured by the export sophistication index for a cross-country dataset from 1992 to 2006 (Zhu & Fu, 2013). Using the Chinese firm-level data from 2000 to 2011, Lin et al. (2021) constructs an institutional index using six dimensions - financial services, open-door policies, government intervention, corruption, property rights protection, and judicial fairness - to analyze their collective impact on export quality. Their findings confirm a positive relationship between institutional quality and export product quality. Especially, this positive impact is more pronounced in the case of corruption and judicial fairness. In Colombia, regulatory quality and the rule of law have been shown to enhance both product quality and export value (Abreo et al., 2021). The impact of institutions on export quality varies significantly between different countries and different levels of development.

The impact of IPRs on export quality attracts many scholars, and this effect is controversial. In theory, Song et al. (2021) suggested two opposite effects of IPRs on export quality - *innovation effect* and *threshold effect*. Specifically, *innovation effect* shows that the strengthened IPRs affect export quality positively since the innovation is less likely to be imitated. Consequently, firms have incentives to invest in innovation and improve their product quality. On the contrary, under the *threshold effect*, strengthened IPRs increase innovation competition and market entry threshold, which discourages firms from upgrading their export quality. Thus, the impact of IPRs on export quality depends on the weight of these two effects. The empirical evidence showing the impact of IPRs on export quality is divided into two groups: positive impact of IPRs on export quality is found in the studies of B. Dong et al. (2022) and

[1] Chai (2023) and D. Zhang (2022) proved the positive effect of green innovation on export quality.

[2] The HNTE program is a government intervention designed to pick winners, aiming to boost enterprise innovation through financial incentives.

Song et al. (2021), while Y. Liu et al. (2021) found a negative nexus between IPRs and export quality. In the recent analysis, Ndubuisi (2023) suggests that patent protection affects quality upgrading through its impacts on innovation and technology inflows from abroad. This research provides the literature with proof that R&D-intensive industries export products with higher quality to partners with stronger patent protection.

2.2.2 Determinants of innovation

There is a wide range of empirical analyses investigating the determinants of innovation in the literature. R&D is a well-known determinant of innovation, and the positive impact of R&D on innovation is proven in various analyses (Hammar & Belarbi, 2021; Harris & Moffat, 2011; Ulku, 2004). Besides R&D, Furman et al. (2002) showed that the other determinants of innovation are intellectual property, trade openness, the share of research by the academic sector, and knowledge stock characterize innovative capacity. Hsu et al. (2014) added the other two factors, which positively affect innovation, are high-tech intensity and external finance.

Attending international trade is one of the effective ways for firms to enhance their productivity and innovation through the learning-by-exporting (LBE) effect. Participation in export activities frequently provides firms with access to heterogeneous knowledge inputs not readily available in their home market. The absorption of this external knowledge can then lead to a learning effect within the focal firm, thereby promoting increased innovative activity (Salomon & Shaver, 2005). As shown by De Loecker (2007) and Wagner (2007), entering export markets encourages firms to improve their productivity to face the severe competition. Firms' innovation is accelerated by importing intermediate inputs (G. Chen & Wu, 2017). There is a two-way relationship between R&D (a measure of innovation input) and export (Girma et al., 2008). Filipescu et al. (2013) point out a Granger cause between innovation and export. Using the European firm data Segarra-Blasco et al. (2022) prove that the spatial LBE is more pronounced for less advanced countries, while temporal LBE is more sensitive for advanced ones. In a recent study, Liang et al. (2024) supported the LBE effect by proving the positive impact of export on the quantity and quality of innovation measured by patent citations in China. Adewumi et al. (2024) confirm the role of export-led innovation on innovative activities of manufacturing and services firms in Norway. In a recent study, Cai and Wu (2024) use a panel negative binomial model with firm-level data from China to investigate the effect of export quality on patents - a measure of innovation output. The results prove the U-shaped relationship between export quality and patents for inventions and between export quality and utility model patents, but there is no evidence showing the nexus between export quality and design patents.

North (1990) address the importance of institutions for innovation in reducing transaction costs. The level of institutional quality in the location of firms affects their innovative performance, namely, Blind (2012), Fuentelsaz et al. (2018), and Tebaldi and Elmslie (2013) point out that firms in countries with high-quality institutions tend to invest more in innovation. Furthermore, firms in these countries can easily get access to advanced knowledge and technologies, which is crucial for innovative activities (Almeida & Kogut, 1999; Fuentelsaz et al., 2018; Hemmert, 2004; R. R. Nelson, 1993; J. Wu et al., 2015). Control of corruption plays an important role in accelerating innovation (Anokhin & Schulze, 2009). Rodríguez-Pose and Di Cataldo (2015) found that the better control of corruption and government effectiveness, the higher firms in Europe conducting innovation in terms of patent applications.

Rodríguez-Pose and Zhang (2020) use the Chinese firm-level data to explore the impact of institutions on innovation. They prove that weak institutions (rule of law, control of corruption, and regulatory quality) hinder the innovation of Chinese firms. In the Emilia-Romagna region of Italy, government effectiveness and voice and accountability are the two institutional components playing the most important role in boosting innovation (Mosconi & D'Ingiullo, 2023). Recently, Sharma et al. (2022) explores the impact of institutional quality on innovation outcomes using the data of 50 countries from 1998 to 2017 and suggests that patent enforcement harms countries with less innovative activity. Furthermore, institutional quality does not foster innovation, especially for countries with weak innovative capacity. Institutions improve innovation measured by the number of patents per capita, especially for high-tech innovation (Donges et al., 2023).

To prevent the imitation of new inventions, the IPRs emerged, played an important role in protecting innovative activities. Different from other institutions, IPRs can be considered one of the incentives for firms to innovate. The impact of strengthening IPR on innovation varies among studies. Specifically, strengthening of IPRs positively affects innovation (Y. Chen & Puttitanun, 2005; Chu et al., 2018; Kanwar & Evenson, 2003; Sweet & Maggio, 2015). However, Gallini (1992), Jaffe (2000), Mazzoleni and Nelson (1998), and Sakakibara and Branstetter (1999) found no impact of stronger IPR on innovation. Cho et al. (2015) use firm-level data to discover the causal effect between IPR and growth through R&D with different paths. They prove that strong IPR policies are detrimental to innovation. Recently, Akbar et al. (2024) found that stronger institutional quality, such as the rule of law, property rights, and access to financing, fosters innovation.

2.2.3 Two-way relationship between export quality and patent intensity, and moderating role of institutions on this bidirectional nexus

Prior studies have used the number of patents or R&D investment as proxies for innovation to explore the relationship between export quality and innovation. This paper is the first to employ patent intensity, defined as patents per unit of export value, to investigate the nexus between export quality and patent intensity. We hypothesize that patent intensity can have both positive and negative effects on export quality. On the one hand, increasing patent intensity can enhance export quality by strengthening the protection of innovative products and making imitation more difficult. Furthermore, innovative products are of higher quality and thus can compete successfully in foreign markets. This encourages firms to invest more in R&D, which, in turn, improves their export quality. This aligns with the *innovation effect* introduced by Song et al. (2021). Additionally, a rise in patent intensity can lead to stronger quality competition in the market, as products are better protected by patents. To stay competitive in foreign markets, firms must innovate further to differentiate themselves, which is known as the *escape-competition effect* outlined by Aghion et al. (2005). On the other hand, from a Schumpeterian perspective, competition can be detrimental to innovation. Specifically, as market competition intensifies, successful innovators earn lower profits and have less incentive to innovate, which is referred to as the *Schumpeterian effect* (Aghion et al., 2005). Griffith et al. (2010) also suggested that monopoly rents, which incentivize R&D investment, are diminished by increased competition. Based on this mechanism, it is plausible that higher patent intensity could lead to a reduction in R&D activities and export quality. Besides, according to the prominent concept of the tragedy of anticommons introduced by Heller (1998), an excessive number of patent holders controlling pieces of a technology can prevent innovation because companies or individuals may not be able to access or combine the necessary patents to create new products or solutions. In such cases, the fragmentation of property rights can hinder progress rather than encourage it. The overall impact of patent intensity on export quality depends on the relative strengths of these effects. If the *Schumpeterian effect* outweighs the *escape-competition effect*, the impact will be negative. Conversely, if the *escape-competition effect* is stronger, patent intensity will have a positive effect on export quality.

Export quality contributes to the success of exports in the international market (Brooks, 2006; Verhoogen, 2008). According to Song et al. (2021) and H. Zhang and Yang (2016), the enhancement in product quality is one of the determinants of export upgrading. Thus, along with exporting activity, export product quality might also affect productivity and innovation. However, as mentioned earlier there is only one study of Cai and Wu (2024) showing the impact of export quality on the number of patents of Chinese firms. There is no analysis investigating the impact of export quality on patent intensity for a sample of countries. We expect that export quality can have both positive and negative impacts on patent intensity. Concerning the negative impact, our intuition is that the increase in export quality induces an increase in export value since firms accelerate their sales thanks to high-quality products. As mentioned by O'Connor et al. (2004), firms' patent output decreases if firms enhance their export product quality by adopting high-quality intermediate inputs. Based on the measure of patent intensity (the ratio of the number of patents to export value), the patent intensity will decrease. The decrease in patent intensity due to an improvement in export quality can be explained in economic terms as follows. First, higher export quality generally means that the products being exported are more sophisticated, have advanced features, or are produced using cutting-edge technology (DeStefano & Timmis, 2024). When a company focuses on producing higher-quality goods, it often relies more on product differentiation rather than competing primarily on innovation in terms of patents (Moresi & Schwartz, 2023). Second, innovative firms will apply for a patent when they introduce new technologies or processes that are distinct enough to warrant protection. However, firms exporting high-quality products might already possess the core technologies, and additional innovations may be minor and may not always lead to patentable inventions. Third, high-export quality products are often possessed by firms operating in more mature industries or sectors with established technologies (luxury goods, specialized machinery). In these industries, firms might already hold a substantial number of patents, and additional patents may not be crucial. Moreover, these firms might achieve economies of scale, relying on established patents rather than seeking new patents to protect incremental enhancements. Fourth, the patent application involves significant costs and long procedures. Firms producing high-quality products may prefer to invest resources in marketing, distribution, or improving existing product features rather than generating a high volume of new patents. Finally, high-quality exports might be associated with firms that innovate in ways that do not always require patents, such as in design, branding, or customer experience (Golovko et al., 2023; L. Liu et al., 2023). Firms operating in industries where quality is key might rely on their brand and reputation, rather than patenting new innovations.

Wang et al. (2016) suggest that enhanced export product quality, by improving resource accumulation and learning capabilities, can boost innovation output, potentially leading to increased patenting. This implies a scenario where the impact of export quality on patent intensity is positive. Such an effect is particularly plausible in high-tech sectors (e.g., electronics, biotechnology, pharmaceuticals, semiconductors) that depend heavily on complex, knowledge-based innovations; if the resulting patent growth outpaces the increase in export value, patent intensity will rise. However, export quality might negatively affect patent intensity in mature industries. Here, firms with extensive existing patent portfolios may prioritize leveraging current IP over seeking numerous new patents, even as quality improves. Moreover, high-quality products might derive their distinction from non-patentable innovations like branding and design, rather than new technological advancements. Thus, we propose that the impact of export quality on patent intensity is likely heterogeneous, varying across sectors and industries.

As mentioned in the literature, institutional quality acts as a determinant of export and innovation. In addition, institutions negatively moderate the impact of firms' spending time in tackling the government regulations on enhancing their innovation (Rodríguez-Pose & Zhang, 2020). The moderating role of institutions on the relationship between innovation and international trade is explored by Hashmi et al. (2022), Sakyi et al. (2023), and Zhuang et al. (2021). Particularly, Zhuang et al. (2021) use quality government regulation as a proxy for institutions, and the results prove that institutional quality, measured by an index of the 7 indicators of governance, enhances the nexus between technological innovation and trade openness. Hashmi et al. (2022) use the data of SMEs in developing countries to investigate the impact of innovation on export performance. The authors confirm the positive moderating role of institutional environment specificity and enforceability on the relationship between innovation and export. Institution (namely, control of corruption, government effectiveness, political stability, regulatory quality, rule of law, voice and accountability, and quality of institutions index) positively moderates the nexus between technology adoption and export performance of 49 African countries (Sakyi et al., 2023).

In addition to directly influencing export quality and patent intensity, we posit that institutional quality critically moderates their interrelationship. We argue that superior institutions incentivize firms to leverage patents more effectively, thereby strengthening the positive link from patent intensity to export quality. While patent intensity's impact on export quality can be ambiguous, high-quality institutional environments marked by government stability, rule of law, and minimal corruption motivate innovation and product upgrading. This enhances the positive effects of patent intensity on export quality or buffers against negative ones.

Conversely, institutional quality also moderates the impact of export quality on patent intensity. An increase in export quality might, in itself, variably affect patenting activity. However, better institutions can steer this effect, for example, by attracting FDI, stimulating R&D, or streamlining patenting procedures. Consider a scenario where rising export quality might reduce patent intensity; strong institutions can encourage firms to channel increased sales revenues back into R&D. This leads to further innovation and subsequent patent applications, thereby lessening any potential decline in patent intensity or even fostering an increase, compared to an environment with weaker institutions.

From the previous evidence and the intuition of the moderation effect of institutional quality on export quality and patent intensity, we suggest that the quality of institutions positively moderates the two-way relationship between export quality and patent intensity.

In summary, the relationship between export quality, patent intensity, and other variables is summarized in the diagram in Figure 2.1.

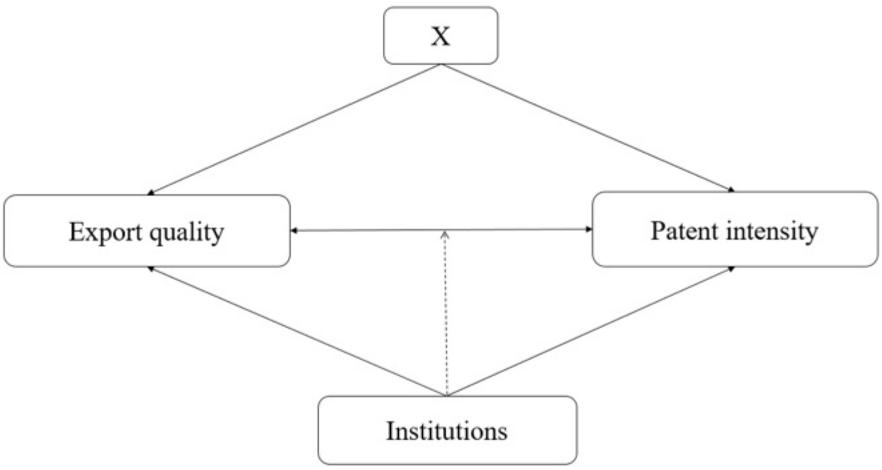


Figure 2.1: Conceptualized the relationship among variables

2.3 Data and Methodology

2.3.1 Data

The data used in this analysis is 3-dimensional panel data. Data on export quality comes from the IMF, covering the SITC 4-digit products. The measure of export quality stems from Henn et al. (2020), in which the trade price of product from exporter x to importer m at year t (P_{mxt}) is a function of unobserved quality (Q_{mxt}), the income per capita of exporter (Y_{xt}), and the distance between exporter and importer ($Dist_{xm}$) as Equation (2.1).

$$lnP_{mxt} = \mu_0 + \mu_1 lnQ_{mxt} + \mu_2 lnY_{xt} + \mu_3 lnDist_{xm} + \nu_{mxt} \tag{2.1}$$

The target is to obtain the estimation of parameters and then use Equation (2.1) to infer the value of dependent variable quality from the independent ones – P_{mxt}, Y_{xt}, and $Dist_{xm}$. According to Henn et al. (2020), to estimate parameter μ_i, it is necessary to specify a quality augmented gravity equation:

$$lnImport_{mxt} = \alpha lnDist_{mx} + \beta I_{mxt} + \delta lnQ_{mxt} lnY_{mt} + FE_m + FE_x + \theta_{mxt} \tag{2.2}$$

FE_m and FE_x are fixed effects of importer and exporter, respectively. The matrix I_{mxt} denotes trade determinants from the gravity equation (common border, common language, the attendance of FTAs). Rearrange Equation (2.1) to gain the unobserved variable (Q_{mxt}) as a function of observed ones, then plug it into Equation (2.2), the new estimation equation is as below:

$$\begin{aligned} lnImport_{mxt} = \alpha lnDist_{mx} + \beta I_{mxt} + \mu_1' lnP_{mxt} lnY_{mt} + \mu_2' lnP_{xt} lnP_{mt} \\ + \mu_3' lnDist_{xm} lnY_{mt} + FE_m + FE_x + \nu_{mxt}' \end{aligned} \tag{2.3}$$

Where $\mu_1' = \frac{\delta}{\mu_1}$, $\mu_2' = -\frac{\delta\mu_2}{\mu_1}$, $\mu_3' = -\frac{\delta\mu_3}{\mu_1}$, and $\nu_{mxt}' = -\frac{\delta\mu_0 + \delta\nu_{mxt}}{\mu_1} lnY_{mt} + \theta_{mxt}$

Equation (2.3) is estimated separately for each category of product to yield the coefficients, which are then applied to extract the value of export quality. Finally, the quality is estimated as the below equation.

$$\text{Quality estimate}_{mxt} = \mu_1' lnP_{mxt} + \mu_2' lnY_{xt} + \mu_3' lnDist_{mx} \tag{2.4}$$

The data on patents, namely the number of patents under International Patent Classification (IPC) codes is from OECD Statistics. The data covers 98 countries (30 OECD and 68 non-OECD countries) from 1999 to 2019. The IPC codes are divided into 8 groups and subgroups, which information is provided in detail in Table B1.1, Appendix B1. To merge the patent and export quality data, it is necessary to use the patent crosswalks, namely International Patent Classification (IPC) Crosswalks[3] introduced by Lybbert and Zolas (2014).

[3]https://sites.google.com/site/nikolaszolas/PatentCrosswalk?pli=1

The merging process is conducted through two steps. First, we merge the data concerning the provided weights and the data of IPC with the key "IPC code", then merge this data and export quality data with two keys "Country" and "Year". To use the crosswalk, the value of the variable in the original classification is simply multiplied by the provided weights. Specifically, in this analysis, to obtain a new export quality index in IPC form, the export quality index is multiplied by the provided weight. Similarly, to get a new patent index in export quality form, the patent index is multiplied by the corresponding provided weight.

The data for control variables are from various sources. Data for R&D investment, FDI inflow, import value, trade openness (the sum of export and import divided by GDP), and human capital, namely the expenditure on education, are collected from the World Bank (WB). The Economic Complexity Index (ECI) based on trade data (ECI trade) is collected from the Observatory of Economic Complexity (OEC).

Concerning institutions, we use two sets of data, one from the International Country Risk Guide (ICRG) and the other from the Worldwide Governance Indicators (WGI). The higher value of each type of institution means higher institutional quality. Seven variables of institutions from ICRG belong to political risk components. They are government stability, socioeconomic conditions, investment profile, corruption, law and order, democratic accountability, and bureaucracy quality. Among these seven components, government stability, socioeconomic conditions, and investment profile possess three subcomponents. Specifically, government stability includes government unity, legislative strength, and popular support; socioeconomic conditions include unemployment, consumer confidence, and poverty; and investment profile includes contract viability/expropriation, profits repatriation, and payment delays.

The data for the instruments are as follows: The average quality imported by trade partners is from the IMF; the exchange rate and the charge for the use of intellectual property are from WB. Charge for the use of intellectual property are the payments and receipts between residents and nonresidents for the authorized use of proprietary rights (such as patents, trademarks, copyrights, industrial processes, and designs including trade secrets, and franchises) and for the use, through licensing agreements, of produced originals or prototypes (such as copyrights on books and manuscripts, computer software, cinematographic works, and sound recordings) and related rights (such as for live performances and television, cable, or satellite broadcast). It is the sum of these above payments or receipts as reported by that country in its Balance of Payments (BoP).

The details of data sources and measurements are provided in Table 2.1. After merging the data, we finally have 774.816 observations covering 16 years from 1999 to 2014 and 89 countries (38 OECD and 51 non-OCED) as shown in Table B1.2, Appendix B1.

Table 2.1: Variables in the analysis

Source	Variables	Measure
IMF	Export quality (EQ) Average quality imported	Index
OECD Statistics	Patent	Unit
The World Bank (WB)	GDP per capita (GDPPC) Trade openness (Openness) Foreign direct investment (FDI) R&D investment (RD) Expenditure for education (Exp-edu) Import value (Import) Exchange rate (Exrate) Charges for the use of intellectual property (charge)	Current US dollar Percentage Current US dollar Percentage (of GDP) Percentage (of GDP) Current US dollar Local currency units per US dollar Current US dollar
Observatory of Economic Complexity (OEC)	Economic Complexity Index (ECI)	Index
World Integrated Trade Solution (WITS)	Herfindahl-Hirschman Index (HHI)	Index
International Country Risk Guide (ICRG)	Government Stability (gov) Corruption (corr) Law and Order (law) Bureaucracy Quality (bureau)	0 - 12 0 - 6 0 - 6 0 - 4

Table 2.2 shows the summary statistics of the variables in the model. Before estimating the model, it is necessary to check for the correlation among the variables. The summary statistics of variables for OECD and non-OECD countries are shown in Table B1.3, Appendix B1. The correlations among variables in the analysis are in Table B1.4, Appendix B1. There is no strong correlation among the variables considered. Thus, all variables can be used to estimate the two-way relationship between export quality and patent intensity. From the results, it can be seen that the correlations between export quality and all the explanatory variables are positive, except HHI. Patent intensity is positively correlated with all the variables, except trade openness and HHI.

Table 2.2: Summary Statistics

Variables	Num.Obs.	Mean	Standard deviation	Min	Max
Export quality	601,600	0.250	0.267	0.00005	1.395
Patent intensity	601,600	0.017	0.626	0	364.384
GDPPC	774,816	17761.61	19707.17	351.839	123678.7
FDI	773,193	$1.86e+10$	$4.74e+10$	$-2.97e+10$	$7.34e+11$
Import	774,816	$1.40e+11$	$2.71e+11$	$3.42e+08$	$2.41e+12$
Openness	774,816	0.726	0.508	0.157	4.199
R&D	616,361	1.112	0.970	0.016	4.417
Expenditure on education	612,604	4.711	1.343	1.151	9.510
ECI	688,391	0.429	0.833	-2.229	2.410
HHI	753,642	0.111	0.102	0.031	0.780
Average quality imported	601,600	0.928	0.106	0.008	1.906
Exchange rate	750,063	4750914	$1.79e+08$	0.025	$6.72e+09$
Charge for the use of IP	638,364	$2.87e+09$	$6.46e+09$	98.84	$5.73e+10$
Government stability	740,206	8.306	1.600	4.042	12
Corruption	740,736	3.002	1.282	0	6
Law and order	740,736	4.149	1.292	0.5	6
Bureaucracy quality	740,736	2.715	0.947	0.5	4

2.3.2 Methodology

To figure out the two-way relationship between export quality and patent intensity, we employ the Simultaneous Equation Model (SEM) with two equations - Equation (2.5) and Equation (2.6). The condition to apply SEM is the autonomy requirement, in which each of the equations in the SEM has economic meaning independently (Wooldridge, 2010). Our equations satisfy the autonomy requirement since we introduce different instruments for the endogenous variables, which are mentioned below.

The two different estimations often used for SEM are two-stage Least Squares estimation (2SLS) and three-stage Least Squares (3SLS). These two approaches are similar in the first two steps. Specifically, in the first step, the endogenous variables are regressed on exogenous variables. The estimated values of endogenous variables and other exogenous variables are obtained in the second step. The third step exists only in the 3SLS - the correlations between the error terms in the two equations are accounted for using Generalized Least Squares (GLS) or Weighted Least Squares (WLS). GLS is used when the error terms are homoscedasticity. while WLS is used when the error terms are heteroscedasticity (Wooldridge, 2010).

In our analysis, first, we estimate each equation with 2SLS separately. The results for the underidentification test and weak identification test to check the strength of the instruments used in the estimation are also extracted. Then, 3SLS is used to estimate both equations simultaneously.

$$EQ_{idt} = \alpha_0 + \alpha_1 PI_{idt} + \alpha_2 lnX_{it} + \delta_i + \delta_d + \delta_t + \varepsilon_{idt} \tag{2.5}$$

$$PI_{idt} = \beta_0 + \beta_1 EQ_{idt} + \beta_2 lnX_{it} + \gamma_i + \gamma_d + \gamma_t + \epsilon_{idt} \tag{2.6}$$

Where i, d, t denote country, product sector, and year, respectively. EQ_{idt} is the export quality of product-sector d of country i at time t, PI_{idt} is the patent intensity index of country i corresponding to product-sector d at time t, which is calculated as Equation (2.7).

X_{it} is the control variable, including GDP per capita, R&D investment, FDI inflow, import value, trade openness, human capital, ECI, and HHI of country i at time t. R&D investment is the ratio of R&D expenditure to GDP. Human capital is government expenditure on education calculated as the ratio of expenditure on education to GDP. R&D expenditure and human capital are two important determinants of creating knowledge and export quality. Human capital is proven as one of the main factors of endogenous technological progress in the theory of new economic growth. Meanwhile, investment in R&D plays an important role in accelerating technological progress, innovation activities, and export quality (H. Zhang & Xing, 2019). Trade openness is another determinant of export quality. It is the ratio of the total export and import value to GDP. Import can enhance export quality directly through the adoption of better intermediate, and indirectly through knowledge spillover (Zhu & Fu, 2013). Import also shows a positive impact on innovation output (Fritsch & Görg, 2015). ECI can have an impact on export quality and patent intensity. The literature shows that countries with higher levels of complexity have higher product quality (Le et al., 2022). Besides, ECI has a positive impact on innovation output (Azam, 2017) and promotes green patents (Donis et al., 2023). HHI is a measure of market concentration, and it affects international trade and innovation. Namely, the competition promotes the innovative activities of the information technology industry (T. Chen et al., 2021).

δ_i and γ_i are country-fixed effects. δ_d and γ_d are product-sector fixed effects, δ_t and γ_t are time fixed effects. These fixed effects are included to control for unobserved variables, which can affect export quality and patent intensity, such as changes in the condition of the countries (politics, pandemics), technological shifts, or demand shocks.

As both quality and patent intensity are endogenous in the model, it is crucial to have instruments to estimate these endogenous variables in the first step of the 2SLS and 3SLS. We use the charge for the use of intellectual property and its lag, lag of patent intensity, and of all the control variables as instruments for patent intensity. Concerning instruments for export quality, exchange rate, the average quality imported by its trade partners (i.e. importers) from all exporters from which they import, their lags, and the lag of export quality and of all the control variables are employed. We believe these instruments are suitable since they are correlated with the endogenous but not with the error terms. Moreover, the charge for the use of intellectual property directly affects patent intensity but does not affect export quality. The exchange rate is used as an instrument for export quality in prior studies (Cai & Wu, 2024). According to Henn et al. (2020) the average quality imported by its trade partners (importers) is useful to gauge if an exporter could upgrade quality without changing its set of trading partners. Thus, it affects export quality but does not influence patent intensity.

To test the strength of the instruments, the underidentification test and the weak identification test are conducted. The underidentification test is an LM test, which checks for the identification of the equation; in other words, it shows if the instruments are relevant. The null hypothesis is that *the equation is underidentified.* A rejection of the null hypothesis proves that the equation is identified and the instruments in the model are relevant. When the instruments are weakly correlated with endogenous variables, weak identification emerges. Thus, it is necessary to test if the model has a weak identification. Weak instruments exist if the value of the Cragg-Donald Wald F statistic is below 10, as the rule of thumb from Staiger and Stock (1994), the cutoff value of 10, or in the range from 9 to 11.52 from Stock and Yogo (2002). Wald tests for country fixed effect, product-sector fixed effect, and time fixed effect are also conducted to test for the existence of these fixed effects. The rejection of the null hypothesis *fixed effects do not exist* indicates that including these fixed effects in the regression is crucial.

In this study, instead of using the number of patents, we use patent intensity calculated as in Equation (2.7) since the number of patents is not as informative as patent intensity. An increase in the number of patents in a sector shows two mechanisms. First, it implies that this rise is due to the increase in the number of firms in the sector. Second, the number of patents increases, but the number of firms in the sector remains unchanged. This can be explained by the increase in the innovative level of firms. We aim at the second mechanism, which is only clarified by investigating patent intensity. Several studies calculate patent intensity as the ratio of patents to the number of population/inhabitants (Frietsch et al., 2014), the number of patents divided by market capitalization (Bena et al., 2023), the number of patents per GDP of a nation (Prathipa & Balasubramanian, 2012) or the ratio of technology patents to population, national GDP, and venture capital investment (Jemala, 2016). However, this measure can only show the patent intensity at the country or firm level. Based on the availability of the data, we suggest a new measure of patent intensity - the number of patents per unit of export value at the country-product-sector level. This gives the number of patents associated with the export value of SITC 4-digit products at a specific 4-digit IPC.

$$\text{Patent intensity (PI)} = \frac{\text{The number of Patents}}{\text{Export value}} \times 100 \tag{2.7}$$

Besides, the quality of institutions may moderate the two-way relationship between export quality and patent intensity, we explore this moderation effect by inserting two interaction variables, namely, the interaction between patent intensity and institutions $PI_{idt} \times W_{jit}$ into Equation (2.5), and the interaction between export quality and institutions $Quality_{idt} \times W_{jit}$ into Equation (2.6). W_{jit} denotes the institutional quality j of country i in year t. Based on the literature, most previous studies adopt government intervention, control of corruption, property rights protection, government effectiveness, bureaucratic efficiency, political stability, rule of law, and voice and accountability as proxies for institutional quality. In this analysis, we select government stability, corruption, law and order, and bureaucracy quality as institutional quality variables. Our choice of these institutional variables: government stability, control of corruption, law and order, and bureaucracy quality stems from their direct and significant influence on firms' strategic decisions regarding innovation, intellectual property (IP) protection, and export activities. Specifically, government stability mitigates investment uncertainty, thereby encouraging R&D and export quality enhancements. This provides firms greater motivation to innovate. Low corruption ensures more secure markets and reduces costs associated with patenting and contract enforcement, which is vital for fostering innovation. Robust law and order is essential for IPR protection, increasing the value of patents and thus incentivizing firms to invest in patentable innovations and utilize them to upgrade export quality. High bureaucracy quality, signifying efficient and transparent government administration, encourages firms to innovate, pursue patent protection, and improve product quality by reducing administrative hurdles.

After adding the interaction terms, Equations (2.5) and (2.6) now become Equations (2.8) and (2.9), respectively. As mentioned in the Literature review, we expect the coefficients of the interaction terms (α_3' and β_3') to be significantly positive.

$$EQ_{idt} = \alpha_0' + \alpha_1' PI_{idt} + \alpha_2' W_{jit} + \alpha_3' PI_{idt} \times W_{jit} + \alpha_4' lnX_{it} + \delta_i + \delta_d + \delta_t + \varepsilon_{idt}' \tag{2.8}$$

$$PI_{idt} = \beta_0' + \beta_1' EQ_{idt} + \beta_2' W_{jit} + \beta_3' EQ_{idt} \times W_{jit} + \beta_4' lnX_{it} + \gamma_i + \gamma_d + \gamma_t + \epsilon_{idt}' \tag{2.9}$$

2.4 Empirical Analysis

2.4.1 Baseline regression

Table 2.3 provides the results of estimating Equation (2.5) and Equation (2.6) using the 2SLS and 3SLS approach for the whole sample. The results from 3SLS are in line with those from 2SLS in terms of signs and significance, but the magnitudes are larger. The significant LM statistic of the underidentification test suggests that the null hypothesis - *the equation is underidentified* is rejected. The value of the Wald F statistic is above 10 as the rule of thumb from Staiger and Stock (1994). Thus, the instruments used in the research are not weak. In 3SLS, all the instruments used in 2SLS are adopted. An advantage of 3SLS compared to 2SLS is that the correlation between the error terms in the two equations is accounted for in the third stage. Moreover, the two equations are estimated simultaneously. The results from the Wald test for fixed effects confirm the existence of the country-fixed effect, product-sector fixed effect, and time-fixed effect. Thus, we add these fixed effects in both 2SLS and 3SLS to extract the plausible results from estimation. The results of the first stage of 2SLS are provided in Table B1.5, Appendix B1.

The results show a two-way relationship between export quality and patent intensity, and these impacts are both negative. The negative impact of patent intensity on export quality supports the *Schumpeterian effect.* An increase in patent intensity leads to severe competition in the market, and this reduces the profit of successful innovators. Firms have less motivation to conduct innovation, and export quality will be reduced consequently. The increase in export quality is also harmful to patent intensity. As per the earlier discussion, the enhancement of export quality might be enacted from product differentiation and additional innovation, but these might not be distinct enough to warrant protection. Especially in mature industries, firms hold a great number of patents, and they prefer to rely on these existing patents to apply for new patents, which incurs high costs in terms of finance and time. Moreover, high-quality products might not be linked with patentable innovation, but with branding and design.

Concerning control variables, GDP per capita, trade openness, imports, and ECI affect export quality positively. These results are as expected. However, the impact of R&D investment and human capital (measured by expenditure on education) on export quality is significantly negative, while FDI and HHI do not affect export quality. Regarding the impact of these controls on patent intensity, the increase in GDP per capita, trade openness, human capital, and HHI is harmful to patent intensity; R&D, import value, and ECI show positive roles, while FDI shows no impact on patent intensity.

2.4.2 Results for different types of countries and levels of income

Table 2.4 provides the results when separating the whole sample into two subsamples - OECD and non-OECD countries, and different levels of income using the 3SLS estimation method. The results are all significant for both subsamples. This reaffirms the findings from the whole sample.

In the first panel, the impact of patent intensity on export quality is significantly negative for both OECD and non-OECD countries but the magnitude of this impact is larger in the non-OECD subsample compared to that from the OECD one. As explained earlier, this negative impact is due to the larger weight of *Schumpeterian effect* to *escape-competition effect*. However, in OECD countries, the number of productive firms with a high level of technology is greater than in non-OECD countries. The competitiveness of these firms is blatantly high. Despite the high level of patent intensity, these firms still engage in innovative activities to compete with one another in the market. The *escape competition effect* of firms in OECD countries is hence stronger than that in non-OECD counterparts. As a consequence, the negative impact of patent intensity on export quality in the OECD subsample is lower than in non-OECD countries.

Regarding the second panel, export quality shows a negative effect on patent intensity for both subsamples. Similar to the first panel, the magnitude of the OECD subsample is smaller than that of the non-OECD one. We provide a possible explanation as follows. Though firms exporting high-quality products already possess cutting-edge technology, have substantial number of patents, and prefer to invest in marketing, distribution or improving the current products in the market, the most productive firms in technology and information & communication technology (ICT) sector and pharmaceuticals and biotechnology sector still conduct innovation, create novel inventions, which need protecting by patents. These firms

Table 2.3: Two-way relationship between export quality and patent intensity results

	2SLS		3SLS	
Variables	**lnEQ**	**lnPI**	**lnEQ**	**lnPI**
	(1)	(2)	(3)	(4)
lnPI	-0.020^{***}		-0.053^{***}	
	(0.006)		(0.001)	
lnEQ		-0.226^{***}		-0.488^{***}
		(0.050)		(0.011)
lnGDPPC	0.029^{***}	-0.115^{***}	0.042^{***}	-0.085^{***}
	(0.003)	(0.012)	(0.006)	(0.017)
lnOpenness	0.011^{***}	-0.085^{***}	0.026^{***}	-0.042^{**}
	(0.003)	(0.012)	(0.005)	(0.016)
lnFDI	-0.0001	0.001	-0.0005	-0.001
	(0.0001)	(0.001)	(0.0002)	(0.0004)
lnRD	-0.007^{***}	0.028^{***}	-0.007^{***}	0.032^{***}
	(0.001)	(0.006)	(0.003)	(0.008)
lnExp-edu	-0.006^{***}	-0.005	-0.012^{***}	-0.027^{**}
	(0.002)	(0.008)	(0.004)	(0.011)
lnImport	0.025^{***}	0.116^{***}	0.016^{**}	0.117^{***}
	(0.003)	(0.011)	(0.006)	(0.016)
lnECI	0.005^{***}	0.014^{***}	0.005^{***}	0.010^{***}
	(0.001)	(0.002)	(0.001)	(0.003)
lnHHI	-0.0003	-0.030^{***}	0.001	-0.023^{**}
	(0.001)	(0.006)	(0.003)	(0.009)
Cons.			-3.240^{***}	-6.883^{***}
			(0.063)	(0.270)
Num.Obs.	239,456	254,693	236,570	236,570
R2	0.0354	0.0035	0.9883	0.3485
Kleibergen-Paap rk LM statistic	247.223^{***}	2055.601^{***}		
Cragg-Donald Wald F statistic	289.903	5590.706		
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Product-sector FE	Yes	Yes	Yes	Yes

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

are often located in OECD countries. Therefore, an increase in export quality can lead to a decrease in patent intensity, but this impact is lower in OECD countries than in non-OECD ones.

Since several high-income nations, such as Hong Kong and Singapore, are classified as non-OECD countries, this distinction may influence the empirical results. To account for this, we re-estimate the model using two subsamples, high-income and low-income countries, based on GDP per capita. Models (3) and (4) in Table 2.4 present the results for countries above and below the 50th percentile of GDP per capita, respectively[4]. The findings reaffirm the existence of a negative bidirectional relationship between export quality and patent intensity. Notably, the impact of patent intensity on export quality is smaller in high-income countries compared to low-income countries, consistent with the earlier findings contrasting OECD and non-OECD nations. Conversely, the effect of export quality on patent intensity is more pronounced in high-income countries than in their low-income counterparts. The increase in the number of observations for high-income countries, relative to the OECD sample, highlights the influence of non-OECD high-income nations on the results. Specifically, Singapore exemplifies this pattern, as it tends to rely more on trademarks than patents to protect its innovations[5].

2.4.3 Results for different levels of technology intensity

We argue that the impact of export quality on patent intensity and the opposite relationship might be different depending on different levels of technology intensity. Cipollina et al. (2016) separated their samples into low-tech, medium-tech, and high-tech intensity based on the number of patents. In this study, we only divided the sample into low technology and high technology since the majority of countries in the data are non-OECD and their patents are not in great numbers. Low-technology sample has a number of patents below the mean, and high-technology sample has a number of patents above the mean. Equation (2.5) and Equation (2.6) are estimated with 3SLS for each subsample, and the results are in Table 2.4. The results are negative and significant, suggesting that the two-way relationship between export quality and patent intensity is confirmed and conformity with that from the baseline regression.

Export quality discourages patent intensity for both subsamples, and the magnitude of the effect is larger in the case of the low technology subsample than the high technology one. This result is similar to that from different types of countries. Analogous explanations can be used in this situation. Particularly, firms in low-technology sectors do not have great motivation to innovate when patent intensity is high because of the severe innovation competition that erodes the monopoly rents. This also happens to high-technology firms. However, in high technology sectors, firms possess strong capability in innovation and inventing novel products. Under high competition, they can still carry out innovative activities. Thus, patent intensity

[4] GDP per capita for low-income countries ranges from 351.84 to 9,101.2 USD, while that for high-income countries ranges from 9,137.5 to 123,678.7 USD.

[5] https://www.wipo.int/edocs/statistics-country-profile/en/sg.pdf

negatively affects export quality but with a smaller weight in the case of high-technology industries.

An increase in export quality demotes patent intensity for both high- and low-technology sectors. Interestingly, the magnitude of this effect is opposite to the outcome from different types of countries' subsamples. Namely, in the high technology sector, this impact is larger than in the low technology sector. High-tech sectors such as electronics, biotechnology, pharmaceuticals, and semiconductors often rely heavily on complex, integrated systems and knowledge-based innovations that extend beyond simple product patents. In these sectors, firms typically invest in trade secrets, proprietary technologies, process innovations, and brands to protect their competitive advantage rather than focusing solely on patents. Besides, firms may protect their innovations through a mix of patents, copyrights, trademarks, and trade secrets. As mentioned by Mezzanotti and Simcoe (2023), firms in high-tech industries engage more actively with various forms of IP protection, including trade secrets, trademarks, and copyrights, while considering utility patents less important. In high-tech sectors, the pace of innovation is rapid, and products can become obsolete quickly. Thus, firms often prioritize speed to market and product differentiation over filing patents for every incremental innovation. For the above reasons, the negative impact of export quality on patent intensity in the high-technology sector is more pronounced than in the low-technology industries.

Table 2.4: Results for different types of countries, levels of income, and levels of technology intensity

	A - Types of countries		**B - Levels of income**		**C - Levels of technology intensity**	
Direction of relationship	**OECD** (1)	**Non-OECD** (2)	**High income** (3)	**Low income** (4)	**High technology** (5)	**Low technology** (6)
$lnPI \longrightarrow lnEQ$	-0.031^{***}	-0.133^{***}	-0.040^{***}	-0.128^{***}	-0.040^{***}	-0.099^{***}
	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)	(0.002)
R2	0.9920	0.9858	0.9910	0.9864	0.9914	0.9875
$lnEQ \longrightarrow lnPI$	-0.501^{***}	-0.615^{***}	-0.592^{***}	-0.510^{***}	-1.520^{***}	-0.463^{***}
	(0.021)	(0.013)	(0.019)	(0.013)	(0.064)	(0.009)
R2	0.3924	0.2797	0.3854	0.2660	0.5559	0.2145
Num.Obs.	148,408	88,162	159,812	76,758	36,065	200,505
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Product-sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Control variables: GDPPC, Openness, FDI, R&D, Expenditure on education, Import, ECI, and HHI.

2.4.4 Results for different levels of export dependence and export quality

The relationship between export quality and patent intensity may vary depending on the level of export dependence. To investigate this, we categorize the data into three levels of export dependence based on the export-to-GDP ratio: low, medium, and high dependence. The results from 3SLS for each group are presented in Table 2.5. Model (1), Model (2), and Model (3) include observations for which the export-to-GDP ratio is below the 33.3th percentile, between the 33.3th and 66.7th percentile, and above the 66.7th percentile, respectively. A consistent negative bidirectional relationship between export quality and patent intensity is observed across all three subsamples. Notably, the magnitudes of the effects are larger in countries with low and high export dependence compared to those with medium dependence.

In countries with low export dependence, the negative relationship between patent intensity and export quality is stronger than in medium export-dependent countries. This could suggest that these countries focus less on exports overall, meaning that increased competition driven by higher patent intensity discourages firms from investing in both innovation and improving export quality, more than in countries with medium export dependence. In contrast, the negative relationship is most pronounced in high export-dependent countries. This may be because these countries prioritize alternative strategies - such as improving distribution, marketing, and advertising to boost export activities, rather than focusing on enhancing product quality.

Regarding the negative impact of export quality on patent intensity, countries with low export dependence are less likely to apply for new patents to protect their products compared to medium export-dependent counterparts. In high export-dependent countries, an increase in export quality can significantly raise export value, which in turn leads to a greater reduction in patent intensity. Additionally, these countries are more likely to use a mix of intellectual property protections (such as copyrights, trademarks, trade secrets, and patents) rather than relying solely on patents.

Beyond categorizing the sample by export dependence, we also examine the two-way relationship between export quality and patent intensity across different levels of export quality. The data is divided into low, medium, and high export quality countries. The regression results are presented in Table 2.5. Model (4), Model (5), and Model (6) include observations for which the export quality is below the 33.3th percentile, between the 33.3th and 66.7th percentile, and above the 66.7th percentile, respectively. These findings reinforce the negative bidirectional relationship between export quality and patent intensity. Consistent with the results from Panel A - Export dependence, the impact of patent intensity on export quality is more pronounced in countries with low and high export quality compared to those with medium export quality. Interestingly, the negative impact of export quality on patent intensity strengthens as we move from the low quality to the medium quality, and then to the high quality subsamples. This suggests that higher export quality is associated with a stronger negative relationship with patent intensity. This can be explained by the fact that high-quality products are often produced by high-tech firms, which tend to rely on a combination of intellectual property protections rather than solely on patents.

Table 2.5: Results for different levels of export dependence and export quality

	A - Export dependence			**B - Export quality**		
Direction of relationship	**Low dependence** (1)	**Medium dependence** (2)	**High dependence** (3)	**Low quality** (4)	**Medium quality** (5)	**High quality** (6)
$lnPI \longrightarrow lnEQ$	-0.063^{***}	-0.016^{***}	-0.074^{***}	-0.062^{***}	-0.025^{***}	-0.044^{***}
	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
R2	0.9851	0.9910	0.9923	0.9466	0.9451	0.9231
$lnEQ \longrightarrow lnPI$	-0.516^{***}	-0.211^{***}	-0.668^{***}	-0.370^{***}	-0.528^{***}	-0.737^{***}
	(0.019)	(0.020)	(0.023)	(0.018)	(0.032)	(0.025)
R2	0.4521	0.3343	0.3013	0.3321	0.3680	0.3548
Num.Obs.	72,738	78,802	85,030	76,484	78,386	81,700
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Product-sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Control variables: GDPPC, Openness, FDI, R&D, Expenditure on education, Import, ECI, and HHI.

2.4.5 The moderation effect of institutional quality

To investigate the moderation effect of institutions on the relationship between patent and export and vice versa, the interaction terms are added. Equation (2.8) and Equation (2.9) are regressed by 3SLS with different institutional quality variables. The estimation results are in Table 2.6.

First, concerning the impact of patent intensity on export quality and vice versa, all the coefficients of export quality and patent intensity in the whole sample, OECD, and non-OECD samples are negative and significant. These findings reaffirm the negative two-way relationship between export quality and patent intensity found in the earlier estimations.

Second, regarding the impact of each institution variable on export quality, government stability, corruption, law and order, and bureaucracy quality promote export quality in three samples. Interestingly, the magnitude of government stability's coefficient is very high in the non-OECD sample. This shows the more important role of government stability in fostering the export quality of non-OECD countries compared to other institutions. The contribution of bureaucracy quality in enhancing the export quality of the OECD sample outweighs that of other institutions. Concerning the nexus of these institutions and patent intensity, only government stability shows a positive impact on patent intensity in three samples. Law and order and corruption are catalysts in fostering patent intensity in the whole sample and OECD countries but do not influence patent intensity in the non-OECD sample. The relationship between bureaucracy quality and patent intensity is positive in the whole sample and OECD countries but this impact is negative in non-OECD countries. Comparing the magnitude of the coefficients of these institution variables, it is blatant that institutional quality has a stronger effect on improving export quality than patent intensity.

Finally, the most compelling result is the coefficient estimates on the interaction terms, which reveal the moderating effects of institutions on the relationship between export quality and patent intensity. In all three samples, every interaction between patent intensity and institutional factors is significantly positive, with the exception of bureaucracy quality in the non-OECD sample. This finding confirms that higher institutional quality positively moderates the relationship between patent intensity and export quality. Patent intensity on its own exerts a negative influence on export quality, as an increase in patent activity, which indicates stronger monopolistic power, tends to discourage investment in product quality. However, when patent intensity interacts with institutional factors, the effect reverses and becomes positive. As discussed earlier, firms generating more patents may acquire increased monopoly power, which can reduce their incentive to invest in superior product quality, thereby lowering export quality. Nonetheless, as shown in the main findings, firms in high-income countries or those with advanced technological capabilities continue to innovate despite intense competition. This innovative activity is further accelerated by higher institutional quality. Specifically, robust law and order and effective control of corruption ensure that patent rights are enforced. High government stability reduces uncertainty, thereby encouraging long-term investments in R&D and facilitating the complex integration of innovations into high-quality export products. Moreover, efficient bureaucracy accelerates the process of translating patented ideas into tangible, high-quality exported goods.

The coefficients of the interaction terms between export quality and each institutional variable are positive and statistically significant in both the full sample and the OECD subsample. While export quality alone has a negative effect on patent intensity, this negative impact is mitigated once the interaction terms with institutional quality are included. Specifically, strong law and order and low levels of corruption enhance the protection of intellectual property, providing firms that produce high-quality goods with greater incentives to patent the key technologies that distinguish their products. Government stability and reliable bureaucratic systems further reduce risks and improve access to financing and skilled labor, both of which are critical for complex, innovation-driven activities that lead to patenting. Moreover, efficient bureaucracies and stable regulatory environments help firms more effectively translate R&D into commercially viable, high-quality exports and secure related patents. Finally, good institutions attract sophisticated foreign firms, which often bring advanced production capabilities and well-developed patenting strategies, further reinforcing the link between export quality and innovation.

Figure 2.2 illustrates the marginal effect of patent intensity on export quality across varying levels of institutional quality. The graphs align with the regression results, indicating that patent intensity negatively affects export quality. However, this impact is mitigated as institutional quality improves, highlighting the positive moderating role of institutions in this relationship. An exception is observed for non-OECD countries, where bureaucracy quality has only a minor influence on the marginal effect of patent intensity on export quality.

Figure 2.3 presents the marginal effect of export quality on patent intensity under different institutional conditions. Consistent with the findings in Table 2.6, all four institutional factors positively moderate the effect of export quality on patent intensity for the full sample and OECD countries. However, for non-OECD countries, only government stability exhibits this positive moderating effect. Notably, in the case of corruption control, the marginal impact of export quality on patent intensity remains nearly unchanged. For the other two institutions, law and order and quality of bureaucracy, only minor variations are observed in this relationship.

We provide several robustness checks, in which we employ an additional measurement for export quality, following the method of Fan, Li, and Yeaple (2015) and Khandelwal et al. (2013) and use the institutional quality data from World Governance Indicators (WGI) instead of International Country Risk Guide (ICRG) to reestimate the model. The results are presented in detail in Appendix B2.

Table 2.6: Moderation effect of institutions on the relationship between export quality and patent intensity

Dependent variables	**Explanatory variables**	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)
1. Government Stability				
lnEQ	lnPI	−2.634***	−1.399***	−10.547***
		(0.135)	(0.106)	(0.931)
	lngov	5.402***	2.841***	21.815***
		(0.284)	(0.222)	(1.961)
	lnPIxlngov	1.219***	0.649***	4.842***
		(0.064)	(0.050)	(0.434)
	R2	0.9763	0.9882	0.8398
lnPI	lnEQ	−0.676***	−0.833***	−0.435***
		(0.020)	(0.034)	(0.025)
	lngov	0.165***	0.198***	0.150***
		(0.016)	(0.023)	(0.020)
	lnEQxlngov	0.078***	0.088***	0.071***
		(0.006)	(0.009)	(0.008)
	R2	0.3473	0.3887	0.2991
2. Corruption				
lnEQ	lnPI	−0.608***	−0.616***	−0.100***
		(0.027)	(0.039)	(0.015)
	lncorr	1.668***	1.726***	0.174***
		(0.088)	(0.120)	(0.061)
	lnPIxlncorr	0.377***	0.392***	0.038***
		(0.020)	(0.027)	(0.014)
	R2	0.9825	0.9880	0.9868
lnPI	lnEQ	−0.853***	−0.933***	−0.421***
		(0.011)	(0.021)	(0.015)
	lncorr	0.070***	0.100***	0.003
		(0.011)	(0.016)	(0.016)
	lnEQxlncorr	0.023***	0.033***	−0.0003
		(0.002)	(0.003)	(0.004)
	R2	0.3306	0.3805	0.2939

Table 2.6: Moderation effect of institutions on the relationship between export quality and patent intensity (cont.)

Dependent variables	**Explanatory variables**	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)
3. Law and Order				
lnEQ	lnPI	−3.799***	−4.534***	−0.817***
		(0.252)	(0.415)	(0.060)
	lnlaw	10.099***	11.947***	2.357***
		(0.710)	(1.139)	(0.198)
	lnPIxlnlaw	2.234***	2.649***	0.522***
		(0.156)	(0.250)	(0.044)
	R2	0.8886	0.9008	0.9820
lnPI	lnEQ	−0.452***	−0.493***	−0.614***
		(0.011)	(0.021)	(0.014)
	lnlaw	0.075***	0.137***	0.017
		(0.009)	(0.015)	(0.014)
	lnEQxlnlaw	0.029***	0.039***	0.005
		(0.002)	(0.003)	(0.003)
	R2	0.3506	0.3935	0.2802
4. Bureaucracy Quality				
lnEQ	lnPI	−0.434***	−4.363***	−0.069***
		(0.023)	(0.312)	(0.008)
	lnbureau	1.263***	14.243***	0.183***
		(0.078)	(1.041)	(0.053)
	lnPIxlnbureau	0.269***	3.156***	0.005
		(0.017)	(0.231)	(0.007)
	R2	0.9848	0.9136	0.9868
lnPI	lnEQ	−0.838***	−0.590***	−0.416***
		(0.011)	(0.023)	(0.015)
	lnbureau	0.175***	0.247***	−0.425***
		(0.041)	(0.046)	(0.098)
	lnEQxlnbureau	0.020***	0.092***	0.001
		(0.002)	(0.005)	(0.002)
	R2	0.3314	0.3931	0.2942
	Num.Obs.	236,570	148,408	88,162
	Control	Yes	Yes	Yes
	Year FE	Yes	Yes	Yes
	Country FE	Yes	Yes	Yes
	Product-sector FE	Yes	Yes	Yes

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Control variables: GDPPC, Openness, FDI, R&D, Expenditure on education, Import, ECI, and HHI.

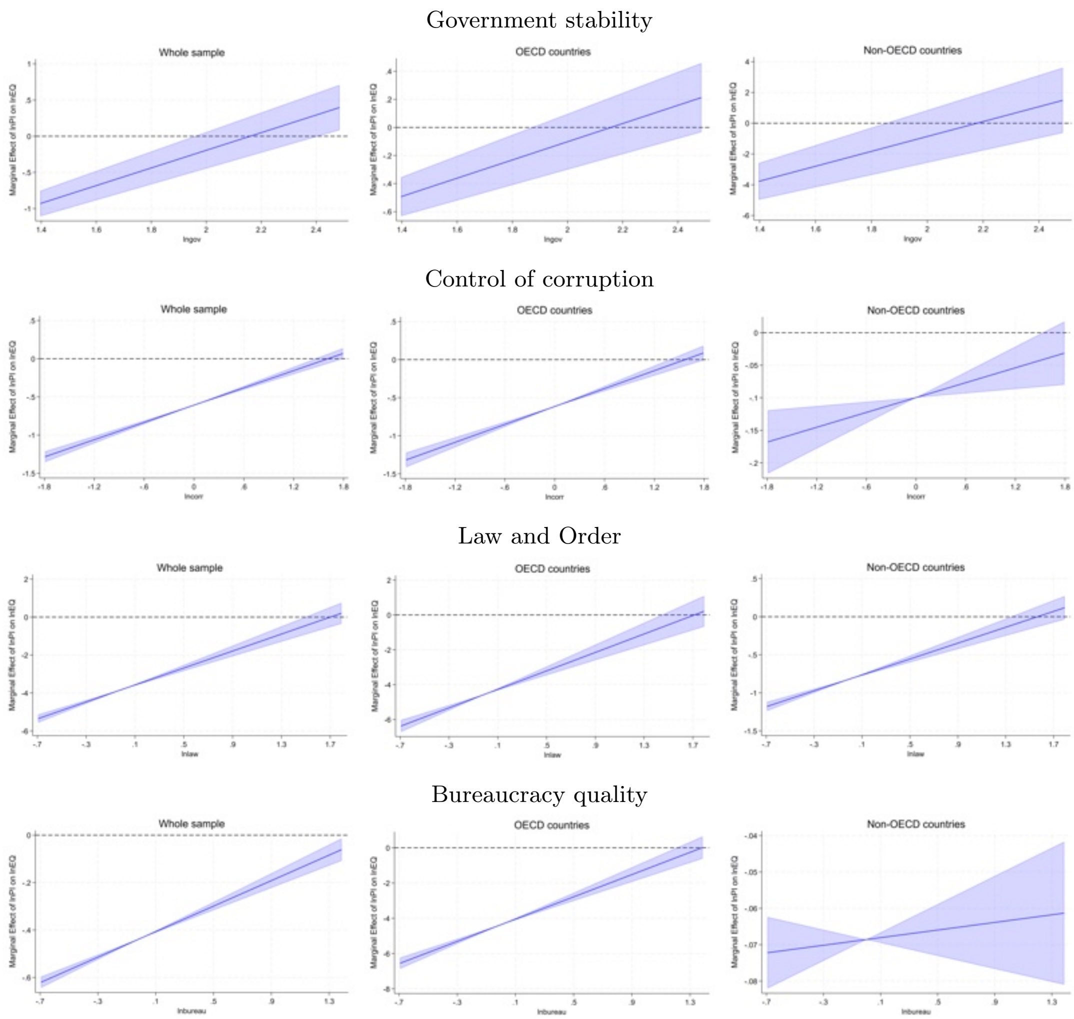


Figure 2.2: Marginal effect of patent intensity on export quality for different institutions

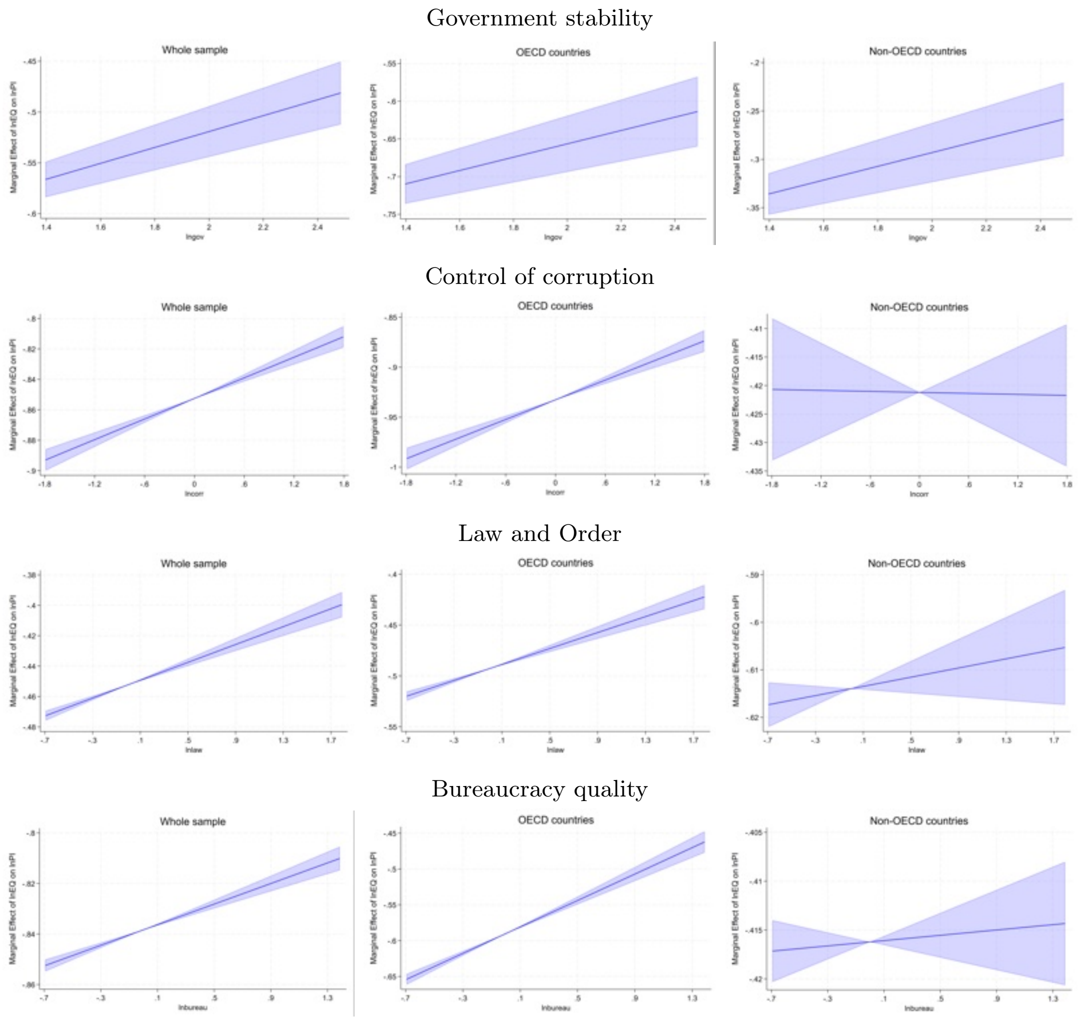


Figure 2.3: Marginal effect of export quality on patent intensity for different institutions

2.5 Theoretical Framework

To explain the observed empirical findings, this section develops a model that extends the foundational work on firm heterogeneity by Melitz (2003) and Kugler and Verhoogen (2012). Our key contribution is to endogenize product quality by introducing a technology cost associated with R&D investment, where higher R&D investment leads to higher quality. We further link innovation to intellectual property by modeling the number of patents a firm secures as an increasing function of its R&D investment. The model is designed to analyze the two-way relationships between patent intensity and export quality, conditional on a country's given level of institutional quality.

First, we frame the firm's decision as a choice of optimal export quality. The firm chooses the quality level that maximizes its profit. This choice simultaneously determines the required R&D investment and the resulting number of patents. We can then observe the patent intensity (patents per unit of revenue) that arises from this quality-focused optimization.

Second, to isolate the impact of patenting incentives on quality, we frame the decision as a choice of the optimal number of patents. Given that the number of patents is a direct function of R&D, choosing a patent portfolio is equivalent to choosing an R&D level. Solving this profit-maximization problem for the optimal number of patents reveals the underlying optimal R&D investment and, consequently, the optimal export quality. This allows us to directly analyze how patenting decisions shape the firm's export quality.

2.5.1 Model setup

Following Kugler and Verhoogen (2012) and Melitz (2003), first from the demand side, we start with the utility of a representative consumer in the destination (export) market:

$$U = \left(\int_{\omega \in \Omega} (\lambda(\omega) q(\omega))^{\frac{\sigma-1}{\sigma}} \, d\omega \right)^{\frac{\sigma-1}{\sigma}} \tag{2.10}$$

Where $q(\omega)$ is the quantity of a firm's variety, $\lambda(\omega)$ denotes the quality of that variety (a higher λ means higher quality). $\sigma > 1$ shows the elasticity of substitution between varieties. Ω is the set of available varieties.

Combining the utility function and the budget constraint $Y = \int_{\omega \in \Omega} p(\omega) q(\omega) d\omega$, the demand curve faced by a single exporting firm for its variety ω is as follows:

$$q(\omega) = Y P^{\sigma-1} (p(\omega))^{-\sigma} (\lambda(\omega))^{\sigma-1} \tag{2.11}$$

Where Y is the aggregate expenditure in the export market. $p(\omega)$ is the price the firm sets for its variety. P denotes the aggregate price index in the market[6]. This equation indicates that demand for a firm's product increases with its quality (λ) and decreases with its price (p). This is the channel through which the firm's product quality impacts its revenue.

Second, the supply side is enacted from the firm's profit maximization as follows:

$$\max_{p(\omega), \lambda(\omega)} \pi_x(\omega) = p(\omega) q(\omega) - \frac{1}{\varphi} q(\omega) - F_{R\&D}(\lambda) \tag{2.12}$$

Where $p(\omega)q(\omega)$ is the firm's revenue. $\frac{1}{\varphi} q(\omega)$ is variable production cost. φ is the firm's idiosyncratic productivity and $1/\varphi$ is the marginal cost, which is assumed to be identical for all firms. More productive firms (higher φ) have lower marginal costs. We introduce innovative technology to the model, a fixed cost of R&D ($F_{R\&D}$) required to achieve a quality level (λ). Following the literature on endogenous quality and technology choice of Bustos (2011) and Kugler and Verhoogen (2012), we assume this cost is firm-specific and convex in quality.

$$F_{R\&D}(\lambda) = \frac{f}{\theta} \lambda^{\beta}, \quad F'_{R\&D}(\lambda) > 0 \quad \text{and} \quad \beta > \sigma - 1. \tag{2.13}$$

f is a cost scaling parameter. $\theta > 0$ represents the firm's innovation capability/efficiency. A firm with a higher θ is better at R&D and can achieve any quality for a lower cost. According to

[6] $P = \left(\int_{\omega \in \Omega} p(\omega)^{1-\sigma} \lambda(\omega)^{\sigma-1} d\omega \right)^{\frac{1}{1-\sigma}}$

Bustos (2011) and Verhoogen (2008), this condition of θ helps to explain why firms with similar production productivity (φ) may nonetheless make different choices regarding innovation and quality. β is the elasticity of R&D costs with respect to quality (λ). For 1% increase in export quality, the cost of R&D increases by β%. The convexity ($\beta > 1$) reflects the increasing marginal cost of quality improvement, a standard feature in models of innovation (Grossman & Helpman, 1993). β represents how fast the cost of R&D rises while σ is related to how much profit a firm can make from an innovation. A high σ means that products are close substitutes, competition is fierce, and profits from innovation are lower. The condition $\beta > \sigma - 1$ guarantees that the costs of R&D (β) rise sufficiently fast relative to the potential profits from innovation (related to σ) to prevent an explosive, unrealistic outcome. At the same time, this condition ensures the profit function is concave and has a unique maximum.

When firm sets the price, it takes Y, P, and λ as given. We solve the profit maximization problem to find the optimal price, which is a constant markup over marginal costs: $p^* = \frac{\sigma}{\sigma-1}\frac{1}{\varphi}$. Plugging this price into the demand equation, we obtain the revenue and variable profit:

$$R(\lambda, \varphi) = A(\varphi)^{\sigma-1}(\lambda)^{\sigma-1}, \quad \pi_{\text{variable}} = R - \frac{1}{\varphi}q = \frac{R}{\sigma} \tag{2.14}$$

Where $A = YP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{1-\sigma}$ is a constant that captures the market conditions.

The number of patents (N_p) is a function of the R&D effort. We assume a concave relationship between patents and R&D investment and diminishing returns to patenting $0 < \alpha < 1$ as suggested by Scherer (1983) that the marginal patent output decreases in response to an increase in the scale of R&D.

$$N_p(\omega) = g(F_{R\&D}(\lambda)) = (F_{R\&D}(\lambda))^{\alpha} \tag{2.15}$$

Patent intensity is the ratio of the number of patents to export value, as shown in the equation below:

$$Patent\ intensity = \frac{N_p(\omega)}{Export\ value} = \frac{N_p(\omega)}{p(\omega)q(\omega)} = \frac{\left(\frac{f}{\theta}\lambda^{\beta}\right)^{\alpha}}{A\varphi^{\sigma-1}\lambda^{\sigma-1}} \tag{2.16}$$

2.5.2 Impact of export quality on patent intensity

To find the impact of export quality on patent intensity, first we need to solve the profit maximization problem to find export quality (λ).

$$\max_{\lambda} \quad \pi_x = \frac{1}{\sigma}A\varphi^{\sigma-1}\lambda^{\sigma-1} - \frac{f}{\theta}\lambda^{\beta} \tag{2.17}$$

Take the first-order condition (FOC) with respect to λ we obtain:

$$\frac{\partial \pi_x}{\partial \lambda} = \frac{\sigma - 1}{\sigma}A\varphi^{\sigma-1}\lambda^{\sigma-2} - \beta\frac{f}{\theta}\lambda^{\beta-1} = 0 \tag{2.18}$$

$$\frac{\sigma-1}{\sigma}A\varphi^{\sigma-1}\lambda^{\sigma-2}=\beta\frac{f}{\theta}\lambda^{\beta-1} \tag{2.19}$$

$$\lambda^{\beta-\sigma+1}=\frac{(\sigma-1)A}{\sigma\beta}\frac{\theta}{f}\varphi^{\sigma-1} \tag{2.20}$$

This gives the optimal quality choice:

$$\lambda^*(\varphi)=\left(\frac{(\sigma-1)A}{\sigma\beta}\frac{\theta}{f}\varphi^{\sigma-1}\right)^{\frac{1}{\beta-\sigma+1}} \tag{2.21}$$

This equation shows that more productive firms (higher φ) and higher innovation efficiency (higher θ) choose higher quality (λ).

From Equation (2.19), we know that at the optimum:

$$\begin{gathered}\frac{\sigma-1}{\sigma}\underbrace{A\varphi^{\sigma-1}(\lambda^*)^{\sigma-1}}_{R^*}(\lambda^*)^{-1}=\beta\underbrace{\frac{f}{\theta}(\lambda^*)^{\beta}}_{F^*_{R\&D}}(\lambda^*)^{-1}\\ \Rightarrow\quad R^*=\frac{\sigma\beta}{\sigma-1}F^*_{R\&D}\end{gathered} \tag{2.22}$$

Thus, optimal patent intensity is:

$$\begin{gathered}PI^*=\frac{N_p^*}{R^*}=\frac{(F^*_{R\&D})^{\alpha}}{R^*}=\frac{\left(R^*\frac{\sigma-1}{\sigma\beta}\right)^{\alpha}}{R^*}=\left(\frac{\sigma-1}{\sigma\beta}\right)^{\alpha}(R^*)^{\alpha-1}\\ \Rightarrow PI^*=\left(\frac{\sigma-1}{\sigma\beta}\right)^{\alpha}\left(A\varphi^{\sigma-1}(\lambda^*)^{\sigma-1}\right)^{\alpha-1}\end{gathered} \tag{2.23}$$

Take the first derivative of λ^* with respect to PI^*, we get:

$$\frac{\partial PI^*}{\partial\lambda^*}=\left(\frac{\sigma-1}{\sigma\beta}\right)^{\alpha}\left(A\varphi^{\sigma-1}\right)^{\alpha-1}(\alpha-1)(\sigma-1)\,(\lambda^*)^{(\sigma-1)(\alpha-1)-1} \tag{2.24}$$

The impact of λ^* on PI^* depends on the sign of $\alpha-1$. Since $0<\alpha<1$, the relationship between λ and PI^* is negative. This result confirms the above empirical findings. Figure 2.4 shows the simulation of the relationship between export quality and patent intensity with different values of α and β. The negative impact of export quality on patent intensity occurs for firms with diminishing returns to patenting in mature industries, where firms do not seek new patents but prioritize other types of IPRs. In this market, the first few quality improvements are highly valuable and worth patenting. However, once a firm has achieved a high level of quality, the marginal benefit of the next innovation is small. The potential profit from a minor, incremental improvement may not cover the cost of patenting it. Thus, as quality rises, patent intensity falls. Quality and patenting are substitutes. At each quality level, firms with lower elasticity of R&D costs experience higher patent intensity. The lower the value of β, the stronger the decrease in patent intensity when export quality rises, since the R&D cost drops more slowly and firms have to sacrifice more patent intensity for an increase in quality.

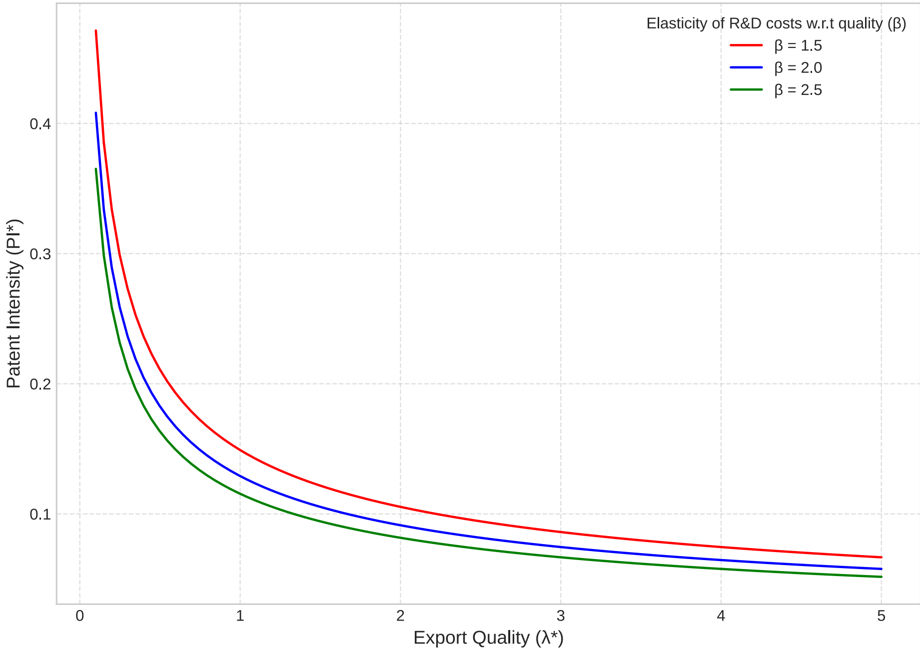


Figure 2.4: The impact of export quality on patent intensity
The simulation is based on the following parameter values: $A = 10$, $\alpha = 0.5$, $\sigma = 2.0$, and $\varphi = 1.5$.

2.5.3 Impact of patent intensity on export quality

To find the impact of patent intensity on export quality, first, we change the profit function, which is now a function of the number of patents. In other words, the firm chooses the number of patent applications to maximize its profit.

From Equation (2.15), solving for $F_{R\&D}$, the cost of patenting is:

$$F_{R\&D}(N_p) = (N_p)^{1/\alpha} \tag{2.25}$$

This equation represents the total R&D budget that a firm spends to achieve its target number of patents (N_p). Next, we find the quality level (λ) that corresponds to this level of R&D spending. From Equation (2.13) and Equation (2.25), we can find the quality (λ) that is implied by the choice of the number of patents (N_p):

$$(N_p)^{1/\alpha} = \frac{f}{\theta}\lambda^{\beta} \quad \Rightarrow \quad \lambda(N_p) = \left(\frac{\theta}{f}(N_p)^{1/\alpha}\right)^{1/\beta} \tag{2.26}$$

To obtain the revenue as a function of N_p we substitute our new expression for $\lambda(N_p)$ into the revenue function:

$$R(N_p) = A\varphi^{\sigma-1}\left(\lambda(N_p)\right)^{\sigma-1} = A\varphi^{\sigma-1}\left(\frac{\theta}{f}(N_p)^{1/\alpha}\right)^{\frac{\sigma-1}{\beta}} \tag{2.27}$$

The full profit function ($\pi_x(N_p)$) now becomes:

$$\max_{N_p} \quad \pi_x(N_p) = \frac{1}{\sigma} A\varphi^{\sigma-1} \left(\frac{\theta}{f}\right)^{\frac{\sigma-1}{\beta}} (N_p)^{\frac{\sigma-1}{\alpha\beta}} - (N_p)^{1/\alpha} \tag{2.28}$$

To find the optimal number of patents (N_p^*), we take the first-order condition (FOC) with respect to N_p and set it to zero. The FOC is:

$$\frac{\partial \pi_x}{\partial N_p} = \frac{1}{\sigma} A\varphi^{\sigma-1} \left(\frac{\theta}{f}\right)^{\frac{\sigma-1}{\beta}} \left(\frac{\sigma-1}{\alpha\beta}\right) (N_p)^{\frac{\sigma-1-\alpha\beta}{\alpha\beta}} - \frac{1}{\alpha}(N_p)^{\frac{1-\alpha}{\alpha}} = 0 \tag{2.29}$$

$$\frac{\sigma-1}{\sigma\beta} A\varphi^{\sigma-1} \left(\frac{\theta}{f}\right)^{\frac{\sigma-1}{\beta}} = (N_p)^{\frac{\beta-\sigma+1}{\alpha\beta}} \tag{2.30}$$

To simplify the expression, set $K = \frac{1}{\sigma} A\varphi^{\sigma-1} \left(\frac{\theta}{f}\right)^{\frac{\sigma-1}{\beta}}$. The optimal number of patents (N_p^*) is:

$$N_p^* = \left(K\frac{\sigma-1}{\beta}\right)^{\frac{\alpha\beta}{\beta-\sigma+1}} \tag{2.31}$$

From Equation (2.29), we get the following:

$$\begin{aligned} &\frac{\sigma-1}{\sigma\beta} \underbrace{A\varphi^{\sigma-1} \left(\frac{\theta}{f}(N_p^*)^{1/\alpha}\right)^{\frac{\sigma-1}{\beta}}}_{R^*} (N_p^*)^{-1} = (N_p^*)^{1/\alpha}(N_p^*)^{-1} \\ &\Rightarrow \frac{\sigma-1}{\sigma\beta} R^* = (N_p^*)^{1/\alpha} \end{aligned} \tag{2.32}$$

From Equation (2.26) and Equation (2.32), we obtain the optimal quality (λ^*) as follows:

$$\begin{aligned} \lambda^* &= \left(\frac{\theta}{f}(N_p^*)^{1/\alpha}\right)^{1/\beta} = \left(\frac{\theta}{f}\frac{\sigma-1}{\sigma\beta} R^*\right)^{1/\beta} = \left(\frac{\theta(\sigma-1)}{\sigma\beta f}\frac{N_p^*}{PI^*}\right)^{1/\beta} \\ \Rightarrow \lambda^* &= \frac{\theta(\sigma-1)}{\sigma\beta f} \cdot (PI^*)^{-1/\beta} \cdot \left(K\frac{\sigma-1}{\beta}\right)^{\frac{\alpha}{\beta-\sigma+1}} \end{aligned} \tag{2.33}$$

Take the first derivative of λ^* with respect to PI^*, we get:

$$\frac{\partial \lambda^*}{\partial PI^*} = -\frac{1}{\beta}(PI^*)^{\frac{-1-\beta}{\beta}} \cdot \frac{\theta(\sigma-1)}{\sigma\beta f} \cdot \left(K\frac{\sigma-1}{\beta}\right)^{\frac{\alpha}{\beta-\sigma+1}} \tag{2.34}$$

Since $\beta > 1$, $\partial\lambda^*/\partial PI^* < 0$. Thus, the impact of patent intensity on export quality is negative. This outcome is in line with that from the empirical model. Figure 2.5 represents the simulation of the impact of patent intensity on export quality with three different values of β. All three downward-sloping curves prove the negative impact of patent intensity on export quality. At the same level of patent intensity, export quality is higher for firms with lower β. Firms with lower β have a slower change in R&D costs with respect to a change in quality. This leads to a stronger sacrifice between patent intensity and export quality. Namely, to increase patent intensity, firms with lower β need to sacrifice a large amount of export quality compared to other firms with higher β.

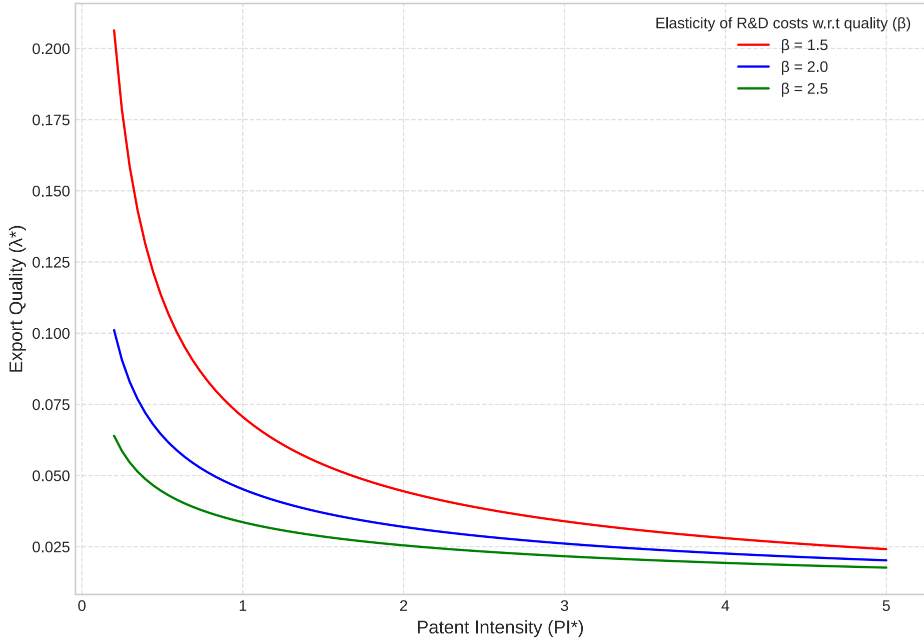


Figure 2.5: The impact of patent intensity on export quality
The simulation is based on the following parameter values: $A = 10$, $f = 10$, $\alpha = 0.5$, $\sigma = 2.0$, and $\varphi = 1.5$.

2.6 Conclusion

The analysis explores the two-way relationship between export quality and patent intensity and the moderating role of institutional quality on this bidirectional nexus. We use SEM with the 2SLS and 3SLS econometric methods to discover this bidirectional nexus for the whole sample of 89 countries, 38 OECD countries, and 51 non-OECD countries.

The results prove that not only does patent intensity affect export quality, but export quality also has a significant impact on patent intensity. In the main regression, patent intensity negatively affects export quality, and the enhancement of export quality is harmful to patent intensity. Besides, we also check this two-way relationship with different subsamples, namely, different types of countries (OECD and non-OECD), levels of income, levels of technology, export dependence, and export quality. The results from these subsamples confirm the negative bidirectional relationship between export quality and patent intensity.

The moderation effect of institutional quality on export quality and patent intensity is investigated by adding the interaction terms. We introduce the interaction term between patent intensity and institutions, and the interaction between export quality and institutions to explain the moderation effect of institutional quality on export quality and patent intensity, respectively. Four mostly used institutions adopted in the study are government stability, control of corruption, law and order, and bureaucracy quality. Similar to the main results, the two-way relationship between export quality and patent intensity remains. Institutions not only directly affect export quality and patent intensity positively, they also positively moderate the reciprocal nexus between export quality and patent intensity. These results show the importance of institutional quality in fostering both export quality and patent intensity. It is credible to promulgate policies to improve institutional quality to have a better effect on firms/industries' activities in upgrading product quality and producing stronger patents. Especially, for OECD and non-OECD countries, the most important institution for export quality and patent intensity can be an insightful reference for the government to focus on the institution with a higher impact on quality and patents.

We construct the new variable for product quality by applying the method of Khandelwal et al. (2013) and re-estimate all the models provided in Appendix B2. Most of the outcomes are in line with the baseline results. Besides, we also adopt the institution variables from different sources (World Governance Indicator - WGI) to test the moderation effect of institutional quality on the two-way relationship between export quality and patent intensity. The findings reaffirm this positive moderating effect in the whole sample and OECD countries but it has several changes in the signs in the case of the non-OECD subsample.

Our analysis was grounded in a theoretical framework designed to explain the observed bidirectional relationship. Extending the work of Kugler and Verhoogen (2012) and Melitz (2003), the model established a direct link between R&D investment, product quality, and patenting. By framing the firm's profit maximization problem from two perspectives, first as a choice of optimal quality, and then as a choice of an optimal patent portfolio, the model formally demonstrated the reciprocal nature of the relationship. Ultimately, the framework shows that both strategic paths converge on the same underlying R&D decision, illustrating that quality enhancement and patent intensity are two facets of a single, integrated strategy. The findings of the theoretical model are consistent with the results from empirical analysis.

The results of this study are credibly obtained after controlling for different fixed effects and passing the underidentification test for the strength of instruments, and weak identification test. Furthermore, the theoretical model's findings confirm the correctness of the outcomes from empirical analysis. However, there exist several limitations. First, the 3SLS estimation uses the same instruments for both equations. Second, the patent intensity variable defined as the number of patents per unit of export value does not account for the changes in price level. Finally, our theoretical model conditions on the given institutional environment and diminishing returns to patenting. Future research might focus on mitigating these drawbacks.

Chapter 3

Innovation Activities of European Firms under Horizon 2020

Subsidy programs have become one of the efficient ways to accelerate a firm's innovation. This paper examines the innovation activities of European firms under the Horizon 2020 program. First, we build a theoretical model to show how receiving funds from the Horizon 2020 program affects a firm's innovation activities and its expenditure on innovation. Then, using data from firms of 9 European countries in 5 waves (2010 - 2018), adopted from the Community Innovation Survey (CIS), we estimate the Difference-in-Difference (DiD) with repeated cross-section estimation to investigate the changes in firms' product innovation, process innovation, organizational innovation, marketing innovation, and expenditure on innovation. The results show that Horizon 2020 subsidies lead to increases in organizational innovation (5.6%), and expenditure on innovation (18.3%) for the whole sample. For Western countries, the results are more remarkable, with 12.6%, 13%, 6.4%, and 3.7% increases in product innovation, process innovation, organizational innovation, and spending on innovation, respectively. Besides, the heterogeneous effects of subsidies are investigated under differences in export orientation, R&D intensity, knowledge intensity, competition levels, firms using different types of IPRs, and different sectors. The findings suggest that the positive impact of receiving funds from the Horizon 2020 on product and process innovation is more pronounced for exporting firms, firms in the Wholesale and retail trade sector, and the Information and communication sector. While R&D-intensive and knowledge-intensive firms show a high increase in organizational innovation.

3.1 Introduction

Innovation plays a vital role in international trade (D'Angelo, 2012; Edeh et al., 2020; Golovko & Valentini, 2011; Tavassoli, 2018; F. Wu et al., 2020), competitiveness (Hombert & Matray, 2018), and economic growth (Aghion & Howitt, 1990). Research and development (R&D) is a well-established driver of innovation and has been shown to positively influence innovation outcomes (Hammar & Belarbi, 2021; Ulku, 2004). To stimulate R&D and foster innovation, many governments have implemented various subsidy programs (Mateut, 2018) and increasingly view innovation as a strategic asset. This perspective is reflected in major policy initiatives such as the European Union's Horizon 2020, China's "Made in China 2025", and the U.S. CHIPS Act (Creating Helpful Incentives to Produce Semiconductors and Science Act).

Horizon 2020 is the European research and innovation funding program from 2014 to 2020 with a budget of around EUR 77 billion over seven years. Horizon 2020 was built on three pillars: support for *Excellent Science*, support for *Industrial Leadership*, and support for research to tackle *Societal Challenges*. The target of the program is to accelerate innovation activities, competitiveness, and economic growth (EC, 2017). Several studies investigate the impact of the Horizon 2020 program on firms' innovation, employment, and sales. Specifically, Mulier and Samarin (2021) explored the effect of Horizon 2020 on firms' performance (investment in tangible and intangible assets, turnover, and employment growth) and innovation (measured by the number of patents). Mitra and Niakaros (2023) suggest that firms receiving Horizon 2020 grants exhibited an average increase of 20% in employment and about 30% in total assets and revenues compared to comparable companies in the control group, in the years after receiving their first grant. Recently, Santoleri et al. (2024) indicate the positive impact of the SME Instrument grant[1] on firms' investment and innovation output measured by cite-weighted patents.

While these studies provide insights into the positive effects of Horizon 2020 on firm innovation and performance, but only use patents as a measure of innovation, comprehensive analyses specifically detailing impacts on product, process, organizational, and marketing innovations remain limited. Thus, this study addresses this gap, focusing on the impact of Horizon 2020 on innovation activities, namely, product innovation, process innovation, organization innovation, marketing innovation, and expenditure on innovation. The data is adopted from the Community Innovation Survey (CIS). Since the data on firms' identity is not available, the Difference-in-Difference (DiD) estimation with repeated cross-section with multiple periods and time heterogeneity suggested by Callaway and Sant'Anna (2021) and linear regression with high-dimensional fixed effects is employed in the analysis to explore the impact of receiving subsidy from Horizon 2020 on firms' innovation.

The findings suggest that firms awarded Horizon 2020 funding experience a positive and comprehensive impact on their innovation activities. Across the full sample, these subsidies are associated with increases of 5.6 percentage points in organizational innovation and 18.3 percentage points in innovation expenditure. Moreover, firms in Western countries' engagement with the Horizon 2020 program is linked to an acceleration in a firm's product, process, and organizational innovation by 12.6, 13, and 6.4 percentage points, respectively, with innovation expenditure simultaneously rising by 3.7 percentage points. In contrast, for firms located in Central and Eastern Europe, the Horizon 2020 program's positive influence is restricted solely to organizational innovation. This effect emerges only within the first year of

[1] One of the funding schemes in the Horizon 2020 program

the intervention, indicating a 3.2% increase.

Besides, the analysis investigates the heterogeneous impact of Horizon 2020 on firm innovation, accounting for export orientation, R&D intensity, knowledge intensity, market competition, IPR types (patents, trademarks, design rights), and firms in different sectors. Substantial variations emerge across subsamples. Horizon 2020 shows no impact on non-exporting firms, non-R&D-intensive firms, non-knowledge-intensive firms, firms relying on trademarks, and those in the Professional, Scientific, and Technical Activities sector. In contrast, exporting firms exhibit increased innovation across four types. R&D-intensive firms experience an increase in their product, organizational, and marketing innovation post-funding, while knowledge-intensive firms only see an increase in organizational innovation. Firms in highly competitive markets improve their process, organizational, and marketing innovation. However, those in less competitive markets only accelerate organizational innovation after Horizon 2020 participation. Firms using patents and design rights demonstrate increased innovation expenditure but no change in other innovation types. Notably, firms in the Wholesale and Retail Trade and Information and Communication sectors experience a strong positive effect on both product and marketing innovation from the subsidies.

The contribution of this study is threefold. First, we introduce a theoretical model showing the impact of receiving the funds from the Horizon 2020 program on firm's innovation activities and investment in innovation. Second, we examine the impact of Horizon 2020 on various types of innovation, including product, process, organizational, and marketing innovations. These are binary variables representing whether firms conduct these types of innovation in the given year or not. Besides, we also examine the impact of subsidies on innovation expenditure, measured as the ratio of expenditure on innovation per real turnover. In addition to the causal effect of Horizon 2020 on the innovation of firms in the whole sample, this impact is scrutinized for the Western Europe (Spain, Germany, and Portugal) and Central and Eastern Europe (Bulgaria, the Czech Republic, Estonia, Hungary, Lithuania, and Romania) subsamples. DiD regression with repeated cross-sections is applied. Third, we check if the impact of obtaining subsidies on innovation varies under the heterogeneity. Specifically, we test the causal effect of receiving funds from the Horizon 2020 program under firm-level heterogeneity, namely, export orientation, R&D intensity, knowledge intensity, competition degree, and types of IPRs protection. While Horizon 2020 seeks to accelerate all innovation types, its specific impact on these diverse forms remains unstudied. This research addresses this gap, offering findings that can guide firms in developing policies to target the innovation types most influenced by the program.

The remainder of the paper is as follows: Section 3.2 provides the Literature Review before the overview of the Horizon 2020 program in Section 3.3. Section 3.4 provides the Theoretical Framework. The Data and Methodology are in Section 3.5. The Empirical Results are discussed in Section 3.6. After that, the Robustness Checks is conducted in Section 3.7. Finally, the Conclusion is in Section 3.8.

3.2 Literature Review

Two key reasons firms may refrain from investing in R&D are knowledge spillovers (Arrow, 1972; R. R. Nelson, 1959) and financial constraints (Hall & Lerner, 2010). Government funding serves as a useful remedy for both issues. However, subsidies to firms are often justified on the basis of market failure, particularly due to the positive externalities associated with the public good nature of knowledge — it is non-rival and non-excludable, making it difficult for firms to fully appropriate the returns from their R&D investments (Bronzini & Iachini, 2014).

According to the theory of marginal incentives, government support should ideally target marginal projects, those that would not occur without the subsidy, rather than inframarginal projects, which would have taken place regardless. Supporting inframarginal projects generates no additional investment and thus fails to address the underlying market failure effectively.

Government funding benefits firms in two main ways. First, it serves as a positive signal of firm quality to private investors and the broader market — a phenomenon known as the *certification effect*. This signaling reduces perceived risk and enhances access to external finance. Second, the *funding effect*, whereby firms directly use subsidies to develop new technologies, plays an even more significant role in improving firm performance than the certification effect (Howell, 2017; Santoleri et al., 2024).

Government subsidies can have two contrasting effects on R&D investment. On the one hand, they may reduce information asymmetries by signaling firm quality and profitability. Additionally, grants can enhance firms' research capacity, increase revenues, and attract more skilled researchers. These mechanisms may lead to increased R&D spending — a phenomenon referred to as the *crowding-in effect* or *incentive effect*, which is supported by empirical evidence (Carboni, 2017; Czarnitzki & Lopes-Bento, 2014). On the other hand, a *crowding-out effect* may occur if public support reduces firms' own incentives to invest, resulting in a lower-than-expected net increase in total R&D expenditure. This effect has been investigated in studies by Acemoglu et al. (2018) and Wallsten (2000).

The impact of subsidy grants on firms' performance has aroused the interest of many scholars. There are various studies examining this effect and finding heterogeneous outcomes. Using the CIS data of Norway and instrumental variables regression, Clausen (2009) found that research subsidies tend to stimulate firms' R&D spending, whereas development subsidies may substitute for firms' R&D investments. Using a regression discontinuity design Bronzini and Iachini (2014) found that the R&D subsidy program in northern Italy does not affect large firms' investment but does enhance that of small enterprises. The same program shows a positive causal effect on patent applications, especially in the case of small firms (Bronzini & Piselli, 2016).

Czarnitzki and Lopes-Bento (2014) analyze the impact of European and national subsidies on German firms' innovation input and output, and indicate that firms receiving both subsidies invest more in innovation and R&D regarding the input side. In terms of output, firms are more active after obtaining funds quantitatively (applying for more patents) and qualitatively (higher value patents). Howell (2017) proves a positive impact of receiving the US Department of Energy's SBIR grant on firms' patents and revenue.

Bérubé and Mohnen (2009) analyze Canadian firm-level data during the period 2002 - 2004 to examine how R&D tax credits and R&D grants influence innovation. They find that firms benefiting from both types of support demonstrate higher levels of innovation, introduce more world-first innovations, and generate a larger portion of their revenue from first-to-market innovations compared to firms that receive only R&D tax credits. Using the firm-level data from 30 Eastern European and Central Asian countries, Mateut (2018) proves the positive impact of public subsidies on firms' innovation. Z. Wu et al. (2022) investigate the effect of government subsidies on innovation investment of Chinese new energy firms from 2007 to 2017 using fixed effect and DiD models. Their findings indicate an inverted U-shaped relationship between subsidies and innovation investment. This suggests a crowding-out effect of high levels of subsidies on firms' R&D investment.

Ghirelli et al. (2023) use a DiD approach to examine a specific component of the EU Framework Programme, focusing on European Research Council (ERC) grants. Their findings show no statistically significant impact of receiving ERC funding on research productivity. Their results align with previous studies of Baruffaldi et al. (2020), Carayol and Lanoë (2017), and Langfeldt et al. (2015), who also employ either DiD or regression discontinuity designs to explore national researcher grant programs, and report little to no effect on research productivity. On the contrary, Jacob and Lefgren (2011) find that stronger positive effects are observed among younger researchers.

In the context of the Horizon 2020 program, three studies examined the effect of this subsidy on firms' performance. Mulier and Samarin (2021) use Orbis-Europe data, considering only for-profit firms from 2010 to 2019, to examine the causal effect of receiving subsidies from Horizon 2020 on firms' performance in terms of assets (tangible and intangible), turnover, employment, and patents. Employing DiD in the analysis, the results prove a positive impact of subsidies on firms' performance. Besides, the study also explores this effect under sectoral heterogeneity, specifically, R&D intensity, knowledge intensity, and competition degree. Investigating a similar issue, Mitra and Niakaros (2023) use private-owned companies' data from 2010 to 2022 and apply the DiD approach, controlling for different time treatment and heterogeneous treatment effect. They indicate that firms applying for Horizon 2020 experience increased employment, total assets, and revenue. Interestingly, the program positively affects firms in the sector *Information and communication* and *Professional, scientific and technical activities*, but no effect is found in other sectors. Santoleri et al. (2024) examines the impact of the SME Instrument grant under the Industrial Leadership pillar[2] on firms' investment by applying a regression discontinuity design. They point out an increase in firms' investment and innovation output measured by cite-weighted patents.

Innovation is induced by various factors, such as international trade, R&D expenditure,

[2] See Table 3.1

knowledge of firms, the level of competition in the market, IPRs, etc. *Export orientation* plays an important role in fostering innovation, as participation in international trade is one of the key channels through which firms enhance their productivity and innovative capacity, often through the learning-by-exporting (LBE) effect. Firms' innovation activities are also accelerated by importing intermediate inputs (G. Chen & Wu, 2017) and acquiring knowledge from international markets (Salomon & Shaver, 2005). Using Spanish firm-level data from 1990 to 2002, Golovko and Valentini (2014) examine the LBE effect on product and process innovation, finding that larger firms tend to focus more on process innovation, whereas SMEs are more inclined toward product innovation after entering foreign markets. Similarly, Love and Ganotakis (2013) explore the LBE effect among manufacturing and service firms in the UK, revealing a complex relationship: while high-tech SMEs improve their innovation performance after exporting, they do not necessarily innovate more intensively. Further evidence for the LBE effect is provided by Liang et al. (2024), who investigate the impact of exporting on innovation, measured through patent citations, among Chinese firms.

The literature has long acknowledged the importance of *R&D intensity* in innovation. Endogenous growth theory emphasizes the importance of human capital, R&D, and innovation as key drivers of economic growth, arguing that increased R&D spending accelerates innovation, which in turn fosters economic development (Aghion & Howitt, 1990; Romer, 1990). However, the relationship between R&D and innovation remains debated. Klaassen et al. (2005) find a positive effect of R&D expenditure on innovation in the wind energy sector in Denmark, Germany, and the UK. Similarly, Heij et al. (2020) report a positive relationship between R&D and product innovation for Dutch firms with low levels of management innovation, while firms with high levels of management innovation exhibit a J-shaped relationship. Y. Dong et al. (2020) identify a U-shaped relationship between R&D intensity and innovation among Chinese artificial intelligence firms. Examining the effect of R&D expenditure in EU countries from 1995 to 2014, Pegkas et al. (2019) show that business, public, and higher education R&D investments all positively contribute to innovation. Furthermore, using data from 311 firms in four advanced countries between 1999 and 2003, Lee et al. (2014) find that higher levels of R&D intensity are associated with more exploitative innovation behavior and less explorative innovation.

The critical role of *knowledge* has been widely discussed in the literature over time. According to resource-based view theory, knowledge serves as a source of competitive advantage (Barney, 1991). It is considered a key resource that distinguishes firms from one another (Spender, 1996), enhances firms' capacity to innovate (Hage & Aiken, 1970), and plays a crucial role within sectoral systems of innovation and production (Malerba, 2002). Using Canadian firm-level data, Thornhill (2006) found a positive impact of firm-level knowledge assets, measured by the ratio of technical and professional employees in the workforce, on firms' innovation performance. Similarly, Tavassoli and Carbonara (2014) demonstrated a positive relationship between knowledge variety and intensity and regional innovation, measured by the number of patent applications in Sweden.

The impact of *competition* on innovation has been broadly debated. (Aghion et al., 2005, 2015; Arrow, 1972; Beneito et al., 2014; Bento, 2014; Greenhalgh & Rogers, 2006; Negassi et al., 2019). There are two opposite effects of competition on innovation: the 'Escape competition effect' and the 'Schumpeterian effect'. As predicted by Arrow (1972), to stay competitive, firms must innovate further to differentiate themselves, which is known as the 'escape-competition effect'. However, from Schumpeterian perspectives, competition can be detrimental to innovation. Specifically, as market competition intensifies, successful innovators earn lower profits and have less incentive to innovate, which is referred to as the 'Schumpeterian effect'. Furthermore, Griffith et al. (2010) also suggested that monopoly rents, which incentivize R&D investment, are diminished by increased competition. Aghion et al. (2005) proved the inverted-U shape relationship between competition and innovation, in which the 'escape competition effect' outweighs the 'Schumpeterian effect' at the low level of competition. However, as the competition level increases, the 'Schumpeterian effect' dominates the 'escape competition effect'. Thus, the net impact of competition on innovation relies on the magnitude of these two effects.

Among the various types of *intellectual property rights (IPRs)*, patents are particularly important for protecting technological innovation, especially in R&D-intensive sectors. However, patents are not always the most critical form of protection across all industries. Firms frequently rely on a combination of IPRs, including trademarks, copyrights, trade secrets, and design rights, depending on the type of innovation and their strategic objectives. The relationship between IPRs and innovation has been explored in numerous studies, yielding heterogeneous results: some find a positive effect (Y. Chen & Puttitanun, 2005; Kanwar & Evenson, 2003), others identify a U-shaped relationship (Allred & Park, 2007), and still others report an inverted U-shaped relationship (Furukawa, 2010; Horii & Iwaisako, 2007). Allred and Park (2007) find that in developing economies, patent strength does not significantly influence R&D investment, whereas in developed economies, stronger patent systems are associated with increased R&D activity. Using CIS data on German firms, Crass et al. (2019) show that new-to-market innovation is significantly enhanced when firms combine patents with secrecy as complementary protection strategies. Trademarks, on the other hand, play a more prominent role in service industries. In particular, their positive effect on product differentiation is especially strong among innovative service firms launching new-to-the-market products, while the impact of trademarks in manufacturing sectors appears to be more limited (Crass & Schwiebacher, 2017).

Based on prior literature, we expect that the impact of Horizon 2020 funding on firm innovation might vary depending on firms' export orientation, R&D intensity, knowledge intensity, competition exposure, and types of IPRs protection.

3.3 Horizon 2020

The Horizon 2020 program is the European research and innovation funding program from 2014 to 2020, with a budget of around EUR 77 billion over seven years. Similar to the preceding 7th Framework Program (FR7), the target of Horizon 2020 is to accelerate innovation activities, competitiveness, and economic growth. It was built on three pillars: support for *Excellent Science*, support for *Industrial Leadership*, and support for research to tackle *Societal Challenges* and two specific objectives: *Spreading excellence & widening participation* and *Science with and for society.*

The first pillar *Excellent Science* aims at attracting research talent, reaching new fields of innovation, developing careers, and advancing cutting-edge research infrastructures. The second pillar *Industrial Leadership* targets key technologies, attracting investment in research and innovation, and accelerating the innovation activities of SMEs in Europe. The third pillar *Societal Challenges* focuses on society and citizens, including health, food security, clean energy, and environmental protection. The summary of the three pillars and the total funds are listed in Table 3.1.

In the first three years after launching the program, the total number of participations was 58,964, with total grants of EUR 24.8 billion. The majority of applicants for the program are secondary and higher education establishments (38%), private for-profit companies (26%), and research organizations (18%). In the third three years of the program (2014 - 2016), the UK has the highest number of Horizon 2020 applications (12.4%). Italy and Germany are in the second rank with 11.2%. France is ranked third with 10.6%. Among the associated countries, Switzerland has the highest number of applications (8,653), followed by Norway, Israel, and Turkey with 5,847, 5,433, and 3,854 applications, respectively. Meanwhile, the top ten most active third countries submitted 12,780 applications, among which the United States, China, Canada, and Australia submitted 30.6%, 7.3%, 5.9%, and 5.7% of all eligible applications, respectively (EC, 2017).

Horizon 2020 focuses on three pillars and the grants are distributed to these pillars as follows: EUR 9,301 (37%) went to *Excellent Science*, *Industrial Leadership* proposals received EUR 5,023 (20%), and EUR 9,074 (37%) belongs to *Societal Challenges.* Horizon 2020 attracted more newcomers compared to its preceding FR7 program, namely, 54.4% of participants did not take part in FR7. 73% of newcomers are private for-profit companies, among which 48.9% are SMEs. Besides, the process of applying for Horizon 2020 is also more efficient than FR7. Specifically, under Horizon 2020 time-to-grant[3] is 110 days faster than under FR7. Over the first three years, the overall success rate of proposals is 87.4%. Regarding different types of organization, *public bodies* have the highest success rate (26.4%), followed by *other entities* (20.3%) and *research organization* (17.7%). Among member states, Belgium has the highest success rate, with 18%. France, the Netherlands, Luxembourg, and Austria rank second with 17%. Germany and Sweden are in the third place with 16% (EC, 2017).

[3] The time between the closing day of the call and the start day of the project

Table 3.1: Horizon 2020 structure and budget

Pillars and objectives	**Total funding for 2014-2020**	**EUR million**
Excellent Science	European Research Council (ERC) *Frontier research by the best individual teams*	13,095
	Future & emerging technologies *Collaborative research to open new fields of innovation*	2,696
	Marie Skłodowska-Curie actions (MSCA) *Opportunities for training and career development*	6.162
	Research infrastructures (including e-infrastructure) *Ensuring access to world-class facilities*	2,488
Industrial Leadership	Leadership in enabling & industrial technologies (LEITs) *ICT, nanotechnologies, materials, biotechnology, manufacturing, space*	13,557
	Access to risk finance *Leveraging private finance & venture capital*	2,842
	Innovation in SMEs *Fostering all forms of innovation in all types of SMEs*	616
Societal Challenges	Health, demographic change & wellbeing	7,472
	Food security, sustainable agriculture and forestry, marine/maritime/inland water research and the bioeconomy	3,851
	Secure, clean & efficient energy	5,931
	Smart, green & integrated transport	6,339
	Climate action, environment, resource efficiency & raw materials	3,081
	Inclusive, innovative & reflective societies	1,310
	Secure societies	1,695
Spreading excellence & widening participation		816
Science with and for society		462

Source: Horizon 2020 Online manual

3.4 Theoretical Framework

In this section, we develop a model that extends the foundational work on firm heterogeneity by Melitz (2003) and Kugler and Verhoogen (2012). Our key contribution is to endogenize a firm's innovation represented in product quality by introducing a technology cost associated with R&D investment and the subsidy from the Horizon 2020 program. Our model is a static one, but we believe that this model can serve as a good starting point to explore the impact of Horizon 2020 on firms' innovation, since Horizon 2020 is a short-run program starting from 2014 to 2020.

First, production occurs as a sequence: at the beginning of the period, firms receive an initial budget (B) and they choose the innovation level that maximizes their profit subject to their budget constraint; at the end of the period, the profit is realized and earned by firms. We apply the Lagrange method to solve the firm's profit maximization problem. The First Order Condition (FOC) allows us to explain the impact of subsidy on a firm's R&D investment with two different cases.

Second, continuing from the first step, we solve the FOC to obtain the optimal innovation, which depends on the Horizon 2020's funding. This allows us to directly analyze how this subsidy shapes the firm's innovation activities.

3.4.1 Model Setup

Following Kugler and Verhoogen (2012) and Melitz (2003), first from the demand side, we start with the utility of a representative consumer in the destination (export) market:

$$U = \left(\int_{\omega \in \Omega} (\lambda(\omega) q(\omega))^{\frac{\sigma-1}{\sigma}} \, d\omega \right)^{\frac{\sigma-1}{\sigma}} \tag{3.1}$$

Where $q(\omega)$ is the quantity of a firm's variety, $\lambda(\omega)$ denotes the quality of that variety (a higher λ means higher quality) and captures the firm's innovation. We assume that the quality of the product increases when firms conduct innovation. Thus, we interpret λ as quality and/or innovation interchangeably. $\sigma > 1$ shows the elasticity of substitution between varieties. Ω is the set of available varieties.

Combining the utility function and the budget constraint $Y = \int_{\omega \in \Omega} p(\omega) q(\omega) d\omega$, the demand curve faced by a single exporting firm for its variety ω is as follows:

$$q(\omega) = Y P^{\sigma-1} (p(\omega))^{-\sigma} (\lambda(\omega))^{\sigma-1} \tag{3.2}$$

Where Y is the aggregate expenditure in the export market. $p(\omega)$ is the price the firm sets for its variety. P denotes the aggregate price index in the market[4]. This equation indicates that demand for a firm's product increases with its quality/innovation (λ) and decreases with its price (p). This is the channel through which the firm's innovation impacts its revenue.

[4] $P = \left(\int_{\omega \in \Omega} p(\omega)^{1-\sigma} \lambda(\omega)^{\sigma-1} d\omega \right)^{\frac{1}{1-\sigma}}$

Second, the supply side is enacted from the firm's profit maximization as follows:

$$\max_{p(\omega),\lambda(\omega)} \pi_x(\omega) = p(\omega)q(\omega) - \frac{1}{\varphi}q(\omega) - \frac{1}{1+s}F_{R\&D}(\lambda) \tag{3.3}$$

Where $p(\omega)q(\omega)$ is the firm's revenue. $\frac{1}{\varphi}q(\omega)$ is variable production cost. φ is the firm's idiosyncratic productivity, and $1/\varphi$ is the marginal cost, which is assumed to be identical for all firms. More productive firms (higher φ) have lower marginal costs. We introduce innovative technology to the model, which involves a fixed cost of R&D ($F_{R\&D}$) required to achieve a certain innovation level (λ). s denotes Horizon 2020's subsidy rate ($0 \leq s \leq 1$), which helps firms to reduce the cost of conducting innovation. We suppose that firms will pay 100% of the R&D costs when they do not receive the subsidy from Horizon 2020 ($s = 0$), and even when Horizon 2020 subsidizes firms 100% ($s = 1$), firms still need to use their internal budget to pay the remaining 50% of the R&D costs. Following the literature on endogenous quality and technology choice of Bustos (2011) and Kugler and Verhoogen (2012), we assume this cost is firm-specific and convex in innovation.

$$F_{R\&D}(\lambda) = \frac{f}{\theta}\lambda^{\beta}, \quad F'_{R\&D}(\lambda) > 0 \quad \text{and} \quad \beta > \sigma - 1. \tag{3.4}$$

f is a cost scaling parameter. $\theta > 0$ represents the firm's innovation capability/efficiency. A firm with a higher θ is better at R&D and can achieve innovation for a lower cost. According to Bustos (2011) and Verhoogen (2008), this condition of θ helps to explain why firms with similar production productivity (φ) may nonetheless make different choices regarding innovation and quality. β is the elasticity of R&D costs with respect to innovation (λ). For 1% increase in export quality, the cost of R&D increases by β%. The convexity ($\beta > 1$) reflects the increasing marginal cost of quality improvement, a standard feature in models of innovation (Grossman & Helpman, 1993). β represents how fast the cost of R&D rises while σ is related to how much profit a firm can make from an innovation. A high σ means that products are close substitutes, competition is fierce, and profits from innovation are lower. The condition $\beta > \sigma - 1$ guarantees that the costs of R&D (β) rise sufficiently fast relative to the potential profits from innovation (related to σ) to prevent an explosive, unrealistic outcome. At the same time, this condition ensures the profit function is concave and has a unique maximum.

When the firm sets the price, it takes Y, P, and λ as given. We solve the profit maximization problem to find the optimal price, which is a constant markup over marginal costs: $p^* = \frac{\sigma}{\sigma-1}\frac{1}{\varphi}$. Plugging this price into the demand equation, we obtain the revenue and variable profit:

$$R(\lambda, \varphi) = A(\varphi)^{\sigma-1}(\lambda)^{\sigma-1}, \quad \pi_{\text{variable}} = R - \frac{1}{\varphi}q = \frac{R}{\sigma} \tag{3.5}$$

Where $A = YP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{1-\sigma}$ is a constant that captures the market conditions.

3.4.2 Impact of Horizon 2020 on R&D investment

To extract the impact of subsidy from the Horizon 2020 on the firm's R&D investment, we solve the firm's profit maximization problem subject to the budget constraint condition $(1/(1+s))F_{R\&D}(\lambda) \leq B$, where B is the firm's budget. The firm's R&D investment should not be larger than its budget.

$$\max_{\lambda} \quad \pi_x = \frac{1}{\sigma} A\varphi^{\sigma-1}\lambda^{\sigma-1} - \frac{1}{1+s}\frac{f}{\theta}\lambda^{\beta} \tag{3.6}$$

By applying the Lagrange method, we have:

$$\begin{aligned} \mathcal{L} &= \frac{1}{\sigma} A\varphi^{\sigma-1}\lambda^{\sigma-1} - \frac{1}{1+s}\frac{f}{\theta}\lambda^{\beta} + \mu\left(B - \frac{1}{1+s}\frac{f}{\theta}\lambda^{\beta}\right) \\ \Leftrightarrow \mathcal{L} &= \frac{1}{\sigma} A\varphi^{\sigma-1}\lambda^{\sigma-1} - (1+\mu)\frac{1}{1+s}\frac{f}{\theta}\lambda^{\beta} + \mu B \end{aligned} \tag{3.7}$$

Where $\mu \geq 0$ is the multiplier. μ represents the shadow price of the firm's budget. In other words, μ shows the marginal increase in the firm's profit when the budget increases by one euro. The F.O.C. is as follows:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \lambda} &= \frac{\sigma-1}{\sigma} A\varphi^{\sigma-1}\lambda^{\sigma-2} - \beta(1+\mu)\frac{1}{1+s}\frac{f}{\theta}\lambda^{\beta-1} = 0 \\ \Rightarrow \frac{\sigma-1}{\sigma} A\varphi^{\sigma-1}\lambda^{\sigma-2} &= \beta(1+\mu)\frac{1}{1+s}\frac{f}{\theta}\lambda^{\beta-1} \end{aligned} \tag{3.8}$$

This FOC is reached under the following condition:

$$\mu\left(B - \frac{1}{1+s}F_{R\&D}(\lambda)\right) = 0 \tag{3.9}$$

This condition assures that either the multiplier (μ) is 0 or the constraint is perfectly binding. Thus, there are two different cases:

Financially unconstrained firm (*The constraint is not binding*)

This means $B > (1/(1+s))F_{R\&D}(\lambda)$. From Equation (3.9), this non-binding constraint infers $\mu = 0$. This means that, for a firm that already has more investment than it needs for its R&D projects, an extra euro for R&D is not necessary, so its shadow price is zero. Equation (3.8) now becomes:

$$\frac{\sigma-1}{\sigma} A\varphi^{\sigma-1}\lambda^{\sigma-2} = \beta\frac{1}{1+s}\frac{f}{\theta}\lambda^{\beta-1} \tag{3.10}$$

This equation implies that the marginal benefit of the firm (the left side) equals the marginal cost of the subsidy from Horizon 2020 (the right side). The firm invests up to the point where the marginal benefit of innovation equals the subsidized marginal cost. Firms receiving the funding from the Horizon 2020 ($s > 0$) are encouraged to have a higher total investment $F_{R\&D}(\lambda)$ compared to non-subsidized firms. However, these subsidized firms are simply substituting their own abundant internal funds with cheaper government funds. This is the crowding-out scenario: the subsidy from the Horizon 2020 program does not enable new activity as much as it displaces private spending.

Financially constrained firm (*The constraint is binding*)

This means $B = (1/(1+s))F_{R\&D}(\lambda)$. From Equation (3.9), this binding constraint infers $\mu > 0$. In contrast to the previous case, the firm is in dire need of capital. Every extra euro added to its budget B would allow it to increase its R&D investment, move closer to its unconstrained optimum, and therefore increase its profit.

The firm's effective marginal cost of R&D is magnified by the term $(1 + \mu)$, reflecting the high opportunity cost of using a scarce internal euro. The Horizon 2020 subsidies work directly to alleviate this high effective cost. By providing funds, the subsidy allows the firm to increase its total investment from B (the no-subsidy level) to $B(1+s)$. The firm's private spending remains at a maximum of B, and all additional R&D is funded by the subsidy. This shows the crowding-in effect of the funds from Horizon 2020.

3.4.3 Impact of Horizon 2020 on innovation

From Equation (3.8), we rearrange to get:

$$\lambda^{\beta-\sigma+1} = \frac{\theta(\sigma-1)}{\sigma f}\frac{1}{\beta(1+\mu)}A\varphi^{\sigma-1}(1+s) \tag{3.11}$$

Thus, the optimal innovation is:

$$\lambda^{*} = \left[\frac{\theta(\sigma-1)}{\sigma f}\frac{1}{\beta(1+\mu)}A\varphi^{\sigma-1}(1+s)\right]^{\frac{1}{\beta-\sigma+1}} \tag{3.12}$$

To simplify the expression, set $K = \frac{\theta(\sigma-1)}{\sigma\beta(1+\mu)f}A\varphi^{\sigma-1}$. Take the first derivative of λ^* with respect to s, we obtain the following:

$$\frac{\partial\lambda^*}{\partial s} = K^{\frac{1}{\beta-\sigma+1}} \cdot \frac{1}{\beta-\sigma+1}(1+s)^{\frac{\sigma-\beta}{\beta-\sigma+1}} \tag{3.13}$$

Since $\beta > \sigma - 1$, we get $\beta - \sigma + 1 > 0$. Thus, $\partial\lambda^*/\partial s > 0$. This proves the positive impact of Horizon 2020's subsidy on firms' innovation.

Figure 3.1 is the simulation of the relationship between subsidy and firms' innovation with different values of elasticity of R&D costs with respect to innovation (β) in two cases: crowding out and crowding in. In both cases, we observe a rise in innovation level when the subsidy from Horizon 2020 increases. When firms receive a higher rate of subsidy from Horizon 2020, they have more motivation to conduct innovation activities. Not surprisingly, this impact is stronger for firms with a lower elasticity of R&D costs with respect to innovation since with the same level of increase in R&D costs, firms with a lower β can conduct more innovative activities than firms with higher β.

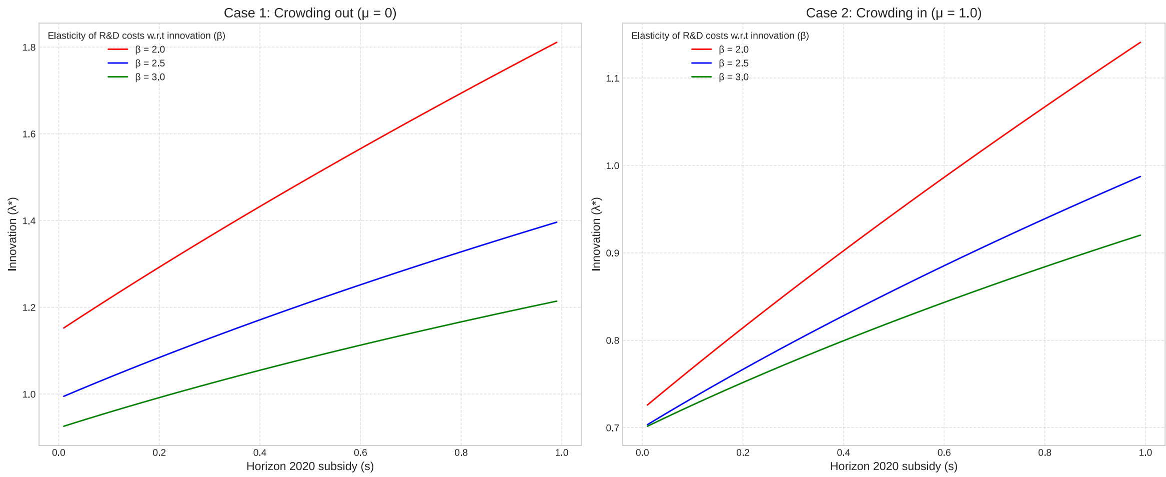


Figure 3.1: The impact of Horizon 2020 subsidy on innovation
The simulation is based on the following parameter values: $A = 2.0$, $f = 1.0$, $\sigma = 1.5$, $\theta = 3.0$, and $\varphi = 1.5$.

3.5 Data and Methodology

3.5.1 Data

The paper uses firm-level data to examine the effect of attending the Horizon 2020 program on European firms' innovation activities. The data is collected from the Community Innovation Survey (CIS) of Eurostat. We use five waves: 2010, 2012, 2014, 2016, and 2018. The data covers 9 countries: Bulgaria (BG), the Czech Republic (CZ), Estonia (EE), Spain (ES), Germany (DE), Hungary (HU), Lithuania (LT), Portugal (PT), and Romania (RO).

Concerning innovation activities, as shown in Figure 3.2, Spain outweighs the rest in all four types of innovation despite experiencing a decreasing trend between 2010 and 2018. Innovation activities of other countries fluctuated during this period.

Innovation activities show considerable variation across 21 sectors, as detailed in Table 3.2. Process innovation is the most prevalent, with nearly 99,000 firms engaging in it, while marketing innovation is the least common, involving only 79,000 firms. The Manufacturing sector leads in all four innovation types, with participation rates of approximately 60% in product, 53% in process, 46% in organizational, and 50% in marketing innovation. Beyond Manufacturing, significant innovation is also observed in Information and Communication, Professional, Scientific, and Technical Activities, and Wholesale and Retail Trade (including motor vehicle repair). Specifically, for product innovation, Information and Communication ranks second at 12%, followed by Professional, Scientific, and Technical Activities at 9%. In process innovation, Wholesale and Retail Trade holds the second position with 9.5%, with Information and Communication close behind at 9%. This pattern continues for organizational innovation, where Wholesale and Retail Trade and Information and Communication account for 11.5% and 19% respectively, and for marketing innovation, at 14% and 10% respectively.

Similar to innovation activities, firms in these abovementioned sectors also attended the

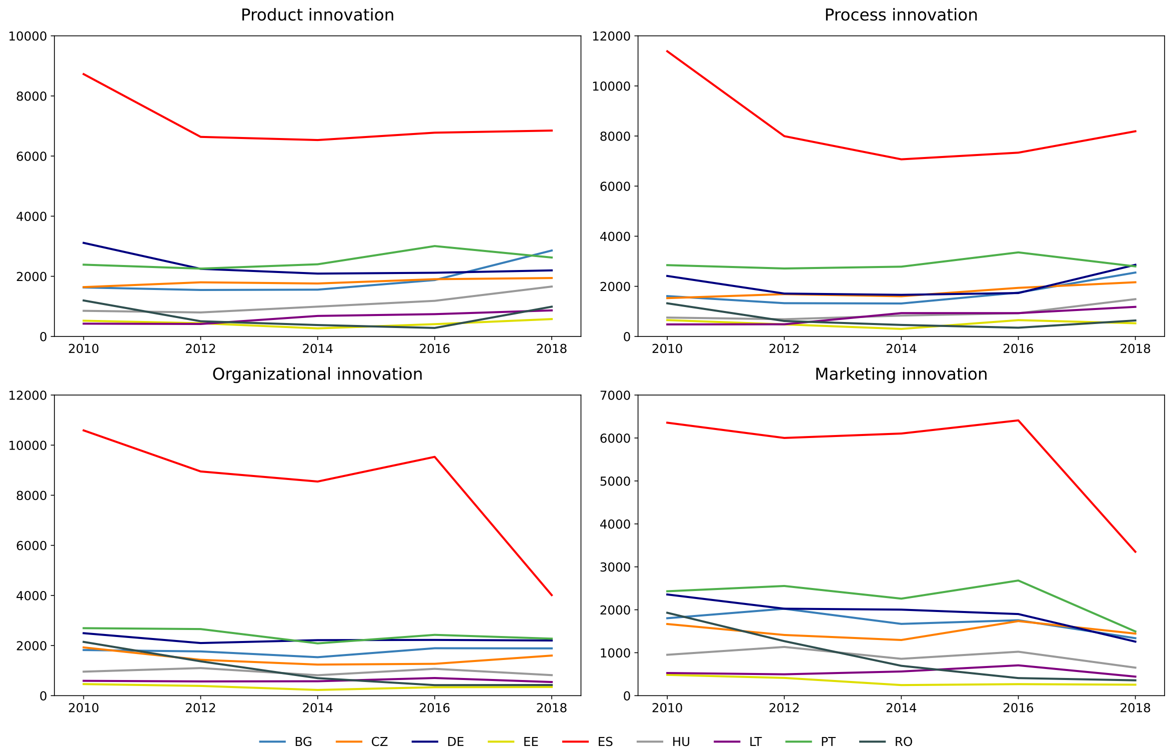


Figure 3.2: Innovation activities of European firms

Horizon 2020 program with high percentages, as shown in Table 3.3. In 2014, 46%, 27%, and 12% of firms in the Manufacturing, the Professional, scientific and technical activities, and the Information and communication sectors attended the Horizon 2020 program. This rank remains unchanged in 2016, with the following percentages: 44%, 28%, and 28%, respectively.

Horizon 2020 started in 2014 and continues until 2020. However, the available data covers only two years, 2014 and 2016. No firm has reported information concerning the attendance of the Horizon 2020 program in 2018. Table 3.4 provides the number of firms in European countries participating in the program in the two years, 2014 and 2016. Spain takes up the highest percentage of firms attending Horizon 2020, up to 45%. Germany is ranked second, and Portugal is in third place. Among Central and Eastern European countries, the Czech Republic has the highest number of firms receiving Horizon 2020 funding, while Romania receives the least funding.

Table 3.2: Firms' innovation in different NACE sectors

Sector	**Product innovation**	**Process innovation**	**Organizational innovation**	**Marketing innovation**
A - Agriculture, forestry and fishing	411	792	693	410
B - Mining and quarrying	421	693	620	453
C - Manufacturing	52,959	52,849	44,369	39,493
D - Electricity, gas, steam, and air conditioning supply	671	1,127	1,145	770
E - Water supply; sewerage; waste managment and remediation activities	1,309	2,335	2,310	1,265
F - Construction	1,060	1,707	2,045	918
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	7,287	9,476	11,020	11,187
H - Transporting and storage	3,054	4,954	5,228	3,343
I - Accommodation and food service activities	280	543	824	811
J - Information and communication	10,945	8,937	9,353	8,050
K - Financial and insurance activities	3,258	3,501	3,871	3,271
L - Real estate activities	57	138	161	102
M - Professional, scientific and technical activities	7,998	7,733	8,445	5,555
N - Administrative and support service activities	1,022	1,594	2,243	1,305
O - Public administration and defence; compulsory social security	0	0	0	0
P - Education	179	189	197	141
Q - Human health and social work activities	1,080	1,571	2,290	1,075
R - Arts, entertainment and recreation	187	253	399	302
S - Other services activities	187	254	313	153
T - Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use	0	0	0	0
U - Activities of extraterritorial organisations and bodies	0	0	0	0
Total	**92,649**	**98,999**	**95,947**	**79,014**

The list of NACE codes is from https://ec.europa.eu/competition/mergers/cases/index/nace_all.html

Table 3.3: Firms in different sectors participating in the Horizon 2020 program

Sector	2014	2016	Total
A - Agriculture, forestry and fishing	5	7	12
B - Mining and quarrying	5	6	11
C - Manufacturing	667	667	1,334
D - Electricity, gas, steam, and air conditioning supply	28	25	53
E - Water supply; sewerage; waste managment and remediation activities	25	29	54
F - Construction	28	23	51
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	40	59	99
H - Transporting and storage	39	37	76
I - Accommodation and food service activities	1	2	3
J - Information and communication	168	175	343
K - Financial and insurance activities	8	4	12
L - Real estate activities	2	0	2
M - Professional, scientific and technical activities	395	429	824
N - Administrative and support service activities	5	3	8
O - Public administration and defence; compulsory social security	0	0	0
P - Education	2	3	5
Q - Human health and social work activities	13	15	28
R - Arts, entertainment and recreation	1	0	1
S - Other services activities	9	9	18
T - Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use	0	0	0
U - Activities of extraterritorial organisations and bodies	0	0	0
Total	**1441**	**1516**	**2957**

The list of NACE codes is from https://ec.europa.eu/competition/mergers/cases/index/nace_all.html

Table 3.4: European firms participating in the Horizon 2020 program

Country	2014	2016	Total
Bulgaria (BG)	29 (2.01)	43 (2.84)	72 (2.43)
Czech Republic (CZ)	117 (8.12)	54 (3.56)	171 (5.78)
Germany (DE)	325 (22.55)	288 (19)	613 (20.73)
Estonia (EE)	29 (2.01)	19 (1.25)	48 (1.62)
Spain (ES)	653 (45.32)	703 (46.37)	1,356 (45.86)
Hungary (HU)	35 (2.43)	49 (3.23)	84 (2.84)
Lithuania (LT)	42 (2.91)	27 (1.78)	69 (2.33)
Portugal (PT)	189 (13.12)	310 (20.45)	499 (16.88)
Romania (RO)	22 (1.53)	23 (1.52)	45 (1.52)
Total	**1,441 (100)**	**1,516 (100)**	**2,957 (100)**

Percentages are in parentheses

3.5.2 Methodology

One of the most popular and efficient approaches to explore the causal effect of Horizon 2020 on firms' innovation is Difference in Difference (DiD), since this method supports comparing the changes in the outcome before and after a firm receiving funds from the Horizon 2020. The two-way fixed effects (TWFE) is often adopted to estimate in DiD regression. However, this estimation does not allow for treatment effect heterogeneity and variation in treatment timing (Goodman-Bacon, 2021). In recent years, many scholars have discovered different approaches to deal with these heterogeneous effects. Among them, the method introduced by Callaway and Sant'Anna (2021) is particularly well-suited for settings with staggered treatment adoption and heterogeneous effects. Thus, we follow their procedure to estimate dynamic treatment effects and conduct an event study analysis for assessing the parallel trends assumption[5]. The regression equation is as follows:

$$Y_{isjtc} = \alpha_1 \sum_{k=2}^{4} T_{jtck} \times (c-k) + \alpha_2 \sum_{k=0}^{2} T_{jtck} \times (c+k) + \alpha_3 X_{isjt} + \delta_i + \delta_s + \delta_t + \varepsilon_{ist} \quad (3.14)$$

Where i, s, j, t denote country, sector, firm, and year, respectively. Dependent variable Y is one of the following types of innovation: product innovation, process innovation, organizational innovation, marketing innovation, and expenditure on innovation. Y_{isjtc} represents the innovation variable for firm j in sector s and country i measured in year t, applying in year c. T_{jtck} is the dummy variable for the treatment ($k = 0, 2, 4$). α_1 and α_2 are vectors of coefficients showing the effect of the funding in each year before year c, and after year c, respectively. To satisfy the parallel trend assumption, these coefficients should be insignificant. While α_2 should be statistically significant. X is the control variable, including turnover, employment growth rate, receiving local funds, and receiving government funds. δ_i, δ_s, and δ_t are country fixed effects, sector fixed effects, and time fixed effects, respectively. ε_{ist} is clustered at country-sector level.

[5] Command `csdid` in STATA

Table 3.5 displays the staggered treatment over time. Around 14% of firms did not receive the funds from Horizon 2020. Most of the firms obtained funding in 2014, with a percentage of 81%. In 2016, only 5% of the firms were selected. For the pre-treatment years (2010, 2012), the vast majority of firms (around 82%) belong to the cohort that will be treated in 2014. For the treatment years, in 2014, the *First treated in 2014* group still forms the largest share (78.9%) of firms observed in that year. The proportion of *Never treated* (14.4%) and *First treated in 2016* (6.7%, still pre-treatment) make up the rest. In 2016, *First treated in 2014* (post-treatment) are 76.7%, *First treated in 2016* (now treated) are 9.2%, and *Never treated* are 14.1%.

Table 3.5: Tabulation of firms for the staggered treatment

Year	Never treated	First treated in 2014	First treated in 2016	Total
2010	5,565 (12)	38,611 (83.4)	2,107 (4.6)	46,283 (100)
2012	5,287 (11.8)	37,197 (83)	2,329 (5.2)	44,813 (100)
2014	1,746 (14.4)	9,589 (78.9)	811 (6.7)	12,146 (100)
2016	1,606 (12.2)	10,552 (80.3)	983 (7.5)	13,141 (100)
Total	**14,204 (12.2)**	**95,949 (82.4)**	**6,230 (5.4)**	**116,383 (100)**

Percentages are in parentheses.

3.6 Empirical Results

3.6.1 Main Results

Figure 3.3 illustrates the effects of the Horizon 2020 program on various types of innovation across the full sample, as well as for Western Europe and Central and Eastern Europe. Detailed estimation results are reported in Table C1.1, Appendix C1. The parallel trend is satisfied in most cases. The DiD estimates for the full sample show a positive impact of Horizon 2020 funding on organizational innovation, as well as innovation expenditure, while no significant effect is found for product, process, and marketing innovation. Particularly, receiving subsidy from the Horizon 2020 program leads to an increase in organizational innovation 5.6%. Concerning innovation expenditure, this variable is in natural logarithm; it is incorrect to interpret directly the impact of the dummy explanatory variable as a percentage change (Schepens, 2016). Thus, we use the formula suggested by Kennedy (1981) as Equation (3.15) to explain the impact of Horizon 2020 on innovation expenditure to obtain the least biased estimate. Following Equation (3.15), attending Horizon 2020 boosts firms' expenditure on innovation 18.3 percentage points[6].

$$p = 100 \cdot \left[\exp\left(\hat{\beta} - 0.5 \cdot \hat{V}(\hat{\beta})\right) - 1\right] \tag{3.15}$$

In the case of Western Europe, subsidies are associated with positive effects on product, process, and organizational innovation, as well as innovation expenditure, but not on marketing

[6] $100 \times (\exp(0.171 - 0.5 \times 0.074^2) - 1)$

innovation. Attending the Horizon 2020 program accelerates a firm's product, process, and organizational innovation by 12.6%, 13%, and 6.4%, respectively. While expenditure on innovation increases by 3.7 percentage points[7]. Interestingly, there is a remarkable increase in product and process innovation in 2016, after two years of receiving the subsidy, up to 18%. This is thanks to the fact that the funding reduces the financial risk of R&D, enabling firms to develop new technologies and products. Especially, in the second pillar *Industrial Leadership*, the funding named *Innovation in SMEs* aims at fostering all forms of innovation. For firms in Central and Eastern Europe, the Horizon 2020 program appears to positively affect only organizational innovation, and the effect is only found in the first year of the treatment, with an increase of 3.2%.

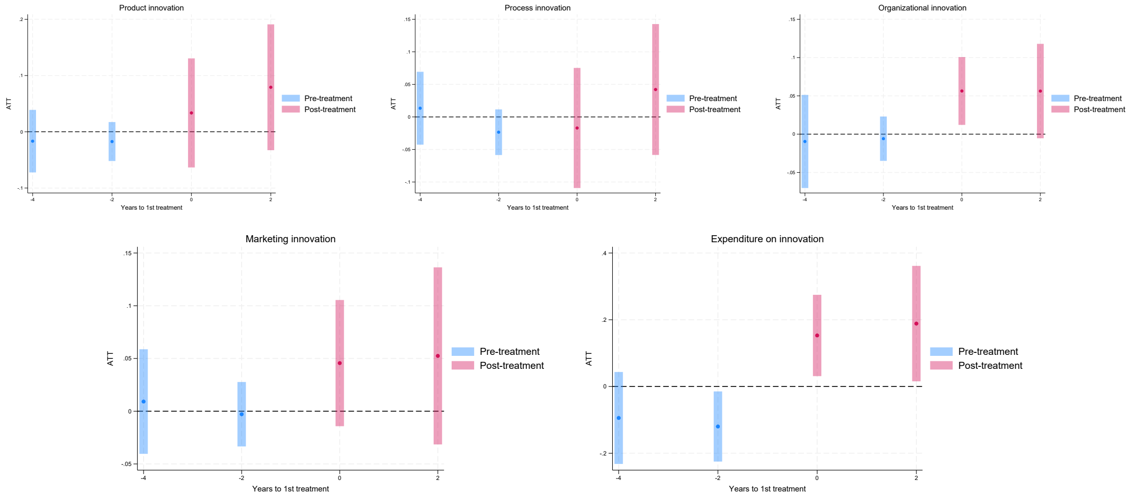
Our findings are in line with those from the theoretical model: Subsidy affects innovation positively. The positive result from spending on innovation proves the crowding-in effect of the theoretical finding. Moreover, the results also align with the evidence from Figure 3.3, which shows that over 80% of funded firms are located in Western Europe. Furthermore, as illustrated in Figure 3.1, companies in these countries are generally more active in pursuing innovation. Consistent with findings from the overall sample, Horizon 2020's impact is strongest on product and process innovation in Western Europe. In Central and Eastern Europe, however, organizational innovation benefits most from the program's funding. This regional difference may arise because marketing innovations are often less capital-intensive, depending more on strategic adjustments and communication enhancements than on significant investment in physical infrastructure or deep scientific discovery, and the costs are more related to human capital than tangible assets. Given that Central and Eastern European firms generally possess fewer resources than their Western European counterparts, they may strategically prioritize these less resource-intensive innovation types.

We also analyze the impact of Horizon 2020 on firms' innovation activities across individual countries, with the results presented in Figure C1.1, Appendix C1. The findings reveal substantial variation across countries. Among the three Western European countries, Germany shows a positive impact on product and marketing innovation. Spain, which has the highest number of firms receiving Horizon 2020 funding, exhibits negative effects on innovation expenditure in the year of treatment (2014). This result shows the crowding-out effect of the subsidy on R&D expenditure in our theoretical model. In Portugal, the subsidy has a significant negative impact on marketing innovation only two years after the treatment.

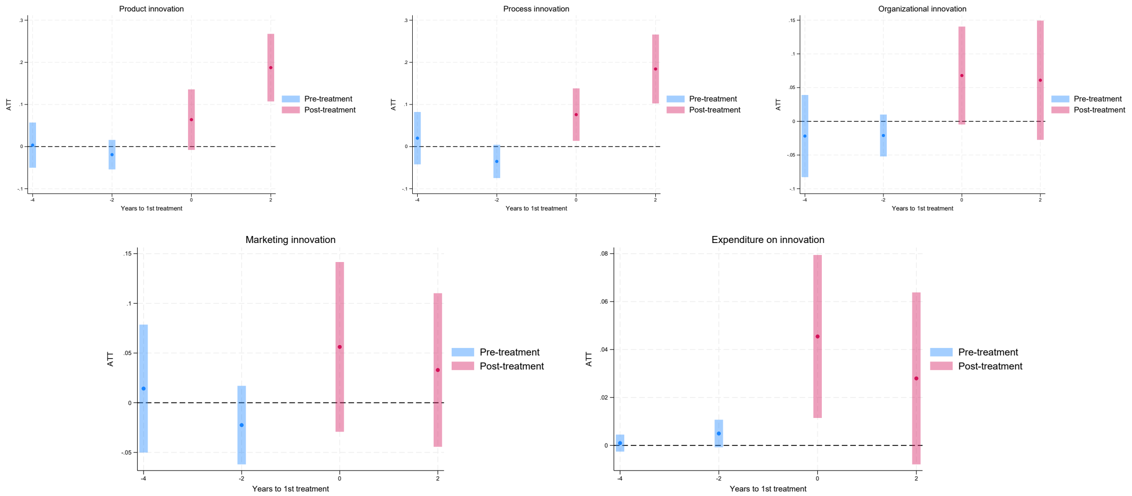
In Central and Eastern Europe, Bulgaria experiences positive effects on marketing innovation and expenditure on innovation. While receiving funds from the Horizon 2020 program does not affect the innovation activities of other countries.

[7] $100 \times (\exp(0.037 - 0.5 \times 0.017^2) - 1)$

(a) Whole sample



(b) Western Europe



(c) Central and Eastern Europe

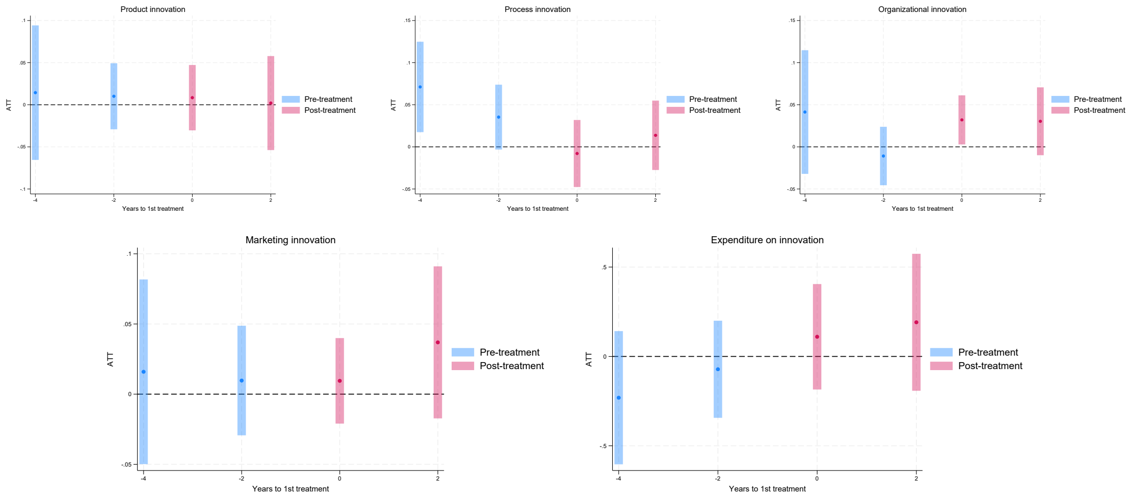


Figure 3.3: The effects of the Horizon 2020 program on firms' innovation

3.6.2 Heterogeneous Effects

To investigate the heterogeneous impact of the subsidies on firms' innovation, we first categorize the data into different subsamples by the firm's heterogeneous characteristics, namely export orientation, R&D intensity, knowledge intensity, degree of competition, different types of IPRs used, and different sectors. Then, Equation (3.14) is reestimated with these different subsamples. The results are discussed in detail below.

Export Orientation

CIS data provides information on the largest market in terms of turnover, which classifies the market into local/regional within the country, national, other European or associated countries, and all other countries. Using this information, we classify firms into two groups of sales destination: export and domestic. In the data, 50.3% of firms export their products to other European countries, and all other countries[8].

The results of estimating Equation (3.14) with two subsamples - exporting firms and non-exporting firms are in Figure 3.4. The results indicate that the Horizon 2020 program does not affect the innovation of non-exporting firms. However, the positive impacts of the subsidy on the four types of innovation and innovation expenditure are found in exporting firms. As the results provided in panel A, Table C1.2, Appendix C1, receiving subsidy from the Horizon 2020 program accelerates product innovation of exporting firms by 10.7%, and process innovation by 8%, organizational innovation by 5.7%, and marketing innovation by 7%. Interestingly, this impact is more pronounced for product and organizational innovation in the first year receiving the funding. While in the case of process innovation, this impact is only significant after two years of obtaining the subsidy.

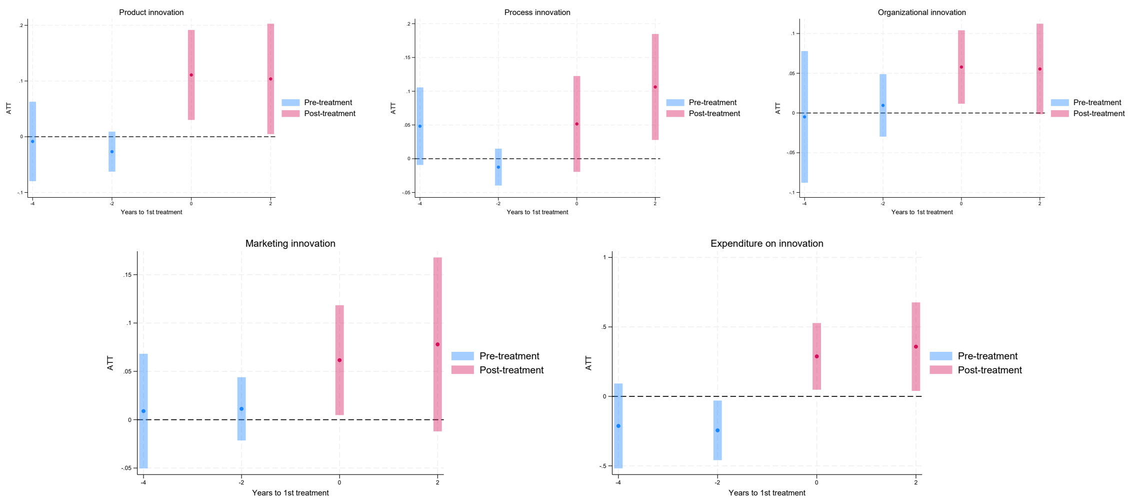
The positive impact of subsidy on firm's innovation is found only for exporting firms but not domestic firms is explained by the fact that exporting firms operate in diverse and competitive international markets, where success often depends not just on good products but also on organizational flexibility, branding, and market positioning. To survive abroad, firms need not only improve their products, but also enhance their organizational structures (e.g., managing international supply chains, complying with multiple regulations) and effective marketing strategies (e.g., adapting products to different cultures, building international brand recognition). Our results are in line with the empirical evidence from the study of Golovko et al. (2023), who use Spanish manufacturing firms from 2007 to 2013 to prove the positive impact of export on marketing innovation.

R&D Intensity

To classify the data into different levels of R&D intensity, we use the data on expenditure on innovation since it includes different types of expenditure, e.g., expenditures in intramural R&D, expenditures in extramural R&D, expenditures in acquisition of machinery, and expenditures

[8] 164,867 firms export while 162,604 firms focus on the domestic market.

(a) Exporting firms



(b) Non-exporting firms

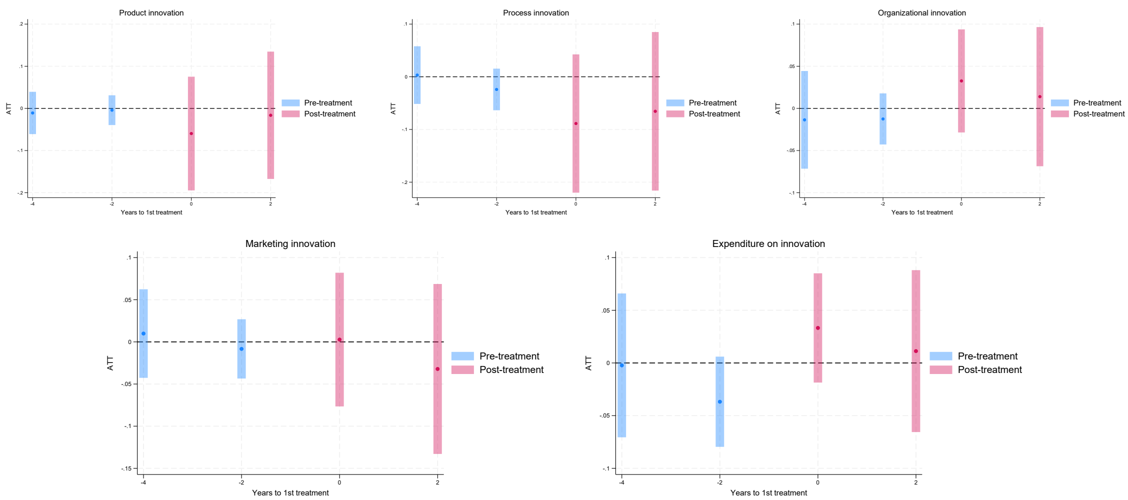


Figure 3.4: The effect of the Horizon 2020 program for different export orientations

in acquisition of external knowledge. This measure will provide more insightful information about firm innovation. According to the taxonomy of economic activities based on R&D intensity developed by OECD, high R&D intensity industries have the ratio of R&D expenditure to gross value added above 24% for manufacturing and 28.94% for non-manufacturing industries, medium-high R&D intensity industries have the ratio of R&D expenditure to gross value added above 5.72% for manufacturing and 5.92% for non-manufacturing industries (Galindo-Rueda & Verger, 2016, p.10). In this study, we use expenditure on innovation instead of R&D spending and classify firms with R&D intensity if their expenditure on innovation per turnover is above 6%. In the sample, 42.3% of firms are R&D intensive[9].

The results, presented in Figure 3.5, suggest that subsidies do not affect innovation activities of non-R&D-intensive firms. While the results are significant for product innovation, organizational innovation, and marketing innovation in R&D-intensive firms. Specifically, as shown in panel B, Table C1.2, Appendix C1, the subsidy from Horizon 2020 increases product, organizational, and marketing innovation of R&D-intensive firms by 8.6%, 11.2%, and 9.3%, respectively. The positive results are found for expenditure on innovation; however, the parallel trend assumption is violated.

Knowledge Intensity

According to Eurostat's taxonomy of knowledge intensity sectors, a sector is considered as knowledge-intensive if the share of persons with tertiary education in that sector is above 33%[10]. Since we only have the information concerning the percentage of employees with a university degree, we classify firms into knowledge-intensive and non-knowledge-intensive categories based on the proportion of employees holding a university degree. Firms with at least 25% of their workforce possessing a university degree are considered to have knowledge intensity. 28.5% of firms in the data are knowledge-intensive firms[11].

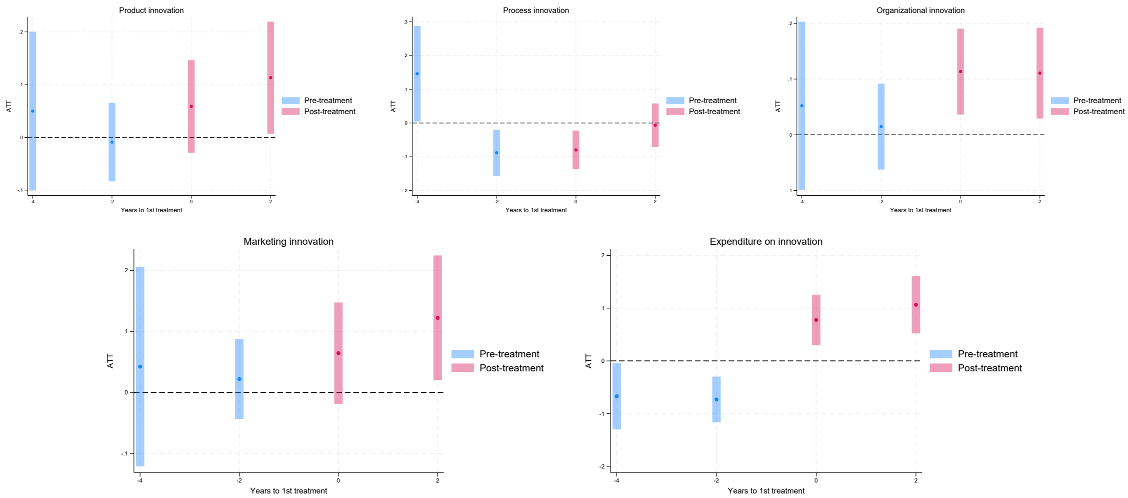
We estimate Equation (3.14) with two subsamples: knowledge-intensive firms and non-knowledge-intensive firms, and the results are presented in Figure 3.6. Different from the two above cases, we only find a positive impact of subsidies on organizational innovation for knowledge-intensive firms. In other cases, the results are insignificant. As shown in panel C, Table C1.2, Appendix C1, the subsidies from the Horizon 2020 program lead to an increase in firm's organizational innovation up to 10.7%, in which 7.5% increase is found in the first year of receiving funds, and 13.8% is obtained after two years of the treatment. Interestingly, knowledge-intensive firms also experienced an increase in expenditure on innovation in 2014, the year they received subsidies. This result is in line with the fact that knowledge-intensive firms likely already have better internal R&D capacity, human capital, and organizational structures to absorb public funding and channel it into spending. This aligns with Cohen,

[9] The number of R&D-intensive firms and non-R&D-intensive firms is 175,741 and 239,599, respectively.

[10] Source: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an_7.pdf

[11] The number of knowledge-intensive firms and non-knowledge-intensive firms is 78,098 and 195,374, respectively.

(a) R&D-intensitive firms



(b) Non-R&D-intensitive firms

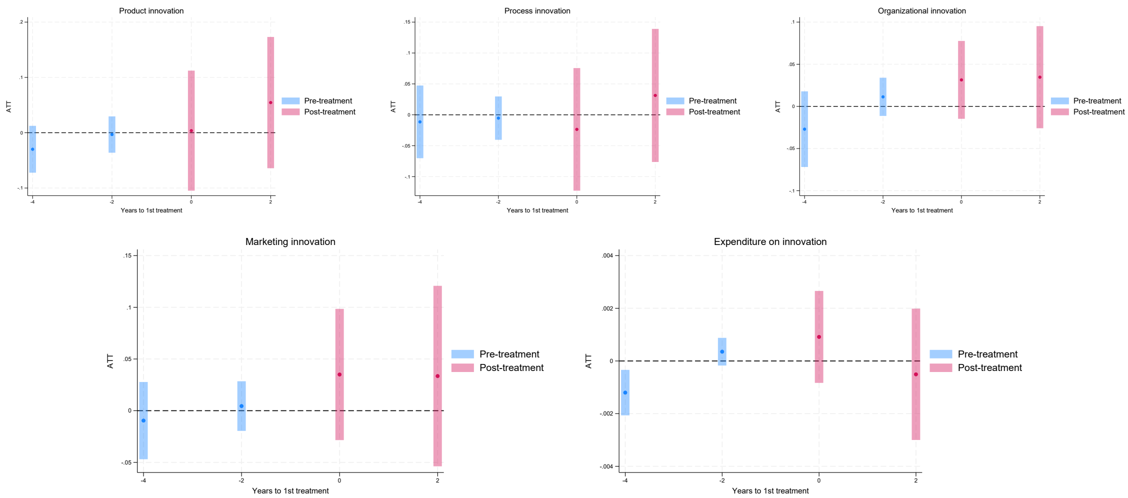
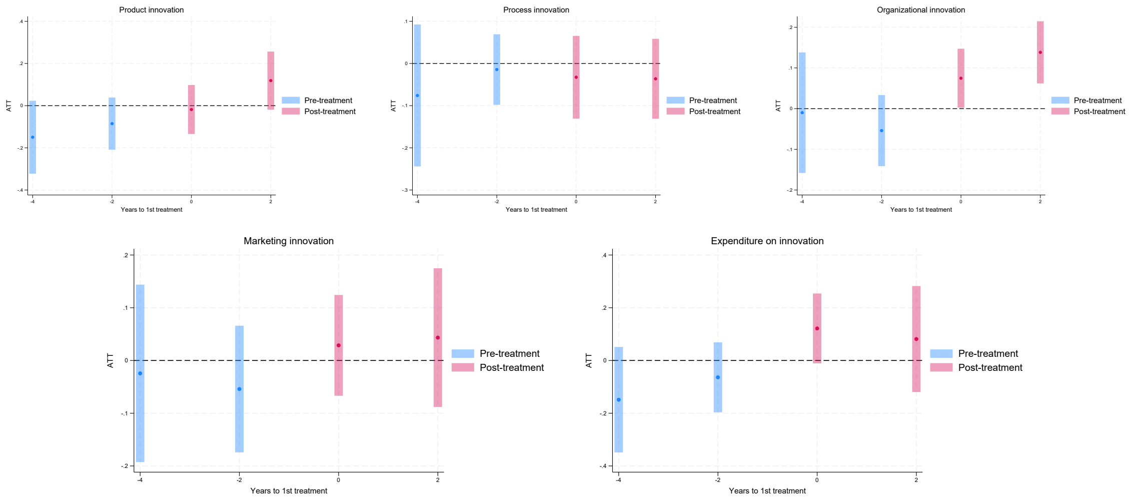


Figure 3.5: The effect of the Horizon 2020 program for different R&D intensity

(a) Knowledge-intensive firms



(b) Non-knowledge-intensive firms

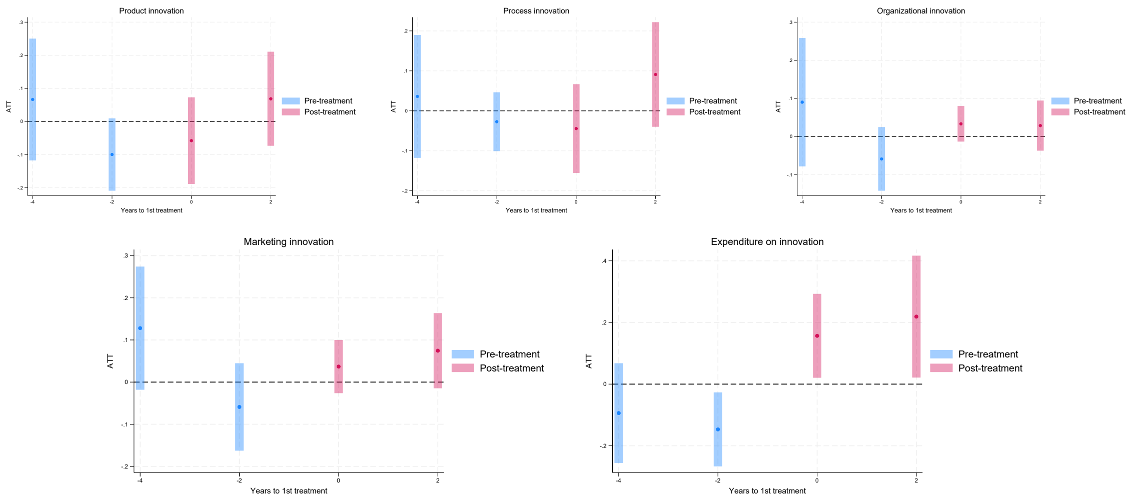


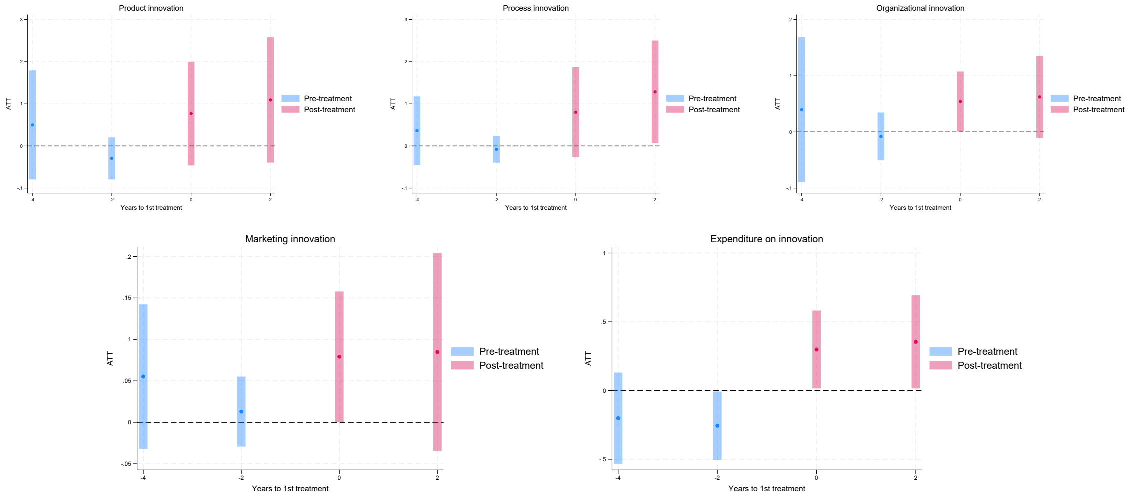
Figure 3.6: The effect of the Horizon 2020 program for different knowledge intensity

Levinthal, et al. (1990)'s theory of absorptive capacity: firms need internal capabilities to effectively exploit external knowledge and funding. Furthermore, knowledge-intensive firms may focus more directly on the goals of the Horizon 2020 program: science, technology, and knowledge-based growth, making them better candidates for larger or more project-intensive grants that require more spending.

Competition Degree

The competition is measured by the Herfindahl-Hirschman concentration index (HHI). The higher the value of HHI, the higher the level of market concentration. In other words, the lower the competition degree, the higher the value of HHI. We calculate HHI based on the turnover of firms in the data at the sector level. Then we divide the sample into four quantiles of HHI. The group below 25 percent is considered the least concentrated (or the highest competition).

(a) High competitive firms



(b) Low competitive firms

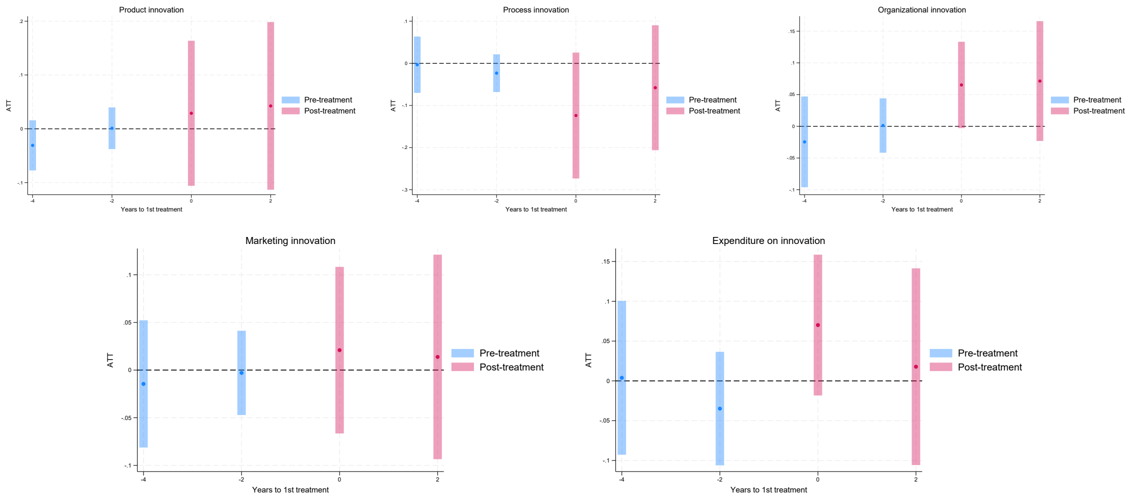


Figure 3.7: The effect of the Horizon 2020 program for different competition degrees

In our data, 60% of firms are in a low concentration or high competition market[12].

We compare the average effect of Horizon on the least concentration *Low* and the rest *High*. The results are in Figure 3.7 and in detail in panel D and panel E, Table C1.2, Appendix C1. For firms in the high competition market, the positive impact of subsidies on process, organizational, and marketing innovation is found, though the results are only significant at the 10% level. Expenditure on innovation increases after firms receive funds from the Horizon 2020 program. This result supports the *escape-competition effect* introduced by Aghion et al. (2005). For firms in the low competition market, only the result of organizational innovation is positive at the 10%-level. Other types of innovation and expenditure on innovation are not affected by the subsidies.

[12] The number of firms in the high/low competition market is 249,001/166,339 firms.

Firms using different types of IPRs protection

CIS data provides information regarding IPRs protection with different types: patents, trademarks, design rights, and copyrights[13]. However, data on copyrights does not cover all the years. Thus, we separate the data into three subsamples: firms using patents, trademarks, and design rights as a way to protect their innovation. Then we regress the model to explore how the impact of attending the Horizon 2020 program on innovation fluctuates under the use of different types of IPRs.

Figure 3.8 presents the effect of the Horizon 2020 program on firms' innovation outcomes across different types of IPR protection. Our findings indicate that subsidies do not affect any types of innovation for firms using patents, design rights, and trademarks. However, expenditure on innovation of firms using patents and design rights is positively affected by the Horizon 2020 program, as shown in detail in panels F and G, Table C1.2, Appendix C1. Specifically, the coefficient of the average impact of subsidies on innovation expenditure is 0.63 and 0.502 for firms using patents and design rights, respectively. Patents, by their nature, protect technological inventions that are typically R&D-intensive, science-based, and costly to develop (e.g., in biotechnology, engineering, and ICT sectors). Firms that utilize patents are generally engaged in formal, structured, and high-investment R&D processes. As a result, Horizon 2020 funding for these firms tends to directly translate into higher R&D expenditures, such as investments in laboratory equipment, research personnel, and technology development. Consequently, the impact of Horizon 2020 on innovation expenditures is particularly pronounced among patent-using firms.

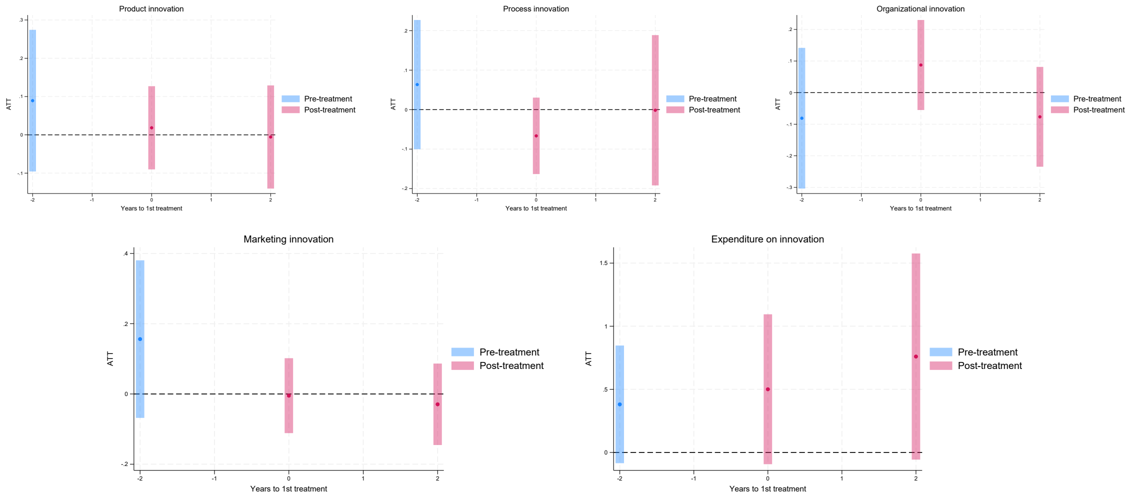
Firms in different sectors

As shown in Table 3.2, firms in the following four sectors conduct the highest amount of innovation: Manufacturing, Wholesale and retail trade; repair of motor vehicles and motorcycles, Information and communication, and Professional, scientific and technical activities. Thus, we categorize the data into four subsamples and estimate Equation (3.14) to figure out how the impact of the Horizon 2020 program on firms' innovation changes in different sectors.

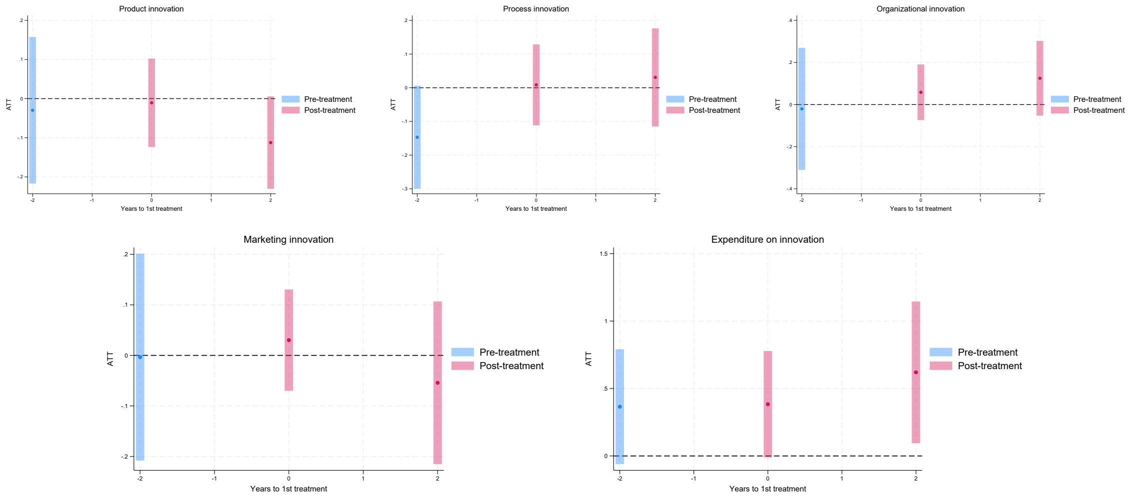
Figure 3.9 and Table C1.3, Appendix C1 provide the results. Our analysis reveals no significant impact of the subsidies on any type of innovation for firms in the Professional, Scientific, and Technical Activities sector. However, positive effects are observed in other sectors. Specifically, Manufacturing firms show an increase in process innovation, but only in 2016, two years after receiving the funds. Furthermore, their overall innovation expenditure is enhanced in both 2014 and 2016. Manufacturing heavily relies on process innovation to boost efficiency, cut costs, and improve quality, often requiring substantial capital investment. Therefore, manufacturing firms increase investment in the first year of receiving funds and again two years later. Furthermore, as process innovation in manufacturing tends to be

[13] The number of firms using patents, trademarks, design rights, and copyrights is 253,017, 252,775, 252,739, and 176,914, respectively

(a) Firms use patents



(b) Firms use design rights



(c) Firms use trademarks

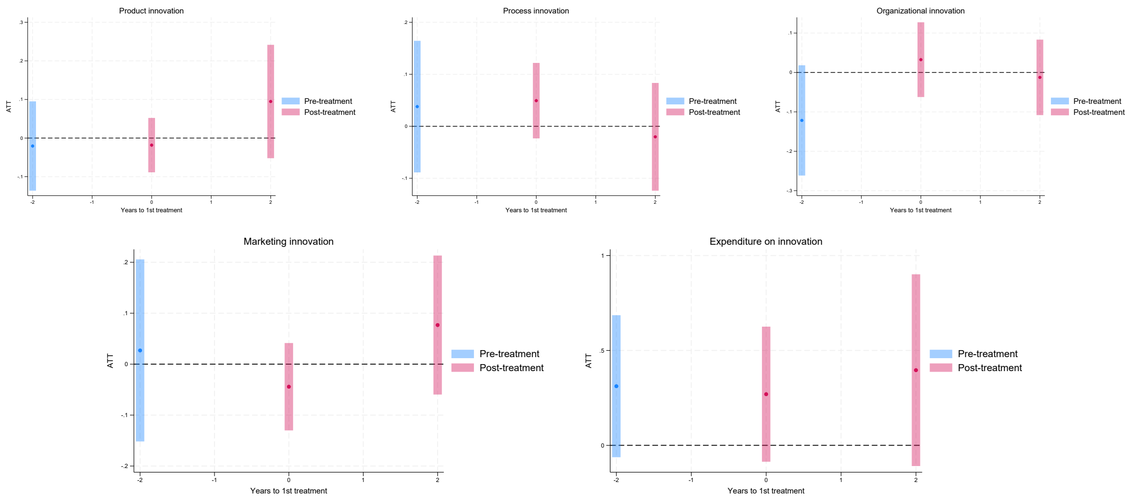


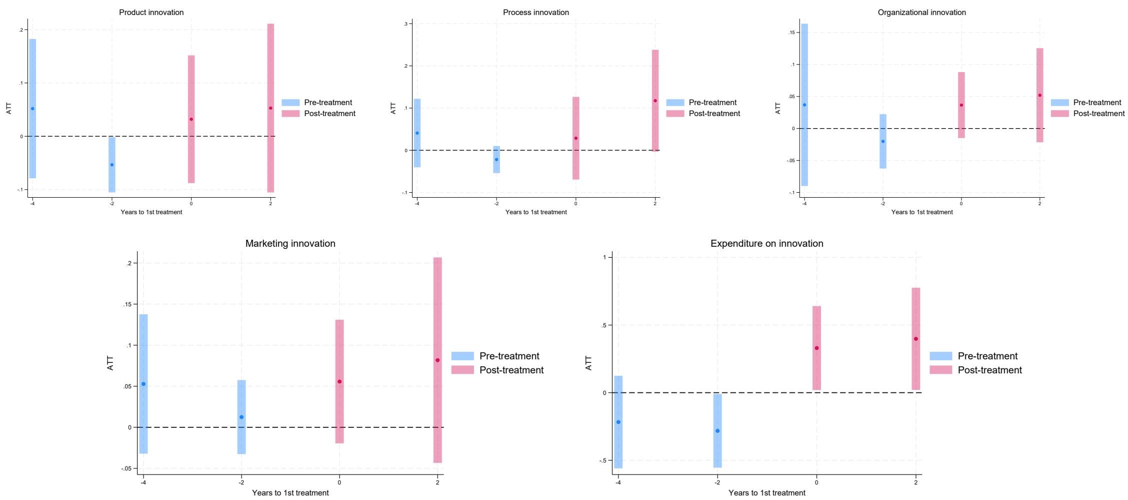
Figure 3.8: The effect of the Horizon 2020 program for firms using different types of IPRs

incremental, the subsidy could facilitate numerous small, continuous improvements, with their accumulated impact becoming measurable by 2016, two year after the treatment.

Firms in the Wholesale and Retail Trade (WRT) sector experience a substantial acceleration in both product and marketing innovation after participating in the Horizon 2020 program. The subsidies led to a 37.7% increase in product innovation and a 28% increase in marketing innovation within this sector. Similar positive outcomes are found for firms in the Information and Communication (ICT) sector. Following the receipt of Horizon 2020 funds, product innovation in this sector increased by 22%, and marketing innovation by 12%.

The results observed are consistent with the highly customer-facing nature of the WRT sector. This orientation provides significant impetus for firms to introduce novel services, innovative business models (such as e-commerce platforms and delivery services), or new approaches to bundling existing products in order to satisfy consumer demand. Hence, marketing innovation emerges as a critical factor for customer attraction and retention. In parallel, the ICT sector is typified by remarkably rapid product development cycles. Innovation within ICT is fundamentally directed towards new products (encompassing software, hardware, and services) and the methods by which they are brought to market (i.e., marketing). Considering the intensely competitive landscape and the prevalence of network effects in ICT, effective marketing (e.g., user acquisition, brand development, platform promotion) is indispensable for the successful adoption of new products. Accordingly, innovation subsidies allocated to this sector would logically extend to marketing strategies to facilitate robust market penetration.

(a) Firms in the Manufacturing sector



(b) Firms in the Wholesale and retail trade; repair of motor vehicles and motorcycles sector

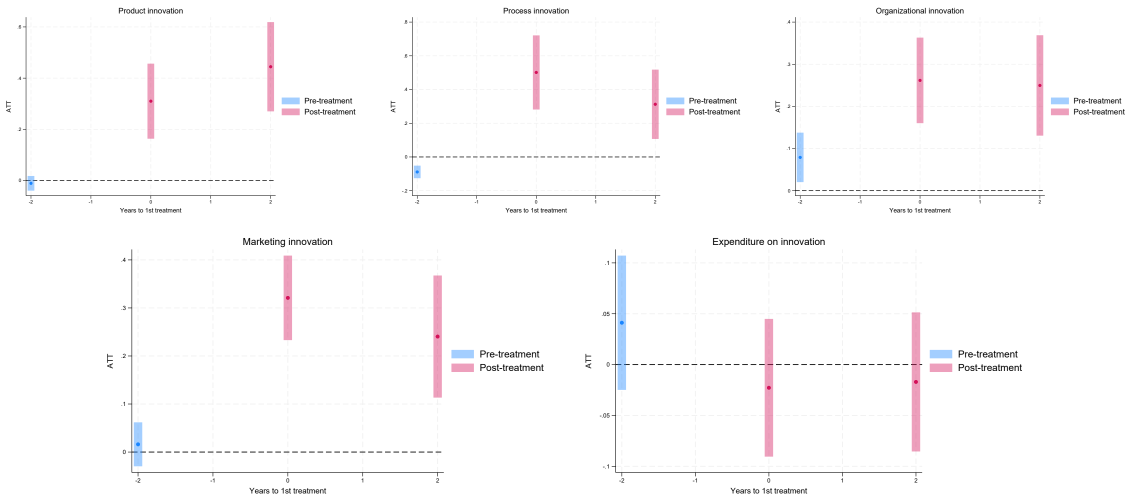
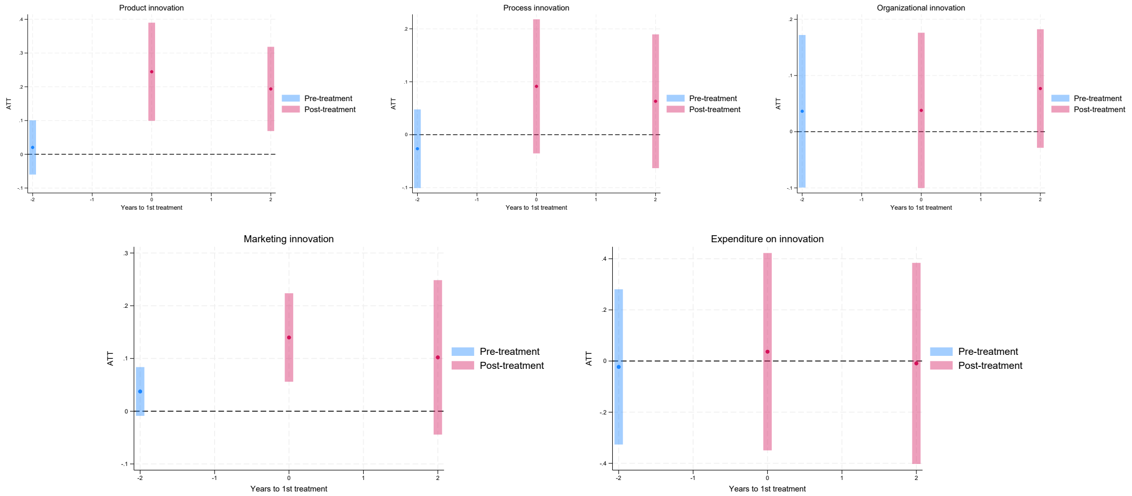


Figure 3.9: The effect of the Horizon 2020 program for firms in different sectors

(c) Firms in the Information and communication sector



(d) Firms in the Professional, scientific and technical activities sector

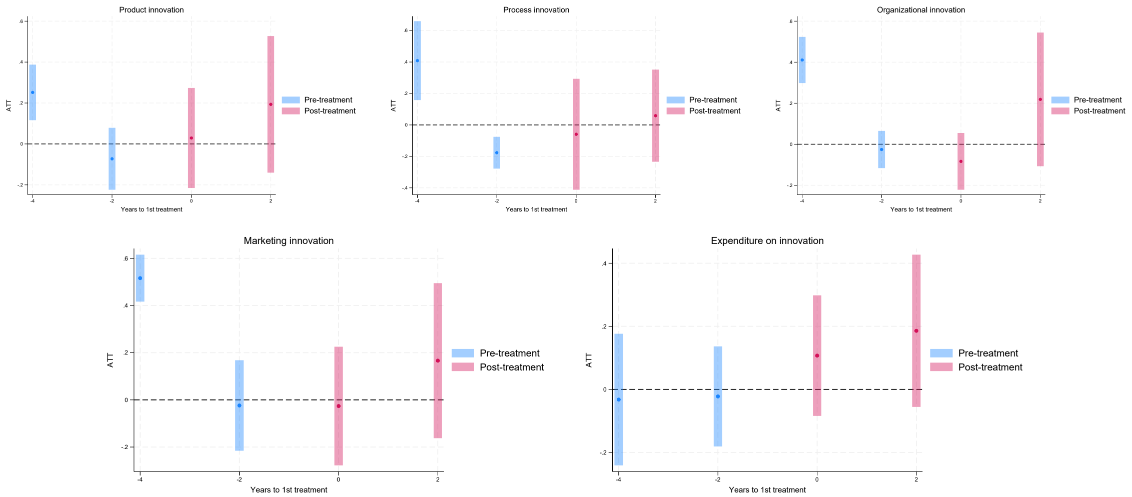


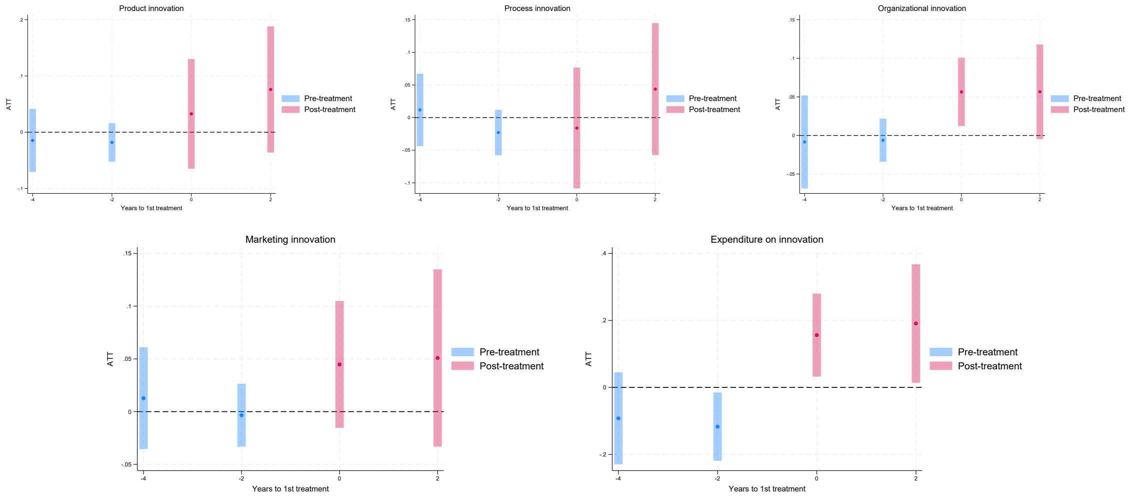
Figure 3.9: The effect of the Horizon 2020 program for firms in different sectors (continued)

3.7 Robustness Checks

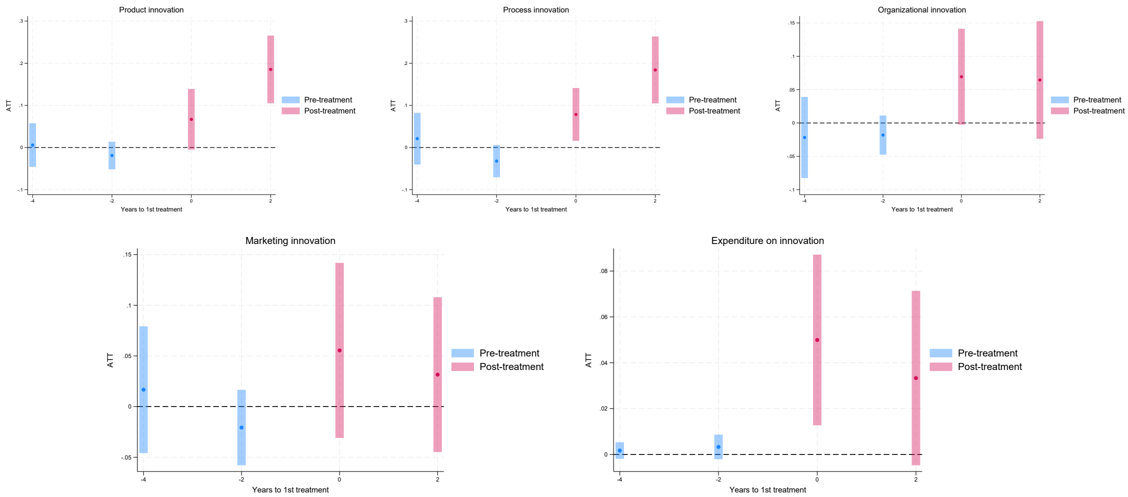
3.7.1 Participation in Preceding Program

Before Horizon 2020, one of the European Union's research and innovation funding programs was named the Seventh Framework Program (FP7) from 2007 to 2013. It was designed to support research, technological development, and demonstration activities in various scientific and industrial fields. To avoid the overlap in the effect of FR7 and Horizon 2020 on innovative activities, we exclude firms receiving funds from FR7 then regress the model. The results are displayed in Figure 3.10. The results are close to the main results from Figure 3.3 for all three samples and types of innovation. Specifically, the positive impact of the Horizon 2020 program on organizational innovation and expenditure on innovation is found for the whole sample. Meanwhile, these positive impacts appear for product, process, marketing innovation, and innovation expenditure for Western European countries. Finally, only organizational innovation in Central and Eastern European countries is affected by the subsidy.

(a) Whole sample



(b) Western Europe



(c) Central and Eastern Europe

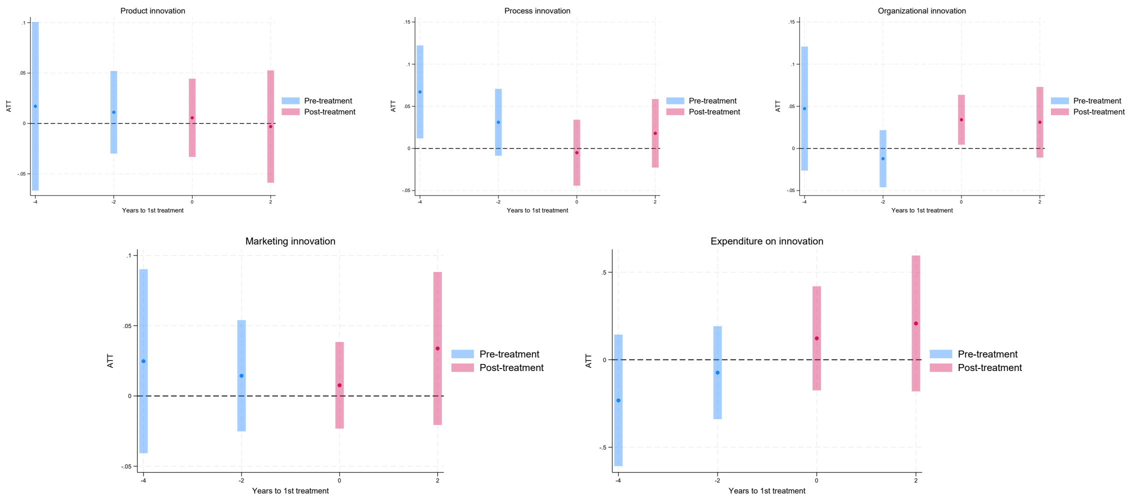


Figure 3.10: The effect of Horizon 2020 program after excluding FR7 participants

3.7.2 Alternative Estimation Methods

Since the majority of firms were first treated in 2014, and only 5% of firms were first treated in 2016 (from Table 3.5). We drop the firms, which were first treated in 2016, and re-estimate the model with Two-Way Fixed Effect (TWFE) to check the impact of receiving funds from the Horizon 2020 on firms' innovation.

As the allocation of grants under the Horizon 2020 program is both unobserved and non-random, it does not qualify as a randomized experiment. Thus, we cannot directly compare the treated firms with a randomly selected group of control firms. This non-random nature of the experiment causes sample selection bias (Heckman, 1979), which is mitigated by employing propensity score matching (PSM) (Rosenbaum & Rubin, 1983). PSM procedure and results are provided in detail in Table C2.1, Appendix C2.

After conducting PSM and reaching the perfect match between the control group and the treated group, we employ TWFE with the DiD method to examine the impact of receiving funds from the Horizon 2020 program on European firms' innovation activities. The estimation equation is below:

$$Y_{isjt} = \beta_0 + \beta_1(\text{post}_t \times \text{treated}_{isj}) + \beta_2 X_{isjt} + \gamma_i + \gamma_s + \gamma_t + \epsilon_{ist} \tag{3.16}$$

Where i, s, j, t denote country, sector, firm, and year, respectively. Dependent variable Y is one of the following types of innovation: product innovation, process innovation, organizational innovation, marketing innovation, and expenditure on innovation. *post* takes the value of 1 if in the year of 2014 and later, 0 otherwise. *treated* takes the value of 1 if firms received funds from the Horizon 2020, 0 otherwise. X is the control variable, including turnover, employment growth rate, receiving local funds, and receiving government funds. γ_i, γ_s, and γ_t are country fixed effects, sector fixed effects, and time fixed effects, respectively. ϵ_{ist} is clustered at country-sector level. We focus on the coefficient β_1, which indicates the average treatment effect on the treated (ATT).

Table 3.6 presents the average effect of participating in the Horizon 2020 program on firms' innovation activities. Overall, firms receiving Horizon 2020 funding exhibit a positive impact across all types of innovation and expenditure on innovation for the whole sample and Western European countries. Regarding CCE, the positive impact is only found for product, organizational, and marketing innovation. Process innovation is positively affected by the funds but only at 10%-level. Interestingly, funding from Horizon 2020 does not affect expenditure on innovation of firms in CCE. Figure 3.11 represents the event study of the impact of Horizon 2020 on firms' innovation. In the whole sample, the positive impact is only found for organizational and marketing innovation. For Western Europe, Horizon 2020 positively affects all types of innovation for both 2014 and 2016, but this impact only appears in 2014 for expenditure on innovation. No impact is found for CCE.

To investigate the heterogeneous impact of the subsidies on firms' innovation, instead of categorizing the whole sample into different subsamples as discussed earlier, we introduce the interaction term between *post* $\times$ *treated* and the firm's heterogeneous characteristics, namely export orientation, R&D intensity, knowledge intensity, degree of competition, different types of IPRs used, and different sectors. Equation (3.16) becomes:

$$\begin{aligned} Y_{isjt} =& \theta_0 + \theta_1(\text{post} \times Z_{isjt}) + \theta_2(\text{post} \times \text{treated} \times Z_{isjt}) \\ &+ \theta_3(\text{post} \times \text{treated} \times (1 - Z_{isjt})) + \theta_4 X_{isjt} + \vartheta_i + \vartheta_s + \vartheta_t + \zeta_{ist} \end{aligned} \tag{3.17}$$

Where Z represents a set of dummy variables capturing sectoral heterogeneity, including export intensity, R&D intensity, knowledge intensity, and market competition. The coefficient θ_2 reflects the differential treatment effect for firms with high export intensity, high R&D intensity, high knowledge intensity, high competition, and using IPRs protection, firms in one of the four sectors: Manufacturing, wholesale and retail trade (WRT), Information and communication (ICT), and Professional, scientific and technical activities relative to those with the opposite characteristics. We employ linear regression with the high-dimensional fixed effects method for estimating the heterogeneous effects of the Horizon 2020 on firms' innovation since it is well-suited for flexibility in modeling higher-order interaction terms (triple-difference specifications), which are not yet supported in DiD with multiple periods and time heterogeneity.

Table 3.7 shows the results of the heterogeneous effect by using DDD estimation. There is no different impact of Horizon 2020 on innovation of exporting firms and firms selling domestically, between knowledge-intensive firms and non-knowledge-intensive firms, between high-competitive firms and low-competitive firms, between manufacturing firms and those in other sectors.

However, we do find the difference in R&D-intensive (RI) and non-R&D-intensive firms. Specifically, the subsidy from Horizon 2020 positively affects expenditure on innovation only for RI firms but is insignificant for non-RI firms. R&D-intensive firms already possess the internal structures, capabilities, and innovation systems necessary to absorb and utilize external funding effectively. Thus, after receiving subsidies, they are able to channel it immediately into R&D projects, e.g., hiring research staff or expanding research facilities. In contrast, non-RI firms often lack absorptive capacity. Consequently, they may use the funding for lower-cost improvements rather than engaging in large, resource-intensive R&D projects. Firms using IPRs (either patents, design rights, copyrights, or trademarks) experience an increase in expenditure on innovation after receiving subsidies, while non-IPR firms show a positive impact on different types of innovation. This result suggests that IPRs firms might be more strategic by using funds to build capacity rather than rushing to the market. Whilst non-IPR firms may be more market-driven, they might translate funding into short-term innovation wins.

Regarding firms in different sectors, interesting results are found in the WRT, ICT, and Professional, scientific, and technical activities sectors. Specifically, there is no difference in the impact of Horizon 2020 on product and organizational innovation of firms in the WRT sector and in other sectors. However, the subsidies boost process innovation, marketing innovation, and expenditure on innovation of firms in other sectors, not those in the WRT sector. The proper explanation for this is that many WRT firms are SMEs and lack absorptive capacity. Thus, they may struggle to absorb and implement complex innovations like advanced technologies or data-driven marketing.

The results from ICT and Professional, scientific and technical activities sector also indicate that no difference in the impact of Horizon 2020 on product, organizational, marketing innovation, and spending on innovation of firms in these sectors compared to the rest. However, process innovation of firms in these two sectors is not affected by the funding from Horizon 2020. This might be because firms in the ICT and scientific sectors often operate at the technological frontier, and the processes are already optimized. Furthermore, the target of Horizon 2020 is to support scientific excellence, disruptive technologies, and market-creating innovation. Hence, firms receiving funds from this program tend to invest in product development, research outputs, or commercialization, rather than accelerate internal processes.

Table 3.6: Average effect of Horizon 2020 subsidies

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
Whole sample					
Post x Treated	0.157***	0.078***	0.151***	0.132***	0.086***
	(0.015)	(0.016)	(0.012)	(0.015)	(0.022)
Observations	107,597	107,551	106,357	106,352	103,907
R-square	0.3252	0.2356	0.1153	0.1419	0.3346
Western Europe countries (DE, ES, PT)					
Post x Treated	0.227***	0.164***	0.175***	0.161***	0.070***
	(0.017)	(0.018)	(0.014)	(0.018)	(0.012)
Observations	81,683	81,637	80,443	80,438	78,475
R-square	0.2981	0.1974	0.1170	0.1219	0.3416
Central and Eastern Europe countries (BG, CZ, EE, HU, LT, RO)					
Post x Treated	0.099***	0.050**	0.113***	0.116***	−0.103
	(0.021)	(0.024)	(0.027)	(0.027)	(0.092)
Observations	25,914	25,914	25,914	25,914	25,432
R-square	0.0841	0.0681	0.0934	0.0846	0.3372
Control	Yes	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Results are estimated from reghdfe; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

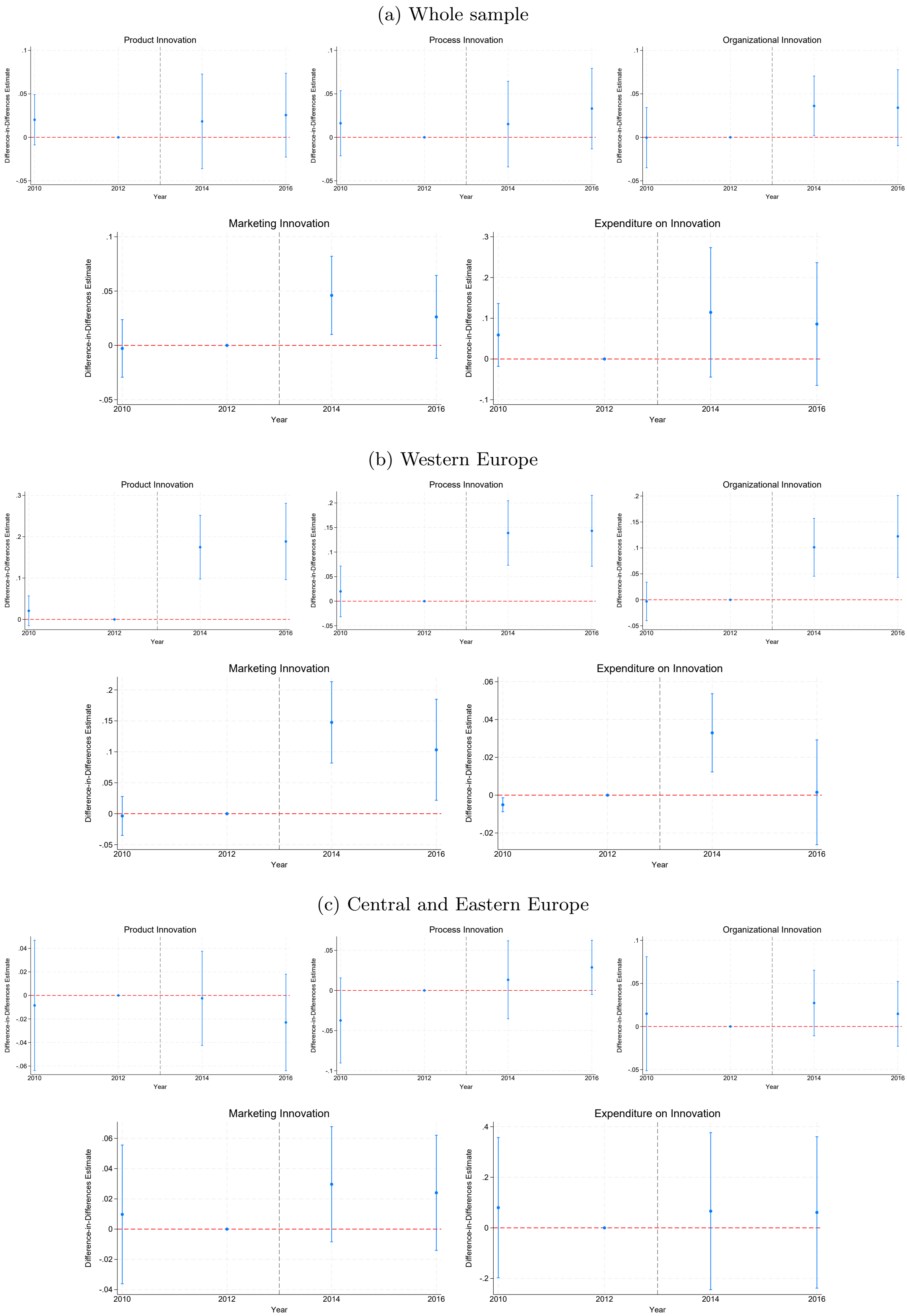


Figure 3.11: Event study

Table 3.7: The heterogeneous effects of the Horizon 2020 program on firms' innovation

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
A - Export orientations					
Post x Export	0.091***	0.079***	0.096***	0.093***	−0.033**
	(0.013)	(0.013)	(0.010)	(0.010)	(0.015)
Post x Treated x Export	0.129***	0.054***	0.130***	0.114***	0.076***
	(0.013)	(0.014)	(0.012)	(0.014)	(0.021)
Post x Treated x Domestic	0.188***	0.107***	0.173***	0.142***	0.164***
	(0.035)	(0.035)	(0.032)	(0.040)	(0.044)
Observations	107,071	107,032	106,255	106,255	103,431
R-square	0.3270	0.2360	0.1167	0.1435	0.3336
B - R&D-intensity					
Post x RI	0.086***	0.126***	0.069***	0.081***	0.106***
	(0.015)	(0.013)	(0.012)	(0.012)	(0.024)
Post x Treated x RI	0.077***	−0.030*	0.099***	0.074***	0.115***
	(0.017)	(0.018)	(0.016)	(0.020)	(0.034)
Post x Treated x (1-RI)	0.193***	0.123***	0.169***	0.149***	0.005
	(0.019)	(0.021)	(0.017)	(0.019)	(0.012)
Observations	107,597	107,551	106,357	106,352	103,907
R-square	0.3261	0.2374	0.1159	0.1428	0.3384
C - Knowledge intensity					
Post x KI	0.091***	0.021	0.075***	0.089***	0.025
	(0.015)	(0.015)	(0.013)	(0.014)	(0.026)
Post x Treated x KI	0.109***	0.040**	0.076***	0.052***	0.158***
	(0.020)	(0.020)	(0.015)	(0.017)	(0.033)
Post x Treated x (1-KI)	0.195***	0.145***	0.133***	0.158***	0.097***
	(0.021)	(0.022)	(0.022)	(0.026)	(0.027)
Observations	65,963	65,969	65,158	65,139	62,091
R-square	0.3255	0.2394	0.1327	0.1471	0.3523
D - Competition level					
Post x Low	0.007	0.048*	0.030	0.005	−0.042
	(0.026)	(0.028)	(0.020)	(0.020)	(0.043)
Post x Treated x Low	0.139***	0.087***	0.149***	0.130***	0.050***
	(0.019)	(0.019)	(0.018)	(0.020)	(0.019)
Post x Treated x High	0.175***	0.085***	0.163***	0.134***	0.110***
	(0.028)	(0.027)	(0.019)	(0.024)	(0.029)
Observations	107,597	107,551	106,357	106,352	103,907
R-square	0.3252	0.2359	0.1154	0.1419	0.3351
E - IPRs used					
Post x IPRs	0.208***	0.110***	0.146***	0.238***	−0.005
	(0.018)	(0.014)	(0.013)	(0.013)	(0.018)
Post x Treated x IPRs	0.016	0.013	0.017	−0.001	0.083**
	(0.018)	(0.016)	(0.020)	(0.018)	(0.035)
Post x Treated x NonIPRs	0.148***	0.083***	0.087***	0.074***	−0.050
	(0.020)	(0.022)	(0.025)	(0.023)	(0.036)
Observations	20,709	20,711	20,367	20,345	20,532
R-square	0.2762	0.2485	0.1331	0.1411	0.4399

Results are estimated from reghdfe; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.
Country-Sector FE, Sector FE, and Year FE are included.

Table 3.7: The heterogeneous effects of the Horizon 2020 program on firms' innovation (cont.)

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
F - Manufacturing sector					
Post x Manu	−0.006	0.037	0.022	−0.004	−0.042
	(0.025)	(0.027)	(0.020)	(0.020)	(0.043)
Post x Treated x Manu	0.133***	0.085***	0.142***	0.132***	0.053**
	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)
Post x Treated x Other sectors	0.175***	0.081***	0.164***	0.130***	0.106***
	(0.026)	(0.025)	(0.019)	(0.023)	(0.030)
Observations	107,597	107,551	106,357	106,352	103,907
R-square	0.3252	0.2358	0.1154	0.1419	0.3351
G - Wholesale and retail trade sector					
Post x WRT	0.041	0.025	0.021	0.029	0.008
	(0.045)	(0.048)	(0.051)	(0.042)	(0.087)
Post x Treated x WRT	0.230***	0.120	0.235***	0.117	0.024
	(0.082)	(0.109)	(0.053)	(0.114)	(0.040)
Post x Treated x Other sectors	0.155***	0.077***	0.149***	0.133***	0.088***
	(0.015)	(0.016)	(0.013)	(0.015)	(0.022)
Observations	107,597	107,551	106,357	106,352	103,907
R-square	0.3253	0.2357	0.1154	0.1419	0.3346
H - Information and communication sector					
Post x ICT	0.016	0.007	0.026	0.032	−0.007
	(0.043)	(0.038)	(0.028)	(0.032)	(0.090)
Post x Treated x ICT	0.153***	0.049	0.026***	0.089**	0.150**
	(0.043)	(0.039)	(0.039)	(0.042)	(0.063)
Post x Treated x Other sectors	0.157***	0.082***	0.154***	0.137***	0.077***
	(0.016)	(0.018)	(0.013)	(0.016)	(0.023)
Observations	107,597	107,551	106,357	106,352	103,907
R-square	0.3252	0.2356	0.1154	0.1420	0.3347
I - Professional, scientific and technical activities sector					
Post x science	0.009	−0.052	−0.025	−0.011	−0.038
	(0.056)	(0.055)	(0.036)	(0.040)	(0.076)
Post x Treated x science	0.135**	0.075	0.152***	0.132***	0.172***
	(0.053)	(0.053)	(0.031)	(0.038)	(0.045)
Post x Treated x Other sectors	0.163***	0.091***	0.157***	0.134***	0.064***
	(0.016)	(0.017)	(0.015)	(0.017)	(0.020)
Observations	107,597	107,551	106,357	106,352	103,907
R-square	0.3252	0.2358	0.1154	0.1419	0.3348

Results are estimated from reghdfe; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.
Country-Sector FE, Sector FE, and Year FE are included.

3.8 Conclusion

This paper develops a theoretical model to investigate the impact of subsidies from the Horizon 2020 program on firms' innovation activities and R&D expenditure. We extend the frameworks of Kugler and Verhoogen (2012) and Melitz (2003) by introducing a subsidy rate into the model. This model establishes a direct link between R&D investment and innovation, and we solve for profit maximization subject to the firm's budget constraint. Our analysis proceeds in two steps. First, we frame the firm's decision as a choice of optimal innovation, where the firm selects the innovation level that maximizes its profit subject to its budget. The results from this stage indicate that the subsidy's impact on R&D expenditure can be either positive (crowding-in) or negative (crowding-out). In the second step, we derive the first-order conditions to determine the optimal innovation level and establish the relationship between the subsidy and innovation, revealing a positive impact of the subsidy on innovation.

Then we use firm-level data from the Community Innovation Survey (CIS) of Eurostat with five waves: 2010, 2012, 2014, 2016, and 2018 to explore the causal effect of attending the Horizon 2020 program on firms' innovation activities. Since there are staggered treatments in the time receiving funds from the Horizon 2020, the Difference-in-difference (DiD) estimation with repeated cross-section with multiple periods and time heterogeneity is employed. The results show that firms receiving Horizon 2020 funding experience a positive impact on organizational innovation and expenditure on innovation for the whole sample. Firms in Western European countries experience an enhancement in all types of innovation, except marketing innovation. While firms in CCE only show the positive impact on organizational innovation.

We further examine the heterogeneous impact of Horizon 2020 on firm innovation, considering various factors: export orientation, R&D intensity, knowledge intensity, market competition, the types of Intellectual Property Rights (IPRs) utilized (patents, trademarks, and design rights), and sector affiliation. The findings reveal significant variation across these subsamples. Specifically, no discernible impact of Horizon 2020 is found for non-exporting firms, firms with low R&D intensity, firms with low knowledge intensity, firms primarily using trademarks, and firms within the Professional, Scientific, and Technical Activities sector. Conversely, exporting firms experience an increase across all four types of innovation. R&D-intensive firms enhance their product, organizational, and marketing innovation after receiving funds. Knowledge-intensive firms, however, only show an increase in organizational innovation. In highly competitive markets, firms improve their process, organizational, and marketing innovation, whereas firms in less competitive markets only accelerate their organizational innovation after participating in Horizon 2020. Firms utilizing patents and design rights show an increase in innovation expenditure, but no other types of innovation change. Interestingly, firms in the Wholesale and Retail Trade sector, and the Information and Communication sector, experience a strong positive impact from the subsidies on both product and marketing innovation.

Before the launch of Horizon 2020, an earlier innovation funding program, the Seventh Framework Program (FP7), was in effect from 2007 to 2013. Therefore, it is necessary to conduct robustness checks to ensure that the impact of Horizon 2020 on innovation is not confounded by firms' prior participation in FP7. We exclude all firms that received FP7 funding from the sample and re-run the model. The results remain robust with the baseline analysis.

Based on the empirical findings, we propose several policy recommendations to enhance innovation activities among European firms: First, broaden Support for Organizational Innovation: The consistent positive impacts of organizational innovation observed across various firm typologies and regions (e.g., CEE firms, knowledge-intensive firms, firms in low-competition markets) underscore the need for policies to broadly prioritize its encouragement and support.

Such initiatives might include financing for change management, process optimization, and the development of novel business models. Second, maintain strategic focus on exporting and R&D-intensive firms: The comprehensive positive response demonstrated by exporting and R&D-intensive firms across multiple innovation categories suggests that their continued prioritization for innovation funding represents an effective strategy for optimizing aggregate innovation output. Third, tailored sectoral intervention for Wholesale & Retail Trade and Information & Communication: Given the pronounced positive effects on product and marketing innovation within the WRT and ICT sectors, policy efforts could explore the replication of successful Horizon 2020 aspects in these domains. Furthermore, allocating dedicated resources or specialized programs could substantially enhance these specific innovation types within these vital sectors.

The results of this study are credibly obtained after controlling for different fixed effects and using the prominent method. Furthermore, the empirical results are also consistent with the theoretical model's findings. The static theoretical model might still be suitable, since the Horizon 2020 program lasts for a short period. However, the impact of subsidies from this program on innovation could take effect after several years, and a dynamic model would be more precise. Future research might develop a dynamic theoretical model to extract the impact of subsidies on a firm's innovation.

Conclusion

In summary, this thesis examines topics that are at the intersection between international trade and economics of innovation by investigating three distinct topics in three chapters. In the current literature, there are various studies investigating the relationship between patents and export performance, and the results are heterogeneous. The impact of innovation in general and patents in particular is widely examined. However, only one study explores the impact of export quality on innovation outputs, and the moderation effect of institutional quality on the nexus between export quality and patent intensity is underexplored. Government subsidies encourage firms to enhance their performance, including revenue, productivity, and innovation. However, the causal effect of subsidies, namely the Horizon 2020 program, on different types of innovation is understudied. Thus, this thesis aims to fill these gaps: first, the overall effect of patents on exports, second, the two-way nexus between export quality and patent quality and the moderating role of institutions on these relationships, and third, the causal effect of funding from the Horizon 2020 on different types of innovation.

In the first chapter, I conduct a literature review with the powerful tool, meta-analysis, to examine the impact of patents on export performance. This chapter is the first study exploring this relationship. After scrutinizing the papers covering these topics, I obtained 42 empirical studies containing 536 estimates during the span from 2005 to 2025. Besides estimating all the studies in the data, I also divide the studies into country-level data, industry-level data, firm-level data, and data for firms in developed, developing, and mixed countries to investigate the heterogeneity in the true effect and the influence of moderators on this effect-size estimate for each specific subsample. The findings suggest that there is a genuine positive patent effect on exports for the whole sample and four subsamples: country-level data, sector-level data, firm-level data, and developed countries data. After controlling for moderating variables, this positive result remains for the whole sample, country-level data subsample, and firm-level data subsample. However, the findings for sector-level data and the data from the developed countries subsample turn out to be insignificant. The moderators help to explain the heterogeneity in the findings of the primary studies significantly.

The second chapter examines the two-way relationship between export quality and patent intensity, as well as the moderating role of institutional quality on this bidirectional nexus. This is the first paper showing the bidirectional relationship between export quality and patent intensity moderated by institutional quality. To explore these impacts, the SEM with the 2SLS and 3SLS econometric methods is applied for the sample of 89 countries, 38 OECD countries, and 51 non-OECD countries. The results prove a negative bidirectional relationship between export quality and patent intensity. This finding is also found in the different subsamples, namely, different types of countries, levels of income, levels of technology, export dependence, and export quality. Besides, the results confirm not only the positive direct impact of institutional quality on the bidirectional nexus between export quality and patent intensity, but institutional quality also plays a positive moderating role in this two-way relationship. This chapter was grounded in a theoretical framework designed to explain the observed bidirectional relationship. Extending the work of Kugler and Verhoogen (2012) and Melitz (2003), the model established a direct link between R&D investment, product quality, and patenting. By framing the firm's profit maximization problem from two perspectives, first as a choice of optimal quality, and then as a choice of an optimal patent portfolio, the model formally demonstrated the reciprocal nature of the relationship. Ultimately, the framework showed that both strategic paths converge on the same underlying R&D decision, illustrating that quality enhancement and patent intensity are two facets of a single, integrated strategy. The findings of the theoretical model are consistent with the results from empirical analysis. The results are credibly obtained after controlling for different fixed effects and consistent with those from robustness checks. However, the 3SLS estimation uses the same instruments for both equations. The patent intensity variable, defined as the number of patents per unit of export value, does not account for the changes in price level. Besides, the theoretical model only considers the diminishing returns to patenting and takes institutional quality as given. Further improvement could mitigate these shortcomings.

Finally, the third chapter is also the first study exploring the causal effect of subsidies, namely, the Horizon 2020 program, on firms' innovation activities. First, I develop a theoretical model to investigate the impact of subsidies from the Horizon 2020 program on firms' innovation activities and R&D expenditure. Similar to the second chapter, the theoretical model in this chapter is based on the frameworks of Kugler and Verhoogen (2012) and Melitz (2003). I introduce a subsidy rate into the model and establish a direct link between R&D investment and innovation, and then solve for profit maximization subject to the firm's budget constraint. First, the firm's decision is framed as a choice of optimal innovation, where the firm selects the innovation level that maximizes its profit subject to its budget. The results from this stage indicate that the subsidy's impact on R&D expenditure can be either positive (crowding-in) or negative (crowding-out). Then, the first-order condition is derived to determine the optimal innovation level and establish the relationship between the subsidy and innovation, revealing the impact of the subsidy on innovation.

Then, the empirical analysis is conducted by using the firm-level data from the Community Innovation Survey (CIS) of Eurostat with five waves: 2010, 2012, 2014, 2016, and 2018 to explore the causal effect of attending the Horizon 2020 program on firms' innovation activities. Since there are staggered treatments in the time receiving funds from the Horizon 2020, I employ DiD estimation with repeated cross-section with multiple periods and time heterogeneity. The results show that firms receiving Horizon 2020 funding experience a positive impact on organizational innovation and expenditure on innovation for the whole sample. Firms in Western European countries experience an enhancement in all types of innovation, except marketing innovation. While firms in CCE only show the positive impact on organizational innovation. The heterogeneous impact of Horizon 2020 on firm innovation is also estimated with different subsamples considering various factors: export orientation, R&D intensity, knowledge intensity, market competition, the types of IPRs utilized, and sector affiliation. The findings reveal significant variation across these subsamples. Especially, the positive impact of Horizon 2020 on firms' innovation is found in all four types of innovation of exporting firms; product, organizational, and marketing innovation of R&D-intensive firms; process, organizational, and marketing innovation of highly competitive firms. Besides, firms in the WRT and ICT sectors experience a strong positive enhancement in product and marketing innovation. Though the impact of subsidies from this program on innovation could take effect after several years, I started with a static theoretical model instead of the dynamic one. Future research could focus on a dynamic model to extract more insightful results.

Appendix A

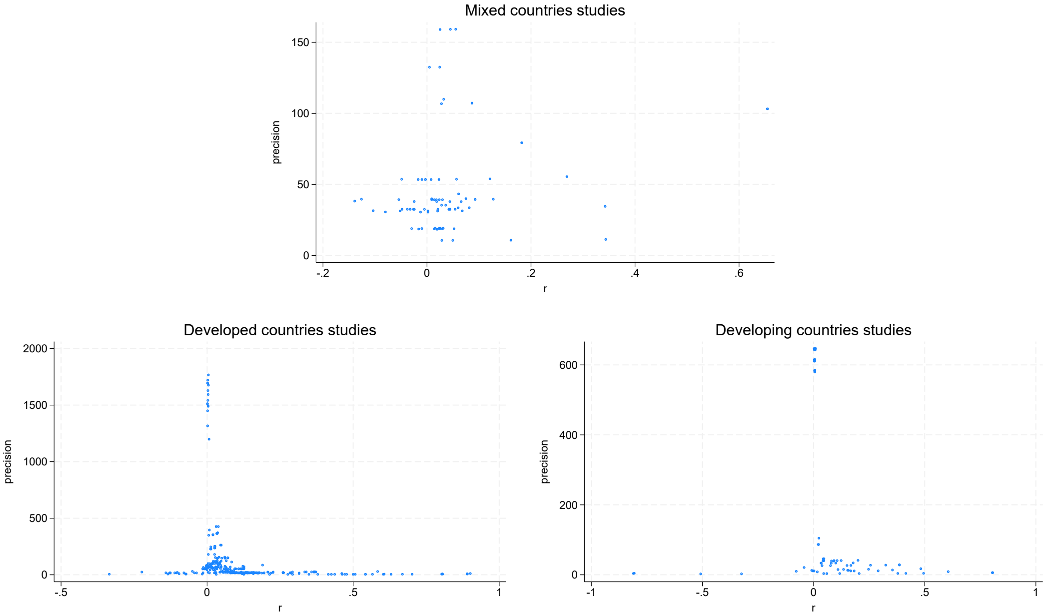


Figure A1: Funnel plot of publication bias in published studies

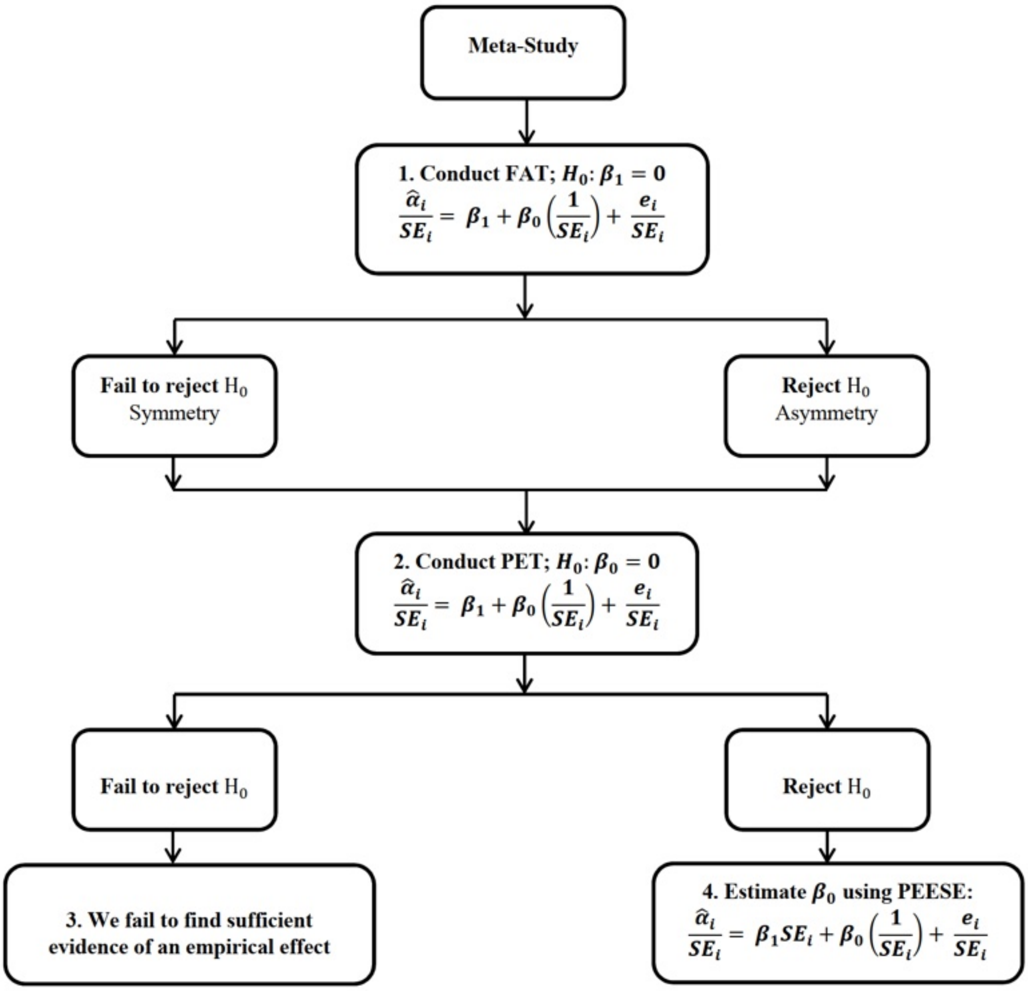


Figure A2: The procedure of FAT, PET, and PEESE
Source: Alinaghi and Reed (2018)

Table A1: Estimation of the WALS routine - dependent variable: t

Variables	**Coefficients**	**Std.err.**	**t-statistics**
Year	0.2339	0.3527	0.6632
Ncitat	0.0581	0.1622	0.3582
Q1Journal	−0.0147	0.0049	−3
Nob	−0.1022	0.1790	−0.5709
Country	−0.1135	0.0843	−1.3464
Firm	−0.1388	0.0797	−1.7415
Hightech	−0.1180	0.0284	−4.1549
Manufacturing	0.0181	0.0058	3.1207
Pharma	−0.0868	0.0474	−1.8312
Dpatent	−0.0051	0.0203	−0.2512
Cpatent	0.0344	0.0142	2.4225
Export	−0.0012	0.0020	−0.6
Panel	0.0142	0.0220	0.6455
OLS	−0.0174	0.0059	−2.9492
FE	−0.0697	0.0140	−4.9786
RE	0.0027	0.0329	0.0821
Instrumented	−0.0745	0.0204	−3.6520
Dynamic	0.0329	0.0199	1.6533
MLE	−0.0142	0.0061	−2.3279
Precision	0.1656	0.0912	1.8158
Constant	1.5454	1.4901	1.0371

t-statistics are calculated by Coefficient / Standard Error. This WALS routine is done by using the command `wals` with the `prior(pareto)` option, which provides a Bayesian-like output with posterior means (coefficients), DS (Double Shrinkage) bias, DS standard errors, DS RMSE, and DS confidence intervals, rather than traditional frequent t-statistics.

Table A2: Estimation of Meta-regression Analysis

Dependent variables: t	All studies	Country-level data studies	Sector-level data studies	Firm-level data studies	Developed countries	Developing countries	Mixed countries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A - With outliers							
Publication characteristics							
Ncitat	0.588	−3.115	78.222	−0.494	−0.319	0.756	16.995
	(0.649)	(2.735)	(54.941)	(0.438)	(0.424)	(1.339)	(25.675)
Year	1.145	−8.298	89.582	−0.775	0.467	−1.462	82.977
	(1.252)	(6.637)	(86.608)	(0.850)	(0.870)	(1.901)	(78.205)
Q1Journal	−0.026***	−0.004	−12.514	−0.020***	−0.017***	−0.828***	−1.210
	(0.010)	(0.135)	(16.953)	(0.005)	(0.005)	(0.225)	(1.013)
Data characteristics							
Nob	−0.951***	−10.001***	−14.435***	0.234	−0.043	−2.718**	−40.105***
	(0.302)	(1.477)	(2.351)	(0.216)	(0.231)	(1.228)	(3.191)
Country	−0.159				−0.005	0.062	-
	(0.179)				(0.031)	(0.781)	
Firm	−0.208				-	−0.600	-
	(0.173)					(0.734)	
High-tech export	−0.153*	0.038	-	-	0.023	-	−0.565
	(0.085)	(0.275)			(0.137)		(1.411)
Manufacturing	0.036***	0.495	-	0.027***	0.029***	0.368***	0.334
	(0.007)	(0.725)		(0.004)	(0.004)	(0.132)	(1.745)
Pharma	−0.098	-	−6.863	−0.029	−0.169	−0.567	-
	(0.103)		(16.385)	(0.052)	(0.134)	(0.711)	
Dpatent	−0.008	-	-	−0.057	−0.004	−1.711**	-
	(0.040)			(0.175)	(0.028)	(0.776)	
Cpatent	0.109***	0.309***	-	−0.061	-	−1.890**	0.158
	(0.037)	(0.099)		(0.175)		(0.788)	(0.172)
Export	−0.001	-	-	−0.001	−0.001	0.002	-
	(0.002)			(0.001)	(0.005)	(0.002)	
Panel	−0.017	0.726*	13.969	0.046*	−0.022	−0.247	-
	(0.052)	(0.421)	(16.896)	(0.026)	(0.060)	(0.204)	
Estimation characteristics							
OLS	−0.005	−0.367***	10.011***	0.015***	0.015***	−0.542	−0.433***
	(0.007)	(0.034)	(2.026)	(0.004)	(0.004)	(0.726)	(0.029)
FE	−0.109***	−0.298***	10.010***	−0.028	0.015	−0.640	−0.436***
	(0.019)	(0.029)	(2.027)	(0.025)	(0.017)	(0.728)	(0.029)
RE	−0.065	−0.245***	-	−0.030	−0.007	−0.713	−0.376***
	(0.046)	(0.054)		(0.071)	(0.074)	(0.729)	(0.045)
Instrumented	−0.150***	−0.429***	9.904***	−0.009	−0.056***	−0.354	−0.448***
	(0.023)	(0.038)	(2.026)	(0.022)	(0.020)	(0.795)	(0.030)
Dynamic	0.115***	0.330**	-	−0.007	0.039*	−0.852	0.832
	(0.025)	(0.155)		(0.023)	(0.021)	(0.696)	(0.967)
MLE	−0.001	−0.379***	-	0.018***	0.019***	−0.577	−0.531***
	(0.007)	(0.052)		(0.004)	(0.004)	(0.727)	(0.043)
Precision	0.270	0.105	−8.711***	0.018	0.031	3.601*	3.300***
	(0.191)	(0.421)	(2.042)	(0.177)	(0.065)	(2.145)	(1.045)
Constant	1.373	68.746***	−407.052	4.091	2.520	7.919	−96.560
	(4.586)	(24.561)	(330.277)	(2.922)	(2.980)	(9.869)	(285.195)
Obs/Studies	493/42	256/20	31/6	206/16	326/21	87/15	80/8
Log restricted-likelihood	−1450.848	−734.329	−52.526	−516.845	−780.563	−207.358	−204.954
Wald test	110.49***	271.46***	226.19***	144.61***	155.09***	45.11***	882.97***
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	0.000	0.011	0.000	0.231	0.000

Table A2: Estimation of Meta-regression Analysis (cont.)

Dependent variables: t	All studies	Country-level data studies	Sector-level data studies	Firm-level data studies	Developed countries	Developing countries	Mixed countries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B - Without outliers							
Publication characteristics							
Ncitat	0.649	−3.115	79.154	−0.328	−0.096	−6.776	16.995
	(0.654)	(2.735)	(84.315)	(0.360)	(0.453)	(4.184)	(25.675)
Year	0.739	−8.298	88.487	−0.589	0.507	−8.811	82.977
	(1.245)	(6.637)	(138.623)	(0.645)	(0.924)	(6.789)	(78.205)
Q1Journal	0.037	−0.004	−11.966	−0.068***	0.015	−0.157	−1.210
	(0.033)	(0.135)	(27.410)	(0.021)	(0.023)	(0.394)	(1.013)
Data characteristics							
Nob	−2.056***	−10.001***	−14.513***	0.248	−0.459	−14.378***	−40.105***
	(0.485)	(1.477)	(2.359)	(0.357)	(0.372)	(3.044)	(3.191)
Country	−0.258				−0.010	−1.164	-
	(0.180)				(0.032)	(3.817)	
Firm	−0.285*				-	−2.840	-
	(0.170)					(3.841)	
High-tech export	−0.115	0.038	-	-	0.025	-	−0.565
	(0.085)	(0.275)			(0.143)		(1.411)
Manufacturing	−0.126***	0.495	-	0.058**	−0.033	1.298***	0.334
	(0.043)	(0.725)		(0.024)	(0.029)	(0.319)	(1.745)
Pharma	−0.103	-	−5.942	−0.066	−0.193	−2.608	-
	(0.105)		(26.966)	(0.047)	(0.142)	(3.638)	
Dpatent	0.090	-	-	−0.119	0.012	−4.905	-
	(0.055)			(0.130)	(0.032)	(3.575)	
Cpatent	0.157***	0.309***	-	−0.100	-	−5.444	0.158
	(0.040)	(0.099)		(0.129)		(3.593)	(0.172)
Export	−0.058*	-	-	−0.030	−0.021	3.398	-
	(0.031)			(0.043)	(0.041)	(3.683)	
Panel	−0.063	0.726*	13.445	0.041*	−0.049	1.584***	-
	(0.054)	(0.421)	(27.358)	(0.023)	(0.065)	(0.551)	
Estimation characteristics							
OLS	−0.040***	−0.367***	3.980	0.008	0.010	−3.379	−0.433***
	(0.013)	(0.034)	(52.343)	(0.009)	(0.007)	(3.683)	(0.029)
FE	−0.128***	−0.298***	3.979	−0.055**	0.004	−3.456	−0.436***
	(0.021)	(0.029)	(52.343)	(0.025)	(0.018)	(3.683)	(0.029)
RE	−0.073	−0.245***	-	−0.047	−0.012	−3.546	−0.376***
	(0.048)	(0.054)		(0.076)	(0.073)	(3.666)	(0.045)
Instrumented	−0.188***	−0.429***	3.874	0.019	−0.066***	−3.039	−0.448***
	(0.027)	(0.038)	(52.343)	(0.043)	(0.020)	(3.975)	(0.030)
Dynamic	0.133***	0.330**	-	−0.054	0.037	−3.494	0.832
	(0.032)	(0.155)		(0.045)	(0.022)	(3.652)	(0.967)
MLE	−0.069**	−0.379***	-	−0.016	−0.006	-	−0.531***
	(0.029)	(0.052)		(0.044)	(0.042)		(0.043)
Precision	0.489**	0.105	−2.683	0.131	0.100	7.587	3.300***
	(0.199)	(0.421)	(52.345)	(0.140)	(0.093)	(6.983)	(1.045)
Constant	6.560	68.746***	−413.020	3.132	3.501	81.432***	−96.560
	(4.762)	(24.561)	(501.228)	(2.425)	(3.363)	(28.621)	(285.195)
Obs/Studies	426/40	256/20	30/6	140/14	289/20	57/14	80/8
Log restricted-likelihood	−1258.759	−734.329	−47.325	−361.914	−685.450	−135.064	−204.954
Wald test	107.48***	271.46***	223.10***	64.58***	59.65***	46.52***	882.97***
LR test vs. linear model ($p > \chi^2$)	0.000	0.000	0.000	0.227	0.000	0.013	0.000

Cluster robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. (-) indicates the coefficient is omitted due to collinearity. Results are estimated using the mixed-effects multilevel model.

Table A3: Estimation of Meta-regression Analysis with OLS

Dependent variables: t	All studies (1)	Country-level data studies (2)	Sector-level data studies (3)	Firm-level data studies (4)	Developed countries (5)	Developing countries (6)	Mixed countries (7)
Panel A - With outliers							
Publication characteristics							
Q1Journal	−0.017	0.123***	−0.529***	−0.027***	−0.021***	−0.167***	0.324***
	(0.010)	(0.032)	(0.078)	(0.001)	(0.003)	(0.043)	(0.078)
Data characteristics							
Country	−0.111**				-	0.349*	-
	(0.048)					(0.191)	
Firm	−0.147**				0.009	0.120	-
	(0.059)				(0.019)	(0.094)	
High-tech export	−0.137*	−0.101*	-	-	−0.008	-	0.125**
	(0.079)	(0.055)			(0.026)		(0.046)
Manufacturing	0.022***	−0.119**	-	0.027***	0.022***	0.102***	0.085
	(0.005)	(0.045)		(0.002)	(0.003)	(0.030)	(0.155)
Pharma	−0.107**	-	−0.438***	−0.091*	−0.201***	0.110	-
	(0.041)		(0.074)	(0.046)	(0.023)	(0.104)	
Cpatent	0.041	0.083***	-	0.028	−0.008	−0.024	0.058
	(0.049)	(0.026)		(0.025)	(0.016)	(0.021)	(0.054)
Estimation characteristics							
OLS	−0.022	−0.225*	0.615***	0.014***	0.014***	0.165	−0.352**
	(0.036)	(0.111)	(0.087)	(0.003)	(0.003)	(0.098)	(0.104)
FE	−0.083	−0.317***	0.616***	−0.034*	0.014	0.080	−0.333**
	(0.066)	(0.100)	(0.086)	(0.016)	(0.021)	(0.093)	(0.096)
Instrumented	−0.084	−0.329***	0.504***	−0.040	−0.012	0.138	−0.412***
	(0.072)	(0.102)	(0.086)	(0.026)	(0.029)	(0.101)	(0.061)
Dynamic	0.029	−0.163***	−0.416*	0.021	−0.011	−0.037	−0.133*
	(0.049)	(0.047)	(0.180)	(0.026)	(0.029)	(0.086)	(0.061)
MLE	−0.017	−0.022	-	0.018***	0.018***	0.123	−0.100
	(0.034)	(0.034)		(0.003)	(0.003)	(0.100)	(0.069)
Precision	0.187**	0.130	-	0.014***	−0.001	−0.166	0.097
	(0.082)	(0.134)		(0.004)	(0.018)	(0.173)	(0.107)
Constant	1.418	2.155*	0.702	1.825***	2.875***	0.791	−4.070
	(0.943)	(1.099)	(0.406)	(0.522)	(0.582)	(1.104)	(4.418)
Obs/Studies	493/42	256/20	31/6	206/16	326/21	87/15	80/8
R2	0.2066	0.5253	0.7592	0.5733	0.4022	0.4340	0.6992
Panel B - Without outliers							
Publication characteristics							
Q1Journal	0.064	0.123***	−0.535***	−0.069***	0.044	−0.133***	0.324***
	(0.046)	(0.032)	(0.085)	(0.022)	(0.029)	(0.038)	(0.078)
Data characteristics							
Country	−0.267**				0.030	0.747***	-
	(0.121)				(0.018)	(0.238)	
Firm	−0.225**				0.016	0.629**	-
	(0.095)				(0.012)	(0.282)	
High-tech export	−0.121	−0.101*	-	-	−0.009	-	0.125**
	(0.076)	(0.055)			(0.023)		(0.046)
Manufacturing	−0.093	−0.119**	-	0.053**	−0.055*	0.078**	0.085
	(0.061)	(0.045)		(0.023)	(0.029)	(0.026)	(0.155)
Pharma	−0.211**	-	−0.444***	−0.082**	−0.233***	0.047	-
	(0.095)		(0.080)	(0.032)	(0.030)	(0.106)	
Cpatent	0.055	0.083***	-	0.028	−0.058**	−0.003	0.058
	(0.048)	(0.026)		(0.016)	(0.026)	(0.017)	(0.054)

Table A3: Estimation of Meta-regression Analysis with OLS (cont.)

Dependent variables: t	All studies	Country-level data studies	Sector-level data studies	Firm-level data studies	Developed countries	Developing countries	Mixed countries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation characteristics							
OLS	-0.060	-0.225^{*}	0.623^{***}	0.009^{**}	0.010	0.124	-0.352^{**}
	(0.066)	(0.111)	(0.093)	(0.003)	(0.008)	(0.100)	(0.104)
FE	-0.138^{*}	-0.317^{***}	0.623^{***}	-0.050^{***}	-0.031	0.037	-0.333^{**}
	(0.081)	(0.100)	(0.093)	(0.010)	(0.028)	(0.096)	(0.096)
Instrumented	-0.124	-0.329^{***}	0.511^{***}	0.044^{**}	-0.056	0.650^{**}	-0.412^{***}
	(0.083)	(0.102)	(0.093)	(0.019)	(0.041)	(0.280)	(0.061)
Dynamic	0.038	-0.163^{***}	-0.108	-0.079^{***}	0.018	-0.014	-0.133^{*}
	(0.053)	(0.047)	(0.231)	(0.019)	(0.042)	(0.074)	(0.061)
MLE	-0.027	-0.022	-	0.010^{**}	0.012^{***}	0.087	-0.100
	(0.037)	(0.034)		(0.004)	(0.003)	(0.100)	(0.069)
Precision	0.308^{**}	0.130	-	0.034^{***}	-	-0.659^{**}	0.097
	(0.145)	(0.134)		(0.006)		(0.264)	(0.107)
Constant	1.835^{**}	2.155^{*}	0.638	1.773^{**}	3.294^{***}	1.693^{*}	-4.070
	(0.819)	(1.099)	(0.424)	(0.619)	(0.681)	(0.874)	(4.418)
Obs/Studies	426/40	256/20	30/6	140/14	289/20	57/14	80/8
R2	0.2573	0.5253	0.7162	0.3955	0.2522	0.4410	0.6992

Cluster robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. (-) indicates the coefficient is omitted due to collinearity.

Appendix B

B1 Supplementary Tables and Figures

Table B1.1: International Patent Classification (IPC) information

IPC group code	IPC group name	IPC subgroups
A	Human necessities	Agriculture Foodstuffs; tobacco Personal or domestic articles Health; life-saving; amusement
B	Performing operations; transporting	Separating; mixing Shaping Printing Transporting Microstructural technology; nanotechnology
C	Chemistry; metallurgy	Chemistry Metallurgy Combinatorial technology
D	Textiles; papers	Textiles or flexible materials Papers
E	Fixed constructions	Building Earth or rock drilling; mining
F	Mechanical engineering; lighting	Engineering in general Lighting; heating Weapons; blasting
G	Physics	
H	Electricity	

More information concerning IPC can be found here https://ipcpub.wipo.int/

Table B1.2: List of countries in the study

OECD Countries		**Non-OECD Countries**	
1. Australia	20. Japan	39. Algeria	65. Moldova
2. Austria	21. Korean	40. Argentina	66. Mongolia
3. Belgium	22. Latvia	41. Armenia	67. Morocco
4. Canada	23. Lithuania	42. Belarus	68. Nigeria
5. Chile	24. Luxembourg	43. Bosnia and Herzegovina	69. North Macedonia
6. Colombia	25. Mexico	44. Brazil	70. Pakistan
7. Costa Rica	26. Netherlands	45. Bulgaria	71. Panama
8. Czech Republic	27. New Zealand	46. China	72. Peru
9. Denmark	28. Norway	47. Croatia	73. Philippines
10. Estonia	29. Poland	48. Cyprus	74. Romania
11. Finland	30. Portugal	49. Ecuador	75. Russia
12. France	31. Slovak Republic	50. Egypt	76. Saudi Arabia
13. Germany	32. Slovenia	51. Georgia	77. Seychelles
14. Greece	33. Spain	52. Guatemala	78. Singapore
15. Hungary	34. Sweden	53. Hong Kong	79. South Africa
16. Iceland	35. Switzerland	54. India	80. Sri Lanka
17. Ireland	36. Turkey	55. Indonesia	81. Thailand
18. Israel	37. United Kingdom	56. Iran	82. Trinidad Tobago
19. Italy	38. United States	57. Jamaica	83. Tunisia
		58. Jordan	84. Ukraine
		59. Kazakhstan	85. United Arab Emirates
		60. Kenya	86. Uruguay
		61. Kuwait	87. Uzbekistan
		62. Lebanon	88. Venezuela
		63. Malaysia	89. Zimbabwe

Table B1.3: Summary Statistics for OECD and non-OECD countries

Variables	**Num.Obs.**	**Mean**	**Standard deviation**	**Min**	**Max**
OECD countries					
Export quality	293,978	0.268	0.279	0.00005	1.395
Patent intensity	293,978	0.029	0.883	0	364.384
GDPPC	337,056	30528.9	21547	2236.073	123678.7
FDI	335,433	2.94e+10	6.23e+10	-2.97e+10	7.34e+11
Import	337,056	2.22e+11	3.35e+11	2.27e+09	2.41e+12
Openness	337,056	0.692	0.361	0.157	1.813
R&D	309,926	1.682	1.011	0.131	4.417
Expenditure on education	311,481	5.164	1.090	3.028	8.560
ECI	303,024	1.015	0.644	−0.487	2.410
HHI	337,056	0.116	0.125	0.033	0.708
Import quality	293,978	0.945	0.094	0.020	1.639
Exchange rate	327,756	140.995	413.131	0.419	2877.543
Charge for the use of IP	301,313	4.79e+09	8.42e+09	5,626,623	5.73e+10
Government stability	337,056	8.148	1.431	4.042	11.083
Corruption	337,056	3.837	1.198	1.5	6
Law and order	337,056	4.900	1.071	1	6
Bureaucracy quality	337,056	3.389	0.690	2	4
Non-OECD countries					
Export quality	307,622	0.233	0.253	0.0001	1.369
Patent intensity	307,622	0.006	0.150	0	38.902
GDPPC	437,760	7931.352	10382.35	351.839	57564.8
FDI	437,760	1.04e+10	2.89e+10	-4.55e+09	2.91e+11
Import	437,760	7.59e+10	1.86e+11	3.42e+08	1.96e+12
Openness	437,760	0.751	0.596	0.166	4.200
R&D	306,435	0.536	0.447	0.016	2.597
Expenditure on education	301,123	4.242	1.417	1.151	9.510
ECI	385,367	−0.032	0.656	−2.229	1.907
HHI	416,586	0.107	0.079	0.031	0.780
Import quality	307,622	0.911	0.115	0.008	1.906
Exchange rate	422,307	8,438,028	2.38e+08	0.025	6.72e+09
Charge for the use of IP	337,051	1.15e+09	3.06e+09	98.84	2.31e+10
Government stability	403,150	8.439	1.717	4.583	12
Corruption	403,680	2.305	0.865	0	4.5
Law and order	403,680	3.522	1.114	0.5	6
Bureaucracy quality	403,680	2.151	0.743	0.5	4

Table B1.4: Correlation among variables (in log form)

	EQ	PI	GDPPC	Openness	FDI	RD	Exp-edu	Import	ECI	HHI	gov	corr	law	bureau
EQ	1.000													
PI	0.062	1.000												
GDPPC	0.0627	0.1164	1.0000											
Openness	0.0182	-0.0920	0.0706	1.0000										
FDI	0.0159	0.0568	0.3984	-0.0700	1.0000									
RD	0.0442	0.1760	0.6655	-0.0300	0.3350	1.0000								
Exp-edu	0.0239	0.0478	0.3253	-0.0785	0.0200	0.3690	1.0000							
Import	0.0192	0.0870	0.4922	-0.1020	0.7682	0.4567	-0.0334	1.0000						
ECI	0.0445	0.1121	0.5959	0.1820	0.3687	0.7053	0.1251	0.5122	1.0000					
HHI	-0.0030	-0.0128	-0.0490	0.0615	-0.0485	-0.1547	0.1037	-0.1259	-0.0282	1.0000				
gov	0.0030	0.0389	-0.0155	0.0174	0.1005	0.1025	-0.0922	0.0170	0.0341	-0.0077	1.0000			
corr	0.0483	0.1077	0.7075	0.0639	0.3058	0.6238	0.3541	0.3108	0.4290	0.0219	0.1997	1.0000		
law	0.0511	0.0996	0.5818	0.2321	0.1837	0.6678	0.2766	0.2279	0.5101	-0.0923	0.1359	0.6070	1.0000	
bureau	0.0458	0.1069	0.6749	0.0270	0.3111	0.5545	0.2551	0.3546	0.4466	0.1062	0.0806	0.7193	0.5045	1.0000

Table B1.5: Results of the first stage of 2SLS

Variables	**lnEQ**	**lnPI**
	(1)	(2)
lnexrate	0.022***	
	(0.003)	
lnexrate (-1)	−0.011***	
	(0.003)	
lnIQ	0.401***	
	(0.012)	
lnIQ (-1)	−0.110***	
	(0.011)	
lnEQ (-1)	0.311***	
	(0.010)	
lncharge		0.005
		(0.003)
lncharge (-1)		−0.003
		(0.003)
lnPI (-1)		0.119***
		(0.008)
lnGDPPC (-1)	−0.025***	−0.043
	(0.005)	(0.027)
lnFDI (-1)	0.0001	−0.0004
	(0.0001)	(0.001)
lnOpenness (-1)	−0.007	−0.054**
	(0.004)	(0.023)
lnRD (-1)	−0.004**	−0.023**
	(0.002)	(0.010)
lnExp-edu (-1)	0.005***	−0.014
	(0.001)	(0.009)
lnImport (-1)	0.013***	0.040**
	(0.004)	(0.020)
lnECI (-1)	0.004***	0.008***
	(0.001)	(0.003)
lnHHI (-1)	−0.001	0.005
	(0.001)	(0.010)
lnGDPPC	0.043***	−0.079***
	(0.005)	(0.029)
lnOpenness	0.008*	−0.035
	(0.004)	(0.025)
lnFDI	−0.0003***	0.0004
	(0.0001)	(0.001)
lnRD	0.003	0.050***
	(0.002)	(0.010)
lnExp-edu	−0.004***	−0.015
	(0.002)	(0.010)
lnImport	0.003	0.068***
	(0.004)	(0.021)
lnECI	−0.0001	0.003
	(0.001)	(0.003)
lnHHI	−0.0005	−0.021**
	(0.001)	(0.010)
Num.Obs.	254,693	239,456
Kleibergen-Paap rk LM statistic	2055.60***	247.22***
Cragg-Donald Wald F statistic	5590.71	289.90
Year FE	Yes	Yes
Country FE	Yes	Yes
Product-sector FE	Yes	Yes

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

B2 Robustness Checks

To check for the correctness of the results, we adopt another measurement for export quality following the method of Fan, Li, and Yeaple (2015) and Khandelwal et al. (2013). The idea is that consumers' perception of an export product's quality, even when prices are high, significantly impacts their purchasing decisions (Crinò & Ogliari, 2017). Thus, the unobserved quality is obtained from the residual of the estimation of Equation (B2.1) with OLS. The export quality is then calculated as Equation (B2.2).

$$lnQ_{\text{pct}} + \sigma lnP_{\text{pct}} = \phi_c + \phi_t + \varepsilon_{\text{pct}} \tag{B2.1}$$

$$\text{quality}_{pct} = \frac{\varepsilon_{\text{pct}}}{\sigma - 1} \tag{B2.2}$$

where Q_{pct} and P_{pct} denote the demand and price of the product p exported by country c in year t, respectively. ϕ_c is the country fixed effect, ϕ_t denotes the year fixed effect, and ε_{pct} is the error term. σ is the elasticity of substitution. Following the literature, we adopt three different values of σ to propagate export quality: $\sigma = 3$, $\sigma = 4$, and $\sigma = 5$ as in Kong and Xiong (2021), Broda and Weinstein (2006) and Broda et al. (2017), and Fan, Li, and Yeaple (2015), respectively.

The results of the two-way relationship between export quality and patent intensity are in Table B2.1. When employing the elasticity of substitution $\sigma = 3$ and $\sigma = 4$, the results are analogous. Particularly, the coefficients are insignificant in the whole sample, significantly positive in the OECD subsample, and significantly negative in non-OECD, high technology, and low technology subsamples. However, with the value of elasticity of substitution equal to 5, the findings of the whole sample, non-OECD, high technology, and low technology subsamples are in line with those from the main results. While the results from OECD countries are significantly positive.

The results from adding the institution variables are shown in Table B2.2 with the elasticity of substitution values of 3, 4, and 5, respectively. The results are similar in terms of signs and significant levels when using different values of elasticity of substitution. Concerning the whole sample results, all institution variables show a positive impact on export quality and patent intensity, except the effect of corruption on patent intensity - turns to be negative in case $\sigma = 3$ and $\sigma = 4$. All the interaction terms are significant and positive, suggesting the positive moderating role of institutions on the two-way relationship between export quality and patent intensity. Most of the coefficients of institution variables are positive in the OECD sample, except the negative coefficients of law and order and bureaucracy quality. The positive moderating effects of government stability and corruption are confirmed. However, law and order negatively moderates the two-way nexus between export quality and patent intensity. Bureaucracy quality positively moderates the relationship between patent intensity but negatively moderates the opposite nexus. For non-OECD countries, the results from government stability and corruption are similar to those from Table 2.6 but the findings from law and order and bureaucracy quality are varied.

Furthermore, we use the second data set for institutional quality from the Worldwide Governance Indicators (WGI) with four variables (Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption) to recheck the moderation effect of institutional quality on the relationship between export quality and patent intensity. The results are in Table B2.3. Despite the varying signs and significant levels of the non-OECD subsample, in the whole sample, there are positive impacts of all four institutions on export quality and patent intensity, except for the insignificant coefficient of control of corruption on patent intensity. All the interaction terms are significant and positive. For OECD countries, the coefficients of all institutions and interaction terms are also significant and positive. This confirms our earlier findings. Figure B2.1 and Figure B2.2 illustrate the marginal effects of export quality on patent intensity and patent intensity on export quality, respectively, under different institutions.

Table B2.1: Two-way relationship between quality and patent intensity (PI) results

Direction of relationship	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)	**High technology** (4)	**Low technology** (5)
			$\boldsymbol{\sigma = 3}$		
$lnPI \longrightarrow lnquality$	0.0001	0.0005***	−0.004***	−0.0003***	−0.0006***
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0002)
Num.Obs.	236,570	148,408	88,162	36,065	200,505
R2	0.9998	0.9999	0.9998	0.9999	0.9998
$lnquality \longrightarrow lnPI$	0.056	0.764***	−1.499***	−1.973***	−0.217***
	(0.057)	(0.139)	(0.079)	(0.674)	(0.051)
Num.Obs.	236,570	148,408	88,162	36,065	200,505
R2	0.3530	0.3948	0.2970	0.5605	0.2266
			$\boldsymbol{\sigma = 4}$		
$lnPI \longrightarrow lnquality$	$-8.10e-06$	0.001***	−0.007***	−0.001***	−0.001***
	(0.0002)	(0.0001)	(0.001)	(0.0001)	(0.0003)
Num.Obs.	236,570	148,408	88,162	36,065	200,505
R2	0.9994	0.9999	0.9991	0.9999	0.9994
$lnquality \longrightarrow lnPI$	−0.015	0.491***	−0.480***	−1.784***	−0.085***
	(0.027)	(0.095)	(0.034)	(0.520)	(0.025)
Num.Obs.	236,570	148,408	88,162	36,065	200,505
R2	0.3530	0.3948	0.2981	0.5605	0.2266
			$\boldsymbol{\sigma = 5}$		
$lnPI \longrightarrow lnquality$	−0.001***	0.001***	−0.013***	−0.001***	−0.002***
	(0.0003)	(0.0002)	(0.001)	(0.0002)	(0.001)
Num.Obs.	236,337	148,408	87,929	36,065	200,272
R2	0.9989	0.9997	0.9982	0.9998	0.9988
$lnquality \longrightarrow lnPI$	−0.075***	0.300***	−0.436***	−1.570***	−0.112***
	(0.023)	(0.060)	(0.028)	(0.392)	(0.022)
Num.Obs.	236,337	148,408	87,929	36,065	200,272
R2	0.3530	0.3948	0.2977	0.5604	0.2266
Control	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Product-sector FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Control variables: GDPPC, Openness, FDI, R&D, Expenditure on education, Import, ECI, and HHI.

Table B2.2: Moderation effect of institutions on the relationship between quality and patent intensity

Dependent variables	Explanatory variables	Whole sample (1)	OECD (2)	Non-OECD (3)
A. Elasticity of substitution $\sigma = 3$				
1. Government Stability				
lnquality	lnPI	−0.554***	−0.113***	−0.548***
		(0.022)	(0.007)	(0.045)
	lngov	1.164***	0.245***	1.151***
		(0.046)	(0.014)	(0.095)
	lnPIxlngov	0.260***	0.054***	0.252***
		(0.010)	(0.003)	(0.021)
	R2	0.9993	0.9999	0.9994
lnPI	lnquality	−1.273***	−1.413***	−1.559***
		(0.059)	(0.142)	(0.081)
	lngov	0.056***	0.062***	0.054***
		(0.009)	(0.013)	(0.012)
	lnqualityxlngov	0.046***	0.044***	0.037***
		(0.004)	(0.006)	(0.005)
	R2	0.3519	0.3942	0.2974
2. Corruption				
lnquality	lnPI	−0.063***	−0.024***	−0.019***
		(0.003)	(0.002)	(0.002)
	lncorr	0.160***	0.045***	0.021***
		(0.009)	(0.006)	(0.006)
	lnPIxlncorr	0.042***	0.016***	0.014***
		(0.002)	(0.001)	(0.001)
	R2	0.9998	0.9999	0.9998
lnPI	lnquality	−3.791***	−1.424***	−2.175***
		(0.057)	(0.150)	(0.083)
	lncorr	−0.050***	0.013	−0.082***
		(0.011)	(0.016)	(0.015)
	lnqualityxlncorr	0.023***	0.028***	0.001
		(0.002)	(0.003)	(0.003)
	R2	0.3417	0.3942	0.2942
3. Law and Order				
lnquality	lnPI	−0.149***	0.104***	−0.002
		(0.010)	(0.011)	(0.002)
	lnlaw	0.394***	−0.239***	−0.009
		(0.029)	(0.029)	(0.008)
	lnPIxlnlaw	0.089***	−0.061***	0.001
		(0.006)	(0.006)	(0.002)
	R2	0.9997	0.9999	0.9998
lnPI	lnquality	−2.876***	4.536***	−0.456***
		(0.055)	(0.142)	(0.080)
	lnlaw	0.019**	−0.084***	0.002
		(0.008)	(0.014)	(0.012)
	lnqualityxlnlaw	0.024***	0.032***	−0.004
		(0.002)	(0.003)	(0.003)
	R2	0.3463	0.3903	0.2994

Table B2.2: Moderation effect of institutions on the relationship between quality and patent intensity (cont.)

Dependent variables	**Explanatory variables**	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)
4. Bureaucracy Quality				
lnquality	lnPI	−0.025***	0.233***	−0.007***
		(0.002)	(0.016)	(0.001)
	lnbureau	0.187***	−0.704***	1.572***
		(0.006)	(0.053)	(0.011)
	lnPIxlnbureau	0.017***	−0.169***	0.003***
		(0.001)	(0.012)	(0.001)
	R2	0.9998	0.9997	0.9998
lnPI	lnquality	−2.068***	3.940***	−1.428***
		(0.057)	(0.133)	(0.079)
	lnbureau	0.341***	−0.112**	1.720***
		(0.041)	(0.045)	(0.151)
	lnqualityxlnbureau	0.020***	0.086***	0.002
		(0.002)	(0.006)	(0.002)
	R2	0.3497	0.3919	0.2972
B. Elasticity of substitution $\sigma = 4$				
1. Government Stability				
lnquality	lnPI	−0.909***	−0.239***	−1.090***
		(0.035)	(0.012)	(0.089)
	lngov	1.909***	0.507***	2.298***
		(0.074)	(0.025)	(0.188)
	lnPIxlngov	0.426***	0.113***	0.502***
		(0.017)	(0.006)	(0.042)
	R2	0.9981	0.9998	0.9976
lnPI	lnquality	−0.811***	−1.333***	−0.740***
		(0.030)	(0.098)	(0.037)
	lngov	0.080***	0.091***	0.079***
		(0.010)	(0.015)	(0.014)
	lnqualityxlngov	0.046***	0.048***	0.036***
		(0.004)	(0.006)	(0.005)
	R2	0.3515	0.3938	0.2971
2. Corruption				
lnquality	lnPI	−0.126***	−0.026***	−0.042***
		(0.006)	(0.002)	(0.004)
	lncorr	0.323***	0.038***	0.051***
		(0.020)	(0.007)	(0.014)
	lnPIxlncorr	0.083***	0.018***	0.031***
		(0.005)	(0.002)	(0.003)
	R2	0.9992	0.9999	0.9991
lnPI	lnquality	−2.050***	−0.454***	−0.874***
		(0.027)	(0.103)	(0.036)
	lncorr	−0.034***	0.048***	−0.069***
		(0.011)	(0.016)	(0.016)
	lnqualityxlncorr	0.024***	0.027***	0.002
		(0.002)	(0.003)	(0.003)
	R2	0.3409	0.3948	0.2949

Table B2.2: Moderation effect of institutions on the relationship between quality and patent intensity (cont.)

Dependent variables	**Explanatory variables**	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)
3. Law and Order				
lnquality	lnPI	−0.276***	0.165***	−0.008
		(0.020)	(0.16)	(0.005)
	lnlaw	0.731***	−0.384***	0.011
		(0.055)	(0.045)	(0.017)
	lnPIxlnlaw	0.164***	−0.097***	0.005
		(0.012)	(0.010)	(0.004)
	R2	0.9989	0.9998	0.9991
lnPI	lnquality	−1.532***	3.314***	−0.169***
		(0.026)	(0.096)	(0.034)
	lnlaw	0.037***	−0.073***	0.003
		(0.009)	(0.015)	(0.012)
	lnqualityxlnlaw	0.024***	0.033***	−0.004
		(0.002)	(0.003)	(0.003)
	R2	0.3461	0.3900	0.2994
4. Bureaucracy Quality				
lnquality	lnPI	−0.053***	0.320***	−0.012***
		(0.003)	(0.022)	(0.001)
	lnbureau	0.369***	−0.958***	2.453***
		(0.013)	(0.073)	(0.026)
	lnPIxlnbureau	0.035***	−0.232***	0.006***
		(0.002)	(0.016)	(0.001)
	R2	0.9994	0.9995	0.9991
lnPI	lnquality	−1.211***	2.845***	−0.478***
		(0.027)	(0.090)	(0.034)
	lnbureau	0.372***	−0.096**	0.654***
		(0.041)	(0.045)	(0.123)
	lnqualityxlnbureau	0.020***	0.086***	0.002
		(0.002)	(0.005)	(0.002)
	R2	0.3488	0.3918	0.2982
C. Elasticity of substitution $\sigma = 5$				
1. Government Stability				
lnquality	lnPI	−1.870***	−0.447***	−4.035***
		(0.070)	(0.021)	(0.312)
	lngov	3.908***	0.942***	8.392***
		(0.147)	(0.044)	(0.657)
	lnPIxlngov	0.876***	0.211***	1.860***
		(0.033)	(0.010)	(0.145)
	R2	0.9936	0.9993	0.9791
lnPI	lnquality	−0.584***	−0.957***	−0.469***
		(0.028)	(0.063)	(0.034)
	lngov	0.110***	0.113***	0.103***
		(0.012)	(0.016)	(0.016)
	lnqualityxlngov	0.053***	0.051***	0.047***
		(0.004)	(0.006)	(0.005)
	R2	0.3518	0.3937	0.2987

Table B2.2: Moderation effect of institutions on the relationship between quality and patent intensity (cont.)

Dependent variables	**Explanatory variables**	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)
2. Corruption				
lnquality	lnPI	-0.107^{***}	-0.029^{***}	-0.032^{***}
		(0.006)	(0.003)	(0.005)
	lncorr	0.280^{***}	0.029^{***}	0.018
		(0.018)	(0.010)	(0.020)
	lnPIxlncorr	0.071^{***}	0.020^{***}	0.021^{***}
		(0.004)	(0.002)	(0.004)
	R2	0.9987	0.9997	0.9982
lnPI	lnquality	-0.932^{***}	0.007	-0.467^{***}
		(0.023)	(0.065)	(0.029)
	lncorr	0.033^{***}	0.077^{***}	-0.028^{*}
		(0.011)	(0.016)	(0.017)
	lnqualityxlncorr	0.021^{***}	0.027^{***}	0.001
		(0.002)	(0.003)	(0.003)
	R2	0.3481	0.3951	0.2974
3. Law and Order				
lnquality	lnPI	-0.436^{***}	0.265^{***}	-0.100^{***}
		(0.029)	(0.026)	(0.011)
	lnlaw	1.143^{***}	-0.619^{***}	0.239^{***}
		(0.082)	(0.072)	(0.037)
	lnPIxlnlaw	0.259^{***}	-0.155^{***}	0.065^{***}
		(0.018)	(0.016)	(0.008)
	R2	0.9977	0.9994	0.9982
lnPI	lnquality	-1.130^{***}	2.167^{***}	-0.561^{***}
		(0.022)	(0.060)	(0.030)
	lnlaw	0.036^{***}	-0.057^{***}	-0.022^{*}
		(0.009)	(0.015)	(0.013)
	lnqualityxlnlaw	0.025^{***}	0.033^{***}	-0.001
		(0.002)	(0.003)	(0.003)
	R2	0.3459	0.3899	0.2960
4. Bureaucracy Quality				
lnquality	lnPI	-0.075^{***}	0.463^{***}	-0.028^{***}
		(0.005)	(0.033)	(0.003)
	lnbureau	0.506^{***}	-1.363^{***}	3.442^{***}
		(0.016)	(0.109)	(0.028)
	lnPIxlnbureau	0.051^{***}	-0.336^{***}	0.015^{***}
		(0.004)	(0.024)	(0.002)
	R2	0.9988	0.9989	0.9982
lnPI	lnquality	-0.840^{***}	1.887^{***}	-0.553^{***}
		(0.023)	(0.056)	(0.028)
	lnbureau	0.358^{***}	-0.099^{**}	1.347^{***}
		(0.041)	(0.046)	(0.135)
	lnqualityxlnbureau	0.020^{***}	0.085^{***}	0.001
		(0.002)	(0.005)	(0.002)
	R2	0.3492	0.3916	0.2961
	Num.Obs.	236,337	148,408	87,929

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Control variables and fixed effects are included.

Table B2.3: Moderation effect of institutions on the relationship between export quality and patent intensity (institutions data is from WGI)

Dependent variables	**Explanatory variables**	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)
1. Government Effectiveness				
lnEQ	lnPI	−13.458***	−7.732***	0.122
		(1.261)	(0.608)	(0.190)
	lnger	13.787***	7.717***	−0.176
		(1.310)	(0.611)	(0.212)
	lnPIxlnger	3.040***	1.721***	−0.041
		(0.287)	(0.136)	(0.047)
	R2	0.8087	0.9785	0.9870
lnPI	lnEQ	−0.435**	−1.182***	−0.422***
		(0.021)	(0.085)	(0.026)
	lnger	0.081***	0.433***	0.037***
		(0.012)	(0.051)	(0.013)
	lnEQxlnger	0.037***	0.171***	0.015***
		(0.004)	(0.017)	(0.004)
	R2	0.3525	0.3911	0.2999
2. Regulatory Quality				
lnEQ	lnPI	−23.465***	−22.967***	−2.659***
		(2.092)	(2.025)	(0.468)
	lnrqr	23.890***	22.249***	2.855***
		(2.150)	(1.970)	(0.523)
	lnPIxlnrqr	5.319***	5.150***	0.630***
		(0.477)	(0.454)	(0.115)
	R2	0.3673	0.8901	0.9737
lnPI	lnEQ	−0.332***	−0.927***	−0.520***
		(0.018)	(0.116)	(0.020)
	lnrqr	0.024**	0.368***	0.002
		(0.012)	(0.072)	(0.012)
	lnEQxlnrqr	0.024***	0.147***	0.013***
		(0.003)	(0.024)	(0.003)
	R2	0.3532	0.3932	0.2943
3. Rule of Law				
lnEQ	lnPI	−12.208***	−8.597***	0.514***
		(0.864)	(0.732)	(0.123)
	lnrlr	12.524***	8.659***	−0.626***
		(0.898)	(0.745)	(0.142)
	lnPIxlnrlr	2.770***	1.921***	−0.140***
		(0.198)	(0.164)	(0.031)
	R2	0.7289	0.9558	0.9865
lnPI	lnEQ	−0.384***	−0.632***	−0.310***
		(0.017)	(0.045)	(0.024)
	lnrlr	0.055***	0.165***	0.019
		(0.014)	(0.031)	(0.016)
	lnEQxlnrlr	0.026***	0.063***	0.008**
		(0.003)	(0.008)	(0.003)
	R2	0.3526	0.3933	0.3028

Table B2.3: Moderation effect of institutions on the relationship between export quality and patent intensity (institutions data is from WGI) (cont.)

Dependent variables	**Explanatory variables**	**Whole sample** (1)	**OECD** (2)	**Non-OECD** (3)
4. Control of Corruption				
lnEQ	lnPI	-11.048^{***}	-8.553^{***}	0.446^{***}
		(0.865)	(0.699)	(0.076)
	lnccr	11.038^{***}	8.523^{***}	-0.528^{***}
		(0.886)	(0.703)	(0.086)
	lnPIxlnccr	2.503^{***}	1.916^{***}	-0.122^{***}
		(0.199)	(0.157)	(0.019)
	R2	0.7270	0.9578	0.9864
lnPI	lnEQ	-0.403^{***}	-0.738^{***}	-0.283^{***}
		(0.017)	(0.049)	(0.023)
	lnccr	0.017	0.181^{***}	-0.028^{*}
		(0.013)	(0.028)	(0.016)
	lnEQxlnccr	0.028^{***}	0.084^{***}	0.007^{**}
		(0.003)	(0.009)	(0.003)
	R2	0.3525	0.3930	0.3035
	Num.Obs.	224,241	139,762	84,479
	Control	Yes	Yes	Yes
	Year FE	Yes	Yes	Yes
	Country FE	Yes	Yes	Yes
	Product-sector FE	Yes	Yes	Yes

Robust standard errors are in the parentheses; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Control variables: GDPPC, Openness, FDI, R&D, Expenditure on education, Import, ECI, and HHI.

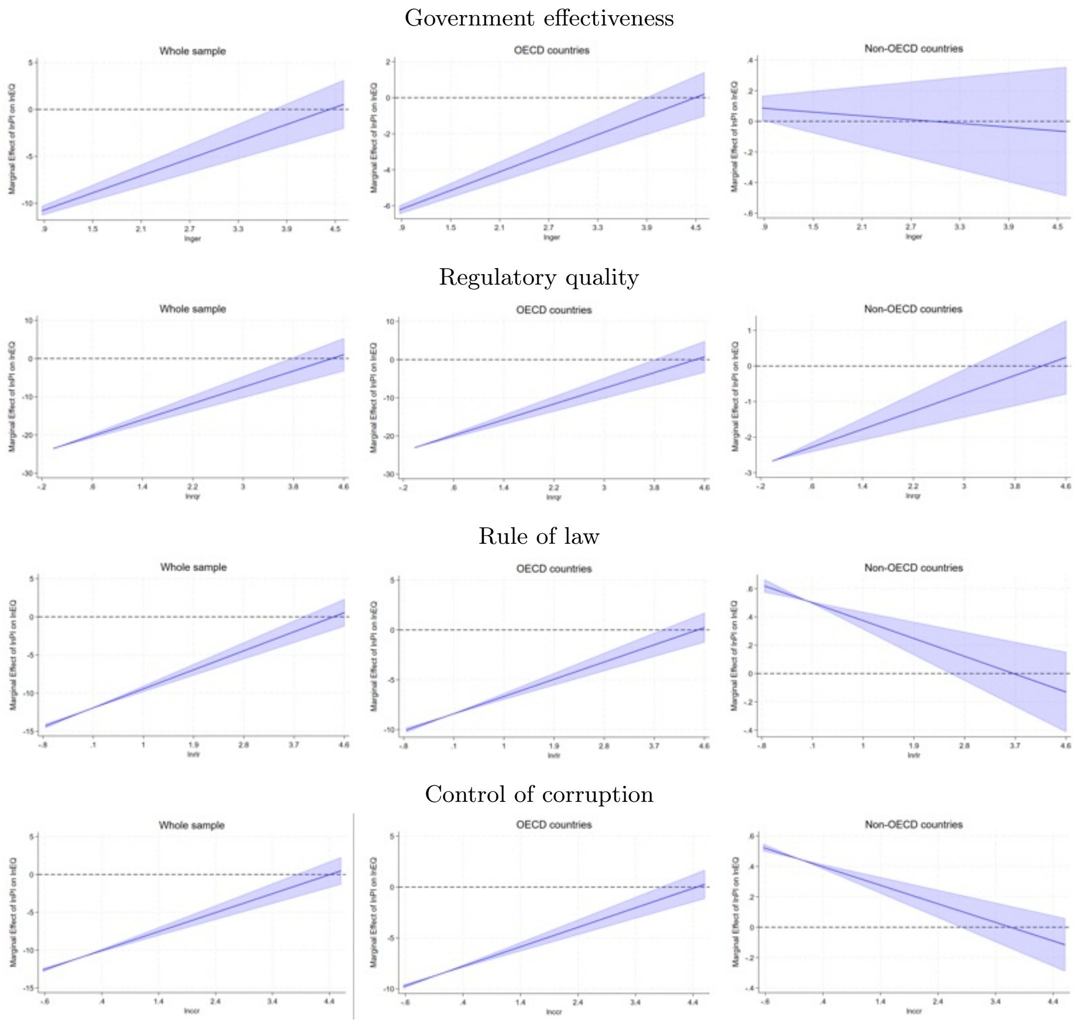


Figure B2.1: Marginal effect of patent intensity on export quality for different institutions (institutions data is from WGI)

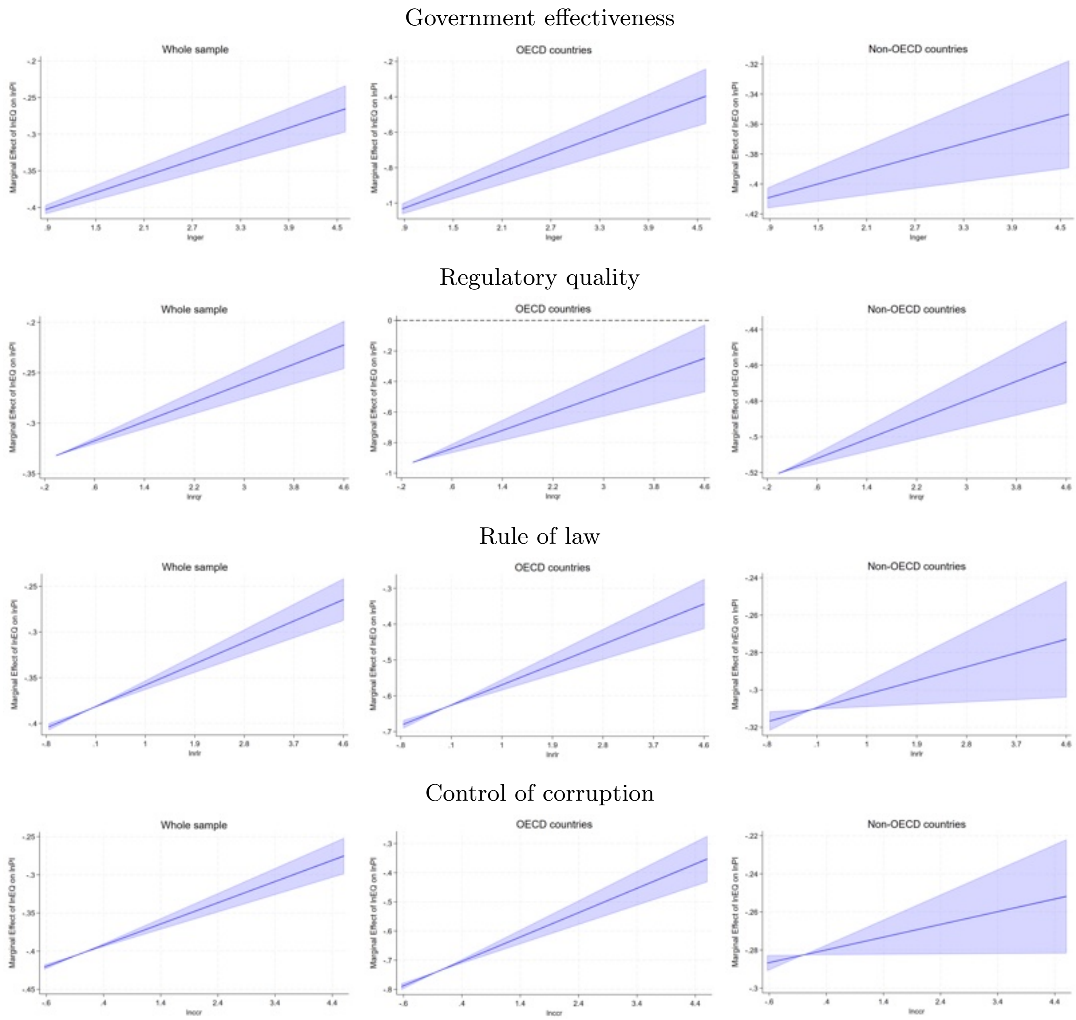


Figure B2.2: Marginal effect of export quality on patent intensity for different institutions (institutions data is from WGI)

Appendix C

C1 Supplementary Tables and Figures

Table C1.1: The effects of the Horizon 2020 program on firms' innovation

	Product innovation (1)	Process innovation (2)	Organization innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
Whole sample					
Pre-average	−0.017	−0.005	−0.008	0.003	−0.107*
	(0.020)	(0.019)	(0.018)	(0.017)	(0.055)
Post-average	0.056	0.013	0.056**	0.049	0.171**
	(0.050)	(0.046)	(0.025)	(0.034)	(0.074)
2010	−0.017	0.013	−0.010	0.009	−0.094
	(0.028)	(0.029)	(0.031)	(0.025)	(0.070)
2012	−0.017	−0.023	0.006	−0.003	−0.120**
	(0.018)	(0.018)	(0.015)	(0.016)	(0.054)
2014	0.034	−0.017	0.056**	0.046	0.153**
	(0.049)	(0.047)	(0.023)	(0.031)	(0.062)
2016	0.079	0.042	0.056*	0.052	0.188**
	(0.057)	(0.051)	(0.031)	(0.043)	(0.088)
Observations	113,898	113,846	112,586	112,579	109,994
Western Europe countries (DE, ES, PT)					
Pre-average	−0.008	−0.008	−0.021	−0.004	0.003
	(0.020)	(0.023)	(0.018)	(0.020)	(0.002)
Post-average	0.126***	0.130***	0.064*	0.045	0.037**
	(0.035)	(0.031)	(0.033)	(0.035)	(0.017)
2010	0.003	0.020	−0.022	0.014	0.001
	(0.027)	(0.032)	(0.031)	(0.033)	(0.002)
2012	−0.019	−0.035*	−0.021	−0.023	0.005*
	(0.018)	(0.020)	(0.016)	(0.020)	(0.003)
2014	0.064*	0.076**	0.068*	0.056	0.045***
	(0.033)	(0.032)	(0.037)	(0.044)	(0.017)
2016	0.187***	0.184***	0.061	0.033	0.028
	(0.041)	(0.042)	(0.045)	(0.039)	(0.018)
Observations	85,301	85,249	83,989	83,982	81,888

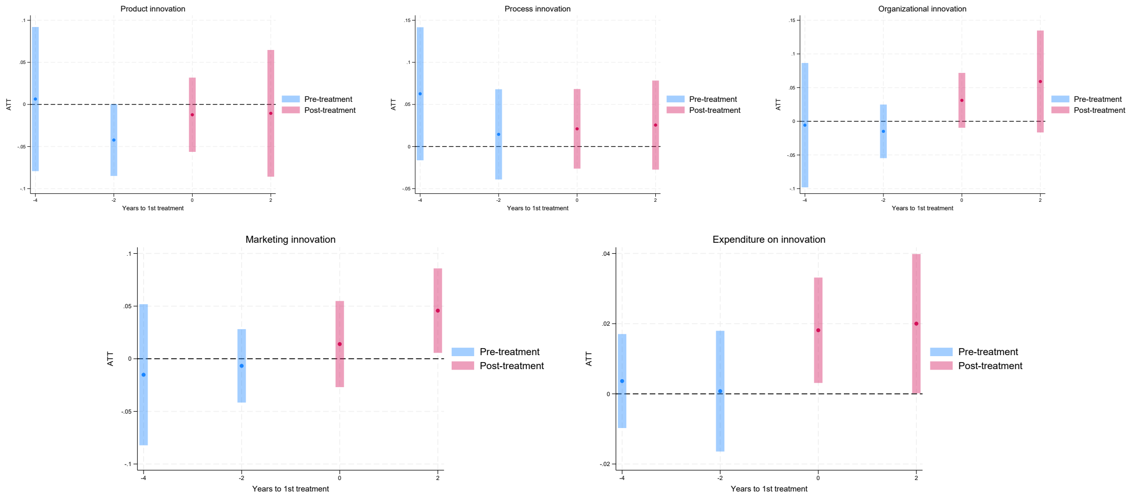
Results are estimated from csdid; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

Table C1.1: The effects of the Horizon 2020 program on firms' innovation (cont.)

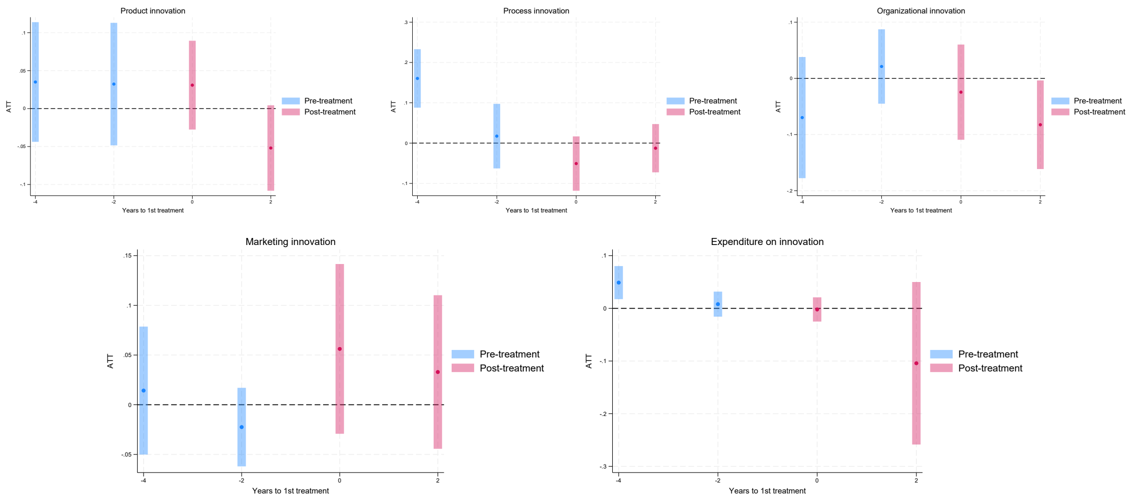
	Product innovation (1)	Process innovation (2)	Organization innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
Central and Eastern Europe countries (BG, CZ, EE, HU, LT, RO)					
Pre-average	0.012	0.053***	0.015	0.013	−0.151
	(0.023)	(0.019)	(0.020)	(0.020)	(0.133)
Post-average	0.005	0.003	0.031**	0.023	0.150
	(0.021)	(0.019)	(0.015)	(0.019)	(0.170)
2010	0.014	0.071***	0.041	0.016	−0.231
	(0.041)	(0.027)	(0.037)	(0.034)	(0.190)
2012	0.010	0.035*	−0.011	0.010	−0.072
	(0.020)	(0.020)	(0.018)	(0.020)	(0.139)
2014	0.008	−0.008	0.032**	0.009	0.110
	(0.020)	(0.020)	(0.015)	(0.016)	(0.150)
2016	0.002	0.014	0.030	0.037	0.191
	(0.028)	(0.021)	(0.021)	(0.028)	(0.195)
Observations	28,597	28,597	28,597	28,597	28,106

Results are estimated from csdid; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

(a) Bulgaria (BG)



(b) Czech Republic (CZ)



(c) Germany (DE)

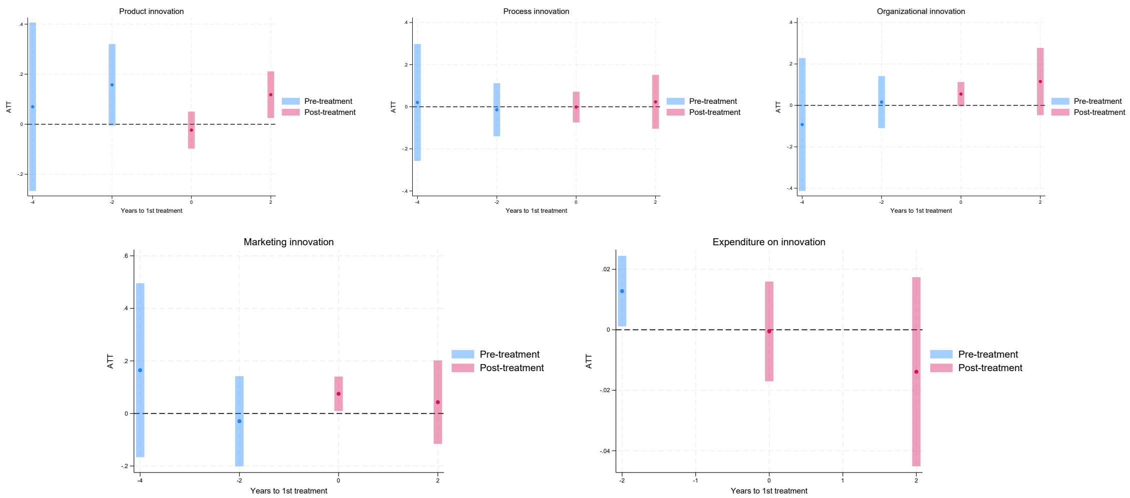
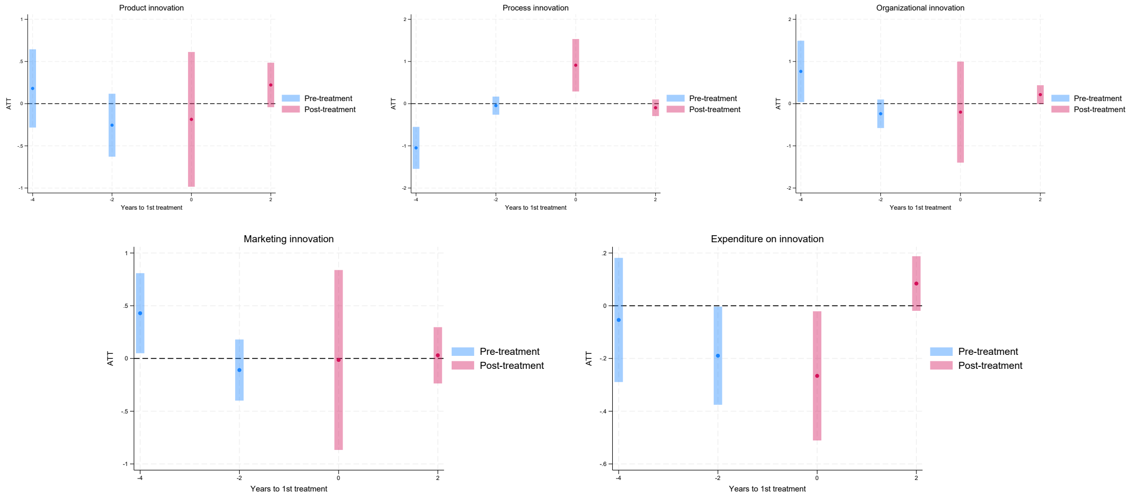
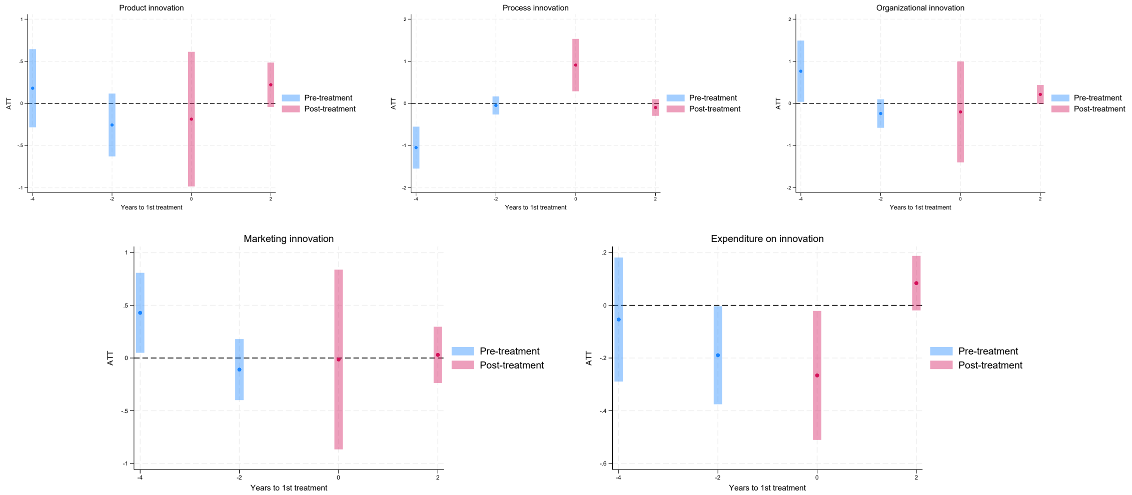


Figure C1.1: The effects of the Horizon 2020 program for different countries

(d) Estonia (EE)



(e) Spain (ES)



(f) Hungary (HU)

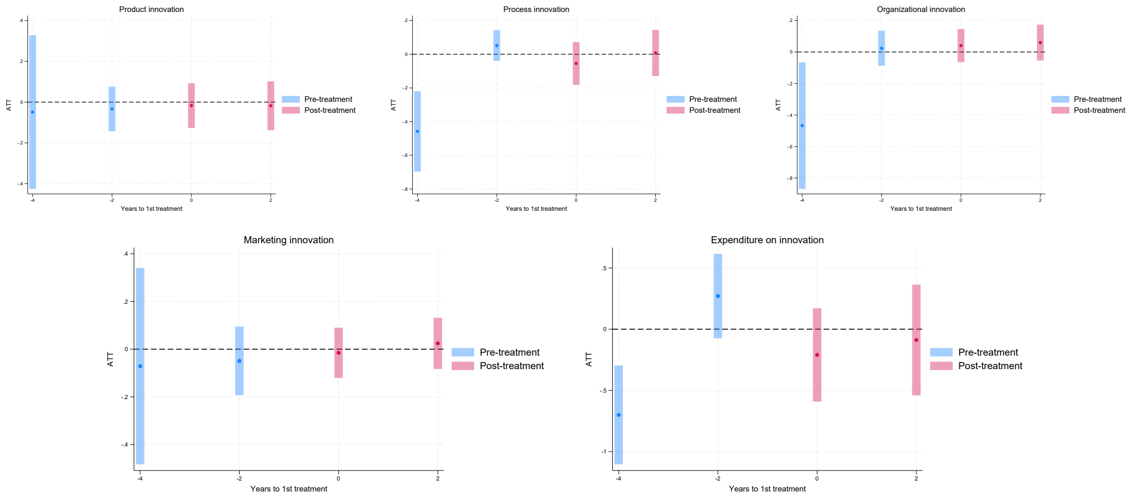
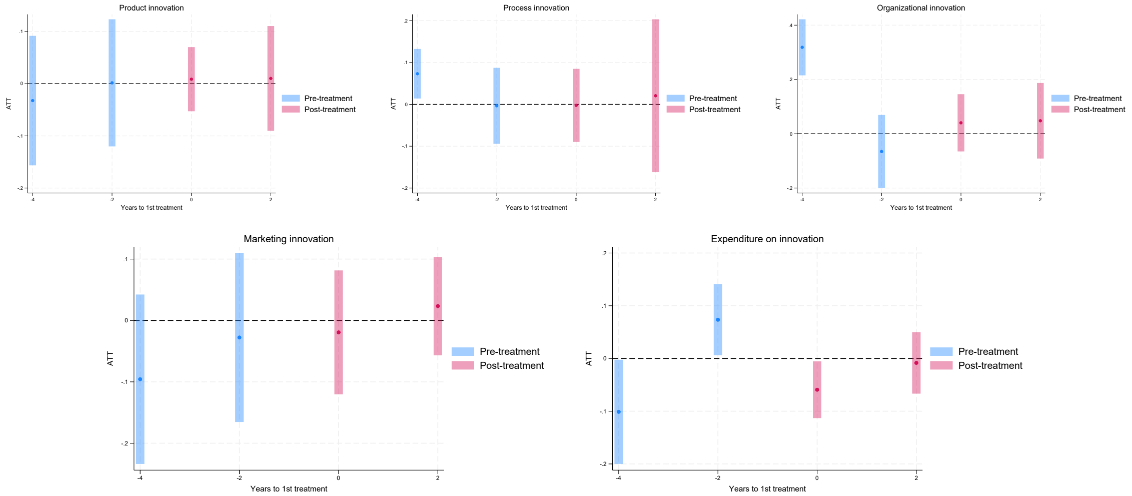
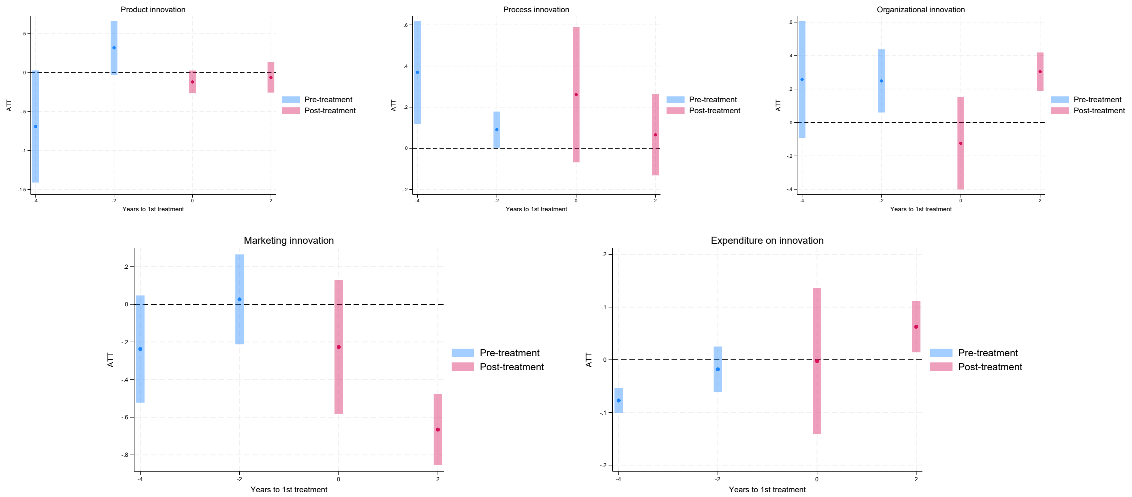


Figure C1.1: The effects of the Horizon 2020 program (cont.)

(g) Lithuania (LT)



(h) Portugal (PT)



(i) Romania (RO)

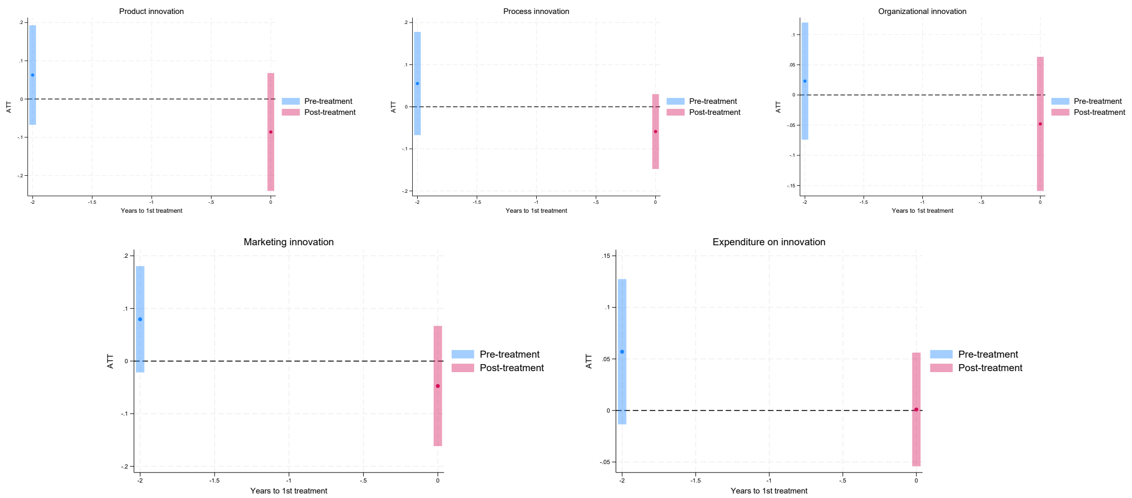


Figure C1.1: The effects of the Horizon 2020 program (cont.)

Table C1.2: The heterogeneous effects of the Horizon 2020 program on firms' innovation

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
A - Exporting firms					
Pre-average	−0.018	0.018	0.008	0.010	−0.229*
	(0.023)	(0.016)	(0.025)	(0.017)	(0.122)
Post-average	0.107**	0.079**	0.057**	0.070**	0.323**
	(0.043)	(0.035)	(0.023)	(0.034)	(0.141)
2010	−0.008	0.048	−0.005	0.009	−0.213
	(0.036)	(0.029)	(0.042)	(0.030)	(0.156)
2012	−0.027	−0.012	0.010	0.011	−0.245**
	(0.018)	(0.014)	(0.020)	(0.017)	(0.110)
2014	0.111***	0.052	0.058**	0.062**	0.288**
	(0.041)	(0.036)	(0.024)	(0.029)	(0.122)
2016	0.104**	0.106***	0.055*	0.078*	0.358**
	(0.051)	(0.040)	(0.029)	(0.046)	(0.162)
Observations	58,315	58,304	57,959	57,975	56,719
B - R&D-intensive firms					
Pre-average	0.021	0.029	0.033	0.032	−0.701***
	(0.044)	(0.043)	(0.045)	(0.040)	(0.228)
Post-average	0.086**	−0.043*	0.112***	0.093**	0.921***
	(0.042)	(0.026)	(0.034)	(0.039)	(0.255)
2010	0.050	0.146**	0.052	0.042	−0.670**
	(0.077)	(0.072)	(0.077)	(0.083)	(0.320)
2012	−0.009	−0.088**	0.015	0.022	−0.732***
	(0.038)	(0.035)	(0.039)	(0.033)	(0.222)
2014	0.059	−0.080***	0.113***	0.064	0.777***
	(0.045)	(0.029)	(0.039)	(0.042)	(0.244)
2016	0.113**	−0.007	0.111***	0.122**	1.066***
	(0.054)	(0.033)	(0.042)	(0.052)	(0.278)
Observations	21,295	21,278	20,892	20,906	16,319
C - Knowledge-intensive firms					
Pre-average	−0.117**	−0.045	−0.032	−0.039	−0.106
	(0.051)	(0.041)	(0.045)	(0.048)	(0.072)
Post-average	0.050	−0.034	0.107***	0.036	0.101
	(0.057)	(0.043)	(0.030)	(0.047)	(0.079)
2010	−0.150*	−0.076	−0.010	−0.024	−0.149
	(0.088)	(0.086)	(0.076)	(0.086)	(0.102)
2012	−0.085	−0.014	−0.054	−0.054	−0.064
	(0.063)	(0.043)	(0.045)	(0.061)	(0.068)
2014	−0.018	−0.033	0.075**	0.029	0.122*
	(0.059)	(0.050)	(0.037)	(0.049)	(0.068)
2016	0.119*	−0.036	0.138***	0.043	0.081
	(0.070)	(0.048)	(0.039)	(0.067)	(0.103)
Observations	23,304	23,320	23,065	23,042	22,161

Results are estimated from csdid; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

Table C1.2: The heterogeneous effects of the Horizon 2020 program on firms' innovation (cont.)

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
D - High-competitive firms					
Pre-average	0.010	0.014	0.016	0.034	-0.228^{*}
	(0.039)	(0.021)	(0.037)	(0.028)	(0.135)
Post-average	0.093	0.104^{*}	0.058^{*}	0.082^{*}	0.326^{**}
	(0.067)	(0.055)	(0.030)	(0.047)	(0.158)
2010	0.050	0.036	0.040	0.055	−0.201
	(0.066)	(0.042)	(0.066)	(0.044)	(0.169)
2012	−0.029	−0.008	−0.008	0.013	-0.256^{**}
	(0.025)	(0.016)	(0.022)	(0.022)	(0.127)
2014	0.077	0.080	0.054^{**}	0.079^{**}	0.299^{**}
	(0.063)	(0.055)	(0.027)	(0.040)	(0.145)
2016	0.109	0.128^{**}	0.062^{*}	0.085	0.354^{**}
	(0.076)	(0.062)	(0.037)	(0.061)	(0.173)
Observations	64,863	64,841	64,229	64,241	62,676
E - Low-competitive firms					
Pre-average	−0.015	−0.013	−0.012	−0.009	−0.015
	(0.020)	(0.025)	(0.023)	(0.022)	(0.028)
Post-average	0.036	−0.091	0.068^{*}	0.017	0.044
	(0.071)	(0.070)	(0.038)	(0.045)	(0.049)
2010	−0.031	−0.003	−0.025	−0.014	0.004
	(0.024)	(0.034)	(0.036)	(0.034)	(0.049)
2012	0.001	−0.023	0.001	−0.003	−0.035
	(0.020)	(0.023)	(0.022)	(0.023)	(0.036)
2014	0.029	−0.124	0.065^{*}	0.021	0.070
	(0.069)	(0.076)	(0.035)	(0.045)	(0.045)
2016	0.043	−0.058	0.071	0.014	0.018
	(0.079)	(0.076)	(0.048)	(0.055)	(0.063)
Observations	49,035	49,005	48,357	48,338	47,318
F - Firms use patents					
Pre-average	0.089	0.063	−0.081	0.156	0.381
	(0.094)	(0.083)	(0.114)	(0.114)	(0.238)
Post-average	0.006	−0.034	0.005	−0.017	0.630^{*}
	(0.052)	(0.062)	(0.061)	(0.046)	(0.355)
2012	0.089	0.063	−0.081	0.156	0.381
	(0.094)	(0.083)	(0.114)	(0.114)	(0.238)
2014	0.018	−0.066	0.087	−0.005	0.501^{*}
	(0.055)	(0.049)	(0.073)	(0.054)	(0.303)
2016	−0.006	−0.002	−0.077	−0.029	0.760^{*}
	(0.069)	(0.097)	(0.081)	(0.059)	(0.417)
Observations	5,262	5,269	5,286	5,292	5,197

Results are estimated from csdid; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

Table C1.2: The heterogeneous effects of the Horizon 2020 program on firms' innovation (cont.)

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
G - Firms use design rights					
Pre-average	−0.030	−0.147*	−0.020	−0.003	0.365*
	(0.096)	(0.078)	(0.148)	(0.104)	(0.217)
Post-average	−0.061	0.020	0.092	−0.012	0.502**
	(0.045)	(0.052)	(0.059)	(0.056)	(0.229)
2012	−0.030	−0.147*	−0.020	−0.003	0.365*
	(0.096)	(0.078)	(0.148)	(0.104)	(0.217)
2014	−0.011	0.009	0.058	0.030	0.384*
	(0.058)	(0.061)	(0.067)	(0.051)	(0.778)
2016	−0.112*	0.031	0.125	−0.054	0.620**
	(0.060)	(0.074)	(0.091)	(0.082)	(0.268)
Observations	2,977	2,974	2,984	2,989	2,914

Results are estimated from csdid; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

Table C1.3: The effects of the Horizon 2020 program on firms' innovation for different sectors

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
A - Manufacturing sector					
Pre-average	−0.001	0.009	0.008	0.033	−0.250*
	(0.040)	(0.021)	(0.036)	(0.028)	(0.143)
Post-average	0.042	0.073	0.044	0.069	0.364**
	(0.068)	(0.053)	(0.029)	(0.047)	(0.174)
2010	0.052	0.041	0.037	0.053	−0.217
	(0.067)	(0.041)	(0.065)	(0.043)	(0.175)
2012	−0.053**	−0.022	−0.020	0.012	−0.282**
	(0.026)	(0.016)	(0.022)	(0.023)	(0.139)
2014	0.032	0.029	0.036	0.056	0.330**
	(0.061)	(0.050)	(0.026)	(0.038)	(0.159)
2016	0.053	0.118*	0.052	0.082	0.398**
	(0.081)	(0.062)	(0.038)	(0.064)	(0.193)
Observations	52,197	52,193	51,626	51,640	50,195
B - Wholesale and retail trade; repair of motor vehicles and motorcycles sector					
Pre-average	−0.011	−0.089***	0.079***	0.016	0.041
	(0.015)	(0.019)	(0.030)	(0.023)	(0.034)
Post-average	0.377***	0.407***	0.256***	0.281***	−0.020
	(0.081)	(0.108)	(0.051)	(0.053)	(0.035)
2012	−0.011	−0.089***	0.079***	0.016	0.041
	(0.015)	(0.019)	(0.030)	(0.023)	(0.034)
2014	0.310***	0.501***	0.262***	0.321***	−0.023
	(0.074)	(0.112)	(0.052)	(0.045)	(0.035)
2016	0.445***	0.313***	0.250***	0.240***	−0.017
	(0.089)	(0.105)	(0.061)	(0.065)	(0.035)
Observations	12,609	12,591	12,546	12,544	12,424

Results are estimated from csdid; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

Table C1.3: The effects of the Horizon 2020 program on firms' innovation for different sectors (cont.)

	Product innovation (1)	Process innovation (2)	Organizational innovation (3)	Marketing innovation (4)	Expenditure on innovation (5)
C - Information and communication sector					
Pre-average	0.020	−0.027	0.036	0.037	−0.023
	(0.041)	(0.038)	(0.069)	(0.024)	(0.155)
Post-average	0.219***	0.077	0.057	0.121**	0.014
	(0.065)	(0.059)	(0.044)	(0.050)	(0.196)
2012	0.020	−0.027	0.036	0.037	−0.023
	(0.041)	(0.038)	(0.069)	(0.024)	(0.155)
2014	0.244***	0.091	0.038	0.140***	0.037
	(0.074)	(0.065)	(0.070)	(0.043)	(0.197)
2016	0.194***	0.063	0.077	0.102	−0.009
	(0.064)	(0.064)	(0.054)	(0.075)	(0.201)
Observations	8,724	8,731	8,642	8,644	8,395
D - Professional, scientific and technical activities sector					
Pre-average	0.090	0.116	0.193***	0.246***	−0.027
	(0.058)	(0.086)	(0.027)	(0.048)	(0.053)
Post-average	0.111	−0.0003	0.068	0.070	0.146
	(0.139)	(0.144)	(0.092)	(0.114)	(0.100)
2010	0.252***	0.409***	.411***	0.516***	−0.032
	(0.069)	(0.128)	(0.057)	(0.051)	(0.106)
2012	−0.073	−0.177***	−0.026	−0.024	−0.022
	(0.077)	(0.052)	(0.046)	(0.098)	(0.081)
2014	0.029	−0.059	−0.084	−0.026	0.107
	(0.125)	(0.180)	(0.071)	(0.128)	(0.098)
2016	0.193	0.059	0.219	0.166	0.186
	(0.170)	(0.150)	(0.166)	(0.168)	(0.123)
Observations	8,706	8,706	8,578	8,565	8,240

Results are estimated from csdid; Clustered standard errors at the country-sector level are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Control variables: Turnover, employment growth, local fund, and government fund.

C2 Robustness Checks

Propensity Score Matching

CIS data provides information concerning firms receiving funds from the Horizon 2020 program. However, it is impossible to observe if firms applied for the program but were rejected from receiving subsidies. Since the allocation of grants under the Horizon 2020 program is both unobserved and non-random, it does not qualify as a randomized experiment. As a result, we cannot directly compare the treated firms with a randomly selected group of control firms. This non-random nature of the experiment causes sample selection bias (Heckman, 1979), which is mitigated by employing propensity score matching (PSM) (Rosenbaum & Rubin, 1983). PSM relies on the conditional independence assumption, meaning that if a set of variables influencing the treatment can be identified, controlling for the propensity score alone is sufficient to ensure that treatment assignment is independent of the outcomes (Asdrubali & Signore, 2015). We apply PSM based on firm characteristics that reflect various aspects of firm activities to create a control group with a distribution of characteristics similar to that of the treated firms (those receiving subsidies). Firm's characteristics used in the study are: firm's types of innovation (product innovation, process innovation, organizational innovation, marketing innovation), expenditure on innovation, turnover, employment growth, turnover growth, firm's size (under 50, 50 - 249, 250 - 499, 500 and more employees), status of firms receiving other funds (local fund, government fund). The nearest neighboring PSM without replacement is employed.

After conducting PSM, it is crucial to test the quality of matching. We provide both *standardized mean difference (SMD)*[14], which is adopted widely in social science (Austin, 2011) and variance ratio. SMD measures the difference in means between the treated and control groups, standardized by the standard deviation. It's robust to sample size and allows for comparison across different covariates. Large raw differences indicate significant pre-treatment differences. Small matched differences indicate good balance. The value of *SMD* less than 0.1 shows perfect balance, above 0.1 and less than 0.2 indicates acceptable balance, and above 0.2 means a poor balance. The variance ratio compares the variance of the covariate in the treated group to the variance in the control group. If the variances are similar, the ratio will be close to 1. This ensures that not only the means but also the distributions of the covariates are similar. The good value of the variance ratio stays in the range ideally between 0.8 and 1.25 or 0.5 and 2. The balancing test results are in Table C2.1. All the values of SMD and the variance ratios prove that the propensity score matching reaches perfect balance.

Table C2.1: Balancing test

Variables	**SMD**		**Variance ratio**	
	Raw	Matched	Raw	Matched
Size1 (under 50)	0.190	0.010	0.962	0.996
Size2 (50 - 249)	−0.045	−0.019	0.961	0.982
Size3 (250 - 499)	−0.075	0.048	0.746	1.244
Size4 (500 and more)	−0.125	−0.022	0.613	0.908
Turnover (log)	0.133	−0.077	0.762	0.781
Employment growth	−0.035	0.004	0.716	1.281
Local funds	0.219	0.094	2.685	1.414
Government funds	0.238	0.105	1.985	1.294

[14] $SMD(X) = \frac{\bar{X}_{treated} - \bar{X}_{control}}{\sqrt{\frac{s^2_{treated} + s^2_{control}}{2}}}$, where $\bar{X}$ is the mean of variable X, s is standard deviation of X.

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