Essays on Offshoring, Innovation and Foreign Ownership

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A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

The University of Sheffield

Faculty of Social Sciences

Department of Economics

September 2023

Abstract

This thesis consists of three empirical studies that examine the implications of globalization on both firms and workers. Using data from Peru and Spain, it evaluates the effect of offshoring on labour market outcomes, along with the impact of R&D outsourcing and foreign ownership on innovation.

Chapter Two evaluates how South-South offshoring, at the occupational level, affects the labour market outcomes in Peru based on the tasks performed by workers. This effect is assessed by building a continuous measure of routine, manual, and abstract intensive tasks, alongside an indicator of occupational exposure using data from the US O*Net and the Eora Global Supply Chain database, respectively. This chapter finds that Peru offshores routine-manual intensive tasks to other southern countries and specialises in routine-cognitive tasks, increasing the wages of formal and informal workers who perform routine intensive tasks. However, this increase is associated with different transitions across occupations and sectors for the formal and informal workers, providing evidence that these two groups of workers respond differently to offshoring. In addition, the results suggest that there is no relationship between South-South offshoring and the transition from formal to informal markets. However, they confirm that informality prevents displaced informal workers from becoming unemployed.

Chapter Three examines the causal relationship between R&D outsourcing and the intensive and extensive margin of R&D based on a theoretical model that explains the firm's decision to outsource as well as the interplay between internal and external R&D. To assess the causal impact of R&D outsourcing on the internal and total R&D investment, this

chapter employs a combination of matching methods and difference-in-difference (DID) approach with multiple time periods, using data from Spanish firms. Results suggest that R&D outsourcing positively affects the internal and total R&D investment, indicating a lower elasticity of substitution between both inputs of knowledge. However, the findings differ according to the firm's export status and type of outsourcing (Domestic or international). For the extensive margin, this study employs an empirical analysis at the industry level, finding that in industries where R&D outsourcing is more profitable, fewer firms invest in total R&D.

Chapter Four assesses the causal effect of foreign ownership on the probability of innovation cooperation using the same data from Spanish firms as Chapter Three. Furthermore, this chapter differentiates the effect of foreign ownership, both in the context of the global financial crisis (GFC) and in regular economic times. This analysis relies on a matching method technique combined with a triple difference-in-difference (DiDiD) approach. The findings indicate that, on average, foreign-acquired firms are less likely to cooperate in innovation with domestic firms compared to non-acquired firms. However, they exhibit a higher propensity to collaborate on innovation with local partners during periods of crisis.

Declaration

I confirm that the thesis I have presented for examination for the Ph.D. degree at the University of Sheffield is solely my work. I am aware of the University's Guidance on the Use of Unfair Means. This work has not been previously presented for an award at this, or any other, university.

Acknowledgements

I would like to express my sincere gratitude to my supervisors, Antonio Navas and Peter Wright, for their valuable support and guidance throughout my PhD journey. Their expertise, feedback, and encouragement have been crucial in shaping the direction and quality of my research. I am thankful for their commitment to my academic growth and confidence in my abilities. I would also like to thank Enrico Vanino for his comments and guidance during the past years.

I am grateful to the Department of Economics of The University of Sheffield for the scholarship that I received to conduct my PhD studies. In addition, I would like to express my gratitude to my Ph.D. colleagues at the Department of Economics, Tom, Maria Petrillo, Maria Padilla, Michael, Bingxue, Lucy, Dongzhe, and Cindy; it has been such a great experience to share this journey together.

My family has been an incredible support during these years of my Ph.D. My parents, Manuel and Maria, always encourage me to work hard and persevere. My siblings, Sandra and David, were also a huge support, taking care of my parents. To my lovely husband, Kevin, who has consistently stood by my side throughout my professional journey, offering support during both my ups and downs. Also, I would like to express my gratitude to my uncles and aunts, Cesar, Susana, Alcira and Oscar, and my in-laws, Carlos and Nery, for their guidance and support. Last but not least, to my dear friends Pierina and Aaron, thanks a lot for the video calls, chats, laughs, and trips together, you made this journey smoother.

I dedicate this thesis to my grandparents, Dalila, Segundo, Jose and Mercelinda.

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Chapter 1

Introduction

1.1 Background and Motivation

In the past seven decades, global trade has grown by 45 times, mainly because of the decrease in trade barriers and the development of new technologies that lowered transportation, communication, and transaction costs. This growth has played a crucial role in global economic expansion, leading to a convergence of incomes between many developing and advanced economies. However, the benefits of trade have not been distributed uniformly across all economies. Even though global trade has mitigated inequality among countries by reducing the gap between emerging and advanced economies, it has also contributed to increasing inequality within economies (WTO 2023).

The same factors that drive global economic growth, such as specialisation, competition, and innovation, which allow producing more and better with less, also create winners and losers in both developed and developing economies, as people and firms may benefit more or less from economic specialisation and technological change (Autor & Handel 2013). Trade enables economies to specialise and export goods and services they can produce at a lower cost while importing those they cannot. This fosters the development of highly competitive sectors and benefits the firms and workers within them. However, the imports of goods and services may compete with the ones produced by local producers. Therefore, trade results not only in the growth of competitive sectors but also in the decline of other sectors. This adverse impact affects both firms and workers within these sectors, leading to the reallocation of workers to other industries and periods of temporary or permanent spells of unemployment. (WTO 2017)

Most of the studies on the effects of trade on labour market outcomes focused on the impact of import competition on the labour market of developed and developing countries. These studies are based on the traditional factor-endowment theory of comparative advantage which states that trade would increase the relative demand for skills in an advanced economy that is relatively skill-abundant, while in a low-income economy, where skills tend to be relatively scarce, trade could lead to an increase relative demand for low-skilled labour thus an increase in their wages. However, the empirical analysis has demonstrated that international trade increases the relative employment of skilled workers both in developed and developing countries (Feenstra & Hanson 1999). Therefore, recent theories propose another channel through which trade can result in a rising demand for skilled workers in both developed and developing countries. This theory highlights the task content of occupations as a determinant of whether a job is susceptible to import competition and whether it is suitable to be offshored. Occupations that involve repetitive, easily codifiable tasks are not only easy to automate but also to relocate. Conversely, non-routine jobs requiring abstract thinking and in-person communication are much less tradeable (Grossman & Rossi-Hansberg 2008, 2012, Baumgarten et al. 2013, Ebenstein et al. 2014).

As offshoring costs fall, the trade in intermediate inputs has also increased during the last two decades, being the most remarkable trade between South-South countries, which rose from 6% in 1988 to 25% in 2013 (WTO 2014). Nevertheless, despite this increase, the empirical and theoretical framework had focused on the effect of offshoring on the labour market of developed countries when North-North or North-South offshoring occurs. However, the consequences of South-South offshoring on the labour market of developing countries remain unexplored. Thus, building upon existing literature and the recent offshoring theory that links the effect on wages to the tasks performed by workers, the second chapter of this thesis aims to assess the effect of South-South offshoring on the labour market in Peru. Given that Peru has a high level of informality in its labour market as many other developing countries, this thesis also aims to explore how informality affects the relationship between offshoring and wages, employment, and worker displacement.

Furthermore, international trade exposes firms to global competition by allowing them to access markets beyond their domestic borders. This access provides an opportunity for growth, but it also opens the door for foreign firms to enter and compete in domestic markets. This dynamic pushes domestic firms to enhance productivity and foster innovation to stay competitive. Consequently, outsourcing of R&D emerges as a strategy to foster innovation. R&D outsourcing offers firms access to external expertise and knowledge, often at lower cost, enabling more efficient resource allocation and accelerating the development of new technologies and products (Chesbrough 2003, García-Vega & Huergo 2018). However, the effect of R&D outsourcing on innovation is not straightforward. The outsourcing of R&D can boost innovation by accessing external resources, yet it can also prevent it. This is because knowledge tends to accumulate over time, and innovation requires prior experience (Griffith et al. 2004, Geroski 2005). Thus, R&D outsourcing may diminish firms' capacity to absorb new knowledge, preventing the creation of innovation.

As a result, the empirical studies have focused on the impact of R&D outsourcing on firms' innovation outputs, such as product or process innovation, and firms' performance, finding that the relationship between internal and external R&D matters for the effect of external R&D on innovation. These studies suggest that firms that invest in both internal and external R&D and foster a complementary relationship between these inputs of knowledge, experience and an increase in innovation performance (Cassiman & Veugelers 2006, Lokshin et al. 2008, Belderbos et al. 2013). Conversely, the substitution of internal R&D for external R&D could weaken innovation performance since it could reduce the firm's ability to recognise, exploit and benefit from external knowledge. However, although R&D outsourcing can affect internal R&D investment by either substituting or complementing it and despite the importance of internal R&D for the internalisation of external R&D and improving firms' innovation performance, there is no evidence regarding the impact of R&D outsourcing on the inputs of innovation, namely the internal and total R&D investment.

Therefore, the third chapter of this thesis contributes to the current literature by assessing the impact of R&D outsourcing on innovation inputs (i.e. internal and total R&D investment) at the firm level and how it affects the number of firms engaged in R&D within an industry. Moreover, previous research has examined how R&D outsourcing influences innovation outputs, drawing from theoretical models such as transaction cost theory[1], knowledge-based view[2], and resource-based view [3] to explain the reason behind R&D outsourcing decisions. Unlike these theories, which primarily focus on the motives to outsource R&D, the empirical analysis presented in this chapter is based on a theoretical model developed by Navas (2021). This model explains a firm's decision-making process regarding R&D and its subsequent implications for both internal and overall R&D activities at the firm level. In addition, this model explores how R&D outsourcing can either encourage or hamper the participation of firms in R&D activities.

Finally, foreign direct investment (FDI), specifically through foreign acquisitions led by multinational corporations (MNCs), represents another mechanism for enhancing efficiency and innovation within firms, thus contributing to economic growth. Multinational corporations engaged in FDI provide acquired firms entry to export markets, lower innovation costs, and access to proprietary technologies, thereby increasing the productivity

[1]It states that a firm's choice between internal and external R&D strategies depend on the costs and risks associated with each option (Croisier 1998, Beneito 2003)

[2]It emphasises the core competence in which firms conduct R&D outsourcing to increase their technological competence and to exploit potential complementarities between internal and external R&D (Becker & Dietz 2004, Cassiman & Veugelers 2006, Lokshin et al. 2008)

[3]It states that R&D outsourcing may provide firms with access to resources that are not available internally (Grimpe & Kaiser 2010, Weigelt 2009, Yasuda 2005)

and innovation of the acquired firms (Guadalupe et al. 2012, García-Vega et al. 2019).

Furthermore, the presence of MNCs' subsidiaries in the host country can impact domestic firms' innovation through the relationship between MNCs' affiliates and local stakeholders such as suppliers, customers, and research institutions. Therefore, MNCs' affiliates provide channels of resource-sharing between the MNCs and the host country, which can contribute to the innovation capabilities of domestic firms (Scott-Kennel et al. 2022). However, the transfer of R&D resources from MNCs to their affiliates does not automatically result in the diffusion of these resources throughout the host economy. Different factors, including concerns about intellectual property protection, workforce expertise limitations, and the absence of incentives for knowledge sharing, can contribute to the lack of knowledge transfer. Therefore, this sharing mechanism is more likely to occur when there is a collaborative innovation effort between foreign subsidiaries and local companies, as foreign affiliates are more motivated to exchange knowledge when it is reciprocal (Veugelers & Cassiman 2004). Thus, innovation cooperation projects serve as an effective means to transfer technology from MNCs' subsidiaries to domestic firms.

Consequently, many studies have examined the relationship between foreign ownership and the likelihood of cooperation in innovation with local partners, finding mixed results (Srholec 2009, 2011, Holl & Rama 2014, García-Sánchez et al. 2016, Veugelers & Cassiman 2004, Knell & Srholec 2005, Ebersberger & Herstad 2012, Guimón & Salazar-Elena 2015). Therefore, unlike these studies, and in light of the lack of consensus on whether foreign subsidiaries are more likely to cooperate in innovation with local partners, the fourth chapter of this thesis aims to assess the causal effect of foreign ownership on the likelihood of innovation cooperation. The latter is achieved by comparing acquired and non-acquired firms before and after foreign acquisition, using data from Spanish firms. Moreover, given that Spain was one of the European countries most severely affected by the Global Financial Crisis (GFC) (García-Sánchez et al. 2016, García-Sánchez & Rama 2022), this chapter also contributes to the current literature on foreign ownership by distinguishing the effect of foreign ownership on the likelihood of innovation cooperation, both in the context of the GFC and in regular economic times.

1.2 Chapter Overview

1.2.1 Overview of Chapter 2

Chapter 2 examines the effect of offshoring on the labour market of a developing country. This chapter is driven by the increasing trade in intermediate inputs among developing countries and the absence of evidence regarding the labour market outcomes when offshoring occurs between developing countries. Consequently, this chapter uses data from the Peruvian National Household Survey (ENAHO) to investigate the influence of offshoring on various aspects, including wages, employment, displacement, and the earnings of displaced workers. Furthermore, motivated by the empirical literature on offshoring (Autor et al. 2003, Blinder & Krueger 2013, Crino 2010), which has demonstrated that the impact of offshoring on workers depends on the task content of occupations rather than the worker's qualifications, the effect of offshoring is analysed at the occupational level according to the tasks that workers perform. In addition, given the high level of informality in the Peruvian labour market (72.8%),[4] the chapter also explores how this informality shapes the relationship between offshoring and wages.

To assess the impact of offshoring at the occupational level according to the tasks performed by workers, an indicator for occupational exposure and a continuous measure for routine, manual, and abstract intensive tasks were created. These measures are built based on the information obtained from the EORA input-output tables and the US O*Net, respectively. The effect of offshoring on workers' wages is assessed using a Mincer wage equation (Mincer 1974). The influence of offshoring on employment and displacement is evaluated by considering the likelihood of transitioning into unemployment, the prob-

[4]Source: Peruvian National Institute of Statistics and Informatics (INEI)

ability of changing occupations within and across sectors, as well as transitions in and out of informality. To explore how offshoring affected the earnings of displaced workers, propensity score matching techniques are employed.

This study finds that Peru offshores routine-manual intensive tasks to other southern countries and specialises in routine-cognitive tasks, increasing the wages of formal and informal workers who perform routine intensive tasks. Nonetheless, in the case of formal workers, this increase is associated with the likelihood of switching occupations upward within the same sector, primarily toward routine cognitive tasks. Conversely, for informal workers, this increase is related to the probability of switching occupations upward across sectors but toward less-exposed occupations, mainly toward manual-intensive tasks. The latter provides evidence that formal and informal workers respond differently to offshoring. In addition, the results suggest that there is no relationship between South-South offshoring and the transition from formal to informal markets. However, they confirm that informality prevents displaced informal workers from becoming unemployed due to offshoring.

1.2.2 Overview of Chapter 3

The chapter is motivated by the literature on R&D outsourcing and innovation (Becker & Dietz 2004, Belderbos et al. 2013, Berchicci 2013, Cassiman & Veugelers 2006, Cohen & Levinthal 1990, Lokshin et al. 2008), which has focused on the effect of R&D outsourcing on the outputs of innovation such as product or process innovation. However, R&D outsourcing can also affect internal R&D investment by substituting or complementing it. Therefore, this chapter contributes to the current literature by analysing the effect of R&D outsourcing on the inputs of innovation (internal and total R&D investment) based on Navas (2021) theoretical model, which explains a firm's decision to outsource R&D and the consequences of this decision on the internal and total R&D investment. Moreover, this theoretical model also sheds light on the implications of R&D outsourcing for the extensive margin of R&D, indicating that in industries where R&D outsourcing is more profitable, fewer firms invest in R&D. Consequently, this chapter also evaluates the relationship between R&D outsourcing and the extensive margin of R&D.

To assess the causal impact of R&D outsourcing on the internal and total R&D investment, this study employs a combination of matching methods and a difference-in-difference (DiD) approach with multiple time periods (Callaway & Sant'Anna 2020), using data from the annual survey of Spanish firms called Panel de Innovación Tecnológica (PITEC). This effect is also differentiated according to the firm's export status and the type of R&D outsourcing (domestic or international). For the extensive margin, the empirical analysis is conducted at the industry level where an ordinary least square (OLS) model is used to assess the profitability of R&D outsourcing on the share of firms investing in R&D.

Results suggest that R&D outsourcing positively affects the internal and total R&D investment, indicating a lower elasticity of substitution between both inputs of knowledge. Following the theoretical framework, R&D outsourcing encourages firms to invest more in R&D by increasing the efficiency of the production of knowledge. The effect on internal and total R&D investment differs according to the firm's export status and type of outsourcing (domestic or international). Exporters and non-exporters experience a positive impact on their internal and total R&D investment. However, the effect on internal R&D for non-exporters is relatively weaker in terms of statistical significance and tends to diminish over time compared to the effect on internal R&D for exporting firms. Regarding the type of outsourcing, firms that undertake domestic R&D outsourcing see a positive impact on both internal and total R&D. In contrast, firms that simultaneously undertake domestic and international R&D outsourcing do not experience a statistically significant increase in their internal R&D investment but in their total R&D, implying more reliance on external R&D. For the extensive margin, this study finds that in industries where R&D outsourcing is more profitable, fewer firms invest in total R&D.

1.2.3 Overview of Chapter 4

Using the same data from Spanish firms, chapter 4 is built upon the literature on knowledge transfer and the influence of Multinational ownership (Srholec 2009, 2011, Ebersberger & Herstad 2012, Holl & Rama 2014, García-Sánchez et al. 2016, García-Vega et al. 2019). These studies suggest that multinational subsidiaries can influence the innovation of domestic firms through collaborative innovation efforts, as they are motivated to share their knowledge when there is a mutual opportunity to access valuable expertise. Therefore, this chapter contributes to the existing literature by examining the causal effect of foreign ownership on the occurrence of innovation cooperation, distinguishing between the propensity to cooperate with domestic and international partners. Furthermore, unlike previous studies, this chapter addresses the issue of selection bias in foreign ownership to prevent post-acquisition outcomes from being influenced by pre-existing characteristics among acquired firms. In addition, given that Spain was severely affected by the 2008 crisis, this study also distinguished the effect of foreign ownership on the likelihood of innovation cooperation, both during the crisis and in regular economic times.

The empirical analysis applies a matching method combined with a DiD approach. Following the matching process, the likelihood of cooperation in innovation is estimated through a DiD regression of the event study type, which captures the dynamic effects of foreign ownership over time. The propensity to cooperate in innovation during the crisis is evaluated by including a triple difference-in-difference (DiDiD) in the regression. The triple difference estimation indicates the difference in the post-acquisition outcome between firms acquired during the crisis and those acquired in regular economic times.

The findings suggest that, on average, foreign-acquired firms are less likely to cooperate in innovation with domestic firms compared to non-acquired firms. In contrast, they exhibit a higher propensity to cooperate in innovation with international partners than non-acquired firms, especially with firms that belong to the same business group located in the United States and Europe. Interestingly, the outcomes indicate that foreign-owned firms are more likely to cooperate in innovation with local partners during the crisis. These results have policy implications, they call for customized policies that facilitate the connection between foreign subsidiaries and domestic firms, especially during harsh economic times.

Chapter 2

South-South Offshoring: The Peruvian Case

2.1 Introduction

The phenomenon of offshoring (i.e. the reallocation of the different stages in the production of goods across industries and countries) has increased over time mainly due to transportation and communication technology advances. The latter has come with an increase in trade in intermediate inputs, accounting for as much as two-thirds of international trade (Johnson & Noguera 2012). In particular, during 1988-2013, South-South trade in intermediate goods increased from 6% to almost 25%, while North-South trade in intermediate goods only increased from 30% to 40% (WTO 2014). The significant increase in the share of trade in intermediate goods between developing countries suggests potential offshoring activities between them.

Even though South-South trade in intermediate inputs has increased, the current literature on offshoring has mainly focused on the impact of offshoring on the labour market of Northern countries when North-North or North-South offshoring occurs. However, there is no evidence of the consequences of offshoring on the labour market of developing countries when offshoring is between Southern countries. Therefore, this study aims to assess, for the first time, the effect of offshoring on a developing country's labour market, such as the effect on wages, employment and the earnings of displaced workers, when offshoring occurs between southern countries, using Peru as a case study.

The effect of offshoring on workers' wages is not theoretically straightforward. Theories of offshoring try to explain the offshoring impact on workers' wages, considering differences in the labour force skills (Feenstra & Hanson 1997, Burstein & Vogel 2010) or the tasks that workers perform (Grossman & Rossi-Hansberg 2008, 2012) between countries. However, most of the empirical evidence has demonstrated that the task content of occupations matters over and above skills since they find different effects on workers who belong to the same skill groups (Autor et al. 2003, Blinder & Krueger 2013, Crino 2010). Under this framework, the impact of offshoring on workers' wages no longer primarily depends on people's qualifications; instead, it will depend on the tasks that workers perform. Namely, even the task a skilled worker performs can migrate to another country if this task is easy to delegate.

The offshoring theory based on the task content of occupations, finds two possible effects on workers' wages when North-South offshoring occurs (Grossman & Rossi-Hansberg 2008). Considering the case in which the South is relatively unskilled labour abundant, a reduction in the cost of offshoring facilitates and increases North-South offshoring. The latter leads to differences in wages across countries, inducing the reallocation of jobs towards the South, where the wages are lower. As a result, employment and domestic wages fall in the offshoring country (price effect). On the other hand, access to cheaper foreign inputs may lower a firm's costs and raise its productivity, allowing it to expand economy-wide employment and raise domestic wages in the offshoring country (productivity effect). Therefore, the effect of offshoring on workers' wages is ambiguous for domestic workers since their wages can increase or decrease depending on the dominant effect. However, the empirical evidence shows that the relative price effect dominates for North-South offshoring because it harms the wages of workers who perform routine intensive tasks in the North, which may imply a substitution of these tasks by the ones carried out in the South (Ebenstein et al. 2014, Hummels et al. 2014, Baumgarten et al. 2013).

However, when offshoring occurs between similar countries, this theory does not explain the effect of it on workers' wages. Grossman & Rossi-Hansberg (2012) argue that, unlike North-South offshoring, which is driven by wage differentials, offshoring between similar countries occurs because of the economies of scale at the task level, where the experience and local knowledge of performing a task play a central role in offshoring. They suggest that similar countries specialise in complementary tasks.[1] Similarly, Harrison & McMillan (2011) show that domestic and foreign employment are complements when North-North offshoring occurs. In contrast, foreign and domestic employments are substitutes when North-South offshoring happens. Up to now, empirical studies have attempted to assess the impact of offshoring on workers' wages when it occurs between similar countries, but they have focused on the North-North offshoring case. These studies show a positive effect on the wages of workers who perform non-routine tasks (both domestic and foreign workers) when North-North offshoring occurs because the latter leads to an increase in the demand for this kind of task in Northern countries(Ebenstein et al. 2014, Spitz-Oener 2006). But how has South-South offshoring affected the wages of domestic workers? Who are the winners and losers of offshoring in this case?

To the best of my knowledge, there is a lack of a conceptual structure and of empirical studies that assess the wage return to tasks and the task specialisation in Southern countries when South-South offshoring happens. However, empirical studies suggest that developing countries specialise in routine-intensive tasks when North-South offshoring occurs (Acemoglu & Autor 2011, Spitz-Oener 2006). Nevertheless, there is no evidence of task specialisation in Southern countries when South-South offshoring occurs.

Therefore, in this paper, I assess the effect of offshoring on workers' wages considering the task content of occupations when South-South offshoring occurs. For this purpose, I use worker-level data from the Peruvian labour survey (ENAHO),[2] industry-level data

[1]For instance, the United States specialises in tasks that are non-routine and either interactive or analytic; likewise, Germany also specialises in non-routine tasks but in a different set of them, namely, those that are more manual (Autor et al. 2003, Spitz-Oener 2006)

[2]ENAHO data cover the Peruvian labour force during 2007-2016, allowing me to track every person

on manufacturing intermediate imports from the EORA input-output table, and the task content of occupations from the US O*NET dataset. To assess the impact of offshoring at the occupational level, I built an occupation measure following the methodology developed by Feenstra & Hanson (1999) and Ebenstein et al. (2014). This measure allows me to capture the offshoring effects on wages of workers in occupation k employed in the manufacturing sector as workers in occupation k employed in non-manufacturing sectors. To consider the task content of occupations, I built a continuous measure of manual, abstract and routine intensity, combining the methodologies developed by Acemoglu & Autor (2011), Autor & Handel (2013), and Casabianca et al. (2018). Then, I merge the worker's level data with task content and the intermediate imports at the occupational level.

Considering that Peru is a developing country, I also explore how its high level of informality (around 72.8% of employees are employed in the informal sector) shapes the relationship between offshoring and wages. [3] Since informality is associated with low education and low social protection, informal workers are more vulnerable to trade shocks and face more earning risks than formal workers. Despite that, the current literature on trade and the labour market of developing countries mainly focuses on the impact of trade on formal workers' wages when informal workers represent a significant share of the labour force in developing countries. Therefore, I estimate the effect of offshoring on wages for formal and informal workers separately. Unlike the literature related to trade and informality, for the first time, my research focuses on the impact of offshoring on formal and informal workers' wages.

Finally, offshoring may also lead to displacement, unemployment, and wage change for workers who reattach to new firms and sectors. For that reason, it is important to

over time, regardless of his/her employment status

[3]According to the Peruvian National Institute of Statistics and Informatics (INEI by Spanish acronym), the informal market is composed of firms neither incorporated nor registered in the tax authority and by workers who do not have benefits stipulated by law such as social security, gratifications, etc.

understand the constraints that informality may impose on the participation of informal workers in offshoring. For instance, the high level of informality may act as a poverty trap preventing the successful reallocation of workers within the formal economy and displacing them to the informal market or towards high-informal occupations. Hence, my research aims to answer the following questions: Is South-South offshoring inducing the reallocation of workers in and out of informality? Does the informal worker respond as the formal to the offshoring impact? To examine the probability of displacement induced by offshoring (switching occupations within and across industries, transitions to unemployment and transitions in and out of informality), I follow the methodology of Liu & Trefler (2019). In addition, I estimate the wage change of displaced workers by calculating the Average Treatment Effect (ATE) that compares each switcher with a similar worker who did not switch.

My results show that workers who perform routine-intensive tasks experience a rise in their wages due to offshoring. This result provides evidence of the effect of South-South offshoring on wages in the context of the emergent Peruvian economy, suggesting that Peru specialises in routine-intensive tasks when Peru-South offshoring occurs. In addition, the results also indicate that both formal and informal workers who perform routine-intensive tasks experience an increase in their wages of 5% and 7%, respectively. However, the increase in formal workers' wages is associated with the likelihood of switching occupations upward within the same sector. In contrast, informal workers' wage growth is related to the probability of switching occupations upward but across sectors, especially towards less-exposed occupations. In addition, informal workers are more likely to switch from routine-intensive to manual-intensive occupations, which prevents them from gaining new skills and competence to specialise in routine-intensive tasks. Therefore, informality is not only a concern in terms of tax collection, but it is also a constraint for task specialisation.

The paper is structured as follows. The next section provides a review of the literature on offshoring and informality. Section 2.3 presents the motivation to measure the effects of Peru-South offshoring. Section 2.4 describes the empirical strategy and data. Section 2.5 reports the results for wages according to the task content. Section 2.6 presents the results of the labour market adjustment. Section 2.7 provides an overview of all the findings. Section 2.8 includes robustness checks, and the last section concludes.

2.2 Literature Review

My work is closely related to the theory of offshoring between similar countries developed by Grossman & Rossi-Hansberg (2012). They use a continuous measure of tasks and analyse the offshoring between similar countries in terms of technology and factor endowments. They state that the basis for offshoring between similar countries is the economies of scale at the task level. The theory suggests that similar countries specialise in complementary tasks. However, the model does not explain the effect of offshoring on workers' wages.

Therefore, my research is also related to and expands on the empirical literature about offshoring and tasks (Spitz-Oener 2006, Harrison & McMillan 2011, Baumgarten et al. 2013, Ebenstein et al. 2014). In particular, it is closely related to Ebenstein et al. (2014), who analyses the offshoring effects on workers' wages in the case of developed countries when North-South and North-North offshoring occurs. They build a measure of offshoring at the occupational level to capture the trade effects on workers' wages, not only from the industry where workers belong but also by offshoring activities in other industries. They find a significant and higher effect of offshoring on workers' wages at the occupational level than at the industry level, showing that workers involved in more routine tasks in the North are positively affected by the offshoring between Northern countries. In contrast, they experience a negative effect on their wages when offshoring occurs between North-South countries. The latter suggests that the tasks performed by the North complement each other, and the tasks performed by The South substitute the North's task. My research differs from these empirical studies since, for the first time, I analyse the South-South offshoring effects. It also differs from the previous studies by assessing the wage change of displaced workers due to offshoring and incorporating the informal workers in the offshoring analysis.

By assessing the wage change of displaced workers, my research is close to the recent work developed by Liu & Trefler (2019). They estimate the effects of offshoring in services on the likelihood of switching occupations (downward and upward) when offshoring takes place between developed (USA) and developing countries (China and India). They find that offshoring in services to China and India increases the likelihood of switching occupations downward and becoming unemployed for USA workers, making their wages fall by 15% and 47%, respectively. Unlike Liu & Trefler (2019), my study focuses on offshoring in the manufacturing sector rather than the service sector in the case of South-South offshoring. It expands the channels through which wages can be affected, considering switching occupations within and across sectors and transitions in and out of the informal market.

Finally, since this study is focused on developing countries, this paper is also related to the empirical studies which seek to assess the impact of trade on the level of informality and labour market adjustment in developing countries (Arias et al. 2018, Cisneros-Acevedo 2022, Dix-Carneiro & Kovak 2019, Dix-Carneiro et al. 2019, Goldberg & Pavcnik 2003, 2007, McCaig & Pavcnik 2015, Casabianca et al. 2018). The results regarding the impact of trade on the level of informality are mixed. On one hand, scholar suggest that trade displaces formal workers to informal employment (McCaig & Pavcnik 2015, Arias et al. 2018, Dix-Carneiro et al. 2019, Morales et al. 2021, Cisneros-Acevedo 2022). For instance, Cisneros-Acevedo (2022), utilizing data from the Peruvian labour survey, demonstrate that trade liberalization contributes to increased informality, primarily due to a rise in intensive-informal employment. Similarly, Morales et al. (2021), also drawing from the Peruvian labour survey, indicates that import competition increases the likelihood of having an informal job. Conversely, Menezes-Filho & M (2011) and Bosch et al. (2012)

do not find a significant relationship between trade and informality.

In contrast to these studies, my research focuses on the impact of offshoring from Southern countries rather than import competition. Moreover, this impact is evaluated at the occupational level rather than at the industry level, as seen in previous research. In addition, while Morales et al. (2021) examines the impact of import competition on formal and informal wages, their analysis relies on cross-sectional data, unlike my study, which utilizes longitudinal data. Furthermore, unlike these investigations, my study extends beyond the impact of trade on informality or wages; it also estimates the effect of offshoring on the labour adjustment of both formal and informal workers.

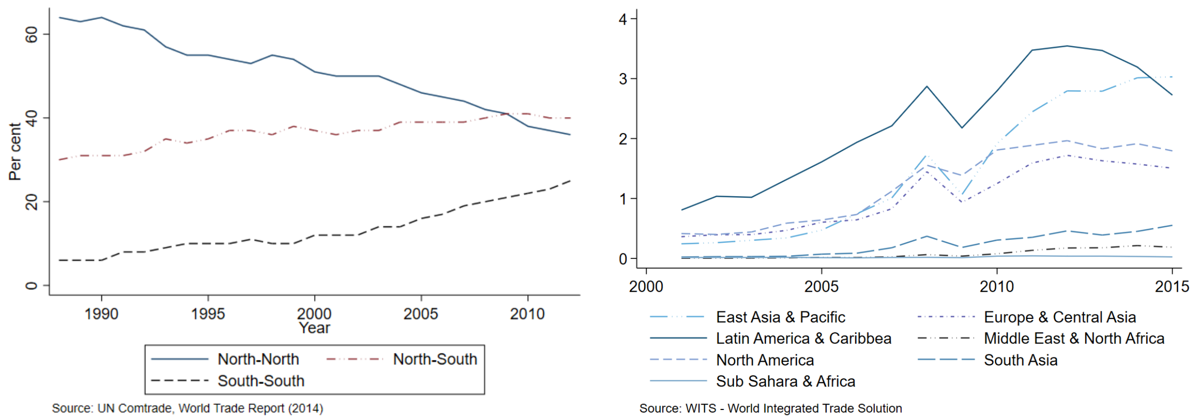
Concerning the labour market adjustment to trade in developing countries, Dix-Carneiro et al. (2019) observe that worker adjustment occurs primarily within the region, with regions more exposed to trade witnessing increased worker movement across industries. However, this reallocation is not large enough to offset the decline in formal employment. In contrast, Goldberg & Pavcnik (2007) state that there is a lack of reallocation of labour across industries in developing countries due to labour market regulations, suggesting that adjustment should occur within industries. These studies examine the reallocation of formal workers across industries or regions in developing countries such as Brazil due to import competition. In contrast, my research assesses labour adjustment, including both formal and informal workers, alongside analysing the reallocation of workers across occupations and spells of unemployment in Peru due to offshoring.

2.3 Offshoring between Developing Countries

More than one-quarter of world trade is in intermediate goods, and the share of trade in intermediate inputs between South-South countries has increased at a higher rate compared to North-South or North-North trade in intermediate goods (WTO 2014). Figure 2.1a shows the share of intermediate inputs between South-South, South-North, and North-North countries.

The increase in the share of trade in intermediate inputs between South-South countries is also reflected in the case of Peru since, in the last ten years, it increased its intermediate imports from developing countries by 134%. Figure 2.1b depicts the case of Peru, where the imports of intermediate goods from developing countries have increased, especially from Latin America and the East Asia region, even compared for instance with the imports from North America. Additionally, as per (UNCTAD 2015), the expansion of South-South trade in the last twenty years has predominantly centered on manufacturing. This is largely due to their complementarity with manufacturing, enabling the efficient combination of the various fragments of the production processes.

Figure 2.1: Share of Inputs in Parts and Components

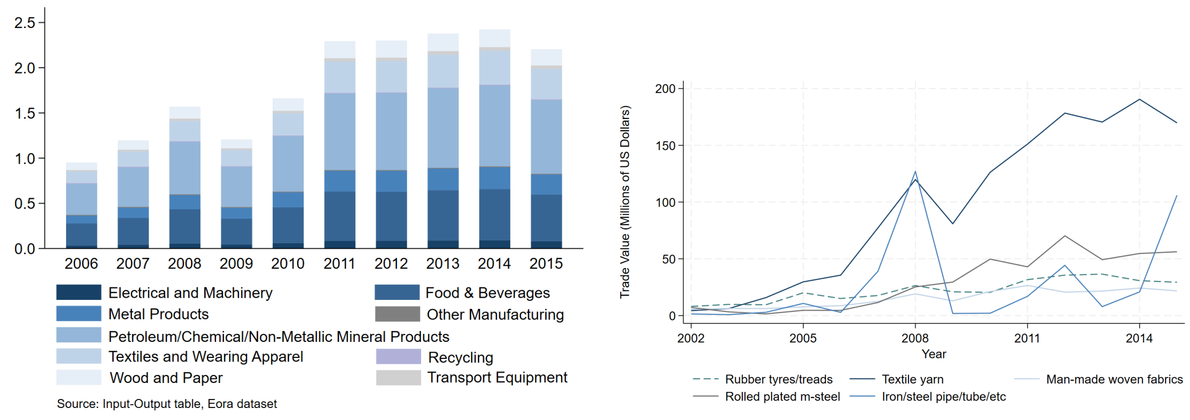


(a) Global **(b) Peru**

The rise in the importation of intermediate goods among developing nations is connected to the spread of Global Value Chains (GVCs) since access to specialized and more affordable inputs allows firms to enhance their efficiency and productivity in exporting, fostering their integration into the GVCs. Indeed, according to WTO (2014) report, the participation of the South on the global value chain has increased in the past one-and-half decades. This trend can be attributed to recent free trade agreements between developing countries, such as those signed by Peru with China, Colombia, Chile, Mexico, Bolivia, and Venezuela. These agreements have the potential to significantly impact the expansion of trade networks among developing countries (UNCTAD 2015).

Another way to measure the increasing participation of developing countries in GVCs is by considering their backward participation, which reflects the import content of exports, and forward participation, which captures the domestic value added in intermediate inputs of other countries' exports. Peru's role in GVCs is mainly to supply primary inputs through forward linkages. Even though Peru relies less on imported inputs for its exports due to limited backward linkages, Peru has still achieved significant success in trade integration (World Bank 2015, OECD 2013). For instance, in the food and beverage industry, Peru has earned a strong position by using a large number of imported inputs in its exports. Similarly, in the Apparel and Plastic industries, Peru has utilized imported inputs to upgrade and diversify its export markets. For example, the importation of high-quality cotton for apparel has led to a 50% increase in the value of products between 1998 and 2014. The increase in Peru's participation in the GVCs reinforces the trend of Peru-South offshoring by fostering specialization, building networks, expanding market access and promoting closer economic cooperation among countries within the Global South.

Figure 2.2: Peru - Manufacturing Intermediate Inputs from Developing Countries



(a) Manufacturing sector **(b) Intermediate Goods**

Moreover, Figure 2.2a depicts the Peruvian manufacturing intermediate imports from developing countries. Most of these imports come from sectors like petroleum, Chemical and non-metallic, textiles and wearing apparel, and metal products. These are the sectors where Peru has established connections with input providers, making it more likely for companies to move some of their operations abroad. In addition, Figure 2.2b illustrates the main intermediate goods imported from these sectors, with the textile yarn being the most imported input, followed by rubber tyres/treads, Man-made woven fabrics, rolled plated m-steel, and iron/steel pipe/tube.

The production of these intermediate goods entails highly routine tasks. For example, workers in the textile handicraft occupation (ISCO 08: 7318) produce textile yarn and man-made woven fabrics, engaging in activities like hand-spinning yarn and weaving cloth on looms, which are highly repetitive. Similarly, occupations associated with rolled plated m-steel or iron/steel pipe/tube involve routine tasks such as shaping metal through hammering or forging, and heating metal for shaping, typically carried out by blacksmiths and metal preparers (ISCO 08: 7221, 7214). Similarly, workers in occupations related to rubber tyre production, like plant machine operators (ISCO 08: 8141), perform routine tasks such as operating machinery to produce rubber sheets, mix rubber compounds, and assemble tyres. As a result, the increase in intermediate imports from developing countries is expected to affect occupations that involve routine-intensive tasks. This may lead workers in these occupations to switch to different occupations or sectors in response to the rise in inputs from developing countries.

Furthermore, alongside the uptick in intermediate manufacturing imports from other developing nations, there was a decline in employment levels within this sector during the same time, dropping from 11% of total employment in Peru in 2007 to approximately 8% in 2015 (International Labour Organization, ILO). These concurrent trends raise concerns about potential offshoring activities in the manufacturing sector, suggesting that Peruvian firms may have shifted a portion of their production to other developing countries. Additionally, unlike the manufacturing sector, the service sector is less competitive, with most of its sectors being non-tradable, resulting in limited information regarding intermediate imports. Consequently, this study focuses on the manufacturing sector, where the majority of workers are engaged in occupations requiring routine-intensive tasks, making them more susceptible to offshoring (refer to Table 2.1 and Figure 2.4).

2.4 Data and Methodology

2.4.1 Data

My primary data source on workers' characteristics and labour market outcomes is the Peruvian National Household Survey (ENAHO) between 2007-2016. The ENAHO is assembled annually by the Peruvian Statistical Agency (INEI) and is representative at the national level. The ENAHO contains information about individuals' characteristics such as wages, spells of unemployment, informal and formal employment, occupation, workers' sector, working hours, gender, age, and education, among others. Its panel nature allows me to address unobserved worker characteristics and differentiate the impact of offshoring among workers who belong to the same group (e.g. sector, occupation or skills), something that industry or firm-level data do not allow to do.

This dataset is available as cross-sectional and longitudinal data. The longitudinal data have a rotating panel sample design with an annual rotation of around 20% to avoid the attrition of the data due to the absence of respondents. Thus, this survey includes eight waves of panels grouped as follows: wave 1 = 2007-2011, wave 2 = 2011-2015, wave 3 = 2012-2016, wave 4 = 2013-2017, wave 5 = 2014-2018, wave 6 = 2015-2019, wave 7 = 2016-2020, and wave 8 = 2017-2021. In these waves of panels, an identification number is included per individual, making it possible to merge these waves by this identifier. Since waves 3 and 4 do not include the main identification number, I work with waves 1, 2, and 5.[4] These waves cover the years from 2007 to 2018, but I only use the information

[4]It is worth mentioning that the sample of workers included in waves 2 and 3 is the same for the years 2012-2015. Similarly, the sample of individuals included in waves 4 and 5 is the same for the years 2014-2017

on workers for the years 2007-2016 because the data about offshoring is only available for the period 2006-2015.

Each wave contains sub-samples, individuals who appear for 2, 3, 4 or 5 consecutive years. I used all the sub-samples and merged wave 1 to wave 2, using the identification number for individuals in 2011, which is the year in common between these two waves. Likewise, I merged waves 2 and 5 using the identification number in 2015, which is the year in common between these two waves. The sample of individuals for 2014 is the same in waves 2 and 5. Accordingly, I got an unbalanced panel for the period 2007-2016.

The data is restricted to a sample of workers who are between 14 and 65 years old.[5] People who worked in the armed forces and the public sector during the period of analysis were dropped. Similarly, people who worked as an unpaid family [6] during the sample period were also dropped. After cleaning the data, I have a final sample of 93,170 observations on 31,342 individuals. This sample includes individuals working in the whole economy. To restrict the analysis to the manufacturing sector, I consider the sample of workers employed in manufacturing in the first period of the analysis. Therefore, the number of observations for the manufacturing sector only is 9,644 on 3,334 individuals.

Table 2.1 reports the average percentage of workers per year during 2007-2016 according to their occupation and formal or informal employment. Workers in the manufacturing sector are mostly concentrated in craft occupations (54%), where 21.6% are informal, followed by elementary occupations (12%) and plant and machine operators (10.4%), where most of the workers are also informal. The chart reveals the high level of informality in Peru, which was, on average, 66% during 2007-2016 for the manufacturing sector. Whereas, considering all the sectors, workers are mostly concentrated in agricultural, and fishery occupations (26%) as well as in elementary (22%) and service and sale (21%) occupations, where the level of informality is also high. On average, the level of informality

[5]According to INEI, in Peru, the active population range in age is 14-65 years old

[6]The survey categorised as "unpaid family" those individuals who are employed within a family-owned business but do not receive a salary for their work.

in the Peruvian economy is around 81% during the term 2007-2016. From Table 2.1, we can also see that most of the workers in the manufacturing sector are concentrated in an occupation characterised by performing routine-intensive tasks (craft workers).

Table 2.1: Informality by Occupation 2007-2016

	Manufacturing Sector			All sectors		
Occupations	Informal	Formal	Total	Informal	Formal	Total
Managers	0.04	0.21	0.25	0.03	0.15	0.19
Professionals	0.64	1.76	2.40	0.99	1.72	2.70
Technicians	2.32	7.32	9.64	2.32	3.62	5.95
Clerical support workers	0.80	2.30	3.11	1.03	1.62	2.64
Service and sale workers	4.57	1.15	5.72	16.52	4.08	20.60
Agricultural and fishery workers	2.84	0.02	2.86	25.60	0.12	25.72
Craft and trade workers	40.25	13.28	53.53	8.37	2.63	11.00
Plant and machine operators	6.56	3.88	10.43	7.21	1.92	9.14
Elementary occupations	8.29	3.77	12.05	19.16	2.90	22.06
Total	66.32	33.68	100.00	81.24	18.76	100.00
Observations	9,076			88,337		

Table 2.2 shows the percentage of employment according to the occupation for workers who started to work in the manufacturing sector during the first year (2007) of the sample period; and the sample of workers who started in any other sector besides the manufacturing sector (all sectors). As we can see from Table 2.2, for the manufacturing sector, the percentage of employment in craft occupations decreased from 69% to 42% in 2016, whereas in other occupations such as service and sales, agricultural, and fishery, and elementary occupations, the level of employment increased notably, and very slightly in occupations such as technicians and clerical support. Likewise, considering all the sectors, there is a significant increase in employment in agriculture and fishery and a slight increase in labour in technicians, professionals, clerical, and service and sales occupations. The latter suggests a reallocation of workers across occupations during 2007-2016.

Table 2.2: Percentage of Employment by Occupation 2007-2016

	Manufacturing Sector		All sectors	
Occupations	2007	2016	2007	2016
Managers	0.13	0.00	0.06	0.17
Professionals	1.32	2.62	2.07	3.20
Technicians	8.56	9.18	5.64	5.72
Clerical support workers	2.50	4.59	2.00	2.92
Service and sale workers	0.26	9.18	19.73	19.88
Agricultural and fishery workers	0.00	6.89	24.94	30.53
Craft and trade workers	69.04	42.30	11.67	8.86
Plant and machine operators	8.56	10.82	8.11	8.92
Elementary occupations	9.62	14.43	25.77	19.80
Total	100.00	100.00	100.00	100.00

The data on offshoring comes from the EORA Global Supply Chain Database, which consists of a multi-region input-output table (MRIO) and contains information about the industry by industry IO table. I use the EORA26 dataset, a simplified model in which all countries are aggregated to a common 26-sector classification.[7] Thus, this dataset includes only symmetric industry by industry IO tables.[8] The EORA26 dataset distinguishes between developing and developed countries since it includes 190 countries.[9]To distinguish between developed and developing countries, I follow the definition of the World Bank, which is used by Bas & Kahn(2013), where developing countries are the ones with 2007 per-capita GNIs under 11,456 US dollars using the Atlas conversion factor. To construct the narrow offshoring variable, I consider 118 developing countries.

Finally, to measure the task content, I use the information from O*NET, The Occupational Information Network of the United States Department of Labour, which provides details about work activities, skills and work context with potential task scales ranging from 1 to 5. The construction of this variable is explained in Section 9.1.2.

[7]It displays information about nine manufacturing industries at the 2-digit level of the ISIC Rev. 3.
[8]The information is available at `https://worldmrio.com/eora26/`
[9]Section 9.1 of the appendix includes the list of countries

2.4.2 Methodology

Since offshoring is the reallocation of tasks across countries, it is important to measure the impact of offshoring at the occupational level (occupational exposure). Therefore, I constructed a measure of occupational exposure following the methodology of Feenstra & Hanson (1999) and Ebenstein et al. (2014). First, I built the narrow offshoring[10] measure at the industry level using the EORA input-output tables. Thus, I focus on the diagonal of the I-O tables because it represents the inputs that an industry could produce, but it decides to offshore them generating a change in the composition of tasks within a firm. The equation is the following:

$$OS_{jt-1} = \frac{IMP_{jjt-1}}{Y_{jt-1}} \tag{2.1}$$

Where OS_{jt-1} is the narrow offshoring of industry j at time t-1, IMP_{jjt-1} is the intermediate inputs of industry j, imported from the same industry j from developing countries at time t-1[11], Y_{jt-1} is the production value of industry j in Peru at time t-1. I use the data from 2006-2015 to evaluate the impact of offshoring on workers' wages during the 2007-2016 period because offshoring requires time to implement, and wage adjustment is not instantaneous. Second, I converted the narrow offshoring at the industry level into narrow offshoring at the occupational level (occupation exposure) using the workers' distribution employed in each occupation across industries in the initial year of offshoring (2006).

[10] Imports of intermediate goods purchased from the same industry (Feenstra & Hanson 1999)

[11] It is worth mentioning that intermediate inputs refer to purchases of manufacturing intermediate goods. The EORA input-output table contains nine manufacturing industries, the aggregate industry has the advantage of producing industry cells with not a too small number of individuals

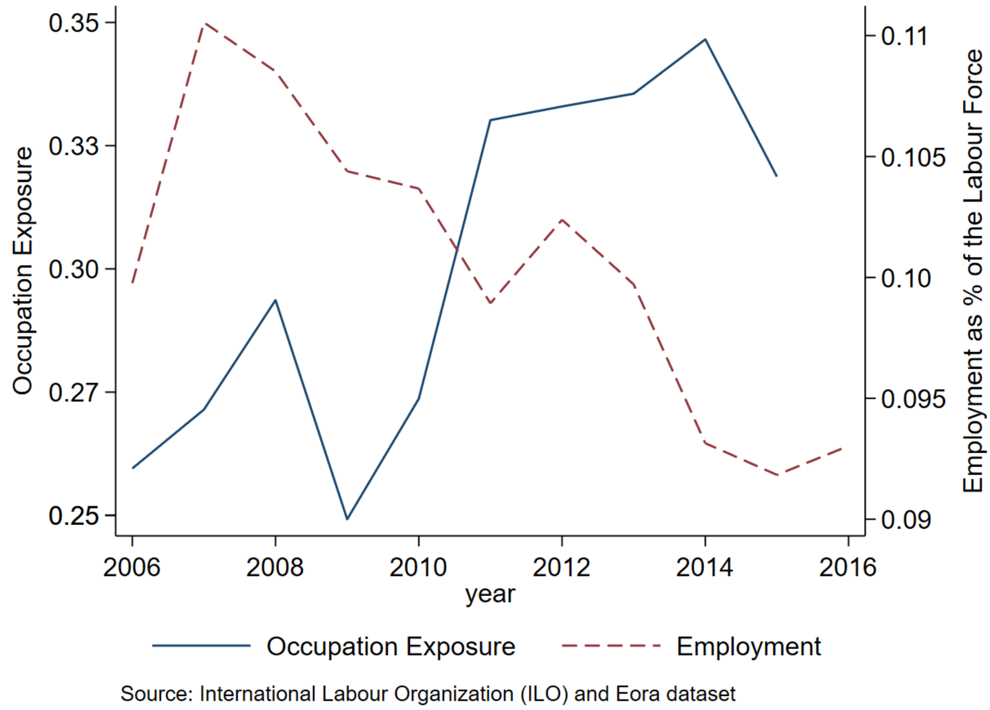
$$OS_{kt-1} = \sum_{j=1}^{J} \frac{L_{kj06}}{L_{k06}} OS_{jt-1} \tag{2.2}$$

Where L_{kj06} is the number of occupation k workers employed in industry j in 2006, L_{k06} is the number of occupation k workers across all industries, thus $\sum \frac{L_{kj06}}{L_{k06}} = 1$. OS_{jt-1} is the narrow offshoring at the industry level, and OS_{kt-1} is the narrow offshoring at the occupational level (occupation exposure).[12] The latter allows considering the wage impact of offshoring for workers in the manufacturing industries as well as workers across the broader economy. Namely, intermediate imports in the manufacturing sector affect workers employed in the manufacturing industry j and occupation k, but it also affects workers in occupation k employed in the non-manufacturing industry.

Figure 2.3 depicts the average increase in occupation exposure compared to the manufacturing sector's employment level. While occupation exposure grew, the employment rate decreased between 2006-2016. From the data in Figure 2.3, it is possible that the increase in intermediate imports from developing countries has caused the substitution of home labour by foreign labour since the employment rate fell.

[12]Due to the high number of workers concentrated in particular occupations in the manufacturing sector, occupational cells at 3-digit level become too small. Thus, my occupational group is based on a one-digit level of ISCO-08, which contains nine broad occupational areas. Therefore OS_{kt-1} is the occupation exposure at the 1-digit occupation level.

Figure 2.3: Occupation Exposure vs. Employment



Regarding the task content of occupations, my study combines the methodology developed by Acemoglu & Autor (2011), Autor & Handel (2013) and Casabianca et al. (2018). First, I linked each O*NET-SOC2010 occupation to the National Classification of Occupations-95 (CNO-95 by acronym in Spanish) from the ENAHO through correspondence tables. I used a correspondence table provided by INEI to convert the CNO-95 classification coding to the International Standard Classification of Occupations 08 (ISCO 08) and then an available crosswalk to convert the O*NET-SOC2010 coding to ISCO 08. In this manner, it was possible to associate the O*NET occupation characteristics with Peruvian occupations.

The O*NET provides details about work activities, skills, and work context, each of these activities has different scores ranging from 1 to 5. Since the O*NET reflects the features of US jobs and the task content of a given occupation in a developed country is not the same in a developing country, I followed Casabianca et al. (2018) methodology to address this issue. Thus, I replaced raw scores from O*NET with the values of their cumulative distribution function in the previous year of my sample (2006). Namely, I will get the percentile rank where each score falls in the Peruvian distribution; this means the percentage of Peruvian workers who score less than or equal to the raw score from the O*Net. For instance, one of the skills from the O*NET is thinking creatively (4.A.2.b.2), whose score ranges from 1 to 5, which has a score of 3.55 for office supervisors in the USA. To replace this score (3.55) with its cumulative distribution, I ranked the occupations according to the raw scores of this variable[13]. Then, I took the relative frequency of Peruvian workers for each ranked score and calculated the cumulative distribution function of each score based on the distribution of workers across occupations in the Peruvian labour market. In this example, I get that 93% of the Peruvian working population has an intensity of thinking creatively lower than or equal to 3.55. Thus, I replaced the O*Net scores with the normalised scores from 0 to 1.

The equation is the following:

$$Score_{hk} = \frac{1}{N_k} \sum_{\bar{h} \leq h} \sum_{i \in N_k} 1\{RawScore_{ki} = \bar{h}\}, \quad k = 1, ...k \tag{2.3}$$

Where $Score_{hk}$ is the cumulative distribution value attributed to the hth value of the raw score in occupation k, $\bar{h}$ is the percentile rank that a raw score in occupation k can take, that is less than or equal to hth value of the raw score, N_k is the number of total workers across occupations, and $1\{.\}$ is an indicator function assuming value 1 when the corresponding condition in brackets is satisfied.

Differently from Casabianca et al. (2018)[14], I followed Acemoglu & Autor (2011) and Autor & Handel (2013) to build three aggregate tasks (Abstract, Manual and Routine task) and avoid the overlap among tasks. For instance, some of the manual character-

[13] From the lowest score (1) to the highest (5)

[14] They constructed two tasks, manual and cognitive, stating that the Peruvian labour market is characterised by less automated job tasks. However, since the literature about the tasks specialisation in developing countries found that these countries are specialised in more routine tasks, it is also necessary to account for this task.

istics used by Casabianca et al. (2018) can be candidates for inclusion in routine tasks such as controlling machines and processes. Therefore, my study works with three task measures rather than two, where abstract tasks refer to problem-solving, organisational, and managerial tasks; routine tasks to codifiable cognitive tasks and tasks that follow specific procedures, while manual tasks require physical adaptability (Autor et al. 2003). First, I built six tasks (non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, non-routine manual physical and non-routine manual interpersonal) by averaging the corresponding normalised scores. Second, I collapsed the six tasks into three task measures; abstract, manual and routine, by averaging the previous tasks[15]. Finally, to avoid potential collinearity problems from the interaction between the task measure and the occupation exposure, I construct a measure of routine, abstract and manual intensity for each occupation k as follows:

$$Task_k = \frac{Task_k}{manual_k + abstract_k + routine_k}, \quad k = 1, ...k \tag{2.4}$$

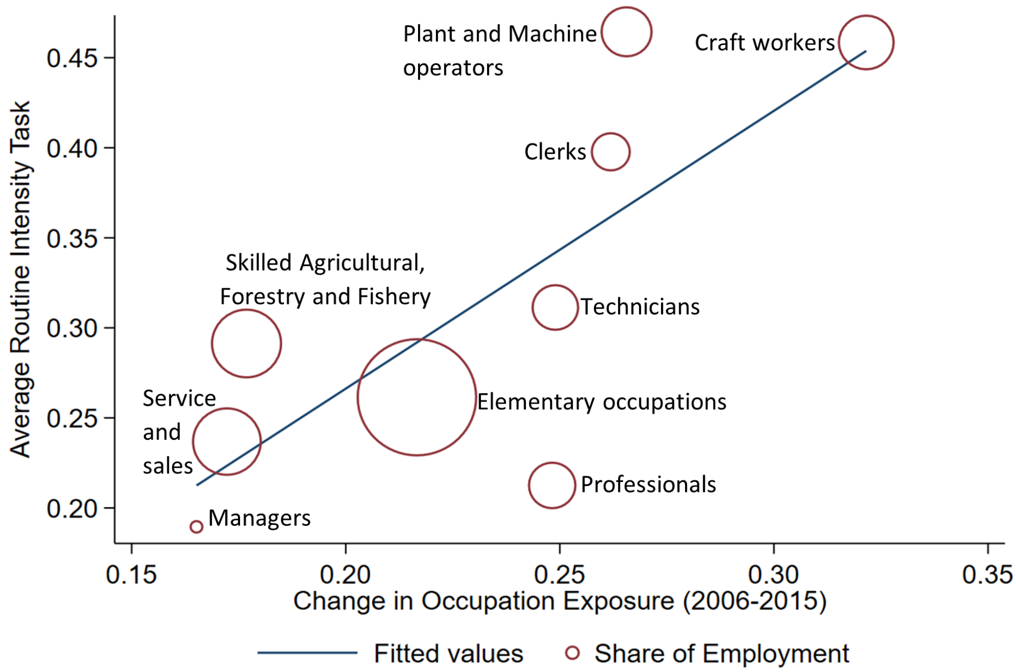
Where tasks can be abstract, manual or routine.

From Figure 2.4, it can be seen that there is a positive correlation between routine-intensive tasks and occupation exposure, which means that workers who perform routine-intensive tasks are more exposed to offshoring. In the case of Peru, craftworkers are the ones who are most exposed to offshoring, and they are also the ones who perform routine-intensive tasks followed by plant and machine operators and clerks. Conversely, managers are less exposed to offshoring as service and sales workers. In addition, in the figure, the size of the circle represents the share of employees by occupation in 2006 at the national level, showing that most Peruvian workers have elementary occupations which require more manual tasks. However, craftworkers, clerks and plant and machine operators together represent 79% of employees in the manufacturing sector[16].

[15] Appendix 9.1.2 and 9.1.3 shows the task types and job characteristics used for each task and the correlation between my task measure and other literature-based task measures

[16] International Labour Organization (ILO) 2006.

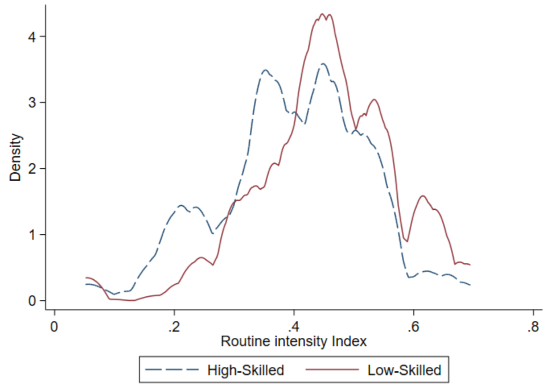
Figure 2.4: Occupation Exposure vs. Routine Intensity Tasks



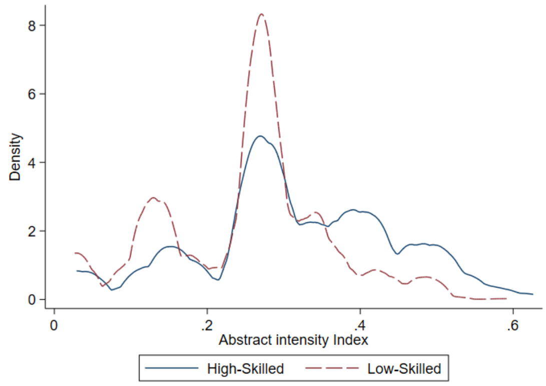
Source: O*Net, ILO (2006) and EORA dataset (2006-2015)

From Figure 2.5, we can see that there is heterogeneity within skill groups. Although high-skilled workers seem to be more correlated to abstract tasks, some low-skilled manufacturing workers perform abstract tasks. Likewise, Figure 2.5a shows that some high-skilled workers perform more routine tasks. In the case of manual tasks, the proportion of high and low-skilled workers who perform manual-intensive tasks is almost the same. Among the high-skilled who perform more routine tasks, a common occupation is a technician and clerk. On the other hand, among the low-skilled who perform more abstract tasks, a usual occupation is service and sale, while a common occupation for manual tasks is agricultural and fishery, and elementary occupations.

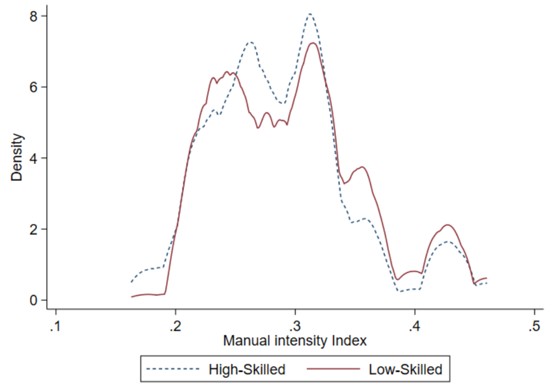
Figure 2.5: Distribution of Task Index by Skill



(a) Routine Index



(b) Abstract Index

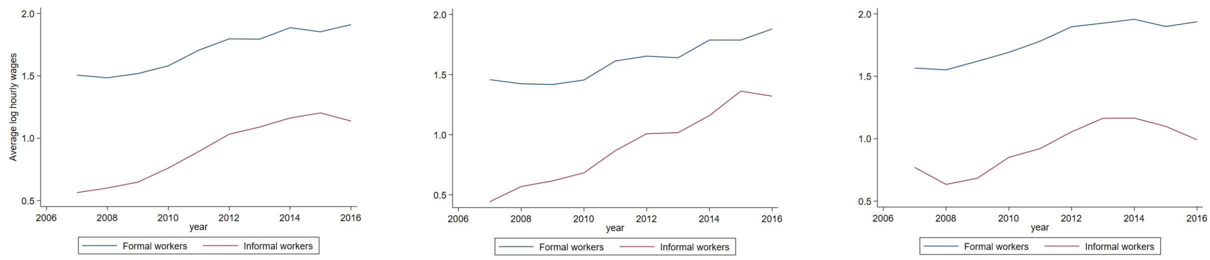


(c) Manual Index

Figure 2.6a shows the trends in wages according to the task content of occupations, Figure 2.6b and 2.6c portray the trends of the average log hourly wages for formal and informal workers who perform routine-intensive tasks and for workers who perform non-routine intensive tasks (manual and abstract tasks). In both cases, wages grew from 2006 to 2014, a year in which wages started to fall at a faster rate for non-routine workers than for routine workers. From Figure 2.3, we can see that the wage decline coincides with the year in which intermediate inputs measured at the occupational level started to decrease (2014). Although wages grew for routine and non-routine workers, the trend for routine workers is steeper, while the trend for non-routine is slightly flat, especially for formal workers. Moreover, Figure 2.6 also presents the difference in wages between formal and informal workers, showing that formal workers have higher wages than informal workers.

The increase in wages between routine and non-routine workers is more notable for the case of informal workers. We can see a higher increase in informal wages for routine workers than for informal non-routine workers.

Figure 2.6: Trends in Wages in the Manufacturing Sector



(a) All workers **(b) Routine** **(c) Non-Routine**

To estimate the effects of offshoring on workers' wages according to the task they perform, I use the Mincer wage model (Mincer 1974), which controls for the individual observed heterogeneity. To control for as much unobserved heterogeneity as possible, I use occupation fixed effects σ_k, time fixed effects μ_t and individual fixed effects τ_i. This model is expanded by including heterogeneous tasks in the model.

Mincer wage equation:

$$\begin{aligned} lnWage_{i,k,t} = \alpha &+ \beta DEMOG_{i,t} + \gamma work_{i,t} + \lambda OS_{k,t-1} \\ &+ \delta TASK_k + \nu OS_{k,t-1} \times Task_k + \rho R\&D/Y_{k,t-1} \\ &+ \mu_t + \tau_i + \sigma_k + \epsilon_{i,k,t} \end{aligned} \tag{2.5}$$

In addition, I also include an interaction between offshoring and whether workers are in the formal or informal labour market. Therefore, I also estimate a variant of the following Mincer wage equation:

$$\begin{aligned} lnWage_{i,k,t} = \alpha &+ \beta DEMOG_{i,t} + \gamma work_{i,t} + \lambda OS_{k,t-1} \\ &+ \delta TASK_k + \nu OS_{k,t-1} \times Formal_{i,t} + \rho R\&D/Y_{k,t-1} \\ &+ \mu_t + \tau_i + \sigma_k + \epsilon_{i,k,t} \end{aligned} \tag{2.6}$$

Where $lnWage_{i,k,t}$ is the logarithm of an individual i's hourly wage in occupation k at time t. $OS_{k,t-1}$ is the narrow offshoring at occupation level (occupation exposure) for occupation k at time t-1, $DEMOG_{i,t}$ controls for individual characteristics such as marital status, education. $work_{i,t}$ controls for workplace characteristics such as tenure, firm size, formal or informal market, and a full or part-time job. $TASK_k$ is the routine intensity task in occupation k. $Formal_{i,t}$ is a dummy variable that takes the value of one when individuals work in the formal market and zero otherwise. $R\&D/Y_{k,t-1}$ is defined as the share of investment in innovation and technology divided by total innovation and technology investment in the manufacturing sector to capture industry-level technology changes. The latter is constructed at the occupational level by applying equation (2.2).

The marginal effect of offshoring (occupation exposure) is:

$$\frac{\partial lnWage_{i,k,t}}{\partial OS_{k,t-1}} = \lambda + \nu Task_k \tag{2.7}$$

According to the literature, developing countries specialise in routine-intensive tasks, and offshoring between similar countries leads to specialising in complementary tasks. Therefore, I would expect that Peru specialises in routine-intensive tasks and offshores complementary routine-intensive tasks to other developing countries, causing a positive effect on Peruvian workers' wages who perform routine-intensive tasks, thus ν is expected to be positive.

Table 2.3 presents the summary statistics for the main variables used in the empirical analysis.

Table 2.3: Descriptive Statistics

		Manufacturing		All workers	
Variables	Notes	Mean	Std. Dev.	Mean	Std. Dev.
Log hourly wages		1.012	1.113	0.739	1.295
D: Married	0/1	0.597	0.490	0.639	0.480
D: High education	0/1	0.269	0.443	0.212	0.409
D: Male	0/1	0.623	0.485	0.637	0.481
Age	in years	39.348	12.824	40.905	12.920
D: High tenure	0/1	0.339	0.480	0.396	0.489
D: Firm Size $<$ 21	0/1	0.682	0.465	0.809	0.393
D: Firm Size 21-50	0/1	0.051	0.220	0.034	0.182
D: Firm Size 51-100	0/1	0.034	0.182	0.021	0.143
D: Firm Size 101-500	0/1	0.034	0.182	0.035	0.184
D: Work experience full-time	0/1	0.684	0.465	0.632	0.482
D: Unemployment	0/1	0.009	0.096	0.009	0.093
D: Economically Inactive Population (EIP)	0/1	0.050	0.217	0.043	0.203
D: Formal	0/1	0.317	0.473	0.178	0.382
R&D/Y	in percent	14.043	6.420	16.088	8.829
Routine intensity task		0.412	0.158	0.315	0.138
$(OS_{k,t-1})$	in percent	2.728	0.915	3.124	1.071
Observations		9,644		93,170	

Log hourly wages is the logarithm of hourly-deflated wages and firm size is related to the number of workers in a firm.

2.4.3 Instrumental Variables

A concern in empirical studies that seek to assess the effects of offshoring is that offshoring may be endogenous in a wage equation. According to Liu & Trefler (2019), the sign of the endogeneity bias depends on the nature of the shock generating the change in intermediate imports. For instance, a domestic-positive shock to the sector j's productivity can decrease the offshoring and simultaneously increase the demand for skilled workers, increasing the wages in that sector. The omission of this unobserved effect may lead the OLS estimates of the offshoring effect to be underestimated. In contrast, foreign shocks such as a decline in foreign wages in sector j can increase offshoring activities while decreasing domestic labour demand, creating a fall in the wages of that sector. However, changes in foreign wages do not have direct impacts on domestic labour demand since they affect labour through changes in imports. Thus, when the source of import shocks originates abroad, OLS produces unbiased estimates.

Accordingly, the empirical model includes innovation investment at the occupational level as well as occupation-fixed effect to control for domestic technological shocks affecting the wages of Peruvian workers. To control for foreign potential shocks I built two instrumental variables following the methodology of Liu & Trefler (2019) and Casabianca et al. (2018).

Gravity Instrument

Liu & Trefler (2019) construct an instrumental variable that explores the exogenous import shocks that originated in foreign countries using a gravity equation for each industry within the service sector. I built the same instrument variable, but for the case of the manufacturing sector, and considered the intermediate imports from developing countries. I regressed lnM_{cjt} on $ln(\frac{Y_{ct}}{L_{ct}})$ and $ln(L_{ct})$ using year and country fixed effects to capture the effects of rising income rather than the effect of cross-country differences income.

The gravity equation is the following:

$$lnM_{cjt} = \alpha_{cj}^{M} + \beta_{j,Y/L}^{M} ln(\frac{Y_{ct}}{L_{ct}}) + \beta_{j,L}^{M} ln(L_{ct}) + \epsilon_{cjt}^{M} \tag{2.8}$$

Where lnM_{cjt} is the logarithm of the Peruvian intermediate imports from developing country c, intermediate imports are based on EORA 26 input-output table; $ln(\frac{Y_{ct}}{L_{ct}})$ is the logarithm of the GDP per capita in current US dollars of developing country c in year t; $ln(L_{ct})$ is the population[17] of developing country c in year t. Using the coefficients of equation (2.8), which are available in Table 2.4, the estimates of imports in levels is:

$$\hat{M}_{cjt} \equiv exp(\hat{\beta}^{M}_{j,Y/L} ln(\frac{Y_{ct}}{L_{ct}}) + \hat{\beta}^{M}_{j,L} ln(L_{ct})) \tag{2.9}$$

The log of aggregate intermediate imports from the 118 developing countries is:

$$ln\hat{M}_{jt} \equiv ln(\sum_{j=1}^{9}\sum_{c=1}^{118} \hat{M}_{c,jt}) \tag{2.10}$$

Where $ln\hat{M}_{jt}$is the instrumental variable which represents the aggregate intermediate imports from developing countries by industry j in year t. Finally, because the instrumental variable is constructed at the industry level j, I convert the instrumental variable to the occupational level $ln\hat{M}_{kt}$ using equation (2).

USA comparative advantage

However, it may be argued that import demand shocks among similar countries could be correlated due to their geographical and cultural diversity, making the IV ($ln\hat{M}_{jt}$) endogenous. Therefore, following Casabianca et al. (2018), I also construct an instrument which controls for the variation in intermediate imports driven by the evolution of foreign suppliers' comparative advantages. Since the US is the major Peruvian import partner for the period 2006-2015 and whose demand shocks are probably not related to the Peruvian demand shocks, I instrument the variation of intermediate imports with the inferred relative change of US comparative advantage. Thus, I control the changes in intermediate imports driven by the Peruvian major partner's changing comparative advantage. To

[17]The information about GDP per capita and population are from the World Bank dataset and the period of the analysis is 2006-2015, same period than occupation exposure analysis.

Table 2.4: Gravity Equations - Bilateral Imports (Developing Countries)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnM_{cjt}	Petroleum Chemical and Non-metallic Mineral Products	Metal Products	Textiles and Wearing apparel	Other Manufac-turing	Food and Beverages	Wood and Paper	Recycling	Electrical and Machinery	Transport Equipment
$ln(\frac{Y_{ct}}{L_{ct}})$	0.172***	0.075*	0.155***	0.167***	0.123***	0.145***	0.115***	0.157***	0.161***
	(0.019)	(0.030)	(0.023)	(0.022)	(0.022)	(0.023)	(0.023)	(0.019)	(0.022)
$ln(L_{ct})$	-0.216**	-0.110	-0.362***	-0.247**	-0.191*	-0.218*	-0.009	-0.156*	-0.272**
	(0.073)	(0.120)	(0.089)	(0.085)	(0.085)	(0.090)	(0.089)	(0.073)	(0.085)
Observations	1188	1188	1188	1188	1188	1188	1188	1188	1188

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All specifications include year and country fixed effects.

calculate the comparative advantage of the US relative to Peru, I estimate a gravity model by regressing the log difference in exports from the US and Peru to developing countries on industry and country dummies as follows:

$$lnExp_{jct}^{US} - lnExp_{jct}^{Peru} = \alpha_j + \alpha_c + \epsilon_{jct} \tag{2.11}$$

Where Exp_{jct}^{US} and Exp_{jct}^{Peru} are USA and Peruvian industry j exports to developing country c, and α_j and α_c are industry and country fixed effects respectively. Country fixed-effects control for any possible demand conditions in the foreign country c, and industry fixed-effects capture the initial US comparative advantage relative to Peru. The residuals of equation (2.11) capture the differential time-varying comparative advantage of the US relative to Peru for industry j. After estimating the gravity model for the period 2006-2015, I take the mean change in the residuals for industry j across developing countries c between years t and $t-1$. For instance, when the change in residuals from 2005 to 2006 is multiplied by the Peruvian intermediate imports from developing countries in industry j in the year 2005, I obtain the changes in Peruvian intermediate imports in the year 2006 predicted by Peruvian major partner's changing comparative advantage.

Concerning task content, there is also a potential endogeneity problem since workers can switch between different bundles of tasks in response to the differential returns associated with them (Autor & Handel 2013). However, unlike Autor & Handel (2013), I do not look at the within-occupation task variation in this setting; each occupation is linked to one task intensity. Thus, this approach considers workers sorting into a continuum of occupations, in which workers with unobserved heterogeneous attributes can sort across occupations, which have heterogeneous returns to these attributes. This potential endogeneity is addressed in the fixed effect model by including individual-fixed effects, which account for unobserved characteristics for determining initial occupational choices. The empirical model also includes occupation-fixed effects, which control for variation within an occupation. Furthermore, to examine how occupational exposure affects sorting behaviour (occupational choice), I follow Liu & Trefler (2019) and estimate labour market outcomes differentiating between workers who switch up and switch down occupations. Further details are developed in Section 6.

To verify that the instrumental variables (IVs) are associated with the endogenous explanatory variables and that their impact on the outcome only occurs indirectly through their influence on the endogenous explanatory variables, in line with the exclusion restriction assumption, I conduct various tests. These tests include the first-stage regression, the endogeneity test, and the assessment for overidentification. Table 2.7 displays the results of the first-stage regression for both instruments. This analysis examines the relationship between the instrumental variables (IVs) and the endogenous variable. Both the gravity and the USA relative comparative advantage instruments exhibit statistical significance, indicating their ability to explain variations in offshoring. Additionally, the table presents the F-test, assessing the joint significance of the instruments. This test confirms that the instruments are relevant and have explanatory power for offshoring, thus supporting their validity in addressing endogeneity.

Under the presence of endogeneity, the explanatory variable is correlated to the error term in the regression, violating the assumption that instrumental variables affect the outcome variable only indirectly through their influence on the endogenous variable. Thus, I perform an endogeneity test, as shown in Table 2.5. The findings indicate that I cannot reject the null hypothesis of exogeneity. This implies that the difference between the estimates from a model that corrects for endogeneity (IV model) and one that does not is not statistically significant, indicating the absence of endogeneity concerns. Another test that indirectly supports the validity of the exclusion restriction assumption is the overidentification test. This test examines whether the instruments used in IV analysis are collectively relevant for explaining the variation in the endogenous explanatory variable.

The outcome of this test, also presented in Table 2.5, indicates that the null hypothesis, stating that the number of instruments equals the number of endogenous variables, cannot be rejected. The latter implies that the instruments are exogenous and do not directly influence the outcome variable, thereby satisfying the exclusion restriction.

Even though these tests indicate that there are no issues of endogeneity, it is important to recognize that the instruments may still have some limitations. For example, the gravity instrument, which relies on import elasticity, requires accurate calculations, but getting accurate results may not always be possible due to limited data or other factors. Additionally, offshoring decisions may be influenced by complex factors beyond import elasticities, including technological advancements, labour costs, and trade policies. Similarly, using changes in the relative comparative advantage of the USA compared to Peru as an instrument for offshoring is limited by the methodology used to measure comparative advantage. This is because various factors beyond trade flows, such as factor endowments, technology, distance, etc., can also influence comparative advantage.

2.5 Results

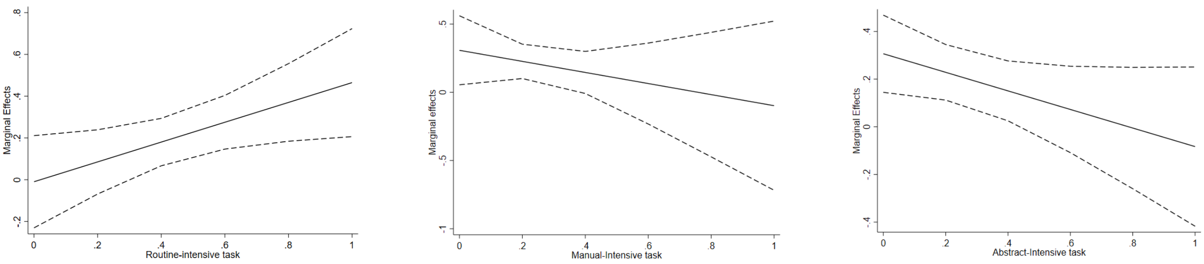
In this section, I analyse the impact of offshoring on workers' wages, measured at the occupation level. To recap, the coefficient on Task reflects how wages change with the routine intensity of occupations, and its overall effects depend on the level of offshoring. These regressions are based on equations (2.5) and (2.6), and a fixed effects model is used to estimate the results and to control for time-invariant occupation and individual characteristics. The regression contains a full set of occupation, time and individual fixed effects.

Table 2.5 reports the impact of Occupation-Specific Exposure to Offshoring between Peru-South countries for individuals working in the manufacturing sector and performing routine-intensive tasks during 2007-2016. I initially include the occupation exposure with the individual, occupation and year fixed effects; columns 2-4 also include individual and work characteristics. In column 4, when the interaction between occupational exposure and the routine-intensive task is added, the coefficient of occupational exposure is no longer significant. However, the coefficient of the interaction term is positive and significant, meaning that workers who perform routine-intensive tasks are positively affected by occupational exposure to Peru-South offshoring.

Column 5 accounts for the possible endogeneity problem. I address this problem by instrumenting for the occupational exposure to offshoring and the associated task-related interaction term. The excluded instruments are the ones described in Section 4.3. To instrument the interaction term, I interact the USA comparative advantage ($IV - USA$) and imports shocks ($IV - Gravity$) instrument with the routine-intensive task ($task$). Column 1 of Table 2.7 reports the first-stage results related to the specifications in column 5 of Table 2.5. The F-test in Table 2.7 shows that the excluded instruments have enough power to predict occupational exposure to offshoring.

The exogeneity and over-identification tests are reported in column 5 of Table 2.5. From the standard Hausman test, I am not able to reject the null hypothesis (HO) of exogeneity, this suggests that OLS and IV are not statistically different. The over-identification test supports the hypothesis that the excluded instruments are exogenous. In addition, the fixed effects and the IV model show a similar pattern for the wage effects of occupational exposure to offshoring. In both specifications, workers who perform routine-intensive tasks experience a positive effect on their wages due to offshoring. However, the coefficients in the IV regression are not statistically significant because the instrumentation increases the confidence intervals around the marginal effect. As there is limited evidence of endogeneity of offshoring, the fixed effect model is preferred to the IV estimation. Therefore, I use the fixed effect estimations to report the magnitude effects. Figure 2.7 provides the marginal wage effect of occupational exposure for routine, manual and abstract intensive tasks. Figure 2.7a shows a significant and positive effect on workers' wages who perform routine-intensive tasks, Figure 2.7c depicts a significant and negative effect on workers who perform abstract-intensive tasks, and Figure 2.7b a negative and statistically not significant effect on workers who perform manual-intensive tasks.

Figure 2.7: Marginal effects of Occupation-Specific Exposure to Offshoring with 95% Confidence Interval



(a) Routine **(b) Manual** **(c) Abstract**

Source: Author's own elaboration based on results of Table 2.5 and 2.20

To estimate the wages occupational exposure effect, I use the shoe-making machine operators (8156, ISCO-08) as an example because they perform routine-intensive tasks. Considering that these workers have experienced an increase in occupational exposure of 27% over the sample period (2006-2015), the value of their routine-intensive tasks (0.69), as well as the coefficients from Table 2.5, I find that the total effect of occupational exposure ($OS_{k,t-1}$) on shoe-making machine operator workers' wages is 8.6%.[18] Applying the same analysis to workers involved in highly abstract tasks, I find that the total effect of occupational exposure on wages is negative. For instance, engineers, who face an increase by 25% of their corresponded occupational exposure measure, have experienced an increase in their wages of about 0.2% as a result of the increase in occupational exposure.[19] This result is similar to the one considering the coefficients for the abstract-intensive task of Table 2.20 (1.5%) in Appendix 9.2.

In summary, this table highlights a positive and significant impact on workers performing routine-intensive tasks due to offshoring between Peru and South countries.

[18] Calculations are as follows: from the marginal effects of column (4) in Table 2.5: (-0.010 + 0.475*(Task))*$\Delta OS_k^{15/06}$ where Task = 0.69 and $\Delta OS_k^{15/06}$ = 0.27 for shoe-making machine operators.

[19] Calculations are as follows: from the marginal effects of column (4) in Table 2.5: (-0.010 + 0.475*(Task))*$\Delta OS_k^{15/06}$ where task = 0.19 and $\Delta OS_k^{15/06}$ = 0.25 for engineer workers.

Table 2.5: Offshoring between Peru-South Countries by Occupation-Specific Exposure, Manufacturing Only

	FE				IV
	(1)	(2)	(3)	(4)	(5)
Lag of occupation exposure ($OS_{k,t-1}$)	0.161***	0.133***	0.202***	-0.010	0.209
	(0.052)	(0.051)	(0.057)	(0.113)	(0.219)
Unemployment	-0.752***	-1.210***	-1.479***	-2.215***	-1.679**
	(0.181)	(0.183)	(0.203)	(0.384)	(0.677)
EIP	-0.464***	-0.912***	-1.188***	-1.925***	-1.396**
	(0.171)	(0.176)	(0.195)	(0.380)	(0.671)
Formal		0.158***	0.155***	0.155***	0.152***
		(0.031)	(0.031)	(0.031)	(0.031)
Routine intensity task (Task)			-0.269	-1.693**	-1.265
			(0.183)	(0.688)	(1.119)
R&D/$Y_{k,t-1}$			-0.017***	-0.021***	-0.027***
			(0.006)	(0.007)	(0.008)
($OS_{k,t-1}$)#Task				0.475**	0.314
				(0.216)	(0.371)
Individual Characteristics					
Married		0.032	0.028	0.030	0.027
		(0.058)	(0.058)	(0.058)	(0.060)
High education		0.046	0.046	0.045	0.048
		(0.038)	(0.038)	(0.038)	(0.039)
High tenure		-0.022	-0.025	-0.025	-0.026
		(0.033)	(0.033)	(0.033)	(0.032)
Firm Size < 21		-0.314***	-0.317***	-0.320***	-0.314***
		(0.044)	(0.044)	(0.044)	(0.042)
Firm Size 21-50		-0.118***	-0.124***	-0.127***	-0.126***
		(0.043)	(0.043)	(0.043)	(0.042)
Firm Size 51-100		-0.031	-0.034	-0.039	-0.040
		(0.044)	(0.044)	(0.043)	(0.044)
Firm Size 101-500		-0.020	-0.022	-0.022	-0.028
		(0.031)	(0.031)	(0.031)	(0.032)
Full time		-0.317***	-0.315***	-0.316***	-0.315***
		(0.032)	(0.032)	(0.031)	(0.032)
Overid test					3.676
p-value					0.159
Endogeneity Test					3.823
p-value					0.148
Observations	9,644	9,644	9,644	9,644	9,644
R-squared	0.123	0.152	0.154	0.154	0.084

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

Table 2.6 provides the results obtained from the regression based on equation (2.6), which seeks to assess the impact of occupational exposure to offshoring on formal and informal workers' wages. Table 2.6 includes the same specification as Table 2.5; the only difference is the interaction term ($Formal_{i,t} \times OS_{k,t-1}$). Column 3 is estimated using the instrumental variables described in section 4.3. The bottom of the table reports the exogeneity and the over-identification test, indicating that occupational exposure to offshoring is exogenous and that the instruments are valid and relevant. In addition, column 2 of Table 2.7 reports the F-Statistic test, showing that the excluded instruments have high predicted power to explain changes in occupational exposure to offshoring. Both the fixed effect and the instrumental coefficients report the same sign for the wages effect of offshoring. Therefore, I report the fixed effect estimations in preference to the instrumental variable regression.

To calculate the effects of occupational exposure to offshoring on formal and informal workers' wages, I use as an example the groups of workers who perform highly informal occupations and who also perform routine intensive tasks (handicraft workers). Using the coefficients in column 2 of Table 2.6, I find that an increase in $OS_{k,t-1}$ leads to a rise in formal handicraft workers' wages by 5% and for the case of the informal handicraft workers this increase is about 7%[20]. The impact of occupational exposure is higher for people who work in the informal market and perform routine intensive tasks. The increase in workers' wages who perform routine-intensive tasks could be associated with the transition of workers across occupations or sectors. This analysis is addressed in Section 6.

In addition, Table 2.8 presents the estimates for equation (2.5), but including workers from all sectors since occupational exposure to offshoring in the manufacturing sector can also affect workers performing routine-intensive tasks in other sectors. The results are similar to the manufacturing analysis, workers who perform routine-intensive tasks are positively affected by offshoring. As can be seen from Table 2.8, adding all workers leads

[20]Calculations are as follows: from the marginal effects in column 2 of Table 2.6: (0.228 - 0.077*(Formal))*$\Delta OS_k^{15/06}$ where Formal = 1 or 0 and $\Delta OS_k^{15/06} = 0.32$ for handicraft workers.

to even stronger results. Column 5 shows the estimations considering the endogeneity problem. The instrument used in this case is the import shocks from other developing countries ($IV - Gravity$) because the USA comparative advantage ($IV - USA$) and the import shocks ($IV - Gravity$) instruments together fail the over-identification test when all workers are added. However, both instruments separately work as valid instruments. I report the results for the $IV - Gravity$ instrument since the F-statistic is higher than the $IV - USA$.[21]

The bottom of Table 2.8 presents the test of exogeneity, which I can reject at 5%, making occupational exposure to offshoring endogenous when all workers are added. Recall Liu & Trefler (2019), if the source of the import shock is domestic, then the IV estimates should be larger than the OLS estimates. Certainly, column 5 of Table 2.8 shows that the coefficients in the IV regression are larger than the fixed effects estimates, suggesting that the source of endogeneity is domestic when all workers are added.

[21] Both IV regressions are reported in appendix 9.2 Table 2.21 and 2.22

Table 2.6: Offshoring in Developing Countries by Occupation-Specific Exposure - Formal and Informal Market, Manufacturing Only

	FE		IV
	(1)	(2)	(3)
Lag of occupation exposure ($OS_{k,t-1}$)	0.249***	0.228***	0.397***
	(0.062)	(0.061)	(0.106)
($OS_{k,t-1}$)#Formal	-0.074**	-0.077**	-0.128**
	(0.037)	(0.037)	(0.056)
Unemployment	-0.923***	-1.404***	-1.059***
	(0.209)	(0.212)	(0.267)
EIP	-0.657***	-1.114***	-0.774***
	(0.200)	(0.204)	(0.255)
Formal	0.406***	0.379***	0.527***
	(0.116)	(0.114)	(0.168)
Routine intensity task (Task)	-0.217	-0.269	-0.325*
	(0.185)	(0.183)	(0.178)
R&D/$Y_{k,t-1}$	-0.019***	-0.017***	-0.024***
	(0.007)	(0.006)	(0.008)
Individual Characteristics			
Married		0.027	0.024
		(0.058)	(0.060)
High education		0.047	0.049
		(0.038)	(0.039)
High tenure		-0.024	-0.025
		(0.033)	(0.033)
Firm Size < 21		-0.314***	-0.307***
		(0.044)	(0.042)
Firm Size 21-50		-0.120***	-0.118***
		(0.043)	(0.042)
Firm Size 51-100		-0.030	-0.031
		(0.043)	(0.044)
Firm Size 101-500		-0.021	-0.026
		(0.031)	(0.031)
Full time		-0.316***	-0.316***
		(0.032)	(0.032)
Overid test			4.402
p-value			0.111
Endogeneity Test			3.743
p-value			0.154
Observations	9,644	9,644	9,644
R-squared	0.130	0.154	0.083

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

Table 2.7: First-Stage Regression for Endogenous Occupation Exposure

	Occupation exposure ($OS_{k,t-1}$)	
	Task interaction	Formal interaction
Excluded Instruments		
IV-USA instrument	0.407***	0.590***
	(0.025)	(0.018)
IV-Gravity instrument	-0.553***	-0.290***
	(0.099)	(0.097)
IV-USA#Task (Formal)	0.469***	0.036***
	(0.039)	(0.008)
IV-Gravity#Task (Formal)	0.608***	-0.012
	(0.107)	(0.015)
Unemployment	-2.777***	-1.628***
	(0.237)	(0.226)
EIP	-2.750***	-1.594***
	(0.235)	(0.224)
Formal	0.005	-0.052**
	(0.005)	(0.026)
Routine intensity task (Task)	-2.394***	0.166***
	(0.240)	(0.034)
R&D/$Y_{k,t-1}$	0.021***	0.026***
	(0.001)	(0.002)
Individual Characteristics		
Married	0.009	0.011
	(0.010)	(0.010)
High education	-0.007	-0.004
	(0.007)	(0.007)
High tenure	0.001	0.000
	(0.005)	(0.005)
Firm Size < 21	-0.006	-0.007
	(0.009)	(0.009)
Firm Size 21-50	-0.002	-0.000
	(0.010)	(0.010)
Firm Size 51-100	0.007	0.007
	(0.010)	(0.010)
Firm Size 101-500	0.019**	0.016**
	(0.008)	(0.008)
Full time	-0.006	-0.002
	(0.005)	(0.005)
F-test	555.376	438.879
p-value	0.000	0.000
Observations	9,644	9,644

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects.

Table 2.8: Offshoring in Developing Countries by Occupation-Specific Exposure, All Sectors

	FE				IV-Gravity
	(1)	(2)	(3)	(4)	(5)
Lag of occupation exposure ($OS_{k,t-1}$)	0.202***	0.151***	0.147***	-0.060	-0.358***
	(0.023)	(0.022)	(0.023)	(0.038)	(0.122)
Unemployment	-0.693***	-1.380***	-1.619***	-2.292***	-3.265***
	(0.079)	(0.080)	(0.101)	(0.141)	(0.410)
EIP	-0.478***	-1.160***	-1.401***	-2.074***	-3.050***
	(0.077)	(0.078)	(0.099)	(0.140)	(0.410)
Formal		0.221***	0.220***	0.221***	0.222***
		(0.014)	(0.014)	(0.014)	(0.014)
Routine intensity task (Task)			-0.214***	-1.962***	-6.090***
			(0.071)	(0.258)	(1.586)
R&D/$Y_{k,t-1}$			-0.006***	-0.009***	-0.012***
			(0.002)	(0.002)	(0.003)
($OS_{k,t-1}$)#Task				0.582***	1.931***
				(0.081)	(0.514)
Individual Characteristics					
Married		-0.012	-0.012	-0.010	-0.008
		(0.025)	(0.025)	(0.025)	(0.025)
High education		0.046***	0.046***	0.046***	0.046***
		(0.017)	(0.017)	(0.017)	(0.017)
High tenure		0.022*	0.021*	0.022*	0.021*
		(0.012)	(0.012)	(0.012)	(0.012)
Firm Size < 21		-0.332***	-0.333***	-0.332***	-0.324***
		(0.017)	(0.017)	(0.017)	(0.018)
Firm Size 21-50		-0.095***	-0.097***	-0.095***	-0.089***
		(0.018)	(0.018)	(0.018)	(0.019)
Firm Size 51-100		-0.049***	-0.049***	-0.047***	-0.042**
		(0.018)	(0.018)	(0.018)	(0.019)
Firm Size 101-500		-0.032**	-0.033**	-0.032**	-0.031**
		(0.015)	(0.015)	(0.015)	(0.015)
Full time		-0.471***	-0.471***	-0.472***	-0.472***
		(0.011)	(0.011)	(0.011)	(0.011)
Endogeneity Test					4.513
p-value					0.034
Observations	93,170	93,170	93,170	93,170	93,170
R-squared	0.091	0.131	0.131	0.132	0.076

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

In other words, when workers from all other sectors are included, there are unobserved domestic effects related to these sectors, such as domestic productivity or innovation shock, omitted in the fixed effect regression leading to underestimated OLS coefficients. Since there is evidence of endogeneity, I use the IV estimation to report the effects of offshoring on wages. Using the previous example, shoe-making machine operators, and the coefficients in column 5, I find that the total effect of occupational exposure to offshoring on shoe-making machine operators' wages is 26%.[22] As reported in Table 2.9, adding all workers leads to more significant and larger results than considering workers only from the manufacturing sector.

Table 2.9: Estimates of Wage Determinants using Occupational Exposure to Offshoring in Developing Countries, 2007-2016

	Manufacturing		**All Sectors**	
	FE	IV	FE	IV
Lag of occupation exposure ($OS_{k,t-1}$)	-0.010	0.209	-0.060	-0.358***
	(0.113)	(0.219)	(0.038)	(0.122)
($OS_{k,t-1}$)#Task	0.475**	0.314	0.582***	1.931***
	(0.216)	(0.371)	(0.081)	(0.514)
Routine intensity task (Task)	-1.693**	-1.265	-1.962***	-6.090***
	(0.688)	(1.119)	(0.258)	(1.586)
Formal	0.155***	0.152***	0.221***	0.222***
	(0.031)	(0.031)	(0.014)	(0.014)
R&D/$Y_{k,t-1}$	-0.021***	-0.027***	-0.009***	-0.012***
	(0.007)	(0.008)	(0.002)	(0.003)
Individual Characteristics	Yes	Yes	Yes	Yes
Endogeneity Test		3.823		4.513
p-value		0.148		0.034
Observations	9,644	9,644	93,170	93,170
R-squared	0.154	0.084	0.132	0.076

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

[22] Calculations are as follows: from the marginal effects of column (5) in Table 2.8: (-0.358 + 1.931*(Task))*$\Delta OS_k^{15/06}$ where Task = 0.69 and $\Delta OS_k^{15/06}$ = 0.27 for shoe-making machine operators

Overall, these results indicate that occupational exposure to Peru-South offshoring positively and significantly impacts workers' wages who perform routine-intensive tasks in the manufacturing sector and from across the broader economy. These results are consistent with the empirical work developed by Casabianca et al. (2018), Ebenstein et al. (2014) and Baumgarten et al. (2013), where workers' wages effects of offshoring are related to the tasks that they perform, both within manufacturing and across the broader economy.

The empirical analysis suggests that when offshoring occurs between Peru and other developing countries, the relative demand for domestic workers who perform routine-intensive tasks increases since they experience a positive effect on their wages due to offshoring. The latter indicates that Peru specialises in routine-intensive tasks when Peru-South offshoring occurs. This type of specialisation is consistent with the literature about the pattern of specialisation for the case of developing countries and with the literature regarding offshoring between similar countries. The first one states that low-income economies are specialised in more routine tasks (Autor et al. 2003), and the last one argues that offshoring has a positive effect on workers who perform the task in which both similar countries specialise since employment in these countries are complementary (Spitz-Oener 2006, Ebenstein et al. 2014).

My results also show that offshoring between Peru-South countries positively impacts the wages of formal and informal workers. To understand what drives the positive effect of offshoring on workers' wages in the manufacturing sector, I examine the Peruvian labour market response to offshoring.

2.6 Labour Market Adjustment

In this section, I try to identify channels through which offshoring affects workers' wages following the methodology of Liu & Trefler (2019). First, I examine how offshoring affects the reallocation of workers across occupations, sectors, and formal and informal markets.

Then I examine the relationship between the reallocation of workers and changes in wages.

2.6.1 Displacement and Unemployment

I estimate the offshoring effects on the likelihood of switching occupations (downward and upward) within and across sectors, transitions in and out of informality and unemployment as well as the wage consequences of the switchers. Using OLS, I estimate the following regression to get the probability of switching induced by offshoring:

$$\begin{aligned} y_{i,k,t} = {} & \alpha_{i,t} + \beta DEMOG_{i,t} + \gamma work_{i,t} + \lambda lnOS_{k,t-1} \\ & + \delta TASK_k + \nu lnOS_{k,t-1} \times Task_k + \rho ln(R\&D/Y_{k,t-1}) \\ & + \mu_t + \sigma_k + \iota_j + \epsilon_{i,k,t} \end{aligned} \tag{2.12}$$

The dependent variable $y_{i,k,t}$ is an indicator for the employment status (switching down and switching up within and across sectors, switching markets[23], and transitions to unemployment) of individual i in occupation k in year t. This equation also includes industry fixed effects (ι_j). The rest of the variables are the same as equation (2.5).

Occupational Switching

An individual is considered a switcher of occupations within the sector if he switches a three-digit occupation between t and t+1 but remains in the same sector. Then, I distinguish those that switch down to an occupation with a lower Inter-Occupational Wage Differential (IOWD) and those that switch up to an occupation with a higher IOWD.

The IOWD is the occupation fixed effects in a Mincer wage equation. It indicates which occupations pay well even after controlling for observed worker characteristics. The IOWD can be obtained from the following equation:

[23]Switching from formal to informal or vice-versa

$$lnWage_{i,k,t} = \alpha + \beta DEMOG_{i,t} + \mu_t + \iota_j + \sigma_k + \epsilon_{i,j,t} \quad (2.13)$$

I regress the logarithm of workers' hourly wage, on their observed worker characteristics (DEMOG) such as marital status, education, tenure, sex, etc. The regression also includes year-fixed effects, industry-fixed effects and occupation-fixed effects. The coefficients of the occupation fixed effects are the IOWD. Based on the IOWD, I create four dummy variables. The first one takes the value of 1 when workers switch up occupations within the same sector, and 0 otherwise. The second dummy is set to 1 when workers switch down occupations within the same sector, and 0 otherwise. The third dummy is equals to 1 when workers both switch up occupations and change sectors, and 0 otherwise. The fourth dummy is set to 1 when workers switch down occupations and also change sectors, and 0 otherwise. Then, I run each of these dummy variables as the dependent variable in equation 2.12.

Concerning the endogenous sorting of workers across occupations, Liu & Trefler (2019) address this problem using a general equilibrium model of occupational choice (Roy model) showing that switching-up or down occupations ($s^{+/-}$) depend on the correlation between observable (s^o) and unobservable (s^u) sorting characteristics. Namely, considering that $s^{+/-} = s^o + s^u$, and assuming that s^o and s^u are positively correlated; when two workers initially choose occupation k, the worker with a higher s^o has a higher s probabilistically. Therefore, if the observable sorting characteristic is education s^o, a worker with higher education is less likely to be in the switching-down interval s^- and more likely to be in the switching-up interval s^+. Hence, the education coefficient should be more negative for those who switch down than for those who switch up in the estimate equations for switching. The implication for earnings is developed in Section 6.2.

Transitions between markets

A worker is considered a switcher across markets if he switched from the formal to the informal market or vice-versa. Thus, a switcher takes the value of 1 if he switched markets between t and t+1 and 0 if he did not switch markets.[24]

Transitions to unemployment

A worker is employed if, in the year t, he was a full-time or part-time worker, and a worker is unemployed if during the year t+1 does not have a job. The sample consists of workers who experience no unemployment during time t and t+1 and workers who became unemployed in time t+1.

Figure 2.8 presents the type of transitions present in the data. For instance, 4,777 workers remain in the same market (formal or informal), but 780 workers switch from the formal to the informal market or vice-versa. The number of workers who did not change their market, occupation, or industry is 1,979; they are considered stayers. Thus, each transition includes the workers who switch plus the stayers.

[24]It is worth noting that a separate analysis was conducted, with the dependent variable being a dummy set to 1 when workers switch from formal to informal market and 0 otherwise, as well as another dummy set to 1 when workers switch from informal to formal market and 0 otherwise. In both cases, the results did not show statistical significance.

Figure 2.8: Transitions Tree - Three-Digit Occupation

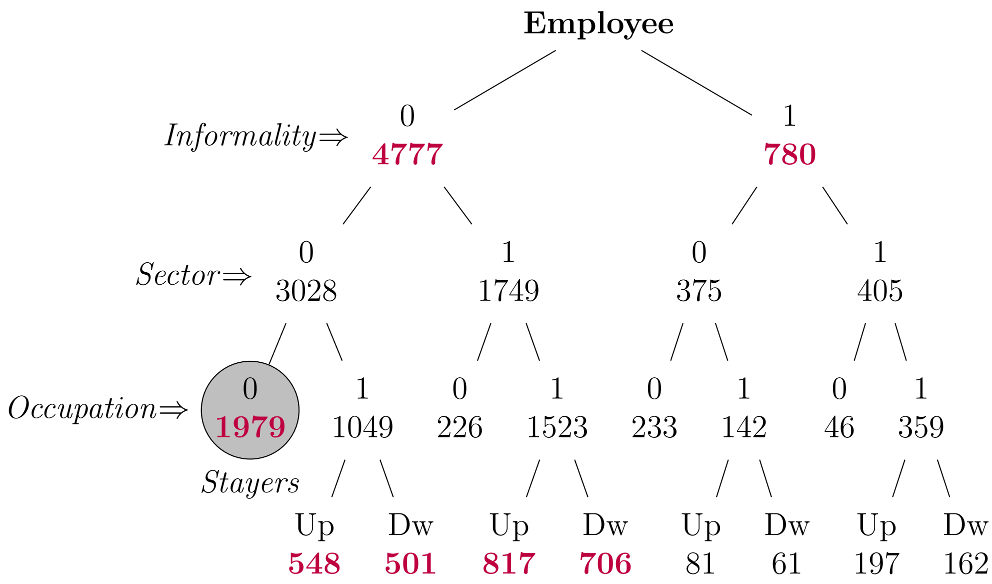


Table 2.10 models the probability of switching induced by occupational exposure to offshoring. The first column shows the likelihood of switching markets (transitions between formal and informal markets) for routine-intensity workers. The sample consists of workers who switched markets and workers who did not switch. As column 1 shows, the Peru-South offshoring does not induce routine intensity workers to switch markets as the coefficients of this variable are not statistically significant (-0.055 and 0.136). However, the coefficient on the dummy variable "formal" is statistically significant and positive, revealing that formal workers are more likely to switch to the informal market rather than informal workers to the formal market. In addition, the coefficient on high education is also statistically significant and positive, implying that workers with a high level of education are more likely to transition out of the informal market.

Columns 3-6 of Table 2.10 shows the results for the case of workers who remain in the same market (formal or informal) and the same sector but switch three-digit occupation. Column 3 reports the results for switching occupations upward. To assess the probability of switching up for routine intensity workers, I use the same example from Table 2.5, Shoe-making machine operator, which is a highly routine-intensive occupation. Applying the coefficients in column 3, I get that the increase of Peru-South offshoring during 2006-2015 increased the likelihood of switching up within the same sector by 0.52 percentage points[25] for the case of shoe-making machine operator workers. Again the coefficient on formal is positive and statistically significant, indicating that formal routine intensity workers, who remain in the same sector, are more likely to switch occupations upwards. Column 5 reports the results for workers who remain in the same sector and market but switch three-digit occupations downwards. Using the same example, I find that during 2006-2015 the likelihood of downward switching induced by offshoring increased by five percentage points[26] for the same group of workers. Although the coefficients are not statistically significant, neither is the coefficient on formal, suggesting that formal workers are less likely to switch occupations downwards in the same sector due to offshoring.

As noted above, if sorting depends on the positive correlation between observable and unobservable characteristics, the coefficient of education should be more negative for those who switch down than for those who switch up. Indeed, comparing column 3 in Table 2.10 and column 5, the education coefficient is higher (0.136) and statistically significant for upward switchers than the coefficient for downward switchers (0.031), which is not statistically significant. The latter suggests a sorting of workers across occupations based on observable characteristics.

Columns 7-10 in Table 2.10 present the analysis for workers who switch sectors and three-digit occupations. Column 7 shows that the likelihood of switching occupations upward (i.e. to a better-paid job), as the previous example, is 3.4 percentage points for the Shoe-making workers.[27] The coefficients on formal and High tenure are negatively

[25]Calculations are as follows: from the marginal effects of column 3 of Table 2.10: (0.233 - 0.310*(Task))*$\Delta lnOS_k^{15/06}$ where Task = 0.69, $\Delta OS_k^{15/06}$ = 0.27 for Shoe-making machine operators

[26]From the marginal effects of column 5 of Table 2.10: (-0.180 + 0.547*(Task))*ΔOS_k where Task = 0.69, $\Delta OS_k^{15/06}$ = 0.27 for Shoe-making machine operator workers.

[27]From the marginal effects of column 7 in Table 2.10: (0.268 - 0.207*(Task))*$\Delta OS_k^{15/06}$ where Task = 0.69, $\Delta OS_k^{15/06}$ = 0.27 for Shoe-making machine operator workers.

and statistically significant, meaning that informal routine intensity workers with less experience are more likely to switch sectors and occupations upward. In contrast, in the case of switching down occupations (column 9), the coefficients on occupational exposure and in the interaction term are not statistically significant, suggesting that routine intensity workers are less likely to switch occupations downwards across sectors. Similarly, the probability of becoming unemployed due to Peru-South offshoring is not statistically significant. Namely, routine-intensity workers are less likely to become unemployed due to offshoring. The sorting mechanism is also confirmed in columns 7 and 9 since the coefficient in education for workers who switch occupations upwards (0.035) is less negative than the coefficient in the education of workers who switch down occupations (-0.006).

The IV column shows the results when the endogenous problem of offshoring is considered. I used the same instruments as in Table 2.5 for occupational exposure to offshoring ($IV-Gravity$, $IV-USA$), and I also instrument the interaction term between occupational exposure and task intensity. The bottom of Table 2.10 presents the test of over-identification for each type of switching, and the orthogonality assumption is not violated in any case. Likewise, for each type of switching, I can not reject the null hypothesis of exogeneity suggesting that OLS and IV should yield similar results, meaning that occupational exposure to offshoring is exogenous and that the source of the import shock is driven by developments in other developing economies (Liu & Trefler 2019). In addition, the first-stage regression shows that both instruments are valid and relevant.[28] Therefore, the results were reported considering the coefficients from the OLS estimates.

Table 2.11 also examines the impact of occupational exposure on the probability of switching occupations between periods but considering a broader classification of occupations (one-digit). As can be seen from Table 2.11, keeping the same sector, offshoring is more likely to induce a switch upward to a new one-digit occupation (1.89 percentage points)[29] Likewise, formal workers are more likely to switch up one-digit occupation and

[28]Table 2.23 of the appendix reports the first-stage results for the IV regressions in Table 2.10

[29]From the marginal effects of column 3 in Table 2.11: (0.293 - 0.323*(Task))*$\Delta OS_k^{15/06}$ where Task

remain in the same sector. Different from Table 2.10, routine intensive workers are more likely to switch down one-digit occupations within the same sector due to offshoring (6.26 percentage points) since the interaction term coefficient is statistically significant. However, it seems that the informal workers are the more likely ones to make this transition.

Column 7 of Table 2.11 presents the likelihood of switching one-digit occupation upwards across sectors. Similar to the case of three-digit occupations, workers who perform routine intensive-task are more likely to switch to one-digit occupations and sectors (3.32 percentage points)[30], and informal workers are more likely to do this transition. In general, workers who perform routine intensive tasks are more likely to move occupations up within and between sectors. It is also clear from the tables 2.10 and 2.11 that formal workers are more likely to switch occupations upward by staying in the same sector, and informal workers are more likely to switch occupations upward when changing sectors.

= 0.69, $\Delta OS_k^{15/06}$ = 0.27 for Shoe-making machine operator workers.

[30]From the marginal effects of column 7 in Table 2.11: (0.233 - 0.159*(Task))*$\Delta OS_k^{15/06}$ where Task = 0.69, $\Delta OS_k^{15/06}$ = 0.27 for Shoe-making machine operator workers.

Table 2.10: Probability of Switching Induced by Offshoring - Three-Digit Occupations

	Switching markets		Transition within sector: Switching up		Transition within sector: Switching down		Transition across sectors: Switching up		Transition across sectors: Switching down		Unemployment	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV	(11) OLS	(12) IV
Lag of occupation	-0.055	-0.031	0.233**	0.158	-0.180	-0.208	0.268**	0.145	0.063	0.039	0.025	0.008
exposure ($OS_{k,t-1}$)	(0.052)	(0.067)	(0.111)	(0.161)	(0.183)	(0.219)	(0.110)	(0.135)	(0.109)	(0.121)	(0.016)	(0.017)
($OS_{k,t-1}$)#Task	0.136	0.137	-0.310	-0.205	0.547	0.605	-0.207	-0.006	-0.118	0.035	-0.059*	-0.026
	(0.114)	(0.142)	(0.194)	(0.275)	(0.333)	(0.403)	(0.198)	(0.241)	(0.164)	(0.225)	(0.031)	(0.033)
Task	-0.217	-0.224	0.077	-0.235	-2.398**	-2.575**	0.138	-0.468	-0.083	-0.546	0.193**	0.092
	(0.379)	(0.461)	(0.684)	(0.912)	(0.981)	(1.220)	(0.685)	(0.755)	(0.592)	(0.734)	(0.095)	(0.111)
Formal	0.074***	0.074***	0.136***	0.136***	0.031	0.031	-0.102***	-0.103***	-0.121***	-0.121***	-0.005	-0.005
	(0.028)	(0.028)	(0.032)	(0.031)	(0.039)	(0.038)	(0.033)	(0.032)	(0.034)	(0.033)	(0.004)	(0.004)
R&D/$Y_{k,t-1}$	0.002	-0.000	0.009	0.010	0.001	0.001	0.008	0.009	0.002	-0.002	-0.001	-0.001
	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)
Married	-0.007	-0.007	-0.006	-0.006	-0.018	-0.018	-0.032*	-0.031*	-0.032*	-0.032**	-0.010***	-0.010***
	(0.011)	(0.010)	(0.014)	(0.014)	(0.014)	(0.013)	(0.017)	(0.017)	(0.017)	(0.016)	(0.003)	(0.003)
Male	0.007	0.007	0.020	0.019	-0.003	-0.003	0.022	0.020	0.009	0.009	-0.002	-0.002
	(0.014)	(0.014)	(0.022)	(0.020)	(0.028)	(0.028)	(0.026)	(0.025)	(0.031)	(0.030)	(0.006)	(0.006)
High education	0.067***	0.067***	0.030	0.030	-0.041	-0.041	0.035	0.035	-0.006	-0.007	0.007	0.007*
	(0.015)	(0.015)	(0.023)	(0.023)	(0.030)	(0.029)	(0.023)	(0.022)	(0.025)	(0.024)	(0.005)	(0.004)
High tenure	-0.029**	-0.029**	-0.028	-0.028	-0.033	-0.033	-0.091***	-0.092***	-0.095***	-0.096***	-0.011***	-0.011***
	(0.014)	(0.014)	(0.028)	(0.027)	(0.022)	(0.021)	(0.023)	(0.022)	(0.016)	(0.016)	(0.003)	(0.002)
Firm Size < 21	0.043	0.044	-0.103	-0.104*	-0.090*	-0.090*	-0.008	-0.009	0.033	0.034	0.002	0.002
	(0.028)	(0.028)	(0.066)	(0.063)	(0.053)	(0.051)	(0.048)	(0.046)	(0.045)	(0.043)	(0.008)	(0.008)
Firm Size 21-50	0.083***	0.083***	0.071	0.070	0.045	0.044	0.061	0.061	0.087	0.084	0.003	0.002
	(0.031)	(0.030)	(0.073)	(0.070)	(0.072)	(0.069)	(0.056)	(0.055)	(0.066)	(0.065)	(0.011)	(0.011)
Firm Size 51-100	0.073*	0.073*	-0.018	-0.021	-0.064	-0.065	0.058	0.055	0.087	0.085	0.010	0.010
	(0.041)	(0.040)	(0.080)	(0.078)	(0.074)	(0.072)	(0.067)	(0.066)	(0.055)	(0.053)	(0.014)	(0.014)
Firm Size 101-500	0.042*	0.042*	0.016	0.016	0.005	0.004	0.038	0.037	0.020	0.018	-0.009	-0.009
	(0.023)	(0.022)	(0.058)	(0.056)	(0.050)	(0.048)	(0.053)	(0.051)	(0.043)	(0.042)	(0.008)	(0.008)
Full time	0.043***	0.042***	0.036*	0.037*	0.021	0.022	-0.058***	-0.058***	-0.064***	-0.064***	0.002	0.002
	(0.015)	(0.014)	(0.021)	(0.020)	(0.022)	(0.021)	(0.021)	(0.021)	(0.023)	(0.022)	(0.004)	(0.004)
Overid test		1.660		4.057		0.233		0.669		1.288		4.529
p-value		0.436		0.132		0.890		0.716		0.525		0.104
Endogeneity Test		1.901		0.265		0.005		1.840		1.373		0.065
p-value		0.168		0.607		0.943		0.175		0.241		0.798
Observations	5,557	5,557	2,527	2,527	2,480	2,480	2,796	2,796	2,685	2,685	5,638	5,638
R-squared	0.069	0.024	0.259	0.078	0.284	0.041	0.224	0.048	0.252	0.051	0.052	0.009

Note: Standard errors clustered at the three-digit occupation appears in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year, sector and two-digit occupation fixed effects. Default category: Firm size > 500.

Table 2.11: Probability of Switching Induced by Offshoring - One-Digit Occupations

	Switching markets		Transition within sector: Switching up		Transition within sector: Switching down		Transition across sectors: Switching up		Transition across sectors: Switching down		Unemployment	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV	(11) OLS	(12) IV
Lag of occupation	-0.055	-0.031	0.293***	0.179	-0.183	-0.342	0.233**	0.142	0.001	-0.034	0.025	0.008
exposure ($OS_{k,t-1}$)	(0.052)	(0.067)	(0.100)	(0.135)	(0.190)	(0.217)	(0.110)	(0.145)	(0.102)	(0.120)	(0.016)	(0.017)
($OS_{k,t-1}$)#Task	0.136	0.137	-0.323*	-0.114	0.601*	0.950**	-0.159	-0.030	-0.018	0.187	-0.059*	-0.026
	(0.114)	(0.142)	(0.165)	(0.221)	(0.345)	(0.418)	(0.177)	(0.239)	(0.163)	(0.225)	(0.031)	(0.033)
Task	-0.217	-0.224	0.063	-0.571	-2.501**	-3.579***	0.111	-0.275	-0.636	-1.249*	0.193**	0.092
	(0.379)	(0.461)	(0.550)	(0.706)	(0.976)	(1.219)	(0.617)	(0.770)	(0.576)	(0.714)	(0.095)	(0.111)
Formal	0.074***	0.074***	0.110***	0.109***	-0.018	-0.018	-0.071**	-0.071**	-0.115***	-0.114***	-0.005	-0.005
	(0.028)	(0.028)	(0.027)	(0.026)	(0.029)	(0.028)	(0.030)	(0.029)	(0.035)	(0.034)	(0.004)	(0.004)
R&D/$Y_{k,t-1}$	0.002	-0.000	0.002	0.003	0.001	-0.002	0.009	0.010	0.005	-0.000	-0.001	-0.001
	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.001)	(0.001)
Married	-0.007	-0.007	-0.002	-0.001	-0.012	-0.011	-0.037**	-0.037**	-0.028*	-0.027*	-0.010***	-0.010***
	(0.011)	(0.010)	(0.014)	(0.013)	(0.012)	(0.011)	(0.018)	(0.017)	(0.015)	(0.015)	(0.003)	(0.003)
Male	0.007	0.007	0.002	0.001	0.015	0.012	-0.000	-0.002	0.018	0.017	-0.002	-0.002
	(0.014)	(0.014)	(0.021)	(0.020)	(0.028)	(0.027)	(0.027)	(0.026)	(0.030)	(0.028)	(0.006)	(0.006)
High education	0.067***	0.067***	0.066***	0.067***	-0.027	-0.026	0.019	0.019	-0.015	-0.016	0.007	0.007*
	(0.015)	(0.015)	(0.024)	(0.023)	(0.025)	(0.024)	(0.023)	(0.022)	(0.022)	(0.022)	(0.005)	(0.004)
High tenure	-0.029**	-0.029**	0.002	0.002	-0.022	-0.022*	-0.084***	-0.084***	-0.097***	-0.098***	-0.011***	-0.011***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.022)	(0.021)	(0.015)	(0.014)	(0.003)	(0.002)
Firm Size < 21	0.043	0.044	-0.076*	-0.078*	-0.085*	-0.083*	-0.006	-0.007	0.048	0.050	0.002	0.002
	(0.028)	(0.028)	(0.043)	(0.042)	(0.050)	(0.048)	(0.046)	(0.044)	(0.039)	(0.038)	(0.008)	(0.008)
Firm Size 21-50	0.083***	0.083***	0.074	0.072	0.019	0.015	0.071	0.071	0.089	0.085	0.003	0.002
	(0.031)	(0.030)	(0.066)	(0.064)	(0.070)	(0.068)	(0.055)	(0.053)	(0.062)	(0.059)	(0.011)	(0.011)
Firm Size 51-100	0.073*	0.073*	-0.021	-0.026	-0.074	-0.082	0.006	0.004	0.084	0.082	0.010	0.010
	(0.041)	(0.040)	(0.067)	(0.064)	(0.079)	(0.077)	(0.071)	(0.069)	(0.061)	(0.059)	(0.014)	(0.014)
Firm Size 101-500	0.042*	0.042*	0.036	0.035	0.012	0.012	0.010	0.009	0.042	0.040	-0.009	-0.009
	(0.023)	(0.022)	(0.049)	(0.047)	(0.047)	(0.046)	(0.051)	(0.049)	(0.036)	(0.034)	(0.008)	(0.008)
Full time	0.043***	0.042***	0.032**	0.032**	0.020	0.021	-0.067***	-0.066***	-0.080***	-0.080***	0.002	0.002
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.025)	(0.024)	(0.024)	(0.023)	(0.004)	(0.004)
Overid test		1.660				0.459		0.606		2.968		4.529
p-value		0.436				0.795		0.739		0.227		0.104
Endogeneity Test		1.901		0.252		0.079		1.835		1.698		0.065
p-value		0.168		0.615		0.779		0.176		0.193		0.798
Observations	5,557	5,557	2,281	2,281	2,270	2,270	2,588	2,588	2,503	2,503	5,638	5,638
R-squared	0.069	0.024	0.311	0.100	0.355	0.047	0.224	0.047	0.227	0.062	0.052	0.009

Note: Standard errors clustered at the three-digit occupation appears in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year, sector and two-digit occupation fixed effects. Default category: Firm size > 500.

2.6.2 Changes in annual earnings

In this section, I analyse the wage changes due to the incidence of switching. Since I am evaluating the impact of offshoring when workers switch occupations, there is a potential endogeneity problem (Liu & Trefler 2019) because workers can choose the occupation that maximizes their earnings. Thus, following Liu & Trefler (2019) and Ebenstein et al. (2014), I assume that workers sort across occupations only on observable characteristics and have no unobserved heterogeneity. Thus, assuming sorting is controlled by observed characteristics, I calculate the Average Treatment Effect (ATE) using propensity score matching (PSM).

This method aims to construct a control group from the sample of workers who did not switch occupations, sectors, or markets and stayed employed the whole sample period, namely the stayers. To get a control group, I first estimate the probability of switching at time t+1 using a probit model with workers' characteristics[31] at time t. Then, I use the propensity scores from the probit model to match the workers who switched with workers who did not switch. Since the number of observations for each switching is small, I apply a 1-to-1 nearest neighbour with a caliper (0.05) with replacement and common support condition. Balancing tests appears in Appendix 9.3.

Table 2.12 presents the changes in wages due to the different transitions by switching three and one-digit occupations. Columns 1 and 2 report the results for individuals who stay in the same sector but switch occupations. Column 1 shows that the average wage change for workers who remain in the same sector and switch occupations upwards is about 7.3% higher than the average wage change for workers who stay in the same sector and occupation (the stayers). Column 2 reports the average wage change for workers who remain in the same sector but switch occupations downward (-11.3%). However, the average wage change is not statistically significant.

Similarly, columns (3) and (4) present the results for workers who switch occupations

[31] It includes all the covariates that appear in Table 2.5

but also change sectors. The average wage change for workers who change sectors and switch occupations upwards is about 22.4% higher than the average wage change for the stayers. In column (4), the average wage change for workers who switch sectors and occupations downward is 36.3% less than the average wage change for the stayers. As noted below, the average wage change for workers who switch occupations and sectors is higher and statistically significant compared to workers who only switch occupations but stay in the same sector. Finally, the average wage change for workers who became unemployed is 95.1%[32] less than for workers who remained employed in the same occupation and the same market (column 5). Table 2.12 also shows the wage changes when workers switch one-digit occupations. The latter is more significant and higher when the transition is across sectors and upward occupations. These results suggest that changing occupations and sectors are more costly than changing occupations but remaining in the same sector.

Table 2.12: Wage Changes of Occupational Switchers and Transitioners to Unemployment - Routine Occupations

	Transitions Within Sectors		Transitions Across Sectors		
	Switching-Up	Switching-down	Switching-up	Switching-down	Unemployment
Occupation switch by switching three-digit occupation					
ATE	0.073	-0.113	0.224^{**}	-0.363^{***}	-0.951^{***}
	(0.138)	(0.125)	(0.092)	(0.132)	(0.159)
Observations	2,435	2,343	2,622	2,623	4,002
Occupation switch by switching one-digit occupation					
ATE	0.073	-0.076	0.380^{***}	-0.261^{**}	-0.951^{***}
	(0.160)	(0.135)	(0.123)	(0.125)	(0.159)
Observations	2,160	2,120	2,366	2,438	4,002

Robust standard errors are reported in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[32] It is important to note that in Peru, individuals who lose their jobs and become unemployed do not receive financial support from the government.

2.7 Summary of Findings

Overall, these results show that formal workers who perform routine-intensive tasks are more likely to switch occupations upward by remaining in the same sector. In contrast, informal workers who perform routine-intensive tasks are more likely to switch occupations upward by changing sectors. The change in wages for workers who switch occupations upward within the same sector is positive but not statistically significant, while the wage change for workers who switch occupations upward across sectors is positive and statistically significant. Therefore, the positive impact of offshoring on formal wages can be explained by the likelihood of switching occupations upward within the same sector, whereas the informal wage increase can be explained by the probability of changing occupations upward but across sectors.

Furthermore, the data show that formal workers who switch occupations upward within the same sector switch from routine-manual intensive tasks toward routine-cognitive intensive tasks. The latter confirms that Peru offshore routine-manual intensive tasks to other developing countries and specialises in routine-cognitive intensive tasks. Therefore, the theory developed by Grossman & Rossi-Hansberg (2012) holds for the case of formal workers since Peru is offshoring routine-manual tasks to other developing countries that complement the routine-cognitive task performed in Peru. The Peru-South offshoring increases the demand for routine-cognitive intensive tasks in Peru, where formal routine-manual intensity workers are more likely to switch occupations upward (routine-cognitive task) within the same sector, increasing their relative wages.

Table 2.13 shows the transitions matrix across occupations for formal workers who switch occupations upward and remain in the same sector; the table confirms that most of the formal labour force (87.4%) transit from high-exposed occupations (Machine operators) to other high-exposed occupations (Technicians). In contrast, most of the informal labour force who switch occupations upwards by changing sectors (62%) transit from high-exposed occupations (Craftworkers) to low-exposed occupations (Elementary occupations, sales), which are more intensive in the performance of manual tasks.[33]

Table 2.13: Transition Matrix - Switching Occupations Upwards

	Within sectors		Across sectors	
	Formal workers		Informal workers	
	High Exposed	Low Exposed	High Exposed	**Low Exposed**
High-exposed	**0.874**	0.126	0.390	**0.620**
Low-exposed	0.792	0.208	0.494	0.506

Therefore, the theory and the empirical evidence of offshoring between similar countries do not fit the case of informal workers, as the increase in the relative wage of informal workers who perform routine-intensive tasks is not associated with the increase in their relative demand. Instead, it is related to switching occupations upward towards low-exposed occupations and more manual-intensive tasks. Unlike the literature on trade and informality, the transition in and out of informality is not statistically significant when offshoring occurs between southern countries. Thus, the informal worker remains informal, losing skills and the possibility to specialise in routine-cognitive intensive tasks.

2.8 Robustness checks

2.8.1 Model misspecification

To account for potential wage changes induced by trade through other channels than imports, I add exports in intermediate inputs to Southern countries ($XS_{k,t-1}$) calculated at the occupational level. I also include the interaction between exports and the task content of occupations. A possible concern is a potential endogeneity arising from the

[33]High-exposed occupations refer to occupations with above-mean positive growth rates of exposure to Peru-South offshoring. Low-exposed occupations have below-mean positive growth rate

joint evolution of exports and wages. Thus I include the interaction term of the pre-sample of exports ($XS_{k,t-1}$) times year dummies (Casabianca et al. 2018). Taking this interaction avoids endogeneity issues driven by some underlying trend. Thus exports should capture any exogenous shock that may affect the competitiveness of the Peruvian economy and workers' wages. Column 3 of table 2.14 shows that the effect of occupational exposure to offshoring is still statistically significant and positive after exports, and the interaction between exports and tasks is included. Similarly, in the case in which the interaction between occupational exposure and formal is included (column 6), the coefficients of the occupational exposure are still statistically significant.

In addition, I also include the intermediate imports from developed countries that could affect the demand for high-skilled workers and their wages but not the task content since it is unlikely that Peru offshore some tasks to developed countries. Thus, the interaction between intermediate imports from developed countries and the task content of occupations is not considered. I also include the interaction between the pre-sample of this variable and year dummies. Column 2 of table 2.14 includes this variable; the results are still positive and statistically significant for workers who perform routine-intensive tasks, same for formal and informal workers (column 5).

Considering that China is one of Peru's main trade partners in the manufacturing sector, the results could be influenced by the trade between Peru and China. Therefore, Table 2.15 estimates the empirical model without the intermediate imports from China. We can see that without China, the impact of offshoring on wages is even higher. In column 3, I consider only the intermediate imports from Latin American countries since these countries are more similar to Peru in terms of culture, geography, and proximity. Thus, I would expect a higher effect of offshoring on workers engaged in routine-intensive tasks, as the tasks performed in Peru and Latin American countries should be more complementary due to their similarities. Column 3 shows that the effect is higher and statistically significant when intermediate imports are from Latin American countries.

Table 2.14: Offshoring by Occupation-Specific Exposure - Robustness to Omitted Variables

	Task interaction			Formal interaction		
	(1)	(2)	(3)	(4)	(5)	(6)
$(OS_{k,t-1})$	-0.010	-0.110	-0.035	0.228***	0.123	0.159*
	(0.113)	(0.323)	(0.133)	(0.061)	(0.310)	(0.089)
$(OS_{k,t-1})$#Task (Formal)	0.475**	0.490**	0.377*	-0.077**	-0.080**	-0.074**
	(0.216)	(0.215)	(0.219)	(0.037)	(0.038)	(0.037)
$(OS_{k,t-1})$ from Northern countries		-0.055			-0.041	
		(0.340)			(0.341)	
$(XS_{k,t-1})$			-0.281			-0.356
			(0.567)			(0.503)
$(XS_{k,t-1})$#Task (Formal)			0.028			0.029
			(0.681)			(0.130)
Unemployment	-2.215***	-2.304***	-2.472***	-1.404***	-1.462***	-1.955**
	(0.384)	(0.386)	(0.889)	(0.212)	(0.216)	(0.784)
EIP	-1.925***	-2.008***	-2.160**	-1.114***	-1.165***	-1.643**
	(0.380)	(0.384)	(0.888)	(0.204)	(0.210)	(0.785)
Formal	0.155***	0.153***	0.153***	0.379***	0.388***	0.308
	(0.031)	(0.031)	(0.031)	(0.114)	(0.117)	(0.308)
Task	-1.693**	-1.726**	-1.423	-0.269	-0.257	-0.232
	(0.688)	(0.686)	(1.397)	(0.183)	(0.184)	(0.183)
R&D/$Y_{k,t-1}$	-0.021***	-0.015*	-0.017**	-0.017***	-0.011	-0.014*
	(0.007)	(0.008)	(0.007)	(0.006)	(0.008)	(0.008)
Married	0.030	0.036	0.032	0.027	0.032	0.030
	(0.058)	(0.057)	(0.058)	(0.058)	(0.057)	(0.058)
High education	0.045	0.044	0.044	0.047	0.045	0.045
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
High tenure	-0.025	-0.028	-0.029	-0.024	-0.027	-0.028
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Firm Size < 21	-0.320***	-0.323***	-0.321***	-0.314***	-0.317***	-0.316***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Firm Size 21-50	-0.127***	-0.125***	-0.125***	-0.120***	-0.119***	-0.119***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Firm Size 51-100	-0.039	-0.039	-0.040	-0.030	-0.030	-0.032
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Firm Size 101-500	-0.022	-0.018	-0.022	-0.021	-0.017	-0.021
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Full time	-0.316***	-0.319***	-0.316***	-0.316***	-0.318***	-0.316***
	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)
Observations	9,644	9,644	9,644	9,644	9,644	9,644
R-squared	0.154	0.158	0.158	0.154	0.157	0.158

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year, and occupation fixed effects. The interaction between pre-sample exports and time dummies is also included. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

Table 2.15: Offshoring by Occupation-Specific Exposure - Robustness to Omitted Variables

	Task interaction			Formal interaction		
	(1) All Southern countries	(2) Without China	(3) Latin America	(4) All Southern countries	(5) Without China	(6) Latin America
$(OS_{k,t-1})$	-0.010	-0.122	-0.162	0.228***	0.229***	0.225***
	(0.113)	(0.146)	(0.158)	(0.061)	(0.073)	(0.076)
$(OS_{k,t-1})$#Task (Formal)	0.475**	0.729**	0.804***	-0.077**	-0.073*	-0.064
	(0.216)	(0.283)	(0.304)	(0.037)	(0.043)	(0.044)
Unemployment	-2.215***	-2.469***	-2.525***	-1.404***	-1.512***	-1.556***
	(0.384)	(0.395)	(0.394)	(0.212)	(0.206)	(0.202)
EIP	-1.925***	-2.179***	-2.235***	-1.114***	-1.219***	-1.263***
	(0.380)	(0.392)	(0.391)	(0.204)	(0.197)	(0.193)
Formal	0.155***	0.156***	0.156***	0.379***	0.320***	0.286***
	(0.031)	(0.031)	(0.031)	(0.114)	(0.104)	(0.096)
Task	-1.693**	-2.006***	-2.033***	-0.269	-0.257	-0.250
	(0.688)	(0.716)	(0.710)	(0.183)	(0.183)	(0.183)
R&D/$Y_{k,t-1}$	-0.021***	-0.021***	-0.021***	-0.017***	-0.016**	-0.016**
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Married	0.030	0.031	0.031	0.027	0.028	0.029
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
High education	0.045	0.045	0.044	0.047	0.047	0.046
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
High tenure	-0.025	-0.024	-0.023	-0.024	-0.023	-0.023
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Firm Size < 21	-0.320***	-0.320***	-0.321***	-0.314***	-0.316***	-0.317***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Firm Size 21-50	-0.127***	-0.128***	-0.128***	-0.120***	-0.122***	-0.123***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Firm Size 51-100	-0.039	-0.038	-0.038	-0.030	-0.031	-0.031
	(0.043)	(0.043)	(0.044)	(0.043)	(0.044)	(0.044)
Firm Size 101-500	-0.022	-0.021	-0.021	-0.021	-0.020	-0.020
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Full time	-0.316***	-0.318***	-0.318***	-0.316***	-0.317***	-0.317***
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)
Observations	9,644	9,644	9,644	9,644	9,644	9,644
R-squared	0.154	0.154	0.154	0.154	0.153	0.153

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

2.8.2 Alternative matching method - Mahalanobis distance matching

I use an alternative matching method as a robustness check, Mahalanobis Distance Matching (MDM). This method matches each treated unit to the nearest control unit. The distance between individuals i and j used for matching is expressed as follows:

$$D_{ij} = (X_i - X_j)' \sum_{-1} (X_i - X_j) \tag{2.14}$$

Where X are the covariates. As in the previous analysis, I use the individual's characteristics in the pre-switching period (t) for matching. Table 2.16 reports changes in wages as a result of the transitions across occupations and transition to unemployment. Similarly to Table 2.12, the average wage change for workers who switch occupations and sectors is higher and statistically significant compared to workers who only switch occupations but remain in the same sector. Likewise, for workers who become unemployed, wages fell by 43%.[34]

Table 2.16: Wage Changes of Occupational Switchers and Transitioners to Unemployment - Routine Occupations

	Transitions Within Sectors		Transitions Across Sectors		
	Switching-Up	Swithcing-down	Switching-up	Switching-down	Unemployment
Occupation switch by switching three-digit occupation					
ATE	0.036	0.028	0.183***	-0.223***	-0.429***
	(0.055)	(0.115)	(0.065)	(0.086)	(0.162)
Observations	2,527	2,480	2,796	2,685	5,638
Occupation switch by switching one-digit occupation					
ATE	0.017	0.200	0.177**	-0.235**	-0.429***
	(0.079)	(0.287)	(0.084)	(0.098)	(0.162)
Observations	2,281	2,270	2,588	2,503	5,638

Robust standard errors are reported in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[34]The balancing tests are presented in Appendix 9.4.2 Tables 2.29-2.33

2.8.3 Additional sensitivity results

In Table 2.17, I present probit marginal effects for switching down and up occupations within and across sectors as well as transitions to unemployment. I consider three-digit and one-digit switching occupations. The results are very similar to the estimations using OLS.

Table 2.17: Probability of Switching Induced by Offshoring: Marginal Effects - Probit Model

			One-digit occupation				**Three-digit occupation**			
			Transitions within sector		Transitions across sectors		Transitions within sector		Transitions across sectors	
	Switching Markets	Transition to Unemployment	Switching Up	Switching Down	Switching Up	Switching Down	Switching Up	Switching Down	Switching Up	Switching Down
$(OS_{k,t-1})$	-0.055	0.009	0.189***	-0.187	0.226*	0.023	0.211**	-0.141	0.281**	0.078
	(0.051)	(0.017)	(0.073)	(0.115)	(0.119)	(0.092)	(0.101)	(0.143)	(0.121)	(0.101)
$(OS_{k,t-1})$#Task	0.143	-0.046	-0.256*	0.486***	-0.186	-0.021	-0.324*	0.435*	-0.249	-0.104
	(0.107)	(0.038)	(0.133)	(0.178)	(0.222)	(0.154)	(0.178)	(0.232)	(0.238)	(0.166)
Task	-0.248	0.157	0.276	-1.914***	0.255	-0.536	0.307	-1.818**	0.330	-0.058
	(0.357)	(0.123)	(0.430)	(0.548)	(0.744)	(0.504)	(0.618)	(0.715)	(0.785)	(0.553)
Formal	0.063***	-0.008	0.098***	-0.022	-0.102***	-0.135***	0.119***	0.026	-0.130***	-0.129***
	(0.021)	(0.005)	(0.023)	(0.026)	(0.038)	(0.032)	(0.028)	(0.035)	(0.039)	(0.028)
R&D/$Y_{k,t-1}$	0.002	-0.001	0.004	0.003	0.007	0.004	0.009	0.002	0.008	0.001
	(0.004)	(0.002)	(0.004)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.006)
Married	-0.007	-0.012***	-0.004	-0.017	-0.043**	-0.027*	-0.005	-0.022	-0.034**	-0.029**
	(0.010)	(0.004)	(0.013)	(0.011)	(0.018)	(0.014)	(0.014)	(0.014)	(0.017)	(0.015)
Male	0.010	-0.004	0.005	0.010	-0.007	0.006	0.027	-0.009	0.016	-0.000
	(0.014)	(0.008)	(0.018)	(0.023)	(0.026)	(0.026)	(0.020)	(0.024)	(0.025)	(0.028)
High education	0.063***	0.009*	0.057***	-0.023	0.023	-0.016	0.025	-0.040	0.041*	-0.007
	(0.013)	(0.005)	(0.018)	(0.019)	(0.024)	(0.023)	(0.020)	(0.025)	(0.023)	(0.025)
High tenure	-0.030**	-0.021***	0.001	-0.023*	-0.089***	-0.103***	-0.023	-0.031	-0.093***	-0.099***
	(0.015)	(0.005)	(0.014)	(0.012)	(0.021)	(0.012)	(0.027)	(0.021)	(0.021)	(0.015)
Firm Size < 21	0.033	-0.004	-0.042	-0.080***	-0.022	0.057	-0.078	-0.084**	-0.016	0.032
	(0.024)	(0.008)	(0.026)	(0.030)	(0.051)	(0.042)	(0.049)	(0.041)	(0.051)	(0.048)
Firm Size 21-50	0.067***	-0.003	0.058*	0.001	0.048	0.082	0.064	0.029	0.039	0.074
	(0.025)	(0.010)	(0.033)	(0.037)	(0.060)	(0.057)	(0.050)	(0.048)	(0.059)	(0.061)
Firm Size 51-100	0.061*	0.009	0.008	-0.041	0.013	0.091	0.005	-0.055	0.064	0.081
	(0.033)	(0.012)	(0.038)	(0.036)	(0.070)	(0.058)	(0.058)	(0.047)	(0.064)	(0.051)
Firm Size 101-500	0.035*	-0.015	0.026	0.005	0.012	0.044	0.016	0.003	0.047	0.016
	(0.020)	(0.011)	(0.027)	(0.024)	(0.058)	(0.035)	(0.040)	(0.034)	(0.057)	(0.043)
Full time	0.051***	0.004	0.045**	0.033*	-0.062**	-0.076***	0.041*	0.026	-0.056***	-0.064***
	(0.017)	(0.005)	(0.019)	(0.018)	(0.024)	(0.020)	(0.021)	(0.025)	(0.021)	(0.019)
Observations	5,393	4,002	2,160	2,120	2,366	2,438	2,435	2,343	2,622	2,623

Note: Standard errors clustered at the three-digit occupation appears in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year, sector and two-digit occupation fixed effects. Default category: Firm size > 500.

2.9 Conclusions

The imports of intermediate goods between Southern countries have increased in the last 20 years, suggesting potential offshoring activities between these countries. The latter provides an opportunity to assess how workers respond to the increase in offshoring between Southern countries. Peru has not been the exception to the increase in intermediate goods from developing countries, showing that it has increased backward linkages in the manufacturing sector since it uses a significant number of imported inputs in its manufacturing exports. In addition, this sector has experienced, at the same time, a reduction in its labour force and an increase in intermediate imports from other developing countries. Those events suggest potential offshoring activities in the manufacturing sector of Peru. For the first time, I explore these recent events to examine how Peruvian workers respond to the offshoring activities between Southern countries.

Working with the Peruvian Labour Survey, the US O*Net, and the Eora Global Supply Chain database, my study finds various results. Primary, offshoring between Peru and Southern countries positively affects workers' wages who perform routine-intensive tasks. This result is consistent with Grossman & Rossi-Hansberg (2012) theory and the recent empirical work, demonstrating that Peru specialises in routine-intensive tasks and complements the routine-intensive tasks performed by other developing countries. Further, since Peru has a high level of informality, I distinguish this effect between formal and informal workers. The results show that over the period 2007-2016, the offshoring at the occupational level increased the wages of formal and informal routine intensity workers by 5% and 7%, respectively. The latter suggests that offshoring increases the demand for formal and informal routine-intensity workers, as the theory suggests.

However, by focusing on the channels through which offshoring affects workers' wages, I find that this effect is different between formal and informal workers. I found that the increase in Peru-South offshoring during 2006-2015 increased the likelihood of switching occupations upwards within the same sector by 0.52 percentage points for routine-intensity workers, being formal workers more likely to make this type of transition. The increase in offshoring also increased the likelihood of switching occupations upwards across sectors by 3.4 percentage points for routine-intensity workers but being informal workers more likely to make this transition. Furthermore, I estimate the wage impact of offshoring-induced occupational switching under the assumption that sorting is only on observable characteristics since I do not have an instrument that estimates wages in the presence of sorting on unobservables. I found positive impacts of offshoring-induced occupational switching upwards. For routine-intensity workers who switched occupations upwards within the same sector, wages increased by 7.3%, although it is not statistically significant. While for routine-intensity workers who switched sectors and occupations upwards, the wage increase is higher and statistically significant (22.4%).

Therefore, the empirical evidence related to offshoring between similar countries fits the case of formal workers since the increase in their wages is associated with the likelihood of switching occupations upward within the same sector. The data indicate that formal routine intensity workers switch occupations towards more routine-cognitive tasks such as technicians and clerks occupations, implying an increase in the demand for these workers when Peru-South offshoring occurs, as the theory predicts. In contrast, the empirical evidence does not fit the case of informal workers since the rise in their wages is not related to the high demand for routine-intensity workers. Instead, the increase in informal wages is explained by the transition to upward occupations across sectors towards low-exposed occupations, from routine-intensive to manual-intensive tasks. This result suggests that informal workers are more vulnerable to trade shocks since they are more likely to switch occupations and sectors due to offshoring, losing the possibility to specialise in specific tasks.

My results provide new evidence regarding the relationship between trade and informality, demonstrating that offshoring does not induce the transition of a formal worker to the informal market or vice-versa as the empirical literature on trade and informality suggests, but it does affect informal workers differently. The response of informal workers to offshoring provides evidence that the high level of informality is a constraint for the specialisation of the labour force in Peru. Since informal workers do not have a fixed contract and do not receive training, they are more likely to switch occupations and sectors, preventing them from gaining new skills and the opportunity to specialise in specific tasks. The results also indicate that workers' adjustment to offshoring occurs mainly by switching occupations within and across sectors; they also confirm that informality works as a buffer to offshoring-displaced informal workers because it is more likely that an informal worker changes occupations and sectors within the informal market than become unemployed.

Therefore, the increase in Peru-South offshoring increases the demand for routine-intensity workers, increasing their relative wages. For the case of formal workers, this increase allows them to specialise in routine-cognitive intensity tasks. However, for the informal workers, the growth in offshoring leads to a reallocation of them across sectors and towards manual-intensive occupations, preventing them from specialising in specific tasks and firms from gaining the necessary high-skill workers and competence to succeed in international markets. There is a lack in the conceptual framework of offshoring between similar countries considering the task content, wages and informal labour; thus, future work should develop a theoretical model which accounts for these results.

2.10 Appendix

2.10.1 Data

List of Southern Countries

Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Chile, Colombia, Congo, Costa Rica, Cote dIvoire, Cuba, DR Congo, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Guatemala, Guinea, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Madagascar, Malawi, Malaysia, Maldives, Mali, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Panama, Papua New Guinea, Paraguay, Philippines, Poland, Romania, Russia, Rwanda, Samoa, Sao Tome and Principe, Senegal, Serbia, Sierra Leone, South Africa, South Sudan, Sri Lanka, Sudan, Suriname, Swaziland, Syria, TFYR Macedonia, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, Uruguay, Uzbekistan, Vanuatu, Venezuela, Viet Nam, Yemen, Zambia and Zimbabwe.

Task Content Construction

- Abstract task
  - Non-routine cognitive analytical
    - 4.A.2.a.4 - Analyzing data/information
    - 4.A.2.b.2 - Thinking creatively
    - 4.A.4.a.1 - Interpreting information for others
  - Non-routine cognitive interpersonal
    - 4.A.4.a.4 - Establishing and maintaining personal relationships
    - 4.A.4.b.4 - Guiding, directing and motivating subordinates
    - 4.A.4.b.5 - Coaching/developing others
- Routine task
  - Routine Cognitive

    * 4.C.3.b.7 - Importance of repeating the same tasks
    * 4.C.3.b.4 - Importance of being exact or accurate
    * 4.C.3.b.8 - Structured v. Unstructured work (reverse)
  - Routine Manual
    * 4.C.3.d.3 - Pace determined by speed of equipment
    * 4.A.3.a.3 - Controlling machines and processes
    * 4.C.2.d.1.i - Spend time making repetitive motions

- Manual task
  - Non-routine manual physical task
    * 4.A.3.a.4 - Operating vehicles, mechanized devices, or equipment
    * 4.C.2.d.1.g - Spend time using hands to handle, control or feel objects, tools or controls
    * 1.A.2.a.2 - Manual dexterity
    * 1.A.1.f.1 - Spatial orientation

Correlation between my task measure and other literature-based task measures

Table 2.18 shows the correlation between Autor & Handel (2013) and the three tasks developed in my study. The correlation between Autor & Handel (AH) manual task and the manual task used in my research is positive and significant (1.241). It can be seen that the correlation between the manual and abstract tasks developed by my study is negative and significant (-0.651), which means that these measures are the opposite. In general, table 2.18 shows that each correlation is significant, suggesting that the task content used in my study is significantly correlated to Autor & Handel (2013) measure.

Table 2.18: Correlation between Autor & Handel (2013) and This Study

	Manual (1)	Routine (2)	Abstract (3)
Manual	1	0.665***	-0.604***
		(0.039)	(0.041)
Routine	0.691***	1	-0.637***
	(0.040)		(0.040)
Abstract	-0.651***	-0.659***	1
	(0.044)	(0.042)	
AH manual	1.241***	0.838***	-0.708***
	(0.028)	(0.056)	(0.060)
AH abstract	-0.972***	-0.870***	1.302***
	(0.075)	(0.076)	(0.049)
AH routine	1.068***	1.465***	-0.851***
	(0.073)	(0.040)	(0.076)

AH: Autor & Handel (2013)

Similarly, Table 2.19 exhibits the correlation between the task used in my study and the one developed byCasabianca et al. (2018). This table also shows that there is a high correlation between both measures.

Table 2.19: Correlation between Casabianca et al. (2018) and This Study

	C Manual (1)	C Cognitive (2)
C cognitive	-0.465***	1
	(0.045)	
Manual	0.738***	-0.497***
	(0.013)	(0.035)
Routine	0.518***	-0.474***
	(0.032)	(0.037)
Abstract	-0.441***	0.707***
	(0.036)	(0.025)

C: Casabianca et al. (2018)

2.10.2 Occupational exposure, task and wages

Table 2.20 compares the results for the three different task content, what stands out in the table is that offshoring ($OS_{k,t-1}$) has different effects on wages for workers who perform the three different tasks. To assess the economic magnitude of offshoring on wages according to the task content of occupations, as an example, I calculate the effect on wages for a highly manual-intensive occupation (fishery workers) and a highly abstract-intensive occupation (engineers).

Using the coefficients in column 3 of Table 2.20, I find that for engineers an increase in ($OS_{k,t-1}$) increases their wages by about 1.5%[35], this result is similar to the one using the coefficients of Table 2.5 (2%) when routine intensive tasks are considered. Working with the coefficients in column 2 of Table 2.20, I find that an increase in ($OS_{k,t-1}$) increases fishery workers' wages about 2.47%.[36] Table 2.21 presents the results using IV estimates for each instrument (IV-Gravity, and IV-USA) when all sectors are considered. Table 2.22 reports the first-stage regressions corresponding to the specifications of Table 2.21.

[35] Calculations are as follows: from the marginal effects of the model (3) of Table 2.20: (0.306 - 0.390*(Abs))*$\Delta OS_k^{15/06}$ where Abstract task (Abs) = 0.63 and $\Delta OS_k^{15/06}$ = 0.25 for engineer workers.

[36] Calculations are as follows: from the marginal effects of column 2 of Table 2.20: (0.308 - 0.406*(Mn))*$\Delta OS_k^{15/06}$ where Manual task (Mn) = 0.42 and $\Delta OS_k^{15/06}$ = 0.18 for fishery workers.

Table 2.20: Occupational Exposure, Wages, Routine, Manual and Abstract Intensity Tasks (Manufacturing Sector)

	Routine Intensity Task (1)	Manual Intensity Task (2)	Abstract Intensity task (3)
Lag of occupation exposure ($OS_{k,t-1}$)	-0.010	0.308**	0.306***
	(0.113)	(0.129)	(0.083)
($OS_{k,t-1}$)#Task	0.475**	-0.406	-0.390*
	(0.216)	(0.427)	(0.220)
Task	-1.693**	1.158	1.331**
	(0.688)	(1.185)	(0.662)
Formal	0.155***	0.156***	0.156***
	(0.031)	(0.031)	(0.031)
R&D/$Y_{k,t-1}$	-0.021***	-0.017***	-0.019***
	(0.007)	(0.006)	(0.006)
Unemployment	-2.215***	-1.069***	-1.058***
	(0.384)	(0.360)	(0.257)
EIP	-1.925***	-0.775**	-0.766***
	(0.380)	(0.357)	(0.251)
Married	0.030	0.030	0.031
	(0.058)	(0.058)	(0.058)
High education	0.045	0.047	0.046
	(0.038)	(0.038)	(0.038)
High tenure	-0.025	-0.026	-0.025
	(0.033)	(0.033)	(0.033)
Firm Size < 21	-0.320***	-0.317***	-0.315***
	(0.044)	(0.044)	(0.044)
Firm Size 21-50	-0.127***	-0.123***	-0.124***
	(0.043)	(0.043)	(0.043)
Firm Size 51-100	-0.039	-0.036	-0.037
	(0.043)	(0.044)	(0.043)
Firm Size 101-500	-0.022	-0.022	-0.022
	(0.031)	(0.031)	(0.031)
Full time	-0.316***	-0.314***	-0.317***
	(0.031)	(0.032)	(0.032)
Observations	9,644	9,644	9,644
R-squared	0.154	0.153	0.154

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

Table 2.21: Occupational Exposure, Wages, all Sectors

	FE	IV	
		Gravity	USA
Lag of occupation exposure ($OS_{k,t-1}$)	-0.060	-0.358***	0.113
	(0.038)	(0.122)	(0.118)
($OS_{k,t-1}$)#Task	0.582***	1.930***	0.691***
	(0.081)	(0.514)	(0.150)
Task	-1.962***	-6.089***	-2.381***
	(0.258)	(1.586)	(0.443)
Formal	0.221***	0.222***	0.220***
	(0.014)	(0.014)	(0.014)
R&D/$Y_{k,t-1}$	-0.009***	-0.012***	-0.007***
	(0.002)	(0.003)	(0.002)
Unemployment	-2.292***	-3.265***	-1.729***
	(0.141)	(0.410)	(0.393)
EIP	-2.074***	-3.050***	-1.513***
	(0.140)	(0.410)	(0.392)
Individual Characteristics			
Married	-0.010	-0.008	-0.012
	(0.025)	(0.025)	(0.025)
High education	0.046***	0.046***	0.046***
	(0.017)	(0.017)	(0.017)
High tenure	0.022*	0.022*	0.021*
	(0.012)	(0.012)	(0.012)
Firm Size < 21	-0.332***	-0.324***	-0.324***
	(0.017)	(0.018)	(0.017)
Firm Size 21-50	-0.095***	-0.089***	-0.093***
	(0.018)	(0.019)	(0.018)
Firm Size 51-100	-0.047***	-0.042**	-0.046**
	(0.018)	(0.019)	(0.019)
Firm Size 101-500	-0.032**	-0.031**	-0.032**
	(0.015)	(0.015)	(0.015)
Full time	-0.472***	-0.472***	-0.470***
	(0.011)	(0.011)	(0.011)
Endogeneity Test		4.511	6.702
p-value		0.034	0.010
Observations	93,170	93,170	93,170
R-squared	0.132	0.076	0.080

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects. Default category: Firm size > 500. Age is not included because age with individual and time-fixed effects can result in perfect collinearity.

Table 2.22: First-stage Regression for Endogenous Occupation Exposure - All Sectors

	Ocupation exposure ($OS_{k,t-1}$)	
	IV-Gravity	IV-USA
Excluded Instruments		
IV	-1.785***	0.062***
	(0.029)	(0.006)
IV#Task	0.917***	0.338***
	(0.076)	(0.019)
Unemployment	-7.430***	-3.104***
	(0.075)	(0.019)
EIP	-7.433***	-3.092***
	(0.075)	(0.017)
Formal	0.001	0.003
	(0.002)	(0.002)
Routine intensity task (Task)	-2.071***	-0.495***
	(0.188)	(0.048)
R&D/$Y_{k,t-1}$	-0.000	-0.012***
	(0.000)	(0.000)
Individual Characteristics		
Married	0.007*	0.011***
	(0.004)	(0.004)
High education	-0.002	-0.000
	(0.003)	(0.003)
High tenure	0.001	0.003
	(0.002)	(0.002)
Firm Size < 21	-0.022***	-0.030***
	(0.004)	(0.004)
Firm Size 21-50	-0.009*	-0.006
	(0.005)	(0.005)
Firm Size 51-100	-0.000	-0.001
	(0.005)	(0.005)
Firm Size 101-500	0.005	0.002
	(0.005)	(0.004)
Full time	-0.003**	-0.008***
	(0.001)	(0.001)
F-test	2993.783	1485.245
p-value	0.000	0.000
Observations	93,170	93,170

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include individual, year and occupation fixed effects.

2.10.3 Displacement and Unemployment

The first-stage results corresponding to the specifications in Table 2.10 and 2.11 are almost identical because the only difference is in the number of workers in the regressions. The specification also includes all the exogenous variables in the second-stage regressions.

Table 2.23: First-Stage Regressions for Endogenous Occupation Exposure - Transitions

	First-Stage
IV-USA	0.455***
	(0.141)
IV-Gravity	0.097
	(0.613)
IV-USA#Task	0.344**
	(0.144)
IV-Gravity#Task	1.058**
	(0.427)
Task	-3.146***
	(1.029)
Formal	0.001
	(0.003)
R&D/$Y_{k,t-1}$	0.020***
	(0.006)
Individual characteristics	Yes
F-test	54.26
p-value	0.000
Observations	9,644

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.10.4 Changes in annual earnings-balancing test

Propensity score matching

Table 2.24: Switching Occupations Upwards within Sectors

	Mean		*Bias*		*Equality of means*	
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	t	$p > t$
$(OS_{k,t-1})$	2.902	2.888	2.3	87.2	0.37	0.709
$(OS_{k,t-1})$#Task	1.269	1.275	-1.6	87.2	-0.27	0.785
Task	0.444	0.450	-4.4	83.5	-0.70	0.486
Formal	0.551	0.576	-5.3	90.8	-0.81	0.415
R&D/$Y_{k,t-1}$	15.056	14.795	5.2	82.9	0.78	0.433
Married	0.634	0.638	-0.8	84.8	-0.13	0.897
Male	0.691	0.669	4.5	63.2	0.73	0.464
High education	0.308	0.298	2.2	90.4	0.34	0.735
High tenure	0.414	0.389	5.1	49.2	0.82	0.410
Firm Size < 21	0.540	0.520	4.3	93.0	0.62	0.534
Firm Size 21-50	0.073	0.060	6.2	71.6	0.87	0.384
Firm Size 51-100	0.044	0.072	-15.2	-19.2	-1.86	0.063
Firm Size 101-500	0.133	0.139	-2.0	92.9	-0.27	0.786
Full time	0.841	0.826	3.8	88.2	0.67	0.505
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias	
	0.052	73.040	0.937	4.5	4	

Table 2.25: Switching Occupations Downwards within Sectors

	Mean		*Bias*		*Equality of means*	
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	*t*	$p > t$
$(OS_{k,t-1})$	2.991	2.977	2.3	93.0	0.35	0.730
$(OS_{k,t-1})$#Task	1.283	1.259	5.6	42.9	0.87	0.386
Task	0.433	0.427	4.9	87.4	0.72	0.471
Formal	0.547	0.558	-2.2	96.3	-0.33	0.745
R&D/$Y_{k,t-1}$	15.666	15.701	-0.7	98.5	-0.11	0.916
Married	0.621	0.625	-0.9	90.3	-0.13	0.894
Male	0.659	0.642	3.5	17.6	0.54	0.587
High education	0.299	0.328	-6.8	69.6	-0.98	0.328
High tenure	0.394	0.432	-7.7	47.4	-1.19	0.236
Firm Size < 21	0.514	0.493	4.7	93.2	0.65	0.517
Firm Size 21-50	0.074	0.084	-4.8	78.1	-0.60	0.548
Firm Size 51-100	0.055	0.055	0.0	100	0.00	1.000
Firm Size 101-500	0.143	0.128	5.1	84.3	0.66	0.508
Full time	0.832	0.813	4.5	85.1	0.76	0.446
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias	
	0.056	72.310	0.976	4.6	4	

Table 2.26: Switching Occupations Upwards across Sectors

	Mean		*Bias*		*Equality of means*	
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	*t*	$p > t$
$(OS_{k,t-1})$	2.776	2.731	7.6	-35.4	1.49	0.138
$(OS_{k,t-1})$#Task	1.265	1.284	-5.5	-3.0	-1.01	0.314
Task	0.463	0.478	-13.1	-1534.1	-2.36	0.018
Formal	0.176	0.15	6.3	74.6	1.38	0.167
R&D/$Y_{k,t-1}$	14.531	14.328	3.8	83.6	0.70	0.485
Married	0.554	0.554	0.0	100	0.00	1.000
Male	0.556	0.525	6.1	45.5	1.18	0.238
High education	0.201	0.200	0.3	-11.5	0.06	0.949
High tenure	0.288	0.285	0.5	98.6	0.11	0.910
Firm Size < 21	0.799	0.82	-5.2	-47.2	-1.04	0.298
Firm Size 21-50	0.043	0.033	5.7	47.3	1.07	0.284
Firm Size 51-100	0.031	0.022	5.7	-8.2	1.11	0.268
Firm Size 101-500	0.065	0.077	-4.9	20.6	-0.89	0.371
Full time	0.614	0.605	1.9	89.3	0.37	0.714
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias	
	0.046	94.360	0.412	4.1	3.6	

Table 2.27: Switching Occupations Downwards across Sectors

	Mean		*Bias*		*Equality of means*	
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	*t*	$p > t$
$(OS_{k,t-1})$	2.859	2.865	-1.0	89.5	-0.18	0.858
$(OS_{k,t-1})$#Task	1.179	1.167	2.8	91.2	0.53	0.598
Task	0.416	0.413	3.0	93.8	0.53	0.596
Formal	0.234	0.244	-2.4	72.9	-0.45	0.654
R&D/$Y_{k,t-1}$	15.495	15.477	0.3	99.0	0.06	0.953
Married	0.563	0.614	-10.4	45.0	-1.89	0.059
Male	0.692	0.714	-4.7	64.2	-0.90	0.371
High education	0.253	0.310	-13.5	-17.9	-2.31	0.021
High tenure	0.268	0.270	-0.3	99.2	-0.06	0.951
Firm Size < 21	0.773	0.773	0.0	100	0.00	1.000
Firm Size 21-50	0.051	0.049	0.8	94.2	0.13	0.900
Firm Size 51-100	0.039	0.025	7.9	23.2	1.39	0.163
Firm Size 101-500	0.064	0.063	0.6	86.9	0.11	0.911
Full time	0.696	0.712	-3.6	-61.9	-0.66	0.511
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias	
	0.059	108.410	0.444	4.9	3.6	

Table 2.28: Transition to Unemployment

	Mean		*Bias*		*Equality of means*	
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	*t*	$p > t$
$(OS_{k,t-1})$	2.941	2.853	14.7	47.0	0.95	0.344
$(OS_{k,t-1})$#Task	1.247	1.233	3.2	72.6	0.22	0.826
Task	0.430	0.437	-5.5	82.3	-0.35	0.723
Formal	0.291	0.291	0.0	100	0.00	1.000
R&D/$Y_{k,t-1}$	15.891	15.187	13.5	54.5	0.83	0.408
Married	0.367	0.468	-20.8	57.9	-1.29	0.199
Male	0.658	0.722	-13.3	-1622.5	-0.86	0.393
High education	0.392	0.329	13.7	58.4	0.82	0.411
High tenure	0.101	0.127	-6.3	90.6	-0.50	0.619
Firm Size < 21	0.646	0.658	-2.7	88.1	-0.17	0.868
Firm Size 21-50	0.101	0.063	14.4	18.7	0.87	0.388
Firm Size 51-100	0.076	0.089	-5.6	69.1	-0.29	0.774
Firm Size 101-500	0.051	0.013	14.9	-156.9	1.36	0.175
Full time	0.759	0.797	-8.8	-87.9	-0.57	0.568
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias	
	0.336	63.150	0.366	9.9	10.6	

Mahalanobis Distance Matching

Table 2.29: Switching Occupations Upwards within Sectors

	Means			*Variances*		
Variable	*Treated*	*Control*	*Std.Dif*	*Treated*	*Control*	*Ratio*
$(OS_{k,t-1})$	2.757	2.840	-0.131	0.383	0.380	1.008
$(OS_{k,t-1})$#Task	1.283	1.275	0.018	0.130	0.140	0.933
Task	0.473	0.455	0.154	0.012	0.013	0.952
Formal	0.381	0.388	-0.014	0.237	0.238	0.994
R&D/$Y_{k,t-1}$	13.226	14.510	-0.249	21.259	27.954	0.761
Married	0.666	0.643	0.048	0.223	0.230	0.970
Male	0.658	0.660	-0.004	0.226	0.225	1.003
High education	0.214	0.213	0.002	0.169	0.168	1.004
High tenure	0.454	0.421	0.066	0.249	0.244	1.017
Firm Size < 21	0.755	0.668	0.193	0.186	0.222	0.835
Firm Size 21-50	0.025	0.042	-0.077	0.025	0.040	0.613
Firm Size 51-100	0.016	0.029	-0.070	0.016	0.028	0.569
Firm Size 101-500	0.073	0.083	-0.034	0.068	0.076	0.892
Full time	0.772	0.778	-0.016	0.177	0.173	1.022

Table 2.30: Switching Occupations Downwards within Sectors

	Means			*Variances*		
Variable	*Treated*	*Control*	*Std.Dif*	*Treated*	*Control*	*Ratio*
$(OS_{k,t-1})$	2.750	2.860	-0.177	0.415	0.375	1.107
$(OS_{k,t-1})$#Task	1.295	1.260	0.081	0.151	0.143	1.060
Task	0.477	0.447	0.252	0.011	0.013	0.832
Formal	0.267	0.437	-0.359	0.196	0.247	0.796
R&D/$Y_{k,t-1}$	13.082	14.725	-0.331	19.060	24.974	0.763
Married	0.545	0.680	-0.281	0.249	0.218	1.139
Male	0.549	0.664	-0.240	0.248	0.224	1.110
High education	0.179	0.301	-0.279	0.147	0.211	0.698
High tenure	0.408	0.455	-0.095	0.242	0.249	0.975
Firm Size < 21	0.801	0.650	0.334	0.160	0.228	0.702
Firm Size 21-50	0.026	0.034	-0.038	0.025	0.033	0.765
Firm Size 51-100	0.018	0.022	-0.018	0.018	0.021	0.835
Firm Size 101-500	0.041	0.103	-0.211	0.040	0.093	0.430
Full time	0.728	0.812	-0.202	0.199	0.153	1.298

Table 2.31: Switching Occupations Upwards across Sectors

	Means			*Variances*		
Variable	*Treated*	*Control*	*Std.Dif*	*Treated*	*Control*	*Ratio*
$(OS_{k,t-1})$	2.704	2.718	-0.022	0.335	0.343	0.977
$(OS_{k,t-1})$#Task	0.237	1.247	-0.024	0.099	0.118	0.843
Task	0.465	0.465	-0.003	0.011	0.013	0.866
Formal	0.147	0.195	-0.114	0.126	0.157	0.799
R&D/$Y_{k,t-1}$	13.247	14.053	-0.151	23.500	29.333	0.801
Married	0.572	0.630	-0.118	0.245	0.234	1.050
Male	0.582	0.548	0.070	0.244	0.248	0.982
High education	0.179	0.163	0.037	0.147	0.137	1.074
High tenure	0.343	0.385	-0.089	0.226	0.237	0.952
Firm Size < 21	0.862	0.830	0.081	0.119	0.141	0.841
Firm Size 21-50	0.020	0.025	-0.023	0.020	0.024	0.825
Firm Size 51-100	0.014	0.015	-0.007	0.014	0.015	0.931
Firm Size 101-500	0.047	0.057	-0.043	0.045	0.054	0.827
Full time	0.627	0.636	-0.018	0.234	0.232	1.010

Table 2.32: Switching Occupations Downwards across Sectors

	Means			*Variances*		
Variable	*Treated*	*Control*	*Std.Dif*	*Treated*	*Control*	*Ratio*
$(OS_{k,t-1})$	2.764	2.818	-0.086	0.366	0.394	0.931
$(OS_{k,t-1})$#Task	1.270	1.204	0.155	0.160	0.166	0.967
Task	0.463	0.431	0.273	0.011	0.013	0.887
Formal	0.125	0.267	-0.324	0.110	0.196	0.560
R&D/$Y_{k,t-1}$	13.871	14.862	-0.190	25.283	28.051	0.901
Married	0.608	0.663	-0.113	0.239	0.224	1.067
Male	0.615	0.699	-0.177	0.237	0.211	1.125
High education	0.161	0.243	-0.192	0.136	0.184	0.737
High tenure	0.320	0.380	-0.128	0.218	0.236	0.924
Firm Size < 21	0.891	0.811	0.195	0.098	0.153	0.636
Firm Size 21-50	0.016	0.016	-0.001	0.016	0.016	0.988
Firm Size 51-100	0.014	0.022	-0.045	0.014	0.021	0.651
Firm Size 101-500	0.036	0.051	-0.064	0.034	0.048	0.713
Full time	0.646	0.736	-0.196	0.229	0.195	1.176

Table 2.33: Transition to Unemployment

	Means			*Variances*		
Variable	*Treated*	*Control*	*Std.Dif*	*Treated*	*Control*	*Ratio*
$(OS_{k,t-1})$	2.518	2.783	-0.420	0.248	0.393	0.631
$(OS_{k,t-1})$#Task	1.157	1.211	-0.128	0.089	0.154	0.576
Task	0.464	0.442	0.182	0.008	0.014	0.578
Formal	0.111	0.322	-0.450	0.100	0.220	0.454
R&D/$Y_{k,t-1}$	12.984	15.176	-0.406	18.337	30.464	0.602
Married	0.488	0.447	0.084	0.253	0.249	1.015
Male	0.536	0.678	-0.299	0.252	0.220	1.144
High education	0.245	0.296	-0.109	0.187	0.210	0.891
High tenure	0.119	0.211	-0.229	0.106	0.168	0.631
Firm Size < 21	0.846	0.683	0.347	0.132	0.218	0.604
Firm Size 21-50	0.045	0.060	-0.058	0.043	0.057	0.759
Firm Size 51-100	0.026	0.065	-0.173	0.025	0.062	0.412
Firm Size 101-500	0.026	0.030	-0.014	0.026	0.029	0.883
Full time	0.725	0.729	-0.008	0.202	0.199	1.012

Chapter 3

Does R&D Outsourcing Diminish or Strengthen the Firm's R&D Investment?

3.1 Introduction

Trade liberalisation and rapid technological change have intensified the competitive pressure on firms, forcing them to seek new technologies and innovative capabilities abroad, thus changing their innovation system towards open innovation, namely tapping into external and internal R&D to establish a competitive advantage through technological innovation (Chesbrough 2003). Accordingly, R&D outsourcing emerges as an efficient strategy to foster innovation, it offers firms access to external expertise and knowledge that may not be available internally, often at lower cost, enabling more efficient resource allocation and accelerating the development of new technologies and products (Han & Bae 2014).

However, the effects of R&D outsourcing on innovation are not straightforward. The outsourcing of R&D can boost innovation by accessing external resources, yet it can also prevent it. Previous studies find that the success of R&D outsourcing on innovation performance depends on the relationship between internal and external R&D.[1] For instance,

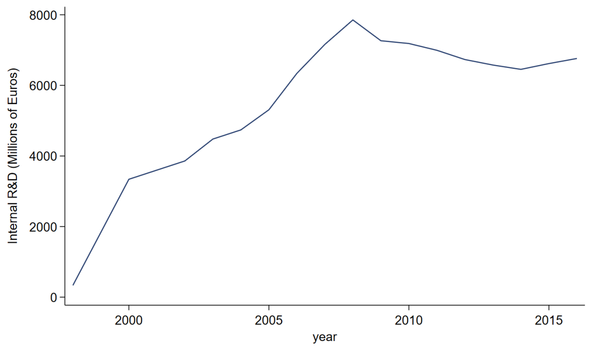
[1] This literature includes Becker & Dietz (2004),Belderbos et al. (2013), Berchicci (2013), Cassiman & Veugelers (2006), Cohen & Levinthal (1990), Lokshin et al. (2008), Tsai & Wang (2008), and Weigelt

firms that complement internal and external R&D activities and have high levels of internal R&D capacities have greater innovative performance than those firms that, despite also complementing these sources, prioritise external R&D activities over internal ones. Conversely, the substitution of internal R&D for external R&D could weaken innovation performance since it could reduce firms' ability to recognise, exploit and benefit from external knowledge. Thus, R&D outsourcing may diminish firms' capacity to absorb new knowledge, preventing the creation of innovation. Despite this, the impact of firms' R&D decisions on internal R&D remains unexplored. Therefore, this study aims to answer the following questions: Is R&D outsourcing a good strategy for the firm in terms of increasing total R&D investment? Does R&D outsourcing weaken the firm's internal R&D investment or reinforce it?

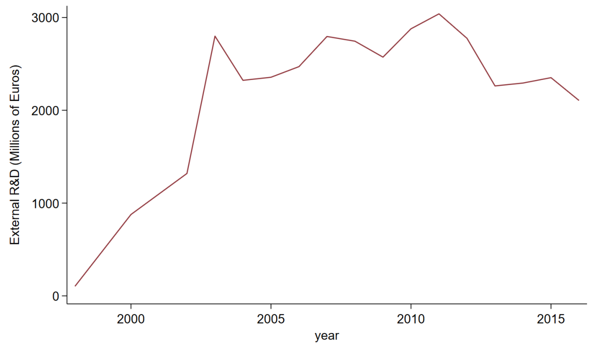
The literature on R&D outsourcing has mainly focused on the effect of internal and external R&D on innovation outputs and the role of internal R&D in moderating this effect. For the first time, this study contributes to the current literature by conducting an empirical analysis of the effect of firms' R&D decisions on the inputs of innovation (i.e. internal and total R&D investment) at the firm level and how it affects the number of firms engaged in R&D within an industry. For this analysis, I use a unique firm panel data survey that contains information on international and national R&D outsourcing for about 10,969 firms operating in Spain between 2003 and 2016. Spanish firms are a good testing case for my research question because external sources of technology are potentially more important for moderating innovative countries like Spain than for technological leaders (García-Vega & Huergo 2021). In addition, the external R&D expenditure has dramatically increased in Spain, at the rate of 19 per cent from 1998 to 2016. This increase in external R&D expenditure calls for a discussion on the implications of it for the total R&D and the internal R&D investment of the Spanish firms.

(2009), among others.

Figure 3.1: R&D Investment of Firms Operating in Spain



(a) Internal R&D investment



(b) External R&D investment

The relevance of both internal and external R&D for Spanish firms is illustrated in Figure 3.1. The investment in internal R&D is depicted in Figure 3.1a, while Figure 3.1b shows the investment in external R&D. Even though both graphs indicate an increase in both internal and external R&D investment, the rate of increase varies annually. For example, in 2009, the external R&D investment rose by 0.12%, whereas internal R&D investment experienced a slight decline of 0.01%. Similarly, in 2010, external R&D increased by 0.05%, while internal R&D investment fell by 0.03% during the same period. Hence, recognizing how R&D outsourcing affects internal R&D investment is crucial, motivating the need for a thorough analysis to understand its impact on both internal and overall R&D investment.

Furthermore, previous research has examined how R&D outsourcing influences innovation outputs, drawing from theoretical models which explain the reason behind R&D outsourcing decisions. The first is the transaction cost theory, which suggests that a firm's choice between internal and external R&D strategies depends on the costs and risks associated with each option (Croisier 1998, Beneito 2003). The second is the knowledge-based view, which emphasises the core competence in which firms conduct R&D outsourcing to increase their technological competence and to exploit potential complementarities between internal and external R&D (Becker & Dietz 2004, Cassiman & Veugelers 2006, Lokshin et al. 2008). Finally, the resource-based view states that R&D outsourcing may provide firms with access to resources that are not available internally (Grimpe & Kaiser 2010, Weigelt 2009, Yasuda 2005). Unlike these theories, which primarily focus on the motives to outsource R&D, for the first time, the empirical analysis presented in this chapter is conducted based on a theoretical model developed by Navas (2021).

The theoretical model, on which this chapter is based, is a general equilibrium model based on the Melitz (2003) model, which considers the firm's heterogeneity and innovation, respectively. The model explains a firm's R&D decision and a firm's decision to outsource R&D, as well as the effect of R&D outsourcing on the internal and total R&D investment, which depends on the relationship between two sources of knowledge (internal and external R&D). It provides two hypotheses regarding the impact of outsourcing on the firm and industry innovation activity. The first one is related to the intensive margin of R&D: (1) a firm that outsources R&D (a) experiences an increase in its total R&D volume (includes both internal and external R&D); (b) has an increase in its internal R&D when the elasticity of substitution between internal and external R&D is lower enough. The second hypothesis is related to the extensive margin of R&D: (2) in industries where R&D offshoring is more profitable fewer firms invest in R&D.

The first hypothesis is assessed empirically using causal inference methods. Unlike previous studies, which seek to assess the relationship between internal and external R&D by estimating the joint effect of both sources on innovation using a probit or logit model, I estimate the direct effect of R&D outsourcing on the intensive margin of R&D (internal and total R&D investment). Following Elliott et al. (2020) and Callaway & Sant'Anna (2020), I apply a combination of matching methods and difference-in-difference (DID) methodology with multiple time periods. This strategy allows me to control for the observable and unobservable self-selection in R&D outsourcing, compare the R&D investment before and after firms start to outsource R&D and contrast this result with a comparable control group of firms that does not outsource R&D. I also differentiate this effect according to the firm's export status and by distinguishing between domestic and international R&D outsourcing. The results support the first hypothesis, showing that R&D outsourcing positively impacts the intensive margin of R&D, increasing the investment in the internal and total R&D. Based on the theoretical framework, it can be concluded that the elasticity of substitution between the different sources of knowledge must be lower enough.

However, the impact of R&D outsourcing on internal R&D differs between exporters and non-exporters. The effect on internal R&D for non-exporters is relatively weaker in terms of statistical significance and magnitude and tends to diminish over time compared to the effect on internal R&D for exporting firms. Regarding the type of outsourcing, firms that undertake domestic R&D outsourcing see a positive impact on both internal and total R&D. In contrast, firms that simultaneously undertake domestic and international R&D outsourcing do not experience a statistically significant increase in their internal R&D investment but in their total R&D, implying more reliance on external R&D.

Regarding the second hypothesis, the empirical analysis is conducted at the industry level. An ordinary least square (OLS) model is used to assess the profitability of R&D outsourcing on the share of firms investing in R&D. Since I do not have information about this variable, I follow Grimpe & Kaiser (2010), and I use the interaction between the mean of cooperation (number of partners for the innovation process) and the intensity of R&D outsourcing (R&D expenditure over sales) at the industry level as a proxy of the profitability of R&D outsourcing. The results also support this hypothesis providing evidence that in industries where R&D outsourcing is more profitable, fewer firms invest in total R&D.

The chapter is structured as follows. Section 2 briefly reviews the literature on R&D outsourcing and innovation. Section 3 introduces the theoretical model of R&D outsourcing. Section 4 presents the data. Section 5 describes the empirical analysis and results for theoretical hypothesis 1. Section 6 reports the methodology and results for theoretical hypothesis 2. Section 7 presents some robustness checks, and the last section concludes.

3.2 Literature Review

My study is closely related to the literature that examines the effect of firms' R&D decisions on innovative performance and the role that internal R&D plays in moderating this effect. This literature highlights the importance of the relationship between internal and external R&D for innovation performance and the role internal R&D plays in a firm's absorptive capacity, namely in recognising, assimilating and applying external knowledge (Cohen & Levinthal 1990).

There are a large number of published studies that examine the relationship between internal and external R&D on firms' performance. For instance, Cassiman & Veugelers (2006), using a multinomial logit model, analyse complementarity between internal and external innovation activities. They classify the innovation strategies in make, buy, and make & buy, and examine the effect of each strategy on innovative performance. They find that the combination of Make&Buy has a greater effect on firms' ability to innovate, inferring a complementarity relationship between internal and external innovation activities. Lokshin et al. (2008) find a complementary relationship between internal and external R&D by examining the impact of the interaction between internal and external R&D expenditure on productivity using the Difference Generalised Method of Moments, fixed effect and random effects maximum likelihood estimators. Similarly, Belderbos et al. (2013) examine the simultaneous impact of local R&D and intra-firm international technology transfer on productivity growth using a linear regression model. They also find that both sources are complementary since both contribute to productivity growth.

This literature indicates that firms' performance depends on how they combine internal and external R&D. When firms consider both sources of knowledge and foster a complementary relationship, their performance tends to improve. The complementary or substitution of these sources of knowledge relies on the firm's absorptive capacity, namely its ability to understand and integrate external knowledge into its current knowledge.

In this vein, many studies have emphasised the role played by internal capabilities in a firm's absorptive capacity. Tsai & Wang (2008), using an ordinary least square (OLS) method, explore how the level of internal R&D increases the effect of external technology acquisition on firms' performance. They find that external acquisition's effect on firms' performance increases with the inclusion of the interaction term between external acquisition and internal R&D expenditure; the effect is larger as the level of internal R&D increases. Escribano et al. (2009) also find that higher internal R&D investment allows firms to absorb external knowledge more efficiently and enhance innovation performance. Using a logit and OLS model, they assess the impact of external information on innovation and how this impact is affected by including the interaction term between internal R&D expenses and external information, finding that this effect increases with the interaction term. Weigelt (2009) assesses the impact of outsourcing on firms' capacity to use and assimilate new technology using a Tobit model. He finds that greater reliance on outsourcing may reduce a firm's internal capabilities, thereby impeding a firm's performance in the market. However, the main limitation of this study is that it focuses on one industry and one technology only. Han & Bae (2014) investigate the extent to which a firm that outsources R&D can increase its performance and how a firm's absorptive capacity via internal R&D (i.e., the ratio of R&D employees over the firm's total employees) moderates this effect. Using a fixed effect model, they find that internal R&D moderates the impact of R&D outsourcing on a firm's performance.

These studies emphasise the importance of internal R&D on firms' capacity to internalise external knowledge, showing an increase in firms' performance when the firm has high levels of internal capabilities. As a result, other scholars attempt to determine the relationship between internal and external knowledge by examining both the individual impact of external knowledge and the impact of the interaction between internal and external knowledge. Grimpe & Kaiser (2010) use a random effect Tobit model to measure the effects of R&D outsourcing on innovation performance considering the interaction between external and internal R&D expenditure. They find that the impact of external R&D on innovation increases with the inclusion of the interaction term, suggesting a complementarity relationship between internal and external R&D. Berchicci (2013), using a Tobit model, investigates how internal R&D capacity (i.e., ratio of R&D employees over the firm's total employees) moderates the relationship between a firm's R&D structure and its innovative performance. He finds that firms with greater R&D capacity can benefit more from their external R&D activities in terms of innovative outputs, increasing their innovation performance. He implies that internal and external R&D are complementarity since the impact of both the external R&D activities and the interaction of it and the internal R&D capacities have a greater effect on innovation.

This literature provides evidence of the importance of the relationship between internal and external knowledge on firms' performance and the role that internal R&D plays in this relationship. The literature has shown that internal R&D is important for the success of the internalisation of external knowledge and for innovation performance. However, there is no evidence of the effect of external R&D on the current state of knowledge. Therefore, in this paper, I estimate the direct effect of R&D outsourcing on internal and total R&D investment at the firm level and how it affects the number of firms investing in R&D at the industry level.

Moreover, unlike earlier studies, I address the issue of self-selection in R&D outsourcing by adopting a matching method and difference-in-difference methodology (Elliott et al. 2020, Callaway & Sant'Anna 2020). This approach helps to control for observable and unobservable characteristics of firms which decide to outsource. In addition, my study conducts an empirical analysis based on a theoretical model which explains a firm's R&D decision-making process. This model also explores the impact of this decision on the intensive margin of R&D (internal and total R&D investment), considering the relationship between internal and external R&D and the associated costs and benefits in the R&D decision.

3.3 Theoretical Motivation

This section presents the theoretical framework that motivates the empirical analysis. The model, developed by Navas (2021), looks at the effect of R&D outsourcing on the internal and total R&D investment. As in the Melitz (2003) framework, the model introduces firm heterogeneity in a monopolistic competition setting and a Constant Elasticity of substitution (CES) demand function. Firms at the moment of entry obtain a productivity draw from a continuous productivity distribution $G(\varphi)$ with support $[0, \infty]$. Firms can also upgrade their productivity (θ) by undertaking an endogenous investment to produce knowledge (z). The production function for knowledge (z) is also CES with an elasticity of substitution ϵ between different sources of R&D. In particular, θ is the endogenous productivity represented by:

$$\theta = (1 + z)^{\frac{1}{\sigma - 1}} \tag{3.1}$$

$$z = \left(\int_0^{\gamma N} (\phi z_i'^{\sigma-1})^{\alpha\epsilon} di + \int_{\gamma N}^{N} (z_i^{\sigma-1})^{\alpha\epsilon} di \right)^{\frac{1}{\epsilon}}$$

Where z represents the firm's aggregate stock of knowledge, which is an aggregation of different sources of knowledge or knowledge varieties (e.g., internal and external R&D). The firm has the option of producing each knowledge source either at home or externally. Following the literature on production outsourcing, the model assumes that a proportion γ of the knowledge varieties can be outsourced while the other one $(N - \gamma N)$ needs to be produced in-house. Let $z_i'^{\sigma-1}$ be the quantity of a knowledge variety i that can be outsourced and $z_i^{\sigma-1}$ the quantity of a knowledge variety which needs to be produced at home. $\phi < 1$ is an adjustment cost.[2] Note that the knowledge production function assumes decreasing marginal returns associated with each source of knowledge ($0 < \alpha <$

[2] The smaller is ϕ the larger will be the cost of adaptability to the firm's local environment

1).

The model is solved by backward induction. The firm decides first whether to stay in the market or to leave, then, it decides whether to undertake R&D and finally, it will decide whether to obtain external R&D or rely on internal R&D. Therefore, if the firm decides to stay and undertake R&D, it should choose the combination of knowledge that maximises its profits given:

$$\max_{\{z_i'^{\sigma-1}, z_i^{\sigma-1}\}} D(\theta\varphi)^{\sigma-1} - \left(\mu\lambda c \int_0^{\gamma N} z_i'^{\sigma-1} di + c \int_{\gamma N}^{N} z_i^{\sigma-1} di\right) \varphi^{(\sigma-1)} - f_R - f_O - f_m \quad (3.2)$$

$$\text{s.t.}\theta = (1+z)^{\frac{1}{\sigma-1}}$$

The cost of outsourcing knowledge is determined by three parameters: $\mu > 1$ which represents a mark-up charged by external R&D producers, $\lambda < 1$ is the advantage in productivity of the external knowledge producers,[3] c is the cost per unit produced of each knowledge source.[4] Firms also bear fixed costs associated with R&D investment f_R and a fixed cost related to R&D outsourcing f_O. D represents the aggregate demand which is common across all varieties,[5] f_m reflects the fixed operational cost to produce.

Solving the problem above, the relative demand for internal ($\bar{z}^{\sigma-1}$) and outsourced ($\bar{z}'^{\sigma-1}$) knowledge is:

[3] The smaller is λ the larger will be the comparative advantage of the external provider. The model considers that λ is exogenous

[4] The cost function is as follows: $C(z) = w\left[c\int\limits_0^N z_i^{\sigma-1} di\varphi^{(\sigma-1)} + f_R\right]$. It is different across firms and it is increasing in firm's productivity ($c\varphi^{(\sigma-1)}$), this is because as the firm advances in the knowledge-ladder, more knowledge is required to increase the productivity of the firm.

[5] $D = \frac{R}{\sigma P^{1-\sigma}}(\frac{\sigma}{\sigma-1})^{1-\sigma}$

$$\begin{aligned}\bar{z}^{\sigma-1} &= \left(\frac{D\alpha\Delta^{1-\epsilon}N^{\frac{1-\epsilon}{\epsilon}}}{c}\right)^{\frac{1}{1-\alpha}} \\ \bar{z}'^{\sigma-1} &= \left(\frac{\phi^{\alpha\epsilon}}{\mu\lambda}\right)^{\frac{1}{1-\alpha\epsilon}}\bar{z}\end{aligned} \tag{3.3}$$

Where $\Delta = \left(\gamma(\psi)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}} + 1 - \gamma\right)^{\frac{1}{\epsilon}}$, $\psi = \frac{\phi}{\mu\lambda}$ represents the relative quality-adjusted cost of the outsourced knowledge versus the non-outsourced knowledge. Δ captures the benefits of outsourcing and it depends on the mass of knowledge that can be outsourced ($N\gamma$) and the potential benefits of outsourcing a knowledge variety compared to making it in-house. The benefits are larger the lower the cost of adaptability (higher ϕ), the lower markup (μ) and the larger the efficiency of the external provider (smaller λ).

The existence of fixed costs associated with R&D outsourcing and R&D investment implies that, in this model, there will be three productivity cut-offs. This study focuses on an equilibrium where the most productive firms invest in R&D and outsource, the least productive firms neither invest in R&D nor outsource, and the ones in the middle decide to undertake R&D activities but only internally.[6] At the firm level, the total and internal R&D investment is given by the following equations:

$$\begin{aligned}R\&D_T &= \left(\mu\lambda\gamma\left(\frac{\bar{z}'}{\bar{z}}\right)^{\sigma-1} + (1-\gamma)\right)cN\bar{z}^{\sigma-1}\varphi^{(\sigma-1)} \\ R\&D_I &= c(1-\gamma)N\bar{z}^{\sigma-1}\varphi^{(\sigma-1)}\end{aligned} \tag{3.4}$$

If the firm does not outsource, the first element of total R&D investment will be equal to one. From equation 3.4, it can be seen that an increase in the number of knowledge sources available (N) or a decrease in the cost of undertaking R&D increases the volume of total R&D invested. Recall that the production of knowledge function assumes

[6]The condition at which this equilibrium holds is: $\frac{\varphi_O}{\varphi_R}^{\sigma-1} > 1$ iff $f_O > \frac{f_R}{\Delta^{\frac{1-\alpha\epsilon}{1-\alpha}} - 1}$

diminishing marginal returns for each knowledge source. Therefore, when firms increase the sources of knowledge, they accumulate more knowledge using the same amount of investment. The latter enhances their productivity, and as a result, they invest more in R&D. From these equations, the model established hypothesis 1 at the firm level and hypothesis 2 at the aggregate level:

Hypothesis 1 *A firm that outsources:*

a) Increases its total R&D volume (i.e. including both internal and external R&D)

b) Increases its internal R&D when the complementarity between internal and external R&D is strong enough

Hypothesis 2 *In industries where R&D outsourcing are more profitable*

a) Fewer firms invest in total R&D

The first hypothesis can be explained using equation 3.1, when firms decide to outsource some R&D tasks, this will increase the firm's efficiency production knowledge (z) and the firm's productivity (θ). The latter leads to an increase in the firm's potential sales, encouraging it to allocate more resources to R&D. Thus, the total R&D investment increases. In contrast, the effect on internal R&D is controlled by the elasticity of substitution ϵ. For instance, when $\epsilon = 1$ the different sources of knowledge are perfect substitutes. In this case, outsourcing will not increase internal R&D as any increase in R&D investment due to an increase in efficiency may be used to increase external R&D which is more efficient. However, when $\epsilon < 1$, the sources of knowledge are less substitutable; thus, the increase in productivity will encourage firms to invest in both external and internal knowledge.

The second hypothesis implies that a rise in the profitability of R&D outsourcing increases the demand for scarce production factors, leading to intensified competition among firms seeking these resources. Accordingly, the prices of these production factors rise, making outsourcing more costly for the least productive firms. Consequently, in equilibrium, there will be fewer firms investing in R&D activities.

3.4 Data

The data are taken from the annual survey of Spanish firms called Panel de Innovación Tecnológica (PITEC).[7]The Spanish Institute of Statistics is responsible for collecting this database following the guidelines of the OECD's Oslo Manual, so it can be compared with similar European innovation surveys (Community Innovation Survey). The survey provides information about a firm's economic characteristics such as size, export, industry, and group membership, among others. Most importantly, the survey also contains information about the innovation activities carried out by different companies, such as innovation output, innovation expenditure, R&D expenditure, firm's acquisition of external R&D, etc.

The survey describes R&D outsourcing as acquiring external R&D services, excluding funds for other companies or research groups, and not covering licenses, royalties, or foreign R&D investments. It defines R&D services as creative work to enhance knowledge and develop new products and processes, including software development. R&D outsourcing predominantly occurs in R&D-intensive sectors like coke, petroleum, nuclear fuel, pharmaceuticals, aircraft, and R&D services (García-Vega & Huergo 2018). Even though the survey does not specify which R&D services Spanish firms outsource, a European study, including Spain, highlights that clinical trials and drug discovery are commonly outsourced services within the pharmaceutical sector. Moreover, European firms outsource other R&D services like customized software development, product design, and the recruitment of R&D personnel (Martínez-Noya & García-Canal 2014).

The dataset comprises an unbalanced longitudinal panel covering the years from 2003

[7]For details of the survey see `https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176755&menu=resultados&secc=1254736195616&idp=1254735576669`

to 2016. In the panel, there are 10,969 firms in 2016, which operate in the manufacturing and services sectors as indicated in table 3.1. The first column presents the number of firms per year. The second column is the number of firms with a positive expenditure in external R&D services in a given year. Column three presents the number of firms that start to outsource R&D for the first time in a given year. Never treated is the number of firms that did not outsource R&D throughout the entire sample period. Finally, the last column represents the number of firms that did not outsource R&D in a given year but had done so in the past or planned to do so in the future. It's noteworthy that a majority of firms started outsourcing R&D early in the sample period.

Table 3.1: Sample Characteristics

Year	Number of observations	With R&D outsourcing	First-time starters	Never treated	With R&D outsourcing (future-past)
2003	6,256	2,022	2,022	2,270	1,964
2004	8,605	2,857	1,534	3,110	2,638
2005	10,933	3,184	1,250	4,077	3,672
2006	10,933	3,053	586	4,077	3,803
2007	10,938	2,872	363	4,080	3,986
2008	10,942	2,512	242	4,082	4,348
2009	10,943	2,299	214	4,082	4,562
2010	10,947	2,216	161	4,085	4,646
2011	10,953	2,060	154	4,087	4,806
2012	10,961	1,846	119	4,091	5,024
2013	10,961	1,702	99	4,091	5,168
2014	10,964	1,455	57	4,092	5,417
2015	10,966	1,266	37	4,093	5,607
2016	10,969	1,007	36	4,095	5,867

Tables 3.2 and 3.3 present the descriptive statistic of the main variables. Table 3.2 shows the descriptive characteristics that distinguish between outsourcers and non-outsourcers of R&D. The survey indicates if firms purchase R&D services from other companies or institutions at foreign or national locations.[8] Therefore, table 3.2 also dis-

[8]R&D outsourcing refers to acquisitions of R&D outside the firm through contracts, informal agreements, etc. It does not include the acquisition of licenses, royalties, intra-group transactions and invest-

tinguishes between domestic and international R&D outsourcing, although; there is also a sample of firms that indicate outsourcing at national and foreign locations at the same time (last two columns of table 3.2). As can be seen, most outsourcing firms outsource R&D to domestic suppliers (87%), 8% outsource R&D to both domestic and international suppliers, and only 5% outsource to international suppliers. The latter suggests potential high fixed costs related to international outsourcing; according to the theoretical model, this cost could be associated with finding the right provider of research services.

Furthermore, table 3.2 shows that firms that outsource R&D have, on average, higher R&D expenditure and productivity, are more likely to export, and are more innovative than never-outsourcing firms. While, among the firms that outsource R&D, firms that outsource to domestic and international suppliers have, on average, a higher R&D expenditure and physical investment and are more innovative than firms which outsource R&D either national or international suppliers. Likewise, firms that outsource only to a foreign supplier have, on average, higher R&D expenditure, and physical investment, are more innovative, and are more likely to belong to a business group and to export than firms that outsource to a national supplier. These features suggest that firms engaged in R&D outsourcing tend to export, and international R&D outsourcing requires a higher R&D expenditure compared to domestic R&D outsourcing. The latter might imply that the costs associated with R&D outsourcing vary between national and international R&D outsourcing.

Table 3.3 shows the descriptive statistics according to firms' export status. As it can be seen, exporters are more likely to outsource R&D than non-exporters. This could be explained by the experience that exporters gain working in the international market, which can facilitate the purchase of R&D tasks to an external supplier. On average, exporters which outsource R&D have a higher R&D expenditure, productivity, and physical investment and are more innovative than non-exporting firms which also outsource

ments in foreign R&D investment; in other words, it excludes all the purchases that do not directly imply purchases of R&D services.

R&D. Similarly, table 3.3 shows differences in these variables between exporters and non-exporters which are non-outsourcers.

Therefore, considering the differences between exporters and non-exporters and between different types of R&D outsourcing, this study also differentiates the effect of R&D outsourcing according to these different groups of firms.[9]

Table 3.2: Descriptive Statistics by Type of Outsourcing

	Non-outsourcers		**R&D outsourcers**					
			Domestic		International		Dom.& Int.	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
External R&D expenditure (log)	0	0	6.539	1.688	7.583	2.051	7.854	2.056
Total R&D expenditure (log)	7.192	1.445	7.873	1.588	8.555	1.703	9.170	1.810
Internal R&D expenditure (log)	7.192	1.445	7.812	1.501	8.349	1.600	8.978	1.729
Export (0/1)	0.421	0.494	0.563	0.496	0.722	0.448	0.707	0.455
Labour productivity	7.071	1.069	7.269	1.060	7.630	0.988	7.614	1.058
Employment (log)	4.072	1.761	4.060	1.654	4.786	1.554	4.706	1.668
Patents (0/1)	0.056	0.229	0.135	0.342	0.119	0.324	0.268	0.443
Physical investment	7.611	2.461	7.872	2.408	8.797	2.391	8.886	2.467
Group (0/1)	0.367	0.482	0.412	0.492	0.714	0.452	0.614	0.487
Cooperation (0/1)	0.132	0.338	0.393	0.488	0.388	0.487	0.538	0.499
Product Innovation (0/1)	0.395	0.489	0.585	0.493	0.615	0.487	0.701	0.458
Process Innovation (0/1)	0.423	0.494	0.579	0.494	0.620	0.485	0.648	0.478
Number of firms	4,095		5,954		359		561	

[9]It is worth mentioning that the sample of firms was restricted to innovative firms, from 12,383 to 10,969 firms.

Table 3.3: Descriptive Statistics by Exporting Status

	Exporters				Non-exporters			
	Non-outsourcing		R&D outsourcers		Non-outsourcing		R&D outsourcers	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
External R&D expenditure (log)	0	0	6.798	1.821	0	0	6.342	1.724
Total R&D expenditure (log)	7.278	1.449	8.110	1.660	6.764	1.348	7.420	1.595
Internal R&D expenditure (log)	7.278	1.449	8.021	1.572	6.764	1.348	7.390	1.464
Labour productivity	7.262	0.982	7.404	0.999	6.550	1.123	6.816	1.261
Employment (log)	4.070	1.640	4.210	1.594	4.078	2.057	3.818	1.995
Patents (0/1)	0.068	0.252	0.160	0.367	0.022	0.147	0.061	0.240
Physical investment	7.705	2.411	8.069	2.372	7.313	2.590	7.649	2.815
Group (0/1)	0.391	0.488	0.466	0.499	0.300	0.458	0.322	0.467
Cooperation (0/1)	0.138	0.345	0.418	0.493	0.115	0.319	0.330	0.470
Product Innovation (0/1)	0.437	0.496	0.624	0.484	0.280	0.449	0.439	0.496
Process Innovation (0/1)	0.440	0.496	0.601	0.490	0.374	0.484	0.505	0.500
Number of firms	2,890		5,715		1,205		1,159	

3.5 Hypothesis 1

A firm that outsources, a) Increases its total R&D volume (i.e. including both internal and external R&D); b) Increases its internal R&D when the complementarity between internal and external R&D is strong enough.

3.5.1 Methodology

The empirical strategy to estimate the effect of undertaking R&D outsourcing on total and internal R&D investment is to follow a difference-in-difference (DiD) approach, which allows the comparison in the R&D investment of firms before and after they start outsourcing R&D with a control group of comparable firms. Since firms outsource R&D at different points in time, and thus the time of the treatment varies across treated firms, I apply a DiD approach with multiple time periods (Callaway & Sant'Anna 2020) rather than the conventional two-way fixed effect difference-in-difference (TWFEDD). According to Goodman-Bacon (2021), the TWFEDD can provide a biased estimation of the treatment effect parameter when treatment takes place at different times. He shows that the TWFEDD is a weighted average of all 2x2 DiD estimators in the sample and, with differential timing, it uses treated groups as controls in future periods, misestimating the average treatment effect on the treated group (ATT). He also demonstrates that the weights on the TWFEDD are proportional to the sample size of each group, and the variability of treatment with comparison groups, in other words, the weight depends on how big the treated and control group in a pair are, and on the timing variance of the treatment. The latter implies that the early and later treated groups carry less weight since they have limited periods before and after treatment, resulting in a minimal timing variance. Conversely, units treated in the middle carry more weight due to having a large number of pre and post-treatment periods. Therefore, Goodman-Bacon (2021) recommends avoiding the TWFEDD estimator when treatment effects vary over time. Instead, he proposes alternative estimators, such as a panel event study or staggered adoption designs, to overcome the bias from time-varying treatment effects.

The Callaway & Sant'Anna (2020) methodology relies on an event study approach and provides a framework for average treatment effects using DiD setup with multiple time periods, and variation in treatment timing. In addition, it enables testing the parallel trend assumption to verify whether the distribution of observed characteristics is the same across treated and control groups during the pre-treatment period. This approach considers aggregation schemes which allow exploring heterogeneity effects along different dimensions such as the ATT by the length of exposure to the treatment (i.e., the event study approach); the ATT as a function of treatment group g and time period t, where a group is defined by the time period when units are first treated (group-time average treatment effect -$ATT_{(g,t)}$); and the ATT by calendar time.

To implement the Callaway & Sant'Anna (2020) estimator, the DiD setup is as follows. There are 14 time periods ($t = 2003, ...2016$) with firms first treated at different time

$g \in \{2003, ...2016\}$, where D_g is a dummy variable that takes the value of 1 if a firm undertakes R&D outsourcing for the first time at g and 0 otherwise. Hence, there are 14 potential groups or cohorts (g) with different numbers of pre and post-treated periods (t). In order to use never-treated and not-yet-treated firms as control groups and to allow for pre-treatment estimations, I construct the data for each cohort restricting the sample within the time window $[t-3, t+3]$. In other words, I consider only the sample of firms first treated at $g = 2006, ...2013$[10] and those firms that do not outsource R&D in the window $[t-3 < g = t < t+3]$.[11] Then, I stacked together cohorts and created a new data identifier by firm i and cohort g because firms may appear in several cohorts.

The group-time average treatment effect is:

$$ATT(g,t) = E[Y_t(g) - Y_t(0)|D_g = 1] \quad t = g, ...2016; \quad g = 2006, ...2013 \tag{3.5}$$

Where $Y_t(g)$ is the post-treatment outcome for the group of firms first treated at time g, in calendar time t. Whereas, $Y_t(0)$ refers to the post-treatment outcome for the firms that never were treated or that were not treated yet during the window $[t-3, t+3)]$. Therefore, $ATT(g,t)$ represents the average treatment effect in all post-treatment periods $t \geq g$ for cohorts that are first treated in period g; each cohort has an ATT. Callaway & Sant'Anna (2020) create long differences, therefore the outcomes $Y_t(g)$ and $Y_t(0)$ are the difference in outcome relative to one period before the treatment, namely the change in total and internal R&D investment. The outcome $Y_t(g)$ is computed as follows:

$$Y_t(g) = Y_t - Y_{g-1}, \quad t \geq g \tag{3.6}$$

For instance, for a firm in cohort$(g) = 2006$ and $t = 2006$, the outcome in 2006 is $Y_{06,06} =$

[10] I exclude firms which started to outsource R&D in 2003-2005 and 2014-2016 because those firms do not have a 3-year pre-treatment or post-treatment period.

[11] Note that a cohort may contain a control group that could be in the treatment group in other cohorts.

$Y_{06} - Y_{05}$, similar if $t = 2008$, cohort$(g) = 2006$, the outcome in 2008 is $Y_{06,08} = Y_{08} - Y_{05}$. The outcome $Y_t(0)$ is computed in the same manner but considering the firms never treated or not yet treated in each cohort g.

This approach makes two assumptions, the no anticipation and the parallel trend assumption. The first one assumes that all pre-treatment effects are zero: $Y_t(g) = Y_t(0)$, $t \in \{2003, ., g-1\}$, $g \in \{2006, ...2013\}$, this implies that $ATT(g,t) = 0$, when $t < g$. The second assumption indicates that the average outcome for the groups of firms first treated in period g and for the group of never-treated and not-yet treated firms would have followed parallel paths in the absence of treatment: For $t = 2004, ...2016$ $E[Y_t(0) - Y_{t-1}(0)|D_g = 1] = E[Y_t(0) - Y_{t-1}(0)|D_g = 0]$. Considering these two assumptions, equation 3.5 identifies the group-time average treatment effect.

The ATT(g,t) highlights treatment effect heterogeneity across different cohorts g, at different points in time t, and across different lengths of treatment exposure $e = t - g$. Thus, it does not restrict heterogeneity concerning timing or the evolution of treatment effects over time. It also provides a way to aggregate the group-time average treatment effect to highlight the dynamic treatment effect based on the duration of treatment exposure as follows:

$$\theta_{es}(e) = \sum_{g=2006}^{2013} w(g,t).ATT(g, g+e) \tag{3.7}$$

$$w(g,t) = \frac{D_g = 1}{\sum_{g=2006}^{2013} D_g = 1}$$

Where $e = t - g$ denotes the time since treatment was adopted. $ATT(g, g+e)$ is the estimated parameter for cohort g during $g+e$ time period. For instance, the instantaneous effect estimator $e = 0$ for a firm in cohort 2007 is $ATT(07, 07+0)$. The weight $w(g,t)$ for each cohort in different periods t is given by the proportion of treated firms in each cohort $D_g = 1$ relative to the total number of treated firms across all cohorts.

The matching method enables controlling for observable self-selection in R&D outsourcing, namely, it reduces the treatment group selection bias since it ensures that the distribution of observed characteristics for the control group is similar as possible to the distribution of treated firms during the pre-treatment period. I match within cohort g so that a firm which outsources R&D in time g is matched with a firm that does not outsource R&D in time g. To consider the dynamic effects of R&D outsourcing, the matching method is undertaken for the outcomes at time $Y_g, Y_{g+1}, Y_{g+2}, Y_{g+3}$ in each cohort g. To perform the matching, I apply 1-to-1 nearest neighbour with a caliper (0.05) with no replacement to match firms within the same industry and year and for which the distance between their propensity scores is the smallest possible within the specific caliper. I also impose a common support condition by excluding treated firms whose propensity scores exceed the maximum or fall below the minimum of those non-treated firms.[12]

The propensity score is generated by a probit model, which calculates the probability of doing R&D outsourcing on firms' characteristics during the pre-treatment period $(g - 1)$. The characteristics included in the probit model are based on the theoretical model, which shows that firms are more likely to outsource R&D when the cost of undertaking it is lower or when the benefits of it are higher than in-house R&D. The costs associated with R&D outsourcing are: the cost of adaptability, the potential productivity advantage of the provider, mark-up that external firms charge and the cost of finding the right partner. While the benefit is related to the potential productivity advantage of the provider. Therefore, to overcome the costs associated with R&D outsourcing, firms should be more productive, innovative, and well-connected to find the proper provider.

Accordingly, I control for firm productivity by including in the probit model: labour productivity (logarithm of sales over number of employees); employment (logarithm of the number of employees), and the logarithm of physical capital. The level of innovation is controlled by including the logarithm of the internal R&D expenditure, the dummy vari-

[12]The matching procedure is performed using psmatch2 implemented by Leuven & Sianesi (2003)

ables patents, product and process innovation, and researchers (logarithm of the number of researchers in R&D). To control for the advantage of selecting the appropriate provider, I include the following variables: group, which is a dummy variable indicating if the firm belongs to a business group; cooperation which denotes whether the firm engages in collaborative innovation with other stakeholders and export which specifies whether the firm operates as an exporter. In addition, I also include industry dummies.

Table 3.4 presents the results of the t-test, which compares the observable characteristics of the treatment and control groups after the matching procedure. The first three columns of table 3.4 compare the observable characteristics one year before the treatment, it can be seen that the difference between the treated and control groups is not statistically significant, meaning that the matching has successfully removed differences between the R&D outsourcers and non-outsourcers samples. The last three columns performed the t-test two years before the treatment, also here, matching has reduced the differences between treated and control groups. There remains a small difference in the propensity to cooperate in innovation (significant at 10%) and a significant difference in the number of researchers. However, the group that does not outsource R&D has a higher level of cooperation and has more researchers before the treatment.[13]

[13] In the appendix section, Tables 3.23-3.29 show the balancing test for each cohort.

Table 3.4: Balancing Test (t-test) for Matched Cohorts

	1 year before the treatment			2 years before the treatment		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure	7.802	7.728	(0.288)	7.872	7.775	(0.229)
Labour productivity	7.211	7.191	(0.703)	7.278	7.229	(0.318)
Employment	4.055	3.980	(0.314)	4.205	4.109	(0.242)
Group	0.379	0.366	(0.542)	0.372	0.370	(0.927)
Patents	0.146	0.150	(0.799)	0.147	0.171	(0.189)
Physical capital	7.819	7.695	(0.255)	8.051	7.963	(0.491)
Product innovation	0.684	0.694	(0.624)	0.686	0.699	(0.580)
Process Innovation	0.693	0.670	(0.284)	0.662	0.639	(0.318)
Researchers in R&D	1.324	1.290	(0.401)	1.298	1.157	(0.003)
Export	0.664	0.648	(0.445)	0.671	0.659	(0.601)
Cooperation	0.411	0.413	(0.927)	0.363	0.323	(0.087)
Observations	971	971		812	812	

After matching, I follow Callaway & Sant'Anna (2020) methodology to get the dynamic effects across different lengths of exposure to the treatment ($\theta_{es}(e)$) and the average treatment effect per cohort ($ATT(g, t)$).

3.5.2 Results

Table 3.5 shows the R&D outsourcing impact on internal and total R&D investment for the groups of firms which started to outsource R&D during the period 2006-2013. The table includes the instantaneous effects $\theta_{es}(e = 0)$, which is the year that firms start to outsource R&D ($t = g$), and the effect for the following three years. Table 3.5 also includes the average treatment effects of the three periods before the treatment. These effects are not statistically significant, indicating that in the absence of treatment, there was no statistically significant difference in the average R&D investment between the treated and control group. Therefore, the parallel trend assumption is satisfied.

The findings presented in Table 3.5 reveal a positive and statistically significant impact of R&D outsourcing on firms' internal and total R&D investment. Moreover, this effect remains consistent in the following years after the treatment. On average, compared to the control group, R&D outsourcing leads to a 14.4 percentage points (pp) increase in a firm's internal R&D investment in the year that firms started to outsource (t), followed by a 17.3 pp increase one year after, a 15.7 pp increase two years later and 19.4 pp increase three years later. Following hypothesis 1 (b), these findings suggest that firms undertaking R&D outsourcing increase their internal R&D investment. Accordingly, the elasticity of substitution between internal and external R&D should be sufficiently low; otherwise, there would not be a statistically significant impact on the internal R&D investment.

Regarding the total R&D investment, Table 3.5 shows that, on average, firms that outsource R&D raise their total R&D investment compared to the control group. This effect is higher than the effect on internal R&D investment and exhibits a statistically significant decline trend over time. In the year firms started to outsource R&D, the total R&D investment increased by 44 pp, 35.2 pp one year later, 30.4 pp two years later and 31.3 pp three years after the outsourcing began. These results confirm hypothesis 1 (a), which states that firms that undertake R&D outsourcing increase their total R&D volume.

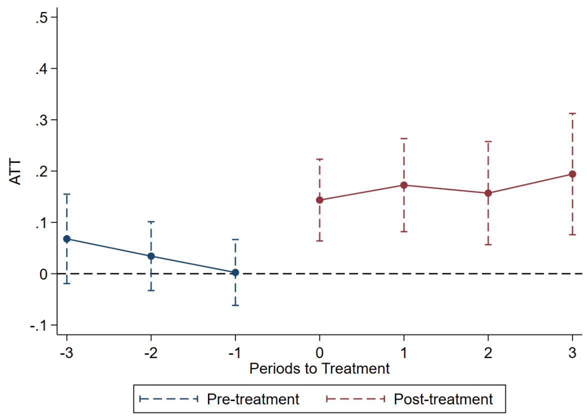
The number of treated and control observations decreases as time (t) increases due to its dependence on the number of treated firms per cohort, the persistence of firms in the sample, and the persistence of observation in the common support-based on the PSM method.

Table 3.5: ATT by Periods Before and After Treatment

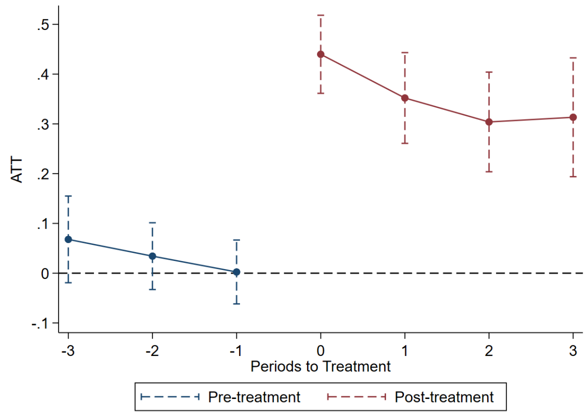
	R&D investment						
	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Internal R&D							
ATT	0.068	0.034	0.002	0.144***	0.173***	0.157***	0.194***
SE	(0.044)	(0.034)	(0.033)	(0.041)	(0.046)	(0.051)	(0.060)
Total R&D							
ATT	0.068	0.034	0.002	0.440***	0.352***	0.304***	0.313***
SE	(0.044)	(0.034)	(0.033)	(0.040)	(0.047)	(0.051)	(0.061)
Treated	1,024	1,024	1,024	971	877	789	690
Control	2,894	2,894	2,894	971	877	789	690

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3.2: R&D Investment of Firms Operating in Spain, Matched Cohorts



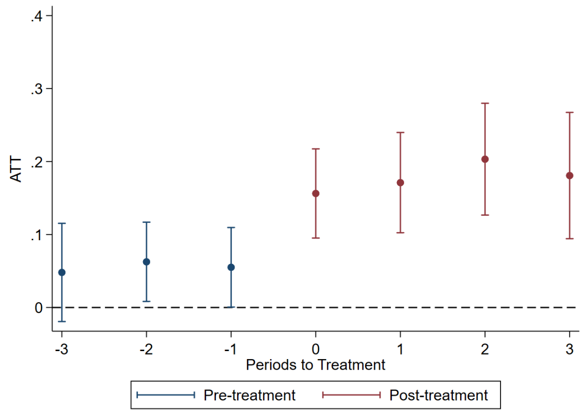
(a) Internal R&D investment



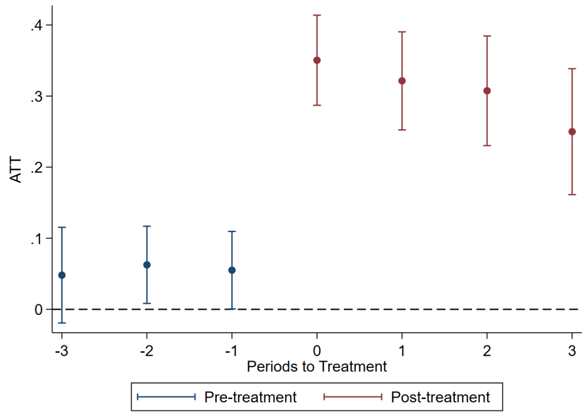
(b) Total R&D investment

Figure 3.2 provides a graphical illustration of the effect of R&D outsourcing on the internal and total R&D investment. This can be compared with the unmatched graph of figure 3.3, which shows that the treatment and control groups differ significantly in their observable characteristics before the treatment since the ATT is not statistically different from zero. After matching, there are no significant differences in R&D investment during the pre-treatment period between the control and treated groups.

Figure 3.3: R&D Investment of Firms Operating in Spain - Unmatched Cohorts



(a) Internal R&D investment



(b) Total R&D investment

The Callaway & Sant'Anna (2020) methodology also allows the examination of treatment effect heterogeneity across different cohorts (g). Table 3.6 reports the group-time average treatment effect $ATT(g,t)$. As can be seen, firms which started to outsource before and in 2009 experienced, on average, a positive and statistically significant effect on internal R&D investment. In contrast, firms that began outsourcing after 2009 did not have a statistically significant impact on internal R&D investment. On the other hand, the ATT on total R&D investment is positive and statistically significant across all the cohorts, although it is lower for firms that started to outsource R&D from 2010 onward.

The findings reported in Table 3.6 suggest that the elasticity of substitution between internal and external R&D is low enough during the period 2006-2009 since there is a positive and statistically significant impact on the internal and total R&D investment. The latter implies that when firms decide to outsource R&D, it leads to increased productivity, encouraging them to invest more in R&D. As a result, this increased expenditure is directed to enhancing both the external and the internal Knowledge. On the other hand, from 2010 to 2013, the impact of R&D outsourcing on the inputs of innovation is less well-determined. The lack of significance or diminished significance in the estimated coefficients may be attributed to two potential factors. One factor could be the decrease in the number of observations starting from the 2010 cohort.[14] Alternatively, it could be linked to the financial crisis, during which the Spanish government enforced austerity measures, resulting in a 50% reduction in R&D subsidies.[15] As a result, during those years, the investment in external R&D may have been relatively modest, not requiring a significant investment in internal R&D, thus having a not statistically significant impact on internal R&D.

Table 3.6: ATT by Cohort

	$InternalR\&D$		$TotalR\&D$		Sample
	$ATT(g,t)$	SE	$ATT(g,t)$	SE	size
Average	0.173***	(0.037)	0.353***	(0.037)	
Cohort 2006	0.168**	(0.069)	0.357***	(0.069)	2,846
Cohort 2007	0.153*	(0.081)	0.358***	(0.081)	1,580
Cohort 2008	0.230**	(0.098)	0.413***	(0.099)	936
Cohort 2009	0.216**	(0.098)	0.416***	(0.103)	906
Cohort 2010	0.121	(0.129)	0.280**	(0.130)	480
Cohort 2011	0.085	(0.121)	0.199*	(0.121)	478
Cohort 2012	0.165	(0.158)	0.285*	(0.161)	362
Cohort 2013	0.253	(0.156)	0.363**	(0.161)	228

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Together these results do not lead to a rejection of hypotheses 1, a) and b) of the theoretical model in R&D outsourcing, showing that firms that outsource R&D increase their internal and total R&D investment compared to firms that do not outsource R&D. However, the statistically significant findings come from the firms that were first treated before 2010.

[14]In the appendix section, Figure 3.8 shows the impact of R&D outsourcing on internal and total R&D investment by cohort and across different lengths of treatment exposure.

[15]Subsidies to R&D decreased from 18% in 2007 to 9% in 2015 (Parellada & Sanz 2017).

The effect of R&D outsourcing according to export status

In this section, I explore the heterogeneous effect of R&D outsourcing on R&D investment according to the firm's export status. Table 3.7 reports the $ATTs$ by length to exposure to the treatment. Panel A shows the results for the case of exporting firms where the treated group is the exporting firms that started to outsource R&D for the first time in time (g) and the control group is the exporting firms that did not outsource R&D during the time window $[t-3, t=g, t+3]$.[16] Panel B reports the findings for the non-exporting firms; similarly, the treated group is the non-exporting firms that started to outsource R&D for the first time in time (g), and the control group is the non-exporting firms that during the time window $[t-3, t+3]$ did not outsource.[17]

Unlike Table 3.5, the sample of exporting and non-exporting firms does not include the 2013 cohort due to the lack of matching between the treated and control groups within the non-exporting firms' sample for that particular cohort.[18] Therefore, Table 3.7 only considers the cohorts from 2006 to 2012. Table 3.7 shows that the impact of R&D outsourcing on internal and total R&D investment is positive and statistically significant for the case of exporting firms, and it is persistent over time. In contrast, for the sample of non-exporting firms, the effect on the internal R&D is positive and statistically significant only in the first year that firms started to outsource (t), and two years later. The impact on the total R&D is positive and statistically significant over time.

Both exporters and non-exporters experience a positive and statistically significant impact on the total R&D investment. However, the effect is higher for the case of non-exporters during the first three years of outsourcing. There are two potential explanations for this result. First, exporting firms may benefit from the experience and knowledge gained in foreign markets, leading to reduced costs of R&D contract enforcement, moni-

[16] A firm is considered an exporter if it started to export for the first time before the treatment period.

[17] A firm is considered a non-exporter whether the firm either started to export after the treatment or never engaged in exporting.

[18] The sample of non-exporting firms is lower than the exporting firms (See Table 3.3).

toring, and the fixed costs associated with finding suitable R&D service providers. As a result, the increase in total R&D investment among exporting firms that engage in R&D outsourcing may be smaller than the increase observed among non-exporting firms that also choose to outsource R&D, in comparison to their respective counterparts (exporters and non-exporters) that do not engage in R&D outsourcing. Secondly, exporting firms are more likely to adopt advanced technology compared to non-exporting firms; thus, exporting firms would not need to invest as much as non-exporting firms in R&D. Finally, it is worth mentioning that reported coefficients represent the difference in differences, which indicates the change in R&D investment relative to the control group.

Regarding internal R&D investment, while the impact is statistically significant for non-exporting firms during the first year (t), this effect does not persist during the following years. However, the absence of significance in the coefficients could be related to the sample size of the non-exporters, which is smaller compared to the case of exporters. [19] This is confirmed in Table 3.21 of the appendix, which shows that the impact of R&D outsourcing on internal R&D is statistically significant over time when the sample size increases.

[19] In the appendix section, Table 3.30 presents the balancing test of the quality of the matching for exporters and non-exporters.

Table 3.7: Impact of R&D Outsourcing on Firms' R&D investment - Exporters vs Non-Exporters

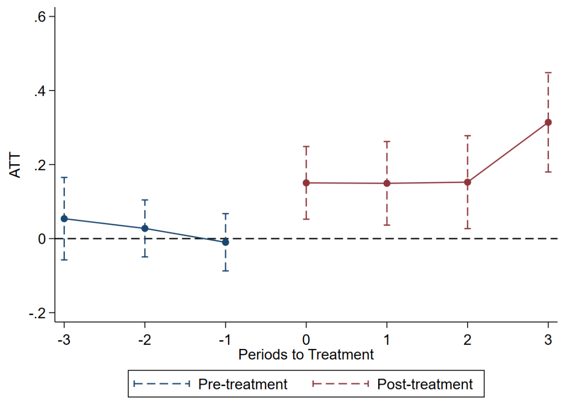
	R&D investment						
	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: Exporters							
Internal R&D							
ATT	0.054	0.028	-0.010	0.151***	0.149***	0.152**	0.314***
SE	(0.057)	(0.039)	(0.039)	(0.050)	(0.058)	(0.064)	(0.068)
Total R&D							
ATT	0.054	0.028	-0.010	0.431***	0.315***	0.290***	0.438***
SE	(0.057)	(0.039)	(0.039)	(0.049)	(0.058)	(0.064)	(0.069)
Treated	632	632	632	604	546	503	446
Control	1,826	1,826	1,826	604	546	503	446
Panel B: Non-Exporters							
Internal R&D							
ATT	0.031	0.048	-0.059	0.219***	0.116	0.175*	0.146
SE	(0.086)	(0.082)	(0.062)	(0.075)	(0.078)	(0.099)	(0.114)
Total R&D							
ATT	0.031	0.048	-0.059	0.537***	0.336***	0.361***	0.272**
SE	(0.086)	(0.082)	(0.062)	(0.073)	(0.079)	(0.098)	(0.115)
Treated	343	343	343	309	280	230	195
Control	775	775	775	309	280	230	195

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

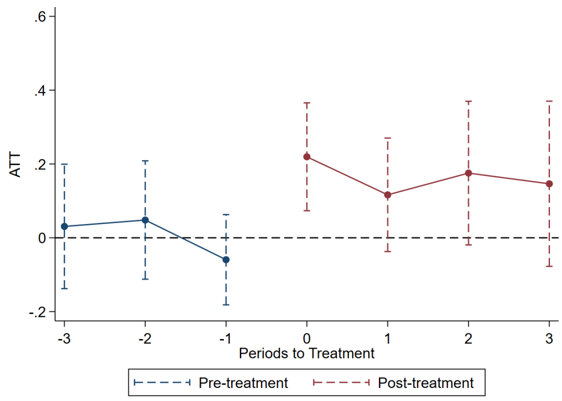
Figure 3.4 depicts a graphical comparison of the impact of R&D outsourcing for exporting (3.4a and 3.4b) and non-exporting firms (3.4c and 3.4d). As is shown, in both cases, the parallel trend assumption is satisfied, as there is no statistically significant difference in the internal and total R&D investment between the treated and control groups before the treatment. Figure 3.4 also demonstrates that the effect on the internal R&D for the exporting firms shows an increasing trend and remains its statistical significance over time. In contrast, for non-exporting firms, this effect becomes statistically insignificant and decreases over time. However, it can be seen that the standard errors for the case of non-exporting firms are higher than in the case of exporters. The latter suggests that the lack of significance could be attributed to the small number of non-exporting firms, as confirmed in the robustness checks section.

Figure 3.4: Exporters vs Non-Exporters

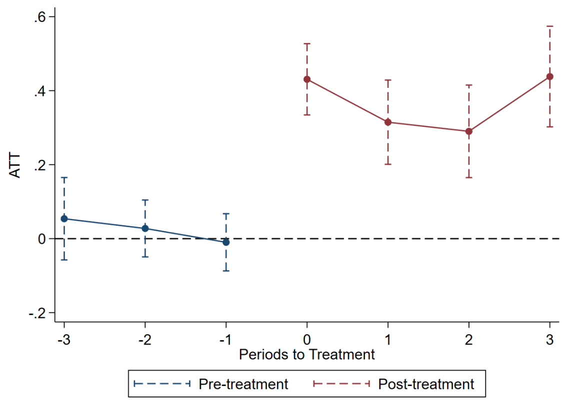
Exporters **Non-exporters**



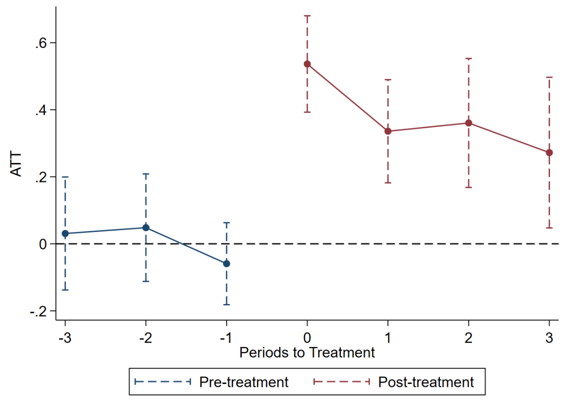
(a) Internal R&D



(c) Internal R&D



(b) Total R&D



(d) Total R&D

Table 3.8 shows the $ATT(g,t)$ by cohort and the average ATT for the whole period. Within the exporters' sample, the positive and statistically significant impact on internal R&D comes from firms first treated before 2009. Similarly, the total R&D investment is no longer statistically significant after 2010. As indicated in the previous section, these findings could be attributed to the austerity policy implemented by the Spanish government in response to the financial crisis. Regarding non-exporting firms, the positive and statistically significant impact on internal R&D in the first year of treatment comes from firms first treated in 2006. During the financial crisis (2009-2012), the effect of R&D outsourcing on the internal R&D was not statistically significant. Likewise, total R&D investment remained statistically significant until 2008, after which it began to decline and was no longer statistically significant, except for the group of firms treated in 2011.

However, on average, both exporting and non-exporting firms experience a statistically significant impact of R&D outsourcing on both internal and external R&D investment. Exporting firms experience a 20.2 pp increase in internal R&D investment and 37.3.pp increase in total R&D compared to the exporting firms that do not outsource. Similarly, non-exporting firms experience a 16.6 pp increase in internal R&D investment and a 37.4 pp increase in total R&D investment compared to non-exporting firms that do not outsource.

Together, these results suggest that R&D outsourcing has a positive and statistically significant impact on internal and total R&D investment for exporters and non-exporters. However, these findings suggest that non-exporting firms were more affected by the financial crisis compared to exporting firms. This is evident as the non-exporting firms that began outsourcing during the crisis period did not exhibit a statistically significant effect on their R&D investment. The latter is also confirmed in Table 3.16 within the robustness check section, which shows that the statistical significance of the coefficients representing the dynamic effects of R&D outsourcing on internal R&D investment for non-exporting firms comes from firms first treated in 2004 and 2005.

Table 3.8: ATT by Cohort - Exporters vs Non-Exporters

	Exporters				Non-Exporters			
	Internal		*TotalR&D*		*Internal*		*TotalR&D*	
	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE
Average	0.202***	(0.045)	0.373***	(0.046)	0.166**	(0.066)	0.374***	(0.066)
Cohort 2006	0.238***	(0.086)	0.409***	(0.086)	0.188*	(0.106)	0.411***	(0.106)
Cohort 2007	0.240**	(0.103)	0.443***	(0.103)	0.159	(0.137)	0.369***	(0.137)
Cohort 2008	0.268**	(0.115)	0.439***	(0.117)	0.251	(0.183)	0.464**	(0.185)
Cohort 2009	0.136	(0.118)	0.356***	(0.125)	-0.016	(0.159)	0.144	(0.151)
Cohort 2010	0.225*	(0.130)	0.368***	(0.136)	-0.156	(0.275)	0.065	(0.281)
Cohort 2011	0.056	(0.142)	0.133	(0.143)	0.358	(0.235)	0.538**	(0.213)
Cohort 2012	0.007	(0.170)	0.113	(0.172)	0.372	(0.441)	0.427	(0.436)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The effect of domestic and international R&D outsourcing on firms' R&D investment

I examine the impact of domestic and international R&D outsourcing on firms' R&D investment. Table 3.9 reports the results for the different cases. The treated groups in the table are classified as follows: in Panel A, the treated group is firms with only domestic R&D outsourcing; in Panel B, I include firms that began outsourcing R&D internationally or simultaneously outsourced both domestic and international R&D.[20]In both cases, the control group is the firms that did not outsource R&D during the time window $[t-3, t+3]$ for each cohort (g). This analysis only includes the firms first treated between 2006 and 2010, namely cohorts 2006-2010, due to the absence of suitable matching between treated and control groups within the international R&D outsourcers' sample for cohorts 2011-2013.[21]

[20]I combine these two groups of firms due to the small numbers of firms that outsource R&D internationally (See Table 3.2)

[21]In the appendix section, Table 3.31 presents the balancing test of the quality of the matching for exporters and non-exporters.

Table 3.9 shows that, on average, firms that outsource R&D domestically experience a positive and statistically significant effect on their internal and total R&D investment. In contrast, the effect of international R&D outsourcing on internal R&D investment is not significantly uplifted until t+3. Similarly, the lack of significance might be associated with the limited number of firms engaging in international R&D outsourcing. However, as demonstrated in the robustness check section, the coefficient remains statistically insignificant even with a larger sample of firms. Additionally, in the appendix section, Table 3.22 also reveals no statistically significant impact of international R&D outsourcing on internal R&D when both the sample size is increased and a different approach is employed to assess this effect. In contrast, the impact of international R&D outsourcing on the total R&D investment is positive, statistically significant, and even higher compared to the effect for the domestic R&D outsourcers. These results indicate that conducting international R&D outsourcing is more expensive than doing so domestically, and the impact on internal R&D is not immediate.

Figure 3.5 compares the impact of domestic and international R&D outsourcing on the internal and total R&D investment graphically. The parallel trend assumption is satisfied in both cases. Table 3.10 reports the average ATT and $ATT(g,t)$ per cohort (g). Similar to previous cases, for the domestic R&D outsourcers, the positive and statistically significant impact on the internal R&D comes from the firms treated early, before 2010. For the case of international R&D outsourcing, there is no statistically significant impact on the internal R&D but on total R&D investment. Likewise, the lack of statistical significance for the years after 2009 could be a result of the financial crisis. However, on average, firms that outsource R&D internationally experience a rise of 19.8 pp in their internal R&D and a 46.6 pp increase in total R&D investment compared to firms that do not outsource R&D, although it is worth noting that the impact on internal R&D is statistically significant at the 10% level. Likewise, on average, firms that engage in domestic R&D outsourcing experience a 16 percentage point increase in internal R&D

and a 34.4 percentage point increase in total R&D investment compared to those that do not outsource.

To summarize, firms that undertake domestic R&D outsourcing experience an increase in both internal and external R&D, indicating a potential complementary between the internal and external R&D, as the theory suggests. Conversely, firms that engage in both domestic and international R&D outsourcing experience a less pronounced statistically significant increase in their internal R&D investment. However, they do experience a positive and statistically significant impact on their total R&D investment. This suggests a greater dependence on external R&D, at least initially, given that the effect on internal R&D is not immediate.

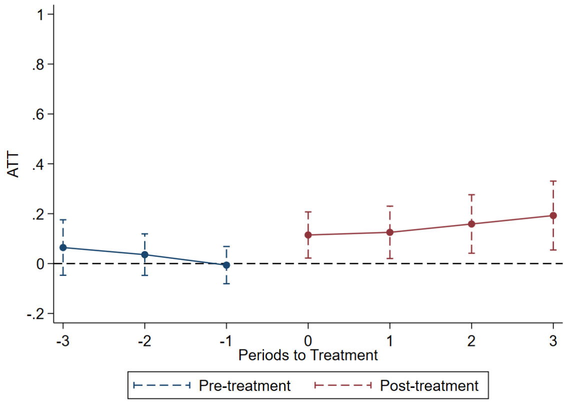
Table 3.9: Impact of R&D Outsourcing on Firms' R&D investment - Domestic vs International Outsourcing

	R&D investment						
	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: Domestic Outsourcing							
Internal R&D							
ATT	0.064	0.036	-0.006	0.115**	0.125**	0.159***	0.193***
SE	(0.057)	(0.042)	(0.038)	(0.047)	(0.054)	(0.060)	(0.070)
Total R&D							
ATT	0.064	0.036	-0.006	0.407***	0.304***	0.315***	0.319***
SE	(0.057)	(0.042)	(0.038)	(0.046)	(0.054)	(0.059)	(0.071)
Treated	788	788	788	746	677	598	516
Control	2,185	2,185	2,185	746	677	598	516
Panel B: International Outsourcing							
Internal R&D							
ATT	-0.017	-0.041	-0.072	0.116	0.085	0.224	0.439**
SE	(0.103)	(0.086)	(0.099)	(0.128)	(0.134)	(0.156)	(0.208)
Total R&D							
ATT	-0.017	-0.041	-0.072	0.536***	0.339**	0.387**	0.628***
SE	(0.103)	(0.086)	(0.099)	(0.130)	(0.138)	(0.157)	(0.212)
Treated	93	93	93	89	77	76	63
Control	302	302	302	89	77	76	63

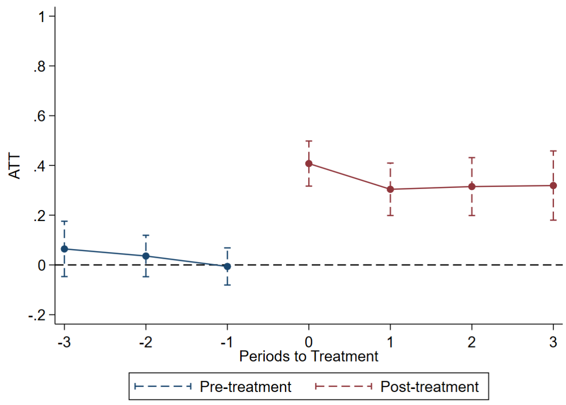
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3.5: Domestic vs International Outsourcing

Domestic

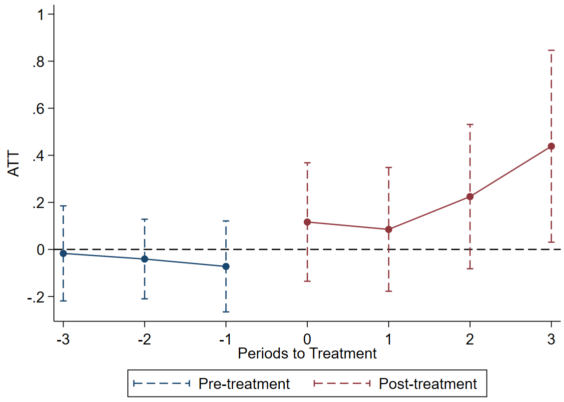


(a) Internal R&D

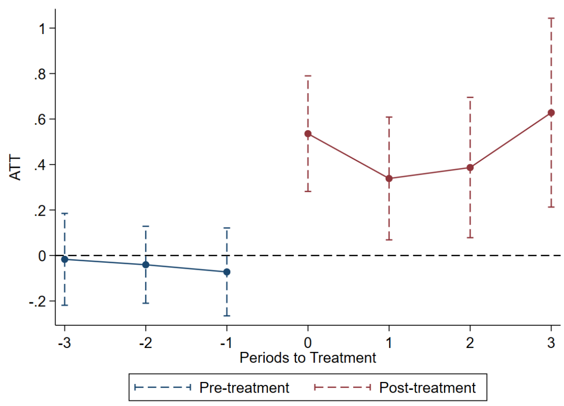


(b) Total R&D

International



(c) Internal R&D



(d) Total R&D

Table 3.10: ATT by Cohort - Domestic vs International Outsourcing

	Domestic				International			
	Internal		*TotalR&D*		*Internal*		*TotalR&D*	
	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE
Average	0.160***	(0.043)	0.344***	(0.043)	0.198*	(0.111)	0.466***	(0.116)
Cohort 2006	0.182**	(0.074)	0.373***	(0.074)	0.276	(0.172)	0.459***	(0.172)
Cohort 2007	0.118	(0.089)	0.311***	(0.088)	0.223	(0.251)	0.529**	(0.268)
Cohort 2008	0.217**	(0.103)	0.402***	(0.105)	0.355	(0.221)	0.518**	(0.226)
Cohort 2009	0.168*	(0.101)	0.325***	(0.100)	-0.138	(0.299)	0.531	(0.344)
Cohort 2010	0.030	(0.130)	0.188	(0.131)	0.053	(0.251)	0.203	(0.273)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Hypothesis 2

In industries where R&D outsourcing is more profitable, a) fewer firms invest in total R&D

3.6.1 Methodology

To assess the profitability of R&D outsourcing, I adopt the methodology outlined by Grimpe & Kaiser (2010), I construct a cooperation index that quantifies the extent of collaboration between firms involved in the innovation process. Then, I calculate the industry-specific average cooperation level by taking the mean of cooperation values across firms within each industry. The innovation cooperation partners are customers, suppliers, competitors, universities, and research institutes. Cooperation with different partners may represent firms' openness to external knowledge. This openness increases firms' likelihood to access a large variety of knowledge resources and gain experience, which enables them to build up skills to carry on activities in the technology market. The cooperation experience helps firms better manage R&D outsourcing relationships, find suitable R&D contractors, reduce informational asymmetries, and better manage and control the R&D outsourcing process (Grimpe & Kaiser 2010). As a result, collaboration with different partners in the innovation activities could increase the efficiency of R&D outsourcing. Therefore, the profitability of R&D outsourcing is measured through the interaction between the mean cooperation and the intensity of R&D outsourcing at the industry level. The latter is calculated by dividing the external R&D expenditure over sales.

Table 3.11 shows the number of partners for innovation per industry. Most of the firms have between 0 and 3 partners. The number of firms decreases for more than 3 partners. Table 3.11 also presents the average number of partners that firms collaborate with per industry during the innovation process. The industries that have firms with a higher average number of partners are pharmaceuticals (1.423), and R&D services, software, and technical analysis (1.420). The manufacture of transport equipment is the third industry where firms have a high average number of partners (1.110).

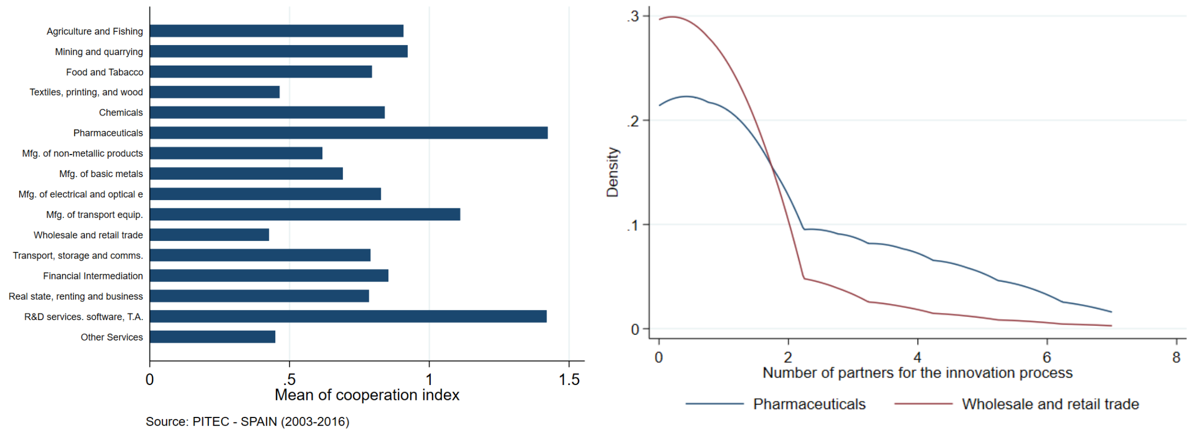
Table 3.11: Number of Partners for Innovation by Industry

	Number of partners for Innovation process									
Industry	0	1	2	3	4	5	6	7	Total	Mean
Agriculture and Fishing	1,004	279	156	114	59	32	26	5	1,675	0.907
Mining and quarrying	4,212	696	341	275	239	163	117	148	6,191	0.923
Food and Tabacco	5,777	1,112	667	428	245	159	143	67	8,598	0.795
Textiles, printing, and wood	8,849	1,198	460	369	231	90	72	31	11,300	0.464
Chemicals	4,679	905	530	435	213	165	85	71	7,083	0.841
Pharmaceuticals	1,054	235	198	168	166	104	53	32	2,010	**1.423**
Mfg. of non-metallic	5,529	1,021	421	345	169	95	64	45	7,689	0.618
Mfg. of basic metals	8,420	1,419	828	587	335	199	107	64	11,959	0.691
Mfg. of elect. and opt. equip.	8,495	1,396	893	595	427	303	187	139	12,435	0.827
Mfg. of transport equip.	2,534	590	287	253	174	94	107	128	4,167	**1.110**
Wholesale and retail trade	6,865	833	404	229	140	72	44	23	8,610	0.427
Transport, stge. and comms.	6,037	1,003	535	382	272	184	132	117	8,662	0.789
Financial intermediation	1,580	386	249	175	58	49	25	19	2,541	0.854
Real state, renting and B.A.	5,662	879	565	434	263	171	126	61	8,161	0.784
R&D services, software, T.A.	5,430	1,450	1,010	747	523	584	490	155	10,389	**1.420**
Other Services	6,660	921	403	179	123	86	74	25	8,471	0.449
Total	82,787	14,323	7,947	5,715	3,637	2,550	1,852	1,130	119,941	

Figure 3.6 shows the average number of partners per industry and the distribution of firms per industry according to the number of partners that firms have for the innovation process. This figure compares the industry where firms have the highest average number of partners (Pharmaceuticals) and the industry with the lowest average number of partners

(Wholesale and retail trade). As can be seen, the pharmaceutical industry has a higher number of firms with more than two partners. In contrast, the wholesale and retail trade industry has a higher number of firms with less than two partners.

Figure 3.6: Number of cooperation by Industry



(a) Average number of partners **(b) Distribution of firms**

Table 3.12: Industry Characteristics

Industry	Mean							Number of firms
	Firms Size	Firms with External R&D	External R&D Expenditure	Firms with Internal R&D	Firms belong to a Group	Firms with patents	Firms Cooperate Innovation	
Agriculture and Fishing	75	0.318	384	0.588	0.346	0.081	0.907	1,675
Mining and quarrying	525	0.241	1,820	0.427	0.519	0.094	0.923	6,191
Food and Tobacco	202	0.272	661	0.553	0.438	0.068	0.795	8,598
Textiles, printing, and wood	119	0.207	296	0.492	0.294	0.102	0.464	11,300
Chemicals	105	0.312	918	0.772	0.443	0.124	0.841	7,083
Pharmaceuticals	277	**0.632**	20,555	0.844	0.706	**0.309**	**1.423**	2,010
Mfg. of non-metallic	157	0.250	711	0.543	0.466	0.130	0.618	7,689
Mfg. of basic metals	143	0.282	784	0.625	0.359	0.166	0.691	11,959
Mfg. of elect. and opt. equip.	112	0.289	1081	0.690	0.357	0.184	0.827	12,435
Mfg. of transport equip.	503	**0.398**	16,953	0.612	0.636	**0.158**	**1.110**	4,167
Wholesale and retail trade	653	0.155	452	0.312	0.474	0.058	0.427	8,610
Transport, stge. and comms.	528	0.176	4,980	0.438	0.462	0.046	0.789	8,662
Financial intermediation	1,448	0.229	10,333	0.331	0.768	0.016	0.854	2,541
Real state, renting and B.A.	317	0.186	866	0.418	0.397	0.070	0.784	8,161
R&D services, software, T.A.	110	**0.348**	3,088	0.824	0.286	**0.196**	**1.420**	10,389
Other Services	795	0.123	271	0.268	0.402	0.030	0.449	8,471

Average expenditure in R&D Outsourcing is in thousands of Euro, size of firms is calculated by the number of employees within the firm. The numbers represent the average over the period 2003-2016.

Table 3.12 displays that the industries with a higher mean in cooperation for innovation are the same industries with a higher share of firms that outsource R&D and a higher proportion of firms with patents. The latter suggests a possible relationship between these activities, where cooperation may have helped firms to use the external R&D efficiently and, as a result, these firms have more innovation outputs such as patents, as Grimpe & Kaiser (2010) suggests. Therefore, I use the interaction between the mean cooperation and the intensity of R&D outsourcing to measure the profitability of R&D outsourcing.

According to hypothesis 2, in industries where R&D outsourcing is more profitable, fewer firms are investing in total R&D. The latter is tested using an ordinary least square (OLS) model at the industry level, where the standard errors are clustered by industry.

$$\begin{aligned} ShareR\&D_{jt} =& \alpha + \beta_2 MeanCoop_{j,t} + \beta_3 OUT_j \\ &+ \beta_4 OUT_j \times MeanCoop_{j,t} + \mu_t + \tau_j + \epsilon_{i,j,t} \end{aligned} \tag{3.8}$$

Where $ShareR\&D_{jt}$ is the share of firms that do R&D in industry j and year t, $MeanCoop_{j,t}$ is the mean number of partners for innovation that firms have in industry j and year t, OUT_j represents the intensity of R&D outsourcing calculated by the total R&D expenditure over total sales in industry j and year t. The interaction term $OUT_{jt} \times MeanCoop_{j,t}$ measures the profitability of R&D outsourcing at the industry level. Time and industry fixed effect are represented by μ_t and τ_j respectively.

3.6.2 Results

Table 3.13 shows the results from equation 3.8, where the coefficient β_4 represents the profitability of R&D outsourcing ($MeanCoop_{j,t} \times OUT_j$), and it is reported in column 2. The coefficient β_4 is negative, implying that in industries where R&D outsourcing is more profitable, fewer firms undertake R&D. The same occurs when the analysis is at the firm level (column 1). In particular, an increase of 1 percentage point in the profitability of R&D outsourcing generates a reduction in the share of firms investing in total R&D by 1.82 percentage points. Hence, these results confirm hypothesis 2. The rise in the profitability of R&D outsourcing within an industry increases the demand for limited production factors, increasing competition among firms to secure these resources. Consequently, the prices of these production factors increase, making R&D outsourcing more costly for the least productive firms. As a result, in equilibrium, fewer firms participate in R&D activities within that industry.

Table 3.13: Profitability of R&D Outsourcing and Proportion of Firms doing R&D Outsourcing

Total R&D	Firm level (1)	Industry level (2)
$MeanCoop_{j,t}$	0.285***	0.334***
	(0.020)	(0.046)
OUT_j	1.459	3.629*
	(1.151)	(1.714)
$MeanCoop_{j,t} \times OUT_j$	-1.116***	-1.823***
	(0.411)	(0.595)
Firm Characteristics	Yes	No
Constant	-0.392***	0.171**
	(0.062)	(0.078)
Observations	117,717	224
R^2	0.331	0.962

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ are clustered by industry in column 2. Column (1) presents the probability of doing R&D. The analysis is at the firm level and the regressions include firms' characteristics. Column (2) present the analysis at the industry level where the dependent variable is the share of firms that do R&D in industry j at time t. All specifications include time, region and industry fixed effect.

3.7 Robustness checks

3.7.1 Additional Cohorts

The firms treated in the early period (2003-2005) and those treated in the late period (2014-2016) were not considered because they do not have three-year pre-treatment or post-treatment periods, respectively. However, to increase the sample size of treated firms, I include in the analysis firms treated in 2004 and 2005, as well as firms treated from 2014-2016.[22] Results reported in Table 3.14 demonstrate that the findings remain positive and statistically significant even when both early-treated and lately-treated firms are considered.

Table 3.14: ATT by Periods Before and After Treatment - Cohorts (2004-2016)

	R&D investment						
	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Internal R&D							
ATT	0.063	0.031	0.005	0.098***	0.159***	0.109***	0.148***
SE	(0.042)	(0.033)	(0.027)	(0.03)	(0.035)	(0.038)	(0.042)
Total R&D							
ATT	0.063	0.031	0.005	0.388***	0.332***	0.263***	0.284***
SE	(0.042)	(0.033)	(0.027)	(0.03)	(0.035)	(0.038)	(0.043)
Treated	1,069	1,464	1,901	1,718	1,562	1,404	1,336
Control	2,972	3,905	4,870	1,718	1,562	1,404	1,336

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The difference in the number of firms during the pre-treatment period varies because the 2004 and 2005 cohorts have different numbers of pre-treatment periods, $t-1$ and $t-2$, respectively.

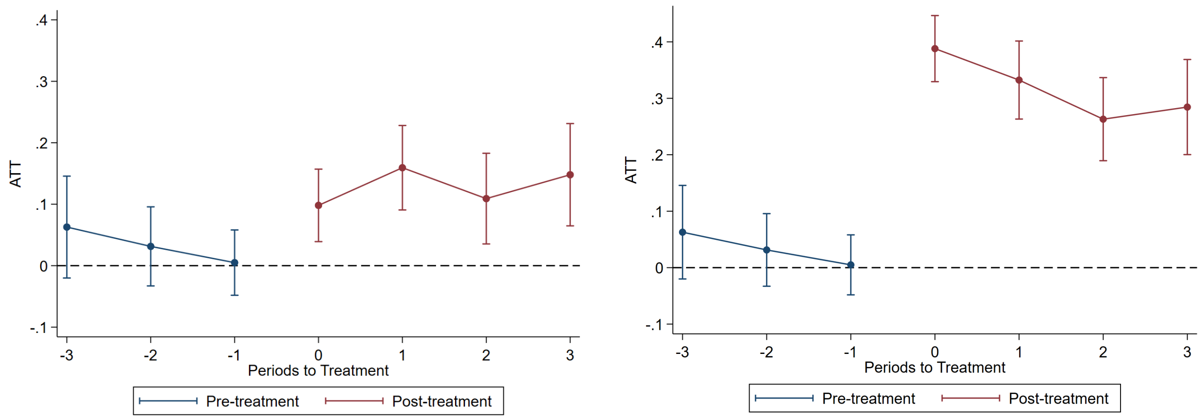
Figure 3.7 shows that the parallel trend assumption is satisfied even when cohorts 2004 and 2005 are included. When comparing Figure 3.7 with Figure 3.2, it becomes evident that both figures depict a similar trend for internal and total R&D investment. Although, Figure 3.2 exhibits a larger impact.

It can be seen from Table 3.15 that firms treated in 2004 experienced a positive and statistically significant impact on their internal and total R&D investment. In contrast, firms that began to outsource R&D in 2015 experienced a negative impact on their internal R&D investment and no statistically significant impact on their total R&D. The negative

[22]Firms treated for the first time in 2003 were not included in the study because it was not possible to observe the changes in total and internal R&D investment relative to the period before the treatment.

sign on the coefficient indicates that the control group experienced a higher increase in their internal R&D than the treated group. Due to the negative impact observed in the 2015 cohort and the lack of statistically significant impact in 2005, 2014 and 2016 cohorts, the magnitude of the coefficients of Table 3.14 is lower compared to Table 3.5, which considers only cohorts from 2006 to 2013.

Figure 3.7: R&D Investment Matched Cohorts (2004-2016)



(a) Internal R&D investment **(b) Total R&D investment**

Table 3.15: ATT by Cohort

	$Internal R\&D$		$Total R\&D$	
	$ATT(g,t)$	SE	$ATT(g,t)$	SE
Average	0.124***	(0.027)	0.311***	(0.027)
Cohort 2004	0.092*	(0.051)	0.283***	(0.052)
Cohort 2005	0.076	(0.064)	0.256***	(0.064)
Cohort 2006	0.168**	(0.069)	0.357***	(0.069)
Cohort 2007	0.153*	(0.081)	0.358***	(0.081)
Cohort 2008	0.230**	(0.098)	0.413***	(0.099)
Cohort 2009	0.216**	(0.098)	0.416***	(0.103)
Cohort 2010	0.121	(0.129)	0.280**	(0.130)
Cohort 2011	0.085	(0.121)	0.199*	(0.121)
Cohort 2012	0.165	(0.158)	0.285*	(0.161)
Cohort 2013	0.253	(0.156)	0.363**	(0.161)
Cohort 2014	0.295	(0.227)	0.507**	(0.251)
Cohort 2015	-0.654**	(0.258)	-0.350	(0.251)
Cohort 2016	-0.455	(0.278)	0.071	(0.370)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Differences Between Exporters vs Non-Exporters

Table 3.16 presents the results for the sample of exporters and non-exporters when early-treated firms are considered. For the case of exporters, the results are very similar to the ones reported in Table 3.7, providing evidence that the findings are robust to the inclusion of early-treated firms. However, for the case of non-exporters, the impact on internal R&D is more positive and statistically significant than the ones reported in Table 3.7 additional treated firms are incorporated into the analysis. The impact on total R&D investment is similar to Table 3.7 for non-exporters. Table 3.16 also shows that the parallel trend assumption is satisfied even considering the 2004 and 2005 cohorts.[23]

[23] Later cohorts (2013-2016) were not considered due to the lack of suitable matching within these cohorts.

Table 3.16: Exporters vs Non-Exporters - Cohorts (2004-2012)

	R&D investment						
	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: Exporters							
Internal R&D							
ATT	0.054	0.028	-0.026	0.095***	0.126***	0.127***	0.239***
SE	(0.057)	(0.039)	(0.032)	(0.037)	(0.042)	(0.045)	(0.05)
Total R&D							
ATT	0.054	0.028	-0.026	0.372***	0.292***	0.271***	0.373***
SE	(0.057)	(0.039)	(0.032)	(0.036)	(0.043)	(0.045)	(0.051)
Treated	632	873	1,117	1,067	983	916	812
Control	1,826	2,443	3,013	1,067	983	916	812
Panel B: Non-Exporters							
Internal R&D							
ATT	0.031	0.048	-0.051	0.171***	0.142**	0.150**	0.185**
SE	(0.086)	(0.082)	(0.054)	(0.055)	(0.064)	(0.073)	(0.088)
Total R&D							
ATT	0.031	0.048	-0.051	0.474***	0.330***	0.329***	0.316***
SE	(0.086)	(0.082)	(0.054)	(0.055)	(0.064)	(0.073)	(0.089)
Treated	343	499	592	540	493	408	352
Control	775	1,016	1,339	540	493	408	352

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The difference in the number of firms during the pre-treatment period varies because the 2004 and 2005 cohorts have different numbers of pre-treatment periods, $t-1$ and $t-2$, respectively.

Table 3.17 shows the group-time average treatment effect ($ATT(g,t)$) and average ATT. It can be seen that for non-exporting, the positive and statistically significant effect on internal R&D comes from the groups of firms treated in 2004 and 2006. However, after 2007 the impact on internal R&D was no longer statistically significant. The latter could be attributed to the financial crisis. Nonetheless, it is important to note that the absence of significance for later cohorts may also be due to the small number of firms that do not export within those cohorts.

Regarding the sample of exporters, the average impact on internal and total R&D

across all cohorts $(0.155, 0.330)$ are lower compared to Table 3.8 $(0.202, 0.373)$, this is because the lack of significance on internal R&D for the 2004 cohort and the lower impact on total R&D for 2004, and 2005 cohorts compared to other cohorts.

Table 3.17: ATT by Cohort - Exporters vs Non-Exporters

	Exporters				Non-Exporters			
	$Internal$		$TotalR\&D$		$Internal$		$TotalR\&D$	
	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE
Average	0.155***	(0.033)	0.330***	(0.033)	0.171***	(0.051)	0.371***	(0.051)
Cohort 2004	0.015	(0.064)	0.203***	(0.065)	0.302***	(0.090)	0.488***	(0.092)
Cohort 2005	0.175**	(0.068)	0.346***	(0.069)	0.005	(0.142)	0.198	(0.146)
Cohort 2006	0.238***	(0.086)	0.409***	(0.086)	0.188*	(0.106)	0.411***	(0.106)
Cohort 2007	0.240**	(0.103)	0.443***	(0.103)	0.159	(0.137)	0.369***	(0.137)
Cohort 2008	0.268**	(0.115)	0.439***	(0.117)	0.251	(0.183)	0.464**	(0.185)
Cohort 2009	0.136	(0.118)	0.356***	(0.125)	-0.016	(0.159)	0.144	(0.151)
Cohort 2010	0.225*	(0.130)	0.368***	(0.136)	-0.156	(0.275)	0.065	(0.281)
Cohort 2011	0.056	(0.142)	0.133	(0.143)	0.358	(0.235)	0.538**	(0.213)
Cohort 2012	0.007	(0.170)	0.113	(0.172)	0.372	(0.441)	0.427	(0.436)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Differences between domestic and international outsourcing

Table 3.18 shows the results when cohorts 2004 and 2005 are considered. These findings are very similar to Table 3.9, although they are lower in magnitude. For domestic outsourcers, the impact on internal and total R&D remains positive and statistically significant. Likewise, for international outsourcers, the results are similar to the ones reported in Table 3.9. In this case, the impact on internal R&D is not statistically significant for at least the first two years after the treatment, but the impact on the total R&D investment is positive and statistically significant.

The addition of the 2004 and 2005 cohorts resulted in a reduction in the magnitude of the impact on internal and total R&D. For the domestic outsourcers, the average ATT

effect decreased from 16 percentage points (see Table 3.10) to 13 pp for internal R&D, and from 34.4 pp to 30.8 pp for total R&D investment (see Table 3.19). Similarly, for international outsourcers, the inclusion of firms treated in 2004 and 2005 led to a decrease in the average *ATT* and its significance from 19.8 pp to 8.8 pp for internal R&D. Whereas, the average *ATT* decreased from 46.6 pp to 35.4 pp for total R&D investment.

Table 3.18: Domestic vs International Outsourcing - Cohorts (2004-2010)

	R&D investment						
	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
Panel A: Domestic Outsourcing							
Internal R&D							
ATT	0.064	0.036	-0.014	0.100***	0.136***	0.110***	0.147***
SE	(0.057)	(0.042)	(0.031)	(0.034)	(0.04)	(0.043)	(0.048)
Total R&D							
ATT	0.064	0.036	-0.014	0.374***	0.300***	0.263***	0.287***
SE	(0.057)	(0.042)	(0.031)	(0.033)	(0.04)	(0.042)	(0.048)
Treated	788	1,129	1,496	1,340	1,238	1,106	1,068
Control	2,185	2,968	3,813	1,340	1,238	1,106	1,068
Panel B: International Outsourcing							
Internal R&D							
ATT	-0.017	-0.041	-0.026	0.068	-0.002	0.207*	0.103
SE	(0.103)	(0.086)	(0.076)	(0.082)	(0.093)	(0.111)	(0.121)
Total R&D							
ATT	-0.017	-0.041	-0.026	0.480***	0.264***	0.407***	0.286**
SE	(0.103)	(0.086)	(0.076)	(0.084)	(0.096)	(0.111)	(0.122)
Treated	93	147	217	190	169	160	160
Control	302	448	638	190	169	160	160

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The difference in the number of firms during the pre-treatment period varies because the 2004 and 2005 cohorts have different numbers of pre-treatment periods, $t-1$ and $t-2$, respectively.

Table 3.19: ATT by Cohort - Domestic vs International Outsourcing

	Domestic				International			
	Internal		*TotalR&D*		*Internal*		*TotalR&D*	
	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE	$ATT(g,t)$	SE
Average	0.130***	(0.031)	0.308***	(0.031)	0.088	(0.072)	0.354***	(0.074)
Cohort 2004	0.094*	(0.056)	0.263***	(0.057)	-0.084	(0.115)	0.221*	(0.122)
Cohort 2005	0.102	(0.068)	0.276***	(0.069)	0.103	(0.157)	0.315**	(0.152)
Cohort 2006	0.182**	(0.074)	0.373***	(0.074)	0.276	(0.172)	0.459***	(0.172)
Cohort 2007	0.118	(0.089)	0.311***	(0.088)	0.223	(0.251)	0.529**	(0.268)
Cohort 2008	0.217**	(0.103)	0.402***	(0.105)	0.355	(0.221)	0.518**	(0.226)
Cohort 2009	0.168*	(0.101)	0.325***	(0.100)	-0.138	(0.299)	0.531	(0.344)
Cohort 2010	0.030	(0.130)	0.188	(0.131)	0.053	(0.251)	0.203	(0.273)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.8 Conclusions

The literature on R&D outsourcing and innovation focuses on the effect of internal and external R&D on innovation and the role of internal R&D in moderating this effect. The literature has shown that internal R&D is important for the success of the internalisation of external knowledge and for innovation performance. However, there is no evidence of the effect of external R&D on the internal and external R&D investment.

Therefore, this study contributes to the current literature on R&D outsourcing by assessing the impact of external R&D on the intensive and extensive margins of R&D investment. The empirical analysis is based on a theoretical model which explains a firm's decision to outsource R&D, as well as the impact of R&D outsourcing on the volume of internal and external R&D investment. The model provides two hypotheses, the first one is related to the intensive margin of R&D, where R&D outsourcing increases the investment of internal R&D when the elasticity of substitution between internal and external R&D is low enough. The second hypothesis is related to the extensive margin, and the analysis is at the industry level. It states that in industries where R&D outsourcing is more profitable, fewer firms invest in R&D.

Using panel data from Spanish firms from 2003 to 2016, I apply a combination of matching methods and difference-in-difference methodology with multiple time periods to assess the first hypothesis and an ordinary least square model to assess the second one. The results support hypothesis 1, showing that R&D outsourcing increases the investment in internal and total R&D. Following the theoretical model, these results suggest that the elasticity of substitution between these two sources of knowledge should be low enough. However, the analysis by cohort indicates that the positive and statistically significant effect on internal and total R&D comes from the firms treated early (2004-2009). For firms treated later (2010-2016), there is no statistically significant impact of R&D outsourcing on internal R&D but a significant effect on total R&D investment. The latter can be attributed to the financial crisis.

Upon conducting a separate analysis based on the firm's export status, the results indicate that both exporters and non-exporters experience an increase in their internal and total R&D investment due to R&D outsourcing. However, the effect on internal R&D for non-exporters is relatively weaker in terms of statistical significance and tends to diminish over time compared to the effect on internal R&D for exporting firms. In addition, the results suggest that non-exporting firms were more affected by the financial crisis than exporting firms since the non-exporting firms which began to outsource during the crisis period did not experience an increase in their internal or total R&D investment.

Likewise, when the analysis is based on the type of R&D outsourcing (domestic and international), the findings suggest that domestic R&D outsourcers exhibit a lower elasticity of substitution between the sources of knowledge. For domestic outsourcers, the effect of R&D outsourcing is positive and statistically significant on both internal and total R&D investment. However, for international outsourcers, this effect is positive and statistically significant on the total R&D investment. In contrast, for internal R&D investment, this effect becomes statistically significant two years after firms started to outsource R&D. The latter suggests that international outsourcers rely more on external R&D, at least during the first years of outsourcing.

Regarding the second hypothesis, I apply an ordinary least square (OLS) model at the industry level to measure the relationship between the profitability of R&D outsourcing and the number of firms investing in R&D. The results demonstrate that in industries where R&D outsourcing is more profitable, fewer firms invest in total R&D. Thus, my results provide new evidence about the effect of R&D outsourcing on the intensive (R&D investment) and extensive (number of firms investing in R&D) margins of R&D investment.

Overall, these findings suggest that R&D outsourcing has a positive and statistically significant effect on internal and total R&D investment. However, the impact of R&D outsourcing varies according to the firm's export status and type of R&D outsourcing. Therefore, these results are relevant for policymakers who seek to enhance firms' R&D investment. Policymakers should consider these differences to facilitate and encourage firms to take advantage of R&D outsourcing opportunities. The latter will enable firms to increase their productivity and maximise their profits.

3.9 Appendix

3.9.1 Alternative approach

As an alternative approach, instead of categorizing the data into cohorts, I apply a PSM and DID estimation using the entire sample of Spanish firms, where the control group are the sample of firms that never outsourced R&D during the sample period (2004-2016). Since firms apply the treatment in different years during the sample period, I re-scale the time so that t = 0 is the year in which a firm first performs the treatment for the case of the treated group. Based on the observations at t = 0, I then measure the change, relative to t-1, in R&D investment over the following three years.[24]For the case of the control group, I use all the observations of the firm during the sample period.

Similar to section 3.5.1, I estimate the probability of doing R&D outsourcing at time t using a probit model with the same firms' pre-treatment characteristics ($t-1$). Next, I use the propensity scores from the probit model to match the treated group with a similar control group. I perform the matching within the same industry and year by applying a 1-to-1 nearest neighbour with caliper (0.05) and no replacement.[25] The main difference between this method and the one presented in section 3.5.1 is that by using the entire sample for matching, I am unable to examine the heterogeneous effects of R&D outsourcing. In other words, I cannot determine whether the impact comes from firms treated early or later in the sample. In addition, this approach does not allow to test the parallel trend assumption.

Table 3.20 presents the findings for the impact of R&D outsourcing on internal and total R&D considering the sample of firms treated from 2004 to 2016. Panel A shows the estimations using PSM, and Panel B reports the coefficients using a different matching method (Mahalanobis Distance Matching (MDM)).[26] It is worth mentioning that, as in the previous analysis, the coefficients represent the difference in differences, which indicates the change in R&D investment relative to the control group. In both cases, the impact on internal and total R&D investment is positive and statistically significant, similar to Table 3.5 and 3.14. These results confirm the previous findings and hypothesis 1 of the theoretical model.

[24]For a firm not be matched with itself or erroneously included in the control group, after identifying treated firm at t = 0, I drop the subsequent observations of the same firm.

[25]In the appendix section, Tables 3.32 and 3.33 show the balancing test of the quality of the matching procedure

[26]PSM uses the propensity scores for matching, while MDM uses the distance between covariates.

Table 3.20: Impact of Outsourcing on Firms' R&D Investment

	R&D investment			
	t	$t+1$	$t+2$	$t+3$
Panel A: Propensity Score Matching				
Internal R&D				
ATT	0.139***	0.137***	0.187***	0.172***
SE	(0.030)	(0.036)	(0.042)	(0.049)
Total R&D				
ATT	0.427***	0.307***	0.335***	0.298***
SE	(0.030)	(0.037)	(0.042)	(0.050)
Treated	1,611	1,455	1,289	1,138
Control	8,989	7,340	6,106	5,070
Panel B: Mahalanobis Distance Matching				
Internal R&D				
ATT	0.115***	0.149***	0.146***	0.204***
SE	(0.028)	(0.032)	(0.036)	(0.041)
Total R&D				
ATT	0.405***	0.322***	0.298***	0.335***
SE	(0.027)	(0.032)	(0.035)	(0.042)
Treated	1,720	1,568	1,413	1,256
Control	8,989	7,340	6,106	5,070

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Difference between exporters vs non-exporters

Like the findings reported in Table 3.16 and 3.7, the effect on internal and total R&D investment is positive and statistically significant for the exporting firms. Furthermore, similar to section 3.5.2, Table 3.21 shows that the impact on non-exporting firms is even larger compared to exporters. Regarding non-exporting firms, these findings are close to the one presented in Table 3.16, in which the firms treated in 2004 and 2005 were included. Therefore, as in section 3.7.1, the positive and statistically significant impact reported in Table 3.21 for non-exporting firms can be attributed to the group of firms treated in 2004. Table 3.21 confirms the earlier findings when the 2004 and 2005 cohorts are considered.[27]

Table 3.21: Exporters vs Non-exporters

	Propensity Score Matching				Multivariate Distance Matching			
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
Panel A: Exporters								
Internal R&D								
ATT	0.129***	0.186***	0.181***	0.255***	0.117***	0.104***	0.112**	0.150***
SE	(0.036)	(0.044)	(0.051)	(0.058)	(0.034)	(0.037)	(0.041)	(0.048)
Total R&D								
ATT	0.408***	0.347***	0.320***	0.380***	0.394***	0.267***	0.252***	0.279***
SE	(0.036)	(0.044)	(0.051)	(0.058)	(0.033)	(0.038)	(0.041)	(0.049)
Treated	1,051	954	872	771	1,122	1,031	957	851
Control	6,513	5,393	4,507	3,763	6,513	5,393	4,507	3,763
Panel B: Non-exporters								
Internal R&D								
ATT	0.195***	0.224***	0.252***	0.306***	0.157***	0.211***	0.218***	0.335***
SE	(0.055)	(0.064)	(0.079)	(0.104)	(0.049)	(0.057)	(0.064)	(0.081)
Total R&D								
ATT	0.498***	0.409***	0.426***	0.436***	0.469***	0.398***	0.393***	0.470***
SE	(0.054)	(0.065)	(0.080)	(0.105)	(0.049)	(0.057)	(0.064)	(0.082)
Treated	505	443	360	312	585	527	440	388
Control	2,476	1,947	1,599	1,307	2,476	1,947	1,599	1,307

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[27] Tables 3.34 and 3.35 present the balancing test of the quality of the matching for exporters and non-exporters, respectively.

Difference between domestic and international outsourcing

Table 3.22 displays the outcomes considering different types of treatment (Domestic and international outsourcing). Unlike the DiD with multiple periods, this approach allows me to work with a larger sample of firms for each treatment category. Therefore, Table 3.22 examines the impact of R&D outsourcing among three groups of firms: those outsourcing R&D only to a national provider (Panel A), those outsourcing only to an international provider (Panel B), and those outsourcing to both national and international providers simultaneously (Panel C).

For domestic outsourcers, the results are similar to the ones reported in Table 3.9 and 3.18. For international outsourcers, the difference between Panel B and C in Table 3.22 sheds light on the findings discussed in section 3.5.2. Table 3.9 reveals that the lack of statistical impact on internal R&D can be attributed to firms that simultaneously outsource R&D to both national and international providers. The latter suggests that this group of firms (Panel C) rely more on external R&D. For International outsourcers, the effect of international R&D outsourcing on internal R&D investment is not significantly uplifted until t+1, suggesting that firms that outsource R&D outside Spain rely more on external R&D during at least the first year.[28]

[28] In the appendix section, Tables 3.36-3.38 present the balancing test of the quality of the matching for Panel A, B, and C.

Table 3.22: Domestic vs International outsourcing

	Propensity Score Matching				Multivariate Distance Matching			
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
Panel A: Domestic outsourcing								
Internal R&D								
ATT	0.144***	0.163***	0.150***	0.141***	0.118***	0.159***	0.144***	0.217***
SE	(0.032)	(0.037)	(0.043)	(0.051)	(0.030)	(0.034)	(0.038)	(0.043)
Total R&D								
ATT	0.412***	0.319***	0.291***	0.262***	0.388***	0.318***	0.289***	0.343***
SE	(0.032)	(0.037)	(0.043)	(0.052)	(0.029)	(0.034)	(0.038)	(0.044)
Treated	1,434	1,295	1,151	1,070	1,504	1,373	1,233	1,095
Control	8,989	7,340	6,106	5,070	8,989	7,340	6,106	5,070
Panel B: International outsourcing								
Internal R&D								
ATT	0.137	0.348**	0.420**	0.171	0.078	0.193	0.309**	0.176
SE	(0.110)	(0.149)	(0.176)	(0.179)	(0.089)	(0.132)	(0.140)	(0.208)
Total R&D								
ATT	0.538***	0.648***	0.578***	0.267	0.487***	0.495***	0.467***	0.272
SE	(0.118)	(0.165)	(0.178)	(0.182)	(0.094)	(0.136)	(0.142)	(0.211)
Treated	88	78	72	64	90	79	72	64
Control	7,636	6,476	5,652	4,665	8,989	7,340	6,106	5,070
Panel C: Domestic and International outsourcing								
Internal R&D investment								
ATT	-0.094	-0.057	0.136	0.210	0.007	-0.034	0.100	0.162
SE	(0.103)	(0.132)	(0.137)	(0.163)	(0.105)	(0.125)	(0.142)	(0.149)
Total R&D Investment								
ATT	0.355***	0.189	0.357**	0.412**	0.451***	0.221*	0.347**	0.388***
SE	(0.110)	(0.129)	(0.143)	(0.165)	(0.109)	(0.122)	(0.144)	(0.149)
Treated	119	109	100	92	130	120	112	102
Control	8,989	7,340	6,106	5,070	8,989	7,340	6,106	5,070

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.9.2 Balancing test by cohort

Tables 3.23-3.29 compare the observable characteristics of the treatment and control groups after the matching procedure. These tables show that the matching has successfully removed differences between the R&D outsourcers and non-outsourcers in each cohort since the difference between the treated and control groups is not statistically significant. Tables 3.30 and 3.31 present the results of the t-test according to the export status and type of R&D outsourcing (domestic or international).

Table 3.23: Balancing Test (t-test) - Cohorts 2004 and 2005

	Cohort 2004			Cohort 2005		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	7.890	7.883	(0.949)	7.848	7.784	(0.587)
Labour productivity$_{t-1}$	7.348	7.274	(0.316)	7.382	7.356	(0.710)
Employment$_{t-1}$	4.271	4.276	(0.964)	4.058	4.143	(0.470)
Group$_{t-1}$	0.458	0.434	(0.508)	0.350	0.356	(0.871)
Patents$_{t-1}$	0.196	0.206	(0.715)	0.234	0.243	(0.784)
Physical capital$_{t-1}$	8.073	8.089	(0.929)	8.047	8.121	(0.674)
Product innovation$_{t-1}$	0.708	0.745	(0.251)	0.723	0.745	(0.538)
Process Innovation$_{t-1}$	0.499	0.512	(0.715)	0.675	0.660	(0.680)
Researchers in R&D$_{t-1}$	1.265	1.231	(0.557)	1.280	1.283	(0.970)
Export$_{t-1}$	0.643	0.633	(0.761)	0.723	0.696	(0.440)
Cooperation$_{t-1}$	0.507	0.488	(0.609)	0.359	0.350	(0.807)
Observations	373	373		329	329	

Table 3.24: Balancing Test (t-test) - Cohorts 2006 and 2007

	Cohort 2006			Cohort 2007		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	7.616	7.574	(0.710)	7.632	7.606	(0.865)
Labour productivity$_{t-1}$	7.003	7.112	(0.270)	7.226	7.172	(0.596)
Employment$_{t-1}$	3.618	3.617	(0.995)	4.107	3.954	(0.365)
Group$_{t-1}$	0.291	0.303	(0.741)	0.379	0.369	(0.838)
Patents$_{t-1}$	0.163	0.174	(0.687)	0.103	0.128	(0.439)
Physical capital$_{t-1}$	7.513	7.433	(0.645)	8.057	7.934	(0.611)
Product innovation$_{t-1}$	0.669	0.700	(0.372)	0.650	0.645	(0.918)
Process Innovation$_{t-1}$	0.706	0.677	(0.414)	0.670	0.665	(0.916)
Researchers in R&D$_{t-1}$	1.188	1.201	(0.829)	1.368	1.292	(0.395)
Export$_{t-1}$	0.614	0.600	(0.699)	0.591	0.606	(0.762)
Cooperation$_{t-1}$	0.397	0.409	(0.758)	0.379	0.399	(0.685)
Observations	350	350		203	203	

Table 3.25: Balancing Test (t-test) - Cohorts 2008 and 2009

	Cohort 2008			Cohort 2009		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	7.882	7.791	(0.658)	8.227	8.039	(0.347)
Labour productivity$_{t-1}$	7.490	7.337	(0.224)	7.366	7.255	(0.416)
Employment$_{t-1}$	4.092	4.026	(0.771)	4.373	4.361	(0.956)
Group$_{t-1}$	0.447	0.386	(0.349)	0.430	0.402	(0.679)
Patents$_{t-1}$	0.211	0.184	(0.619)	0.150	0.150	(1.000)
Physical capital$_{t-1}$	8.025	7.956	(0.830)	8.130	7.970	(0.631)
Product innovation$_{t-1}$	0.658	0.675	(0.780)	0.776	0.738	(0.526)
Process Innovation$_{t-1}$	0.640	0.605	(0.587)	0.654	0.654	(1.000)
Researchers in R&D$_{t-1}$	1.341	1.282	(0.610)	1.290	1.374	(0.487)
Export$_{t-1}$	0.702	0.632	(0.263)	0.766	0.738	(0.637)
Cooperation$_{t-1}$	0.395	0.421	(0.688)	0.467	0.439	(0.682)
Observations	114	114		107	107	

Table 3.26: Balancing Test (t-test) - Cohorts 2010 and 2011

	Cohort 2010			Cohort 2011		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	8.378	8.105	(0.362)	8.198	8.030	(0.555)
Labour productivity$_{t-1}$	7.310	7.315	(0.974)	7.288	7.105	(0.343)
Employment$_{t-1}$	4.651	4.492	(0.572)	4.537	4.241	(0.344)
Group$_{t-1}$	0.469	0.438	(0.725)	0.567	0.500	(0.468)
Patents$_{t-1}$	0.063	0.078	(0.732)	0.233	0.150	(0.250)
Physical capital$_{t-1}$	7.981	7.741	(0.582)	7.923	7.384	(0.230)
Product innovation$_{t-1}$	0.672	0.766	(0.242)	0.817	0.817	(1.000)
Process Innovation$_{t-1}$	0.734	0.688	(0.562)	0.850	0.833	(0.805)
Researchers in R&D$_{t-1}$	1.706	1.378	(0.087)	1.603	1.444	(0.442)
Export$_{t-1}$	0.797	0.750	(0.530)	0.700	0.700	(1.000)
Cooperation$_{t-1}$	0.344	0.391	(0.586)	0.533	0.417	(0.204)
Observations	64	64		60	60	

Table 3.27: Balancing Test (t-test) - Cohorts 2012 and 2013

	Cohort 2012			Cohort 2013		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	7.892	7.718	(0.594)	7.188	7.597	(0.254)
Labour productivity$_{t-1}$	7.354	7.228	(0.521)	7.338	7.321	(0.943)
Employment$_{t-1}$	4.775	4.418	(0.333)	4.295	4.601	(0.409)
Group$_{t-1}$	0.415	0.341	(0.501)	0.344	0.469	(0.316)
Patents$_{t-1}$	0.000	0.073	(0.083)	0.188	0.156	(0.745)
Physical capital$_{t-1}$	7.827	7.620	(0.717)	7.342	7.774	(0.493)
Product innovation$_{t-1}$	0.732	0.585	(0.166)	0.563	0.625	(0.617)
Process Innovation$_{t-1}$	0.634	0.561	(0.505)	0.719	0.719	(1.000)
Researchers in R&D$_{t-1}$	1.395	1.392	(0.989)	1.191	1.395	(0.402)
Export$_{t-1}$	0.805	0.780	(0.788)	0.688	0.719	(0.788)
Cooperation$_{t-1}$	0.488	0.415	(0.512)	0.438	0.469	(0.806)
Observations	41	41		32	32	

Table 3.28: Balancing Test (t-test) - Cohorts 2014 and 2015

	Cohort 2014			Cohort 2015		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	8.140	7.903	(0.658)	7.672	7.928	(0.630)
Labour productivity$_{t-1}$	7.792	7.697	(0.744)	7.130	7.422	(0.429)
Employment$_{t-1}$	4.909	4.996	(0.855)	4.059	4.682	(0.198)
Group$_{t-1}$	0.650	0.650	(1.000)	0.462	0.538	(0.709)
Patents$_{t-1}$	0.050	0.050	(1.000)	0.000	0.000	(.)
Physical capital$_{t-1}$	8.153	7.773	(0.580)	7.515	8.567	(0.230)
Product innovation$_{t-1}$	0.850	0.800	(0.687)	0.692	0.692	(1.000)
Process Innovation$_{t-1}$	0.900	0.850	(0.643)	0.692	0.692	(1.000)
Researchers in R&D$_{t-1}$	1.731	1.683	(0.883)	1.337	1.231	(0.668)
Export$_{t-1}$	0.900	0.850	(0.643)	1.000	0.923	(0.337)
Cooperation$_{t-1}$	0.300	0.400	(0.520)	0.615	0.538	(0.705)
Observations	20	20		13	13	

Table 3.29: Balancing Test (t-test) - Cohort 2016

	Cohort 2016		
	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	7.850	8.163	(0.727)
Labour productivity$_{t-1}$	7.259	7.477	(0.550)
Employment$_{t-1}$	3.791	4.479	(0.189)
Group$_{t-1}$	0.667	0.750	(0.670)
Patents$_{t-1}$	0.167	0.167	(1.000)
Physical capital$_{t-1}$	7.497	7.837	(0.742)
Product innovation$_{t-1}$	0.750	0.750	(1.000)
Process Innovation$_{t-1}$	0.750	0.583	(0.409)
Researchers in R&D$_{t-1}$	1.722	1.808	(0.876)
Export$_{t-1}$	0.667	0.750	(0.670)
Cooperation$_{t-1}$	0.667	0.500	(0.430)
Observations	12	12	

Table 3.30: Exporters vs Non-exporters

	Exporters			Non-exporters		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	7.921	7.846	(0.397)	7.457	7.432	(0.827)
Labour productivity$_{t-1}$	7.386	7.410	(0.624)	6.756	6.731	(0.802)
Employment$_{t-1}$	4.188	4.215	(0.760)	3.364	3.383	(0.883)
Group$_{t-1}$	0.396	0.402	(0.814)	0.214	0.252	(0.254)
Patents$_{t-1}$	0.172	0.175	(0.879)	0.071	0.091	(0.377)
Physical capital$_{t-1}$	8.062	8.014	(0.699)	6.916	6.993	(0.695)
Product innovation$_{t-1}$	0.740	0.743	(0.896)	0.608	0.612	(0.934)
Process Innovation$_{t-1}$	0.674	0.705	(0.238)	0.579	0.589	(0.807)
Researchers in R&D$_{t-1}$	1.360	1.316	(0.399)	1.223	1.190	(0.562)
Export expenditure$_{t-1}$	6.990	6.937	(0.836)			
Cooperation$_{t-1}$	0.412	0.406	(0.815)	0.398	0.408	(0.806)
Observations	604	604		309	309	

Table 3.31: Domestic vs International

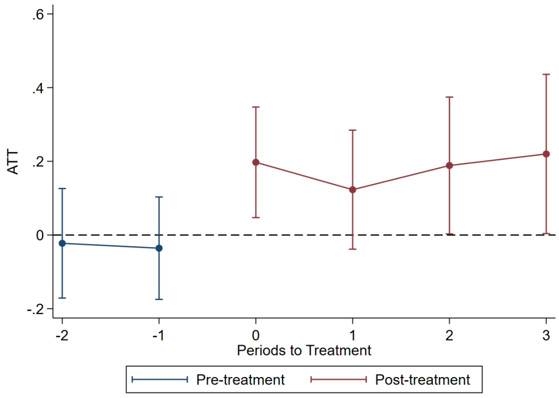
	Domestic			International		
	$D_g = 0$	$D_g = 1$	$p - value$	$D_g = 0$	$D_g = 1$	$p - value$
Internal R&D expenditure$_{t-1}$	7.665	7.615	(0.507)	8.309	8.394	(0.703)
Labour productivity$_{t-1}$	7.197	7.175	(0.710)	7.319	7.306	(0.925)
Employment$_{t-1}$	3.900	3.861	(0.637)	4.011	4.310	(0.223)
Group$_{t-1}$	0.345	0.349	(0.870)	0.393	0.382	(0.879)
Patents$_{t-1}$	0.150	0.151	(0.942)	0.112	0.180	(0.205)
Physical capital$_{t-1}$	7.707	7.642	(0.585)	8.101	8.380	(0.424)
Product innovation$_{t-1}$	0.708	0.685	(0.339)	0.730	0.742	(0.866)
Process Innovation$_{t-1}$	0.668	0.664	(0.869)	0.596	0.629	(0.647)
Researchers in R&D$_{t-1}$	1.219	1.219	(0.996)	1.406	1.626	(0.124)
Export$_{t-1}$	0.603	0.622	(0.457)	0.742	0.753	(0.864)
Cooperation$_{t-1}$	0.393	0.397	(0.874)	0.461	0.506	(0.551)
Observations	746	746		89	89	

3.9.3 ATT per cohort by periods before and after the treatment

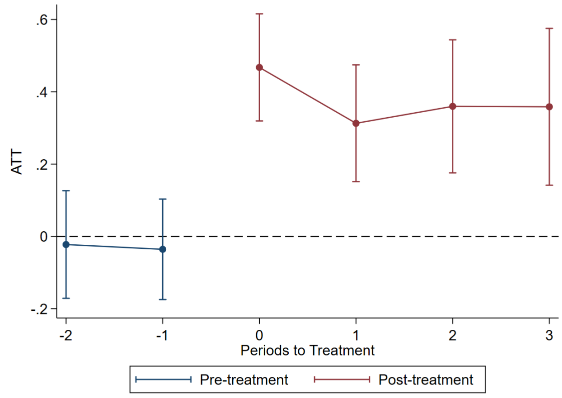
Figure 3.8 shows the impact of R&D outsourcing on internal and total R&D investment by cohort and according to the length of exposure to the treatment. As observed, firms treated early (in 2006) exhibit a positive and statistically significant impact on both internal and total R&D over the years. However, for firms treated later (2010-2013), the impact on the internal R&D is not statistically significant for most years after the treatment.

Figure 3.8: ATT by Periods Before and After the Treatment - Cohorts 2006-2013

Cohort 2006

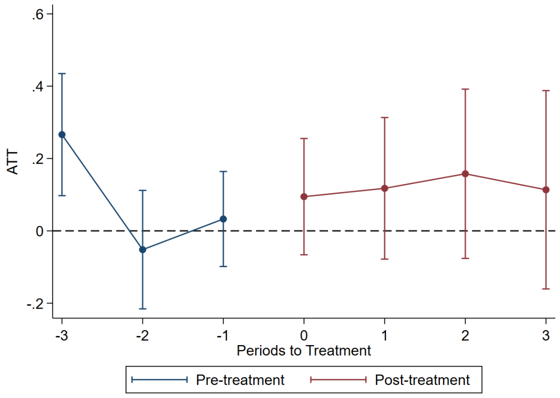


(a) **Internal R&D**

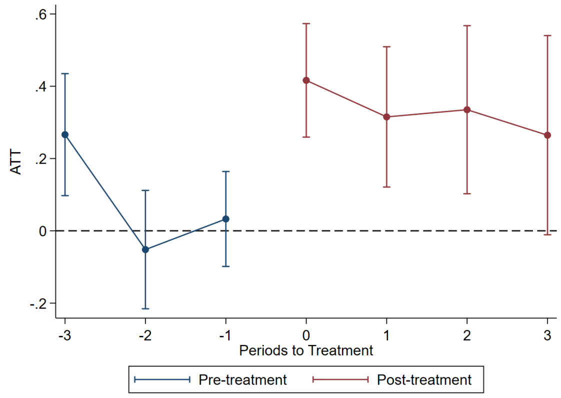


(b) **Total R&D**

Cohort 2007

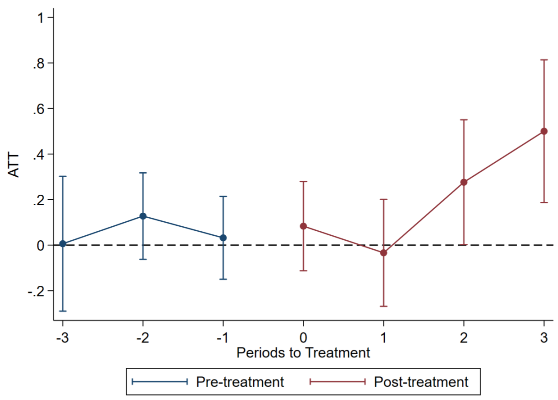


(c) **Internal R&D**

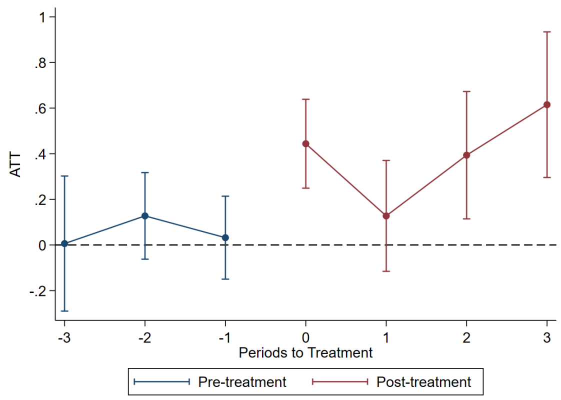


(d) **Total R&D**

Cohort 2008

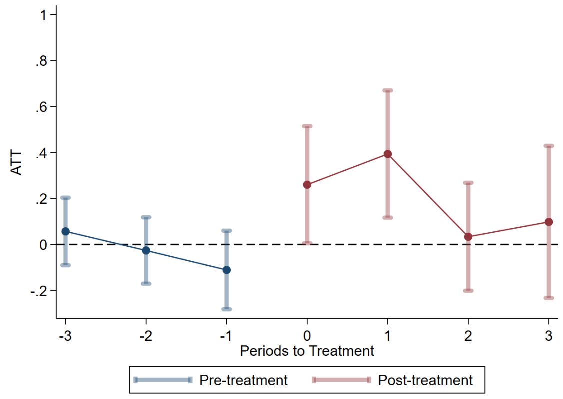


(e) **Internal R&D**

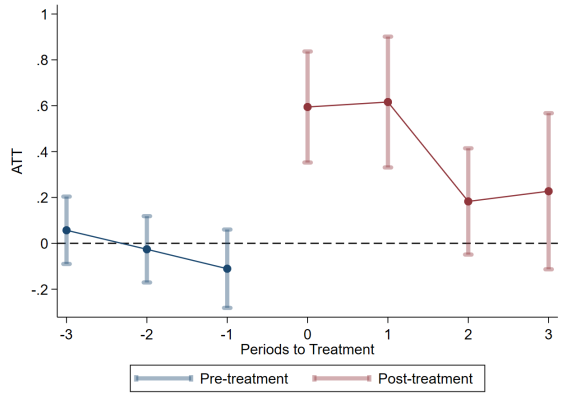


(f) **Total R&D**

Cohort 2009

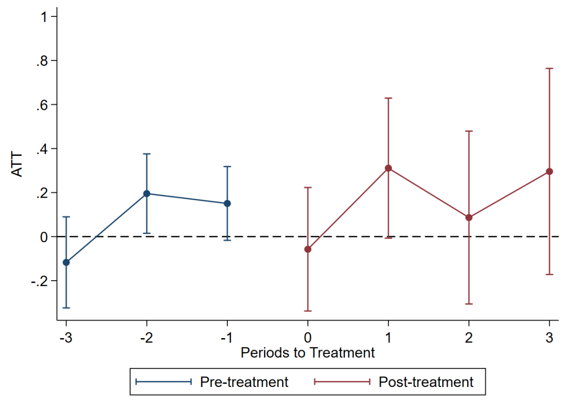


(g) **Internal R&D**

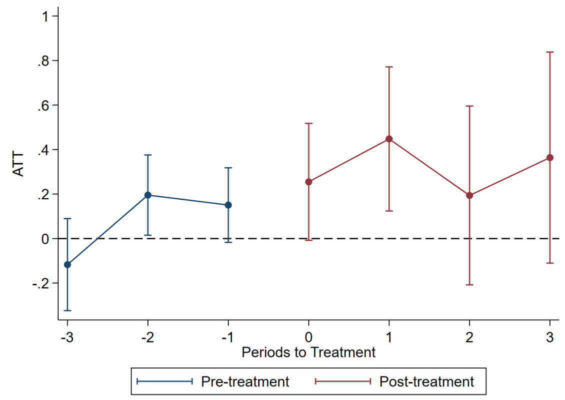


(h) **Total R&D**

Cohort 2010

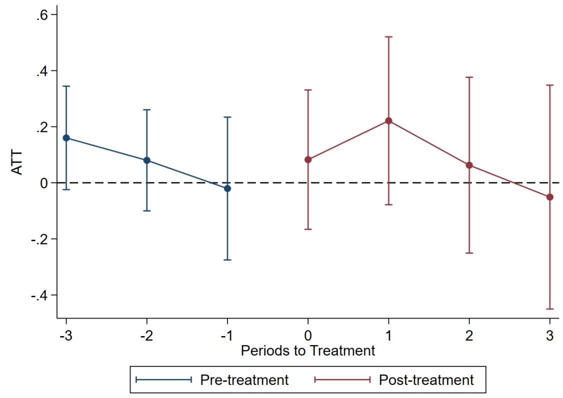


(i) **Internal R&D**

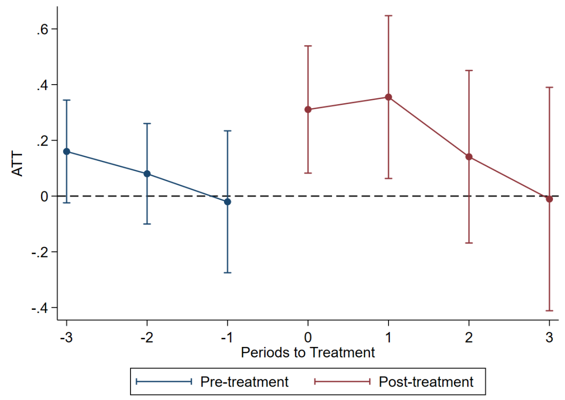


(j) **Total R&D**

Cohort 2011

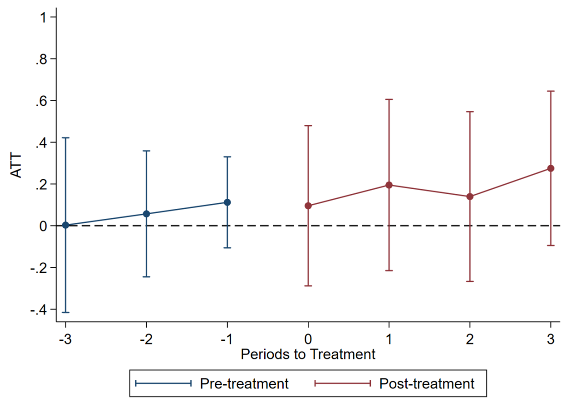


(k) **Internal R&D**

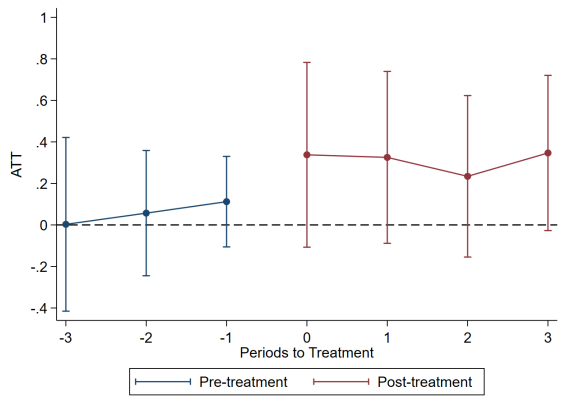


(l) **Total R&D**

Cohort 2012

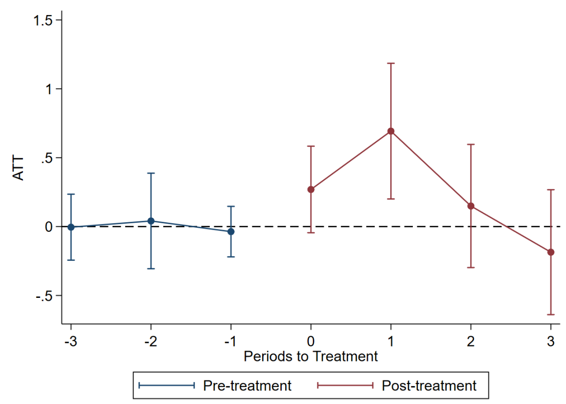


(m) Internal R&D

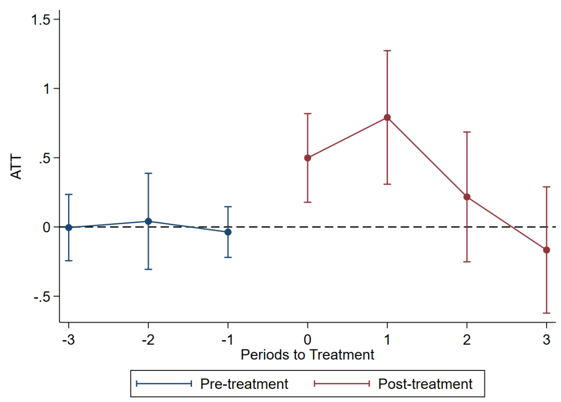


(n) Total R&D

Cohort 2013



(o) Internal R&D



(p) Total R&D

3.9.4 Balancing tests - Alternative approach

Table 3.32 shows the balancing test of the quality of the matching procedure for the R&D outsourcing propensity score in the case of internal and total R&D investment. Columns (2) and (3) depicts the mean value of each control variable for firms in the treated and control group. The matching data are almost perfectly balanced with low bias (column 4) and differences not statistically significant (column 7). Table 3.33 shows the quality and robustness of the MDM method.

Table 3.32: Matching Propensity Average Test for the R&D Outsourcing Propensity Score, Internal and Total R&D Investment

	Mean		*Bias*		*Equality of means*		$V(T)/$
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	t	$p > t$	$V(C)$
Internal R&D expenditure$_{t-1}$	7.657	7.720	-4.3	83.4	-1.28	0.200	0.92
Labour productivity$_{t-1}$	7.205	7.248	-4.4	11.1	-1.21	0.226	1.18*
Employment$_{t-1}$	4.003	4.038	-2.3	67.6	-0.64	0.520	0.95
Group$_{t-1}$	0.359	0.379	-4.0	60.3	-1.13	0.258	.
Cooperation$_{t-1}$	0.387	0.389	-0.5	98.6	-0.14	0.885	.
Patents$_{t-1}$	0.171	0.169	0.5	95.6	0.14	0.888	.
Physical capital$_{t-1}$	7.700	7.740	-1.7	93.3	-0.51	0.613	0.91
Product innovation$_{t-1}$	0.711	0.719	-1.9	64.9	-0.55	0.585	.
Process Innovation$_{t-1}$	0.626	0.637	-2.2	-232.7	-0.62	0.535	.
Researchers in R&D$_{t-1}$	1.246	1.250	-0.6	96.1	-0.18	0.861	0.87*
Export intensity$_{t-1}$	5.257	5.409	-3.0	-39.6	-0.84	0.399	0.98
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias		
	0.001	5.12	1.000	0.7	0		

Note: The last row provides summary statistics for the entire sample. The pseudo R^2 is from the probit estimation of the treatment on covariates, while the corresponding X^2 statistic and P-value are obtained from the likelihood-ratio test of joint significance of covariates. Furthermore, the mean and median bias are summary indicators of bias distribution across the samples.

Table 3.33: Mahalanobis Distance Matching, Balancing Test - Internal and Total R&D Investment

	Means			*Variances*		
Variable	*Treated*	*Control*	*Std.Dif*	*Treated*	*Control*	*Ratio*
Internal R&D expenditure$_{t-1}$	7.776	7.441	0.230	2.103	1.663	1.265
Labour productivity$_{t-1}$	7.252	7.196	0.057	1.152	0.688	1.674
Employment$_{t-1}$	4.101	3.883	0.142	2.487	1.929	1.289
Group$_{t-1}$	0.386	0.313	0.151	0.237	0.215	1.102
Cooperation$_{t-1}$	0.422	0.322	0.215	0.244	0.218	1.118
Patents$_{t-1}$	0.177	0.149	0.075	0.146	0.127	1.145
Physical capital$_{t-1}$	7.880	7.431	0.193	5.243	4.186	1.252
Product innovation$_{t-1}$	0.715	0.740	-0.056	0.204	0.193	1.059
Process Innovation$_{t-1}$	0.637	0.645	-0.016	0.231	0.229	1.009
Researchers in R&D$_{t-1}$	1.286	1.130	0.196	0.656	0.482	1.361
Export intensity$_{t-1}$	5.353	5.211	0.028	26.542	25.398	1.045

Table 3.34 and 3.35 show the balancing test of the quality of the matching procedure for exporting and non-exporting firms. In addition, Table 3.36, 3.37, and 3.38 present the balancing test comparing the treated and control samples after propensity score matching for the various types of treatment (Domestic and international outsourcing).

Table 3.34: Exporters

	Mean		*Bias*		*Equality of means*		$V(T)/$
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	t	$p > t$	$V(C)$
Internal R&D expenditure$_{t-1}$	7.785	7.829	-3.0	87.9	-0.71	0.476	0.91
Labour productivity$_{t-1}$	7.434	7.485	-6.1	28.5	-1.38	0.168	0.98
Employment$_{t-1}$	4.272	4.298	-1.8	85.2	-0.42	0.674	0.9
Group$_{t-1}$	0.406	0.442	-7.4	33.2	-1.68	0.094	.
Cooperation$_{t-1}$	0.381	0.382	-0.2	99.5	-0.04	0.964	.
Patents$_{t-1}$	0.197	0.188	2.2	84.4	0.50	0.619	.
Physical capital$_{t-1}$	8.061	8.120	-2.7	90.9	-0.64	0.524	0.88*
Product innovation$_{t-1}$	0.748	0.755	-1.6	46.5	-0.35	0.724	.
Process Innovation$_{t-1}$	0.665	0.665	0.0	100	0.00	1.000	.
Researchers in R&D$_{t-1}$	1.260	1.260	0.1	99.6	0.02	0.987	0.86*
Export intensity$_{t-1}$	8.059	8.175	-2.7	87.3	-0.63	0.528	0.97
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias		
	0.002	5.26	1.000	0.7	0		

Note: The last row provides summary statistics for the entire sample. The pseudo R^2 is from the probit estimation of the treatment on covariates, while the corresponding X^2 statistic and P-value are obtained from the likelihood-ratio test of joint significance of covariates. Furthermore, the mean and median bias are summary indicators of bias distribution across the samples.

Table 3.35: Non-Exporters

	Mean		*Bias*		*Equality of means*		$V(T)/$
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	t	$p > t$	$V(C)$
Internal R&D expenditure$_{t-1}$	7.338	7.358	-1.4	95.9	-0.26	0.798	1.05
Labour productivity$_{t-1}$	6.713	6.802	-7.8	33.7	-1.25	0.211	1.78*
Employment$_{t-1}$	3.418	3.462	-2.6	55.5	-0.46	0.649	1.08
Group$_{t-1}$	0.244	0.257	-3.1	79.3	-0.51	0.612	.
Cooperation$_{t-1}$	0.392	0.406	-2.9	90.7	-0.45	0.653	.
Patents$_{t-1}$	0.115	0.109	2.0	81.7	0.30	0.765	.
Physical capital$_{t-1}$	6.878	6.891	-0.6	98.0	-0.10	0.924	0.92
Product innovation$_{t-1}$	0.646	0.671	-5.4	15.4	-0.86	0.389	.
Process Innovation$_{t-1}$	0.560	0.541	4.0	49.5	0.63	0.527	.
Researchers in R&D$_{t-1}$	1.173	1.164	1.2	92.1	0.22	0.829	1.24*
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias		
	0.003	4.60	1.000	0.8	0		

Note: The last row provides summary statistics for the entire sample. The pseudo R^2 is from the probit estimation of the treatment on covariates, while the corresponding X^2 statistic and P-value are obtained from the likelihood-ratio test of joint significance of covariates. Furthermore, the mean and median bias are summary indicators of bias distribution across the samples.

Table 3.36: National Outsourcing

	Mean		*Bias*		*Equality of means*		$V(T)/$
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	t	$p > t$	$V(C)$
Internal R&D expenditure$_{t-1}$	7.605	7.660	-3.8	80.3	-1.05	0.293	0.86*
Labour productivity$_{t-1}$	7.188	7.228	-4.0	-70.4	-1.06	0.291	1.25*
Employment$_{t-1}$	3.973	4.022	-3.2	-40.7	-0.84	0.402	0.93
Group$_{t-1}$	0.351	0.370	-4.1	31.3	-1.09	0.276	.
Cooperation$_{t-1}$	0.390	0.387	0.6	98.3	0.15	0.878	.
Patents$_{t-1}$	0.172	0.174	-0.8	92.1	-0.20	0.844	.
Physical capital$_{t-1}$	7.650	7.742	-4.0	80.9	-1.11	0.268	0.87*
Product innovation$_{t-1}$	0.709	0.704	1.1	85.1	0.29	0.774	.
Process Innovation$_{t-1}$	0.632	0.645	-2.6	-146.6	-0.70	0.484	.
Researchers in R&D$_{t-1}$	1.219	1.229	-1.3	86.9	-0.36	0.719	0.84*
Export intensity$_{t-1}$	5.084	5.382	-5.9	-96.9	-1.56	0.119	0.96
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias		
	0.001	5.38	1.000	0.8	0		

Note: The last row provides summary statistics for the entire sample. The pseudo R^2 is from the probit estimation of the treatment on covariates, while the corresponding X^2 statistic and P-value are obtained from the likelihood-ratio test of joint significance of covariates. Furthermore, the mean and median bias are summary indicators of bias distribution across the samples.

Table 3.37: International Outsourcing

	Mean		*Bias*		*Equality of means*		$V(T)/$
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	t	$p > t$	$V(C)$
Internal R&D expenditure$_{t-1}$	8.138	8.161	-1.6	97	-0.11	0.910	1.18
Labour productivity$_{t-1}$	7.405	7.378	3.1	86.9	0.20	0.842	0.82
Employment$_{t-1}$	4.528	4.416	7.7	82	0.52	0.602	1.02
Group$_{t-1}$	0.568	0.545	4.7	91	0.30	0.763	.
Cooperation$_{t-1}$	0.386	0.398	-2.5	92.2	-0.15	0.878	.
Patents$_{t-1}$	0.159	0.159	0.0	100	0.00	1.000	.
Physical capital$_{t-1}$	8.367	8.341	1.2	97.7	0.08	0.937	0.94
Product innovation$_{t-1}$	0.750	0.818	-15.6	-302.3	-1.10	0.274	.
Process Innovation$_{t-1}$	0.682	0.682	0.0	100	0.00	1.000	.
Researchers in R&D$_{t-1}$	1.483	1.428	6.8	84.4	0.45	0.652	1.34
Export intensity$_{t-1}$	7.449	7.630	-3.6	92.3	-0.23	0.815	1.04
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias		
	0.012	2.90	1.000	1.3	0		

Note: The last row provides summary statistics for the entire sample. The pseudo R^2 is from the probit estimation of the treatment on covariates, while the corresponding X^2 statistic and P-value are obtained from the likelihood-ratio test of joint significance of covariates. Furthermore, the mean and median bias are summary indicators of bias distribution across the samples.

Table 3.38: Domestic and International Outsourcing

	Mean		*Bias*		*Equality of means*		$V(T)/$
Variable	*Treated*	*Control*	*Std.Bias*	*ReductBias*	t	$p > t$	$V(C)$
Internal R&D expenditure$_{t-1}$	8.399	8.266	8.5	89.4	0.72	0.472	1.08
Labour productivity$_{t-1}$	7.359	7.390	-3.3	87.4	-0.25	0.799	0.93
Employment$_{t-1}$	4.373	4.448	-4.7	88.0	-0.38	0.707	0.89
Group$_{t-1}$	0.454	0.378	15.5	50.0	1.18	0.238	.
Cooperation$_{t-1}$	0.471	0.445	5.4	89.9	0.39	0.698	.
Patents$_{t-1}$	0.235	0.227	2.1	93.8	0.15	0.878	.
Physical capital$_{t-1}$	8.354	8.541	-7.8	86.7	-0.68	0.495	1.02
Product innovation$_{t-1}$	0.773	0.849	-17.6	-96.6	-1.49	0.137	.
Process Innovation$_{t-1}$	0.563	0.496	13.7	-20.4	1.04	0.301	.
Researchers in R&D$_{t-1}$	1.529	1.444	8.4	84.3	0.64	0.523	1.11
Export intensity$_{t-1}$	6.776	6.908	-2.6	91.8	-0.20	0.845	1.04
Sample Stat.	R_2	$LRchi_2$	$p > chi_2$	Mean Bias	Med. Bias		
	0.030	10.05	1.000	2.3	0		

Note: The last row provides summary statistics for the entire sample. The pseudo R^2 is from the probit estimation of the treatment on covariates, while the corresponding X^2 statistic and P-value are obtained from the likelihood-ratio test of joint significance of covariates. Furthermore, the mean and median bias are summary indicators of bias distribution across the samples.

Chapter 4

Multinational Ownership and Cooperation in Innovation: Stability vs. Crisis

4.1 Introduction

It is well-documented that multinational corporations (MNCs) play a crucial role in the creation and transfer of knowledge across borders, accounting for close to half of global R&D expenditures, and at least two-thirds of business R&D expenditures (UNCTAD 2005, Veugelers & Cassiman 2004). Consequently, countries around the world aim to attract FDI through foreign acquisitions in the belief that this strategy would promote technology transfer to the host country. In particular, many studies have provided evidence that firms acquired by foreign MNCs experience more product and process innovation than domestic firms, leading to higher productivity (García-Vega et al. 2019, Guadalupe et al. 2012).

However, the transfer of R&D resources from MNCs to their affiliates does not automatically result in the diffusion of these resources throughout the host economy. Different factors, including concerns about intellectual property protection, workforce expertise limitations, and the absence of incentives for knowledge sharing, can contribute to the lack of knowledge transfer. Conversely, reviews of the empirical literature suggest that technology transfer is facilitated when foreign subsidiaries (FS) engage in cooperation for innovation with local partners since FS have strong incentives to share their knowledge when there is reciprocal access to know-how (UNCTAD 2005, Veugelers & Cassiman 2004). Hence, innovation alliances can function as an effective means for establishing connections with MNCs through their FS. But, are firms more likely to engage in innovation cooperation with local partners after being acquired by MNCs? For instance, FS might find the technological resources they need within the multinational network or prefer to cooperate with independent firms or institutions rather than with local firms, potentially limiting the transfer of knowledge to the host country.

The literature on innovation cooperation and multinational ownership has focused on the relationship between FS and the likelihood of cooperation in innovation with local partners, finding mixed results. Some scholars find a positive relationship (Srholec 2009, 2011, Holl & Rama 2014, García-Sánchez et al. 2016), while others a negative relationship (Veugelers & Cassiman 2004, Knell & Srholec 2005, Ebersberger & Herstad 2012, Guimón & Salazar-Elena 2015). Therefore, there is no consensus on whether FS are willing to cooperate with local partners. The differences in these findings can partly be explained by different factors such as model specification, definition of FS, and methodology. But more importantly, previous studies did not address the selection bias in foreign acquisition. For instance, FS may be more likely to cooperate in innovation due to their superior pre-acquisition performance than solely because they are foreign-acquired since MNCs cherry-pick the best domestic firms.[1]

Thus, this research contributes to the existing literature on innovation cooperation and FS by examining the causal effect of foreign ownership on the occurrence of innovation cooperation and addressing the selection bias into foreign ownership by using a matching method combined with a difference-in-difference (DID) approach. This approach allows for the control of observable and unobservable characteristics that lead to the selection

[1]Among the papers that provide evidence about the cherry-pick of domestic firms by MNCs are Guadalupe et al. (2012) and García-Vega et al. (2019)

of foreign ownership and creates a comparable control group of domestic firms. This strategy enables a comparison of the likelihood of innovation cooperation between acquired and non-acquired firms before and after foreign acquisition. In addition, unlike previous research, this research differentiated the propensity to cooperate among domestic and international partners such as suppliers, customers, competitors, and universities, among others. The empirical analysis uses a unique dataset from Spanish firms covering the years 2004-2006. This dataset provides details on foreign ownership, innovation collaboration, and the types of partners involved.

Considering that Spain is one of the European Countries most severely affected by the 2008 crisis, during which the Spanish government implemented an austerity policy, leading to a 50% reduction in R&D subsidies, innovation cooperation may have been impacted (Parellada & Sanz 2017). Few studies attempted to assess the impact of foreign ownership on innovation cooperation during the financial crisis, with their findings indicating either an increase or decrease in cooperation during the global financial crisis (GFC) García-Sánchez & Rama (2020, 2022). Therefore, this study also contributes to the current literature by distinguishing the effect of foreign ownership on the likelihood of innovation cooperation, both in the context of the GFC and in regular economic times. For this analysis, this study combines the matching approach with triple DID regression which enables the exploration of variations in the causal effect of foreign ownership on the probability of cooperation in innovation for firms acquired during regular and adverse economic periods.

The results indicate that foreign-acquired firms, on average, are less likely to cooperate in innovation with local partners, especially with local suppliers. In contrast, foreign-acquired firms exhibit a higher propensity to cooperate in innovation with international partners, especially with firms that belong to the same business groups. However, in times of the GFC period, acquired firms are more likely to cooperate with local partners, especially with firms within the same business group, local universities and public research centres. Regarding international cooperation, there is not a statistically significant impact on the probability of cooperation in innovation.

Many scholars in the literature on cooperation in innovation and foreign ownership argue that the lower propensity to cooperate in innovation with local partners following acquisition is related to the local environment. They point out that innovation cooperation occurs as long as both partners possess knowledge or technology that is mutually beneficial and relevant to each other. Considering that Spain is characterised as a moderately innovative country (García-Vega et al. 2019, Knell & Srholec 2005) and that 41% of foreign acquisitions involve firms headquartered in technologically advanced countries (such as the United States (USA), Sweden, Switzerland, Germany, Hong Kong, Singapore, Netherlands, Finland, and Belgium)[2], the local environment may not provide attractive opportunities for innovation cooperation. Thus, following the acquisition, firms are not prone to cooperate in innovation with local partners but with international partners that belong to the same business group, especially with partners based in Europe and the USA.[3] These findings are also consistent with the results reported in García-Vega et al. (2019), which indicate no statistically significant innovation spillover effects to Spanish firms from foreign-acquired firms. These findings suggest that knowledge transfer from foreign subsidiaries to domestic firms in Spain is limited.

Following Aghion & Howitt (1998), the increase in the propensity to cooperate in innovation with local partners during the GFC can be explained by the change in the opportunity cost of innovation, in which the search for new technologies becomes optimal during recessions as the revenue for current production falls. In this context, foreign-acquired firms may seek cooperation with domestic partners to develop new technologies, enabling them to effectively navigate the uncertainties present in the host country. These results are consistent with the findings in García-Vega et al. (2023). They provide evidence for persistent change in the direction of innovation for firms acquired during the crisis.

[2]Source: PITEC and UNCTAD (2023)

[3]Table 4.16 in the appendix shows these results.

The paper is structured as follows. Section 2 provides a review of the literature on innovation cooperation and foreign ownership. Section 3 presents the data and the variables used in this study. Section 4 describes the empirical strategy. Section 5 reports the effect of foreign ownership on the likelihood of innovation cooperation. Section 6 includes robustness checks, and the last section concludes.

4.2 Literature Review

In the literature focused on FS and cooperation for innovation, many studies have explored the relationship between foreign ownership and cooperative efforts in innovation. For instance, Srholec (2009) examines whether foreign ownership makes it more or less likely to cooperate on innovation compared with domestic-owned firms. Using a probit model, he finds that foreign ownership is positively associated with national cooperation, although this relationship is more robust with partners abroad. Srholec (2011) also finds a positive relationship between foreign ownership[4] and domestic cooperation in innovation using bivariate and multinomial probit models. He estimates the likelihood of cooperating with domestic or international partners by type of partner (supplier, customer, competitor, institutions, universities, government institutions), finding a positive and statistically significant relationship between foreign ownership and each type of partner. Similarly, Holl & Rama (2014) find a positive propensity for domestic cooperation for innovation using a multivariate probit regression model. They suggest that a possible explanation for the willingness of FS to establish greater cooperation for innovation with local partners is to adapt their products to the host country. Likewise, using a multivariate test, García-Sánchez et al. (2016) also find that FS are more likely to cooperate with local partners throughout the business cycle than affiliated domestic firms (i.e. firms belonging to a group headquartered in Spain).

[4]Srholec (2009) and Srholec (2011) use firms affiliated with a business group headquartered in a foreign country as a proxy of foreign ownership.

On the other hand, other scholars point out that FS might be concerned about knowledge spillovers, leading them to restrict information sharing within the host country. For instance, research conducted by Veugelers & Cassiman (2004) indicate that FS are not more likely than local firms to share technology with the domestic economy. They employ a Heckman procedure for probit analysis to correct bias from non-randomly selected samples to measure the incidence of local cooperation. The latter is measured through the cooperation in R&D between FS and domestic non-affiliated partners. Similarly, Knell & Srholec (2005) use a probit model to examine the relationship between foreign ownership and innovation cooperation. They find that foreign ownership does not facilitate knowledge spillovers to the local economy. They also distinguish the analysis by foreign and domestic ownership, finding that the latter is more likely to have a local cooperation partner. Ebersberger & Herstad (2012) analyse the effect of FS and local linkages using a probit model, their findings indicate that domestic subsidiaries are more likely to participate in local collaborative knowledge activities than FS. Similarly, Guimón & Salazar-Elena (2015) explore how FS collaborate in innovation but with a particular partner, universities, using a probit model. They find that FS have a lower propensity to collaborate with Spanish universities than domestic firms.

The body of literature focusing on the cooperation between affiliates of MNCs and local partners in innovation does not present a unanimous consensus on whether multinational subsidiaries are willing to cooperate with local partners. While these studies are sensitive to how the model is defined, one possible reason for these mixed results can be attributed to the comparison group used for the analysis. The studies that identify a positive relationship between cooperation in innovation and FS use the domestic affiliated firm (i.e. firms that belong to a group whose headquarters is in the host country) as a reference group (Holl & Rama 2014, García-Sánchez et al. 2016) or all domestic firms regardless of whether they are affiliated or not (Srholec 2009, 2011). These studies indicate that FS are more likely to cooperate with local partners than domestic subsidiaries. In contrast, most of the research that highlights a negative relationship between innovation cooperation and FS employs as a comparison group domestic firms not affiliated to a group (Veugelers & Cassiman 2004, Guimón & Salazar-Elena 2015), or consider foreign ownership, instead of FS, as the independent variable (Knell & Srholec 2005).[5]

Another potential explanation for the different findings within the academic literature might be the time frame under consideration. Some authors examine very early periods. For instance, Veugelers & Cassiman (2004) analyse data for 1990-1992, Srholec (2009) and Srholec (2011) focus on 1998-2000, and Knell & Srholec (2005) consider the period from 1999-2001. Conversely, other scholars cover the years 2002-2008, before the financial crises (Ebersberger & Herstad 2012, García-Sánchez et al. 2016), while others only consider a few years within the financial crisis, specifically 2005-2011 (Holl & Rama 2014, Guimón & Salazar-Elena 2015).

Recent research has also explored the connection between FS and local cooperation in innovation, both in the regular and recession phases of the business cycle (García-Sánchez & Rama 2020, 2022). By analysing the Spanish Information and Communication Technology sector, García-Sánchez & Rama (2020) find that the most advanced foreign subsidiaries are reluctant to cooperate for innovation with local partners than domestic firms (domestic affiliated or unaffiliated firms). However, during the 2008 crisis, FS had more capability than domestic firms in increasing their collaboration with local partners. They employ three logit models along with panel data to assess this effect. The outcomes support the theory in international business that multinational firms might shift to networked forms of organisation as a response to uncertainty in host countries (Cantwell et al. 2010). In contrast, García-Sánchez & Rama (2022) find that foreign subsidiaries do not react differently during economic crises. They use logit models with panel data to calculate the likelihood of cooperating with local partners considering the type of firms

[5]Previous studies consider foreign subsidiaries as firms linked to a parent company headquartered in a foreign country regardless of the share equity owned by the foreign headquarter. In contrast, Knell & Srholec (2005) define foreign ownership as the situation where over 50% of firms' shares are owned by foreign MNCs.

(i.e. foreign subsidiaries, unaffiliated firms, domestic business groups). Their findings indicate that foreign subsidiaries do not seem more prone than domestic business groups to engage in cooperative innovation either in the boom or uncertain times. However, FS are more likely to cooperate with local suppliers than unaffiliated domestic firms. The main difference between these two studies is that the former refers only to the Spanish Information and Communication Technology sector, while the latter includes a sample of Spanish firms in the manufacturing and services sectors.

There are several differences between this research and earlier studies. First, unlike prior studies that concentrate on FS as firms affiliated with a foreign headquarters group, this study centres on MNCs that possess at least 50% ownership equity in the firm (foreign ownership).[6] As stated by Bircan et al. (2021) and Scott-Kennel et al. (2022), MNCs play a central role in both the creation and diffusion of knowledge. Therefore, in this study, foreign ownership is defined as domestic firms that have been acquired by MNCs holding a controlling ownership equity of at least 50%.

Second, this research examines the cause-and-effect relationship between multinational ownership and the occurrence of innovation cooperation rather than solely the likelihood of innovation cooperation for FS. This study applies a combination of propensity score matching and difference-in-difference (DiD) methodology to assess the causal effect of multinational ownership on innovation cooperation. The matching strategy permits the creation of a group of non-acquired domestically owned firms that share a similar distribution of a large set of observable attributes. The DiD method enables a comparison of the average effect of multinational ownership on innovation cooperation between acquired firms and non-acquired domestic firms and controls for unobservable differences between these two groups that could remain after the matching.

Finally, in contrast to earlier studies, this research accounts for the potential bias of selection into foreign ownership. This selection is tackled by applying the combined

[6]This percentage ensures the control of the MNC over the firm, and it is consistent with Guadalupe et al. (2012), Javorcik & Poelhekke (2017), and García-Vega et al. (2023).

matching and DiD techniques, which control for observable and unobservable pre-existing differences in the participation of cooperation in innovation between the acquired and matched domestic firms. This approach mitigates the concerns that the post-acquisition change in innovation cooperation among acquired firms can be driven by pre-existing differential trends.

4.3 Data

The data used in the analysis is from the Spanish Innovation Survey (Panel Innovación Tecnológica, PITEC)[7] collected by the Spanish National Statistics Institute since 2004. The database is collected following the recommendations of the Oslo Manual of the OECD on innovation statistics. This survey constitutes a panel dataset at the firm level, which provides details on innovation activities, covering R&D investment, innovation outcomes, and the acquisition of external R&D. It also incorporates economic metrics like workforce size, sales figures, and export performance. Importantly, it includes details on multinational ownership, cooperation in innovation, and the type of partners involved in innovation cooperation, such as business groups, suppliers, clients, and universities, with a distinction made between local and international partners. As indicated by the Spanish Institute for Foreign Trade (ICEX), this cooperation often involves partnerships with universities or domestic private companies. For example, Google acquired a technology company in Malaga in 2012, collaborating with the University of Malaga to establish a cybersecurity centre. Similarly, GKN Automotive joined an R&D project led by Mondragon University to create a more efficient and sustainable electric motor. Additionally, Hewlett Packard Enterprise has established its Global Center of Excellence in Artificial Intelligence (AI) and Data in Madrid, collaborating closely with local universities and startups to develop AI use cases and data platforms for various sectors, including public

[7]For details of the survey see https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176755&menu=resultados&secc=1254736195616&idp=1254735576669

administration.

This study examines firms engaged in innovation from 2004 to 2016. These are firms that have engaged in innovative activities for at least one year, including product or process innovation and R&D investment, resulting in a total of 10,969 firms. The sample comprises both acquired and non-acquired firms, with ownership details provided, particularly the proportion of equity controlled by the foreign owner. Foreign ownership is indicated by a dummy variable set to 1 if a firm is controlled by foreign entities to at least 50% in a given year. The control group consists of firms that have never been under foreign ownership or have ownership shares below 50%, referred to as domestic-owned firms.[8] The survey also includes data on the industries where acquired firms operate. Firms within sectors such as manufacturing of non-metallic products, metal manufacturing, machinery and equipment production, electrical and optical equipment manufacturing, as well as transport, storage, and communication, are primarily targeted by foreign multinationals in Spain.

To focus on the acquisition of private firms, those that are government-owned in any year in the sample period are excluded. In addition, to assess the effect of foreign acquisition compared to a counterfactual of non-acquired firms, firms that are always foreign-owned are excluded. To effectively isolate the effects of foreign ownership on innovation cooperation, my research focuses on the first time a firm is acquired within the sample period. Hence, firms that transit between domestic and foreign ownership multiple times are dropped to ensure that the estimates remain unaffected by the reversal of their status. After applying these restrictions, there are 8,926 firms, of which 576 are foreign-owned.

Building upon the existing literature that determines the factors affecting foreign ownership, this study considers different variables to reduce the potential bias in the selection

[8]The sample of firms from 2004-2007 does not include information about foreign ownership below 50%. Thus, to capture any potential effect from firms foreign-owned below 50%, additional information is incorporated to determine whether the firm is affiliated with a larger business group and if they source their R&D from within the same business group.

into foreign ownership. As indicated by Guadalupe et al. (2012), foreign firms tend to target productive, larger companies and exporters. Therefore, this study includes control variables such as firm size (measured by the natural logarithm of the number of employees), export status (as a dummy variable), sales proportion (logarithmically transformed to gauge market reach), and labour productivity (measured by the natural logarithm of sales over the number of employees). Additionally, following the findings of García-Vega et al. (2019) and García-Vega et al. (2023), this research incorporates additional control variables: physical capital investment (represented by the inverse hyperbolic sine of physical investment),[9] business group affiliation (a dummy variable), and local market presence (another dummy variable). In terms of innovation, this study includes dummy variables to assess internal R&D expenditure, external R&D acquisition, internal R&D sourcing within the business group, patent ownership, innovation cooperation, and R&D expenditure (represented by the inverse hyperbolic sine transformation).

Table 4.1 demonstrates that firms acquired by foreign firms are different from non-acquired firms. It can be seen that acquired firms are larger in terms of employment, are more productive, and have a greater investment in physical capital compared to non-acquired firms. They are also more likely to be exporters, be affiliated with business groups, and, on average, have a larger market share than non-acquired firms. In terms of innovation, acquired firms are more prone to conducting both internal and external R&D activities. They have a greater expenditure in total R&D, a greater inclination to engage in innovation cooperation, and a higher probability of holding patents in comparison to non-acquired firms. Interestingly, non-acquired firms exhibit a higher propensity to obtain R&D from within their business group than the acquired firms. As indicated in Table 4.1, there are differences between acquired and non-acquired firms. Thus, a potential selection bias into foreign ownership exists, which could influence the changes observed after acquisition. This concern is discussed further in the following section.

[9] As stated by García-Vega et al. (2023), the inverse hyperbolic sine transformation is well-defined for zeroes.

Table 4.1: Descriptive Statistics by Type of Ownership

	Acquired		Non-acquired	
	Mean	S.D.	Mean	S.D.
Employment (log)	4.904	1.485	3.841	1.612
Labour productivity (log)	7.678	1.121	7.163	1.009
Physical investment (IHS)	7.384	4.293	5.818	4.247
Group (0/1)	0.860	0.347	0.321	0.467
Exporter (0/1)	0.728	0.445	0.500	0.500
Sells in local market (0/1)	0.919	0.273	0.954	0.209
Relative Sales	-6.485	1.826	-8.037	2.005
Does internal R&D (0/1)	0.579	0.494	0.544	0.498
Does external R&D (0/1)	0.265	0.441	0.196	0.397
R&D from business group (0/1)	0.183	0.387	0.216	0.411
R&D expenditure (IHS)	5.756	4.545	4.755	4.258
Patent (0/1)	0.124	0.330	0.111	0.314
Innovation cooperation (0/1)	0.341	0.474	0.290	0.454
Number of firms	576		8,350	

Note: The table shows the mean and standard deviation between acquired and non-acquired firms. IHS refers to the inverse hyperbolic sine of physical investment and R&D expenditure.

4.4 Methodology

The empirical method to analyse and assess the impact of foreign ownership on the propensity to cooperate in innovation is to combine a matching method and difference-in-difference (DiD) approach (Elliott et al. 2020). The matching method allows the creation of a control group the most similar possible to the acquired firms before the acquisition based on observable characteristics where the comparable group are non-acquired domestic firms. This procedure mitigates the concerns that changes in the likelihood of cooperation in innovation might be affected by pre-existing differential trends between acquired and non-acquired firms. In addition, the DiD approach controls for unobservable selection into foreign ownership and time-invariant firm characteristics. This strategy allows the comparison of the likelihood of cooperation in innovation between acquired and non-acquired firms before and after the acquisition.

Firms are acquired in different years along the sample period. Therefore, a DiD methodology with multiple periods would likely be the most suitable approach. Nonetheless, as shown in Table 4.2, the number of firms acquired each year is quite limited, posing significant challenges for conducting a cohort-specific analysis. Therefore, this study imposes the assumption that all firms are acquired at time t and that the effect of foreign ownership remains constant in relation to the acquisition year. Furthermore, to include many observations, the treated group consists of firms that were domestically owned in time $t-1$ but became foreign-owned at time t. It also includes firms that maintained this foreign ownership status until four years after the acquisition $(t+1, t+2, t+3, t+4)$. Therefore, the sample of treated firms varies following acquisition.

Table 4.2: Number of Firms per Year

Years	First time treated	Not yet treated	Never treated	Total
2005	98	204	8,327	8,629
2006	37	310	8,327	8,674
2007	30	352	8,329	8,711
2008	45	354	8,333	8,732
2009	33	250	8,334	8,617
2010	17	186	8,338	8,541
2011	23	159	8,341	8,523
2012	19	161	8,346	8,526
2013	17	154	8,346	8,517
2014	28	164	8,347	8,539
2015	36	140	8,348	8,524
2016	54	100	8,350	8,504

Note: Total is the total number of firms in each year. First time treated is the number of firms acquired for the first time in a given year.

As a first step, the time is re-scaled so that t is the year in which a firm is first foreign acquired for the case of the treated group. Then, leads of cooperation in innovation are created over the following four years.[10] To create a control group similar to the treated group, a logit model is used to estimate the likelihood of being acquired by a foreign firm at time t, based on the pre-treatment characteristics $t-1$ from Table 4.1. Industry and year-

[10]For a firm not to be matched with itself or erroneously included in the control group, after identifying the treated firm at t, the subsequent observations of the same firm are dropped.

fixed effects are also included to control for industry-specific macroeconomic conditions that could attract a selective inflow of foreign investment into a particular industry during a specific year. Table 4.3 presents the results for the likelihood of acquisition based on characteristics before the acquisition year.

Next, the propensity scores from the logit model are used to match the treated group with a similar control group. The matching is performed within the same industry and year by applying a 1-to-1 nearest neighbour with a caliper (0.05) and no replacement. Employing a caliper guarantees that the gap between the propensity scores of the treated and control group is the smallest possible within the specific caliper. Common support condition is also imposed by excluding treated firms whose propensity scores exceed the maximum or fall below the minimum of those non-treated firms. Table 4.4 shows the outcomes of the t-test, which compares the observable characteristics of the treated and control group one year before the treatment. Table 4.4 demonstrates that the difference in mean values between the treated and control groups is not statistically significant, meaning that the matching has successfully removed pre-existing differences between the foreign-owned and domestic-owned samples.

With the matched sample of firms, the dynamic effects of foreign ownership on the likelihood of cooperation in innovation is estimated using a DiD regression of event study type as follows:

$$y_{it} = \alpha + \sum_{r=-1}^{4} \delta_r (D_i T_t^r) + \beta D_i + \lambda_j + \lambda_t + \varepsilon_{it} \tag{4.1}$$

The variable y_{it} is the outcome, and it is a dummy that takes the value of one if firm i cooperates in innovation and 0 otherwise. The dummy variables T_t^r indicate the periods before and after the acquisition year. Thus, $T_t^r = 1\{t = \tau_i + r\}$ if $r \leq 4$ or $r \geq -1$, $r \in \{-1, ..4\}$. $1\{...\}$ is an indicator function, and τ_i is the year in which firm i is acquired. The dummy variable D_i indicates if firm i is foreign acquired or domestically owned. These dummies are applied to both the treated and the control group. The coefficients

δ_r represent the difference in the post-acquisition outcome between acquired and non-acquired firms, δ_{-1} is normalised to zero. Therefore, the calculated coefficients are relative to the year before the acquisition. Industry and year fixed effects are denoted by λ_j and λ_t, respectively. As stated earlier, the analysis considers a range of at least two years $(t-1, t)$ to a maximum of six years of observation $(t-1, ...t+4)$. This period includes the years before and after the acquisition year.

In line with the approach undertaken by García-Vega et al. (2023), this study also evaluates whether the propensity to cooperate in innovation is enhanced or diminished by foreign ownership in the GFC period, including a triple difference-in-difference specification (DiDiD) as follows:

$$y_{it} = \alpha + \sum_{r=-1}^{4} \delta^r (D_i T_t^r) + \sum_{r=-1}^{4} \omega^r (D_i T_t^r GFC_i) + \beta D_i + \theta GFC_i + \lambda_j + \lambda_t + \varepsilon_{it} \tag{4.2}$$

Where GFC is a dummy variable that takes the value of one for firms acquired between 2008 and 2013 (amid the global financial crisis)[11] along with their respective matches. The coefficients denoted as ω_r indicate a triple difference estimation that measures the difference in the post-acquisition outcome between firms acquired during the GFC and those acquired in periods of normal economic conditions.[12] Thus, the coefficients δ_r estimate the effect of foreign ownership on innovation cooperation during normal economic conditions, whereas $\delta_r + \omega_r$ estimate the effect of foreign ownership during the period of the GFC.

[11] The GFC period is defined by earlier research (García-Sánchez & Rama 2020, 2022).

[12] It is worth mentioning that, as outlined by García-Vega et al. (2023), the characteristics for selection into foreign ownership are not significantly different during the GFC period.

Table 4.3: Logit Regression

Characteristics	Foreign Ownership
Employment$_{t-1}$	0.401
	(0.255)
Labour productivity$_{t-1}$	0.401
	(0.261)
Physical investment$_{t-1}$	-0.043***
	(0.014)
Group$_{t-1}$	1.018***
	(0.145)
Exporter$_{t-1}$	0.324**
	(0.152)
Sells in local market$_{t-1}$	-0.219
	(0.236)
Relative Sales$_{t-1}$	-0.148
	(0.254)
Does internal R&D$_{t-1}$	-0.161
	(0.259)
Does external R&D$_{t-1}$	-0.449***
	(0.160)
R&D from business group$_{t-1}$	0.105
	(0.237)
R&D expenditure$_{t-1}$	0.062*
	(0.033)
Patent$_{t-1}$	0.199
	(0.162)
Innovation cooperation$_{t-1}$	-0.088
	(0.128)
constant	-11.646**
	(5.005)
Observations	75,459
Industry FE	Yes
Year FE	Yes
Pseudo R^2	0.085

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4: Balancing Test (t-test) for Matched Sample

	1 year before the treatment		
	$D_g = 0$	$D_g = 1$	$p - value$
Employment	4.768	4.807	(0.749)
Labour productivity	7.492	7.542	(0.545)
Physical investment	6.764	6.916	(0.650)
Group	0.706	0.674	(0.369)
Exporter	0.751	0.749	(0.931)
Sells in local market	0.943	0.940	(0.872)
Relative Sales	-9.378	-9.293	(0.540)
Does internal R&D	0.640	0.649	(0.813)
Does external R&D$_{t-1}$	0.269	0.283	(0.673)
R&D from business group	0.054	0.077	(0.223)
R&D expenditure	5.979	6.236	(0.442)
Patent	0.146	0.177	(0.259)
Innovation cooperation	0.386	0.363	(0.533)
Observations	350	350	700

4.5 Results

4.5.1 The Effect of Foreign Ownership

This section presents the results of the effect of foreign acquisition on the likelihood of co-operation in innovation. The survey enables distinction among domestic and international cooperations. Therefore, column (1) of Table 4.5 shows the effect of foreign acquisition on the likelihood of cooperation in innovation, and columns (2) and (3) differentiate between domestic and international cooperation. Namely, whether the firm collaborates in innovation with a local or international partner. Table 4.5 reports estimates of δ^r from equation 4.1, where r is expressed as the number of periods after the acquisition year t $(r = t, t + 1, ...t + 4)$.

The estimate coefficients from Table 4.5 are not statistically significant for cooperation. However, in column (2), the estimated coefficient for four years after the acquisition (δ^{t+4}) is negative and statistically different from zero. This indicates that foreign acquisition had negative effects on the probability of engaging in innovation cooperation with a local partner. This likelihood reduces by 9.6 percentage points (pp) compared to domestic-owned firms after four years of acquisition. Similar to cooperation, the estimated coefficients for international cooperation are not statistically significant, which suggests that foreign ownership did not have an impact on the likelihood of international cooperation.

Table 4.5: Effect of Foreign Acquisition on Innovation Cooperation

	Cooperation (1)	Domestic (2)	International (3)
δ^t	-0.020	-0.031	-0.005
	(0.023)	(0.022)	(0.017)
δ^{t+1}	-0.014	-0.031	-0.001
	(0.032)	(0.032)	(0.024)
δ^{t+2}	-0.015	-0.040	0.026
	(0.036)	(0.036)	(0.028)
δ^{t+3}	-0.042	-0.061	0.023
	(0.039)	(0.039)	(0.032)
δ^{t+4}	-0.065	-0.096**	-0.006
	(0.041)	(0.040)	(0.031)
β	-0.014	-0.008	0.041
	(0.034)	(0.034)	(0.025)
Observations	3,229	3,229	3,229
R^2	0.031	0.032	0.043

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The survey also allows for differentiation of innovation cooperation by type of partners. Table 4.6 displays the outcomes for innovation cooperation according to the kind of partner that the firm cooperates with. Column (2) shows that the likelihood of innovation cooperation with suppliers decreases by 5.4 pp for foreign-acquired firms compared to non-acquired firms after one year of acquisition. In addition, this probability experiences a decline of 7 pp four years after acquisition. Similarly, four years after the acquisition, the likelihood that an acquired firm cooperates in innovation with clients decreases by 5.2

pp compared to the control group. After four years of acquisition, there is also a decrease of 6.3 pp in the probability of innovation cooperation with public research centres for acquired firms compared to the control group. The likelihood of cooperation in innovation with competitors, external consultants and universities is not statistically significant. In other words, foreign ownership does not have an impact on the likelihood of cooperation in innovation with these partners.

Table 4.6: Cooperation in Innovation by Partners

	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	0.007	-0.014	-0.028	-0.006	0.015	-0.011	-0.026
	(0.017)	(0.019)	(0.018)	(0.014)	(0.017)	(0.018)	(0.018)
δ^{t+1}	0.010	-0.054**	-0.031	-0.009	-0.012	-0.001	-0.021
	(0.023)	(0.025)	(0.024)	(0.019)	(0.022)	(0.025)	(0.025)
δ^{t+2}	0.040	-0.032	-0.018	-0.011	-0.010	-0.005	-0.038
	(0.027)	(0.028)	(0.026)	(0.021)	(0.023)	(0.027)	(0.028)
δ^{t+3}	0.038	-0.042	-0.027	-0.001	0.014	-0.007	-0.029
	(0.031)	(0.030)	(0.030)	(0.023)	(0.028)	(0.031)	(0.033)
δ^{t+4}	0.047	-0.070**	-0.052*	-0.007	-0.034	-0.045	-0.063**
	(0.033)	(0.032)	(0.030)	(0.024)	(0.025)	(0.030)	(0.031)
β	0.008	-0.008	0.013	-0.005	-0.013	-0.011	0.001
	(0.026)	(0.027)	(0.025)	(0.020)	(0.022)	(0.026)	(0.027)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.040	0.041	0.035	0.030	0.024	0.034	0.045

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7 shows the results for the cooperation in innovation according to the type of domestic partners. The likelihood of cooperation in innovation with suppliers decreases for acquired firms compared to non-acquired firms. This decline varies from 4.3 pp after one year of acquisition to 6.2 pp after four years of foreign ownership. Regarding the other domestic partners, foreign ownership only has a statistically significant impact on the probability of innovation cooperation with public research centres, which reduces by 6.2 pp after four years of acquisition compared to domestic firms.

Concerning international partners, Table 4.8 presents the results for the probability of innovation cooperation with international partners. As can be seen, foreign ownership has a positive and statistically significant impact on the likelihood of innovation cooperation with partners that belong to the same business group. This likelihood increases from 2.2 pp in the year of acquisition to 5.8 pp four years after for acquired firms compared to domestic-owned firms.[13] Conversely, foreign ownership decreases by 1.8 pp the probability of cooperation in innovation with external consultants for acquired firms compared to domestic firms.

Table 4.7: Cooperation in Innovation by Domestic Partners

	Domestic Cooperation						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	-0.015	-0.009	-0.019	-0.010	0.015	-0.009	-0.023
	(0.014)	(0.019)	(0.016)	(0.012)	(0.016)	(0.017)	(0.017)
δ^{t+1}	-0.027	-0.043*	-0.027	-0.017	-0.011	-0.007	-0.017
	(0.019)	(0.024)	(0.022)	(0.017)	(0.022)	(0.024)	(0.024)
δ^{t+2}	-0.006	-0.026	-0.020	-0.009	-0.008	-0.010	-0.037
	(0.021)	(0.027)	(0.024)	(0.018)	(0.023)	(0.026)	(0.028)
δ^{t+3}	-0.021	-0.048*	-0.037	-0.001	0.011	-0.003	-0.022
	(0.024)	(0.028)	(0.028)	(0.019)	(0.027)	(0.030)	(0.032)
δ^{t+4}	-0.019	-0.062**	-0.047	-0.021	-0.035	-0.041	-0.062**
	(0.026)	(0.029)	(0.029)	(0.020)	(0.024)	(0.030)	(0.030)
β	-0.033	-0.014	0.009	-0.012	-0.013	-0.012	-0.001
	(0.023)	(0.025)	(0.024)	(0.018)	(0.021)	(0.026)	(0.027)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.043	0.040	0.033	0.031	0.026	0.035	0.047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[13]Table 4.16 of the appendix section shows that the likelihood of cooperating in innovation with partners from the same business group is statistically significant when the partner is located in Europe or the USA.

Table 4.8: Cooperation in Innovation by International Partners

	International Cooperation						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	0.022*	-0.013	-0.013	-0.004	0.001	-0.003	-0.005
	(0.013)	(0.014)	(0.011)	(0.011)	(0.008)	(0.009)	(0.009)
δ^{t+1}	0.034*	-0.018	-0.005	-0.005	-0.018*	0.001	-0.013
	(0.018)	(0.018)	(0.016)	(0.014)	(0.009)	(0.014)	(0.012)
δ^{t+2}	0.046**	-0.003	0.001	-0.015	-0.013	0.016	-0.005
	(0.020)	(0.021)	(0.018)	(0.015)	(0.010)	(0.016)	(0.014)
δ^{t+3}	0.046*	-0.002	0.009	-0.011	-0.011	0.002	-0.000
	(0.024)	(0.022)	(0.021)	(0.017)	(0.014)	(0.016)	(0.016)
δ^{t+4}	0.058**	-0.015	-0.013	-0.013	-0.010	-0.001	-0.007
	(0.026)	(0.024)	(0.019)	(0.017)	(0.015)	(0.018)	(0.017)
β	0.050***	0.014	0.012	0.019	0.009	0.010	0.013
	(0.017)	(0.018)	(0.015)	(0.015)	(0.012)	(0.014)	(0.013)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.056	0.041	0.031	0.031	0.026	0.026	0.040

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In general, these results indicate that foreign-acquired firms, on average, are less likely to cooperate in innovation with local partners, specifically with domestic suppliers, compared to domestic-owned firms. These outcomes are different from Srholec (2009), Srholec (2011), Holl & Rama (2014), and García-Sánchez et al. (2016), who find a positive association between FS and domestic cooperation for innovation. However, these results support those previous studies that find a negative association between FS and domestic cooperation in innovation (Veugelers & Cassiman 2004, Knell & Srholec 2005, Ebersberger & Herstad 2012, Guimón & Salazar-Elena 2015). The results are also consistent with those reported by García-Vega et al. (2019), who did not find statistically significant innovation spillover effects from foreign-acquired firms to Spanish firms. In addition, these results provide evidence that foreign-acquired firms, on average, exhibit a higher propensity to cooperate in innovation with international partners than non-acquired firms, especially with firms that belong to the same business group located in the USA and Europe.

These findings support the hypothesis stated by previous studies (Veugelers & Cassiman 2004, Knell & Srholec 2005, Ebersberger & Herstad 2012), which suggests that foreign-owned firms rely on the innovations strengths of affiliated firms located abroad while keeping their research and cooperation links restricted in the host economy. This happens especially when the local conditions do not offer attractive projects for mutual knowledge sharing in contrast to other locations.

4.5.2 The Effect of Foreign Ownership - Global Financial Crisis

In this section, the effect of foreign ownership is distinguished across two periods: regular economic periods and periods marked by the GFC. Table 4.9 shows the effect of foreign ownership on the likelihood of cooperating in innovation across these periods. The estimate coefficients (ω^r) from equation 4.2 are reported in this table, where r is expressed as the number of periods after the acquisition year t ($r = t, t+1, ...t+4$). Column (1) of Table 4.9 shows the likelihood of innovation cooperation, and columns (2) and (3) differentiate between domestic and international innovation cooperation.

The coefficient δ^{t+3} indicates a statistically significant reduction in the propensity to cooperate in innovation three years after acquisition for acquired firms compared to non-acquired firms when foreign ownership occurs in regular economic periods. Similarly, there is a significant decline in the likelihood of innovation cooperation after four years of acquisition (δ^{t+4}) during regular economic periods. In contrast, the coefficient ω^{t+3} demonstrates a statistically significant increase in the probability of collaborative innovation three years post-acquisition for firms acquired during the GFC compared to those acquired during regular economic times. The effect of foreign ownership amid the GFC can be calculated by adding the coefficients $\delta + \omega$. The magnitude of most of these coefficients suggests that, on average, foreign ownership leads to a rise in the likelihood of innovation cooperation for acquired firms compared to non-acquired firms when acquisition occurs in the GFC period. Similar dynamic effects are observed in the case of domestic cooperation in innovation, whereas there is no statistically significant effect of foreign ownership on international cooperation in innovation.

Table 4.9: Effect of Foreign Acquisition on Innovation Cooperation during Financial Crisis

	Cooperation (1)	Domestic (2)	International (3)
δ^t	-0.023	-0.038	-0.026
	(0.036)	(0.036)	(0.027)
δ^{t+1}	-0.042	-0.074	-0.021
	(0.048)	(0.048)	(0.035)
δ^{t+2}	-0.065	-0.095*	0.030
	(0.054)	(0.053)	(0.042)
δ^{t+3}	-0.168***	-0.185***	-0.022
	(0.057)	(0.056)	(0.044)
δ^{t+4}	-0.150**	-0.153**	-0.046
	(0.060)	(0.060)	(0.046)
ω^t	-0.001	0.008	0.048
	(0.058)	(0.057)	(0.045)
ω^{t+1}	0.050	0.082	0.040
	(0.068)	(0.068)	(0.051)
ω^{t+2}	0.079	0.090	-0.012
	(0.076)	(0.075)	(0.060)
ω^{t+3}	0.210***	0.209***	0.079
	(0.079)	(0.078)	(0.063)
ω^{t+4}	0.140*	0.091	0.072
	(0.085)	(0.084)	(0.066)
β	-0.009	-0.003	0.042*
	(0.034)	(0.033)	(0.025)
θ	-0.081**	-0.082**	-0.032
	(0.039)	(0.039)	(0.026)
Observations	3,229	3,229	3,229
R^2	0.036	0.036	0.045

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.10 presents the likelihood of innovation cooperation with domestic partners when an acquisition occurs during regular and crisis times. There is a statistically significant decline in the propensity to cooperate in innovation with local partners, especially with partners from the same business group, supplier, and public research centres, for acquired firms compared to the control group when acquisition takes place in regular economic periods (δ^r). This decline occurs especially after three and four years of acquisition. On the other hand, this likelihood significantly increases for firms acquired during the GFC compared to firms acquired during regular economic periods.

Table 4.10: Cooperation in Innovation by Domestic Partners - Financial Crisis

	Domestic Cooperation - Financial Crisis						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	-0.023	0.005	-0.039	-0.013	0.007	-0.003	-0.056**
	(0.024)	(0.029)	(0.026)	(0.020)	(0.024)	(0.026)	(0.027)
δ^{t+1}	-0.070**	-0.044	-0.057*	-0.011	-0.032	-0.018	-0.050
	(0.028)	(0.034)	(0.031)	(0.026)	(0.028)	(0.034)	(0.034)
δ^{t+2}	-0.035	-0.044	-0.034	-0.008	-0.029	-0.017	-0.079**
	(0.035)	(0.039)	(0.038)	(0.031)	(0.032)	(0.041)	(0.038)
δ^{t+3}	-0.086**	-0.112***	-0.063	-0.036	-0.046	-0.070	-0.089**
	(0.037)	(0.038)	(0.041)	(0.031)	(0.034)	(0.046)	(0.042)
δ^{t+4}	-0.046	-0.081**	-0.048	-0.013	-0.075**	-0.118***	-0.126***
	(0.041)	(0.041)	(0.044)	(0.037)	(0.032)	(0.045)	(0.043)
ω^t	0.013	-0.035	0.044	0.007	0.014	-0.017	0.072
	(0.038)	(0.043)	(0.039)	(0.031)	(0.039)	(0.043)	(0.045)
ω^{t+1}	0.084**	-0.002	0.060	-0.015	0.041	0.016	0.065
	(0.042)	(0.047)	(0.046)	(0.035)	(0.041)	(0.051)	(0.054)
ω^{t+2}	0.045	0.028	0.022	-0.006	0.036	-0.000	0.075
	(0.049)	(0.054)	(0.050)	(0.041)	(0.046)	(0.057)	(0.057)
ω^{t+3}	0.105**	0.109**	0.041	0.058	0.098*	0.106*	0.119*
	(0.051)	(0.054)	(0.052)	(0.043)	(0.053)	(0.064)	(0.061)
ω^{t+4}	0.038	0.031	-0.005	-0.022	0.072	0.125*	0.118*
	(0.055)	(0.055)	(0.056)	(0.047)	(0.050)	(0.066)	(0.063)
β	-0.029	-0.012	0.011	-0.010	-0.011	-0.008	0.001
	(0.023)	(0.025)	(0.024)	(0.018)	(0.021)	(0.026)	(0.027)
θ	-0.071**	-0.017	-0.051*	-0.023	-0.027	-0.055*	-0.044
	(0.029)	(0.029)	(0.027)	(0.023)	(0.025)	(0.032)	(0.030)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.049	0.042	0.036	0.033	0.028	0.038	0.050

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Considering both coefficients (δ and ω), foreign ownership generally results in a decreased likelihood of innovation cooperation with local suppliers for firms acquired during the economic crisis, although this decrease is less pronounced compared to acquisitions taking place in regular economic times. In contrast, foreign acquisitions typically increase the propensity to cooperate in innovation with local firms within the same business group for firms acquired during the GFC. However, this likelihood diminishes when acquisitions take place during regular economic periods. A similar dynamic pattern can be observed when cooperation occurs with local universities and public research centres, but the effect on innovation cooperation is generally statistically significant after four years of acquisition.

Table 4.11 shows the effect of foreign ownership on the likelihood of cooperation in innovation with international partners. The coefficients are not statistically significant except when cooperation occurs with foreign public research centres. The likelihood of cooperation with this type of partner decreases for firms acquired during regular economic times compared to non-acquired firms, while it increases by 4.5 pp for firms acquired during the GFC compared to firms acquired during normal times. The effect is statistically significant only during the year of acquisition. Generally, foreign acquisitions tend to increase innovation cooperation with foreign public research centres for acquired firms compared to domestic firms during the GFC period. Even though the coefficients of innovation cooperation with foreign partners within the same business group are not statistically significant, it can be seen that those are positive during regular economic times and when both δ and ω are considered. The latter is consistent with prior findings from Table 4.8, in which foreign ownership increases the likelihood of cooperating in innovation with foreign partners within the same business group for acquired firms.

Overall, these findings suggest that acquired firms tend to cooperate less with local partners in normal circumstances. However, in times of the GFC period, acquired firms are more likely to cooperate with local partners, especially with firms within the same business group, local universities and public research centres. Concerning international cooperation, most of the results do not show a statistically significant impact on the likelihood of cooperating in innovation with international partners, whether during regular periods or in crisis times. These results are consistent with the international business theory, which proposes that MNCs might shift to networked forms of organisation as a response to uncertainty in host countries (Cantwell et al. 2010). Furthermore, they align with the theory concerning the opportunity cost of innovation, which suggests that during economic downturns, the cost of investing in technology decreases due to a decline in revenue from existing production. Consequently, firms tend to seek opportunities to invest in new technologies and innovate products during crisis Aghion & Howitt (1998).

Table 4.11: Cooperation in Innovation by International Partners - Financial Crisis

	International Cooperation - Financial Crisis						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	0.021	-0.024	-0.013	-0.003	-0.007	-0.010	-0.024**
	(0.020)	(0.021)	(0.016)	(0.016)	(0.012)	(0.015)	(0.012)
δ^{t+1}	0.037	-0.019	-0.002	0.003	-0.028*	-0.001	-0.024
	(0.029)	(0.026)	(0.023)	(0.021)	(0.015)	(0.021)	(0.016)
δ^{t+2}	0.050	0.006	-0.005	-0.033	-0.014	0.028	0.000
	(0.035)	(0.031)	(0.025)	(0.020)	(0.018)	(0.026)	(0.021)
δ^{t+3}	0.008	0.000	-0.014	-0.033	0.003	0.011	-0.008
	(0.034)	(0.033)	(0.027)	(0.023)	(0.025)	(0.024)	(0.020)
δ^{t+4}	0.016	-0.031	-0.003	-0.017	-0.026	-0.008	-0.015
	(0.036)	(0.033)	(0.030)	(0.027)	(0.020)	(0.024)	(0.020)
ω^t	0.003	0.026	-0.001	-0.003	0.019	0.017	0.045*
	(0.033)	(0.032)	(0.026)	(0.024)	(0.022)	(0.025)	(0.023)
ω^{t+1}	-0.009	0.002	-0.007	-0.017	0.022	0.005	0.025
	(0.039)	(0.034)	(0.031)	(0.027)	(0.020)	(0.028)	(0.024)
ω^{t+2}	-0.011	-0.017	0.010	0.033	0.002	-0.025	-0.007
	(0.049)	(0.042)	(0.036)	(0.028)	(0.024)	(0.035)	(0.029)
ω^{t+3}	0.068	-0.001	0.041	0.040	-0.026	-0.018	0.019
	(0.050)	(0.045)	(0.039)	(0.031)	(0.028)	(0.033)	(0.030)
ω^{t+4}	0.080	0.032	-0.019	0.007	0.028	0.009	0.020
	(0.055)	(0.048)	(0.037)	(0.035)	(0.028)	(0.036)	(0.032)
β	0.050***	0.014	0.012	0.019	0.009	0.011	0.012
	(0.017)	(0.018)	(0.015)	(0.014)	(0.012)	(0.014)	(0.013)
θ	0.004	0.003	-0.003	-0.002	-0.010	-0.012	0.002
	(0.017)	(0.018)	(0.016)	(0.014)	(0.012)	(0.014)	(0.012)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.059	0.042	0.032	0.032	0.027	0.027	0.042

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6 Robustness Checks

Because the outcome variable is a binary (dummy) variable, the logit model is employed rather than ordinary least squares (OLS) to evaluate the effect of foreign ownership on the likelihood of cooperation. Table 4.12 and Table 4.13 display the logit marginal effects for innovation cooperation, focusing on domestic and international partners, respectively.

Table 4.14 reports the marginal effects distinguishing between good and bad times. The results are very similar to those obtained through an OLS model.

Table 4.12: Cooperation in Innovation by Domestic Partners: Marginal Effects - Logit Model

	Domestic Cooperation						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	-0.013	-0.010	-0.019	-0.009	0.015	-0.009	-0.022
	(0.013)	(0.019)	(0.015)	(0.012)	(0.017)	(0.017)	(0.017)
δ^{t+1}	-0.024	-0.040*	-0.025	-0.015	-0.011	-0.008	-0.017
	(0.016)	(0.021)	(0.021)	(0.014)	(0.021)	(0.023)	(0.024)
δ^{t+2}	-0.005	-0.026	-0.021	-0.007	-0.008	-0.010	-0.036
	(0.021)	(0.025)	(0.023)	(0.017)	(0.022)	(0.025)	(0.025)
δ^{t+3}	-0.019	-0.043*	-0.035	-0.001	0.011	-0.003	-0.023
	(0.021)	(0.023)	(0.024)	(0.019)	(0.028)	(0.029)	(0.030)
δ^{t+4}	-0.017	-0.053**	-0.042*	-0.018	-0.030	-0.037	-0.055**
	(0.023)	(0.022)	(0.023)	(0.016)	(0.018)	(0.025)	(0.024)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.13: Cooperation in Innovation by International Partners: Marginal Effects - Logit model

	International Cooperation						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	0.024	-0.015	-0.014	-0.005	0.001	-0.003	-0.007
	(0.015)	(0.014)	(0.010)	(0.011)	(0.008)	(0.009)	(0.010)
δ^{t+1}	0.037*	-0.019	-0.005	-0.005	-0.016**	0.002	-0.013
	(0.022)	(0.016)	(0.016)	(0.014)	(0.007)	(0.014)	(0.011)
δ^{t+2}	0.053**	-0.006	0.001	-0.015	-0.011	0.019	-0.004
	(0.026)	(0.021)	(0.019)	(0.013)	(0.009)	(0.020)	(0.016)
δ^{t+3}	0.051*	-0.004	0.008	-0.011	-0.010	0.002	-0.000
	(0.030)	(0.022)	(0.022)	(0.015)	(0.012)	(0.017)	(0.018)
δ^{t+4}	0.064*	-0.016	-0.013	-0.013	-0.010	-0.001	-0.007
	(0.033)	(0.021)	(0.016)	(0.015)	(0.012)	(0.017)	(0.017)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.14: Cooperation in Innovation by Domestic Partners - Financial Crisis: Marginal Effects

	Domestic Cooperation - Financial Crisis						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	-0.013	0.004	-0.038	-0.012	0.008	-0.003	-0.055**
	(0.020)	(0.028)	(0.026)	(0.019)	(0.023)	(0.025)	(0.027)
δ^{t+1}	-0.060**	-0.041	-0.054*	-0.008	-0.032	-0.018	-0.050
	(0.028)	(0.031)	(0.031)	(0.022)	(0.029)	(0.034)	(0.035)
δ^{t+2}	-0.024	-0.043	-0.032	-0.006	-0.028	-0.015	-0.079**
	(0.032)	(0.038)	(0.036)	(0.026)	(0.032)	(0.037)	(0.038)
δ^{t+3}	-0.076**	-0.112***	-0.057	-0.034	-0.054	-0.065	-0.092**
	(0.036)	(0.040)	(0.036)	(0.031)	(0.041)	(0.042)	(0.043)
δ^{t+4}	-0.032	-0.071**	-0.038	-0.008	-0.077**	-0.101**	-0.122***
	(0.035)	(0.035)	(0.036)	(0.025)	(0.035)	(0.040)	(0.044)
ω^t	0.002	-0.036	0.045	0.006	0.016	-0.019	0.071
	(0.037)	(0.042)	(0.041)	(0.030)	(0.040)	(0.044)	(0.045)
ω^{t+1}	0.074*	-0.001	0.060	-0.018	0.042	0.017	0.065
	(0.040)	(0.045)	(0.046)	(0.034)	(0.040)	(0.050)	(0.053)
ω^{t+2}	0.037	0.028	0.023	-0.009	0.034	-0.002	0.077
	(0.045)	(0.052)	(0.050)	(0.037)	(0.045)	(0.054)	(0.055)
ω^{t+3}	0.094**	0.110**	0.040	0.055	0.100*	0.099*	0.118**
	(0.047)	(0.053)	(0.050)	(0.041)	(0.053)	(0.058)	(0.058)
ω^{t+4}	0.027	0.029	-0.009	-0.034	0.076	0.106*	0.117*
	(0.047)	(0.050)	(0.053)	(0.043)	(0.047)	(0.060)	(0.060)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.15: Cooperation in Innovation by International Partners - Financial Crisis: Marginal Effects

	International Cooperation - Financial Crisis						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	0.024	-0.029	-0.014	-0.003	-0.009	-0.010	-0.036*
	(0.024)	(0.024)	(0.016)	(0.019)	(0.014)	(0.015)	(0.021)
δ^{t+1}	0.044	-0.020	-0.001	0.003	-0.029*	0.002	-0.030
	(0.036)	(0.026)	(0.023)	(0.023)	(0.018)	(0.020)	(0.023)
δ^{t+2}	0.064	0.006	-0.004	-0.038	-0.012	0.039	0.006
	(0.049)	(0.032)	(0.028)	(0.024)	(0.017)	(0.031)	(0.030)
δ^{t+3}	0.013	-0.001	-0.018	-0.037	0.002	0.020	-0.010
	(0.048)	(0.034)	(0.034)	(0.026)	(0.020)	(0.032)	(0.034)
δ^{t+4}	0.020	-0.033	-0.003	-0.017	-0.027	-0.006	-0.018
	(0.050)	(0.036)	(0.027)	(0.025)	(0.021)	(0.028)	(0.029)
ω^t	-0.000	0.030	0.000	-0.005	0.021	0.021	0.071
	(0.037)	(0.034)	(0.027)	(0.027)	(0.024)	(0.028)	(0.045)
ω^{t+1}	-0.015	0.004	-0.009	-0.020	0.025	0.005	0.030
	(0.047)	(0.035)	(0.033)	(0.031)	(0.023)	(0.029)	(0.030)
ω^{t+2}	-0.024	-0.021	0.007	0.037	0.001	-0.032	-0.014
	(0.063)	(0.043)	(0.039)	(0.033)	(0.026)	(0.042)	(0.038)
ω^{t+3}	0.058	-0.003	0.039	0.044	-0.028	-0.025	0.016
	(0.064)	(0.045)	(0.042)	(0.035)	(0.032)	(0.043)	(0.040)
ω^{t+4}	0.076	0.030	-0.019	0.007	0.030	0.009	0.019
	(0.071)	(0.047)	(0.038)	(0.037)	(0.030)	(0.038)	(0.037)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.7 Conclusions

Collaborating on innovation has been viewed as an effective means to build relationships with FS, as it facilitates the reciprocal sharing and management of knowledge between FS and domestic firms, thereby contributing to the knowledge advantages of domestic firms. This study uses data from Spanish firms to explore whether foreign-acquired firms engage in innovation cooperation with domestic partners by evaluating the effect of foreign ownership on the likelihood of innovation cooperation with domestic partners. Furthermore, since Spain experienced one of the most severe impacts of the GFC in Europe, this research also distinguishes between the effect on the propensity to cooperate of firms acquired during the crisis and those acquired during regular economic times.

By employing a combination of matching techniques and the DiD method, this study provides evidence that foreign-acquired firms are more likely to cooperate with international partners than with domestic partners, especially with firms within the same business group. These results suggest that the transfer of knowledge or technologies from FS to domestic firms in Spain is limited. According to the scholars in the literature on innovation cooperation and FS, the restricted link between FS and domestic firms can be a consequence of the local environment. They suggest that FS may have lower incentives to cooperate in innovation locally when the local partners can not provide reciprocal know-how as compared to other countries. Therefore, the lower propensity to cooperate in innovation with local suppliers could be associated with unfavourable conditions for such cooperation in Spain. This stands in contrast to the initiatives undertaken by the Spanish government to boost the R&D activities of the FS, such as the use of the European Technology Fund from 2007 to 2013 (García-Sánchez et al. 2016). However, specific government incentives are rarely effective when other conditions in the host country are not met (UNCTAD 2005). Therefore, despite Spain's success in attracting foreign direct investment (FDI), these findings highlight the necessity for customised policies that facilitate the connection between FS and domestic firms. This approach would allow the host country to fully capitalise on the knowledge and technology offered by MNCs.

Moreover, this study also provides evidence that foreign-owned firms are more likely to cooperate in innovation with local partners during the GFC, especially with firms within the same business group. These results are consistent with the international business theory and the opportunity cost of innovation. Both point out that during the crisis, firms are more likely to change their organisational network and invest in new technologies to face the uncertainties present in the host country. These results also have policy implications, they call for policies that support collaboration in innovation during harsh economic times.

A potential direction for future research is to investigate how foreign ownership impacts innovation cooperation by distinguishing between acquisitions from technologically advanced countries and those from countries behind the technology frontier. This approach can help determine whether the absence of cooperation between foreign-owned firms and domestic partners is related to disparities in shared technology. Furthermore, knowledge spillovers from foreign-owned firms to domestic counterparts are linked with partial rather than complete foreign ownership (Javorcik 2004). Therefore, another promising avenue for future research would involve examining the influence of partially foreign ownership, where foreign-owned firms hold less than 50% equity, as opposed to full foreign ownership, where the ownership share exceeds 50%. This analysis could help confirm whether partially foreign-owned firms are more inclined to engage in innovation cooperation with local partners.

4.8 Appendix

The survey also classifies international partners into three main groups. One group consists of partners located in Europe, the other group includes partners based in the United States (USA), and another considers partners from the rest of the world.[14] As seen from Table 4.16, the effect of foreign ownership on the likelihood of innovation cooperation with partners in Europe is statistically significant when it occurs with firms that belong to the same business group. This likelihood increases compared to non-acquired firms. It varies from 1.9 pp in the year of acquisition to 5.6 pp four years after. In contrast, foreign ownership decreases the probability of cooperation in innovation with external consultants in Europe compared to domestic firms. The likelihood declines by 1.5 pp after one year

[14] From 2008 onward, China and India are included as another category. However, to keep the consistency throughout the sample, China and India are considered part of other countries group.

of acquisition.

Similarly, in the case of foreign partners in the USA, the effect of foreign ownership on the likelihood of innovation cooperation is statistically significant when it occurs with firms that are part of the same business group. This probability also increases compared to domestic firms. It ranges between 1.9 pp one year after acquisition and 3 pp four years later. However, unlike European external consultants, partners located in the USA with this kind experience a rise in the probability of innovation cooperation due to foreign acquisition. This probability increases by 0.7 pp in the year of acquisition compared to non-acquired firms. Finally, in relation to partners based in other countries, the effect of foreign ownership on the probability of cooperation in innovation is only significant when it occurs with clients, external consultants and universities. Acquired firms are less likely to cooperate in innovation with these types of partners compared to non-acquired firms.

Table 4.16: Cooperation in Innovation by International Partners

(a) Europe

	Europe						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	0.019*	-0.010	-0.004	0.002	0.008	0.004	-0.000
	(0.011)	(0.014)	(0.011)	(0.010)	(0.007)	(0.009)	(0.008)
δ^{t+1}	0.032**	-0.016	0.001	-0.002	-0.015*	0.008	-0.008
	(0.016)	(0.018)	(0.015)	(0.014)	(0.009)	(0.014)	(0.011)
δ^{t+2}	0.034*	0.001	0.009	-0.010	-0.013	0.021	-0.003
	(0.018)	(0.020)	(0.017)	(0.015)	(0.010)	(0.016)	(0.013)
δ^{t+3}	0.040*	-0.003	0.017	-0.001	-0.001	0.006	0.006
	(0.021)	(0.021)	(0.020)	(0.017)	(0.013)	(0.016)	(0.015)
δ^{t+4}	0.056**	-0.012	-0.005	-0.004	-0.001	0.002	-0.002
	(0.023)	(0.023)	(0.019)	(0.016)	(0.014)	(0.017)	(0.016)
β	0.042***	0.016	0.005	0.016	0.002	0.010	0.010
	(0.014)	(0.017)	(0.014)	(0.013)	(0.011)	(0.013)	(0.012)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.054	0.050	0.033	0.028	0.028	0.027	0.049

(b) USA

	USA						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	0.003	-0.001	-0.002	-0.001	0.007*	0.001	0.006
	(0.006)	(0.004)	(0.006)	(0.001)	(0.004)	(0.003)	(0.005)
δ^{t+1}	0.019*	0.006	-0.003	-0.000	0.003	0.000	0.001
	(0.010)	(0.009)	(0.007)	(0.005)	(0.003)	(0.005)	(0.005)
δ^{t+2}	0.025**	0.007	-0.001	0.001	0.005	-0.007	0.001
	(0.011)	(0.009)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)
δ^{t+3}	0.019*	0.015	0.012	-0.003	0.006	-0.001	0.007
	(0.011)	(0.011)	(0.012)	(0.007)	(0.006)	(0.005)	(0.008)
δ^{t+4}	0.030**	0.005	0.000	0.001	0.005	0.004	0.007
	(0.014)	(0.009)	(0.010)	(0.007)	(0.006)	(0.008)	(0.008)
β	0.006	0.001	0.005	0.001	0.000	0.001	0.001
	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.028	0.023	0.020	0.022	0.027	0.024	0.040

(c) Other countries

	Other Countries						
	Bus. Group	Suppliers	Clients	Competitors	Consultants	Universities	Public RC
δ^t	-0.004	-0.003	-0.004	-0.006	-0.007*	-0.007	-0.002
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
δ^{t+1}	-0.004	-0.011	0.000	0.002	-0.009*	-0.013**	0.000
	(0.008)	(0.008)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)
δ^{t+2}	0.009	-0.009	-0.006*	0.001	-0.008	-0.007	0.004
	(0.010)	(0.010)	(0.004)	(0.006)	(0.005)	(0.008)	(0.006)
δ^{t+3}	0.012	-0.008	-0.001	-0.008	-0.008	-0.000	-0.001
	(0.013)	(0.011)	(0.007)	(0.008)	(0.006)	(0.008)	(0.008)
δ^{t+4}	0.000	-0.008	0.006	-0.007	-0.007	-0.004	0.005
	(0.012)	(0.011)	(0.009)	(0.005)	(0.006)	(0.006)	(0.009)
β	0.002	0.010	0.001	0.007	0.007	0.005	0.002
	(0.009)	(0.007)	(0.005)	(0.006)	(0.006)	(0.007)	(0.005)
Observations	3,229	3,229	3,229	3,229	3,229	3,229	3,229
R^2	0.020	0.016	0.008	0.015	0.014	0.013	0.015

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5

Conclusions

This thesis focuses on examining the consequences of different forms of trade on both workers and firms. Chapter 2 centres on the impact of South-South offshoring on the labour market outcomes. Using data from the Peruvian National Household Survey, the EORA input-output table and the US O*Net, this study explores how Peruvian workers who perform routine-intensive tasks have been affected by the increase in South-South offshoring. The study assesses the effect in terms of salary changes, job displacement, and unemployment at the occupational level. In addition, it explores how these effects vary when individuals work in the informal labour market. Chapter 3 focuses on the impact of R&D outsourcing on the inputs of innovation, internal and total R&D investment, along with the number of firms engaged in R&D activities within the industry. This analysis relies on a theoretical framework which explains firms' R&D decisions and their implications for the firm' total and internal R&D investment, as well as how R&D outsourcing affects, within an industry, the participation of firms in R&D activities. Chapter 4, using data from Spanish firms, examines whether firms are more likely to cooperate with national partners following foreign acquisition. Furthermore, this study offers insights into how foreign ownership influences the occurrence of collaborative innovation with local partners during the GFC.

5.1 Summary of Findings

Chapter 2 shows the results of the effect of Peru-South offshoring on the Peruvian labour market. They indicate that Peru-South offshoring positively affects workers' wages engaged in routine-intensive tasks. This demonstrates that Peru specialises in routine-intensive tasks and complements the routine-intensive tasks undertaken by other southern countries. Furthermore, this effect increases the wages of formal and informal routine-intensity workers by 5% and 7%, respectively. This suggests that offshoring increases the demand for both formal and informal workers engaged in routine-intensive tasks. However, looking at the labour market adjustment outcomes, the findings suggest that the increase in Peru-South offshoring increases the likelihood of switching to higher-level occupations within the same sector for routine-intensity workers, being formal workers more likely to make this type of transition. Likewise, Offshoring raises the probability of routine-intensive workers transitioning to higher-level occupations in different sectors. However, informal workers are more prone to making this type of transition.

In addition, the data shows that the transition across occupations within a sector for formal routine-intensity workers is towards more routine cognitive tasks, while the transition across occupations and sectors for informal routine-intensity workers is towards manual-intensive tasks. The latter provides evidence that informal workers are more vulnerable to trade shocks since they are more likely to switch both their occupations and sectors. Consequently, this switch due to offshoring results in a loss of the opportunity to specialise in particular tasks. This chapter also provides new evidence regarding the relationship between trade and informality. It demonstrates that offshoring does not induce the transition of a formal worker to the informal market. However, it confirms that informality works as a buffer to offshoring displaced informal workers, as these workers are more likely to switch both their occupations and sectors within the informal market rather than becoming unemployed.

Chapter 3 presents the results of how R&D outsourcing affects the internal and total R&D investment, as well as its impact on the number of firms engaged in R&D activities within an industry. The results support the main hypothesis of the theoretical model showing that R&D outsourcing increases the investment in internal and total R&D. Therefore, the model suggests that the elasticity of substitution between these two sources of knowledge should be low enough and that R&D outsourcing encourages firms to invest more in R&D by increasing the efficiency of the production of knowledge. Considering the export status of the firms, the results show that, during the treatment period, R&D outsourcing has a positive and statistically significant effect on both internal and total R&D for exporters and non-exporters. However, the effect on internal R&D for non-exporters is relatively weaker in terms of statistical significance and tends to diminish over time compared to the effect on internal R&D for exporting firms.

Likewise, when the analysis is based on the type of R&D outsourcing (domestic and international), the findings indicate that firms outsourcing R&D domestically tend to have a lower degree of substitutability between their knowledge sources. For domestic R&D outsourcers, the impact of R&D outsourcing is positive and statistically significant for internal and total R&D investments. Conversely, for international R&D outsourcers, this impact is only statistically significant for total R&D investment; for the internal R&D investment, the effect becomes statistically significant two years after firms started to outsource R&D. This suggests that international R&D outsourcers depend more on external R&D, at least during the first years of outsourcing.

Regarding the number of firms engaged in R&D activities within an industry, the results demonstrate that in industries where R&D outsourcing is more profitable, fewer firms invest in total R&D. The latter provides new evidence into how R&D outsourcing impacts the extensive margin of R&D.

Chapter 4 outlines the results of the effect of foreign ownership on the likelihood of innovation cooperation with domestic partners. These findings suggest that, on average, foreign-acquired firms are less likely to cooperate in innovation with local partners during regular economic times, but they exhibit a higher propensity to do so during the GFC. The low propensity to cooperate with local partners may be attributed to the local business environment (Veugelers & Cassiman 2004, Ebersberger & Herstad 2012). Specifically, this could be because local firms do not have sufficient innovative capabilities to provide reciprocal know-how. In contrast, the higher likelihood of innovation cooperation with domestic firms during the GFC could be related to the opportunity cost theory, in which foreign-acquired firms are more likely to invest in new technologies to face the uncertainties present in the host country, thus they are more likely to seek a local partner.

5.2 Policy implications, limitations and future research

The evidence provided in the previous chapters has policy implications to ensure that the benefits of the different forms of trade are distributed evenly across workers and firms. The analysis of the impact of South-South offshoring on the Peruvian labour market has demonstrated that formal and informal workers adjust differently to trade shocks. Informal workers are more vulnerable to trade shocks since they are more likely to switch occupations and sectors due to South-South offshoring. This transition involves a change in the tasks performed and a potential loss of the skills already acquired in their previous occupations. Therefore, given that the informal workers represent a higher share of the labour market in Peru, the country is not taking full advantage of the benefits of South-South offshoring, which has led to the specialisation in routine cognitive tasks only for the formal workers. As a result, Peru may have a limited specialised workforce.

Considering the findings presented in Chapter 2, they call for policies aimed at tackling informality and facilitating the introduction of training initiatives for informal workers engaged in routine-intensive tasks. Given the lack of a conceptual framework for offshoring between similar countries, taking into account tasks, wages, and informal labour, a prospective avenue for further research could entail the development of a theoretical model that incorporates these findings.

Chapter 3 provides the findings regarding the impacts of R&D outsourcing on internal and total R&D investment, indicating a positive effect. However, this effect varies depending on factors such as export status and whether the outsourcing is domestic or international. Therefore, these results are relevant for policymakers who seek to enhance firms' R&D investment. Policymakers should consider these differences to facilitate and encourage firms to take advantage of R&D outsourcing opportunities. The latter will enable firms to increase their productivity and maximise their profits.

The analysis in Chapter 3 relies on a theoretical model which provides insights into the impact of R&D outsourcing on internal and total R&D investment. However, this model also includes additional propositions related to outsourcing, such as its effect on productivity. Hence, future research may explore and expand upon an empirical analysis by considering the various propositions outlined by the model.

Finally, Chapter 4 provides evidence regarding the likelihood of cooperation in innovation following foreign acquisition. It demonstrates that firms acquired by MNCs are less likely to engage in innovative partnerships with local firms compared to their domestic counterparts, although this propensity increases during the GFC. Therefore, these findings highlight the necessity for customised policies that promote connections between foreign-acquired firms and domestic firms. This approach would enable the host country to fully take advantage of the knowledge and technology offered by MNCs. Furthermore, these findings call for policies that support collaborative innovation during harsh economic periods.

A potential direction for future research is to investigate how foreign ownership impacts innovation cooperation by distinguishing between acquisitions from technologically advanced countries and those from countries behind the technology frontier. This approach could shed light on whether the lack of cooperation between foreign-owned and domestic firms is linked to differences in the technologies they possess. Another potential future research would be to investigate the influence of partially foreign ownership, where foreign-owned firms hold less than 50% equity, as opposed to full foreign ownership, where the ownership share exceeds 50%. This analysis could help confirm whether partially foreign-owned firms are more inclined to engage in innovation cooperation with local partners.

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