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Can Small Firms Be the Leaders of Innovation?

Finding the Determinants of Product and Process Innovation

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Resumo

A relação tamanho da empresa-inovação é um tema caracterizado por falta de consenso académico, sobretudo quando a inovação é segmentada em inovação de processo e inovação de produto. A frequente exclusão de uma categoria conjunta de inovação torna os estudos empíricos mais insuficientes por não considerarem a interrelação existente entre diferentes tipos de inovação. Por isso, estudamos a relação tamanho da empresa-inovação, considerando a inovação de produto e de processo quando verificadas em conjunto e de forma isolada. Consequentemente, partindo da teoria *exploration-exploitation*, questionamos a literatura que estabelece que estratégias de inovação conjunta estimulam desempenhos mais elevados. Para isto, analisamos possíveis fricções originadas pela junção de ambos os tipos de inovação no desempenho da inovação de empresas de diferentes tamanhos.

Utilizando as bases de dados do Inquérito Comunitário à Inovação (CIS) e do Sistema de Contas Integradas Empresariais (SCIE), entre 2008 e 2018, em Portugal, verificamos que as pequenas empresas têm vantagem na inovação de produto, as médias na inovação de processo e as grandes na categoria de inovação conjunta. Adicionalmente, descobrimos que as grandes empresas são as que mais beneficiam da estratégia de inovação conjunta, seguidas pelas empresas pequenas. É possível apurar ainda que as empresas que empregam entre 276 e 3,055 trabalhadores acabam por experienciar um pior desempenho quando juntam a inovação de processo à de produto. Este estudo mostra, assim, que as estratégias conjuntas de inovação devem ser analisadas em maior profundidade e contribui para a clarificação do papel da dimensão da empresa no domínio de possíveis *trade-offs* entre inovações de produto e de processo.

Palavras-Chave: Dimensão da Empresa, Estratégias de Inovação Conjuntas, *Exploitation*, *Exploration*, Inovação de Processo, Inovação de Produto.

Abstract

The determinant of innovation firm size has fostered an intensive debate in the literature reaching little consensus. This schism is further hindered when we separate innovation into product and process. Moreover, the usual absence of joint innovation categories makes studies fall short in analysing the interrelationship between product and process innovations. Thus, we carry out an empirical study on the innovation-firm size relationship and consider the choices of engaging in product, process, or in both innovations. Then, from the exploration-exploitation standpoint, we tackle the assumption that joint innovation strategies increase innovation performance by analysing potential trade-offs faced by firms that follow both types simultaneously and explore how they vary with firm size.

Using the Portuguese Community Innovation Survey (CIS) and the Integrated Business Accounts System (SCIE), between 2008 and 2018, we deploy two econometric models. The first, a multinomial probit model, finds that small firms have relative advantage on product innovation, medium on process innovation, and large firms on the joint category. Our second analysis deploys Heckman's selection model and finds that large firms benefit the most from joint innovation strategies, with small firms following. When we disaggregate firm size into a numerical variable, we learn that firms employing between 276 and 3,055 workers have contracted innovation performances. Certainly, our work provides sustained evidence that joint innovation strategies must be further researched to broaden policymakers' agenda towards its determinants, benefits, and downsides. Likewise, we cast light on the role of firm size in mastering possible trade-offs between product and process innovations.

Keywords: Exploitation, Exploration, Firm Size, Joint Innovation Strategies, Process Innovation, Product Innovation.

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1. Introduction

Over the years innovation management has been evolving towards a broader disciplinary set with increasing importance on the global stage. While in the 1970s, most of the efforts centred on the research and development (R&D) department of large companies, its current scope backs on multiple frameworks and case studies. The latter show that innovation must be holistically implemented, supported by a shared goal throughout the organisation, and developed by having the competition outlook in mind (Capon, Farley, Lehmann, & Hulbert, 1992; M. de Jong, Marston, & Roth, 2015; Gailly, 2011). Thus, innovation, and its management, has become a strategic pillar for companies and nations to foster higher economic growth and tackle social, environmental, and financial challenges (Acs & Audretsch, 2005; Baregheh, Rowley, & Sambrook, 2009; W. M. Cohen, 2010; Pavitt, 1984; World Bank Group, 2020, Chapter 2). This reality made governments realize that innovation should be fostered as a key ingredient of any endeavour to enhance the quality of life of societies (Acs & Audretsch, 2005; Baumol, 2002; ECB, 2017; OECD, 2010; Rosenberg, 2004; World Bank Group, 2020, Chapter 6).

Abramovitz's (1956) paper provides further evidence on innovative activity as a hallmark of long-term economic growth. The author discusses that the economic output can be leveraged either by increasing the amount of input that goes into the production process or by getting more output from the same amount of input. By analysing the US economy between 1870 and 1950, Abramovitz finds that production inputs' growth only accounts for about 14% of the actual growth in the output of the economy, which leaves an 86%-residual unexplained. This finding made most economists realise that technological innovation would have to play a role in the growth of output (Baldwin, Hanel, & Sabourin, 2002; Rosenberg, 2004). In light of more recent data, one may analyse a South Korean case study presented by The Economist (2020b), questioning the Republic of Korea's long-term growth since the overall GDP has slowed towards the Organisation for Economic Cooperation and Development (OECD) average over the past years. To overcome this, the government pursues a deeper innovative atmosphere through a greater presence of start-ups, which has improved productivity and expanded consumption through new market offers.

Consequently, innovation has become a phenomenon involving a vast array of actors more than ever before (Capon et al., 1992; Laursen & Salter, 2006). For instance, universities and research departments are expected to fulfil possible knowledge gaps, philanthropic organisations to finance and support innovative projects, and governments to put in place the right policies to stimulate innovation through the business environment. Despite the importance of these entities, one shall not forget that companies and entrepreneurs make the final decision of whether or not to innovate (Baldwin et al., 2002; OECD, 2010) — which Nelson & Winter (1977) termed purposive process. In this respect, firms have increasingly perceived innovation as an essential part of their business. Harnoss, Grassl, & Baeza (2019) find that 75% of firms put innovation in one of their top three management priorities and that 35% ranked it above all others. They also add another perspective in that innovation has become a fundamental source of firm survival and profitability — the companies listed in BCG's annual ranking of the world's 50 most innovative firms have delivered an annual shareholder return 3.6 percentage points higher than those in the Global Morgan Stanley Capital International index (MSCI).[1] This further reconfirms the findings of Solow (1957) about the contribution of technological change, including innovation, to economic growth.

Albeit the unquestionable role of firm innovation, there are differences between its application in small and large firms (Arrow, 1993). The question of how firm size is related to the ability to innovate is one of the oldest in political economy (Harrison, 1994). This is underpinned on a puzzling set of different theories that highlight little consensus (Karlsson & Olsson, 1998; Rothwell, 1989; Tsai & Wang, 2005). Schumpeter (1942) defends one of those theories in his book entitled *Capitalism, Socialism and Democracy*, arguing that economic growth comes from innovation with monopoly power and large firm size. Moreover, inventive output increases proportionately more than firm size due to the existence of scale economies and other incentives related to larger companies (Scherer, 1965a; Soete, 1979). Although some scholars (e.g. Acs & Audretsch [1987], W. M. Cohen & Klepper [1996], and Mansfield [1964]) recognize that the use of patents, as a measure of innovative output, increases with firm size, they begin to diverge from Schumpeter's findings.

For instance, different industries are identified as more or less prone to hold large firms' innovative advantage (W. M. Cohen, 2010; Kohn & Scott, 1982). Moreover, different size measures, either through assets or employees, are found to sustain different validations of these findings and the idea that being small could be advantageous to the creation of patentable inventions is further developed (W. M. Cohen & Klepper, 1996; Scherer, 1965a). Even though, during the first three decades after the end of the Second World War, large firms with market power are seen as the prevailing driving engine of innovative activity, a wave of new studies challenge this paradigm (Acs & Audretsch, 2005; Nicholas, 2003). Fellner (1951) and Arrow (1962) defend that firms in competitive markets have a greater incentive to innovate. W. M. Cohen (2010) finds that, either due to the loss of managerial control or excessive bureaucratic procedure, R&D productivity is negatively associated with firm size. Furthermore, larger firms are found to generate fewer innovations than their smaller counterparts (W. M. Cohen, 2010; W. M. Cohen & Klepper, 1996; Mansfield, 1964).

The existence of such vast literature shows the importance of the relationship between innovation and firm size and the lack of consensus about the sign of the relationship (Acs & Audretsch, 2005). This subject becomes paramount when we consider the 2018 enterprise outlook in Portugal — small and medium enterprises (SME) comprised 99.9% of the total national market, while large companies only represented 0.1%, with around 23% of the total personnel employed.[2,3] Agreement on the role of firm size is even scarcer when we disaggregate innovation into each type (Hervas-Oliver, Sempere-Ripoll, & Boronat-Moll, 2014; Keupp, Palmié, & Gassmann, 2012). This hinders our understanding of the economic dynamics arisen by technological change as each type of innovation has different economic

[1] MSCI is a leading index that measures the performance of a basket of securities intended to capture large and mid-cap representation across developed markets. It comprises 1,640 companies and 23 countries. Source: https://www.msci.com/developed-markets.

[2] These figures assume that an SME employs less than 250 workers and a maximum annual sales volume of €50M or total assets below €43M.

[3] Source: INE, PORDATA. Retrieved from https://www.pordata.pt/DB/Portugal/Ambiente+de+Consulta/Tabela/5811860.

impacts (Cabagnols & Le Bas, 2002; W. M. Cohen, 2010; Keupp et al., 2012). To fulfil this gap, we carry out an empirical study on the innovation-firm size relationship, analysing in particular product and process innovations, in Portugal. Furthermore, we provide evidence on an often-overlooked aspect, the relationship between product and process innovation when a firm follows them simultaneously (Ballot, Fakhfakh, Galia, & Salter, 2015; Bauer & Leker, 2013). Our results contribute for a broad set of literature and provide evidence-based guidance for developing policies aimed at fostering innovation, consequently contributing to welfare and economic growth (Fasil, 2009; Nelson & Winter, 1977; Rammer, Czarnitzki, & Spielkamp, 2009).

It is widely recognized that joining both product and process innovation can yield better performance results (e.g. Ballot et al. [2015], Damanpour & Gopalakrishnan [2001], and Schmidt & Rammer [2006]). However, with scholars' increasing interest on the exploitation-exploration dilemma (Benner & Tushman, 2015), one should explore an under-researched issue: the possibility that firms' returns from innovations may decrease when pursuing both types of innovation simultaneously that, although related, are largely driven by different factors (Bauer & Leker, 2013; Gailly, 2011; Rouvinen, 2002; Vaona & Pianta, 2008). This bears resemblance to the tension between exploitation and exploration of innovation activities (Lavie, Stettner, & Tushman, 2010; March, 1991), in which the concept of ambidexterity is presented as a possible solution for allowing an organisation to undertake both innovation paths while buffering their contrasting effects (Benner & Tushman, 2015; Lavie et al., 2010).

In this regard, Ikea has been featured as a case study of how large firms should adapt to adverse scenarios through balancing both explorative and exploitative strategies (Milne, 2020). Amid the COVID-19 pandemic, the giant retail seller saw its sales drop 4% to €39.60 billion in the financial year, to the end of August, due to global lockdown-related measures (BBC News, 2020). Additionally, increasing competition from Amazon and Alibaba taking hold of online shopping has created further pressure on the Swedish brand (Milne, 2020). To drum up its business, Ikea is leading a series of experiments encompassing everything from renting out furniture to second-hand selling (Milne, 2020; The Economist, 2020a). Although success is not guaranteed, one cannot criticize Ikea for joining an exploration strategy through new experiments underpinned on the knowledge and reputation driven by their long-lasting business model followed since the 1970s (Milne, 2020).

Firms are constrained by their organisational characteristics (Jin, Li, & Wu, 2016; Lavie et al., 2010), which raises the possibility that different firm sizes may have distinct impacts on strategies that follow product and process innovations simultaneously. Large firms do business underpinned on a larger base of resources and small firms benefit from their niche market seller competencies (Baldwin et al., 2002; Gailly, 2011; M. Rogers, 2004). Only by acknowledging the existence of these same frictions in joint innovation strategies and how these depend on firm size, will we understand the role of ambidextrous firms when pursuing different types of innovation. Hence, we carry out a subsequent analysis to explore the impact of developing product and process innovations simultaneously on innovation performance and its relationship to firm size.

Our empirical study makes use of the Community Innovation Survey (CIS), a database that has been widely deployed in the literature of the determinants of innovation (e.g. Ballot et al. [2015], Rammer et al. [2009], and Rouvinen [2002]). We analyse the Portuguese version between 2008 and 2018, which comprises 5 waves of this survey. The CIS is part of an EU statistics-based programme in the scientific and technological field carried out biannually by EU member states and some of the European Social Survey participant countries (European Social Survey, 2001; Eurostat, 2017).[4] In order to obtain a richer set of measurements to aid in our analysis and minimize missing data issues, we combine the CIS with comprehensive administrative data from the Portuguese Integrated Business Accounts System database (SCIE).

In our first analysis, we find that small firms have an advantage at developing product innovation, medium firms at process innovation, while large firms are more likely to introduce both product and process innovations at the same time. These results support existing literature that gives small firms the dominance in product innovation and broadens its knowledge by exploring the role of firm size when product and process innovations are simultaneously followed. The fact that size advantage goes towards large firms in the joint category may explain why small firms lead product innovation in our results. We hence lay down the motivation for policymakers to also look into the determinants of joint innovation strategies. Our finding for the effect of firm size on process innovation is not less relevant as this realm has yet to be fully explored and debated when compared to product innovation.

In our second analysis, we find evidence of an overall positive impact on innovation performance when firms engage in joint innovation strategies, although dependent on firm size. This relation is shaped by a non-linear U-curve where large firms have the greatest benefit. When we disaggregate firm size from a 3-level categorical to a numerical variable, we actually note that joining both product and process innovation harms the innovation performance of firms with a workforce size between 276 and 3,055 employees. This is of further interest to firms' managers, as it supports, for instance, the unit separation ambidexterity strategy, in which both types of innovations are followed in different units, as a possible remedy.

The structure of this work is as follows. In the next section, we provide an overview of the problem that has motivated our research. Then, we present a review of the literature on the determinants of innovation commonly used in this type of analysis as well as on the exploration-exploitation innovation activities. Section 4 depicts the data characterization to further the understanding of how the CIS and the SCIE data sets are organised and processed. Here, we also develop a descriptive analysis as a first step in testing our hypotheses in order to understand the main patterns. We describe the econometric models and their mathematical basis in Section 5 and, in Section 6, we present the results and back them with a robustness analysis. Section 7 provides a discussion of our findings in light of the existing literature and Section 8 consummates our work with the main conclusions.

[4] The European Social Survey is an academically driven cross-national survey aiming to measure the attitudes, beliefs, and behaviour patterns of more than thirty nations.

2. Problem Definition

This study is motivated by two main reasons. First, few studies in the literature address the role of the size of the firm determinant on each type of innovation. Second, the impact of joint innovation strategies on performance, considering possible trade-offs between product and process innovation, has not deserved the greatest attention by recent investigation.[5]

The first reason arises due to the existence of a much broader set of studies focused on product than on process innovation (Hervas-Oliver et al., 2014; Reichstein & Salter, 2006; Yin & Zuscovitch, 1998). When we compare the literature against the existing variety of types of innovation, we see that many of them are still unexplored. For instance, Keupp et al. (2012) found that among 342 articles, published in the top-tier strategic management innovation journals since 1992, only 11 clearly comprise process innovations. This is mainly related to a lack of data and agreement on the kinds of measures that should be used to examine each type (Polder, Van Leeuwen, Mohnen, & Raymond, 2010). In fact, to measure product innovation is much less ambiguous since its metric turns out to be more quantitative, *i.e.*, based on simple figures such as the number of patents (Polder et al., 2010). To bridge this gap, we conduct our analysis either for product or process innovation, by deploying a data set capable of measuring both types of innovation. Furthermore, we also include a joint class to account for the interdependencies between these two.

Additionally, although several studies use the exploration-exploitation literature to describe, for instance, the balance between incremental and radical innovations (Benner & Tushman, 2015; Gailly, 2011; Simsek, Heavey, Veiga, & Souder, 2009; Smith & Tushman, 2005), it is not common to see the same dilemma applied to product and process innovation, to the best of our knowledge. The latter is likely due to the wide-spread belief that following joint innovation strategies boosts innovation performance (Ballot et al., 2015; Bauer & Leker, 2013; Damanpour & Gopalakrishnan, 2001). We tackle this assumption by looking at possible downturns in firms' innovation performance when both product and process innovation are held in the same firm. Through this, we are able to identify the firm size most likely to feel frictions when joint innovation strategies are followed.

The decision of using Portuguese data to perform our study is motivated by the Portuguese government's aim to continuously strengthen its economic structure through a more innovative and productive economic outlook (Governo de Portugal, 2014). Indeed, by consulting the Global Innovation Index report for 2019, we see that Portugal is still behind some EU member states with similar geographic and economic structures, showing room for improvement and future efforts related to innovation (Global Innovation Index, 2019; OECD, 2019).[6] Likewise, to understand how firm size relates to innovation is of further importance when we consider the Portugal's corporate spectrum, as small firms are one of the main drivers for technological change and innovative activity in specific industries (Hall, Lotti, & Mairesse, 2009).

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[5] See Figure A, in Appendix, for further details on the scope of the present study.

[6] Portugal ranked number 31 in the Global Innovation Index 2019, although in the European Innovation Scoreboard 2020 was considered the 12th country innovating the most in the European Union (Hollanders, Es-Sadki, Merkelbach, & Khalilova, 2020).

Thus, we advance two research questions that contemplate the specific subjects we intend to analyse and add to, throughout this study:

- How might firm size leverage the implementation of product and process innovations, in the Portuguese economy?
- How does innovation performance vary when firms balance product and process innovations simultaneously and to what extent does this variation depend on firm size?

Although we implement on Portuguese data, one should bear in mind that our findings and recommendations are not solely scoped to Portugal. In fact, by answering these two questions, we aim to help policymakers develop and implement new measures or, not least, understand the policies fostering innovation, in particular, concerning firm size, in any economy where this study proves suitable. Likewise, firms' managers may also benefit from our findings whenever they want to define an innovation strategy based on both product and process innovations.

3. Literature Review

3.1 Innovation Typology

Over the last years, innovation has become increasingly relevant to nations and businesses due to its role in economic development and technological progress (W. M. Cohen, 2010; Gailly, 2011; Keupp et al., 2012). The belief that innovation only consists in disruptive creations has changed, as we now know that the concept is more complex and affects our lives in distinct ways (W. M. Cohen, 2010; Gailly, 2011; Kotsemir & Abroskin, 2013; Pavitt, 1984, 1990). From new products that establish new industries, new ways of producing and organizing a flow of information that save companies' time and money, and to new services that offer added value putting an end to older, obsolete and undesired ones, we see its potential for shaping human beings' evolution (Chandy & Prabhu, 2010; Ettlie & Reza, 1992). Therefore, innovation practices started being adopted in almost every sector — marketing and advertising specialists, policymakers, consultants, and many more — promoting new business strategies and frameworks (e.g. blue ocean innovation) fostering more efficient and sustainable competitive markets (Gailly, 2011; Kotsemir & Abroskin, 2013).

First-hand, it is important to define innovation and distinguish it from invention. For this, we look at the latest version of the Oslo Manual (OECD/Eurostat, 2018), which is the common definition used in various data collection instruments such as the Community Innovation Survey (CIS). The Manual states the following:

- "An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)", cited from OECD/Eurostat (2018).
- An invention is an innovation that was not implemented and is rather mainly a source of knowledge and not a marketable product or service (OECD/Eurostat, 2018).

To enhance our understanding of both concepts, we shall visit other studies. The first one addresses the very beginning of the innovation concept history to bring one of the most influential theories developed by Joseph Schumpeter (Baker, 2007; Malerba & Orsenigo, 1996). Here, the concept of creative destruction, famous for its role in the economic growth literature to investigate the determinants of long-term growth, is introduced. This concept describes the disruption of existing economic activity through innovation, which is defined as a large scale or small change that has a significant impact on the way of producing goods or services or on the industry structure (Schumpeter, 1911). Thus, innovation is not only an idea, but also its concretization and sale in the market to create the sense of substitution that Schumpeter's creative destruction concept explains. A second example comes from Edwards & Gordon (1984), also aligned with Nelson & Winter (1977), who highlight that an invention that does not go beyond the laboratory scope or a product that is not developed, manufactured and marketed cannot be considered an innovation since it does not create economic value. Regarding both ideas, we can say that innovation is an invention that needs to be developed, produced, and marketed in order to achieve commercial success, creating, therefore, an effect of substitution in the existing products, services or processes.

Consumer's adoption rate of innovations is added to this process through the stage of diffusion, as one's usual aversion towards change has a critical effect on an innovation's success (Gailly, 2011; Garcia & Calantone, 2002). It is not only about finding the right customers' wishes and market necessities, but also overcoming possible fears and resistance (Gailly, 2011). The degree to which a firm manages these setbacks influences diffusion, as innovations (an invention successfully commercialized) become widely used and diffuse to other fields (Garcia & Calantone, 2002; E. M. Rogers, 1995). An idea that is capable of going through every step — development, commercialization, and diffusion — has a higher likelihood of generating greater economic value (Garcia & Calantone, 2002). It is also important to stress the difference between innovation process and process innovation. While the former is the technological development of an invention and its market introduction through adoption and diffusion, the latter is the type of invention that achieves commercial impact and is related to the firm's processes (Garcia & Calantone, 2002).

Over the years, new tools and computational techniques have evolved and new empirical and case studies have been created and analysed, fostering a greater awareness of innovation. The major pattern around this knowledge boom was unorganized and confusing, making typology frameworks well suited for its arrangement (Benner & Tushman, 2015; J. P. J. De Jong & Marsili, 2006; Garcia & Calantone, 2002). Typology frameworks aim at improving the way we manage innovation through the translation of this abstract concept into concrete classes, in order to better predict their sources and impacts (Coccia, 2006; J. P. J. De Jong & Marsili, 2006; Eiriz, Faria, & Barbosa, 2014). However, as there is no right framework and each author adds on past classifications to give the most suitable view to their study, inconsistency also arises in these typologies and leads to incongruent categorizations. For instance, one researcher's "really new" term may equate another researcher's "discontinuous" (Coccia, 2006; Damanpour, Walker, & Avellaneda, 2009; Garcia & Calantone, 2002; Utterback & Abernathy, 1975).

The *Multitype classification* represented in Table 1, adopted from Kotsemir & Abroskin (2013), is many times deployed in empirical studies that analyse the determinants of innovation (e.g. Cabagnols & Le Bas [2002], Fonseca [2014], and Rouvinen [2002]) and supported by the guidelines established in the OECD Oslo Manual (OECD/Eurostat, 2018). This classification breaks down innovation between product and process innovations and defines them as follows: product innovation is a good or service that was significantly improved and transacted in the market and process innovation is the implementation of new or significantly improved methods of production or delivery of the product. Both types of innovation are further grouped in technological innovations (Damanpour et al., 2009; Kotsemir & Abroskin, 2013).

Table 1 | Multitype classification model adopted from Kotsemir & Abroskin (2013).

Type of Innovation	Sphere of Application	Distinctive Characteristic
Product Innovation[7]	Innovations related to goods and services	Significant improvements in the technical specifications, components and materials in the embedded software in the degree of friendliness to the user or other functional characteristics
Process Innovation	Innovations related to methods of production or delivery of the product	Significant improvements in technology, production equipment and / or software

Moreover, product innovation expands the product demand curve, while process innovation contributes to the expansion of the supply curve. The former enhances the value proposition that a company gives to its clients, which increases the desire of new and old customers to get the product, whereas process innovation contributes primarily to improve the efficiency of a firm's production and service operations (Damanpour & Gopalakrishnan, 2001; Eiriz et al., 2014; Ettlie & Reza, 1992). Both behaviours are prone to induce the rise of the industry's potential output and, therefore, create economic value (Garcia, 2015). Although some authors defend that process innovation is somehow dependent from product innovation, one easily identifies cases that do not follow this rule, such as saving costs process innovations (Rammer et al., 2009).

It is important not to see product and process innovation as absolute values, in that a company is not restricted to only one type (Karlsson & Olsson, 1998). A company that develops product innovation may be the same company undergoing process innovation later on or even at the same time (Baldwin et al., 2002; Ballot et al., 2015; Damanpour & Gopalakrishnan, 2001; Eiriz et al., 2014; Gailly, 2011). For instance, Utterback & Abernathy (1975) argue that product innovation happens first in order to stimulate customers through new products or the enhancement of already existing ones, while process innovation is implemented over the company's lifetime. This would then boost cost savings given that less variety of products would remain in the market, opening space to standardization, greater efficiency, and economies of scale. Effectively, what should prevail is not a specific type of order, but the understanding that all types may vary along the life of a company. Thus, firm's age may be an important factor to consider when exploring the determinants of innovation.

3.2 How to Measure Innovation

Data available to scholars have always constrained the way innovation has been gauged. There is no direct measure to quantify the impact of each innovation across industries; such data are always misleading or incomplete, raising proxy measures that reflect some part of the innovation process (Acs & Audretsch, 2005; Capon et al., 1992; W. M. Cohen & Levin, 1989; Gailly, 2011). The efforts to assess innovation can be grouped in innovation inputs and outputs, and have posed a long debate about the best to use (W. M. Cohen & Levin, 1989; Gailly, 2011). The inputs to innovation activities are usually

[7] The interest of splitting service innovation from product has been increasing (Garcia, 2015); however, for the present discussion, we maintain both in the same category.

composed of R&D data or personnel engaged in R&D. A clear limitation is that R&D only reflects what the firm assigned to produce innovative output, saying nothing about the number of innovations that introduced or their impact (Acs & Audretsch, 2005; W. M. Cohen & Levin, 1989; Crepon, Duguet, & Mairesse, 1998; Gailly, 2011). Furthermore, although R&D influences firms' innovative activity, many small firms do not have formal operations. Their research activities are typically unmeasured as they often mix R&D with other tasks and frequently do so outside regular working hours (Kleinknecht, 1987; Mansfield, 1984).

The outputs of innovation can be broken into intermediate measures, often represented by the number of patents, and direct measures, which come from innovation-oriented surveys (Acs & Audretsch, 2005). Patents are an intermediate indicator as they reflect a potential future innovation; meaning, they replicate new technical knowledge, but do not indicate an economic impact (W. M. Cohen & Levin, 1989; Rammer et al., 2009; Scherer, 1965a). Patents are not suitable for within and between-industry comparisons (Mansfield, 1984). For instance, according to W. M. Cohen & Levin (1989), in the electronics industry, many innovations are typically not patentable, and when they are, many firms prefer to keep their inventions secret. Innovation-oriented interviews inquire either experts or firms' managers to identify the company's innovations (Acs & Audretsch, 2005; Baldwin et al., 2002; Simonetti, Archibugi, & Evangelista, 1995). Both forms of survey have the same disadvantage: the identification relies on the interviewee's perspective and has, therefore, a high degree of subjectivity (Simonetti et al., 1995). Furthermore, innovation-oriented interviews do not account for different innovations' economic impact (Acs & Audretsch, 2005). One well-known data source compiled by experts, the U.S. Small Business Administration's Innovation Data Base (SBIDB), is used, for instance, by Acs & Audretsch's (1987, 1988b) seminal works, while the CIS database, used throughout this study, represents one example of a data source built from managers' perspectives (Ballot et al., 2015).

3.3 Measuring Innovation Performance

It is important to take stock of innovation propensity as it quantifies whether the firm has introduced innovations or not, but the capability of measuring their real effects in firm's operations and market dynamics is of more importance to policy makers and scholars (Birchall, 2011; Dewangan & Godse, 2014). Early studies start by deploying firm performance measures (e.g. Calantone, Vickery, & Droge [1995], Capon et al. [1992], and Mansfield [1964]). However, these come to be regarded unsuitable as they have other sources of firm heterogeneity beyond the innovation scope influencing their results (Alegre, Lapiedra, & Chiva, 2006; Ballot et al., 2015; Cassiman & Veugelers, 2006).

From the late 1980s and early 1990s, innovation performance measures start to evolve, in particular, towards two directions (W. M. Cohen, 2010; Dewangan & Godse, 2014; Kremp & Mairesse, 2004). The first backs on a combination between the direct and intermediate types of measure of Section 3.2, creating many times an overlap between innovation propensity and performance measures (e.g. Prajogo & Ahmed [2006], and Kim, Kim, Miller, & Mahoney [2016]). The second direction focuses on a crucial component of innovation: firms' ability to translate innovation activities into market success (Birchall, 2011; Fonseca, de Faria, & Lima, 2019). To gauge this, scholars have used the resulting turnover from the sale of innovative products or the costs savings originated from the implementation of new processes (e.g. Fonseca et al. [2019], Grimpe & Kaiser [2010], and Cassiman & Veugelers [2006]). Although this last direction seems to have a higher degree of objectivity and comparability, it is hard to find data to set-up this type of metric (W. M. Cohen, 2010; Grimpe & Kaiser, 2010). For example, deploying process innovation performance measures may be highly subjective due to the difficulty of gauging the exact savings coming from the implementation of a new process (Bauer & Leker, 2013; Hervas-Oliver et al., 2014). Thus, choosing suitable indicators to measure the innovation performance of firms is neither an easy nor a direct path, and there is still little consensus on this matter (Birchall, 2011; Lazzarotti, Manzini, & Mari, 2011; Romijn & Albaladejo, 2002).

3.4 Firm Size and Innovation

The relationship between firm size and innovation has been a hotbed of theoretical speculation and empirical investigation for many decades. Covering different time periods, firms and industries, measures of innovative activity, and models explain the wide range of findings across studies (W. M. Cohen, 2010; Fritsch & Meschede, 2001; Reichstein & Salter, 2006; M. Rogers, 2004; Vaona & Pianta, 2008). Schumpeter shaped the period of time where large firms are thought to have the advantage in innovative activity. In *Capitalism, socialism and democracy*, Schumpeter argues that large enterprises with market power, especially monopolists, conduct greater growth of innovative output than smaller firms in competitive markets (Acs & Audretsch, 2005; Link, 1980; Malerba & Orsenigo, 1996; Nicholas, 2003; Plehn-Dujowich, 2007; Schumpeter, 1942). This is further backed by Galbraith (1952) who considers the arguments defending small firms' relative advantage to innovate to be fictitious. However, even Schumpeter puzzled over the effect of firm size on innovation. In an earlier book, *The Theory of Economic Development*, Schumpeter develops the concept of creative destruction, where innovative activity is characterized by technological ease of entry and innovators with small economic size (Andersson, Braunerhjelm, & Thulin, 2011; Harrison, 1994; Kirchhoff, 1989; Malerba & Orsenigo, 1996; Nicholas, 2003; Schumpeter, 1911). These views are not entirely separable as they relate to time — small firms' advantage usually occurs at the early stages of the industry's life cycle, while large firms tend to hold an advantage during technologies' evolution (Harrison, 1994; Malerba & Orsenigo, 1996; Nicholas, 2003; Rothwell, 1989).

Schumpeter's theories on the relationship between firm size and innovation have evolved in literature as follows. Up until the 1970s, the prevalent assumption is based on an S-shaped curve — small firms have a relative low share of innovative activity, which increases in medium and large companies and then slows down among the very large ones (Pavitt, Robson, & Townsend, 1987). This pattern is underpinned on indivisibilities and risk precluding most small firms and by monopoly power which usually stalls market pressure on firms (Acs & Audretsch, 1988a; Nelson & Winter, 1977; Pavitt et al., 1987). Later, this shape evolves towards a non-linear U-curve. Pavitt et al. (1987) are one of the first to discuss the finding that firms with less than 1,000 employees are responsible for only 3.3% of R&D in 1975, but for a higher share (34.9%) of identifiable significant innovations between 1970 and 1979. Thus, they conclude that R&D data are not suited to depict the real innovative activity of firms.

The U-shaped curve is further supported by studies applied to different geographical scopes which defend the same trend (e.g. for German data from the 3rd Community Innovation Survey see Peters

[2005], for a high intensive technological sector in Taiwan see Tsai [2005]). However, the number of studies arguing in favour of Schumpeter's theory on large firms do not diminish. Several authors add to this last theory, yet maintaining the R&D-firm size relation: larger firms possess a greater incentive to pursue R&D than smaller firms (e.g. W. M. Cohen & Klepper [1996], Fritsch & Meschede [2001], Kohn & Scott [1982] and Scherer [1965a]). For instance, Arvanitis (1997) recognizes that R&D expenditures rise with firm size but less than proportionally. This is also supported by Fritsch & Meschede (2001) who along with W. M. Cohen & Klepper (1996) find that the size relation is stronger for process innovation than for product. On the contrary, other studies reinforce the size disadvantage theory, attributing a higher rate of innovation, in particular for product innovation, among small firms (Acs & Audretsch, 2005; W. M. Cohen & Klepper, 1996; Huergo & Jaumandreu, 2004; Tsai, 2005).

Another important contribution in this literature is found in Acs & Audretsch's (1987) seminal work, contradicting Schumpeter's hypothesis that large firms are not more innovative by themselves — more context has to be given in order to draw any conclusions. The authors argue that large firms have a relative advantage in innovation in capital-intensive, concentrated, and advertising-intensive industries, whereas small firms have relative advantage in industries with a relatively high proportion of large firms and in the early stages of its life-cycle, where innovation and a skilled workforce are crucial. Their work suggest that small and large firms may have different determinants of innovation.

Several arguments feed this discussion with different viewpoints regarding both types of firms. Large firms have an advantage due to having access to more funds to invest in innovation and larger assets to pledge as collaterals on loans which ease their access to external borrowing (Acs & Audretsch, 2005; Baldwin et al., 2002; Plehn-Dujowich, 2007; M. Rogers, 2004; Rothwell, 1989). A larger size also promotes greater independence over the external environment, providing greater flexibility for their businesses' innovation strategy (Gailly, 2011; Karlsson & Olsson, 1998). Due to higher diversification, these firms also attain greater ability to internalise R&D spillovers (W. M. Cohen & Klepper, 1996; Karlsson & Olsson, 1998; Plehn-Dujowich, 2007; Tsai & Wang, 2005). Furthermore, concerning a knowledge-based perspective, large firms access a broader range of knowledge and higher skilled technical specialists than their smaller counterparts (W. M. Cohen & Klepper, 1996; Harrison, 1994; M. Rogers, 2004; Rothwell, 1989). Likewise, economies of scale and scope are expected, although these may be exhausted as firms grow larger (Baldwin et al., 2002; Gailly, 2011). Finally, large firms also profit from spreading their R&D costs over a wider volume of sales, which increases their incentive to engage in R&D (Baldwin et al., 2002; W. M. Cohen & Klepper, 1996; Rothwell, 1989).

Conversely, small firms benefit from faster decision processes in recognizing opportunities and a more adjustable organisational structure. Doing so prevents the isolation of the decision-making body from specific customer requirements and facilitates employee motivation towards innovative tasks (Pavitt, 1990; M. Rogers, 2004; Rothwell, 1989). Small firms tend to enjoy lower levels of bureaucracy, greater flexibility to overcome unexpected scenarios, and easier internal communication than large firms, which favour small firms' propensity to innovate (W. M. Cohen, 2010; Gailly, 2011; Nicholas, 2003; Pavitt, 1990; Rothwell, 1989; Tsai, 2005). Although a smaller size benefits the firm's efforts in satisfying customers' needs, it also hinders the variety of products offered (Audretsch, Segarra, & Teruel, 2014). The focus on innovation-related tasks rather than on management control also allows small firms to fully exploit the expertise of their skilled employees as they remain at the heart of the innovative activity and — as it often happens in large enterprises — are not promoted to administrative functions (W. M. Cohen, 2010; Gailly, 2011; Pavitt, 1990; M. Rogers, 2004).

The firm size-innovation relation can be further deepened, if we look at product and process innovations. Previous studies show that firm size has a positive impact on both types, meaning that larger firms are more likely to pursue them (e.g. Baldwin et al. [2002], Hall et al. [2009], Harrison [1994], Kraft [1990], Reichstein & Salter [2006], Schmidt & Rammer [2006], and Tether [2002]). Yet, Pavitt et al. (1987) and W. M. Cohen & Klepper (1996) attain a different relation: using process R&D expenditure as a measure of innovation, they defend that smaller firms have an advantage at pursuing product innovation, while larger firms at process innovation.

From our analysis, it is reasonable to expect a positive relation between firm size and both types of innovation and we thus hypothesise that:

H1: A firm's propensity to introduce technological innovation (either product or process innovation propensity) is positively affected by its size.

H2: A firm's propensity to introduce joint technological innovations (product and process innovation simultaneously) is positively affected by its size.

3.5 Other Determinants

We now provide an overview of the determinants of innovation, although not an extensive list of all those already present in the literature as it goes outside of our scope. The analysis of the determinants of innovation contribute to the understanding of the drivers behind the success or failure of firms' innovation activities (Acs & Audretsch, 1987, 1988b; Arvanitis & Bolli, 2013; Hall et al., 2009; M. Rogers, 2004). The characteristics of the environment that a firm faces as well as its internal resources, such as human capital and R&D investment level, influence firms' innovation strategic performance (Cabagnols & Le Bas, 2002; Damanpour et al., 2009; J. P. J. De Jong & Vermeulen, 2006; Fasil, 2009; Gailly, 2011; Mohnen & Röller, 2005; Reichstein & Salter, 2006; Utterback & Abernathy, 1975).

Despite the firm size, or the industry where it may operate, a firm is ultimately a group of people working under the same rules and towards the same goals (Belousova & Gailly, 2013; Coase, 1937). Thus, the importance of human capital has been shown to be key in the innovation process (Andries & Czarnitzki, 2014; Gailly, 2011; Van de Ven, 1986) and a central element of economic growth theory, given that a larger stock of human capital at a firm-level contributes to greater performance (Andries & Czarnitzki, 2014; D. Cohen & Soto, 2007; Storper & Scott, 2009). Although its comprehensive and abstract nature, we characterize human capital as the individuals' abilities and knowledge that can be enhanced through formal training and education (D. Cohen & Soto, 2007; Dakhli & de Clercq, 2004; Santos-Rodrigues, Lousinha, & Cranfield, 2013). Considering smaller and larger firms separately, training and education show a positive impact in both types of innovation for small firms, but larger firms only have a positive relation between training and process innovation (Baumann & Kritikos, 2016; McGuirk, Lenihan, & Hart, 2015). As McGuirk et al. (2015) recognise, this last result for large firms is surprising given the emphasis of the policy set by the European Commission (2010) on education for innovation. Looking at the economic impact, formal education of the employees increases the likelihood of introducing innovations with higher commercial success (Rammer et al., 2009).

R&D activities play a major role on innovation (Acs & Audretsch, 1988b; Gailly, 2011; Rammer et al., 2009). Extensive works support the idea that R&D awards competitive advantage to a firm and stimulates innovation, although the rate at which innovation increases with R&D expenditures is less than proportional (Acs & Audretsch, 1988b; Baldwin et al., 2002; Becker & Dietz, 2004; M. Rogers, 2004; Shefer & Frenkel, 2005). Breaking down between product and process innovations, we find these two types are positively impacted by R&D expenditures (Baldwin et al., 2002; Crepon et al., 1998; Hall et al., 2009; Reichstein & Salter, 2006; Schmidt & Rammer, 2006), although a stronger connection is usually found in the first type (Baumann & Kritikos, 2016; Pavitt, 1984; Rouvinen, 2002).

Concerning the intensity of economic competition, there are two opposite theories that link its effect, through market structure, with innovation (Cabral, 2017) — Schumpeter's (1942) and Arrow's (1962). The first one defends that innovation tends to happen in markets with imperfect competition, being the monopoly the extreme case. In such markets, firms enjoy a better access to capital beyond other advantages that come from the larger size that firms usually have and from the monopolist market power. Arrow's (1962) theory argues that firms in competitive markets have more to gain from innovation since their survival may depend on their ability to produce market or technological discontinuities to outperform their peers. Schmidt & Rammer (2006) identify a positive impact of stronger competition on product and process innovation; Cabagnols & Le Bas (2002) only find a significant relation with product innovation, which is also supported by Kraft (1990). Reichstein & Salter (2006) suggest that competition would play a major role in the determinants of process innovation.

The firm's industrial sector also impacts the innovative activity of companies (Malerba & Orsenigo, 1996; Nelson & Winter, 1977; M. Rogers, 2004; Rothwell, 1989). It is expected to see a larger rate in high-tech industries than in traditional ones, especially for product innovation (Hall et al., 2009; Tether, 2002; Tsai, 2005; World Bank Group, 2020, Chapter 5). However, it is also important to mention that a greater transition from more rudimentary processes to digital ones has been the focus of companies in less technological sectors (Ringel, Grassl, Baeza, Kennedy, & Manly, 2019).

The exports' level also shapes a firm's innovation strategy (Cassiman & Veugelers, 2002; Fonseca, 2014; Kraft, 1990). A company that goes beyond its national market by selling outside that region has access to a broad range of resources and best practices that induce a firm's learning (Golovko & Valentini, 2014; The World Bank, 1997, Chapter 4). Thus, exports are positively associated with innovation and in particular with product and process, although M. Rogers' (2004) study overlooks this relation for non-manufacturing firms (Ballot et al., 2015; Baumann & Kritikos, 2016; Bhattacharya & Bloch, 2004; Cassiman & Veugelers, 2002; Golovko & Valentini, 2014; Kraft, 1990; M. Rogers, 2004).

Following Fonseca (2014), advanced capital — defined as the use of advanced machinery, hardware, and software — influences firms' innovative activity too. As the author argues, when companies evolve toward a system with the latest organisational techniques, the use of capital increases due to the adoption of high-tech machinery and computer-controlled equipment. Advanced capital has a positive impact on product and process innovation, since it creates structures that increase the firm's productivity and ease the complexity associated with product innovation strategies (Fonseca, 2014; Hall et al., 2009; Schmidt & Rammer, 2006).

Cooperation is the active participation in joint R&D and other technological innovation projects with other organisations, not implying immediate profits (DGEEC, 2016). Since the 1980s, greater attention has been devoted to firm's external relationships, especially with other firms, as a means to build the expertise required and reduce the risks associated with the innovation process (Becker & Dietz, 2004; Tether, 2002; Varis & Littunen, 2010). In this sense, cooperation is key for its success which has become increasingly important due to the current complex and demanding environment where knowledge rises in quantity and specificity (Camacho & Rodríguez, 2005; de Faria, Lima, & Santos, 2010; Gailly, 2011). Cooperation with external partners is usually linked with strategies that combine both product and process innovations (Piga & Vivarelli, 2004; White, Braczyk, Ghobadian, & Niebuhr, 1988) and international cooperation shows a positive effect on the innovative performance of firms (Arvanitis & Bolli, 2013; Rammer et al., 2009).

A firm's involvement in an economic group also affects its innovation strategy. Such a group is defined as an association of organisations segmented by the existence of parent and subsidiary firms that function as a unique economic entity (The Council of the European Communities, 1993). It allows a firm to operate with larger resources and deeper experience, besides the risk-sharing advantage that it provides (Ballot et al., 2015; Eurostat, 1993; Fonseca, 2014; Tether, 2002). As such, firms belonging to an economic group are more likely to be innovators (Mohnen & Röller, 2005; Tether, 2002), although, in a study conducted by Fonseca (2014), only service firms have a higher probability of being engaged in innovation in such a group, since for manufacturing firms no relation is found.

Finally, time gives experience and this factor is also valid for companies. Indeed, Teece & Pisano (1994) conclude that experience is a source of competitive advantage that enables companies to demonstrate prompt responsiveness, management capability and effective reallocation of internal and external competences to thrive in the market. Pavitt (1990) also argues that firms (whose performance is judged in the long-term) accumulate knowledge from current and past projects, benefiting the exploitation of future technological opportunities. Thus, firm's age, as a measure of accumulated experience, is expected to have a positive impact on innovation (Fonseca et al., 2019; Sorensen & Stuart, 2000), in particular, for product innovation (Baumann & Kritikos, 2016). Furthermore, this factor can also reveal some trends on the choice between product and process innovation as we mention in the last paragraph of Section 3.1.

3.6 The Impact of Joint Product and Process Innovations Strategies

The existing interdependencies between product and process innovations suggest that many studies, scoped by only one type of innovation, may have overlooked important relationships between these two (Ballot et al., 2015; Gailly, 2011). Similarly, literature often reinforces that joint strategies of different forms of innovation leverage higher economic value and focuses especially on the combination of product and process innovations (Ballot et al., 2015; Bauer & Leker, 2013; Damanpour & Gopalakrishnan, 2001; Damanpour et al., 2009; Schmidt & Rammer, 2006). However, this idea dwindles when considering it from a exploration-exploitation dilemma point of view: joining both product and process innovation may hamper performance if firms do not balance these through proper mechanisms (Benner & Tushman, 2015; Lavie et al., 2010).

March's (1991) seminal work is mainly responsible for introducing the fundamental distinction between exploration and exploitation in organisational learning. March conceptualises exploration as the engagement of organisations in search, experimentation, and variation, while exploitation as organisations' activities to increase productivity and efficiency through choice, execution, and variance reduction. His framework received substantial interest from scholars to study such phenomena in a wide variety of fields; however, for the purpose of our analysis, we constrain our scope to the organisational macro-level (Lavie et al., 2010). In this regard, exploitation is built on the firm's past, as it consists of improving the organisation's existing capabilities as long as it persists within an existing technological trajectory (Gailly, 2011; Lavie et al., 2010; Lewin, Long, & Carroll, 1999; Smith & Tushman, 2005). Exploration creates the firm's future by decoupling it from its current capabilities through new technical skills and market expertise (Gailly, 2011; Lavie et al., 2010; Smith & Tushman, 2005).

Resource-allocation decisions therefore create a trade-off between exploration and exploitation of innovation activities. Either a firm gains new information to have future returns or it uses existing information to improve present returns (He & Wong, 2004; Lavie et al., 2010; March, 1991). Choosing exploration implies a weaker production system, higher business uncertainty and risk, but also long-term economic growth, higher flexibility, and a larger pool of alternatives to problem-solving. Following exploitation implies stability and immediate reliability, but excessive rigidity towards new opportunities and a higher probability of becoming obsolete in the years ahead (Gailly, 2011; Katila & Ahuja, 2002; Lewin et al., 1999; March, 1991; O´Reilly & Tushman, 2013; Sorensen & Stuart, 2000). Despite this trade-off, firms are still able to mutually benefit from both exploration and exploitation depending on their resources. In this way, firms are able to outperform their competitors today, while ensuring a sustainable advantage tomorrow (Gailly, 2011; He & Wong, 2004; Katila & Ahuja, 2002; Koza & Lewin, 1998, 2000). The degree to which a firm should balance exploration and exploitation activities depends on the organisation's reality; however, effective management is as essential to survival as the generation of new alternative practices (Benner & Tushman, 2003; Caspin-Wagner, Ellis, & Tishler, 2012; Gailly, 2011; He & Wong, 2004; March, 1991).

The idea of balancing both activities creates a new type of organisational strategy to distinguish firms that somehow are capable of complementing exploration with exploitation — this is termed ambidexterity (Birkinshaw & Gibson, 2004b; Lubatkin, Simsek, Ling, & Veiga, 2006; Tushman & O´Reilly, 1996). An ambidextrous firm is capable of competing in markets with low cost and high efficiency levels, while developing new products for emerging markets where speed and flexibility are key (Simsek et al., 2009; Tushman & O´Reilly, 1996). It is important to note that ambidextrous firms still experience the resulting tensions of joining both exploration and exploitation activities, but these firms find ways of managing them in the same organisation (Benner & Tushman, 2003; Birkinshaw & Gibson, 2004b; He & Wong, 2004; Lewin et al., 1999; Simsek et al., 2009). Whether or not a firm accomplishes a superior performance compared to exploitative or explorative organisations, depends on how it deploys its ambidextrous strategy (Caspin-Wagner et al., 2012; Geerts, Blindenbach-Driessen, & Gemmel, 2010; He & Wong, 2004; Lin, Yang, & Demirkan, 2007). For instance, either pushing both exploration and exploitation levels to extreme limits or keeping low levels of both does not contribute to superior performance (Caspin-Wagner et al., 2012; He & Wong, 2004).

One of the possible remedies for the trade-off between exploration and exploitation goes through a strategy of not pursuing them concurrently in the same organisational unit (Benner & Tushman, 2003; Birkinshaw & Gibson, 2004a; Lavie et al., 2010). Structurally ambidextrous organisations are split into highly differentiated units that exhibit a single and internal consistency in tasks and culture, while across units they reveal inconsistency in their organisational layout (Benner & Tushman, 2003; Tushman & O´Reilly, 1996). Hence, the parent company breaks down into exploitative and explorative units, where the former is larger, more centralized, and aims to maximize efficiency, and the latter is smaller, more flexible, and aims to innovate through trial and error (Benner & Tushman, 2003). Although some scholars classify this approach outside the ambidexterity spectrum (e.g. Lavie et al. [2010]), others see it as a form of ambidexterity (e.g. Venkatraman, Lee, & Iyer [2007]). For the purpose of this research, we follow the latter since the firm heading the corporate group bares the responsibility of deciding which strategy each unit must follow. Although from the unit’s point of view both activities are isolated, from the parent firm’s perspective, exploitation and exploration activities are followed inwards (Benner & Tushman, 2003).

Literature also presents two other types of ambidexterity: contextual and sequential strategies (Birkinshaw & Gibson, 2004a; Foss & Kirkegaard, in press; O´Reilly & Tushman, 2013). When employees are responsible for managing their time and attention between explorative and exploitative activities, a firm makes use of a contextual strategy (Birkinshaw & Gibson, 2004a; Lavie et al., 2010). Here, an organisation embraces a flexible attitude and trusts employees' judgement to balance its efforts towards exploration and exploitation (Birkinshaw & Gibson, 2004a, 2004b). Alternatively, in a sequential strategy, a firm switches between cycles of either explorative or exploitative activities by changing its structures over time (Birkinshaw & Gibson, 2004a; Foss & Kirkegaard, in press). In doing so, the organisation evades conflicting pressures of pursuing exploration and exploitation simultaneously, although in time of transitions — which usually involves slow and gradual processes — some frictions may arise (Lavie et al., 2010). Literature usually regards different types of ambidexterity as discrete values (Foss & Kirkegaard, in press), however new evidence supports that these may actually coexist (Birkinshaw & Gibson, 2004b; Foss & Kirkegaard, press; O´Reilly & Tushman, 2013).

The exploration-exploitation stream of literature becomes so influential partially because it challenges the beliefs under process management (Benner & Tushman, 2015). Without disregarding the benefits also derived from process improvement practices, this stream provides a plausible set of arguments based on the idea that process management may also be harmful for some organisations (Benner & Tushman, 2003; Ittner & Larcker, 1997). By developing a model to assess how process management activities affect technological innovation, Benner & Tushman (2003) find that the implementation of new process management techniques favour exploitative innovation at the expense of explorative innovation. This finding backs the intuition that, as process management practices spread in an organisation, the firm’s objectives get increasingly focused on speed, efficiency, and reductions in costs or waste, leading to a selection bias towards innovations that may only boost the firm’s processes (Benner & Tushman, 2003).

By bridging the exploration-exploitation theory with the decision of following product and process innovation, we argue that firms hamper their innovation performance by pursuing both types of innovation. Following this, we reflect on the literature advocating for a combination of product and process innovation which leverages a higher economic value. In case of performance hindrances, ambidextrous strategies may remediate each firm’s innovation propensity strategy. Moreover, by recognizing that firms are constrained by their organisational characteristics (Jin et al., 2016; Lavie et al., 2010), we narrow our focus to the effect of firm size. In this regard, there is some evidence that large firms are less harmed by their decision of joining both explorative and exploitative activities through their ability to leverage a larger amount of resources (Lin et al., 2007; O´Reilly & Tushman, 2013). Hence, we extend these findings on the exploration-exploitation construct to assess the effect of firm size on the decision of pursuing joint innovation strategies.

From our analysis, it is reasonable to expect that joint innovation strategies contribute to innovation performance hindrances and that large firms are less effected than their counterparts. We thus hypothesise that:

H3: Depending on firm size, there are frictions between product and process innovation when these two are followed simultaneously in the same firm.

> H3.1: A large firm experiences fewer trade-offs than a smaller firm when both product and process innovations are followed.

4. Data Characterisation

4.1 The Community Innovation Survey

The Community Innovation Survey (CIS) is one of the mechanisms employed in the European Policy context to measure and analyse innovation. It provides comparable information between European countries, unveiling relative strengths and weaknesses of national innovation systems (Commission of the European Communities, 2003; Hollanders, Es-Sadki, & Merkelbach, 2019; OECD, 2006; Reichstein & Salter, 2006). Implemented in 1991, the CIS is used to collect microdata on firms' innovative activities and various factors that comprise the development of innovation. This firm-level survey is implemented via Eurostat and national statistics offices and is not mandatory for the targeted countries — EU and ESS member countries. Furthermore, it follows the conceptual framework established in the Oslo Manual and has a two-year frequency (DGEEC, n.d.; Eurostat, 2017; OECD, 2006).

Regarding the CIS infrastructure, each version corresponds to one wave which comprises a time gap of three years. The questionnaire administrated by each country needs to follow the Eurostat guidelines although some additional questions can be added regarding the context of each participant country. Although it is based on self-reported information from firm managers, which might give rise to some subjectivity, after several trials of piloting and testing before implementation the survey has a high degree of reliability and validity (Laursen & Salter, 2006; OECD/Eurostat, 2018). Furthermore, studies using more than one wave tend to get more stable results, as well as macroeconomic events reflected in the outcome analysed, which enriches their own quality and interpretability degree. It is, therefore, a tool to be a cornerstone of any country's policy that aims to better understand firms' innovative performance and strategy (Fonseca, 2014; Laursen & Salter, 2006).

To measure innovation, the CIS uses a binary variable that classifies each firm as an innovator or not for each type of innovation in the data set (DGEEC, 2016). The survey defines an innovator as a firm that made at least one type of innovation during the surveyed period. Hence, a firm that introduced at least one new or significantly improved good or service is designated a product innovator. The same would happen for process innovation, if a firm introduced either new or significantly improved methods of production, logistics, delivery, or supporting activities (DGEEC, 2016). Moreover, the data set provides a measure to quantify innovations' economic impact through the percentage of the total sales derived from new products. It is also important to note that the CIS measures "new to the firm" and "new to the market" intensity-types of product innovation. In this work, we consider both forms which make an innovation within the firm enough to classify it as an innovator. Following this, the variable age may have an opposite result from what we were expecting for product innovation, as newly established firms will always have to implement new products in order to start their businesses (Tether, 2002).

4.2 Integrated Business Accounts System Data Set

The Integrated Business Accounts System data set *(Sistema de Contas Integradas das Empresas — SCIE*), collects firms' administrative information to characterize their financial behaviour, allowing the analysis and assessment of the economic evolution of Portugal's corporate conjuncture. Statistics

Portugal provides the data set, whose information results from the combination of the Simplified Business Information System with data from the Tributary and Customs Authority and the Statistic Units File. Thus, the data set covers vast statistical information and specific variables related to Portuguese firms' activity (INE, 2012).

The database is released annually, and its population comprises both the self-employed and firms that produced goods and/or services during the reference period in Portugal. It excludes organisations from the agricultural, financial, and public administration and defence sectors, as well as non-market-oriented firms. Its variables represent firms' economic figures (balance sheet and income statement) and their respective economic and financial ratios. The data set also includes information on economic activity, number of employees, and operational regions (INE, 2012).

4.3 Working Sample

We analyse the Portuguese version of the CIS from the 7th wave, 2010 edition, and finish in the 11th wave, 2018 edition, due to the absence of more recent versions at the time of writing. We are thus analysing the time gap between 2008 and 2018. The CIS comprehends any inquired manufacturing or service firm with ten or more workers, established in Portugal. Firms may appear either in a single wave or in multiple waves, as the CIS is not a longitudinal data set. Additionally, some sectors are not included in the CIS. For instance, the agriculture, animal production and fishing activities.[8] Furthermore, the information provided reports on a subsidiary level (DGEEC, 2016).

In order to work with a greater level of detail, we pair the CIS with the SCIE data set. This allows us to overcome the disadvantage of micro-aggregated level data entailed in the CIS. Here, the information is a composite of multiple firms rather than a single organisation, which hinders the interpretation of the effects of different types of innovation (Ballot et al., 2015; DGEEC, 2016; Mohnen & Röller, 2005). By adding the data from the SCIE, we are able to complement the CIS data with additional variables important to our analyses. To match both databases, we drop economic activity sectors present in only one of them. Therefore, from the sectors initially included in the CIS, we remove section K from CAE-Rev.3. Additionally, some classes from section B, D, E, and F are dropped as these are not contemplated in NACE-Rev.2, the nomenclature we use to build our industry aggregation level. Overall, our sample is composed of 32,621 observations, in which 55.93% belongs to the manufacturing sector and 44.07% to the service sector.[9]

4.4 Variables Definition

In this section, we assign concrete measures to build the variables of the following econometric models. It is very important to keep our literature review in mind, as we target our main variable of study, firm size, and discuss other possible determinants that we find to impact a firm's innovation strategy. We

[8] See Table A and Table B, in Appendix, for further details on the set of sectors included in the survey.

[9] The final number of observations may vary across the analysis due to the absence of some variables in their respective database at the beginning of our study.

point out human capital, R&D activities, competitive markets, exports, advanced capital, cooperation, type of industry, economic group, and age.

Starting from the dependent variables, we assess product and process innovations through two different methods. The first one looks at a firm's probability to innovate, while the second looks at its innovation performance. We operationalize the former using a set of dummies for each innovation type. The variable for product innovation takes the value of one when the firm introduces a product and zero otherwise. The same happens for process innovation, which is one when the firm introduces a process innovation through manufacturing methods, logistic and delivery methods, or support activities to the firm's processes. Additionally, we create a dummy variable for firms that engage in both product and process innovation at the same time: the dummy takes the value of one when the company does both product and process innovation and zero otherwise. These values are retrieved from the CIS database.

Regarding innovation performance, we measure firms' ability to translate innovation activities into market success, aware that it constraints our analysis only to the product innovation performance, as discussed in Section 3.3. In fact, none of our databases provides us with the right information to account for process innovation performance. Conversely, we have a direct and objective metric through the CIS database that provides firms' revenues from the sale of product innovations. Thus, in joining this with the total revenues of each company, retrieved from the SCIE, we are able to construct the total sales of innovative products sold. Additionally, we use a logarithmic transformation as well as GPD deflators for the last wave-year, to approximate the data to a normal distribution and to consider the time value of money, respectively.[10]

Looking now at the independent variables. Many indicators can be used to measure firm size. Either through sales, total assets, market value, or total employment, firm size has played out a crucial role in applied microeconomics (Shalit & Sankar, 1977). However, different measures usually lead to disparate results (Scherer, 1965b; Smyth, Boyes, & Peseau, 1975). We measure firm size as the number of employees, in line with Acs & Audretsch (1987, 1988b, 1988a), through a 3-level categorical variable, whose first level corresponds to small firms (10 to 49 workers), the second to medium firms (50 to 249 workers), and the last to large firms (250 workers or more). We alternatively measure firm size in the numerical form using the number of employees collected from the SCIE.

Besides firm size, we also control for other factors, such as firm characteristics and industry effects, in our econometric models (W. M. Cohen, 2010; Wooldridge, 2016). For each determinant, we build more than one metric in order to get the most stable and significant results out of our estimations. This cross-check method is only possible due to the fact we use two databases that often provide different information for the same determinant. Furthermore, all the following measures indicate values for each period corresponding to each CIS wave.[11]

Human capital is broken down into two components: training and education (also referred to as college degree). We use a dummy variable to assess whether a company perform training activities and a

[10] Source: INE, PORDATA. Retrieved from https://www.pordata.pt/en/DB/Portugal/Search+Environment/Table/5813910.
[11] See Table C, Table D, and Table E, in Appendix, for a summary of the full set of variables considered throughout our analysis.

numerical variable for the total expenses on training activities. For education, we use an indicator that measures six categorical levels in terms of percentage of employees that have university studies (0=0%; 1=1–4%; 2=5–9%; 3=10–24%; 4=25–49%; 5=50–74%; 6=75–100%). However, we group it into a binary variable by its sample average. Hence, we are capturing if firms' college labour is higher or lower than the average. All metrics are retained from the CIS, except the numerical variable that comes from the SCIE.

Additionally, R&D activities and advanced capital are also gauged through the original database. For the first one, we build dummy variables that report whether internal and external R&D activities are performed in each period. These metrics are complemented with their expenditure level, aggregated in a 3-cluster dimension of firm size, region, and economic activity sector. Note that, internal R&D extends to every activity realized within the statistical unit whose information is being reported, while external extends to every activity acquired from the outside of this same unit (DGEEC, 2016). These may be further grouped into one variable, total R&D activities. For advanced capital, we apply the same structure: a dummy variable that takes a value of one if a firm acquired machinery, equipment, and software for each period and zero otherwise, and a numerical variable with the aggregated expenditure on advanced capital.

Exports level has two different set of dummies. In the first one, we measure whether a company is an exporter, with information provided in the CIS. The second one is an intensity-oriented measure and gauges both if a firm is an exporter and the importance of its foreign markets — the variable takes one if the firm's largest geographical market is outside Portugal, and zero if it is a national market. This variable combines information both from the CIS and the SCIE. The economic group determinant embodies the same dummy variable structure and comes from the CIS: we observe the value one if the company belongs to a group such as this, and zero otherwise.

As we have already discussed, the cooperation related literature has been burgeoning as a key component of the innovation process. It gives entities a shared knowledge and technological resources in a two-way approach which allows them to develop innovations at a faster rate. Thus, cooperation can come in a variety of forms, linking any type of entity that wants to strengthen its market position with knowledge from others' experiences and resources (de Faria et al., 2010). For this reason, we do not intend to get deeper into this stream of literature by providing a proper background of the key elements that are related to the importance of cooperation. Yet, we add a dummy variable that takes the value of one if the company cooperated with any other entity and zero otherwise.

Competition and additional industry-related effects are contemplated in a 4-level categorical variable based on the NACE (*Nomenclature statistique des activités économiques dans la Communauté européenne*) framework, the Statistical classification of economic activities in the European Community. We use the Eurostat aggregation of the manufacturing and service industries according to their technological or knowledge intensity to join some NACE categories in order to provide a higher level of aggregation (Eurostat, 2016b, 2016a, 2018; OECD, 2003; Tether, 2002).[12] Finally, age is a numerical

[12] See Table F, in Appendix, for further details on the industry aggregation level here defined, as well as the allocation of each class of CAE-Rev.3.

variable representing how old each firm is, which comes from the *Quadros de Pessoal* (QP) database, and the economic cycle is considered through CIS wave-year dummies (Fonseca et al., 2019).[13]

4.5 Descriptive Statistics

4.5.1 Sample Description

In this section, we look to describe our sample to give a clearer view of the issue at hand. A special focus towards firm size is followed since our primary goal is to study its variation against each type of innovation. Regarding this metric there are three possible classes defined in our data set: small firms range from 10 to 49 workers, medium firms from 50 to 249 workers and large firms have 250 workers or more. Moreover, Figure 1 shows the distribution of firms over firm size categories, which allows to see that about 70% of the total firms sampled have less than 50 employees.

By breaking down industries based on their technological intensity (Figure 2), we find that 46.34% of the firms in the sample belong to the low-technology manufacturing sector. Less knowledge-intensive services comes in second with a share of 27.24%. The two sectors that require higher level of technology or knowledge appear after, manufacturing being the smallest segment with 9.59%.

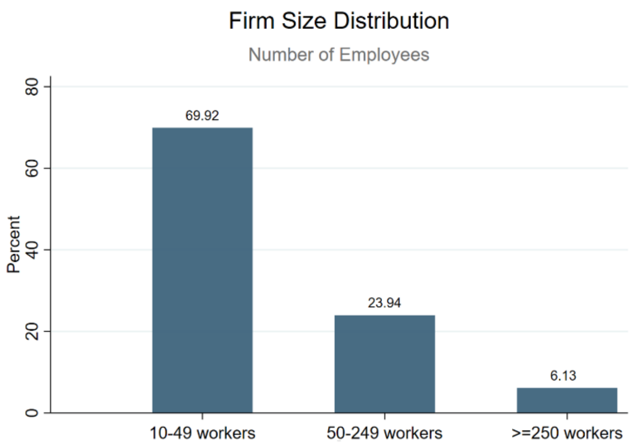

Figure 1 | Firm size percentage distribution in the data set. Analysis for 32,621 observations.

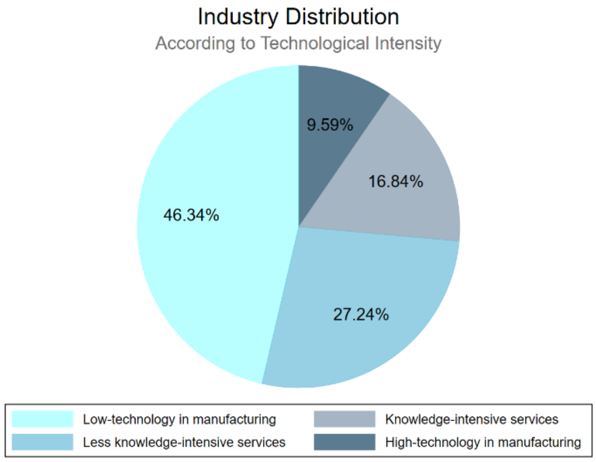

Figure 2 | Sample distribution over the industry aggregation level defined in this study. Analysis for 32,621 observations.

4.5.2 Preliminary Analysis

We now focus on how innovation is distributed over our sample, as well as its link with our main variable of interest — firm size. Following this, we aim to understand how often firms conduct innovative activities and which types of innovation are commonly pursued. Likewise, by targeting our main objective, we also hope to identify patterns of innovation over firm size categories which might provide insights to the subsequent parts of our study. Note that we classify innovators into three groups: one for firms that are only product innovators, other for firms that are only process innovators, and a joint class that groups firms that did both types of innovation.

[13] *Quadros de Pessoal* data set was consulted to retrieve information only on the variable age, despite its variables' broad scope.

We see in Figure 3 a balanced distribution with 48.59% belonging to innovators, and 51.41% to firms that did not introduce any type of innovation, over the period 2008 to 2018. This result suggests that the CIS probably oversamples innovating firms. Among innovators, 15.97% are only product innovators, 26.62% are only process innovators, and 57.41% are product and process innovators (Figure 4). This is not surprising as joint strategies of different forms of innovation may leverage higher economic value.

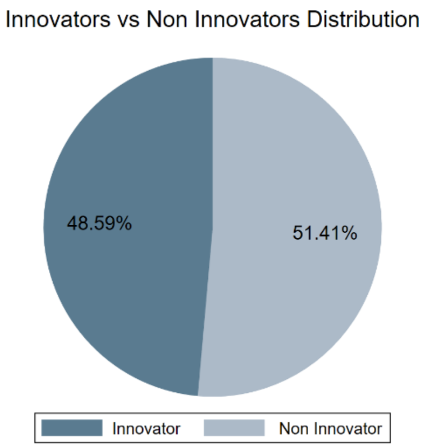

Figure 3 | Percentage of innovators and non-innovators in the data set. Analysis for 32,621 observations.

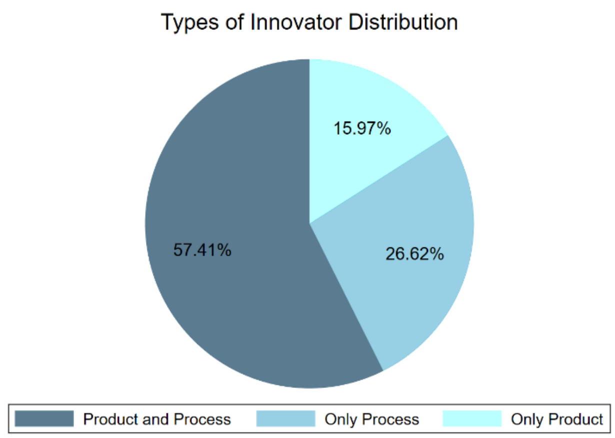

Figure 4 | Percentage of types of innovator in the data set. Analysis for 15,850 observations.

Figure 5 presents the four most relevant barriers to innovation reported by non-innovators. Competitive markets and uncertain demand accurately represent a firm's uncertainties when facing innovation, while funding and skilled workers are two key resources that hinder the capture of innovation opportunities (Gailly, 2011). We see that the greatest setback is the lack of funding and that lack of skilled workers comes in last. If we consider that the larger the firm, the greater the access to funds is, we may expect a positive relation between firm size and the propensity to do innovation. Similarly, less competitive markets also seem to induce a higher level of innovation.

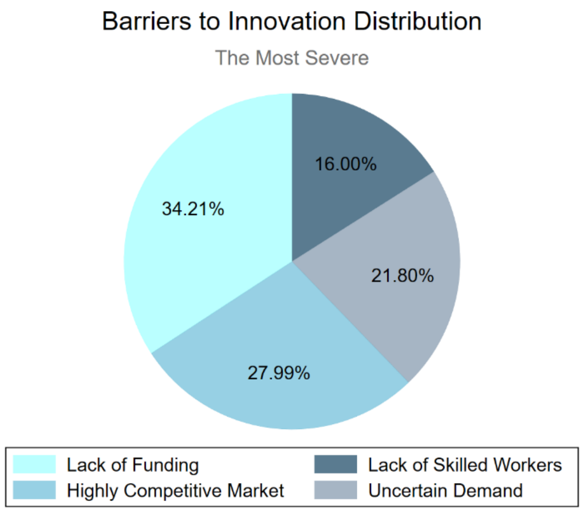

Figure 5 | Percentage distribution of the four most relevant barriers to innovation reported by non-innovators. Analysis for 16,771 observations.

We now devote our attention to our first analysis on the firm size-innovation relationship and segment the data by each firm size class. While Figure 1 presents results over the total sample, Figure 6 only considers the innovators. We see that the gap between the total number of firms with 10–49 workers prevails over the other categories. However, small firms now account for a lower percentage (61.43%) in detriment of the other two size classes, compared to Figure 1 (69.92%).

By analysing the percentage distribution of innovators and non-innovators within each size class (Figure 7), we can properly size the extent to which each class contributes to the number of innovators. Thus, we see that large firms have the largest concentration of innovators, where almost 75 firms innovate for every 100 large firms. Conversely, the class with the lowest percentage, small firms, is the same with the greatest expression among the total number of innovators in Figure 6.

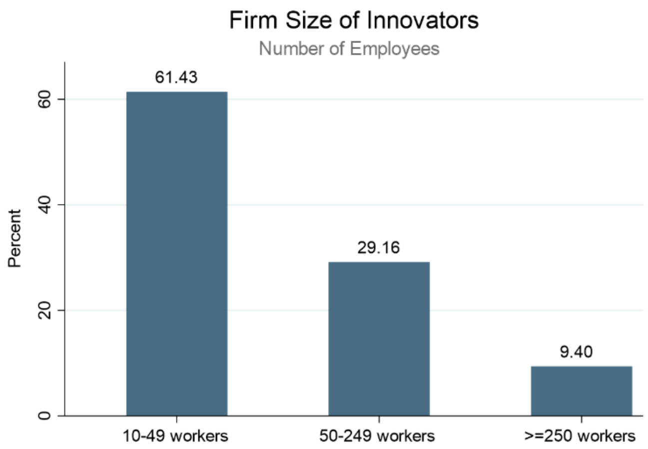

Figure 6 | Firm size percentage distribution among innovators in the data set. Analysis for 15,850 observations.

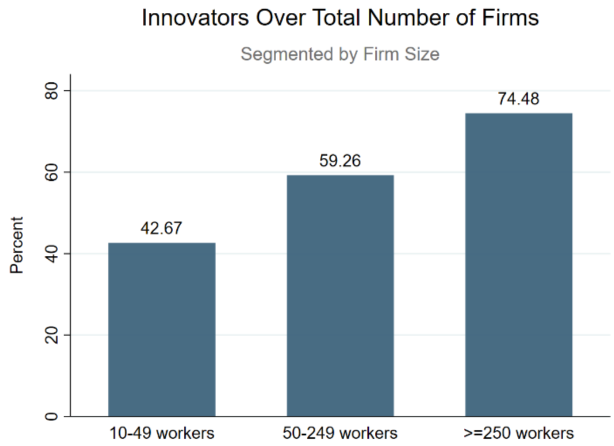

Figure 7 | Percentage of innovators within each class in the data set. Analysis for 32,621 observations.

By breaking innovators into the three types here studied, we add on our analysis findings related to the type of innovation that is most used in each category. In Figure 8, we see that every size class engages more in the joint category of product and process, but small firms have more innovators pursuing only product or only process innovation in detriment to the joint class. We also notice that large firms are the most engaged size class in joining both product and process innovation.

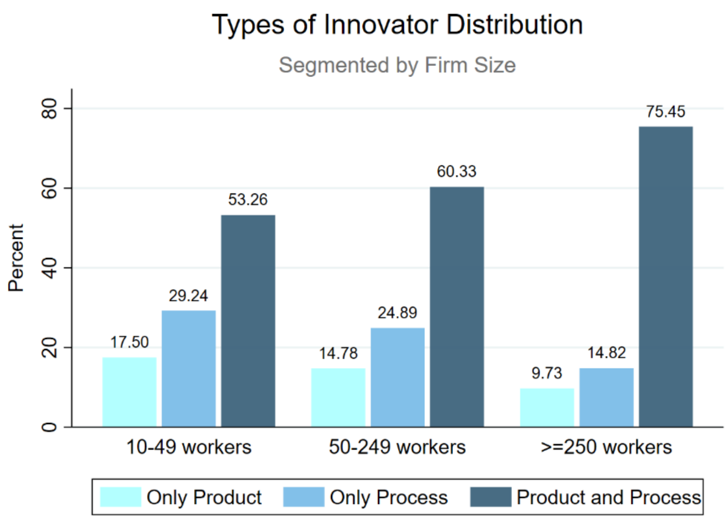

Figure 8 | Percentage of types of innovators in the data set, segmented by firm size. Analysis for 15,850 observations.

Delving now into the purpose of our second analysis — to study the effects of joint innovation strategies on firm's innovation performance — Figure 9 presents the mean of the revenues from product innovations earned by a firm depending on its innovation propensity strategy. An organisation only following product innovation receives, on average, €2.13 million, while one following both product and process innovations, at the same time, earns €6.83 million, on average. A firm that does not engage in both types simultaneously only makes 31.19% of what it would make if it followed a joint innovation strategy. Hence, firms that join both types of innovation experience superior performance.

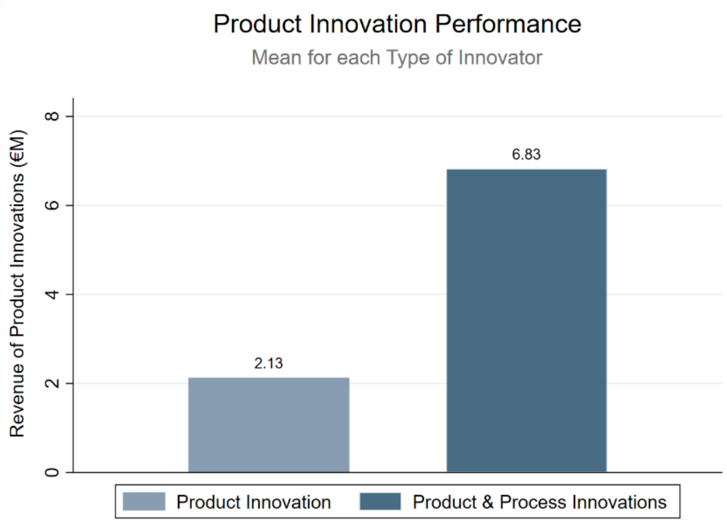

Figure 9 | Mean of product innovation performance for each type of innovator. Analysis for 2,532 product innovators and 9,099 product and process innovators.

However, different patterns arise when we segment by each size class. Following Figure 10, we see each firm's average revenue from the sale of product innovations, depending on the types of innovation followed and on its dimension class. Large firms benefit the most in pursuing both product and process innovations at the same time, attaining on average €30.54 million more in revenue. Conversely, medium firms benefit the least from following joint innovation strategies, receiving an average of €0.1 million more in their product innovation revenues. The difference between the motivation of different size class is further understood when we look at the percentages. Large firms only achieve 26.25% of revenues from joint product and process innovations, small firms receive 74.29%, and medium firms maintain 99.78% of their revenues when they do not follow joint innovation strategies.

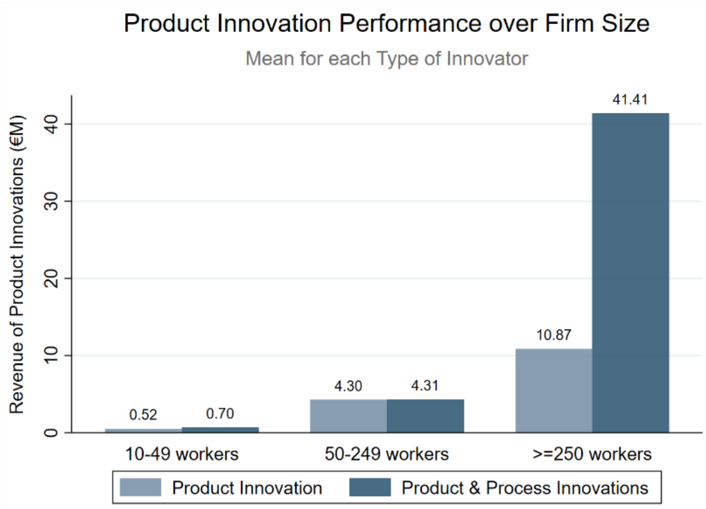

Figure 10 | Mean of product innovation performance for each type of innovator over firm size. Analysis for 2,532 product innovators and 9,099 product and process innovators.

Therefore, we expect to see in the upcoming models a greater incentive for large firms pursuing innovation propensity strategies that join both product and process innovation than for small and medium firms. Through further analysis, we can also observe which size class, between the small and medium ones, has the largest gain in engaging in both types of innovation.

4.5.3 Summary Statistics

Table 2 presents summary statistics of the variables defined in Section 4.4. We see that firms that belong to an economic group have a higher probability of innovating, especially in the joint class. In the advanced capital variable, the same trend is observed but less for product innovation — it seems not to have a great impact on this type, while it is the most relevant in strategies that join both product and process innovations. Likewise, firms that pursue both types of innovation at the same time perform more training activities. This trend is further reinforced by the expenditures' figure: firms that do both types of innovation invest more in this class when compared to other types of innovators. However, there is still a significant gap between non-innovators and innovators in general, which indicates that training possibly has a significant role in the upcoming econometric models. Regarding education, it has a greater impact on the product and joint category. The employees of process innovators have a low percentage of university degrees, following the same trend of firms that do not innovate. Smaller firms have a higher expression in every type of innovation and are the only class with a joint category share lower than the other two. This reinforces our findings of the preliminary analysis: small firms pursue more product and process innovations separately than their counterparts. Firm size numerical variable also shows that, on average, product and process innovators are smaller than firms that follow both types of innovation simultaneously.

In the industry variable, we find that either for the product, process, or joint class, the industry that is most represented is the low-tech manufacturing. However, it is also important to notice that the majority of firms sampled (46%) belongs to this industry. R&D activities in general are not often pursued among process innovators, which opposes the other two types. The numerical figures of this determinant clearly show that the product and process innovators represent the class that invests the most in R&D, following product innovators. The level of exports has a higher expression in firms that do both types of innovation with around 79% of these firms selling abroad. Between product and process innovation, by gathering the two export related dummies, we conclude that although product innovators are the second ones that export more (74% against 67%), both groups have the same percentage of firms perceiving the foreign market as their largest one. Concerning cooperation, it reveals that firms doing both types of innovation at the same time cooperate more than any other type. Finally, age is fairly constant over classes.

Table 2 | Summary statistics.

SUMMARY STATISTICS						
Variables		All	Non-Innovator	Type of Innovation Strategy		
				Product	Process	Both
Economic Group		0.26	0.20	0.31	0.24	0.36
		(0.44)	(0.40)	(0.46)	(0.43)	(0.48)
		1 = "Belonged to an economic group" ; 0 = " Otherwise"				
Advanced Capital		0.44	0.19	0.40	0.65	0.78
		(0.50)	(0.39)	(0.49)	(0.48)	(0.42)
		1 = "Acquired advanced capital" ; 0 = " Otherwise"				
Training	Num	6.90	3.02	6.67	6.28	14.31
		(54.86)	(30.68)	(35.21)	(72.91)	(78.44)
		€ x1000				
	Dum	0.36	0.14	0.44	0.48	0.67
		(0.48)	(0.35)	(0.50)	(0.50)	(0.47)
		1 = "Carried out this activity" ; 0 = " Otherwise"				
College Degree		0.42	0.33	0.53	0.41	0.55
		(0.49)	(0.47)	(0.50)	(0.49)	(0.50)
		0 = "0 to 9% of employees have degree" ; 1 = "10 to 100% have degree"				
Firm Size	1	0.70	0.78	0.67	0.68	0.57
		(0.46)	(0.41)	(0.47)	(0.47)	(0.50)
	2	0.24	0.19	0.27	0.27	0.31
		(0.43)	(0.39)	(0.44)	(0.45)	(0.46)
	3	0.06	0.03	0.06	0.05	0.12
		(0.24)	(0.17)	(0.23)	(0.22)	(0.33)
		1 = "10-49 workers" ; 2 = "50-249 workers" ; 3 = ">=250 workers"				
	Num	82.74	47.70	70.65	73.76	154.03
		(445.86)	(103.59)	(159.71)	(249.45)	(802.26)
Cooperation		0.12	0.01	0.16	0.10	0.30
		(0.32)	(0.97)	(0.37)	(0.30)	(0.46)
		1 = "Cooperated" ; 0 = " Otherwise"				
Industry	1	0.10	0.06	0.14	0.08	0.16
		(0.44)	(0.24)	(0.34)	(0.27)	(0.36)
	2	0.46	0.48	0.39	0.49	0.45
		(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
	3	0.17	0.16	0.23	0.13	0.18
		(0.37)	(0.37)	(0.42)	(0.34)	(0.39)
	4	0.27	0.30	0.25	0.30	0.21
		(0.45)	(0.46)	0.43	(0.46)	(0.41)
		1 = "High-tech (manuf.)" ; 2 = "Low-tech (manuf.)" ; 3 = "KIS" ; 4 = "LKIS"				
R&D Activities	Ext Dum	0.12	0.01	0.19	0.14	0.31
		(0.33)	(0.09)	(0.39)	(0.35)	(0.46)
		Ext = "External" ; 1 = "Carried out this activity" ; 0 = " Otherwise"				
	Int Dum	0.32	0.02	0.58	0.36	0.77
		(0.65)	(0.20)	(0.78)	(0.71)	(0.80)
		Int = "Internal" ; 1 = "Carried out this activity" ; 0 = " Otherwise"				
	Int Num	98.04	4.89	173.91	28.52	278.31
		(1,376)	(142.87)	(2,121.59)	(198.88)	(2,318.17)
		Int = "Internal" ; € x1000				
	Ext Num	19.00	0.73	22.44	7.93	56.36
		(0.33)	(30.59)	(267.92)	(100.74)	(600.17)
		Ext = "External" ; € x1000				
Exports	Dum	0.66	0.57	0.74	0.67	0.79
		(0.48)	(0.50)	(0.44)	(0.47)	(0.41)
		1="Exporter" ; 0 = " Otherwise"				
	Inten Dum	0.21	0.16	0.21	0.21	0.29
		(0.44)	(0.37)	(0.41)	(0.41)	(0.45)
		Inten = "intensity" ; 0 = "Largest market at home" ; 1="Largest market abroad"				
Age	Num	22.02	21.47	23.29	21.94	22.71
		(17.69)	(16.53)	(18.51)	(17.07)	(19.62)
Innovation Performance	Num	-	-	2,131	-	6,828
				(12,300)		(60,030)
		€ x1000				

Note: The values are the mean and the standard deviation between parentheses; "Dum" stands for dummy variable; "Num" stands for numerical variable.

5. Research Methodology

An empirical analysis uses data to test a theory or to estimate a relationship. Through econometric methods, we aim to shed light on new findings for the literature and support other existing ones. We used cross sectional and non-experimental data through the CIS and the SCIE data sets. To estimate economic relationships, test economic theories, and evaluate government and business policies, we need to find associations between two or more variables, maintaining the notion of *ceteris paribus*. In other words, when we compare the effect of a variable x_1 on y in a model with k more variables, we need to hold all the other variables constant. In this way, we know that the final result of this interaction does not have perturbations from the variation of the other factors considered in the model. Hence, based on the purpose of this study, the effects we want to study, and the assumptions that each model must hold, we use the multiple regression and the probit models. The former is used in the last step of the selection model, while the latter is used in all other equations.[14]

5.1 Theoretical Background

5.1.1 Multiple Regression Model

Multiple regression analysis is more suitable to *ceteris paribus* analysis because it allows us to explicitly control for other factors that simultaneously affect the dependent variable. This becomes even more important when we rely on nonexperimental data. This model allows us to predict the value of a variable based on the value of two or more other variables. Hence, it can be written in the population as:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + u$$

Equation 1 | Multiple regression model with k independent variables.

Where β_0 is the intercept, u is the error term, β_1 is the parameter associated to x_1, and so forth. More precisely, u represents the other factors that also affect y but are not included in the regression. To estimate the parameters, we deploy the Ordinary Least Squares (OLS) method. Generally, the estimators $\widehat{\beta_0},\ \widehat{\beta_1}, \ldots, \widehat{\beta_k}$ are chosen simultaneously in order to minimize the sum of squared residuals:

$$min \sum_{i=1}^{n} (y_i - \widehat{\beta_0} - \widehat{\beta_1}\, x_{i1} - \cdots - \widehat{\beta_k}\, x_{ik})^2$$

Equation 2 | Minimization of the sum of squared residuals.

Where n represents the total number of observations and i each observation number. So, x_{ij} is the i^{th} observation on the j^{th} independent variable. It is from this operation where the name of Ordinary Least Squares arises. The final result gives the OLS regression line:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_k x_k$$

Equation 3 | Ordinary least squares regression line.

[14] For the main reference of this section number 5 see Cameron & Trivedi (2005), Enders (2010), Long & Freese (2014), Wooldridge (2002), and Wooldridge (2016).

Thus, we see that the OLS method chooses the intercept and the slope estimators for a particular sample, so that:

- The residuals approximate zero, which comes from the aforementioned minimization problem. We define residual for an observation i as:

$$\widehat{u_i} = y_i - \widehat{y_i} = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_k x_k)$$

Equation 4 | Residual for observation i.

- The sample correlation between each independent variable and the residuals equals zero, which can be summarized by:

$$E(\hat{u}|x_1, x_2, \dots, x_k) = 0$$

Equation 5 | Zero conditional mean assumption.

By getting these estimators, we can now interpret them and understand how to use them in an econometric model. The intercept $\hat{\beta}_0$ depicts a scenario where all explanatory variables equal zero. Despite not always tangible, we always need this figure to obtain any prediction for the dependent variable. The estimators associated to the explanatory variables have an interpretation of partial effects or, in other words, a *ceteris paribus* interpretation. So, the coefficient on x_1, $\hat{\beta}_1$, measures the change in $\hat{y}$ due to a one-unit increase in x_1, if we hold all other k independent variables fixed. In terms of change, turns into:

$$\Delta\hat{y} = \hat{\beta}_1 \Delta x_1 + \cdots + \hat{\beta}_k \Delta x_k$$

Equation 6 | Independent variables variation in the ordinary least squares regression line.

Holding all variables constant, except the one whose partial effect we want to measure on the predicted dependent variable, x_1, makes $\Delta x_j = 0$, and so:

$$\Delta\hat{y} = \hat{\beta}_1 \Delta x_1$$

Equation 7 | Partial effect of variable x_1 in y.

In order to measure how well the explanatory variables describe the dependent variable, one may compute the R-Squared. This goodness of fit measure summarizes how well the OLS regression line fits the data. Before introducing its formula, we need to define the following:

- The total sum of squares that measures the total sample variation, in other words, how y_i is distributed in the sample:

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2$$

Equation 8 | Total sum of squares.

  Note that, if we divide SST by $n - 1$ we get the sample variance.

- The explained sum of squares that measures the total sample variation, but this time in $\hat{y}_i$:

$$SSE = \sum_{i=1}^{n} (\hat{y}_i - \bar{\hat{y}})^2$$

Equation 9 | Explained sum of squares.

Note that, $\bar{\hat{y}} = \bar{y}$ because one of the algebraic properties of OLS estimates is $\sum_{i=1}^{n} \hat{u}_i = 0$ which is equivalent to $\sum_{i=1}^{n}(y_i - \widehat{\beta_0} - \widehat{\beta_1}\, x_{i1} - \cdots - \widehat{\beta_k}\, x_{ik}) = 0 \Leftrightarrow \sum_{i=1}^{n}(y_i - \hat{y}_i) = 0 \Leftrightarrow \sum_{i=1}^{n} \frac{(y_i)}{n} = \sum_{i=1}^{n} \frac{\hat{y}_i}{n} \Leftrightarrow \bar{\hat{y}} = \bar{y}$.

- The residual sum of squares which is equation number Equation 10 and represents the total sample variation in the $\hat{u}_i$:

$$SSR = \sum_{i=1}^{n} (\hat{u}_i)^2$$

Equation 10 | Residual sum of squares.

These three formulas are combined in the following way: $SST = SSE + SSR$.

So, assuming that $SST \neq 0$, the R-squared is represented by the ratio of the explained variation compared to the total variation. In other words, the OLS regression line explains the fraction of the sample variation in y:

$$R^2 \equiv \frac{SSE}{SST} = 1 - \frac{SSR}{SST}$$

Equation 11 | R-squared formula.

By definition, R^2 is a number between 0 and 1. However, since it never decreases and usually increases when another independent variable is added to a regression with the same set of observations, it is sometimes a poor tool. This happens because with new variables SSR usually becomes lower. Therefore, it is also important to work with the adjusted R-squared ($\bar{R}^2$), which imposes a penalty for adding independent variables to a model.

5.1.2 Probit Model for Binary Response

Our set of dependent variables has a binary response. To deal with these cases, econometrics provides in a first instance the Linear Probability Model (LPM), which offers an easy application procedure as well as a simple interpretation of its outcomes. However, the LPM lacks two important points: first, it is possible to get fitted probabilities either less than zero or greater than one, which invalidates any kind of interpretation since these must range between zero and one; second, as the LPM takes a linear approach, predicted probabilities do not maintain the same level of coherence over all possible values of the explanatory variable. For instance, in an example where the dependent variable is the probability of working and the independent one is the number of offspring, the partial effect of having the first child would have the same impact than the probability of having the second one — this does not reflect reality as subsequent children are believed to have a smaller marginal effect.

Thus, in order to overcome these shortfalls, we select a more complex binary response model underpinned on non-linear relationships. Before we proceed into its theoretical background, we must clarify that in every model whose response is of a binary type, the major interest of study relies on this event:

$$P(y = 1\,|\boldsymbol{x}) = P(y = 1|x_1, \dots, x_k)$$

Equation 12 | Response probability of a binary response model.

Where $\boldsymbol{x}$ is shorthand for the full set of explanatory variables and k is the total number of independent variables. So, in order to get away from the LPM linearity and its setbacks, we must add a function responsible for the non-linear transformation (designated by G), which ensures that the predicted probabilities are strictly laid down between zero and one:

$$P(y = 1\,|\boldsymbol{x}) = G(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)$$

Equation 13 | Class of binary response models.

This means that this function is able to transform any number, between $-\infty$ and $+\infty$, that comes from the aggregated sum of each independent variable, in another within the probability's main condition, $0 \leq P(x) \leq 1, \forall\, x \in \mathbb{R}$. We can easily inspect this effect in a graph, as Figure 11 shows.[15]

There are few models that offer this transformation with different G functions. We select the probit model, although, it is important to refer that the logit is often also pursued in these cases. The reasons that sustain one choice in detriment of the other are not as clear as the difference between the LPM and these two. Indeed, both statistical models are similar and often give practically identical results.

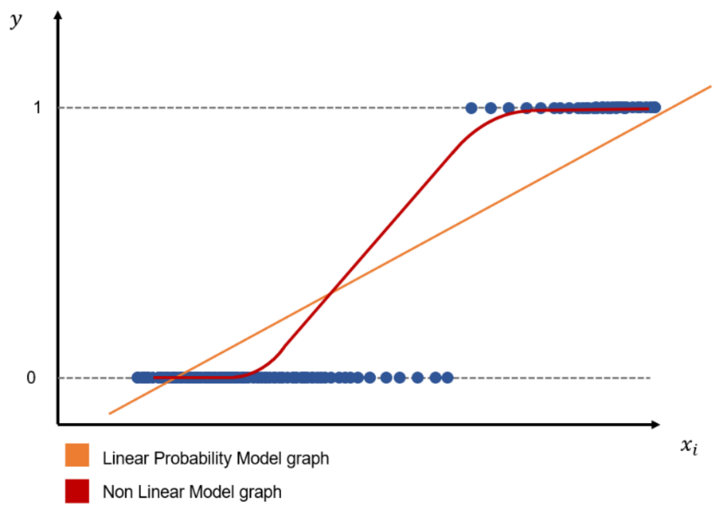

Figure 11 | Possible representation of a linear probability model and a non-linear model graphs.

[15] As we can see through this Figure, a Linear Probability Model would induce values that are not compatible with the probability's theory - indeed, we see the orange line going either below 0 or above 1. Contrarily, we have a much better scenario in the red line where its limits do not go beyond these two values and even offer a better representation of the points observed. So, to every value that xi may take the correspondent G function will guarantee a value between 0 and 1. Finally, it is important to mention that the Figure is not up to scale.

The probit model has a specific G associated with, the standard normal cumulative distribution function:

$$G(x) = \Phi(x) \equiv \int_{-\infty}^{x} \phi(v)dv,$$

Equation 14 | Standard normal cumulative distribution function in the probit model.

Where $\phi(x)$ is the standard normal density:

$$\phi(x) = (2\pi)^{-\frac{1}{2}} * e^{\frac{-x^2}{2}}$$

Equation 15 | Standard normal density function.

To understand the process through which this model is derived helps to understand the logic behind it. We have a dependent variable that takes either two binary values, and we want to know the probability of success, usually associated with the case $y = 1$. However, we already know that the possible outcome from the sum of all independent variables can be any number, from the lowest to the highest possible value. Then, we want to implement a function that allows us to go from the step on the left-hand side to the step on the opposite side, according to Figure 12.

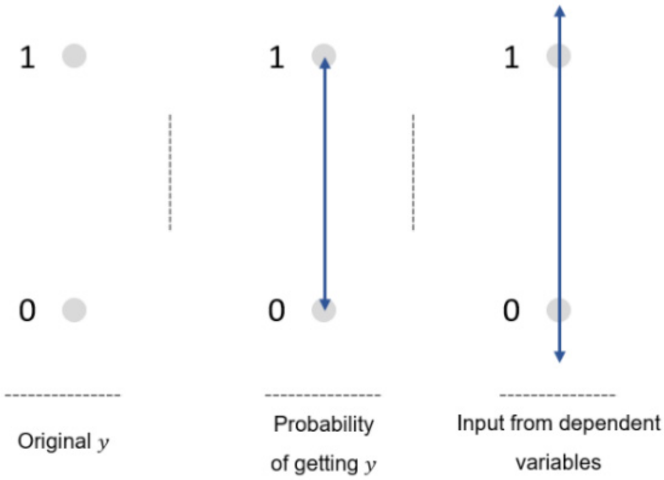

Figure 12 | Dependent variable - scale redefinition; adapted from O'Halloran (2005).

Putting this logic into a mathematical perspective, we want an expression fed with binary values ($y = 1 \vee y = 0$) and provided with a number between $-\infty$ and $+\infty$ ($y^* \in]-\infty, +\infty[$). The cumulative normal distribution function, usually identified by $\Phi(x)$, makes partially this. So, by working on it, we build:

$$y' = \Phi(\beta_0 + \boldsymbol{x\beta} + e)$$

Equation 16 | Cumulative normal distribution function.

Being y' the subset of values ranging from 0 to 1. This function allows one to go from the step on the right side of Figure 12 to the one in the middle. However, since we want the opposite direction, we adjust it as follows:

$$\Phi^{-1}(y') = \Phi^{-1}\big(\phi(\beta_0 + \boldsymbol{x\beta} + e)\big) = \beta_0 + \boldsymbol{x\beta} + e$$

Equation 17 | Inverse of the cumulative normal distribution function.

Finally, we can notice that this part $\Phi^{-1}(y')$ transforms a number between 0 and 1 into another which belongs to the $\mathbb{R}$ group (y^*), as we wanted. To this expression we call a latent variable model. This represents the effect of unobserved variables that have impact on the response variable. Let y^* be an unobserved variable and assume that:

$$y^* = \beta_0 + \boldsymbol{x\beta} + e, \;\; y = 1\,[y^* > 0]$$

Equation 18 | Latent variable model.

This means that when $y = 1$, $y^* > 0$ and for the opposite case, $y = 0$, $y^* \leq 0$. It is also assumed that e is independent from $\boldsymbol{x}$ and also has a standard normal distribution ($e \sim N(0,1)$). This last assumption allows one to work on the symmetry of e around 0 and implies that, $1 - G(-x) = G(x), \vee\, x \in \mathbb{R}$. Thus, from Equation 18 (identified by number 1 between brackets in gray) and by gathering the normal distribution assumption with Equation 13 (identified by number 2 between brackets in gray), we can write the following and link a path between these two equations.

$$[1]P\;(y = 1|x) = P(y^* > 0|\boldsymbol{x}) = \; P(\beta_0 + \boldsymbol{x\beta} + e > 0\;|\boldsymbol{x}) = P(e > -(\beta_0 + \boldsymbol{x\beta})|\boldsymbol{x}) =$$

$$= [2]1 - G(-(\beta_0 + \boldsymbol{x\beta})) = G(\beta_0 + \boldsymbol{x\beta})$$

Equation 19 | Equation 3 demonstration from equation 8.

So, now makes sense why the G function of a profit model is the one we describe in Equation 14. In a nutshell and following Figure 12, we go from the left step to the middle by applying Equation 13. This shows a probability associated with the event of success (usually $y = 1$). Then, to go from the middle step to the one on the right-hand side, we apply the latent variable model, described in Equation 18. This allows to associate the probability of success to a real number, which represents the outcome from the independent variables. The function that makes this transformation has to be a standard normal distribution, given the assumptions related to the latent variable model. Thus, from here, we construct Equation 15. Lastly, Equation 14 is simply the integral of this last one in order to get the cumulative distribution function and thus the probability of any number that may come from the independent variables side. The G function is therefore demonstrated since its mathematical expression respects the assumptions of the latent variable model and allows us to go from the step on the left side to the one on the right side.

5.1.3 Maximum Likelihood Estimation of Probit Model

To estimate this model, due to the nonlinear nature of E(y|**x**), one must apply the Maximum Likelihood Estimation (MLE) instead of the Ordinary Least Squares (OLS) procedure. Before explaining how to obtain this estimator, we briefly give some theoretical background to ease its understanding. What we intend to do is to discover a set of estimations for the $\boldsymbol{\beta}$ parameter that allows us to get the maximum probability of finding, given a set of factors $\boldsymbol{x_i}$, the right value for y, being this 1 or 0. So, if we look at this in a single observation perspective, represented by i, we want to maximize the probability corresponding to the following density function.

$$f(y_i = j|\boldsymbol{x_i\beta}) = G(\boldsymbol{x_i\beta})^j * [1 - G(\boldsymbol{x_i\beta})]^{1-j}, j = 1, 0$$

Equation 20 | Density function of y_i given x_i.

Then, if the y value of this observation is, for instance, 0 ($j = 0$), we want to maximize the probability of selecting this value, given a set of parameters $\boldsymbol{x_i}$ and $\boldsymbol{\beta}$. We denote this probability by $\ell(y_i|\boldsymbol{x_i\beta})$. Note that if $y_i = 1$, $f(y_i = 1|\boldsymbol{x\beta}) = G(\boldsymbol{x\beta})^1$, but if $y_i = 0$, $(y_i = 0|\boldsymbol{x\beta}) = [1 - G(\boldsymbol{x\beta})]^1$. We absorbed the intercept into the vector $\boldsymbol{x}$ for simplicity.

If we extend our reasoning to the entire sample and assume that each observation is independent of the others, we can multiply the likelihoods of the n observations to get the total sample likelihood. Thus,

$$\ell_{sample} = \prod_{i=1}^{n} f(y_i = j|\boldsymbol{x_i\beta}),\ j = 1, 0$$

Equation 21 | Likelihood of the entire sample.

As we have already said, we want to maximize the ℓ_{sample} value, given a vector $\boldsymbol{\beta}$. Figure 13 shows a practical example of this application to smooth things out. In orange and green, we see two possible candidates for the maximization result of the sample likelihood. In other words, these two lines represent Equation 13, given the set of estimates $\widehat{\boldsymbol{\beta}}'$ and $\widehat{\boldsymbol{\beta}''}$. As we check by analysing the graph, choosing one can lead us closer to certain points but further away from others, which is why we proceed with the maximization problem — to find the set of estimators that best fits all the observations.

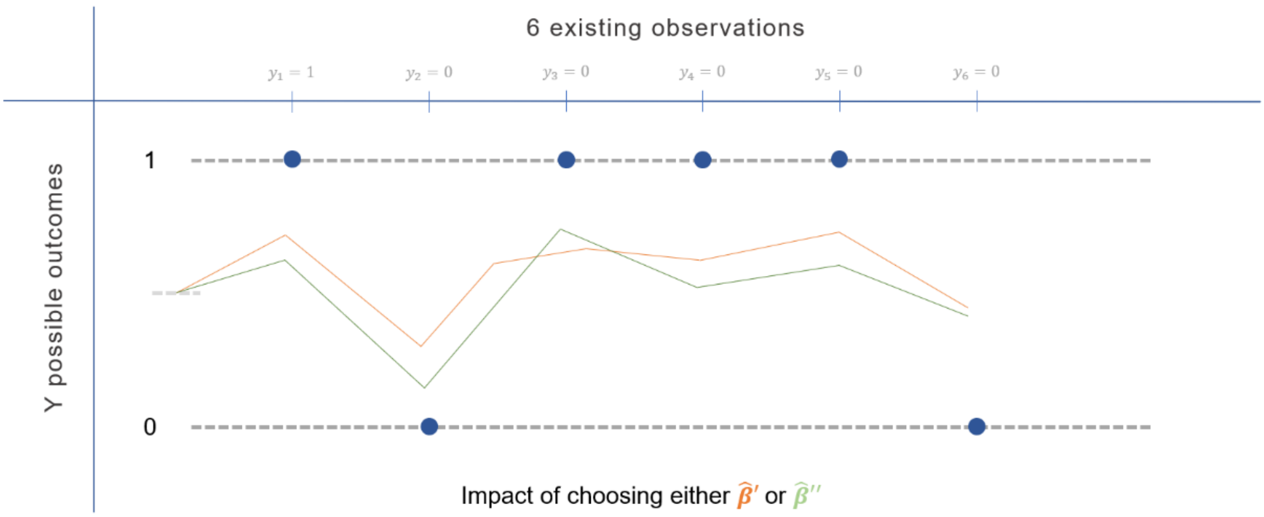

Figure 13 | Graphical representation of the MLE optimization; adapted from O'Halloran (2005).

The maximization of Equation 20 does not happen before we take the logarithmic form to ease this task. Consequently,

$$\log\,(\ell_{sample}) = \sum_{i=1}^{n} \log[f(y_i = j|\boldsymbol{x_i\beta})] =$$

$$= \sum_{i=1}^{n} j * \log\,[\,G(\boldsymbol{x_i\beta})] + (1-j)\log\,[1 - G(\boldsymbol{x_i\beta})] =$$

$$= \mathcal{L}(\boldsymbol{\beta}),\quad j = 1, 0$$

Equation 22 | Log-likelihood function for n observations.

The optimization of Equation 22 results in the Maximum Likelihood Estimation of $\boldsymbol{\beta}$, denoted by $\widehat{\boldsymbol{\beta}}$. Since G is the standard normal cumulative distribution function, then $\widehat{\boldsymbol{\beta}}$ is also the Probit Estimator. Furthermore, the MLE theoretical background implies that, under very general conditions, this method is consistent, asymptotically normal, and asymptotically efficient for random samples.

Note that, there are substantial differences in what we interpret from $\widehat{\boldsymbol{\beta}}$ of a multiple regression and a probit model. In the former, we can see the direct impact of a 1-unit increase in x_i through $\hat{\beta}_i$, while in the latter an estimated coefficient of 0.75, for instance, does not say anything about the magnitude of the impact on the probability of y. Instead, it means that the z-score of $P(y=1)$ is raised by 0.75. It only allows us to know whether the impact of each x_j is negative or positive on the response probability. While for a multiple regression model we have the following relationship:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$$

$$\frac{\partial y}{\partial x_1} = \beta_1$$

Equation 23 | Partial effect of x_1 on the magnitude of y in a multiple regression model.

For a probit model, we would need to have a starting point whose value would define the real impact on the dependent variable. For instance,

$$y = \Phi(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)$$

$$\frac{\partial y}{\partial x_1} = \beta_1 \phi(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)$$

Equation 24 | Partial effect of x_1 on the magnitude of y in a probit model.

Following these equations, we note that a variation of 0.75 points starting when the result from $\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$ equals 0.2 has a completely different impact than one starting at 0.6. Then, as the marginal impact of changing a variable is not constant, there are two common methods to compute it: either through the average marginal effects or to the marginal effects at the mean. We proceed with the first one.

5.1.4 Multinomial Probit

If the dependent variable is a categorical and unordered variable that represents the possible alternatives that can be selected, one can use the multinomial probit model. This type of model is non-linear and the magnitude of the change in the outcome probability depends on the levels of all the independent variables. Here, y represents the possible alternatives selected by each individual, who only chooses a single outcome of the dependent variable. Thus, we are interested in studying the impact on the response probability of a change in one of the elements of $\boldsymbol{x}$, given a set of m total alternatives.

$$P(y = j|\boldsymbol{x}), \qquad j = 0, 1, \ldots, m$$

Equation 25 | Response probability of a multinomial response model.

Where j is one of the m possible outcomes of the dependent variable y. Then, for an alternative j, we have a latent variable corresponding to each individual:

$$y_{ij}^{*} = \boldsymbol{x}_i \boldsymbol{\beta}_j + u_{ij}$$

Equation 26 | Latent variable for alternative j and individual i.

Where $\boldsymbol{x}_i$ is the observed values for each independent variable of the individual i, $\boldsymbol{\beta}_j$ is the coefficient of each independent variable for each alternative, and u_{ij} are distributed independently and identically standard normal errors. The individual chooses the alternative that yields a higher latent variable. Thus, the individual i chooses alternative j over m if ${y^*}_{ij} > {y^*}_{im},\ for\ j \neq m$. Given that the sum of the probabilities of choosing each outcome for every individual must sum one, we do not need to compute $P(y = 0|x)$. The alternative corresponding to $j = 0$ calls outcome base and all estimates are computed based on this level. For instance, consider a dependent variable for the employee status of each individual where $j = 0$ means that the individual is in school, $j = 1$ means that the individual is unemployed, and $j = 2$ means that the individual is working. In a model with just one independent variable, education, we would get one coefficient for the level $j = 1$ and another for the level $j = 2$. The former would tell us the impact that another year of education has on the probability that an individual would be unemployed instead of studying — it is hence, a pairwise comparison between one level of the categorical variable and the base outcome level.

There is yet an important limitation to the multinomial probit deployed in Stata — the software tool used to perform our econometric analyses — through the command *mprobit*: the independence of irrelevant alternatives (Stata, 2013). The pairwise comparison method deployed in this model does not consider the characteristics of alternatives other than the pair under consideration. Using a classical example of the transportation field, if we have the option of travelling by car, a blue bus, or a red bus, the probability of using a car instead of a blue bus is not affected by having another red bus as an option. But, in reality, assuming that people are indifferent to the bus colour, the possibility of taking a blue bus would split the use of the red bus. Thus, the probability of getting a car instead of getting the blue bus would be higher. Although the multinomial probit model assumes that the errors are normal, which makes it possible to have correlated errors across alternatives eliminating this limitation, *mprobit* assumes that we have uncorrelated errors, and, consequently, the independence of irrelevant alternatives.

5.1.5 Sample Selection

The availability of a random sample from the underlying population is commonly assumed. However, due to how some data sets are collected and the behaviour of the units sampled, this is not always realistic. Working with a non-random sample, whose values depend in part on the dependent variable output, makes the parameter estimates inconsistent unless corrective measures are put in place. One of the existing remedies to this problem is Heckman's sample selection model (Heckman, 1979). Here, two equations are set in place:

- The regression equation for the j^{th} individual:

$$y_{1j} = \boldsymbol{x}_{1j}\boldsymbol{\beta}_1 + u_{1j}$$

Equation 27 | Outcome equation in Heckman's selection model for individual j.

- The selection equation for the same individual:

$$y_{2j}^{*} = \boldsymbol{x}_{2j}\boldsymbol{\beta}_2 + u_{2j}$$

Equation 28 | Selection equation in Heckman's selection model for individual j.

Note that, the index number two in the last equation is only relevant to distinguish the parameters of both equations. These two are related as follows: if $y_{2j}^{*} > 0$, then y_{1j} is observed for the j^{th} individual. Furthermore, to exist a selection bias:

$$u_1 \sim N(0, \sigma)$$

$$u_2 \sim N(0,1)$$

$$corr(u_1, u_2) = \rho, \qquad \rho \neq 0$$

Equation 29 | Condition for the existence of selection bias.

Having the error terms of these two equations correlated means that the unobserved factors that influence y_2^{*} also influence y_1, which sustains the use of a sample selection model. For instance, if we reject the null hypothesis that $\rho = 0$, then there is a selection effect that would bias the results of the regression equation, in case we ignore the first step of the model.

A classic example of the application of these two equations has ${y_{2j}}^{*}$ determining whether or not the j^{th} individual works, and y_{1j} representing how much wage the same individual earns. An individual does not have a wage if she does not work, so y_{2j}^{*} has to be greater than zero to make $y_{2j} = 1$ which in turn corresponds to a value in the dependent variable y_1 for this observation. Furthermore, it is expected to observe different variables conditioning the option of working and the wage earned. For instance, the cost of commuting may influence the decision of taking a job but hardly the money you get from it. Hence, $y_{1j} \neq y_{2j}^{*}$. To compute the estimates of this model, we use the maximum likelihood estimator.

5.2 Econometric Model Choice

Throughout this study, we perform two different analyses with a special focus on firm size. In the first one, we explore the relationship between firm size and innovation considering three possible types: product innovation, process innovation, and joint product and process innovations. In the second analysis, we explore how innovation performance varies when firms join both product and process innovations. In this part, we explicitly define the econometric model of each analysis.

5.2.1 Determinants of Product, Process Innovation, or Joint Innovation

For the first analysis, we particularize the multinomial probit model as follows, given the variables summarized in Section 4 as well as the literature review of Section 3.

$$P(y = j|\boldsymbol{X}), \qquad j = 0, 1, 2, 3.$$

$$y_j^* = \beta_0 + \beta_1 Firm\ Size + \beta_2 College\ Degree + \beta_3 R\&D\ Activities + \beta_4 Exports\ Intensity + \beta_5 Economic\ Group + \beta_6 Advanced\ Capital + \beta_7 Age + \beta_8 Industry + \boldsymbol{\gamma Time} + u_j$$

Equation 30 | Multinomial probit model for probability of product, process, or joint innovation.

Where, y_j^* is the latent variable that determines if a firm engages in innovation type j. Each j level represents a type of innovation (product, process, or the joint product and process innovation) plus the decision of not innovating. Regarding the independent variables, apart from firm size, we also include college degree, which represents the human capital determinant, R&D activities, exports intensity, the economic group, advanced capital, the firm's age, the industry aggregated level, and the time control for each CIS wave.[16]

5.2.2 Innovation Performance of Joint Strategies and Firm Size

In the second analysis, since product innovation performance is only observed for firms that develop product innovation, we face a possible selection bias if innovative firms have unobserved characteristics that are correlated with performance. To account for this, we follow the model developed by Heckman (1979). We first use a probit model for the firm's decision of whether or not to introduce product innovation and then a multiple regression model (Cameron & Trivedi, 2005, Chapter 16; Wooldridge, 2002, Chapter 17) to find the effect of firm size on product innovation performance when firms deploy joint innovation strategies. Following this, we are also tackling a common flaw of econometric studies that usually do not make any attempt to study the presence or the effects of sample selection bias (W. M. Cohen, 2010; Griliches, 1990; John, Clint, Zvi, Bronwyn, & Adam, 1984).

Given the variables summarized in Section 4 as well as the literature review of Section 3, we particularize the following econometric model:

- Selection equation:

$$P(y_{Product\ Innovation} = 1\ |\boldsymbol{X}) = G(\beta_0 + \beta_1 Firm\ Size + \beta_2 Process\ Innovation + \beta_3 College\ Degree + \beta_4 R\&D\ Activities + \beta_5 Exports\ Intensity + \beta_6 Economic\ Group + \beta_7 Advanced\ Capital + \beta_8 Age + \beta_9 Industry + \boldsymbol{\gamma Time})$$

Equation 31 | Selection equation in Heckman's model followed in this study's second analysis.

- Regression equation:

$$y_{Product\ Innovation\ Performance} = \beta_0 + \beta_1 Firm\ Size + \beta_2 Process\ Innovation + \beta_3 (Process\ Innovation\ \times Firm\ Size) + \beta_4 Training + \beta_5 College\ Degree + \beta_6 R\&D\ Activities + \beta_7 Economic\ Group + \beta_8 Advanced\ Capital + \beta_9 Age + \beta_{10} Industry + \boldsymbol{\gamma Time} + u$$

Equation 32 | Outcome equation in Heckman's model followed in this study's second analysis.

In the first equation, the dependent dummy variable measures whether the firm introduced product innovation or not. Then, we add the same explanatory variables as in Equation 30 and the dummy

[16] See Table G, in Appendix, for further details on the correlation between these variables.

variable for process innovation. The exports variable represents an exclusion restriction since the interrelationship between the variables measuring product innovation performance and the introduction of product innovation leads to an identification problem (Enders, 2010; Fonseca et al., 2019). In fact, being an exporter may help a firm to engage in innovation due to higher competitive pressures coming from broader and external markets, but we believe it does not change the market success of firm's product innovations. Hence, exports level is again measured through its intensity variable. By doing this, we aim to strengthen our exclusion restriction since, for instance, market pressures coming from the export of a very small percentage of the total business unlikely induces any behaviour towards innovation. We thus only account for organisations that have their largest market abroad. In doing so, we guarantee the existence of a market pressure coming from operating in a wider market.

Finally, the regression equation's dependent variable is product innovation performance, which is here defined as the total revenue from the sale of product innovations. Additionally, this equation introduces the interaction between process innovation and the number of employees to give us the impact of firm size on innovation performance when process is simultaneously joined to product innovation. The variable training is also accounted for in this equation and the exports intensity variable is removed since it is an exclusion restriction.[17]

[17] See Table H and Table I, in Appendix, for further details on the correlation between these variables.

6. Results

In this chapter, we lay down the results starting with the multinomial probit model that explores the role of firm size in each type of innovation. Then, we proceed to Heckman's selection model to explore the impact on innovation performance when small, medium, and large firm pursue product and process innovations at the same time. Firm size categorical and numerical variables are analysed in order to depict clearer patterns. Finally, we assess the robustness of our findings.

Every variable included in the following econometric models is debriefed in Section 4.4, and set in each model in Section 5.2, although some of them may be transformed with the natural logarithm to approximate their distribution to a normal one.[18] Furthermore, the number of observations varies between models depending on their variables. Since some were still not defined in their respective database at the beginning of our study, they induced a few missing values. We would overcome this problem if we only used values from the CIS; however, we would also lose information. As the variation among the number of observations is always residual, we keep the combination of the databases. Moreover, every model is significant, following their respective goodness of fit measure.

6.1 Determinants of Product, Process Innovation, or Joint Innovation

In Table 3, we present the marginal effect analysis of a multinomial probit model with a 4-level categorical dependent variable.[19] Each level represents a type of innovation plus the decision not to innovate. Thus, the base outcome is no innovation, level 1 is for product innovation, level 2 is for process innovation, and level 3 is for product and process innovation. Concerning the explanatory variables, we deploy the dummy variable for the level of education and the economic group. Additionally, exports are gauged through its intensity-oriented dummy variable. The age of the firm is measured in its logarithmic form. Concerning R&D activity and advanced capital determinants, we include the logarithm of their expenditures. We also consider industries' technological or knowledge intensity and control for CIS wave years. Finally, we add our variable of interest, firm size, through its 3-level categorical form.

The average marginal effects reveal that, *ceteris paribus*, for product innovation exclusively, large firms are 2.5 percentage points less likely to introduce product innovations than small firms, on average, while the propensity of medium firms is not significantly different than firms with fewer than 50 employees. For process innovation, medium firms have a higher probability of innovating than small firms, with a difference of 1.5 percentage points, on average, while large firms did not present a significant difference to small firms. Concerning the joint class, on average, large firms have a probability of 4.8 percentage points higher than small firms of engaging in both types of innovation, while, for medium firms, we did not find significant results. Beyond the effect of firm size, education has a positive impact in product and joint innovation, with the largest result in the product and process class. R&D activities and advanced capital induce more product and process innovations, either at the same time or separately. Economic group has a positive effect in product and joint innovation: if all firms belong to an economic group, the probability of engaging in both product and process innovation, for instance, increases 1.9

[18] See Figure B, in Appendix, for further details on the transformation of the distribution of each numerical variable.
[19] See Table J, in Appendix, for further details on the multinomial probit model estimates.

percentage points. Finally, exports intensity only has a positive impact on joint innovation and age on product innovation.

Table 3 | Marginal effects of the determinants of innovation.

MARGINAL EFFECT ANALYSIS			
VARIABLES	1 | Product Innovator	2 | Process Innovator	3 | Product & Process Innovator
Firm Size: 50-249 workers	-0.005	0.015***	0.001
	(0.004)	(0.005)	(0.006)
Firm Size: >=250 workers	-0.025***	0.003	0.048***
	(0.007)	(0.010)	(0.013)
College Degree	0.012***	0.005	0.034***
	(0.004)	(0.005)	(0.005)
R&D Expense (log)	0.008***	0.003***	0.029***
	(0.000)	(0.000)	(0.000)
Exports Intensity	-0.006	0.002	0.017***
	(0.004)	(0.005)	(0.006)
Economic Group	0.009**	-0.003	0.019***
	(0.004)	(0.005)	(0.006)
Advanced Capital Expense (log)	0.005***	0.017***	0.030***
	(0.000)	(0.000)	(0.000)
Age (log)	0.007***	-0.002	-0.001
	(0.002)	(0.002)	(0.002)
Industry: Low-tech manuf.	-0.027***	0.025***	-0.031***
	(0.007)	(0.007)	(0.009)
Industry: KIS	-0.002	0.003	-0.057***
	(0.008)	(0.008)	(0.010)
Industry: LKIS	-0.021***	0.043***	-0.050***
	(0.007)	(0.007)	(0.010)
Time Dummies	Yes	Yes	Yes
Observations	32,101	32,101	32,101
Chi2	4,571.223		
Log pseudolikelihood	-27,263.611		

*Marginal effects from a multinomial probit model (robust standard errors in parentheses). The type of innovation is a dependent categorical variable with four levels. The base outcome is the decision of not innovating, the first level is the decision of introducing at least one product innovation, the second level is the decision of introducing at least one process innovation, and the third level is the decision of introducing both a product and a process innovation. Marginal effects for the base outcome are not displayed. All regressions include industry dummies for CIS waves; * significant at 10%, **significant at 5%, and *** significant at 1%.*

6.2 Innovation Performance of Joint Strategies and Firm Size

In Model 4 of Table 4, we display the coefficients of Heckman's selection model, in which we consider beforehand the decision to engage in product innovation (the selection equation) and only then estimate the product innovation performance model (the outcome equation).[20] It is worth to note that since our main interest relies on the outcome equation, we do not display the results of the selection equation. The explanatory variables included in the selection model are: dummy variable for process innovation, college degree, exports intensity, economic group, advanced capital, and industry; the categorical variable of firm size; the R&D expenditures and age in their logarithmic form. Also, we control for the CIS waves. The outcome equation adds the training dummy variable and the interaction term between firm size and process innovation. The latter shows us how the product innovation performance of a firm that joins both product and process innovations varies with firm size.

The results show that the independence between the two equations is rejected ($\rho = 0$ is rejected at the 5% level), confirming our assumption that the error terms of both equations are correlated. Additionally, we see that all firms increase their performance by pursuing both product and process innovations simultaneously; yet, the increase is not linear since it is larger for small (58.7%) and large (89.8% by adding up 31.1% and 58.7%) than for medium firms (41.2% by adding up 58.7% and -17.5%). Further information is provided on the average effect of firm size and process innovation by deploying an average marginal analysis: being a large rather than a small firm increases a firm's product innovation performance by 266%, on average, regardless of pursuing process innovation. In other words, for every €1,000 euros a small firm may receive from the sale of product innovations, a large firm would earn €2,660. This could be expected as large firms usually have larger markets, which means a greater customer target for buying their products. Regarding the decision of joining both product and process innovation, firms increase their performance by 56%, on average, when compared to firms only pursuing product innovation, regardless of their size.

Disaggregating firm size from a 3-level variable into its continuous form gives us a clearer image of the relationship of firm size with product innovation performance when joint innovation strategies are followed. Furthermore, we can thoroughly look for possible non-linear relations and add more information to our previous results. Thus, Model 5 in Table 4 displays the coefficient estimates of the same previous econometric model, this time with firm size included as a second-degree polynomial (the squared component is divided by 1000 in order to readjust the size of the coefficients).[21] Once more, we only present the estimates for the outcome equation.

In order to better understand the quadratic and interaction terms, we plot their variation over firm size in Figure 14. The average marginal effect of process innovation on product innovation performance — denoted by $f(x)$ — has a nonlinear relationship when we make firm size varying. This is aligned with the results of the Model 4, in the same table, although we can further see that:

$$f(x) = 0 \Leftrightarrow x = 0.276 \lor x = 3.055$$

Equation 33 | Zeros of the function $f(x)$, that graphs the effect of firm size on product innovation performance.

[20] See Table K, in Appendix, for further details on Heckman's selection model maximum likelihood estimator coefficient estimates when firm size is a categorical variable.
[21] See Table L, in Appendix, for further details on Heckman's selection model maximum likelihood estimator coefficient estimates when firm size is a numerical variable.

Table 4 | Coefficient estimates of Heckman's selection model.

COEFFICIENT ANALYSIS		
ALTERNATIVES / VARIABLES	4 | Outcome Eq. Product innovation performance (log)	5 | Outcome Eq. Product innovation performance (log)
Firm Size (Dummy): 50-249 workers	1.489***	
	(0.072)	
Firm Size (Dummy): >=250 workers	2.534***	
	(0.141)	
Process Innov.*Firm Size (Dummy): 50-249 workers	-0.175**	
	(0.075)	
Process Innov.*Firm Size (Dummy): >=250 workers	0.311**	
	(0.143)	
Process Innovation	0.587***	0.968***
	(0.061)	(0.080)
Firm Size		5.591***
		(0.439)
Firm Size^2		-1.224***
		(0.238)
Process Innov.*Firm Size		-3.830***
		(0.470)
Process Innov.*Firm Size^2		1.150***
		(0.237)
Training	0.130***	0.153***
	(0.029)	(0.031)
College Degree	0.382***	0.404***
	(0.034)	(0.038)
R&D Expense (log)	0.052***	0.086***
	(0.005)	(0.006)
Economic Group	0.535***	0.977***
	(0.039)	(0.049)
Advanced Capital	0.237***	0.353***
	(0.042)	(0.047)
Age (log)	0.006	0.132***
	(0.018)	(0.021)
Industry: Low-tech, manufacturing	-0.406***	-0.374***
	(0.051)	(0.055)
Industry: KIS	-0.754***	-0.922***
	(0.061)	(0.067)
Industry: LKIS	-0.050	-0.200***
	(0.059)	(0.063)
Constant	11.378***	10.630***
	(0.153)	(0.189)
ρ	0.316**	0.418**
	(0.047)	(0.047)
Time Dummies	Yes	Yes
chi2	4,396.323	3,043.230
Log pseudolikelihood	-33,136.130	-34,009.170
Observations	32,101	32,101
Selected	11,500	11,500
Non Selected	20,601	20,601

*Coefficients estimates of Heckman's selection model maximum likelihood estimator (robust standard errors in parentheses). Dependent variable is product innovation performance, measured through the sales of innovative products. Only the outcome equation is displayed. In Model 4, firm size is a categorical variable. In Model 5, firm size is a continuous variable divided by 1000 in order to readjust the size of the coefficients. All regressions include CIS wave-year dummies; * significant at 10%, **significant at 5%, and *** significant at 1%.*

This means that when firms employing between 276 and 3,055 workers join both product and process innovations, their performances contract. Moreover, the worst case happens in firms with 1,565 employees with a performance reduction of 2.22%. Focusing on the relationship between small and large firms, the latter only starts to overcome small firms when it surpasses the gain in product innovation performance that a firm with ten workers attains from the decision of pursuing both types of innovation simultaneously. Thus, a large firm needs to have 3,320 employees to enjoy a relative advantage over its counterparts.

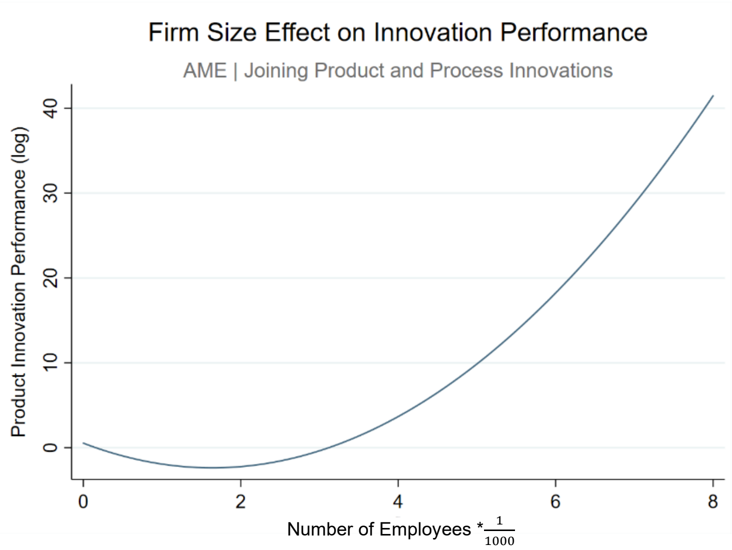

Figure 14 | Firm size effect on innovation performance, $f(x)$, based on the coefficient estimates of Heckman's selection model.

6.3 Robustness Analysis

To assess the robustness of our findings, we run several additional model specifications for both previous analyses. For the multinomial probit (Table 5 and Table 6), we start with alternative Model A by removing all controls we used in the original model except for firm size (being our variable of interest), and R&D figures (for its importance in the innovation process). We also keep control variables for industry and time effects. Then, from alternative Models B to E, we gradually approach our original model in order to test our results for different controls. Alternative Model B adds the variable age, alternative Model C adds exports intensity and the economic group, alternative Model D includes the variable education, and alternative Model E reconstitutes the original model with two more variables, advanced capital and training. Through these, we see that the results attached to the firm size variable keep their significance and interpretation, regardless of the specifications set. Hence, the robustness check confirms our first analysis' findings.

For the product innovation performance analysis, we follow the same procedure, only changing the variables of the outcome equation. Note that, we only use the model with the firm size variable's numerical form to do the robustness check, as our main findings in this second analysis mainly came from it. Table 7 shows alternative Model F with the interaction term and their respective variables, the R&D figure, and the industry and time control variables. Alternative Model G adds firms' age, alternative

Model H adds the economic group, and alternative Model I adds training and advanced capital. In contrast to what we do in the alternative Model J for the previous analysis, we do not add different controls than those included in the original model. Here, we test our results in a multiple regression model and therefore, without sample selection. We observe significant results for our variables of interest firm size, process innovation, and their interaction term throughout every alternative. This robustness check shows that our findings are not significantly influenced by the inclusion of specific variables in the econometric model since the coefficients hold a similar magnitude and precision. To smooth out the visualization of this table as well as the interpretation of its results, we do not display the selection equation — note that, its results are the same for each alternative presented below.

To provide a thorough robustness check, we also analyse Figure 14 with further detail and test the significance of our results (Figure 15). As expected, the variation rises with the increase of firm size, since firms with lower number of employees have a higher frequency in our data set. The lowest number of workers that a large firm must have to attain a better improvement than any small firm within a 95% confidence interval is 5,079 employees. Hence, a firm with a workforce greater or equal to this dimension will always be better prepared to join both product and process innovation than any other smaller firm. In the same confidence interval, a medium firm employing at least 122 workers always attains a smaller improvement than any small firm. Likewise, a workforce of 4,845 or more employees provides a higher rise in the firm's product innovation performance than any medium firm, within a 95% confidence interval.

Through Figure 15, we are also able to provide more information on the employee number that makes a firm's product innovation performance decrease with joint innovation strategies. While Equation 33 pinpoints workforces between 276 and 3,055 employees, the same analysis within a confidence interval of 95% provides a broader range of values. Firms with a workforce equal to or smaller than 225 workers never experience hindrances, and neither do those whose workforce is equal to or greater than 4,766 workers.

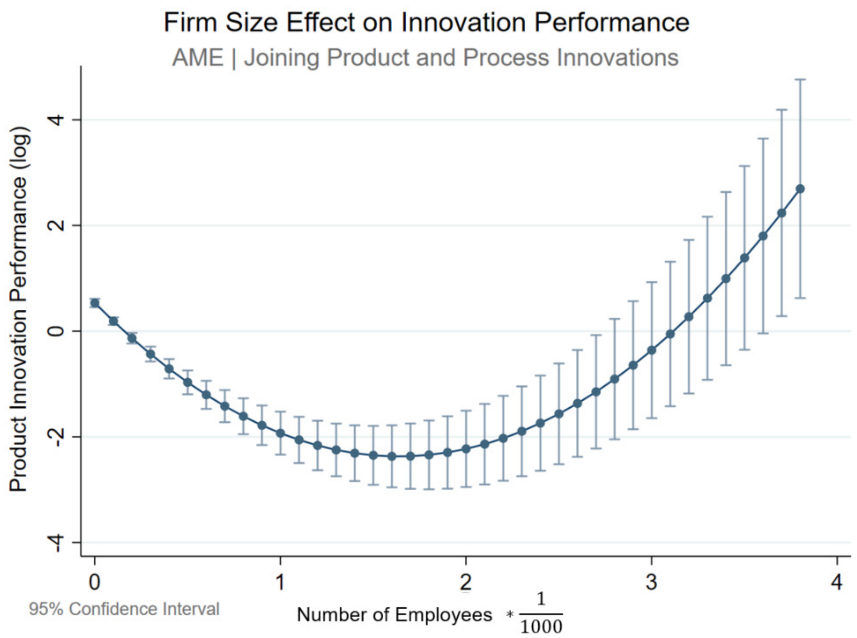

Figure 15 | Variation of the firm size effect on innovation performance, within a 95% confidence interval.

Table 5 | Robustness analysis of the multinomial probit models A, B, and C.

ROBUSTNESS ANALYSIS | AVERAGE MARGINAL EFFECTS (AME)									
ALTERNATIVES	AME | MODEL A			AME | MODEL B			AME | MODEL C		
VARIABLES	Product	Process	Product & Process	Product	Process	Product & Process	Product	Process	Product & Process
Firm Size: 50-249 workers	0.001	0.023***	0.026***	-0.002	0.024***	0.028***	-0.005	0.024***	0.018***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)
Firm Size: >=250 workers	-0.020***	0.009	0.094***	-0.024***	0.010	0.094***	-0.028***	0.011	0.074***
	(0.007)	(0.010)	(0.015)	(0.006)	(0.010)	(0.015)	(0.006)	(0.010)	(0.015)
College Degree									
R&D Expense (log)	0.009***	0.008***	0.039***	0.009***	0.008***	0.039***	0.009***	0.008***	0.039***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Exports Intensity							-0.005	0.008	0.028***
							(0.004)	(0.005)	(0.007)
Economic Group							0.012***	-0.004	0.018***
							(0.004)	(0.005)	(0.006)
Advanced Capital Expense (log)									
Age (log)				0.008***	-0.003	-0.006**	0.008***	-0.003	-0.005*
				(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Industry: Low-tech manuf.	-0.031***	0.025***	-0.045***	-0.031***	0.025***	-0.045***	-0.030***	0.025***	-0.040***
	(0.007)	(0.007)	(0.010)	(0.007)	(0.007)	(0.010)	(0.007)	(0.007)	(0.010)
Industry: KIS	0.001	-0.001	-0.067***	0.006	-0.002	-0.068***	0.003	-0.001	-0.063***
	(0.007)	(0.008)	(0.011)	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.011)
Industry: LKIS	-0.021***	0.036***	-0.072***	-0.020***	0.037***	-0.071***	-0.021***	0.039***	-0.065***
	(0.007)	(0.008)	(0.011)	(0.007)	(0.008)	(0.011)	(0.007)	(0.008)	(0.011)
Training									
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,621			32,101			32,101		
chi 2	4,931.800			4,901.685			4,887.360		

*Marginal effects from multinomial probit models A, B, and C (robust standard errors in parentheses). The type of innovation is a dependent categorical variable with four levels. The base outcome is the decision of not innovating, the first level is the decision of introducing at least one product innovation, the second level is the decision of introducing at least one process innovation, and the third level is the decision of introducing both a product and a process innovation. Marginal effects for the base outcome are not displayed. All regressions include industry dummies for CIS waves; * significant at 10%, **significant at 5%, and *** significant at 1%.*

Table 6 | Robustness analysis of the multinomial probit models D and E.

ROBUSTNESS ANALYSIS | AVERAGE MARGINAL EFFECTS (AME)						
ALTERNATIVES	AME | MODEL D			AME | MODEL E		
VARIABLES	Product	Process	Product & Process	Product	Process	Product & Process
Firm Size: 50-249 workers	-0.005	0.024***	0.017***	-0.005	0.013**	-0.005
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)
Firm Size: >=250 workers	-0.027***	0.011	0.075***	-0.027***	-0.004	0.032***
	(0.006)	(0.010)	(0.015)	(0.006)	(0.009)	(0.012)
College Degree	0.012***	0.011**	0.043***	0.010***	0.001	0.021***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)
R&D Expense (log)	0.009***	0.008***	0.038***	0.007***	0.001**	0.023***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Exports Intensity	-0.005	0.007	0.027***	-0.006	0.001	0.016***
	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.006)
Economic Group	0.009**	-0.007	0.008	0.007*	-0.006	0.012**
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)
Advanced Capital Expense (log)				0.004***	0.014***	0.024***
				(0.000)	(0.000)	(0.001)
Age (log)	0.008***	-0.003	-0.005*	0.007***	-0.003	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Industry: Low-tech manuf.	-0.028***	0.026***	-0.032***	-0.027***	0.027***	-0.027***
	(0.007)	(0.007)	(0.010)	(0.007)	(0.007)	(0.009)
Industry: KIS	-0.003	-0.005	-0.079***	-0.002	0.003	-0.059***
	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.010)
Industry: LKIS	-0.021***	0.038***	-0.063***	-0.021***	0.042***	-0.055***
	(0.007)	(0.008)	(0.011)	(0.007)	(0.007)	(0.009)
Training				0.021***	0.081***	0.199***
				(0.004)	(0.006)	(0.006)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,101			32,101		
Chi2	4,881.050			5,177.660		

*Marginal effects from multinomial probit models D and E (robust standard errors in parentheses). The type of innovation is a dependent categorical variable with four levels. The base outcome is the decision of not innovating, the first level is the decision of introducing at least one product innovation, the second level is the decision of introducing at least one process innovation, and the third level is the decision of introducing both a product and a process innovation. Marginal effects for the base outcome are not displayed. All regressions include industry dummies for CIS waves; * significant at 10%, **significant at 5%, and *** significant at 1%.*

Table 7 | Robustness analysis of Heckman's selection model.

ROBUSTNESS ANALYSIS | COEFFICIENT ESTIMATES | OUTCOME EQUATION					
ALTERNATIVES	MODEL F	MODEL G	MODEL H	MODEL I	MODEL J
VARIABLES	Product Innovation Performance (log)	Product Innovation Performance (log)	Product Innovation Performance (log)	Product Innovation Performance (log)	Product Innovation Performance (log)
Process Innovation	0.596***	0.604***	0.652***	0.920***	0.536***
	(0.055)	(0.054)	(0.133)	(0.087)	(0.041)
Firm Size	6.949***	6.795***	5.447***	5.549***	5.342***
	(0.490)	(0.485)	(0.444)	(0.435)	(0.298)
Firm Size^2	-1.591***	-1.548***	-1.198***	-1.221***	-1.158***
	(0.241)	(0.273)	(0.236)	(0.236)	(0.114)
Process Innov.*Firm Size	-4.740***	-4.633***	-3.634***	-3.785***	-3.539***
	(0.543)	(0.529)	(0.472)	(0.468)	(0.299)
Process Innov.*Firm Size^2	1.497***	1.455***	1.121***	1.146***	1.082***
	(0.282)	(0.272)	(0.234)	(0.234)	(0.114)
Training				0.173***	0.160***
				(0.031)	(0.030)
College Degree					0.360***
					(0.032)
R&D Expense (log)	0.054***	0.054***	0.066***	0.089***	0.054***
	(0.010)	(0.009)	(0.009)	(0.007)	(0.003)
Economic Group			1.028***	1.049***	0.965***
			(0.049)	(0.049)	(0.032)
Advanced Capital				0.319***	0.139***
				(0.051)	(0.033)
Age (log)		0.128***	0.120***	0.130***	0.123***
		-0.023	(0.021)	(0.021)	(0.015)
Industry: Low-tech, manufacturing	-0.412***	-0.416***	-0.381***	-0.444***	-0.305***
	(0.064)	(0.061)	(0.057)	(0.055)	(0.042)
Industry: KIS	-0.761***	-0.691***	-0.764***	-0.799***	-0.877***
	(0.075)	(0.073)	(0.065)	(0.066)	(0.049)
Industry: LKIS	-0.034	-0.027	-0.141**	-0.209***	-0.119**
	-0.072	(0.070)	(0.067)	(0.064)	(0.048)
Constant	13.204***	12.822***	12.040***	10.938***	11.782***
	(0.187)	(0.188)	(0.264)	(0.208)	(0.079)
ρ					
Time Dummies	Yes	Yes	Yes	Yes	Yes
chi2	1,288.360	1,419.190	2,418.420	2,821.710	
Log pseudolikelihood	-35,994.640	-35,963.100	-34,132.270	-34,083.010	
R^2-Adj.					0.385
Observations	32,101	32,101	32,101	32,101	11,500
N_selected	11,500	11,500	11,500	11,500	
N_nonselected	20,601	20,601	20,601	20,601	

Coefficients estimates of Heckman's selection models maximum likelihood estimator F, G, H, I, and J (robust standard errors in parentheses). Dependent variable is product innovation performance, measured through the sales of innovative products. Only the outcome equation is displayed. Firm size is a continuous variable divided by 1000 in order to readjust the size of the coefficients.
*All regressions include CIS wave-year dummies; * significant at 10%, **significant at 5%, and *** significant at 1%.*

7. Discussion

In this section, we formulate our findings by building on the aforementioned results. First, we discuss the role of firm size in product and process innovations, when followed separately or concurrently. We also look at the effects that other firms and industries' characteristics have on the propensity to innovate. Second, we analyse the existence of possible frictions when product and process innovations are engaged at the same time, considering different sizes of organisations. In light of the literature review, we are then in a position to argue for our study's hypotheses. Finally, we tackle both research questions and extend our findings to real economies by providing policymakers with valuable information regarding the behaviour of different firm sizes and lay down the main limitations of this study.

7.1 Determinants of Product, Process, or Joint Innovation

The preliminary results start to cast light on the main trends we find in Section 6: small firms are more induced to engage in product innovation than their counterparts, and large firms are the most engaged size class in both product and process innovations. In fact, we do not find a specific size outperforming the others in every type of innovation. For product, we find that small firms have relative advantage over medium and large firms. For process, medium firms take the lead over small firms, while in the joint category, large firms have a relative advantage. Before comparing our results with the literature, it is important to call for their main singularity: few studies consider the possibility of pursuing product and process innovations simultaneously. Thus, having a greater number of small firms engaging in product innovation or medium firms in process innovation may be biased towards large firms' preference for joining both types instead of just one.

Our study follows W. M. Cohen & Klepper (1996), Mansfield (1964), and Scherer and Ross (according to W. M. Cohen [2010]), who consider small firms as the engine of innovative activity. However, it is also important to note that these scholars have different forms of accounting for innovation, mainly constrained to firms' R&D figures. If we deepen our discussion into the firm's organisational field, our result is supported by several other arguments. Small firms have lower levels of bureaucracy and a greater organisational flexibility which eases the process of invention (W. M. Cohen, 2010; Nicholas, 2003; Rothwell, 1989; Tsai, 2005). Moreover, their faster decision processes in recognizing market opportunities, and their organisational structure, that closes the gap between the decision-making body and specific customer requirements, boost the successful commercialization of their product innovations (Pavitt, 1990; M. Rogers, 2004; Rothwell, 1989).

Concerning process innovation, our result contradicts a significant stream of literature that supports that large firms are more likely to engage in this type of innovation (e.g. Baldwin et al. [2002]; Hall et al. [2009], Kraft [1990], and Tether [2002]). However, these scholars only scope one possible choice for large firms: introduce either product or process innovation. Here, we scope three options, which surely offset the records of previous studies on large firms' decisions to seek process innovation. Moreover, we are not displaced on what Scherer observed for R&D: the share of process innovation relative to product innovation increases as firm size grows (according to Vaona & Pianta [2008]). Despite all this, we reject our first hypothesis: firm size is not positively related to the propensity to engage either in product or process innovation. Conversely, there is evidence to not reject our second hypothesis: a firm's propensity to introduce product and process innovation simultaneously is positively affected by its size.

Regarding other firms and industry's characteristics, we find that human capital, composed by education, has a positive impact on product and joint innovation, which is supported by Rammer et al. (2009). For the R&D and advanced capital determinants, our results are aligned with the respective literature (e.g. Baldwin et al. [2002], Hall et al. [2009], and Reichstein & Salter [2006]): greater expenditures are found to positively affect every type of innovation, having a stronger impact on product innovators after considering the joint class. Regarding the exports intensity, we are aligned with the literature for joint product and process innovations, although we do not find a significant result when both types of innovation are separately followed. In the economic group, albeit we do not observe a significant relation with process innovation, our results go hand in hand with Mohnen & Röller (2005) and Tether's (2002) studies that defend that belonging to such a group makes firms more likely to innovate. Finally, firm's age has the expected effect on product innovation which aligns our findings with those presented by Baumann & Kritikos (2016), Fonseca et al. (2019), and Sorensen & Stuart (2000). As we do not find significant results for the other types of innovation, we are not able to observe the pattern of how firms choose between each type of innovation over their life cycle, as we consider at the end of Section 3.1.

7.2 Innovation Performance of Joint Strategies and Firm Size

Our results are aligned with those of Ballot et al. (2015), Damanpour & Gopalakrishnan (2001), and Schmidt & Rammer (2006): joint innovation strategies improve firms' innovation performance. However, this does not completely invalidate our theory developed under the exploration-exploitation trade-offs. In fact, large firms have a higher increase in their performance than small firms, and small firms than medium firms, as we state in the preliminary analysis. This suggests that large organisations are better fitted to join innovation strategies than their counterparts. If we look at this from the exploration and exploitation theory perspective, the result is not surprising — large firms have more resources (Baldwin et al., 2002; Lin et al., 2007; O´Reilly & Tushman, 2013; M. Rogers, 2004) and thus might better tackle the possible existing trade-offs. If, on the one hand, the greater amount of resources that large firms have helps them join innovation strategies, on the other hand, medium firms do not benefit from the same characteristic over small firms. A possible explanation of this effect is small firms' agile and task-oriented behaviour (W. M. Cohen, 2010; Lubatkin et al., 2006; Pavitt, 1990; M. Rogers, 2004), as well as their niche market seller competencies (Gailly, 2011; Lubatkin et al., 2006; Pavitt, 1990), that may leverage a greater expertise and flexibility for the process of deploying both types of innovation at the same time.

We take a further leap into this interaction when we disaggregate the variable firm size. Instead of grouping firms into three-dimension classes, the opportunity to gauge this effect, through the number of a firm's employees, proves fruitful to understand the type of companies harmed by the trade-offs of joining both product and process innovation. While, through the categorical variable, we see that every firm has an incentive to join both product and process innovation, we now observe that some firms are indeed hamstrung by this strategy. This relation is shaped by a non-linear U-curve, in which firms employing between 276 and 3,055 workers in our sample are associated to performance hindrances when they join product and process innovations. In these cases, to adopt the units-separation or the contextual ambidexterity strategy may be possible remedies since they leverage better performances and allow the parent company to develop both types of innovation simultaneously (Benner & Tushman, 2003, 2015; Lavie et al., 2010). It is worth to note that a sequential ambidexterity strategy is also viable to overcome potential frictions, although product and process innovation would be pursued at different times. Still, regarding some companies' size, it is possible to follow both types of innovation without diminishing the expected returns from the sale of new products.

In light of the explorative and exploitative dilemma literature, these findings do not reject the third hypothesis: for some sizes, to join product and process innovations in the same firm creates frictions in innovation performance. Likewise, the sub hypothesis is also not rejected: a large firm experiences fewer trade-offs than a smaller firm when they follow joint innovation strategies. In fact, as firms grow larger, the impact of following joint innovation strategies start to reward firms' innovation performance instead of leading to frictions.

7.3 Research Questions

After the aforementioned discussion, we are ready to delve into the two research questions we set to transform our findings into concrete guidelines to policymakers. Regarding the first one, *how might firm size leverage the implementation of product and process innovations, in the Portuguese economy?,* we learn that different sizes reveal a specialization behaviour towards each type of innovation. That is, small firms tend to foster higher levels of product innovation propensity, medium firms have leverage on process innovation, and large firms overcome their counterparts in the joint category. Hence, we advise policymakers to implement diversified measures when supporting each type of firm size. Moreover, greater attention to joint innovation strategies should emerge from empirical studies in order to provide proper assistance to large firms.

Regarding the second research question, *how does innovation performance vary when firms balance product and process innovations simultaneously and to what extent does this variation depend on firm size?, w*e learn that, in general, every firm size increases their innovation performance when they engage in product and process innovation simultaneously. Still, large firms over than 3,320 employees reach higher innovation performance than their smaller counterparts, suggesting that a larger amount of resources enhances the payoff from joint innovation strategies. Moreover, firms employing between 276 and 3,055 workers have a contracted innovation performance. To overcome the negative impact of joining both types of innovation at the same time, we propose three types of ambidextrous strategy: organisational unit's separation strategy, where a firm develops both types of innovation but in different units, which then offsets the existing trade-offs between these two; contextual strategy, where employees are responsible for balancing their own efforts, which gives the flexibility to different workers develop each type of innovation simultaneously; and sequential strategy, where each type of innovation is pursued within specific cycles of time, which prevents joint innovation strategies but avoids potential frictions.

7.4 Research Limitations

We argue for the stability and validity characteristics of our data set, emphasizing its innovation-related purpose and the high amount of information we attain by matching it with another database. Similarly, we perform a robustness analysis to buttress our findings and show how our results are robust regardless of the inclusion of specific variables in the econometric models. Yet, we are unable to overcome some limitations summarized:

- We do not deploy a panel data analysis which would produce more stable and reliable results (Ballot et al., 2015; de Faria et al., 2010). However, the CIS structure does not provide an inquiry of a panel of companies, hampering this task. Hence, joining observations from different waves may favour large firms as they are more likely to be sampled by the CIS. Given this, we also do not study innovation performance with the most appropriate type of data set, since the impact of an innovation extends over time (Damanpour et al., 2009; Roberts & Amit, 2003). For instance, we only look at the effect of an innovation for a 2-year period while it may take longer to influence a firm's innovation performance;
- Still related to the CIS sample structure, it is possible that innovating firms are oversampled in this data set, as we mention in Section 4.5.2 Preliminary Analysis;
- Although we merge two different databases, due to lack of data, we are unable to set up some determinants. However, it is important to bear in mind that the literature regarding the determinants of innovation is widely vast and many factors are usually proxied in empirical studies, making this constraint something usual in such analyses. Nevertheless, the set of variables we use proved to be sufficient to find the main pattern of firm size in innovation, as we see through the robustness analysis;
- We measure innovation performance through a dedicated metric for product innovation, instead of complementing both types of innovation, which hinder our second analysis' results. In fact, this is a shortage widely spread in the literature as there are substantial difficulties in measuring the commercial success of an innovation related to the firm's processes (Hervas-Oliver et al., 2014; Keupp et al., 2012). This also does not allow us to measure the degree to which a firm engages in innovation, but only if it introduces at least one innovation of each type, in our first analysis;
- Our empirical strategy does not allow us to establish a causal link between innovation and our independent variables. The latter have the risk of simultaneity which lead to an endogeneity problem. For instance, a firm that cooperates in innovative activities may increase its propensity to innovate; however a firm innovating also induces higher levels of this type of cooperation. This means we would violate the exogeneity assumption of the ordinary least squares method: $E(u|\boldsymbol{x}) = 0$.

8. Conclusion

Innovation has increasingly played out as paramount in the global arena. On the one hand, innovation gives countries new ways of ramping up economic growth, while supporting higher living standards and tackling current environmental challenges. On the other hand, innovation enables firms to be more competitive, adaptable to change, and endurable to macroeconomic shocks. It is, therefore, crucial to deepen our knowledge on the factors that influence innovation and the way they are interrelated.

In this line, the role of firm size has been a hotbed of intensive debate, which is underpinned on a puzzling set of different theories that highlight little consensus. While some authors defend that larger firms engage more in innovation, others recognise that small firms are the engine of innovative activity. To a certain extent, the contrasting conclusions are due to the lack of available data on measuring innovation, however different economic and technological contexts play an important role too. Some scholars argue that large and small firms depend on their industry's characteristics to have a comparative advantage to innovate. Likewise, due to the ambiguity in measuring, especially, process innovation, there is a significant gap in the literature on the firm size's role in each type of innovation. Furthermore, it is also recognized that many studies have overlooked important relationships by not considering the interactions between both product and process innovation.

The literature has been assertive in attributing a possible cause of higher economic growth to joint innovation strategies. Yet, analysing this relation from the lens of the explorative-exploitative dilemma, motivates research on the existence of possible trade-offs inherent to the coexistence of product and process innovations in the same firm. Exploration engages organisations in research, experimentation, and variation, while exploitation leads firms to increase productivity and efficiency through choice, execution, and variance reduction. Resource-allocation decisions therefore create a substitution effect between these two: either one uses existing information to improve present returns or it gains new information for future returns. To solve this dilemma, a wide stream of literature has been supporting ambidextrous strategies.

By merging the Portuguese CIS data set and the SCIE, between 2008 and 2018, this dissertation aims to study the innovation-firm size relationship, in Portugal, analysing in particular product and process innovations. Following this, we set a clear pattern between firm and each type of innovation. By allowing for both types simultaneously, we are providing a thorough analysis to our study. In a second step, we assess the effect of firm size on innovation performance when firms engage in joint innovation strategies. Triggered by the exploration-exploitation dilemma, we aim to check the existence of possible trade-offs within these strategies. Although we analyse Portuguese data, our findings and recommendations are not only limited to Portugal. We aim to encourage the development and implementation of new measures to foster innovation in any economy where this study may prove suitable.

In our first analysis, we find that, for product innovation, small firms have the relative advantage over large ones. For process innovation, medium outperform small firms, while, in the joint category, large firms have a relative advantage over small firms. It is important to note that few studies consider the possibility of engaging in both product and process innovation. Hence, our results may be biased towards large firms' preference to join both types. Following these findings, we reject the first hypothesis by stating that firm size is not positively related to product or process innovation, separately. Additionally, we do not reject our second hypothesis as large firms have a higher propensity to follow joint innovations strategies. In our second analysis, every firm size has an incentive to join both product and process innovations, medium firms do not achieve the same increase in innovation performance of small and large firms, and large firms achieve the highest scores. Through the exact number of employees, we deepen our knowledge and see that firms employing between 276 and 3,055 workers actually experience hampered innovation performance when they join both product and process innovations. In these cases, to adopt the unit's separation, contextual or sequential ambidexterity strategy may remedy the situation. Hence, by examining the importance of firm size as a conditioning factor shaping the ability of firms to benefit from joint innovation strategies, we do not reject the third and its sub hypothesis. Accordingly, our results show the existence of frictions in joint innovation strategies for some smaller large firms. Additionally, they also exhibit that these trade-offs do not affect very large organisations as they affect small and medium firms in their innovation performance.

In both analyses, we provide sustained evidence that joint innovation strategies must be researched in higher depth to broaden policymakers' agenda towards the determinants, benefits, and downsides of this type of innovation. As such, they will better grasp the complex interactions between product and process innovations, preparing the economy to take advantage of the resulting benefits. Our finding of the effect of firm size on process innovation is not less relevant as this realm is still to be fully explored as is the one of product innovation. Furthermore, our study presents a pattern of specialization towards each type of innovation that should motivate the revision of the current policy in order to tackle possible flaws that exclusively support innovative activity initiated by large firms. We also contribute to the literature by developing an unexplored perspective of the decision of pursuing joint innovation strategies. To bring new light to the understanding of the role of different firm sizes in mastering possible trade-offs between product and process innovations is of further interest for policymakers and managers alike. By acknowledging to what extent each firm enjoys the benefits from these strategies and is affected by its threats unveils whether ambidexterity may be a possible bridge for product and process innovations. Moreover, to deepen the literature of possible trade-offs would allow the development of strategies to overcome these, as well as case studies to guide new practitioners in the field.

Considering our findings and subsequent limitations, we contribute to future research with proposals that complement our insights as well as the literature in general. Further investigation ought to focus on the role of firm size in each type of innovation through different sets of variables. In order to better understand the interrelations between each factor of the innovation process, it should replicate this study with other determinants and ways of measuring our variable of interest, firm size. It is also important to measure the degree to which a firm pursues process innovation, in particular. Likewise, enlarging the study of the effect of joint innovation strategies in firms' innovation performance may bolster the understanding of the dynamics and implications of joining both product and process innovations. For instance, besides replicating our findings on the existing frictions, observing potential synergies may bring important insights to the field.

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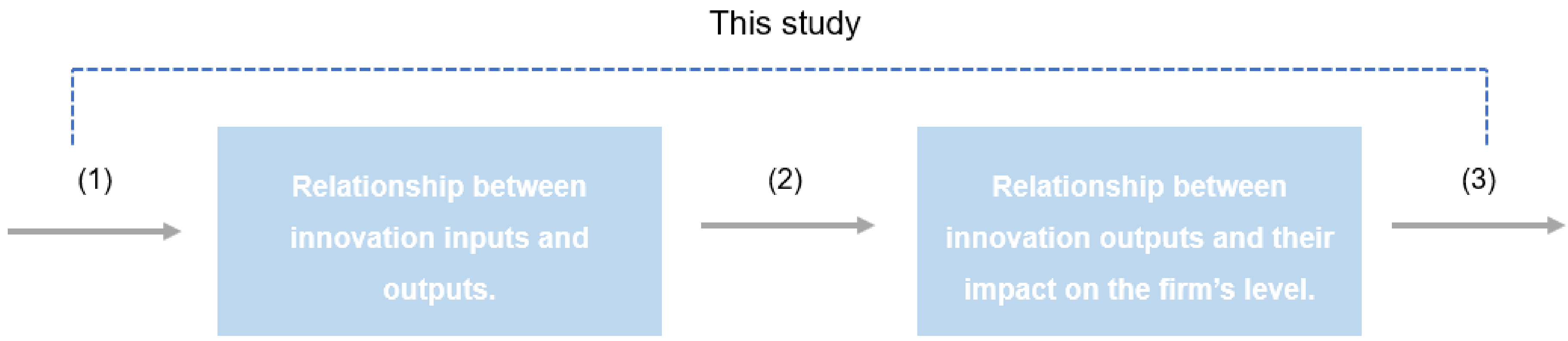
Appendix



(1) R&D levels, exports, firm size | (2) Number of innovations produced, their type | (3) Impact on productivity, profitability

Note: This enumeration is just an example of the possible inputs, outputs and impacts.

Figure A | The Scope of this study.

Table A | Portuguese Economic Activities in the CIS, part 1. [22,23]

PORTUGUESE ECONOMIC ACTIVITIES INCLUDED IN THE CIS Retrieved from CAE-Rev.3		
GROUP	2-LEVEL CODE	NAME
B	5	Mining of coal and lignite
	6	Extraction of crude petroleum and natural gas
	7	Mining and preparation of metal ores
	8	Other mining and quarrying
	9	Mining and quarrying related service activities
C	10	Manufacture of food products
	11	Manufacture of beverages
	12	Manufacture of tobacco products
	13	Manufacture of textiles
	14	Manufacture of w earing apparel
	15	Manufacture of leather and related products
	16	Manufacture of w ood and of products of w ood and cork, except furniture; manufacture of articles of straw and plaiting materials
	17	Manufacture of paper and paper products
	18	Printing and reproduction of recorded media
	19	Manufacture of coke, refined petroleum products and fuels briquettes
	20	Manufacture of chemicals, chemical products and man-made fibres, except pharmaceutical products
	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
	22	Manufacture of rubber and plastic products
	23	Manufacture of other non-metallic mineral products
	24	Manufacture of basic metals
	25	Manufacture of fabricated metal products, except machinery and equipment
	26	Manufacture of computer, communication equipment, electronic and optical products
	27	Manufacture of electrical equipment
	28	Manufacture of machinery and equipment n.e.c.
	29	Manufacture of motor vehicles, trailers, semi-trailers and parts and accessories for motor vehicles
	30	Manufacture of other transport equipment
	31	Manufacture of furniture
	32	Other manufacturing activities
	33	Repair, maintenance and installation of machinery and equipment

[22] Source: DGEEC (2016).
[23] Despite the 2-level disaggregation, the group G, in division 47, is split into a 3-level code since only the category 471 is included in the CIS.

Table B | Portuguese Economic Activities in the CIS, part 2.

PORTUGUESE ECONOMIC ACTIVITIES INCLUDED IN THE CIS Retrieved from CAE-Rev.3		
GROUP	2-LEVEL CODE	NAME
D	35	Electricity, gas, steam, cold and hot w ater and cold air
E	36	Water collection, treatment and distribution
	37	Collection, drainage and treatment of sew age
	38	Waste collection, treatment and disposal activities; materials recovery
	39	Remediation and similar activities
F	42	Civil engineering
	43	Specialised construction activities
G	46	Wholesale trade (include commission trade), except of motor vehicles and motorcycles
	47(1)	Retail sale in non-specialised stores
H	49	Land transport and transport via pipelines
	50	Water transport
	51	Air transport
	52	Warehousing and support activities for transportation (include cargo handling)
	53	Postal and courier activities
J	58	Publishing activities
	59	Motion picture, video and television programme production, sound recording and music publishing activities
	60	Radio and television activities
	61	Telecommunications
	62	Computer programming, consultancy and related activities
	63	Information service activities
k	64	Financial service activities, except insurance and pension funding
	65	Insurance, reinsurance and pension funding, except compulsory social security
	66	Activities auxiliary to financial services and insurance activities
M	69	Legal and accounting activities
	71	Architectural, engineering and related technical activities; technical testing and analysis
	72	Scientific research and development
	73	Advertising, market research and public opinion polling
	74	Other consultancy, scientific and technical activities
	75	Veterinary activities
Q	86	Human health activities

Table C | Constructed variables to perform this study, Part 1.

Dimension	Determinant Measured	Original Variable | Indicator / Proxy	Original Variable | Description	Origin	MV | Indicator / Proxy Calculation	MV | Description
Innovation	Product innovation	Dummy Variable | 1 = if it performed this type of innovation in each wave period; 0 = otherwise	If the company introduced a product innovation through goods	CIS	Dummy Variable | 1 = if it performed this type of innovation between 2008-2018; 0 = otherwise	If the company introduced at least one type of the following innovations: prod. Innov. through goods or services
		Dummy Variable | 1 = if it performed this type of innovationin each wave period; 0 = otherwise	If the company introduced a product innovation through services	CIS		
	Process innovation	Dummy Variable | 1 = if it performed this type of innovation in each wave period; 0 = otherwise	If the company introduced new manufacturing methods	CIS	Dummy Variable | 1 = if it performed this type of innovation between 2008-2018; 0 = otherwise	If the company made at least one of the following: process innovation through manufacturing methods, logistic and delivery methods, or support activities to the firm's processes
		Dummy Variable | 1 = if it performed this type of innovation in each wave period; 0 = otherwise	If the company introduced new methods of logistics and delivery	CIS		
		Dummy Variable | 1 = if it performed this type of innovation in each wave period; 0 = otherwise	If the company introduced new support activities to the firm's processes	CIS		
	Product innovation performance (Share)	Numerical Variable	Percentage of sales resulting from innovative products either new to the market or new to the firm for each wave period	CIS	Numerical Variable	Total amount of sales corrected by GDP deflators resulting from innovative products either new to the firm or new to the market
	Revenue	Numerical Variable	Total income generated from business operations for each wave period	SCIE		
Firm Size	Number of employees	Numerical Variable	Total number of employees working in the company	SCIE	-	-
		Categorical Variable | 3 levels	Aggregation of the number of employees working in the company: 1 = 10 to 49 workers; 2 = 50 to 249 workers; 3 = more than 250 workers	CIS	-	-
Human Capital	Training	Dummy Variable | 1 = if it performed training activities between 2008-2018; 0 = otherwise	If the company developed among its workforce activities related to training	CIS	-	-
	Training expenditure	Numerical Variable	Expenditures in employees' training	SCIE	-	-
	College degree (share)	Categorical Variable | 7 levels	Percentage of employees that have university studies: 0=0%; 1=1-4%; 2=5-9%; 3=10-24%; 4=25%-49%; 5=50%-74%; 6=75%-100%)	CIS	Dummy Variable | 1 = if the firm's college labour is above the average; 0 = otherwise	If the firm's college labour is higher or lower than the sample average

Table D | Constructed variables to perform this study, Part 2.

Dimension	Determinant Measured	Original Variable | Indicator / Proxy	Original Variable | Description	Origin	MV | Indicator / Proxy Calculation	MV | Description
R&D activities	Internal R&D	Dummy Variable | 1 = if it took R&D activities within the company in each wave period; 0 = otherwise	If the company developed R&D activities inwards	CIS	Dummy Variable | 1 = if it took R&D activities within the company or acquired these same activities from outside in each wave period; 0 = otherwise	If the company developed R&D activities inwards or acquired R&D activities from outside
	External R&D	Dummy Variable | 1 = if it acquired R&D activities from the outside in each wave period; 0 = otherwise	If the company acquired external R&D activities (not developed within the company)	CIS		
	Internal R&D expenditures	Numerical Variable	Firm's expenditures in R&D acitivities developed inside the company, 3-cluster average	CIS	Numerical Variable	Total amount of expenditures in R&D activities either performed inwards or acquired outside, for each wave period
	External R&D expenditures	Numerical Variable	Firm's expenditures in R&D acitivities acquired from outside the company, 3-cluster average	CIS		
Exports	Exports intensity	Categorical Variable | 4 levels	Geographic market with greatest importance for the company: 1=local/regional; 2=national; 3=EU countries and its associates; 4=other countries	CIS	Dummy Variable | 1 = the firm's most important market is abroad; 0 = otherwise	The geographical market with greatest importance for the company is either inside the country (regional/local & national markets) or outside the country (EU countries/ its associates & other countries)
		Numerical Variable	Percantage of sales coming from Portugal	SCIE		
		Numerical Variable	Percentage of sales coming from the EU	SCIE		
		Numerical Variable	Percentage of sales coming from outside the EU	SCIE		
	Exports	Dummy Variable | 1 = if it traded in other countries in each wave period; 0 = otherwise	If geographic market of the firm comprises other countries	CIS	-	-
Advanced Capital	Advanced capital	Dummy Variable | 1 = if it acquired advanced capital in each wave period; 0 = otherwise	If the company acquired machinery, equipments and software	CIS	-	-
	Advanced capital expenditures	Numerical Variable	Firm's expenditures in the acquisiton of machinery, software, equipment and buildings, 3-cluster average	CIS	-	-
Cooperation	Cooperation	Dummy Variable | 1 = the company cooperated with any other entity; 0 = otherwise	Cooperation with any entity in innovation-related activities	CIS	-	-

Table E | Constructed variables to perform this study, Part 3.

Dimension	Determinant Measured	Original Variable | Indicator / Proxy	Original Variable | Description	Origin	MV | Indicator / Proxy Calculation	MV | Description
Economic Group	Economic group	Dummy Variable | 1 = if it belongs to a corporate groupin each wave period; 0 = otherwise	If the company is part of a group of companies	CIS	-	-
Competition and industry control	Type of industry - High-technology Manuf.	Dummy Variable | 1 = if the firm belongs to this industry group; 0 = otherwise	If the firm's CAE class belongs to the high-technology manufacturing group based on a higher aggregation level	SCIE	-	-
	Type of industry - Low-technology Manuf.	Dummy Variable | 1 = if the firm belongs to this industry group; 0 = otherwise	If the firm's CAE class belongs to the low-technology manufacturing group based on a higher aggregation level	SCIE	-	-
	Type of Industry - Knowledge-intensive services	Dummy Variable | 1 = if the firm belongs to this industry group; 0 = otherwise	If the firm's CAE class belongs to the KIS group based on a higher aggregation level	SCIE	-	-
	Type of Industry - Less knowledge-intensive services	Dummy Variable | 1 = if the firm belongs to this industry group; 0 = otherwise	If the firm's CAE class belongs to the LKIS group based on a higher aggregation level	SCIE	-	
Age	Age	Numerical Variable	Number of existing years that each firm has in each wave period	QP	-	-
Time	CIS version	Categorical Variable | 5 levels	The observation belongs to the CIS version : 1"16-18" 2"14_16" 3"12_14" 4"10_12" 5"08_10"	CIS	-	-

Table F | Industry aggregation level based on NACE-Rev.2.

AGGREGATION ACCORDING TO TECHNOLOGICAL INTENSITY			
	Nace Framework	**This Study's Classification**	**Allocation of CAE-REV.3 (2-digit level)**
Manufacturing	High-technology	High-technology	C(21); C(26); C(30); C(20); C(27); C(28); C(29)
	Medium-high-technology		
	Medium-low-technology	Low-technology	C(18); C(19); C(22); C(23); C(24); C(25); C(33); C(10); C(11); C(12); C (13); C (14); C(15); C(16); C(17); C(31); C(32)
	Low-technology		
Services	High-tech knowledge-intensive services	Knowledge-intensive services	J(59); J(60); J(61); J(62); J(63); M(72)
	Knowledge-intensive market services		H(50); H(51); M(69); M(70); M(71); M(73); M(74); N(78); N(80)
	Knowledge-intensive financial services		K(64); K(65); K(66)
	Other knowledge-intensive services		J(58); M(75); O(84); P(85); Q(86); Q(87); Q(88); R(90); R(91); R(92); R(93)
	Less Knowledge-intensive market services	Less knowledge-intensive services	G(45); G(46); G(47); H(49); H(52); I(55), I(56); L(68); N(77); N(79); N(81); N(82); S(95)
	Other less knowledge intensive services		H(53); S(94); S(96); T(97); T(98); U(99)

Figure B | Variables transformation into their logarithmic form.

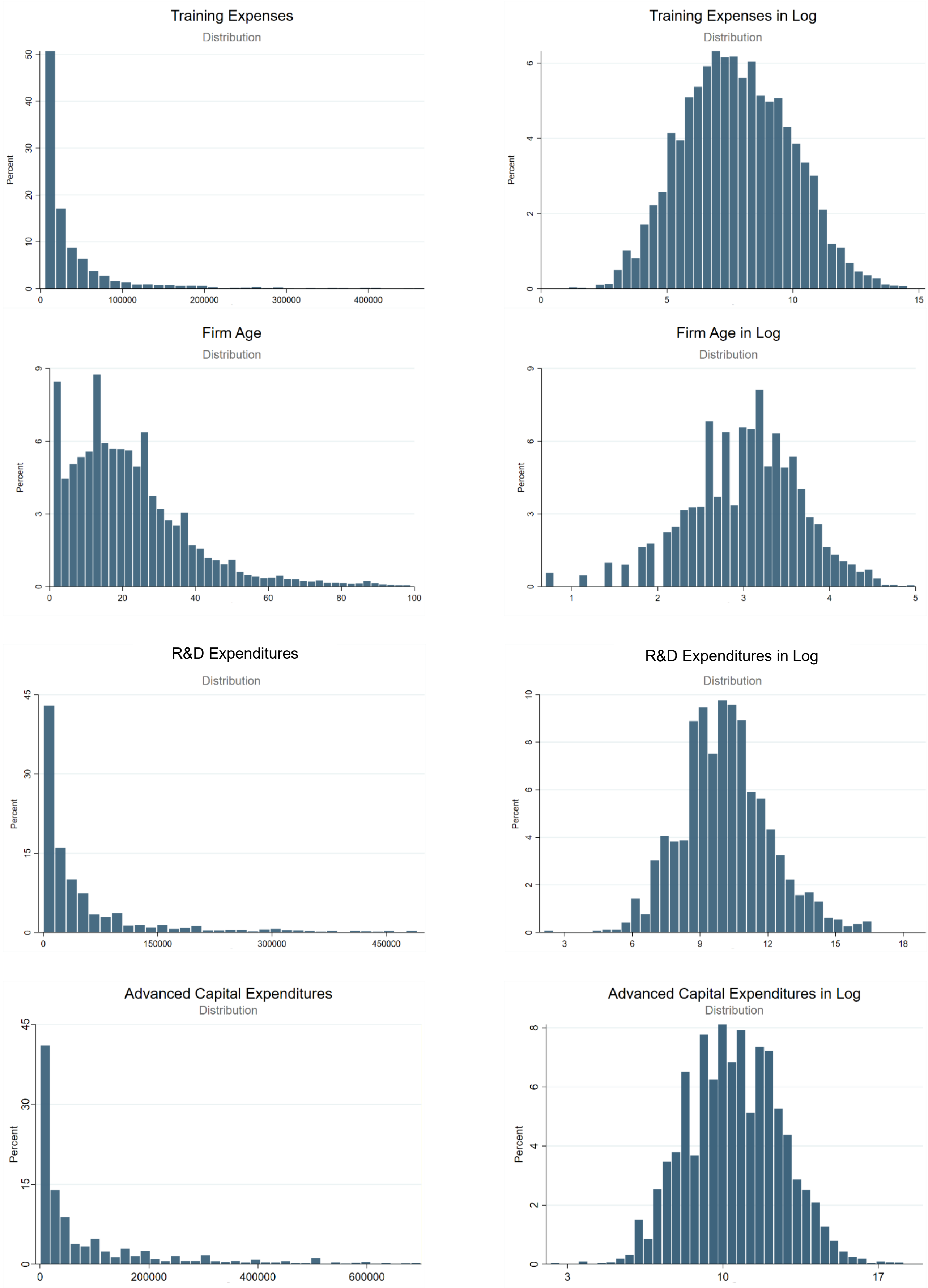


Table G | Correlation matrix of the variables within the multinomial probit model.

CORRELATION MATRIX | MULTINOMIAL PROBIT VARIABLES													
	10-49 workers	50-249 workers	>=250 workers	College Degree	R&D Expense (log)	Exports Intensity	Economic Group	Adv. Capital Expense (log)	Age (log)	High-Tech manuf.	Low-Tech manuf.	KIS	LKIS
10-49 workers	1.000												
50-249 workers	-0.854	1.000											
>=250 workers	-0.390	-0.145	1.000										
College Degree	-0.119	0.069	0.104	1.000									
R&D Expenditures (log)	-0.301	0.171	0.270	0.277	1.000								
Exports Intensity	-0.236	0.172	0.146	0.033	0.177	1.000							
Economic Group	-0.361	0.215	0.307	0.307	0.244	0.116	1.000						
Adv. Capital Expense (log)	-0.145	0.098	0.102	0.076	0.300	0.095	0.053	1.000					
Age (log)	-0.173	0.134	0.092	-0.031	0.040	-0.001	0.019	0.001	1.000				
High-Tech manuf.	-0.070	0.039	0.065	0.072	0.199	0.142	0.067	0.073	0.042	1.000			
Low-Tech manuf.	-0.035	0.059	-0.038	-0.323	-0.062	0.110	-0.168	0.038	0.054	-0.305	1.000		
KIS	0.045	-0.055	0.012	0.404	0.091	-0.071	0.123	-0.018	-0.149	-0.147	-0.419	1.000	
LKIS	0.048	-0.046	-0.010	-0.026	-0.139	-0.158	0.041	-0.076	0.037	-0.200	-0.567	-0.274	1.000

Table H | Correlation matrix of the variables within the selection equation of Heckman's Selection Model.

CORRELATION MATRIX | HECKMAN'S SELECTION MODEL | SELECTION EQUATION														
	10-49 workers	50-249 workers	>=250 workers	Process Innovation	College Degree	R&D Expenditures (log)	Exports Intensity	Economic Group	Advanced Capital	Age (log)	High-Tech manuf.	Low-Tech manuf.	KIS	LKIS
10-49 workers	1.000													
50-249 workers	-0.854	1.000												
>=250 workers	-0.390	-0.145	1.000											
Process Innovation	-0.175	0.110	0.137	1.000										
College Degree	-0.119	0.069	0.104	0.146	1.000									
R&D Expenditures (log)	-0.301	0.171	0.270	0.432	0.277	1.000								
Exports Intensity	-0.236	0.172	0.146	0.117	0.033	0.177	1.000							
Economic Group	-0.361	0.215	0.307	0.121	0.307	0.244	0.116	1.000						
Advanced Capital	-0.144	0.086	0.121	0.504	0.126	0.300	0.097	0.091	1.000					
Age (log)	-0.173	0.134	0.092	0.014	-0.031	0.040	-0.001	0.019	0.014	1.000				
High-Tech manuf.	-0.070	0.039	0.065	0.100	0.072	0.199	0.142	0.067	0.061	0.042	1.000			
Low-Tech manuf.	-0.035	0.059	-0.038	-0.002	-0.323	-0.062	0.110	-0.168	-0.008	0.054	-0.305	1.000		
KIS	0.045	-0.055	0.012	0.001	0.404	0.091	-0.071	0.123	0.028	-0.149	-0.147	-0.419	1.000	
LKIS	0.048	-0.046	-0.010	-0.064	-0.026	-0.139	-0.158	0.041	-0.056	0.037	-0.200	-0.567	-0.274	1.000

Table I | Correlation matrix of the variables within the outcome equation of Heckman's Selection Model.

	CORRELATION MATRIX | HECKMAN'S SELECTION MODEL | SELECTION EQUATION													
	10-49 workers	50-249 workers	>=250 workers	Process Innovation	College Degree	R&D Expenditures (log)	Training	Economic Group	Advanced Capital	Age (log)	High-Tech manuf.	Low-Tech manuf.	KIS	LKIS
10-49 workers	1.000													
50-249 workers	-0.854	1.000												
>=250 workers	-0.390	-0.145	1.000											
Process Innovation	-0.175	0.110	0.137	1.000										
College Degree	-0.119	0.069	0.104	0.146	1.000									
R&D Expenditures (log)	-0.301	0.171	0.270	0.432	0.277	1.000								
Training	-0.153	0.089	0.133	0.442	0.185	0.350	1.000							
Economic Group	-0.361	0.215	0.307	0.121	0.307	0.244	0.145	1.000						
Advanced Capital	-0.144	0.086	0.121	0.504	0.126	0.300	0.480	0.091	1.000					
Age (log)	-0.173	0.134	0.092	0.014	-0.031	0.040	0.017	0.019	0.014	1.000				
High-Tech manuf.	-0.070	0.039	0.065	0.100	0.072	0.199	0.069	0.067	0.061	0.042	1.000			
Low-Tech manuf.	-0.035	0.059	-0.038	-0.002	-0.323	-0.062	-0.085	-0.168	-0.008	0.054	-0.305	1.000		
KIS	0.045	-0.055	0.012	0.001	0.404	0.091	0.070	0.123	0.028	-0.149	-0.147	-0.419	1.000	
LKIS	0.048	-0.046	-0.010	-0.064	-0.026	-0.139	-0.009	0.041	-0.056	0.037	-0.200	-0.567	-0.274	1.000

Table J | Coefficient estimates of the determinants of innovation.

COEFFICIENT ANALYSIS			
VARIABLES	Product Innovator	Process Innovator	Product & Process Innovator
Firm Size: 50-249 workers	0.001	0.118***	0.045
	(0.045)	(0.039)	(0.039)
Firm Size: >=250 workers	-0.123	0.115	0.263***
	(0.094)	(0.083)	(0.087)
College Degree	0.270***	0.204***	0.309***
	(0.039)	(0.035)	(0.033)
R&D Expense (log)	0.208***	0.157***	0.255***
	(0.006)	(0.006)	(0.006)
Exports Intensity	-0.001	0.055	0.109***
	(0.045)	(0.040)	(0.039)
Economic Group	0.165***	0.074*	0.165***
	(0.043)	(0.040)	(0.039)
Advanced Capital Expense (log)	0.221***	0.270***	0.300***
	(0.006)	(0.006)	(0.006)
Age (log)	0.069***	-0.003	0.008
	(0.018)	(0.015)	(0.015)
Industry: Low-tech manuf.	-0.326***	0.027	-0.230***
	(0.066)	(0.062)	(0.059)
Industry: KIS	-0.222***	-0.191***	-0.418***
	(0.074)	(0.072)	(0.069)
Industry: LKIS	-0.260***	0.136**	-0.276***
	(0.068)	(0.065)	(0.062)
Constant	-2.231***	-2.034***	-1.372***
	(0.086)	(0.079)	(0.075)
Time Dummies	Yes	Yes	Yes
Observations	32,101		
Chi2	4,571.223		

*Coefficients estimates of a multinomial probit model (robust standard errors between parentheses). The type of innovation is a dependent categorical variable with four levels. The base outcome is the decision of not innovating, the first level is the decision of introducing at least one product innovation, the second level is the decision of introducing at least one process innovation, and the third level is the decision of introducing both a product and a process innovation. All regressions include industry dummies for CIS waves; * significant at 10%, **significant at 5%, and *** significant at 1%.*

Table K | Coefficient estimates of Heckman's selection model, firm size as a categorical variable.

COEFFICIENT ANALYSIS		
VARIABLES	1.1 | Selection Eq. **Product Innovator**	1.2 | Outcome Eq. **Product innovation performance (log)**
Firm Size: 50-249 workers	-0.046*	1.489***
	(0.026)	(0.072)
Firm Size: >=250 workers	-0.037	2.534***
	(0.054)	(0.141)
Process Innov.*Firm Size: 50-249 workers		-0.175**
		(0.075)
Process Innov.*Firm Size: >=250 workers		0.311**
		(0.143)
Process Innovation	1.029***	0.587***
	(0.021)	(0.061)
Training		0.130***
		(0.029)
College Degree	0.129***	0.382***
	(0.022)	(0.034)
R&D Expense (log)	0.102***	0.052***
	(0.003)	(0.005)
Exports Intensity	-0.022	
	(0.027)	
Economic Group	0.099***	0.535***
	(0.025)	(0.039)
Advanced Capital	0.612***	0.237***
	(0.023)	(0.042)
Age (log)	0.029***	0.006
	(0.010)	(0.018)
Industry: Low-tech, manufacturing	-0.247***	-0.406***
	(0.039)	(0.051)
Industry: KIS	-0.199***	-0.754***
	(0.044)	(0.061)
Industry: LKIS	-0.300***	-0.050
	(0.040)	(0.059)
Constant	-1.560***	11.378***
	(0.052)	(0.153)
ρ	0.316**	
	(0.047)	
Time Dummies	Yes	Yes
chi2	4,396.323	
Log pseudolikelihood	-33,136.130	
Observations	32,101	
N_selected	11,500	
N_nonselected	20,601	

*Coefficients estimates of Heckman's selection model maximum likelihood estimator (robust standard errors between parentheses). Dependent variable of the selection equation is the decision of engaging in product innovation, and in the outcome equation is product innovation performance measured through the sales of innovative products. Firm size is a categorical variable. All regressions include CIS wave-year dummies; * significant at 10%, **significant at 5%, and *** significant at 1%.*

Table L | Coefficient Estimates of Heckman's selection model, firm size as a continuous variable.

COEFFICIENT ANALYSIS		
VARIABLES	1.1 | Selection Eq. **Product Innovator**	1.2 | Outcome Eq. **Product innovation performance (log)**
Process Innovation	1.033***	0.968***
	(0.021)	(0.080)
Firm Size	0.015	5.591***
	(0.027)	(0.439)
Firm Size^2		-1.224***
		(0.238)
Process Innov.*Firm Size		-3.830***
		(0.470)
Process Innov.*Firm Size^2		1.150***
		(0.237)
Training		0.153***
		(0.031)
College Degree	0.127***	0.404***
	(0.022)	(0.038)
R&D Expense (log)	0.102***	0.086***
	(0.003)	(0.006)
Exports Intensity	-0.075***	
	(0.029)	
Economic Group	0.097***	0.977***
	(0.024)	(0.049)
Advanced Capital	0.605***	0.353***
	(0.023)	(0.047)
Age (log)	0.027***	0.132***
	(0.010)	(0.021)
Industry: Low-tech, manufacturing	-0.249***	-0.374***
	(0.039)	(0.055)
Industry: KIS	-0.210***	-0.922***
	(0.044)	(0.067)
Industry: LKIS	-0.313***	-0.200***
	(0.040)	(0.063)
Constant	-1.542***	10.630***
	(0.052)	(0.189)
ρ	0.418**	
	(0.047)	
Time Dummies	Yes	Yes
chi2	3,043.230	
Log pseudolikelihood	-34,009.170	
Observations	32,101	
Selected	11,500	
Non Selected	20,601	

*Coefficients estimates of Heckman's selection model maximum likelihood estimator (robust standard errors between parentheses). Dependent variable of the selection equation is the decision of engaging in product innovation, and in the outcome equation is product innovation performance measured through the sales of innovative products. Firm size is a continuous variable divided by 1000 in order to readjust the size of the coefficients. All regressions include CIS wave-year dummies; * significant at 10%, **significant at 5%, and *** significant at 1%.*