UNIVERSITAT ROVIRA I VIRGILI

EXPLORING CORPORATE FINANCE, EXPORTS AND KNOWLEDGE AS DETERMINANTS OF INNOVATION

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Exploring corporate finance, exports and knowledge as determinants of innovation

DOCTORAL THESIS

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FAIG CONSTAR que aquest treball, titulat "Exploring corporate finance, exports and knowledge as determinants of innovation", que presenta Josep Tomàs-Porres per a l'obtenció del títol de Doctor, ha estat realitzat sota la meva direcció al Departament d'Economia d'aquesta universitat.

HAGO CONSTAR que el presente trabajo, titulado "Exploring corporate finance, exports and knowledge as determinants of innovation", que presenta Josep Tomàs-Porres para la obtención del título de Doctor, ha sido realizado bajo mi dirección en el Departamento de Economía de esta universidad.

I STATE that the present study, entitled "Exploring corporate finance, exports and knowledge as determinants of innovation", presented by Josep Tomàs-Porres for the award of the degree of Doctor, has been carried out under my supervision at the Department of Economics of this university.

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Chapter 1:

Introduction

1.1. General framework and motivation

The systematic and comprehensive understanding of innovation began in the first half of the 20th century, based on ideas extracted from Schumpeter's works. It gained prominence following the publication of *An evolutionary theory of economic change* by Nelson and Winter (1982). Currently, the economics of innovation has become a subject of interest to both researchers and policymakers, in view of the fundamental role that innovation has in guaranteeing economic growth and of its potential to transform society.

The initial neoclassical framework laid the groundwork for the study of entrepreneurship, technological change, and economic dynamics. Despite not explicitly focusing on innovation, it identified the relevance of entrepreneurship and technological advance in fostering economic development (Marshall, 1890; Veblen, 1899). Their approach treated innovation as an individual choice problem, in which firms identify the uncertainty of innovation processes, and know the probability of succeeding. They would thus invest in innovation if the expected rewards were sufficient to overcome the costs (Knight, 1921; Arrow, 1962; Nelson, 1991).

Schumpeter stands out from earlier authors as a seminal figure due to his approach to innovation, as not an ex-ante problem, but as a context-dependent process, subject to market conditions and previous actions and behaviours executed by all actors involved in the economic activity. His initial approach to technical change and innovation in *The theory of economic development* (Schumpeter, 1934), emphasized that, under equilibrium, the economy enters a circular pattern with rents flowing to and from a fixed combination of factors, without generating additional value and resulting in economic stagnation.

Under these conditions, entrepreneurs assume a pivotal role as generators of additional value. They are the driving force behind creative destruction processes, which arise from the development of new factor combinations, and which are realised in the introduction of new products (radical innovations), the improvement of existing products (incremental innovations), changes at the organisational level (organisational innovations) or new methods to address markets and consumers (marketing innovations), and other innovations addressing additional production and market processes. These innovations trigger competitive gains, replacement mechanisms and wealth redistribution, forcing incumbent firms to adapt or face obsolescence. Ultimately, they foster technical advance and economic progress.

In later works such as *Capitalism, socialism and democracy* (Schumpeter, 1942), the author presented a diametrically distinct perspective. Despite maintaining the interpretation of innovation as an endogenously evolutive and transformative process (Rosemberg, 2011) and the foundations of the idea of creative destruction, Schumpeter abandoned the notions of circular flows and economic stagnation, defending the thesis that reaching market equilibria is virtually impossible.

Under this new reasoning, innovation requires extensive efforts in terms of research and development (R&D) and accumulation of skills. Consequently, it is mainly the biggest and most experienced firms who can generate a solid stock of knowledge, because these are the primary R&D investors and attractors of skilled and specialized personnel. In this alternative paradigm, incumbents can, and do, develop all types of innovation, from the most incremental to the most radical, emerging as the principal engine of technical advance and economic growth.

After Schumpeter's death, the study of innovation drifted to the background of economic science, which, at the time, was dominated by growth theories focusing mainly on factor accumulation and neoclassical models which neglected the dynamic and disruptive nature of innovation processes. One of the main reasons for this secondary role was a significant lack of comprehensive data and measurement tools to capture the characteristics of innovation processes (Yoguel et al., 2013). However, during the 1980s and 1990s the field of innovation attracted increasing attention, and, throughout those decades, the contemporary understanding of the Schumpeterian approach was modernized.

The current field of innovation studies has emerged from several schools of thought. The configuration, knowledge management, cluster, and system schools (Miller and Friesen, 1982; Porter, 1990; Nonaka, 1994) aim at better understanding innovation processes, focusing primarily on either internal determinant (firm characteristics, organizational structure, knowledge management, etc.) or external forces (suppliers, customers, competitors, etc.). Their approach highlights the heterogeneity in innovation behaviours which results in a non-strictly causal relationship between innovation and firm performance (Ram and Jung, 1991; Huang and Rice, 2009).

Although each of these schools develops a distinguishable and valuable contribution, they often lack a dynamic and more comprehensive approach to fully understanding the complexities of the innovation phenomenon (Tzeng, 2009). More comprehensive perspectives on innovation include the evolutionary theory and the dynamic capabilities approach.

This evolutionary theory was first proposed in *An evolutionary theory of economic change* (Nelson and Winter, 1982) and, even to the present day, is adopted by many researchers. In opposition to the neoclassical understanding, which focuses on individual choice and providing adequate incentives to foster innovation, the evolutionary approach opposes the assumption of equilibrium and interprets the economy as a dynamic, continuously evolving, and interlinked system, in which firms do not act as isolated entities but as part of regional, national and global innovation systems.

The dynamic capabilities approach (Cepeda and Vera, 2007; Teece, 2007) incorporates the role of capabilities (knowledge) into the generation of innovation, arguing that without a process of knowledge development, firms cannot generate wealth. Both the evolutionary theory and the dynamic capabilities approach offer complementary interpretations. They understand innovation as a cumulative process in which formal and informal practices integrate into a firm's organisational culture, shaping its capabilities, and contributing to increased competitiveness. From a dynamic perspective, firms test their capabilities continuously, adapting to new circumstances through innovative development which addresses a multitude of dimensions. Consequently, eventually, only the most innovative and knowledge-intensive firms emerge as the most successful, continuously expanding the technological envelope.

Within the conceptual framework of the cumulative and dynamic analysis of innovation processes, this thesis adopts a methodological approach to the topic of innovation, providing evidence on three dimensions: *i)* the financial patterns of innovative firms (by examining which combination of short-term and long-term capital investments provide the highest returns to innovation and productivity); *ii)* the role of learning-by-exporting on innovation and its persistence (by exploring how venturing into different markets and accumulating an extensive exporting experience incentivizes firms to engage and persist in innovation activities); *iii)* how knowledge generation influences the development of radical innovations, (by determining the profile of internal and external knowledge generators and its effects on innovations new to the market).

Aiming to advance the comprehension of innovation and knowledge generation patterns, the three contributions broadly capture the nature and implications of being an innovative firm. Thus addressing a relevant question in the literature in regard of which dimensions inside the firm have a tangible potential of fostering innovation efforts, outcomes, and performance gains (Demirel and Mazzucato, 2009). Note that, despite sharing a common discursive line, each chapter of this thesis constitutes an independent piece of research, making separate contributions to the field of innovation economics.

The outputs of the thesis expand the ideas identified by previous researchers in the field of evolutionary economics, knowledge generation and its benefits, and provide new interpretations of the topics addressed. Much of the research in this thesis focuses on combining different dimensions of the economic literature by applying diverse econometric tools. This ranges from determining the non-linear effects of debt acquisition on R&D and innovation, to the implications of diverse export dynamics on the persistence of the same innovation activities. Together, these converge to a thesis on the effects of knowledge on future innovative developments. Consequently, they provide additional understanding of the interlinks between innovation, finance, trade, and knowledge dynamics.

Additionally, each chapter attempts to identify heterogeneous effects in terms of firm age, sector activity, exporting experience and characteristics of the markets addressed. This disaggregated analysis aims to provide additional precision and to enrich the implications of the ideas presented.

Beyond the academic scope of this project, this thesis also offers insights into the design and implementation of policy solutions. The relevance of the ideas presented is found in a context based on transformative change. In this new paradigm, governments address social and environmental challenges widely and with more effectiveness as compared to previous decades. This provides new opportunities for the development of science, technology, and innovation (Schot and Steinmueller, 2018).

Here, several EU designed initiatives are relevant. Take for example the European Green Deal whereby, through innovation, European countries are expected to reduce dramatically their emissions by 2030 and become completely net-zero by 2050, thus aligning with the Paris climate change agreements. Similarly, the United Nations has formulated a set of Sustainable Development Goals targeting green production, justice, and welfare.

To deliver these changes, a comprehensive understanding of the interplay between technology and policy is fundamental. This thesis contributes to the topic by shedding light on R&D, innovation, and knowledge generation, so providing a basis for future developments of this line of research.

1.2. Thesis outline and chapter overview

Chapter 2, *Financing patterns of working capital and physical investment: their effects on innovation and firm productivity*, aims to quantitatively assess the effects of debt financing on R&D, innovation, and productivity. Acknowledging the need for firms to access credit markets to overcome resource constraints to develop effective innovation projects (Gilmore et al., 2013; García-Quevedo et al., 2018), this chapter examines the boundaries of debt financing. An excessive reliance on debt moderates innovative behaviour, due to heightened expected standards, which lead to stricter objectives, requirements, and transparency standards (Christensen et al., 2008).

In this regard, recent evidence suggests the existence of an optimal volume of financial resources that maximize firm value and R&D (Ang et al., 2019; Li et al., 2021). This chapter expands on this in two ways. First, by differentiating between investments as short-term resources (working capital) and long-term resources (physical investment), allowing for heterogeneous implications on firm behaviour while simultaneously capturing complementary effects between the two (Fazzari and Petersen, 1993). This disaggregation allows a deeper study on the effects of debt financing based on specific needs and on how effectively firms design their investment projects. Second, the chapter quantifies the effects of the financial dimension across all the steps of the R&D-innovation-productivity relationship. For this purpose, we use a variation of the CDM (Crépon, et al., 1988) model based on a system of simultaneous equations aimed at partially overcoming the limitations and biases of the classical approach (Baum et al., 2017; Mairesse and Robin, 2017).

The findings obtained reveal that observed firms tend to under-finance their working capital and over-finance their physical investment, resulting in an inefficient resource distribution that fails to maximize innovation. This inefficient distribution originates from the complexity of identifying future working capital requirements. Thus, when designing investment plans, firms tend to focus predominantly on long-term needs, which are easier to identify, resulting in a relative neglect of future short-term needs. Furthermore, this chapter tests if the results vary according to firm age and sector of activity. According to this disaggregation, young firms tend to benefit more from the complementarities of investing simultaneously in working capital and physical investment, while mature firms focus on building more complex financial structures. Additionally, firms operating in low-tech sectors design their investments to maximize productivity over innovation, while in high-tech sectors firms focus on innovation and exhibit more complex returns to capital investment.

This chapter utilizes data from the World Bank Enterprise Survey (WBES), which serves as a useful tool to match the study of innovation with other dimensions of interest such as having access to financial or non-financial resources, competition, and other characteristics. In comparison to other data sources emphasizing the innovation dimension such as the Community Innovation Survey (CIS), or other examples, the WBES provides significantly less information regarding a firm's innovative behaviour. However, as the interest of this chapter is not solely on innovation, WBES provides rich information regarding the debt profile of firms in reference to short-term (working capital) and long-term (physical investment) resources. The principal limitation of the survey is its cross-sectional nature, which limits the dynamic analysis of the topic addressed, as well as in identifying individual heterogeneity.

In reference to the methodology, the classical structure of the CDM model is reinterpreted and implemented as a system of three simultaneous equations through Generalized Structural Equation Models (GSEM), following Baum et al. (2017). The system consists of a selection equation that determines the unobserved characteristics of innovative firms, and two bilateral equations to estimate R&D investment and productivity, based on the previously identified unobserved characteristics. As compared to the classical approach, this methodology provides robust outcomes with cross-sectional data and surpasses the limitations of bilateral interlinkages and omitted-variable bias (Aw et al., 2011).

Chapter 3, *Export and variability in the innovative status,* focuses on the determinants that guarantee the adoption and stability of innovation activities. More concretely, it addresses the interaction between export and innovation dynamics. Departing from Melitz's (2003) self-selection perspective, the most creative and productive firms are, at the same time, the most likely to successfully enter international trade. However, building upon this insight, De Loecker (2007) finds that export entrants experience productivity gains when persisting in international markets. This productivity gap increases over time, pointing out the existence of a learning-by-exporting process that provides new capabilities that substantially affect a firm's innovative capacity and productivity.

In this chapter, we implement this trade dimension to determine both the innovation status and persistence of Spanish firms. The innovation status is categorized into five groups: *i) persistent innovators*, that conduct innovation activities during all sample periods; *ii) persistent non-innovators,* which never conduct innovation activities; *iii) transitioning towards innovation,* firms that previously were not innovating and start to innovate persistently; *iv) transitioning towards to stop innovation,* previous innovations that stop their innovation activities; *v) non-persistent innovators,* firms that in some periods conduct innovation, but not consistently.

We adopt an alternative to the traditional approach on innovation persistence. Following Altuzarra (2017), the researcher must distinguish between true state persistence, which refers to the path-dependence generated by innovation activities, and spurious state persistence, which associates innovative behaviour with other firm characteristics. In our case, we determine the likelihood of experiencing a variation in the innovative status from period *t-2* to *t.* This approach allows us to bypass the notion of true state persistence, as we already impose non-continuity in innovation activities, greatly simplifying the modelling structure and providing more flexibility in the methodology, so allowing us to explore more deeply the effects of the trade dimension.

The results indicate several interesting insights. Firstly, the temporal dimension of learning-by-exporting significantly increases the likelihood of being a persistent innovator, in accordance with to our intuition. Simultaneously, it also discourages non-innovative firms from starting innovation projects, as initially these firms do not benefit from the cumulative effects of learning processes. Secondly, the spatial dimension of trade reveals the diversity of the effects related to the knowledge obtained from exporting activities. Firms exporting only to the EU are more likely to transition towards innovation but experience more variability in their innovative behaviour than those exporting to a broader geographical range, suggesting that EU markets provide comparatively safer environments for Spanish firms, leading to less competitive pressure, which discourages persistent innovation.

The Spanish Technological Innovation Panel (PITEC) provides the information for the development of this chapter. It follows the definitions and structure of the CIS, but instead of being collected biannually, PITEC offers a panel from 2003 to 2016 with extensive information addressing the innovative behaviour of 12,000 Spanish firms. The advantage of PITEC is related to its wide coverage of the Spanish innovative structure, in terms of horizon, number of firms, and variables addressed. Hence, innovation researchers have widely used it. Nevertheless, PITEC, like other questionnaires addressed to firms (such as CIS), tends to overestimate the degree of innovativeness (Mairesse and Mohnen, 2010).

In this chapter, the methodologies applied are well-known econometric strategies. Firstly, to estimate the likelihood of belonging to each persistence profile we apply multinomial models, as each category is mutually exclusive with the others. Secondly, to analyse transitions of status, probabilistic random effects are applied. This sets a methodological framework similar to the one proposed by Wooldridge (2005), but without the need for correction instruments due to the incorporation of non-continuity, and so limiting the biases of true state persistence.

Chapter 4, *The dynamics of knowledge generation and their effects on innovation*, examines the complementarities between organisational exploitation and exploration strategies. It determines the drivers of continuous internal and external knowledge generation and the effects on the intensity of radical innovation.

According to the Schumpeterian understanding of innovation, deepening patterns are related to the continuous development of innovation activities, resulting in an accumulation of technological capabilities and knowledge, which crystallize in a consistent R&D investment and continuous development of incremental innovations (Grant, 2000; Santamaría et al., 2009). Widening patterns are related to a continuously growing knowledge base, driven by radical innovations, and resulting in an erosion of the competitive and technological capabilities of incumbents.

Although these two patterns seem in opposition to each other, recent evidence suggests that they are complementary in nature (Bergek et al., 2013; Delgado-Verde et al., 2016; Forés and Camisón, 2016). The successful development of complex, radical innovation requires a solid knowledge creation and absorption base (Tseng and Goo, 2005; Stieglitz and Heine, 2007). Thus, effective innovators use their knowledge stock to develop completely new technologies to enter new market segments and disrupt market distributions (Zhou and Li, 2012).

In our approach, we determine the firm profile of internal and external generators of knowledge, finding that the firms with more human capital, productivity, and exporting activity are the predominant generators of internal knowledge. Afterwards, we impute the effects of knowledge generation on the intensity of radical innovations.[1]

The findings confirm the positive implications of knowledge in the development of complex innovations. More concretely, the development of internal knowledge is key to generating capabilities that differentiate a firm from its competition. Nonetheless, the benefits of knowledge do not distribute homogeneously across the sample, mature firms obtain larger returns during a more prolonged period from knowledge, as their experience grants them a greater ability to adapt knowledge into the firm's culture and managerial structure.

Similarly to Chapter 3, PITEC provides the information for the development of Chapter 4. In this case, the methodology is considerably more sophisticated. It follows a multi-step structure based on dynamic models. In the initial step, we determine the profile of continuous generators of internal or external knowledge by applying dynamic random-effects probabilistic models. Then, we impute the effects of this continuous development of knowledge into the intensity of radical innovations applying dynamic censored models.

1.3. Thesis outputs

We are currently incorporating the ideas developed in this thesis into three research articles. Attending many conferences was a pivotal element for expanding the scope of

[1] According to the Oslo Manual, a distinction can be made between innovations new to the firm and to the market. The first corresponding to innovations new only to the firm, but already existing in the market. And the second addressing entirely new, substantially improved, or marginally improved innovations (Mohnen and Hall, 2013). The subjectivity of innovations surveys makes difficult to precisely measure the degree of novelty when developing innovations. Nonetheless, we consider innovations new to the market a step forward from innovations new to the firm in terms of technical and knowledge requirements, thus referring to them as radical innovations, despite not all innovations in this group necessarily classifying as radical.

the contributions, contributing to a better fit into ongoing discussions in the literature, improved precision in the methods, and improving the overall quality of the investigations. In this section, we summarize the scientific outcomes from the thesis, the conferences in which they were presented, and additional elements of interest.

i) Tomàs-Porres, J., Segarra-Blasco, A., & Teruel, M. (2024). Financing patterns of working capital and physical investment: their effects on innovation and firm productivity. Currently, this paper is under review in *Economics of Innovation and New Technology*, listed in SCOPUS and JCR. Different versions of this study were presented at Knowledge Dynamics, Industry Evolution, Economic Development (KID) (2023), the XXV Applied Economic Meeting (2023), and the 12th PhD-Student Workshop on Industrial and Public Economics (WIPE) (2024).

ii) Tomàs-Porres, J., Segarra-Blasco, A., & Teruel, M. (2023). Export and variability in the innovative status. *Eurasian Business Review*, 13(2), 257-279. Being published, the working paper version was presented at the XXIV Applied Economics Meeting (2022).

iii) Tomàs-Porres, J., Segarra-Blasco, A., & Teruel, M. (2024). The dynamics of knowledge generation and their effects on innovation. A previous version of this paper was published in *SSRN* (SSRN 4486366). Preliminary versions of this research were presented at the SBEJ 1st Online Conference for Young Researchers (2022), the 11th PhD-Student Workshop on Industrial and Public Economics (WIPE) (2023), and the DRUID Academy (2024). Additionally, it received the INNOVA prize for the best paper related to innovation topics in WIPE (2023).

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Chapter 2:

Financing patterns of working capital and physical investment: their effects on innovation and firm productivity

2.1. Introduction

As a strategic resource allocation method, debt financing has long been recognized as a vital determinant of innovation. It serves as a tool to surpass financial constraints and barriers (Hall, 2002; Canepa and Stoneman, 2008). Debt financing, as a strategy to generate additional short-term and long-term resources, addresses key financial barriers that impede the correct development of innovation activities and hamper firm performance (Gilmore et al., 2013; García-Quevedo et al., 2018; Khan et al., 2021). Yet, relying excessively on debt financing generates intricate ties with external agents that moderate creativity and innovative behaviour, as firms must adhere to stricter disclosure requirements (Christensen et al., 2008; Shi et al., 2019). Recently, Ang et al. (2019) demonstrate the existence of an optimal acquisition of debt financing which maximizes firm value. However, these ideal proportions have not been uncovered or approximated in the field of innovation economics.

This chapter addresses this gap by examining the debt profile of innovative firms and determining the optimal debt boundaries of working capital and physical investment. Our research objectives are three-fold: *i)* to determine the nature of the effects of debt financing on innovation and productivity, searching for the critical point at which the marginal gains from debt financing reach their maximum; *ii)* to explore the complementarities between short-term and long-term financial assets, building on a relatively underexplored literature strand based on Fazzari and Petersen's (1993) foundational notions; *iii)* to examine potential heterogeneous effects related to the particular characteristics and needs of high-tech sectors and young firms (Pellegrino, 2017; Cowling et al., 2021).

To achieve these purposes, this research employs a robust sample of 7,051 European manufacturing firms. The dataset is derived from a combination of several World Bank Enterprise Surveys (WBES) for European economies. The WBES questionnaires address firm behaviour in many dimensions: resources, performance, capital composition, etc. In this case, we focus specifically on the dimensions that cover finance, innovation, and performance.

Designing a multi-equation framework based on Generalized Structural Equation Models (GSEM)[2], we capture the complex associations between the financial dimension of a firm and its effects on R&D, innovation, and productivity, providing comprehensive insights into the nature of capital composition, innovation, and firm performance. The methods employed are built on a reformulation of the CDM model (Crépon et al., 1998) proposed by Baum et al. (2017).

The results obtained confirm the intuition of Christensen et al. (2008) by demonstrating that the returns from debt financing on innovation activities and productivity are diminishing by nature. From our estimations, we derive a numerical expression that proves the existence, and thresholds, of an optimal combination of working capital and physical investment that allows a firm to maximize its innovative behaviour and performance. This optimal investment strategy envisages significant complementary effects between working capital and physical investment, as firms leverage long-term assets more effectively if they simultaneously expand their short-term capital. This conclusion has implications for the interpretation of short-term and long-term needs, as the analysis of one dimension would be incomplete if the other is ignored.

Contrasting our findings with the WBES data, European manufacturing firms tend to under-finance their working capital and over-finance their physical investment, despite this result being sample-specific, it provides a valuable intuition on the inefficiencies when designing investment plans. When planning the development of their innovation activities, firms tend to over-value the role of long-term assets. This leads to an inefficient acquisition of working capital, relevant for short-term operations overlooked during the planning process.

Differentiating sector clusters, the findings reveal that in low-tech industries, the role of working capital is crucial in determining innovation activities, while physical investment influences firm productivity. In high-tech sectors, the interplay between short-term and long-term is more complex and resembles the baseline outcomes more closely. Finally, young firms benefit the most from the complementarities between working capital and

[2] GSEM are Generalized Linear Models (GLM) applied to Structural Equation Models (SEM).

physical investment, while mature firms design more complex strategies to maximize their innovation performance.

In this context of suboptimality, driven by misalignments during investment design, the principal role of policymakers should be improving information availability and the quality of public agencies regarding efficient financial strategies to boost innovation. Furthermore, additional credit lines targeting short-term capital needs should be designed for firms with investment structures that under-finance working capital. Given the different needs of firms operating in different industries, it is important to increase the heterogeneity and flexibility of credit lines to address each sector properly. The differences between young firms and incumbents also need to be considered.

The paper is structured as follows. Section 2.2 presents a literature review addressing the interconnections between working capital, physical investment, and firm behaviour. Section 2.3 describes the database and the variables used in the analysis, differentiating innovative firms, high-tech sectors, and young firms. Section 2.4 addresses the modelling structure. Section 2.5 shows the baseline results and the heterogeneous effects across different subsamples and, finally, Section 2.6 discusses the results and concludes the research.

2.2. Literature review

2.2.1. Corporate finance, debt financing, and innovation

The uncertain nature of innovation generates a trade-off between expectations, innovation outcomes, and firm value which shapes market entry and exit patterns, becoming a key mechanism of business selection in an evolutionary context (Nelson and Winter, 1982). In this framework, Joseph Schumpeter (1911) was the first author to analyse the influence of financial markets on business cycles, innovation and, therefore, productivity and economic growth. He demonstrated that, despite the risks inherent in innovation, firms need to address financial markets to develop their innovation activities effectively and boost their performance. Undoubtedly, the complementarities between the development of the financial sector and innovation generate the optimal ground for sustained growth (Prah, 2022).

To conduct their operations, firms rely on various options to finance their activities. In a perfect framework, with abundant resources, firms would rely only on their internal assets to develop their operations, as acquiring them externally results in obligations which might hinder firm performance (Hall and Lerner, 2010). However, reality is far from this idealized conception, as a firm's resources are inherently limited. Then, access to financial markets serves as a determinant of a firm's success, and it is a relevant generator of a competitive business environment (Beck and Demirguc-Kunt, 2006; Lv and Xiong, 2023).

Besides internal funds or retained earnings, there are two additional mechanisms to expand a firm's resources: i) capital expansions due to owner contributions or newly issued equity shares; ii) acquiring funds by accessing external agents, most commonly through debt financing.

Durand (1952) provides valuable insights for understanding the implications of these two strategies, which allows us to identify the trade-offs associated with each strategy. On the one hand, if firms decide to finance their capital internally, they have incentives to take more risks at higher prices, as shareholders will demand higher returns in exchange. On the other hand, debt-financed capital is comparatively cheaper but involves long-term obligations that restrict firm behaviour.

Examining the implications of equity markets, they have long been considered relevant to finance innovation (Santarelli, 1991; Müller and Zimmermann, 2009), since firms acquire capital according to their value. However, a relevant literature strand has emphasized the negative effects of equity market imperfections on R&D investment and innovation decisions (Bloch, 2004). More concretely, if equity markets operate under asymmetric information, the allocation of resources is inefficient, resulting in an undervaluation of firms with more valuable, yet unidentified, opportunities (Yulianto et al., 2021).

Consequently, these firms, which have larger growth potential, tend to issue more debt than equity, as this strategy limits the agency problem arising from ex-ante information asymmetry (Leland and Pyle, 1977; Ross, 1977). This sends, at the same time, a positive signal to equity markets.

Therefore, debt financing has raised a significant amount of attention as a driver of a firm's innovative behaviour (Hall, 2002; Canepa and Stoneman, 2008). Perfect credit markets would generate long-run productivity-enhancing investments, as they directly address key barriers to innovation, such as a lack of own resources, insufficient (or too expensive) credits and funding shortages due to inefficient equity markets (Savignac, 2008; Ughetto, 2009; Silva and Carriera, 2011). There is a point of agreement that, if financial barriers are not efficiently surpassed, they can lead to slower development, abandonment, or non-pursuit of innovation projects (Gilmore et al., 2013; García-Quevedo et al., 2018).

However, an excessive reliance on debt can moderate creativity and innovation outcomes, as firms need to adhere to stricter objectives, requirements, and must be more transparent regarding their activity (Christensen et al., 2008; Shi et al., 2019). This dichotomy between the need for debt financing and its potential negative effects if there is an over-reliance on debt, provides the intuition that an optimal level of debt financing should maximize innovation and productivity.

Some recent studies demonstrate the existence of this optimal proportion, maximizing firm value (Ang et al., 2019). Additionally, Li et al. (2021) provide thresholds for an optimal volume of aggregate financial resources on R&D and innovation for a sample of Chinese firms. Based on this, we propose the following.

H1. There exists an optimal level of debt financing that maximizes innovation and firm performance.

2.2.2. The role of working capital and physical investment

To provide a more comprehensive and coherent analysis, one needs to differentiate between long-term and short-term investments. Physical investment has long and extensively been considered a significant determinant of innovation. It provides firms with the necessary infrastructure, equipment, and other long-term liabilities to develop R&D and innovation in a consistent and sustained manner (Hall et al., 2016; Carboni and Medda, 2020).

In contrast, a firm's working capital has crucial implications in the short term (Fazzari, 1988). It provides firms with sufficient resources to cover operational expenses before revenue is obtained. Therefore, it serves as a good measure of a firm's liquidity and ability to meet its most immediate financial obligations.

Working capital alleviates financial constraints when the financial system is not efficient (Ding et al., 2013) and allows it to provide more effective responses to market demands (Kahl et al., 2014). Limited availability of working capital forces firms to ration all their resources at a suboptimal level, which significantly hampers firm performance (Chan, 2014). For these reasons, the most innovative firms accumulate an extensive volume of short-term resources to alleviate the risk to innovation activities (Baldi and Bodmer, 2016). In sum, working capital becomes essential for the proper development of R&D investment and innovation (Mulkay et al., 2001; Brown et al., 2009).

Despite the effects of physical investment and working capital on innovation having been extensively analysed separately, the complementarities between both have received limited attention in the literature. Fazzari and Petersen (1993) provide coherent reasoning for the strategies combining working capital and physical investment, highlighting that it is relatively costlier to adjust physical investment levels as compared to adjusting the volume of working capital. Consequently, firms tend to rely more on short-term resources to address financial constraints and alleviate the effects of negative shocks on fixed capital investment (Ding et al., 2013).

Building on this overlooked dimension in the literature, we propose the following hypothesis:

H2. An extensive acquisition of physical investment through debt cannot be sustained without expanding the base of working capital.

2.2.3. The heterogeneous effects of debt financing

It is reasonable to assume that firms will not uniformly benefit from debt financing, as some firms will depend more systematically on external sources of capital. Therefore, it becomes necessary to identify the sources of potential heterogeneity in the effects of debt financing on innovation.

Focusing first on the differences related to firm age, young firms are more likely to face stronger financial constraints (Pihkala et al., 2002; Pellegrino, 2017). Additionally, their access to financial markets is more limited (Fazzari et al., 1998), and they have more incentive to differentiate themselves from their established competition in a market, leading to a stronger reliance on debt financing to develop market innovations (Robinson, 2014). Overall, the implications of debt financing on the growth of new firms are positive and well-backed by recent evidence (Fryges et al., 2015).

Conversely, successful mature firms are more long-term oriented and tend to focus on the sustainability of their financial structure, while maintaining a lower dependence on external sources of capital (DeAngelo and DeAngelo, 2007; Cincera et al., 2015).

Consequently, we propose a third hypothesis:

H3. Young firms leverage resources more extensively, while mature firms build more complex structures to guarantee long-term financial stability.

Finally, a firm's capital structure varies significantly depending on the industry in which it operates. The literature, however, has mixed results in this regard. While some authors find that firms operating in high-tech sectors are more sensitive to debt financing (Causholli and Knechel, 2012), others explain that these differences are more directly linked to the innovative capabilities of the firm rather than to the technological intensity of its sector (Cowling et al., 2021).

Inherently, firms operating in high-tech sectors are subject to higher risks (Hutton and Nightingale, 2011). Consequently, the relations between the firm and external financier are affected (Han et al., 2009; Cole and Sokolyk, 2016), encouraging innovative high-tech firms to design more sustainable and robust financial structures which minimize risk and guarantee stability. Consequently, we propose a final hypothesis:

H4. The debt structure of firms operating in high-tech sectors is more complex than in low-tech sectors.

2.3. Data and descriptive statistics

2.3.1. The database

This chapter utilizes establishment-level information from the World Bank Enterprise Survey (WBES), encompassing 22 European economies. The WBES presents representative information of registered firms, ensures comparability across countries and is collected via face-to-face interviews with business owners or top managers. To ensure representation, the sample is stratified by industry, size, and location within each country. The WBES employs standardized sampling instruments and a uniform methodology to minimize measurement error.

It is important to remark that each observation pertains to the most relevant establishment within each firm. Manufacturing firms are represented by production plants. However, to enhance readability and coherence, we consistently refer to these establishments as firms throughout the paper.

Our dataset comprises 7,051 European manufacturing firms. Although the data is cross-sectional, and limits the adaptation of panel data models, firms appear in different fiscal years. This temporal variation allows us to control for year fixed-effects, enabling the identification of homogenous shocks across the period 2017–2021, such as the COVID-19 crisis.

The WBES offers distinct advantages for the objectives of this article. Firstly, it provides granular information on a firm's working capital composition and fixed investment over a specific fiscal year, enabling a clear identification of the proportion of these resources financed through debt.

Secondly, it includes the necessary information to establish connections between this financial dimension and R&D investment, innovation, and productivity. Additionally, the data availability and quality are remarkable, as the information is obtained rapidly, and most of the sample exhibits comprehensive and consistent data.

2.3.2. Descriptive statistics

This research examines the effect of debt financing on all stages of the innovation process. For this purpose, we address innovation from three different perspectives. Firstly, the variable Sel is a dichotomous indicator that distinguishes innovative firms from the rest. These are firms that have consistently invested in R&D and introduced at least one innovation new to the market during the last three years.[3] Firms meeting this criterion are assumed to possess different and non-observable characteristics and behaviours which differentiate them from other firms.

Secondly, we employ a firm's total R&D investment over the number of employees to approximate the intensity of the R&D investment. This variable is referred to as RD_int. Thirdly, productivity is introduced to capture the monetary gains resulting from the development of innovation activities, it is calculated as the total sales during a fiscal year over firm size. It is denoted by $prod$.

[3] In reference to the fiscal year the information belongs to.

Table 2.1. Definition of the variables.

Dependent variables	
Sel	Dummy indicating a firm has invested in R&D and introduced innovations new to the market during the last three years
RD_int	Research and development per employee.
Prod	Labour productivity as sales per employee.
Firm characteristics	
Size	Plant size measured as number of full-time employees.
Age	Difference between the fiscal year and the year in which the firm started operations.
WC	Working capital borrowed from financial or non-financial institutions as a proportion of the total working capital.
PI	Last year's investment in physical assets borrowed from financial or non-financial institutions as a proportion of the total investment in physical assets.
Trade status	
	Dummy indicating if the establishment…
Non-exporter	…does not sell directly or indirectly to foreign markets.
Direct exporter	…sells directly to foreign markets.
Indirect exporter	…sells indirectly to foreign markets.
Importer	…acquires supplies or intermediate products from foreign markets.
	Dummy indicating if the market scope of the establishment is…
Local scope	…local.
National	…national.
International	…international.
Perceived competition	
	Dummy indicating if the establishment …
No competition	…does not perceive any direct competitor.
One competitor	…perceives only one direct competitor.
Between 2 and 3 competitors	…perceives two or three direct competitors.
Between 4 and 10 competitors	…perceives between four and ten direct competitors.
Between 10 and 30 competitors	…perceives between ten and thirty direct competitors.
More than 30 competitors	…perceives more than thirty direct competitors.
Sector	
Supplier-dominated, Scale-intensive, Science-based, Specialized suppliers	Dummy indicating if the firm belongs to a supplier-dominated sector, a scale-intensive sector, a science-based sector, or a sector dominated by specialized suppliers.
Country	
Eastern, Mediterranean, Nordic, Centre	Dummy indicating if the firm is located in Eastern Europe, the Mediterranean, Nordic countries, or Central Europe.

The financial dimension of the firm is approached from two perspectives: short-term and long-term. On the one hand, the weight of debt financing for working capital is derived by summing the working capital borrowed from banks, both private or state-owed, along with working capital borrowed from non-bank financial institutions, such as microfinance institutions, credit cooperatives, credit unions or finance firms. This variable is relativized as a proportion of a firm's total working capital. On the other hand, the share of debt financing for physical investment is proxied as the weight of investment borrowed from the same bank and non-bank financial institutions over the firm's total investment in physical assets during a specific fiscal year.

Additionally, the analysis incorporates traditional explanatory variables such as firm age, size, trade status (exports, imports and market scope), the perceived number of direct competitors, as well as geographic and sector dummies. Table 2.1 presents the definitions of all variables.

Table 2.2 provides a summary of all the variables used in the analysis. Notably, approximately one-third (34%) of our data comprises firms engaging in both R&D activities and innovations new to the market. For ease of reference, we will refer to these firms as selected firms. On average, firms finance 15.7% of their working capital from financial institutions. Excluding those firms which do not borrow working capital, this rises to 41.1%. The distribution for the level of physical investment is similar; on average the dependence on debt is 13% but considering only firms borrowing money to invest in physical assets this increases to 64.6%.

As expected, selected firms exhibit higher R&D investment per employee and greater productivity on average. Furthermore, they rely more on debt to finance their working capital and physical investment compared to other firms. They also demonstrate a higher level of direct interaction with foreign markets and their market scope is, also, more international. Non-innovators perceive a higher degree of competition.

High-tech firms are identified as those operating in science-based and specialized-suppliers sectors. They display a higher level of innovativeness and productivity compared to the average enterprise. Again, they depend more on foreign markets. Rather surprisingly, they do not rely more on debt financing for short-term or long-term capital expansions. Lastly, young firms[4] are the least innovative, are smaller, and depend more on local markets to develop their business activities. Their reliance on debt financing is also relatively limited.

[4] Young firms are less than 10 years old.

Table 2.2. Description of the variables.

Dependent variables	**All firms**	**Selected**	**High-tech**	**Young**
Sel	0.340 (0.474)	1.000 (0.000)	0.426 (0.495)	0.309 (0.462)
RD_int (thou. EUR)	2.236 (31.276)	5.145 (53.234)	5.130 (54.054)	1.814 (7.535)
Prod (thou. EUR)	199.673 (856.639)	231.356 (735.359)	214.290 (658.465)	129.563 (207.406)
Firm characteristics				
Size	86.542 (550.275)	122.906 (891.356)	115.956 (936.200)	40.299 (88.590)
Age	31.901 (26.688)	36.274 (30.708)	31.774 (24.757)	6.330 (2.619)
WC (Including Zeros)	0.157 (0.264)	0.270 (0.331)	0.153 (0.261)	0.144 (0.257)
WC (Without Zeros)	0.411 (0.279)	0.421 (0.284)	0.409 (0.281)	0.411 (0.281)
PI (Including Zeros)	0.130 (0.293)	0.206 (0.346)	0.121 (0.283)	0.119 (0.285)
PI (Without Zeros)	0.646 (0.302)	0.638 (0.297)	0.646 (0.304)	0.646 (0.302)
Trade status				
Non-exporter	0.343 (0.475)	0.235 (0.424)	0.216 (0.411)	0.447 (0.497)
Direct exporter	0.567 (0.496)	0.684 (0.464)	0.703 (0.457)	0.435 (0.496)
Indirect exporter	0.090 (0.286)	0.080 (0.272)	0.081 (0.273)	0.118 (0.322)
Importer	0.521 (0.500)	0.672 (0.470)	0.664 (0.472)	0.427 (0.495)
Local scope	0.197 (0.398)	0.140 (0.347)	0.088 (0.283)	0.255 (0.436)
National	0.515 (0.500)	0.500 (0.500)	0.509 (0.500)	0.506 (0.500)
International	0.287 (0.453)	0.360 (0.480)	0.403 (0.491)	0.239 (0.427)
Perceived competition				
No competition	0.035 (0.184)	0.034 (0.182)	0.044 (0.205)	0.049 (0.217)
One competitor	0.027 (0.162)	0.029 (0.167)	0.036 (0.186)	0.022 (0.146)
Between 2 and 3 competitors	0.166 (0.372)	0.188 (0.391)	0.211 (0.408)	0.163 (0.370)
Between 4 and 10 competitors	0.394 (0.489)	0.460 (0.499)	0.433 (0.496)	0.339 (0.473)
Between 10 and 30 competitors	0.086 (0.280)	0.094 (0.292)	0.082 (0.275)	0.076 (0.265)
More than 30 competitors	0.292 (0.455)	0.194 (0.396)	0.195 (0.396)	0.351 (0.478)
Sector				
Supplier-dominated	0.583 (0.493)	0.492 (0.500)	0.000 (0.000)	0.623 (0.485)
Scale-intensive	0.087 (0.282)	0.094 (0.292)	0.000 (0.000)	0.054 (0.226)
Science-based	0.139 (0.346)	0.188 (0.391)	0.421 (0.494)	0.127 (0.333)
Specialized suppliers	0.191 (0.393)	0.225 (0.418)	0.579 (0.494)	0.195 (0.397)
Country				
Eastern	0.262 (0.440)	0.180 (0.385)	0.234 (0.423)	0.347 (0.476)
Mediterranean	0.314 (0.464)	0.226 (0.418)	0.245 (0.430)	0.316 (0.465)
Nordic	0.171 (0.377)	0.275 (0.447)	0.214 (0.410)	0.208 (0.406)
Centre	0.252 (0.434)	0.318 (0.466)	0.308 (0.462)	0.129 (0.335)
Observations	7,051	2,396	2,327	1,054

Regarding the geographical dummies, Eastern European countries refer to those that joined the European Union (EU) in the 2000s and, during the Cold War, were socialist economies. These countries include Bulgaria, Croatia, Czech Republic, Hungary, Lithuania, Poland, Romania, and Slovenia. Mediterranean countries are EU members located in southern Europe, namely Greece, Italy, Spain, and Portugal. The Nordic countries consist of EU members situated in the Scandinavian peninsula, more specifically Denmark, Finland, and Sweden, with the inclusion of Estonia, which we consider to have stronger technological ties with Nordic rather than Eastern countries. Finally, the Centre-European countries encompass Austria, Belgium, France, Germany, Ireland, and the Netherlands. The sector clusters in our analysis are based on Pavitt's taxonomy (Pavitt, 1984) which is linked to the NACE classification system by Bogliacino and Pianta (2016).

2.4. Methodology

2.4.1. Empirical strategy

To capture the nature of the interrelations between R&D, innovation, and productivity, Crépon et al. (1998) proposed a multi-equation framework connecting past productivity to R&D as a first step, innovation outcomes as a second, and present productivity as the final step. This methodology is known as the CDM model and is widely used in the innovation literature. However, the original CDM model is limited in many ways, as it lacks dynamic interlinkages between dependent variables (Aw et al., 2011), suffers from endogeneity issues, and omitted-variables bias (Baum et al., 2017).

Employing an estimation approach based on Generalized Structural Equation Modelling (GSEM) (Rabe-Hesketh et al., 2004) we construct a system of recursive equations that handles sample selection and captures bidirectional effects between innovation and productivity. The econometric structure presented in this section follows most of the suggestions made by Baum et al. (2017), with some modifications to better adapt to the characteristics of our data and improve the coherence of the estimator.

In the first step, we design a selection equation that determines the likelihood that a firm engages extensively in innovation, this is defined as investing in R&D and developing innovations new to the market simultaneously over the last three years. Traditionally, the selection equation in a CDM model considers firms investing only in R&D. However, in our case, we lack a continuous variable measuring the intensity of innovation outputs for subsequent equations. Therefore, incorporating innovation outputs into the selection equation imposes more restrictions on the sample, but allows for a more effective implementation of this dimension.

As an outcome of the selection equation, we approximate the effects of a latent variable, through the variance-covariance between all observed and dependent variables. This latent variable captures the unobserved factors that differentiate R&D investors and innovators from other firms (which we cannot approximate through our observed variables), mitigating the omitted-variables bias. The first equation is specified as follows:

$$Sel_i = \beta_0 + \beta_1 X_i + L_i + \beta_{i,s} + \beta_{i,c} + \beta_{i,t} + \varepsilon_i \ (2.1)$$

where Sel_i indicates the likelihood of being an R&D investor and introducing at least one innovation new to the market, assumed to follow a probabilistic distribution function; β_0 is the intercept; β_1 are the coefficients multiplying the set of variables X_i; L_i is the latent variable, restricted with a mean of 0 and a standard error of 1, as its scale cannot be determined initially; $\beta_{i,s}$, $\beta_{i,c}$ and $\beta_{i,t}$ are sector, country and time-specific fixed-effects; ε_i are error terms.

In a second step, we implement two simultaneous equations that allow for endogenous effects between the intensity of the R&D investment and firm productivity:

$$\ln(RD\_int_i) = \gamma_0 + \gamma_1 Z_i + \gamma_2 L_i + \gamma_{i,s} + \gamma_{i,c} + \gamma_{i,t} + e_i \ (2.2)$$

$$\ln(prod_i) = \lambda_0 + \lambda_1 K_i + \lambda_2 L_i + \lambda_{i,s} + \lambda_{i,c} + \lambda_{i,t} + v_i \ (2.3)$$

In equation *(2.2)* RD_int_i is the intensity of the R&D investment; γ_0 is the intercept; γ_1 is a vector of coefficients multiplying the set of variables Z_i; γ_2 allows the latent variable L_i to be unrestricted; $\gamma_{i,s}$, $\gamma_{i,c}$ and $\gamma_{i,t}$ are sector, country and time-specific fixed-effects; e_i are error terms.

In equation (2.3) $prod_i$ is the productivity of firm *i;* λ_0 is the intercept; λ_1 are the coefficients determining the effects of variables K_i; λ_2 allows L_i to be unrestricted; $\lambda_{i,s}$, $\lambda_{i,c}$ and $\lambda_{i,t}$ are sector, country and time specific fixed-effects; v_i are error terms.

Note that in this case, the variance-covariance matrix of the error terms allows for non-zero elements in the diagonal, enabling $Cov(e_i, v_i) \neq 0$.

In contrast to Baum et al. (2017), equations *(2.2)* and *(2.3)* are estimated using full information. In this case, the latent variable defined in equation *(2.1)* will determine the qualitative differences between innovators and non-innovators, both in terms of R&D investment and firm productivity.

As a relevant remark to the econometric strategy, the dataset does not allow us to identify individual heterogeneities, due to the cross-sectional nature of the data. However, part of this heterogeneous behaviour is addressed by the country fixed-effects, that capture common regulations, culture, similar conduct, etc.

2.4.2. Treatment of the financial dimension and identification

The disaggregated information provided by the World Bank's Enterprise Survey allows us to examine the structure of working capital and physical investment during a specific fiscal year. We can thus identify the weight of debt financing within these short-term and long-term investment indicators.

To test our hypotheses, we need to incorporate into the modelling an expression that captures non-linear effects and complementarities between the two types of investment. To achieve this, we introduce the following expression equations *(2.1)*, *(2.2)*, and *(2.3)*:

$$\tau_i = \delta_1 WC_i^2 + \delta_2 WC_i + \delta_3 PI_i^2 + \delta_4 PI_i + \delta_5 WC_i \times PI_i \quad (2.4)$$

where τ_i represents the impact of the expression on the regression outcomes, and δ_k are the marginal impacts.

Note that if δ_1 and δ_3 are smaller than 0, they indicate that the marginal gains from debt financing are negative. Additionally, if δ_5 is statistically different from 0, it implies that the marginal impacts of both working capital and physical investment cannot be interpreted separately, as their effects are interdependent.

Another critical aspect to consider is the identification of which variables need to be introduced in each step of the system to ensure coherent and robust results while minimizing endogeneity issues and capturing maximum information. In addition to the financial dimension of the firm, which is introduced in all the equations of the system, firm age and size are also present in all steps, as well as sector, country, and time dummies. These are suggested by prior studies (Morris, 2018).

Export and import dummies are included to capture potential learning-by-exporting effects (De Loecker, 2007). In equations *(2.1)* and *(2.2)* these dummies indicate whether a firm engages in import or export activities, either directly or indirectly. In Equation *(2.3)* we substitute these dummies with the market scope of the firm, which can be classified as local, national, or international.

Finally, the amount of perceived competition provides essential information, as it captures the incentives (or disincentives) that a specific market position provides for the development of market activities (Marshall and Parra, 2019). This dimension is introduced to determine the likelihood of being a selected firm and its productivity. It is relevant to remark that we do not assume direct effects on the intensity of R&D investment, but rather indirect effects through determining whether it is an innovative firm.

2.5. Regression outcomes

2.5.1. Baseline outcomes

Table 2.3 presents the coefficients that determine the various steps of the multi-equation framework.[5] In column *(1)* we can only interpret the sign of a parameter, but not its exact value. However, in columns *(2)* and *(3)*, the coefficients can be directly interpreted.

In the selection equation (column 1), we observe that the proportion of working capital borrowed from financial institutions and the interaction between working capital and physical investment have a positive impact at $\alpha = 0.1$ confidence level. Note that the quadratic form of working capital does not provide any significant impact. In contrast, the physical investment exhibits a clear non-linear effect, indicating diminishing marginal returns in determining the likelihood of being an innovative firm at $\alpha = 0.05$ confidence level.

Conceptually, the selection equation demonstrates that for innovative firms, the accumulation of short-term resources is fundamental for conducting their R&D and innovation activities. Alternatively, the marginal effect of adding an additional unit of physical investment decreases more rapidly, leading to a lower optimal debt acquisition of long-term resources. Furthermore, the positive effect of the interaction between working capital and physical investment indicates the need for developing complex strategies based on the complementarities between the two dimensions, maximizing the returns obtained from debt financing. Considering the remaining explanatory variables, we find that firm size, being a direct exporter, importing, and not facing direct competition, or having between 2 and 10 competitors have a significant positive impact.

[5] The introduction of equation *(2.4)* in the modelling does not seem to cause multicollinearity issues. Providing only a linear expression or omitting the interaction between working capital and physical investment does not provide relevant differences in the coefficients, standard errors, or significance levels.

Table 2.3. GSEM outcomes for the R&D-Innovation-Productivity relationship.

Variables	**(1) Selection equation**	**(2) R&D intensity**	**(3) Productivity**
Financial variables			
WC	0.448*	1.183***	-0.139
	(0.266)	(0.432)	(0.180)
WC × WC	-0.484	-1.193**	0.002
	(0.319)	(0.521)	(0.155)
PI	1.242***	2.385***	0.324**
	(0.341)	(0.566)	(0.168)
PI × PI	-1.396***	-2.618***	-0.340*
	(0.375)	(0.622)	(0.184)
WC × PI	0.449*	0.934**	0.101
	(0.236)	(0.393)	(0.116)
Firm characteristics			
Age (logs)	-0.000	-0.041	0.137***
	(0.029)	(0.048)	(0.014)
Size (logs)	0.070***	0.313***	0.110***
	(0.020)	(0.033)	(0.010)
Trade status			
Exporting directly	0.161***	0.928***	
	(0.059)	(0.094)	
Exporting indirectly	0.050	0.512***	
	(0.089)	(0.139)	
Importing	0.448***	0.732***	
	(0.052)	(0.084)	
National market scope			0.374***
			(0.030)
International market scope			0.483***
			(0.036)
Perceived competition			
No competition	0.287**		0.038
	(0.127)		(0.062)
One competitor	0.212		0.262***
	(0.142)		(0.069)
2–3 competitors	0.299***		0.242***
	(0.071)		(0.034)
3–10 competitors	0.293***		0.234***
	(0.058)		(0.028)
10–30 competitors	0.168*		0.247***
	(0.089)		(0.043)
Sector dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
L	Constrained	1.132***	0.023
		(0.064)	(0.021)
Cov(e, v)		0.131*** (0.038)	
Observations	7,051	7,051	7,051

*p<0.10, **p<0.05, ***p<0.01. Coefficients (Std. Err.) Reported. Non-exporters are the base outcomes for trade dummies. Having a local market scope is the base outcome for scope dummies. Firms identifying more than 30 direct competitors are the base outcome for perceived competence dummies. Supplier-dominated sectors are the base outcomes for sector dummies. Centre-European countries are the base outcome for country dummies.

Column *(2)* provides the determinants that influence the intensity of R&D investment. In this case, the relationship between all the items in the financial dimension exhibits complex non-linear and complementary links. The quadratic expression of both working capital and physical investment has a significant moderating effect, determining a clear limit to the external acquisition of the two variables. Besides, the interaction between working capital and physical investment appears positive and significant, demonstrating that the most effective financial strategies combine the acquisition of short-term and long-term resources.

Given the results obtained in both equations, it is relevant to compute the values where the effect of debt financing reaches its optimal value. Although relatively specific, this will provide valuable insights to the analysis. In column (1), the marginal impact of working capital and physical investment on the probability of being an innovative firm is given by the following equation:

$$\tau_i = -0.113WC_i^2 + 0.104WC_i - 0.325PI_i^2 + 0.290PI_i + 0.105WC_i \times PI_i \quad (2.5)$$ [6]

where the optimal acquisition debt financing for working capital and physical investment fulfils the following conditions:

$$\begin{aligned} \frac{\partial \tau_i}{\partial WC_i} &= -0.226WC_i + 0.104 + 0.105PI_i = 0 \\ \frac{\partial \tau_i}{\partial PI_i} &= -0.65PI_i + 0.29 + 0.105WC_i = 0 \end{aligned} \quad (2.6)$$

which is solved at $WC_i = 0.686$ and $PI_i = 0.487$. Therefore, on average, the critical shares of working capital and physical investment borrowed from financial institutions, at which we observe the maximum influence on the likelihood of being an innovative firm, are approximately two-thirds (68.6%) and one half (48.7%) respectively. Beyond, these thresholds, the marginal gains from debt financing decrease exponentially.

In column (2), the marginal impacts of working capital and physical investment are specified as follows:

$$\tau_i = -1.193WC_i^2 + 1.183WC_i + -2.618PI_i^2 + 2.385PI_i + 0.934WC_i \times PI_i \quad (2.7)$$

Equation *(2.7)* reveals the non-linear relationships between working capital, physical investment, and debt financing at $\alpha = 0.01$ confidence level. Additionally, it highlights

[6] The coefficients of column *(1)* cannot be interpreted directly as marginal effects. Equation *(2.5)* shows the marginal effects. Non-significant values must also be introduced to avoid biases in the interpretation of the marginal effects.

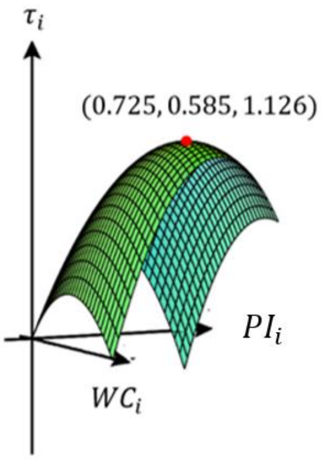
the complementary effects of financing working capital and physical investment through debt.

The values that maximize equation *(2.7)* fulfil the following conditions:

$$\begin{aligned} \frac{\partial \tau_i}{\partial WC_i} &= -2.386WC_i + 1.183 + 0.934PI_i = 0 \\ \frac{\partial \tau_i}{\partial PI_i} &= -5.236PI_i + 2.385 + 0.934WC_i = 0 \end{aligned} \quad (2.8)$$

where $WC_i = 0.725$ and $PI_i = 0.585$ define the maximum returns from debt financing. Equations *(2.5)* and *(2.7)* and their maximization offer several key insights. Firstly, the critical proportion of working capital borrowed from financial institutions (0.686 to 0.725) is considerably higher than the proportion of physical investment (0.487 to 0.585),[7] emphasizing the importance of working capital as a significant driver of R&D investment.

Figure 2.1. Effects of the acquisition of working capital and physical investment on R&D intensity. Equation (2.7).



Source: Own elaboration using CalcPlot3D

Secondly, there is clear evidence supporting strong complementarities between the acquisition of short-term and long-term assets. According to Figure 2.1, which graphically represents equation *(2.7)*,[8] if firms decide to exclusively increase one of the two variables, the returns they will obtain are considerably lower compared to complementing working capital and physical investment. Specifically, firms deciding to solely invest in physical

[7] These proportions have base one.
[8] The representation of equation *(2.5)* is similar to the shape presented in Figure 2.1.

assets during a given period, without expanding their volume of working capital, find moderate returns on R&D intensity when the level of investment is relatively low, and negative returns when the same investment is relatively higher. Consequently, strategies combining the acquisition of short-term and long-term assets appear to provide the best returns for research and development activities.

Regarding the other explanatory variables, firm size and involvement in international trade, whether direct or indirect, have a positive impact on R&D intensity. Additionally, the unobserved characteristics of innovative firms, captured in the latent variable, are associated with the number of resources devoted to R&D.

Moving to column *(3)*, which captures the determinants of firm performance measured as sales per employee, we find that only the volume of physical investment borrowed from financial institutions has a significant impact. In this case, the non-linear effects of debt financing are less clear, as they are associated with firm performance at $\alpha = 0.1$ confidence level. However, accounting for the highly significant correlation between columns *(2)* and *(3)*, the complex links found in the determination of R&D investment indirectly influence firm productivity.

In this case, mature and bigger firms are the most productive, along with those with a market scope beyond their local environment and those that face a moderate number of competitors. We observed in the selection and productivity equations that not having competition does not provide sufficient incentives to boost creativity and performance, confirming the replacement effect (Arrow, 1962; Tirole, 1997). Also, having many competitors disincentivizes the development of innovation activities, confirming the U-shaped pattern between innovation and market concentration demonstrated by Aghion et al. (2005).

Summarizing all the baseline results, we find consistent evidence supporting the relevance of debt financing in determining the innovative behaviour of a firm and its performance, although this relationship is far from linear. There are clear limits to the acquisition of working capital and physical assets through debt, confirming the first hypothesis *(H1)*, suggesting that exceeding these limits may potentially hamper innovation activities.

Furthermore, we demonstrate the existence of complementarities between the acquisition of working capital and physical assets in the intensity of R&D investment, supporting the second hypothesis *(H2)*. According to previous evidence, this relationship is not bidirectional. An expansion of the working capital base improves the gains from an increase in physical investment, due to the need for increased flexibility to alleviate unexpected financial constraints (Ding et al., 2013).

These complementarities require us to simultaneously interpret the two dimensions, as changes in one of them affect the returns obtained from the other. Based on our estimates, to maximize their innovative behaviour, firms should finance 68.6% to 72.5% of their working capital with debt, while for the physical investment, this value falls within the range of 48.7% to 58.5%.

Considering that, on average, firms rely on debt for 41.1% of their working capital and 64.6% of their physical investment,[9] we observe a clear tendency to under-leverage short-term resources and over-leverage long-term resources for the development of their innovation activities. According to Deloof (2003), approximating the optimal investment of working capital in the long term is comparatively more difficult than for physical investment. This provides a suboptimal distribution of resources, which has its origins in the design of the investment plan.

2.5.2. Sources of heterogeneity

This section examines whether the effects obtained in the baseline model differ depending on the technological intensity of the sector (low-tech or high-tech) and firm age (younger than 10 years or older than that).

Table 2.4 presents the effects of the financial dimension across technological clusters. In low-tech sectors, we observe that the working capital plays a more relevant role in the selection equation, but its influence diminishes substantially in the determination of R&D intensity. In high-tech sectors, there are no notable differences in the selection equation compared to the baseline model. However, the non-linear effects of debt financing are less clear in the restricted sample.

Comparing the two clusters, we find that innovative firms operating in low-tech sectors rely more on borrowing working capital as compared to innovative firms in high-tech. However, higher levels of R&D investment in high-tech sectors are associated with extensively leveraging working capital. Additionally, the volume of physical investment

[9] These are the values which do not include zeros.

emerges as a key determinant of firm productivity in low-tech industries, but not in high-tech industries. Regarding the effect of physical investment in the selection equation and the determination of R&D intensity, there are no statistical differences between the two groups.[10]

Table 2.4. GSEM outcomes for the R&D-Innovation-Productivity relationship across technological clusters.

	Low-tech			**High-tech**		
Variables	**(1) Selection equation**	**(2) R&D intensity**	**(3) Productivity**	**(1) Selection equation**	**(2) R&D intensity**	**(3) Productivity**
Financial dimension						
WC	0.663** (0.327)	0.850* (0.475)	-0.051 (0.160)	0.056 (0.462)	1.894** (0.874)	-0.323 (0.210)
WC × WC	-0.584 (0.387)	-1.010* (0.568)	-0.007 (0.191)	-0.322 (0.567)	-1.607 (1.076)	0.008 (0.258)
PI	1.062*** (0.412)	2.404*** (0.615)	0.462** (0.206)	1.635*** (0.615)	2.373** (1.181)	0.036 (0.283)
PI × PI	-1.143** (0.451)	-2.566*** (0.675)	-0.497** (0.227)	-1.856*** (0.680)	-2.467* (1.298)	-0.005 (0.311)
WC × PI	0.432 (0.285)	0.633 (0.427)	0.109 (0.144)	0.286 (0.427)	1.520* (0.820)	0.145 (0.196)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
L	Constrained	0.794*** (0.071)	0.008 (0.027)	Constrained	1.764*** (0.123)	0.064* (0.034)
Cov(e, v)		0.292*** (0.099)			0.063 (0.075)	
Observations	4,724	4,724	4,724	2,327	2,327	2,327

*p<0.10, **p<0.05, ***p<0.01. Coefficients (Std. Err.) Reported. Non-exporters are the base outcomes for trade dummies. Having a local market scope is the base outcome for scope dummies. Firms identifying more than 30 direct competitors are the base outcome for perceived competence dummies. Supplier-dominated sectors are the base outcomes for sector dummies. Centre-European countries are the base outcome for country dummies.

Table 2.5 shows the effects of the same variables across age groups, with young firms being less than 10 years old and mature firms being older than that.

On the one hand, for young firms, the complementarities between working capital and physical investment play a crucial role in fostering their R&D investment. These complementarities enable young firms to optimize their innovation efforts by combining short-term and long-term capital resources. This suggests that for start-ups and young

[10] We applied the following test: $(\tau_i^{HT} - \tau_i^{LT})/\sqrt{\sigma_{HT}^2 + \sigma_{LT}^2} \sim N_{0,1}$, under the null hypothesis that the two coefficients are equal.

businesses, it is essential to leverage extensively working capital and physical investment to enhance their R&D intensity.

Moreover, the effect of physical investment borrowed from financial institutions has a larger impact on young innovative firms. For them, accessing external funding is crucial to drive their innovation efforts effectively, as it is more challenging for them to generate internal funds for extensive investment projects.

Table 2.5. GSEM outcomes for the R&D-Innovation-Productivity relationship across age groups.

	Young			Mature		
Variables	**(1) Selection equation**	**(2) R&D intensity**	**(2) Productivity**	**(1) Selection equation**	**(2) R&D intensity**	**(2) Productivity**
Financial aspects						
WC	0.309 (0.754)	1.626 (1.040)	0.057 (0.373)	0.399 (0.286)	0.999** (0.472)	-0.171 (0.136)
WC × WC	-0.597 (0.917)	-0.979 (1.275)	-0.404 (0.455)	-0.400 (0.343)	-1.130** (0.569)	0.051 (0.164)
PI	3.484*** (0.997)	1.095 (1.412)	-0.045 (0.504)	0.913** (0.365)	2.438*** (0.615)	0.409** (0.177)
PI × PI	-3.396*** (1.096)	-1.653 (1.532)	0.220 (0.547)	-1.091*** (0.401)	-2.578*** (0.677)	-0.440** (0.195)
WC × PI	0.270 (0.667)	2.227** (0.942)	-0.521 (0.336)	0.459* (0.254)	0.716* (0.430)	0.199 (0.124)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
L	Constrained	0.723*** (0.155)	0.017 (0.063)	Constrained	1.187*** (0.070)	0.026 (0.023)
Cov(e, v)		-0.010 (0.091)			0.156*** (0.041)	
Observations	1,054	1,054	1,054	5,997	5,997	5,997

*p<0.10, **p<0.05, ***p<0.01. Coefficients (Std. Err.) Reported. Non-exporters are the base outcomes for trade dummies. Having a local market scope is the base outcome for scope dummies. Firms identifying more than 30 direct competitors are the base outcome for perceived competence dummies. Supplier-dominated sectors are the base outcomes for sector dummies. Centre-European countries are the base outcome for country dummies.

On the other hand, mature firms need to design intricate combinations of working capital and physical investment to achieve optimal R&D intensity. This implies that, as firms mature and grow, their financial strategies become more sophisticated and tailored to their specific need to effectively drive innovation. Additionally, mature firms rely more on external sources of physical investment to boost their productivity, as they must seek additional financing to fund their long-term projects, potentially due to their larger scale and capital requirements.

2.6. Discussion and conclusions

This chapter delves into the financial determinants of innovation and firm performance, specifically focusing on the implications of debt financing by differentiating the role of working capital, which provides firms with the resources to cover daily operations (Chan, 2014), and physical investment, which provides firms with the long-term resources to develop their activities.

The aim is threefold. Firstly, determine the optimal acquisition of working capital and physical investment by approximating the inflexion point at which the marginal gains from debt financing on innovation and firm performance shift from positive to negative. Secondly, explore the complementarities between short-term and long-term financial resources, expanding a relatively unexplored literature strand that departs from concepts developed by Fazzari and Petersen (1993). Lastly, identify potential heterogeneous effects related to the technological intensity of the sector and firm age.

To test these ideas, we apply a multi-equation framework, based on Generalized Structural Equation Models (GSEM), to capture the effects of different combinations of working capital and physical investment on all steps of the innovation process, differentiating innovating firms from the rest, and estimating their R&D intensity and productivity.

From the outcomes presented in the baseline model, the research confirms the relevance of debt financing in determining innovative behaviour and performance. However, the relationship between debt financing and firm performance is non-linear, as there are limits to the acquisition of working capital and physical assets. Additionally, the study reveals the existence of complementarities between the external acquisition of working capital and physical assets, highlighting the need to interpret these two dimensions simultaneously, and emphasizing the importance of developing strategies combining both to obtain the maximum returns to innovation and performance.

The empirical evidence obtained from the WBES sample highlights that European manufacturers tend to under-leverage working capital and over-leverage physical investment, resulting in suboptimal returns to innovation. Despite being relatively specific, this suggests the tendency to overestimate the effects of long-run investments, overlooking the crucial role of short-term resources to cover operations efficiently. This behaviour is related to the nature of financial constraints. When designing future investment plans is easier to compute long-term needs rather than short-term future necessities.

Distinguishing high-tech and young firms from the rest of the sample, our findings indicate that in low-tech sectors, working capital plays a more critical role in determining innovation activities, while physical investment influences firm productivity. Conversely, in high-tech sectors, the interplay between the financial dimension and innovation is more complex due to the higher risk inherent in more technologically sophisticated industries. In addition, the analysis reveals that young firms benefit greatly from the complementarities of leveraging working capital and physical investment simultaneously. In contrast, mature firms need to develop more intricate financial combinations to maximize their innovation performance, as their objectives are more long-term focused.

The findings provide valuable insights to policymakers and firm managers. They point towards the need to adapt financial strategies to maximize innovative behaviour and firm performance, fostering sustainable growth and competitiveness. This can be achieved by improving the advice of public agencies regarding a firm's financial composition and delving into the relevance of properly identifying potential short-term needs in the future. Additionally, designing additional credit lines targeting short-term assets is fundamental in improving capital compositions. With relatively lower interest rates than bank loans, or with public guarantees, these credit lines would offer incentives to increase the volume of available working capital, increasing the manoeuvrability of operations and innovation. These policies need to account for the heterogeneous needs and financing patterns of a firm according to the technological characteristics of the sector in which it operates and its age, as the financial constraints and the use of resources vary greatly in reference to these dimensions.

The principal limitation of the article is the cross-sectional structure of the data, which limits the analysis of dynamics in the R&D-innovation-productivity relationship and the identification of asynchronous effects between short-term and long-term financial resources. Further research in this line should be developed using panel data to include this temporal dimension. Additionally, we can only observe the acquisition of working capital and physical investment during the last fiscal year, with only the relative shares over the absolute values. With more information about the cumulative investments during additional periods and the outstanding debt the analysis could address the topic more in depth and gain additional consistency.

As a concluding remark, we highlight that improving financial strategies in high-tech and oligopolistic markets is crucial to enhance competition and innovation in all European economies. Given that current social and political interests are shifting towards increasing sustainability and private social responsibility, guaranteeing a dynamic and competitive innovation environment will facilitate the transition towards more sustainable environments and increased social welfare.

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2.8. Appendix 2A

Table 2A.1. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Sel	1																
(2) RD_int	0.356	1.000															
(3) prod	0.027	0.049	1.000														
(4) WC	0.067	0.092	-0.006	1.000													
(5) FI	0.078	0.107	-0.002	0.294	1.000												
(6) age	0.091	0.130	0.048	0.051	0.040	1.000											
(7) size	0.098	0.184	0.010	0.071	0.069	0.261	1.000										
(8) Exporting directly	0.171	0.293	0.045	0.056	0.084	0.186	0.350	1.000									
(9) Exporting indirectly	-0.025	-0.027	-0.021	-0.014	-0.010	-0.067	-0.022	-0.360	1.000								
(10) Importing	0.216	0.287	0.037	0.052	0.056	0.116	0.275	0.420	-0.053	1.000							
(11) Nat. market scope	-0.023	-0.063	0.010	0.009	0.036	0.014	-0.093	-0.095	0.074	-0.030	1.000						
(12) Int. market scope	0.116	0.249	0.037	0.022	0.002	0.073	0.347	0.447	-0.013	0.291	-0.655	1.000					
(13) No competition	-0.004	-0.031	-0.008	-0.033	-0.016	-0.035	-0.032	0.010	-0.006	0.001	-0.032	0.020	1.000				
(14) One competitor	0.008	0.011	0.015	0.000	-0.022	0.019	-0.031	0.012	-0.022	0.022	-0.018	0.016	-0.032	1.000			
(15) 2–3 competitors	0.043	0.035	-0.003	0.016	0.009	-0.004	0.006	0.045	-0.043	0.060	-0.004	0.005	-0.085	-0.074	1		
(16) 3–10 competitors	0.097	0.111	0.016	0.048	0.051	0.077	0.079	0.076	-0.021	0.083	0.003	0.019	-0.154	-0.135	-0.359	1	
(17) 10–30 competitors	0.022	0.059	0.005	0.004	0.017	0.025	-0.004	0.023	-0.020	0.034	0.013	-0.010	-0.059	-0.051	-0.136	-0.247	1

Chapter 3:

Exports and variability in the innovative status

3.1. Introduction

Undoubtedly, innovation is a fundamental strategy for increasing productivity and overall firm performance (Mohnen and Hall, 2013; Expósito and Sanchis-Llopis, 2019), increasing a firm's chances of market success. The effects of innovation on firm performance can be approached from two perspectives. Under self-selection processes, the most efficient and creative firms are the ones most likely to enter more complex activities and become successful. Alternatively, another interpretation considers learning processes that positively affect the innovative capacity and productivity of firms.

From a dynamic perspective, recent literature highlights the relevance of maintaining continuity in innovation activities to foster performance and overcome idiosyncratic business cycles (Antonioli and Montresor, 2021), becoming considerably more relevant, given the rapid transformation of production relationships and the distribution of labour skills driven by technological change (Piva and Vivarelli, 2018). Consequently, the topic is of special interest for policymakers intending to design policies to guarantee steady economic growth and mitigate current economic backlashes.

In Chapter 2, we determined the likelihood of being an innovative firm and the intensity of the innovative behaviour in a determined period. Here, we continue our analysis focusing on the elements that cause firms to persist or induce changes in their innovation patterns. Our vehicle to conduct this approach is the interaction with international markets, in this case, the geographical reach and experience in exporting activities. Similarly, exports are also subject to self-selection and learning patterns (Melitz, 2003; De Loecker, 2007).

Using an exhaustive database such as the Spanish Technological Innovation Panel (PITEC), we focus solely on the learning and cumulative links between R&D investments, the introduction of innovation, and the export capacity of firms. Being more specific, this chapter aims to analyse how a firm's export behaviour affects its ability to persist in, or transform, its innovation strategies, focusing on the factors that favour variability.

The topic is addressed from two dimensions. Firstly, classifying firms into five categories, according to whether they are: *i)* persistent innovators; *ii)* persistent non-innovators; *iii)* non-persistent innovators; *iv)* transitioning to innovation; *v)* transitioning to abandon innovation. Determining, then, the profile of the firms in each group. Secondly, modelling the likelihood of changing from one innovative status to another. Considering the causal and endogenous issues when modelling innovation and firm activity (Segarra-Blasco et al., 2022), it is important to remark that the interest of this chapter lies in the correlations between export activity and innovation variability, and not in the determination of the exact causality between these two dimensions.

The findings obtained suggest several relevant ideas. On the one hand, the export experience appears to foster persistent behaviours, both in terms of innovation and non-innovation. According to our reasoning, veteran exporters are more likely to be intensive and persistent innovators. However, non-innovators with an established market position in foreign markets feel sufficiently secure and do not have sufficient incentives to accept the risk entailed to innovation. On the other hand, export activities should not be treated as a homogenous block, the geographical reach of firms provides a considerable volume of granularity to the analysis. We observe how firms exporting solely to the EU are considerably less persistent, experiencing the same variability in innovation activities than non-exporters, while firms addressing a broader geographical range are statistically persistent innovators.

We argue that innovation success is the result of two synchronized processes: the accumulation of new capabilities and the ability to explore further competitive advantages, leading towards less volatile R&D strategies and innovation outcomes, isolating the firms more from negative expected returns and economic situations. This contribution is relevant to the open debate about the true nature of innovation processes, providing evidence of the complementarities between the evolutionary theory and capability-based approaches (Cohen and Levinthal, 1990; Rosenberg, 1990; Baber et al., 1991; Kor and Mahoney, 2005; Gilsing and Nooteboom, 2006).

For the remaining sections, the chapter is organized as follows. Section 3.2. presents a review of existing theoretical and empirical foundations. Section 3.3. describes the database and the variables introduced in the econometric analysis. Section 3.4 explains the methodological approach. Section 3.5. presents the results and robustness checks. Finally, Section 3.6. concludes the chapter.

3.2. Innovation persistence, self-selection, and learning-by-exporting

Since the last decades of the 20^{th} century, with the reappearance of innovation as a relevant field of study, the determinants and motivations that cause firms to persist in their innovation activities have captured a significant level of attention. The most prominent approaches that explain this subject are the success-breeds-success theory (Stoneman, 1983; Flaig and Stadler, 1994), the sunk costs theory (Sutton, 1991), and the evolutionary theory (Nelson and Winter, 1982). Thanks to them, we know the relevance of knowledge accumulation processes through experience, creating and testing diverse ideas and generating a path dependence which determines greatly future activities.

The economics of innovation interprets persistence in diverse manners. For instance, Altuzarra (2017) states the importance of distinguishing between true and spurious state persistence. Tru state dependence refers to a positive causal relationship between the decision to innovate in one period and maintaining this decision during the following periods (Ayllón and Radicic, 2019).

Conversely, spurious state dependence associates the variability in a firm's activity with other characteristics such as firm size, ownership, exports, or public support. Mainly, the factors related to spurious dependence can be divided into internal factors, related to firm characteristics such as strategy and creativeness (Le Bas and Scellato, 2014), as well as firm size, productivity, and other financial capabilities (Antonelli et al., 2013; Clausen and Pohjola, 2013). External factors are defined by the structure of the sector in which the firm operates (Latham and Le Bas, 2006; Matvejeva, 2014), access and volume of private and public funding, inter-firm and institutional cooperation, and access to stocks of knowledge (Freitas et al., 2011; Le Bas and Scellato, 2014).

One of the main drivers of spurious dependence is the relation of the firm with international markets. Over the last decade, new literature addressing the dynamic interrelations between innovation and internationalization has appeared (Damijan et al., 2010; Casillas et al., 2012; Becker and Egger, 2013; Máñez et al., 2015). The links between innovation and trade fall under two paradigms. The notion of self-selection (Bernard et al., 2003; Melitz., 2003) explains why only a restricted proportion of firms internationalize successfully. Under their reasoning, the decision to undertake complex behaviours is not random, only the most productive firms have the sufficient capabilities and margins to act effectively and assume the risks related to complexity. The other paradigm calibrates how export activities enhance firm performance through the adoption of innovation (De Loecker, 2007). This process of acquisition of knowledge is identified as learning-by-exporting (LBE), and it can be differentiated into two dimensions, spatial and temporal (Segarra-Blasco et al., 2022).

Although there are few studies aiming to disentangle the association between innovation persistence and trade, relevant sources do exist. For instance, Andersson and Lööf (2009) show how persistent behaviours favour the consistency of LBE effects in the acquisition of knowledge, concluding that the exporting activity and the continuity in innovation activities are highly correlated, having both a positive effect on the evolution of firm productivity (Lööf et al., 2015). To develop further this idea, we approach the accumulation of capabilities from trade through temporal and spatial dimensions. On the one hand, based on the number of consecutive years in which a determined firm has conducted exports, we assume the following hypotheses:

H1a: Being a persistent exporter increases the likelihood of being a persistent innovator.

H1b: Being a persistent exporter increases the incentives to undertake innovation activities.

On the other hand, approaching the spatial dimension of trade from a proximity perspective, we test the following ideas:

H2a: Firms addressing farthest markets are more likely to be persistent innovators.

H2b: Firms addressing farthest markets are more prone to undertake innovation activities.

3.3. Data and descriptive statistics

3.3.1. The database

Spain is a moderate innovator, with a large share of non-innovative firms but with the potential to undertake innovation activities (Ministerio de Industria, C. y T., 2020; European Commission, 2021). Given this mixed nature and unexploited potential, we consider this country an interesting case for studying the drivers of innovation persistence. Additionally, the Spanish National Institute of Statistics (INE) and the

Spanish Foundation for Science and Technology (FECYT), conducted a highly detailed firm-level survey which contains expensive information regarding innovative and non-innovative Spanish firms.

The Spanish Technological Innovation Panel (PITEC) follows the surveying methodology and definitions given by the Oslo Manual (OECD and Eurostat, 1997), ensuring international comparability, and allowing the data to serve as an input for the Community Innovation Survey. It is restricted to firms located in Spain, covering agriculture, industry, construction and services, indexing the sectors according to the NACE-2009 classification. The population of firms with more than 200 employees are introduced to the sample by census, while for smaller firms the sample is stratified by sector of activity. The time horizon covered by the panel is considerably wide, ranging from 2003 to 2016. Despite the survey has not been continued to address our current context, it is still extremely useful to capture a wide range of associations related to innovation activities.

To conduct our analysis, several filters are applied to the original data. First, we restrict our time coverage to the period 2005-2016, as from 2005 several relevant variables were introduced to the survey. Second, to provide more robustness and balancedness to the panel we keep only the firms with, at least, ten successive observations, limiting our scope only to manufacturing and service sectors. Finally, firms founded before the year 1800 are also dropped from the sample, as they are usually not agile firms and, in many cases, they are cooperatives and firms with a moderate innovation and export capacity. As a result, we obtained a relatively unbalanced panel composed of 62,171 firm-year observations corresponding to 5,176 firms.

3.3.2. Descriptive statistics

To properly develop the empirical methodology, we need to define and classify innovative behaviours consistently, depending on a firm's level of persistence. Thus, two categorical variables are created, one addressing internal R&D investment and the second identifying firms introducing product or process innovations.

These variables allow us to identify five mutually exclusive categories, identifying if a firm conducts innovation activities in every period of the sample (Persistent innovator), in no period (persistent non-innovator), if it changes its innovation status multiple times (non-persistent innovator), changing it once to start innovation (transitioning to innovation), changing it once to abandon innovation (transitioning to stop innovation).

Table 3.1. Cross-table showing the R&D and innovation categorization

R&D	Innovation (1)	(2)	(3)	(4)	(5)
(1)	68.78	1.3	9.16	12.6	8.16
(2)	9.38	34.12	19.68	8.62	28.2
(3)	23.78	1.11	30.45	23.13	21.52
(4)	29.63	0.63	19.93	40.77	9.04
(5)	15.33	3.68	21.21	11.35	48.44

All values show relative frequencies. (1) Persistent innovators. (2) Persistent non-innovators. (3) Non-persistent innovators. (4) Firms transitioning to innovation. (5) Firms transitioning to abandon innovation.

Table 3.1 cross-tabulates these categorical variables, which show several relevant facts. Most persistent R&D investors are, also persistent innovators (68.78%) and, secondly, transitioning towards innovation (12.6%). However, approximately two-thirds of the firms never invest in R&D and do not introduce innovations (34.12%), transition towards stopping innovation activities (28.2%), or experience variability in the innovation status (19.68%).

For non-persistent R&D investors, the distribution among categories distributes more heterogeneously in terms of innovation. Firms transitioning to start investing in R&D are also more likely to transition towards innovation (40.77%) or persistently introduce them (29.63%). For firms that transition towards stopping R&D investment, they also shift to stop innovation (48.44%) or are inconsistent innovators (21.21%).

Complementary to the analysis of these categories, we also undertake a more discrete and granular approach to the determination of consistency in the development of innovation activities. With this purpose, we build a set of dichotomous variables that take value 1 whenever a firm changes its innovation status in the period *t-2* and sustains this change over *t-1* and *t*. Differentiating R&D investment and the introduction of innovations, there are two potential directions: *i)* Starting R&D or innovation if the firm did not conduct any activity in *t-2* and does so in *t-1* and *t*; *ii)* Stopping R&D or innovation if the firm did conduct these activities in *t-2* and did not during *t-1* and *t.*

Table 3.2. Definition of the variables.

Dependent variables	
	Categorical variable identifying…
R&D status	… the degree of persistence in R&D.
Innovation status	… the degree of persistence in innovation.
	Dummy variable indicating if…
Start R&D	… the firm has changed its R&D status from non-investor to investor during the period *t-2* to *t*.
Stop R&D	… the firm has changed its R&D status from investor to non-investor during the period t-2 to t.
Start innovation	… the firm has changed its innovation status from non-innovator to innovator during the period *t-2* to *t*.
Stop innovation	… the firm has changed its innovation status from innovator to non-innovator during the period *t-2* to *t*.
Trade activity indicators	
Experience	Number of consecutive years exporting
	Dummy variable indicating if…
Exporting only to the EU	… the firm exports only to the EU.
Exporting only outside the EU	… the firm exports only outside the EU.
Exporting inside and outside the EU	… the firm exports both inside and outside the EU.
Firm characteristics	
Sales per employee	Sales over the number of employees.
Size	Firm size measured in the number of employees
Human capital	The proportion of employees with higher education
Age	Firm age
Physical investment	Investment in plants, machines, equipment, and ICT as a percentage of total turnover.
	Dummy variable indicating if…
Public financing	… the firm receives public financing.
Cooperation	… the firm cooperates with other agents.
Head	… the firm is the head of a group.
Subsidiary	… the firm is a subsidiary of a group.
Sector-specific controls	
Cluster	A set of dummy variables identifying the technological cluster in which the firm operates (High-tech or low-tech manufacturers, KIS or non-KIS sectors).

Table 3.3. Description of the variables.

Variables	Mean (Std. dev.)
Dependent variables	
R&D status	
Persistent investor	0.316 (0.465)
Persistent non-investor	0.175 (0.380)
Non-persistent investor	0.132 (0.338)
Transitioning to invest	0.105 (0.306)
Transitioning to stop investing	0.272 (0.445)
Innovating status	
Persistent innovator	0.338 (0.473)
Persistent non-innovator	0.076 (0.265)
Non-persistent innovator	0.182 (0.386)
Transitioning to innovation	0.159 (0.366)
Transitioning to stop innovation	0.245 (0.430)
Start R&D	0.024 (0.152)
Stop R&D	0.042 (0.200)
Start innovation	0.035 (0.183)
Stop innovation	0.041 (0.197)
Trade activity indicators	
Consecutive years exporting	3.530 (3.598)
Exporting status	
Non exporter	0.309 (0.462)
Exporting only to the EU	0.116 (0.320)
Exporting only outside the EU	0.133 (0.339)
Exporting inside and outside the EU	0.442 (0.497)
Firms' characteristics	
Sales per employee (thou. Euros)	273.052 (4,445,950)
Size	234.541 (941.381)
Human capital	25.928 (26.218)
Age	28.840 (20.224)
Physical investment	0.088 (1.351)
Public financing	0.341 (0.474)
Cooperation	0.290 (0.454)
Group	
No group	0.583 (0.493)
Parent	0.085 (0.278)
Subsidiary	0.332 (0.471)
Sector-specific controls	
Technological cluster	
Low-tech manufactures	0.451 (0.498)
High-tech manufactures	0.340 (0.474)
KIS sectors	0.125 (0.331)
Non-Kis sectors	0.084 (0.278)
Observations (Firms)	47,066 (4,905)

Table 3.2. shows the definition of all variables, and Table 3.3 shows the main descriptive statistics. Approximately one-third of the observations present a persistent behaviour in terms of both R&D and innovation. Transitioning to stop innovation activities is the second most present pattern, with 27.2% and 24.5% in R&D and innovation respectively.

The proportion of persistent non-investors (17.5%) is considerably larger than the proportion of persistent non-innovators (7.6%), additionally, firms are more likely to transition towards introducing innovations (15.9%) and introducing them in a non-persistent manner (18.2%) rather than present the same behaviour in terms of R&D, pointing out towards the increased complexity of R&D in reference to innovation. Regarding the direction of the status changes, firms are more prone to stop innovation activities rather than start them, indicating a slight abandonment of innovation during the period of analysis.

As key determinants, we use a set of proxies of export dynamics. The first of these is a continuous variable identifying the number of consecutive years that a firm has been exporting, this variable approaches the temporal dimension of LBE. On average, firms present an exporting experience of 3.53 years. Regarding the spatial dimensions of LBE, most of the firms export simultaneously outside and inside the EU (44.2%) or do not conduct any exporting activity (30.9%). On a lesser scale, firms export only outside the EU (13.3%) or only inside the EU (11.6%). This heterogeneity in exporting patterns gives room to analyse if there exist heterogeneous effects on a firm's innovative behaviour regarding which markets they address and for how long they have been conducting trade activities. Additional determinants include classic controls such as productivity, size, age, human capital, and the technological intensity of the sector of activity, among others.

3.4. Methodology

To analyse our hypotheses, we undertake two different econometric analyses. Firstly, we apply multinomial models to analyse the most common firm profile for each R&D and innovation status according to the definitions in Section 3.3. These are persistent non-innovators *(k=0)*, persistent innovators *(k=1)*, non-persistent innovators *(k=2)*, transitioning to innovation *(k=3*), and transitioning to stop innovation *(k=4)*.[11] Hence, the probability of belonging to each classification is determined by:

[11] The ordering of the categories is not relevant, in this case, *k=0* indicates the baseline outcome, persistent non-innovators.

$$\Pr(Y_{i,t} = k) = \frac{e^{\beta kXi,t}}{1 + e^{\beta 1Xi,t} + e^{\beta 2Xi,t} + e^{\beta 3Xi,t} + e^{\beta 4Xi,t}} \text{ }, if\ k \in \{1,2,3,4\} \quad (3.1)$$

$$\Pr(Y_{i,t} = 0) = \frac{1}{1 + e^{\beta 1Xi,t} + e^{\beta 2Xi,t} + e^{\beta 3Xi,t} + e^{\beta 4Xi,t}} \text{ }, if\ k \notin \{1,2,3,4\} \quad (3.2)$$

where $\Pr(Y_{i,t} = k)$ identifies if the firm *i* belongs to the k_{th} category; $X_{i,t}$ is a matrix with the exogenous variables; β_k measures the relative change to the base outcome $(Y_{i,t} = 0)$, being β_0 set to *0* as it belongs to the reference group. The estimation parameters are interpreted as follows:

$$\frac{\Pr(Y_{i,t} = k)}{\Pr(Y_{i,t} = 0)} = \frac{e^{\beta kXi,t}}{e^{\beta 0Xi,t}} = e^{(\beta k - \beta 0)Xi,t} = e^{\beta kXi,t}, if\ k \in \{1,2,3,4\} \quad (3.3)$$

where $e^{\beta kXi,t}$ indicates the likelihood of the outcome to fall in the comparison group compared to the probability of belonging to the reference category (Greene, 2003).

Note that the objective of this first estimation is not the exact determination of the whole innovation-productivity-export process. We intend to examine the correlations between the explanatory and the dependent variables to provide some insights into the characteristic factors that the average firm belonging to the group *k* has.

In the second approach, we focus on the event of transitioning from a particular R&D or innovation state to another. With this purpose, we create dichotomous variables taking value one whenever a firm changes its innovative behaviour in the period *t-2* and maintains the new status up to period *t*. Note that, according to our consideration, the determinants prompting non-innovative firms to start innovation activities are not the counterfactuals for an innovative firm to stop innovation. Therefore, these two patterns are differentiated and treated independently.

Compared to previous methodologies that apply dynamic perspectives (Wooldridge, 2005; Peters, 2009), the construction of our objective variables allows us to focus specifically on spurious state persistence. This is possible because the notion of status variability bypasses the need to estimate true state persistence, as it is imposed that previous innovation activities have not been continued in the present. This simplifies in a great manner the dynamic framework of the modelling structure, providing more flexibility to the methodology.

Ideally, when operating with panel data, we should account for unobserved heterogeneity by treating the constant parameter as fixed effects to steer clear of any biases due to unobserved effects related to individual heterogeneity (Heckman, 1987). Nevertheless, theory shows that the Fixed Effects estimator provides a bias of order *O(T-1)* when using maxim likelihood in finite samples, which is the case with probabilistic models as the one applied here.

Corrections such as the one proposed by Arroyabe and Schumann (2022) might be applied. However, they would restrict greatly the number of observations to be included in the regressions, as most of them do not comply with the criteria necessary to apply the methodology. As a consequence, we decide to select the random-effects estimator, which allows us to circumvent the bias problem by explicitly modelling the unobserved heterogeneity parameter without losing a significant proportion of the sample.

In a probabilistic setting, the value of the dependent variable $Y_{i,t}$ takes value one whenever:

$$Y_{i,t} = 1\{\theta X_{i,t} + c_i + t_{i,t} + e_{i,t} > 0\} \quad (3.4)$$

where $X_{i,t}$ are the exogenous variables whose impact is determined by the vector of parameters θ; c_i is the individual-specific random-effects constant term; t_i are time-specific effects designed to control for homogeneous shocks across the sample; $e_{i,t}$ are non-linear error terms with the following profile:

$$e_{i,t} \mid X_{i,t}, c_i, t_{i,t} \sim NIID\ (0,1) \quad (3.5)$$

which leads to the final expression:

$$Pr\left(Y_{i,t} \mid X_{i,t},\ c_i\ , t_i, t\right) = \Phi(\theta X_{it} + c_i + t_i) \quad (3.6)$$

Additional modifications are applied to correct potential issues. Some of these are the transformation of all continuous variables to logarithms, to improve the normality of the data (Bellemare and Wichman, 2020). As well as lagging all explanatory variables to limit endogenous effects and other time-specific issues.

3.5. Regression outcomes

3.5.1. Multinomial analysis

This section presents the outcomes obtained from the multinomial regressions for R&D investment, in Table 3.4, and the introduction of product and process innovations, in Table 3.5. All the parameters refer to the probability of being (1) persistent investors/innovators, (2) non-persistent investors/innovators, (3) transitioning to invest/innovate, (4) transitioning to stop investing/innovation, all of them compared to the base outcome (0) persistent non-investors/innovators.

Table 3.4 shows how firms exporting only to the EU are less likely to be persistently investing in R&D, but more prone to start investing if they did not used to perform R&D activities. Similarly, exporting only outside the EU does not increase the likelihood of being a persistent investor in R&D but increases the likelihood of transition towards this activity, as well as performing it inconsistently, with diverse changes of status, or abandoning it. The only firms that present a persistent pattern of R&D investment are the ones addressing markets inside and outside the EU simultaneously.

Comparing the same dimensions in Table 3.5, which explains the determinants of the persistent development of innovation, the pattern is relatively similar. While firms addressing only EU markets or markets outside the EU are less prone to be persistent innovators, but more likely to change their innovation status, firms exporting to both spaces simultaneously are more likely to be persistent innovators.

This heterogeneity in the results reflects the strong implications of the spatial dimension of LBE on the determination of innovation activities. As could be expected, the most extensive exporters, which cover markets inside and outside the EU, present the most persistent innovative behaviour, while firms addressing a more limited spatial dimension tend to be more inconsistent regarding their R&D investment and innovation. The are competitive forces entailed within each categorization of trade, being the incentives inherent to the firms addressing a wider spatial dimension the strongest.

Furthermore, this intuition is complemented by the effect of the temporal dimension of LBE, which is strongly associated with both persistent R&D investors and innovators. Overall, these results align with hypotheses *H1a* and *H2b*, providing strong evidence of the association between all dimensions of LBE and innovation persistence.

Table 3.4. Multinomial logit for R&D investors. Base outcome: persistent non-investors.

Variable	(1) Persistent	(2) Non-persistent	(3) Transitioning to invest	(4) Transitioning to stop investing
Exporting only to the EU	-0.191*** (0.072)	-0.054 (0.072)	0.402*** (0.080)	0.044 (0.059)
Exporting only outside the EU	0.110 (0.127)	0.445*** (0.128)	0.668*** (0.142)	0.354*** (0.111)
Exporting inside and outside the EU	0.470*** (0.074)	0.475*** (0.075)	0.934*** (0.083)	0.351*** (0.064)
Consecutive years exporting	0.098*** (0.009)	-0.005 (0.010)	-0.030*** (0.010)	0.005 (0.008)
Turnover per employee (Logs)	-0.092*** (0.022)	0.057** (0.023)	0.071*** (0.026)	0.056*** (0.018)
Size (Logs)	0.138*** (0.016)	-0.138*** (0.016)	0.025 (0.018)	-0.243*** (0.013)
Human capital (Logs)	0.443*** (0.015)	0.196*** (0.015)	0.320*** (0.017)	0.195*** (0.012)
Age (Logs)	-0.158*** (0.032)	-0.208*** (0.034)	-0.191*** (0.037)	-0.240*** (0.029)
Physical investment (Logs)	-0.048*** (0.009)	-0.014 (0.009)	-0.041*** (0.010)	-0.003 (0.007)
Public financing	1.647*** (0.062)	1.142*** (0.066)	1.446*** (0.067)	0.758*** (0.064)
Cooperation	1.031*** (0.056)	0.575*** (0.059)	0.628*** (0.061)	0.407*** (0.057)
Parent	0.568*** (0.078)	0.438*** (0.082)	0.261*** (0.089)	0.346*** (0.073)
Subsidiary	-0.230*** (0.046)	-0.184*** (0.048)	-0.329*** (0.053)	-0.113*** (0.041)
High-tech manufactures	0.982*** (0.043)	0.270*** (0.046)	0.384*** (0.050)	0.348*** (0.040)
KIS sectors	1.590*** (0.090)	0.853*** (0.092)	1.333*** (0.097)	0.804*** (0.082)
Non-KIS sectors	-1.877*** (0.087)	-1.006*** (0.075)	-1.032*** (0.091)	-0.614*** (0.055)
Time dummies		Yes		
Joint significance of time dummies		(0.000)***		
Observations		47,066		
Number of firms		4,905		
LR test		0.000***		
Pseudo-R2		0.196		

*p<0.1; **p<0.05; ***p<0.01. All values show coefficient estimates (Std. Error). Non-exporters are the baseline outcome of the trade dummies. Firms not belonging to a group are the baseline outcome of group dummies. Low-tech manufacturers are the baseline outcome of the sector dummies.

Other variables that determine the profile of each degree of persistence provide significant results. Labour productivity is positively associated with the degree of persistence in innovation but not in R&D. Firm size and the share of employees with higher education also increase the likelihood of being persistent investors and innovators, as well as transition towards innovation. Young firms are more likely to fall within all degrees of persistence except for the baseline outcome. The volume of physical investment negatively impacts the probability of persistently conducting innovation activities or starting them, and receiving public financing and cooperating with other actors favours all kinds of R&D investors, especially persistent and transitioning; however, public financing is not associated with the introduction of innovations.

Table 3.5. Multinomial logit for innovators. Base outcome: persistent non-innovators.

Variable	(1) Persistent innovators	(3) Diverse changes of status	(4) Transitioning to innovate	(5) Transitioning to stop innovating
Exporting only to the EU	0.071 (0.095)	0.169* (0.090)	0.395*** (0.097)	0.173** (0.085)
Exporting only outside the EU	-0.034 (0.158)	0.046 (0.152)	0.355** (0.160)	-0.078 (0.146)
Exporting inside and outside the EU	0.297*** (0.099)	0.174* (0.095)	0.619*** (0.100)	0.298*** (0.090)
Consecutive years exporting	0.044*** (0.013)	-0.016 (0.012)	-0.050*** (0.013)	-0.006 (0.012)
R&D investment	0.481*** (0.118)	-0.672*** (0.119)	-0.195 (0.120)	-0.741*** (0.119)
Turnover per employee (Logs)	0.263*** (0.028)	0.195*** (0.027)	0.182*** (0.029)	0.140*** (0.025)
Size (Logs)	0.167*** (0.019)	-0.072*** (0.018)	0.069*** (0.020)	-0.158*** (0.017)
Human capital (Logs)	0.201*** (0.019)	0.139*** (0.017)	0.156*** (0.020)	0.158*** (0.016)
Age (Logs)	-0.093** (0.045)	-0.277*** (0.044)	-0.150*** (0.047)	0.070* (0.042)
Physical investment (Logs)	-0.028** (0.011)	-0.004 (0.011)	-0.024** (0.012)	0.009 (0.010)
Public financing	-0.146 (0.103)	-0.182* (0.105)	-0.244** (0.105)	-0.191* (0.105)
Cooperation	0.877*** (0.123)	0.286** (0.125)	0.601*** (0.125)	0.315** (0.126)
Lead	0.359*** (0.111)	0.394*** (0.111)	0.384*** (0.114)	0.254** (0.107)
Subsidiary	-0.019 (0.062)	0.155** (0.060)	0.048 (0.064)	0.024 (0.058)
High-tech manufactures	0.250*** (0.062)	-0.018 (0.061)	0.148** (0.064)	0.038 (0.058)
KIS sectors	-0.281*** (0.100)	-0.169* (0.097)	0.022 (0.102)	-0.121 (0.093)
Non-KIS sectors	-0.731*** (0.093)	-0.553*** (0.079)	-0.361*** (0.090)	-0.550*** (0.073)
Time dummies	Yes			
Joint significance of time dummies	(0.000)***			
Observations	47,066			
Number of firms	4,905			
LR test	0.000***			
Pseudo R2	0.177			

*p<0.1; **p<0.05; ***p<0.01. All values show coefficient estimates (Std. Error). Non-exporters are the baseline outcome of the trade dummies. Firms not belonging to a group are the baseline outcome of group dummies. Low-tech manufacturers are the baseline outcome of the sector dummies.

Finally, firms operating in high-tech manufactures tend to be persistent R&D investors and innovators compared to low-tech manufacturers, the same pattern occurs for firms belonging to KIS sectors. Non-KIS sectors tend to be less active and persistent in both R&D and innovation.

3.5.2. Analysis of status changes

In this section, the focus is set on the determinants that provoke a variation, independently of the overall degree of persistence, in the R&D or innovation status. Table 3.6 reports the estimations for R&D (columns *1* and *2*) and innovations (columns *3* and *4*) about the changes between investing/innovating to stop conducting these activities. Table 3.7 addresses the estimations for changes between not investing/innovating to start the development of these activities.

In both cases, the trade dimension, both in terms of the spatial and temporal derivatives, is negatively associated with both changes in status. Firms exporting only outside the EU and extensive exporters are less likely to stop innovation activities, being this effect more substantial for R&D. Additionally, each consecutive year of exporting decreases the probability of both stopping or starting innovation activities.

The rationality of this outcome explains that trade discourages variability for both innovators and non-innovators. While for the first group, this result is self-explanatory, as the dynamics of learning processes from exports impact positively the robustness of the innovative conduct, the interpretation from previous non-innovators is more challenging. Nevertheless, the intuition behind this effect is rather simple. Successful non-innovative firms addressing international markets do not have incentives to undertake risky strategies, such as the development of innovation activities, as their relatively secured position does not provide sufficiently high expected returns to innovation. This result counters the intuition presented in *H1b* and *H2b*. Note, however, the exception of firms exporting only outside the EU, that are more likely to start investing in R&D.

Additional dimensions such as firm age and size are associated with innovation persistence. The human capital decreases the likelihood of abandoning R&D investment, increasing, simultaneously, the likelihood of starting this activity. The effects of private and public investment are opposites, discouraging and encouraging respectively persistence in innovation activities. Cooperation is associated with movements towards starting R&D and discourages the abandonment of all activities. Regarding the sector of activity, high-tech manufacturers are less likely to abandon R&D compared to low-tech manufacturers. Additionally, firms operating in KIS and non-KIS are more prone to innovation variability than manufacturing firms.

Table 3.6. Random-effects probit for stopping innovation activities.

	R&D investment		Innovation	
Variable	(1)	(2)	(3)	(4)
Exporting only to the EU		-0.040 (0.039)		0.022 (0.040)
Exporting only outside the EU		-0.187*** (0.039)		-0.091** (0.045)
Exporting inside and outside the EU		-0.135*** (0.030)		-0.033 (0.032)
Consecutive years exporting	-0.025*** (0.004)		-0.007* (0.004)	
Sales per employee (Logs)	0.025* (0.014)	0.016 (0.013)	0.007 (0.015)	-0.001 (0.014)
Size (Logs)	-0.128*** (0.010)	-0.134*** (0.009)	-0.083*** (0.010)	-0.088*** (0.010)
Human capital (Logs)	-0.085*** (0.009)	-0.105*** (0.008)	0.017* (0.010)	0.011 (0.009)
Age (Logs)	-0.004 (0.020)	-0.011 (0.018)	-0.005 (0.022)	-0.024 (0.020)
Physical investment (Logs)	0.033*** (0.005)	0.035*** (0.005)	0.011* (0.006)	0.009* (0.005)
Public financing	-0.417*** (0.028)	-0.422*** (0.026)	-0.020 (0.033)	-0.030 (0.031)
Cooperation	-0.205*** (0.028)	-0.212*** (0.026)	-0.274*** (0.036)	-0.297*** (0.033)
Lead	0.025 (0.046)	0.034 (0.044)	-0.013 (0.051)	0.005 (0.048)
Subsidiary	0.103*** (0.029)	0.099*** (0.027)	0.045 (0.031)	0.043 (0.029)
High-tech manufactures	-0.156*** (0.026)	-0.162*** (0.025)	-0.008 (0.029)	-0.016 (0.027)
KIS sectors	-0.068 (0.044)	-0.070* (0.040)	0.144*** (0.045)	0.118*** (0.042)
Non-KIS sectors	0.313*** (0.050)	0.323*** (0.046)	-0.045 (0.050)	-0.004 (0.046)
Time dummies	Yes	Yes	Yes	Yes
Joint significance of time dummies	(0.001)***	(0.000)***	(0.000)***	(0.000)***
Observations	34,863	38,587	38,625	43,010
Number of firms	4,274	4,291	4,780	4,797
Wald test for zero slopes	0.000***	0.000***	0.000***	0.000***
Log likelihood	-7,062.212	-8,161.390	-6,376.275	-7.182.337

*p<0.1; **p<0.05; ***p<0.01. All values show coefficient estimates (Std. Error). All values show coefficient estimates (Std. Error). Non-exporters are the baseline outcome of the trade dummies. Firms not belonging to a group are the baseline outcome of group dummies. Low-tech manufacturers are the baseline outcome of the sector dummies.

Table 3.7. Random-effects probit for starting innovation activities.

	R&D investment		Innovation	
Variable	(1)	(2)	(3)	(4)
Exporting only to the EU		-0.056 (0.050)		-0.045 (0.044)
Exporting only outside the EU		0.106** (0.049)		-0.070 (0.043)
Exporting inside and outside the EU		0.042 (0.039)		-0.103*** (0.035)
Consecutive years exporting	-0.021*** (0.005)		-0.023*** (0.005)	
Sales per employee (Logs)	-0.011 (0.019)	-0.012 (0.018)	-0.003 (0.016)	-0.006 (0.015)
Size (Logs)	0.013 (0.013)	0.008 (0.012)	-0.014 (0.011)	-0.016 (0.010)
Human capital (Logs)	0.034*** (0.012)	0.038*** (0.012)	-0.019* (0.011)	-0.018* (0.010)
Age (Logs)	-0.013 (0.025)	-0.010 (0.023)	-0.068*** (0.023)	-0.066*** (0.020)
Physical investment (Logs)	-0.021*** (0.007)	-0.017*** (0.006)	-0.047*** (0.006)	-0.045*** (0.006)
Public financing	0.283*** (0.031)	0.270*** (0.029)	0.026 (0.029)	0.028 (0.027)
Cooperation	0.073** (0.032)	0.061** (0.030)	0.026 (0.030)	0.026 (0.028)
Lead	0.099* (0.057)	0.078 (0.054)	0.037 (0.052)	0.052 (0.049)
Subsidiary	0.013 (0.037)	0.012 (0.035)	0.029 (0.033)	0.020 (0.031)
High-tech manufactures	0.028 (0.033)	0.019 (0.032)	-0.025 (0.030)	-0.027 (0.029)
KIS sectors	0.115** (0.054)	0.138*** (0.050)	-0.031 (0.049)	0.001 (0.044)
Non-KIS sectors	-0.274*** (0.068)	-0.164*** (0.063)	0.068 (0.057)	0.084 (0.052)
Time dummies	Yes	Yes	Yes	Yes
Joint significance of time dummies	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	19,252	22,114	18,417	21,168
Number of firms	3,139	3,291	3,084	3,235
Wald test for zero slopes	0.000***	0.000***	0.000***	0.000***
Log likelihood	-4,462.551	-4,961.392	-5,593.563	-6,455.144

*p<0.1; **p<0.05; ***p<0.01. All values show coefficient estimates (Std. Error). All values show coefficient estimates (Std. Error). Non-exporters are the baseline outcome of the trade dummies. Firms not belonging to a group are the baseline outcome of group dummies. Low-tech manufacturers are the baseline outcome of the sector dummies.

3.5.3. Further results and robustness checks

This section addresses potential issues related to the robustness of our results. In previous sections, the assumption regarding the sector of activity is that the real values of the parameters (the slope) are uncorrelated with each cluster. However, its necessary to assure the correctness of this assumption. We manage this issue by regressing the determinants of persistent R&D investors[12] in each technological cluster, which information is presented in Table 3.8.

Table 3.8. Determinants of persistent R&D investors by the technological cluster of activity. Base outcome: persistent non-innovators.

Variable	(1) High-tech manufactures	(2) Low-tech manufactures	(3) KISS	(4) Non-KISS
Exporting only to the EU	-0.731*** (0.138)	-0.077 (0.104)	-0.211 (0.303)	-0.177 (0.354)
Exporting only outside the EU	-0.080 (0.223)	-0.068 (0.200)	0.188 (0.487)	0.497 (0.780)
Exporting inside and outside the EU	0.186 (0.141)	0.496*** (0.106)	0.023 (0.324)	0.848* (0.435)
Consecutive years exporting	0.060*** (0.017)	0.088*** (0.013)	0.175*** (0.050)	0.180*** (0.069)
Sales per employee (Logs)	-0.173*** (0.050)	0.139*** (0.035)	-0.477*** (0.100)	-0.164** (0.063)
Size (Logs)	0.228*** (0.035)	0.238*** (0.025)	-0.235*** (0.053)	0.158*** (0.048)
Human capital (Logs)	0.491*** (0.027)	0.488*** (0.023)	0.510*** (0.054)	0.220*** (0.053)
Age (Logs)	0.104* (0.062)	-0.283*** (0.046)	0.269 (0.210)	-0.259** (0.105)
Physical investment (Logs)	-0.097*** (0.016)	-0.044*** (0.013)	-0.044 (0.037)	-0.095*** (0.033)
Public financing	1.613*** (0.125)	1.421*** (0.083)	2.900*** (0.341)	2.033*** (0.202)
Cooperation	0.896*** (0.111)	1.225*** (0.084)	1.214*** (0.278)	0.791*** (0.157)
Lead	1.070*** (0.254)	0.558*** (0.114)	2.293*** (0.746)	-0.495** (0.222)
Subsidiary	-0.930*** (0.093)	-0.014 (0.066)	0.416** (0.205)	-0.820*** (0.183)
Time dummies	Yes	Yes	Yes	Yes
Joint significance of time dummies	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	16,693	21,140	5,557	3,676
LR test	0.000***	0.000***	0.000***	0.000***
Pseudo R2	0.172	0.168	0.236	0.174

*p<0.1; **p<0.05; ***p<0.01. All values show coefficient estimates (Std. Error). All values show coefficient estimates (Std. Error). Non-exporters are the baseline outcome of the trade dummies. Firms not belonging to a group are the baseline outcome of group dummies. Low-tech manufacturers are the baseline outcome of the sector dummies.

As previously determined, firms with more experience in exporting activities are more likely to be persistent R&D investors, confirming the robustness of the temporal dimension of LBE. However, there is a significant loss of significance in the geographical dimensions of LBE. In this case, exporting inside and outside the EU simultaneously is only associated with R&D persistence in low-tech manufacturers and non-KIS sectors.

[12] To reduce the volume of outcomes the robustness of the effects across sectors is only quantified for the persistence in R&D activities, which are the main interest group.

Still, we observe that exporting only to the EU is not a determinant of persistent R&D investment in high-tech manufacturers.

Table 3.9. Random-effects probit for stopping innovation activities. Only persistent innovators and firms transitioning to stop innovation activities are considered.

	R&D investment		Innovation	
Variable	(1)	(2)	(3)	(4)
Exporting only to the EU		-0.036 (0.049)		0.063 (0.056)
Exporting only outside the EU		-0.278*** (0.048)		-0.235*** (0.065)
Exporting inside and outside the EU		-0.147*** (0.038)		0.000 (0.044)
Consecutive years exporting	-0.029*** (0.005)		-0.006 (0.006)	
Sales per employee (Logs)	0.026 (0.018)	0.020 (0.016)	0.017 (0.020)	-0.006 (0.019)
Size (Logs)	-0.153*** (0.013)	-0.159*** (0.012)	-0.107*** (0.014)	-0.106*** (0.014)
Human capital (Logs)	-0.085*** (0.011)	-0.108*** (0.011)	0.007 (0.013)	-0.005 (0.013)
Age (Logs)	-0.001 (0.025)	-0.001 (0.022)	0.055* (0.032)	0.036 (0.029)
Physical investment (Logs)	0.029*** (0.007)	0.032*** (0.006)	0.013* (0.008)	0.017** (0.007)
Public financing	-0.476*** (0.037)	-0.473*** (0.034)	-0.055 (0.047)	-0.068 (0.044)
Cooperation	-0.286*** (0.036)	-0.296*** (0.033)	-0.336*** (0.051)	-0.349*** (0.048)
Lead	0.044 (0.058)	0.064 (0.055)	-0.005 (0.069)	0.019 (0.066)
Subsidiary	0.129*** (0.036)	0.126*** (0.034)	0.061 (0.042)	0.050 (0.040)
Technological cluster (High-tech manufacturers)	-0.169*** (0.033)	-0.185*** (0.031)	-0.004 (0.039)	-0.016 (0.037)
Technological cluster (KISS)	-0.053 (0.055)	-0.069 (0.050)	0.239** (0.064)	0.220*** (0.059)
Technological cluster (Non-KISS)	0.381*** (0.062)	0.385*** (0.055)	-0.008 (0.068)	0.036 (0.063)
Time dummies	Yes	Yes	Yes	Yes
Joint significance of time dummies	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	24,777	27,393	24,521	27,115
Number of firms	3,050	3,066	3,020	3,034
Wald test for zero slopes	0.000***	0.000***	0.000***	0.000***
Log likelihood	-4,499.051	-5,303.268	-3,427.336	-3,821.343

*p<0.1; **p<0.05; ***p<0.01. All values show coefficient estimates (Std. Error). All values show coefficient estimates (Std. Error). Non-exporters are the baseline outcome of the trade dummies. Firms not belonging to a group are the baseline outcome of group dummies. Low-tech manufacturers are the baseline outcome of the sector dummies.

Table 3.10. Random-effects probit for starting innovation activities. Only persistent non-innovators and firms transitioning to start innovating are considered.

	R&D investment		Innovation	
Variable	(1)	(2)	(3)	(4)
Exporting only to the EU		0.000 (0.080)		-0.035 (0.070)
Exporting only outside the EU		0.208*** (0.080)		-0.114 (0.071)
Exporting inside and outside the EU		0.077 (0.063)		-0.100* (0.054)
Consecutive years exporting	-0.032*** (0.009)		-0.022*** (0.007)	
Sales per employee (Logs)	0.002 (0.030)	-0.006 (0.028)	0.005 (0.025)	0.007 (0.024)
Size (Logs)	0.001 (0.020)	-0.004 (0.019)	-0.037** (0.018)	-0.038** (0.017)
Human capital (Logs)	0.057*** (0.020)	0.066*** (0.019)	-0.007 (0.017)	-0.004 (0.016)
Age (Logs)	-0.027 (0.040)	-0.031 (0.037)	-0.028 (0.035)	-0.016 (0.032)
Physical investment (Logs)	-0.014 (0.011)	-0.009 (0.010)	-0.041*** (0.010)	-0.041*** (0.009)
Public financing	0.243*** (0.050)	0.230*** (0.048)	0.008 (0.045)	0.000 (0.042)
Cooperation	0.064 (0.052)	0.062 (0.049)	-0.022 (0.045)	-0.026 (0.043)
Lead	0.066 (0.089)	0.088 (0.058)	0.031 (0.077)	0.057 (0.074)
Subsidiary	-0.038 (0.061)	-0.035 (0.058)	0.037 (0.051)	0.030 (0.048)
Technological cluster (High-tech manufacturers)	0.106* (0.054)	0.085 (0.052)	-0.037 (0.048)	-0.037 (0.046)
Technological cluster (KISS)	0.266*** (0.086)	0.283*** (0.081)	0.013 (0.074)	0.065 (0.069)
Technological cluster (Non-KISS)	-0.392*** (0.104)	-0.269*** (0.098)	-0.016 (0.088)	0.018 (0.083)
Time dummies	Yes	Yes	Yes	Yes
Joint significance of time dummies	(0.004)***	(0.002)***	(0.000)***	(0.000)***
Observations	6,718	7,613	6,473	7,117
Number of firms	1,185	1,247	1,073	1,086
Wald test for zero slopes	0.000***	0.000***	0.000***	0.000***
Log likelihood	-1,809.040	-1,988.626	-2,408.463	-2,688.192

*p<0.1; **p<0.05; ***p<0.01. All values show coefficient estimates (Std. Error). All values show coefficient estimates (Std. Error). Non-exporters are the baseline outcome of the trade dummies. Firms not belonging to a group are the baseline outcome of group dummies. Low-tech manufacturers are the baseline outcome of the sector dummies.

In addition to the sectorial disaggregation, we include sample discrimination in the discrete analysis of variability, to assess the consistency of the outcomes. On the one hand, for changes from investing/innovating to stop these activities we restricted the sample to only persistent innovators and firms transitioning to stop investing/innovating. Table 3.9. provides the estimations. On the other hand, for changes from not investing/innovating to starting these activities, we consider only persistent non-innovators and firms transitioning to invest/innovate. Table 3.10 shows the regression outcomes. Note that, despite a slight loss of significance in some controls, all the effects maintain their sign and impact on the probability of changing from one status to another.

3.6. Discussion and conclusions

Having determined the short-term and long-term capital resources necessary to conduct R&D and innovation in Chapter 2. This chapter aims to explore the continuity in the development of these activities based on the exporting behaviour of the firm. A firm's international scope is subject to two patterns of different natures. On the one hand, self-selection explains that the most productive and innovative firms are the most likely to dominate international markets, due to their enhanced capabilities (Melitz, 2003). On the other hand, the notion of learning-by-exporting defends that firms involved in internal trade are subject to improvement processes that allow them to improve their market position, developing additional dimensions such as innovation (De Loecker, 2007).

Using firm-level information from the Spanish Technological Innovation Panel (PITEC) we focus on the impact of learning-by-exporting on the persistence and variability of innovation activities. Being these innovation activities R&D investment and the introduction of product or process innovations. We determine the associations between exports and innovation from two approaches. Firstly, by applying a multinomial perspective to model the stylized determinants of persistent innovators, persistent non-innovators, non-persistent innovators, firms transitioning to innovate and firms transitioning to stop innovation. Secondly, we isolate changes in the R&D and innovation status and analyse their nature by applying a random-effects probabilistic approach.

The results show significant differences in the level of persistence between exporting and non-exporting firms, confirming earlier evidence (Anderson and Lööf, 2009; Lööf et al., 2015). However, the main contribution arises from the distinction between the temporal and spatial dimensions of LBE. Firms with more consecutive years conducting trade activities are more persistent in all innovation activities. Reducing, simultaneously, the incentives to stop these activities or start them if the firm is non-innovative. This suggests that firms already established in foreign markets but not innovating have fewer incentives to undertake these activities, as their expected returns to innovation do not compensate for the risks associated with innovation.

Other outcomes expose that the distribution of LBE effects is not homogeneous across geographical areas. Firms exporting only to the EU are comparatively less persistent than those with a broader geographical range. Nevertheless, exporting to only EU markets is strongly associated with firms transitioning to start R&D and innovations. This provides insights into the nature of the competitive incentives that EU markets provide to Spanish firms. Currently, countries at a distance from the technological frontier must pursue an ambitious industrial policy to foster innovation in a wider spectrum of firms. Consequently, understanding that approaching nearer and safer markets in the EU is a useful tool to provide incentives to transition towards innovation is key. Complementing, in later stages, broader trade endeavours to foster additional competitiveness and persistence in innovation activities.

3.7. References

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3.8. Appendix 3A

Table 3A.1. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
(1) Persistently investing	1.00																													
(2) Persistently not investing	-0.18	1.00																												
(3) Diverse change of status (R&D)	-0.13	-0.16	1.00																											
(4) Transitioning to start investing	-0.24	-0.28	-0.21	1.00																										
(5) Transitioning to stop investing	-0.26	-0.31	-0.23	-0.42	1.00																									
(6) Persistently innovating	0.12	0.02	0.02	0.05	-0.16	1.00																								
(7) Persistently not innovating	-0.10	0.46	-0.09	-0.09	-0.16	-0.14	1.00																							
(8) Diverse change of status (Inn.)	0.08	-0.09	0.23	-0.08	-0.06	-0.21	-0.12	1.00																						
(9) Transitioning to start innovating	-0.03	0.04	-0.12	0.34	-0.26	-0.27	-0.16	-0.25	1.00																					
(10) Transitioning to stop innovating	-0.08	-0.24	-0.03	-0.24	0.50	-0.34	-0.20	-0.31	-0.41	1.00																				
(11) Undertake R&D	0.19	-0.07	0.17	-0.09	-0.11	0.03	-0.04	0.07	-0.03	-0.03	1.00																			
(12) Stop R&D	0.12	-0.09	-0.07	0.19	-0.15	0.04	-0.04	0.00	0.07	-0.07	-0.03	1.00																		
(13) Undertake innovation	0.04	-0.01	0.05	0.00	-0.06	0.17	-0.05	0.16	-0.11	-0.14	0.17	0.03	1.00																	
(14) Stop innovation	0.01	0.02	-0.02	0.09	-0.09	0.14	-0.05	-0.09	0.15	-0.15	0.01	0.06	-0.04	1.00																
(15) Consecutive years exporting	-0.01	-0.16	0.02	-0.10	0.21	-0.07	-0.11	-0.01	-0.10	0.20	0.00	-0.01	0.00	0.00	1.00															
(16) Non exporter	0.01	0.14	-0.04	0.05	-0.15	0.07	0.09	-0.02	0.05	-0.14	0.01	0.02	0.02	0.05	-0.63	1.00														
(17) Exporting only to the EU	0.01	0.00	0.01	0.02	-0.03	0.03	-0.02	0.00	0.00	-0.02	0.01	0.02	0.02	0.02	0.02	-0.18	1.00													
(18) Exporting only outside the EU	0.00	-0.06	0.00	-0.02	0.07	-0.02	-0.05	0.00	-0.03	0.07	-0.01	-0.02	-0.02	-0.05	-0.08	-0.19	-0.11	1.00												
(19) Exporting inside and outside the EU	0.01	-0.15	0.02	-0.10	0.20	-0.05	-0.11	0.00	-0.09	0.18	0.03	0.00	0.01	0.01	0.70	-0.42	-0.23	-0.25	1.00											
(20) Sales per employee (logs)	0.02	-0.07	0.03	-0.03	0.05	-0.03	-0.11	0.00	-0.06	0.13	0.01	-0.01	-0.01	-0.02	0.24	-0.24	0.02	0.06	0.20	1.00										
(21) Size (logs)	-0.04	0.02	0.03	-0.18	0.16	-0.08	-0.03	0.03	-0.16	0.20	-0.01	-0.07	-0.02	-0.07	0.16	-0.13	-0.03	0.05	0.13	0.24	1.00									
(22) Human capital	-0.02	-0.24	0.06	-0.05	0.21	-0.02	-0.15	0.04	-0.06	0.11	0.02	-0.03	0.01	-0.01	0.08	-0.07	0.00	0.01	0.06	-0.03	-0.10	1.00								
(23) Age (logs)	-0.01	0.06	-0.01	-0.06	0.03	-0.06	0.00	-0.03	-0.01	0.08	0.01	-0.01	-0.01	0.01	0.25	-0.08	0.00	-0.02	0.23	0.23	0.33	-0.12	1.00							
(24) Physical investment (logs)	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	-0.07	-0.01	0.02	-0.02	1.00						
(25) Public financing	-0.02	-0.26	0.06	-0.17	0.33	-0.07	-0.15	0.03	-0.14	0.23	0.04	-0.09	-0.01	-0.08	0.07	-0.13	-0.02	0.05	0.07	-0.01	0.10	0.20	-0.08	0.01	1.00					
(26) Cooperation	-0.01	-0.22	0.03	-0.17	0.33	-0.09	-0.17	0.03	-0.16	0.29	0.03	-0.06	0.01	-0.09	0.10	-0.06	0.01	0.05	0.12	0.07	0.19	0.17	0.00	0.00	0.41	1.00				
(27) Group	-0.02	-0.03	0.01	-0.09	0.12	-0.03	-0.06	0.02	-0.11	0.13	0.00	-0.02	0.00	-0.03	0.15	-0.09	0.01	0.02	0.11	0.33	0.49	0.02	0.12	0.00	0.06	0.18	1.00			
(28) Low-tech manufactures	-0.02	-0.15	-0.01	-0.04	0.18	-0.05	-0.08	0.00	-0.06	0.14	-0.01	-0.02	-0.01	-0.03	0.19	-0.19	0.00	0.07	0.16	0.13	-0.02	0.07	0.07	0.00	0.06	0.04	0.05	1.00		
(29) High-tech manufactures	0.05	0.09	0.00	0.06	-0.16	0.03	0.03	-0.03	0.06	-0.07	0.01	0.02	-0.01	0.01	0.06	-0.09	0.03	0.00	0.05	0.14	0.02	-0.31	0.10	0.00	-0.09	-0.09	-0.03	-0.65	1.00	
(30) KIS sectors	-0.02	-0.12	0.04	-0.03	0.11	0.02	-0.04	0.05	-0.02	-0.01	0.01	-0.01	0.02	0.00	-0.16	0.16	0.00	-0.03	-0.14	-0.32	-0.14	0.34	-0.30	0.00	0.17	0.12	-0.06	-0.27	-0.34	1.00
(31) Non-Kis sectors	-0.03	0.23	-0.03	0.00	-0.15	0.01	0.13	0.00	0.02	-0.10	-0.01	0.01	0.00	0.01	-0.25	0.31	-0.05	-0.09	-0.21	-0.09	0.17	0.02	0.07	0.01	-0.14	-0.05	0.05	-0.22	-0.28	-0.11

Chapter 4:

The dynamics of knowledge generation and their effects on innovation

4.1. Introduction

The wide range of innovation activities that firms can develop fall under the umbrella of two paradigms. On the one hand, deepening innovation patterns are based on knowledge exploitation strategies, the continuous accumulation of technological capabilities, R&D investment, and incremental innovations (Grant, 2000; Santamaría et al., 2009). On the other hand, widening patterns follow exploration strategies, leading to a continuously growing innovation base (Levinthal and March, 1993; Malerba and Orsenigo, 1995).

Despite both patterns being based on resource-competing strategies, interpretations rooted in the dynamic capabilities approach defend their complementary nature (Teece et al., 1997; Teece and Pisano, 2003). Firms endowed with a larger knowledge stock are more prone to improve their innovation performance, obtaining new capabilities that increase their degree of innovation by an increased level of radicalness (Cepeda and Vera, 2007; Teece, 2007; Tödtling et al., 2009; Kim et al., 2012).

Until this point, the conceptual development of this thesis addressed, firstly, innovation with a non-dynamic perspective. Secondly, the factors associated with the persistent development of innovation activities and the elements that cause variability in innovation behaviour. This chapter culminates the project by developing another crucial step of the innovation process, understanding innovation as a knowledge-intensive activity, analysing the determinants of the continuous generation of knowledge, and its effects on the intensity of radical innovations.

We expand the scope of recent contributions by identifying the effects of knowledge on product lines (Forés and Camisón, 2016), creative capabilities (Delgado-Verde et al., 2016), and market dynamics (Bergek et al., 2013), by proposing a multi-step methodology. Firstly, we apply dynamic random-effects models to study the profile of firms engaged in internal knowledge generation or external knowledge absorption.

Secondly, we determine the effects of each knowledge source on the intensity of radical innovations through dynamic censored models. Using data from the Spanish Technological Innovation Panel (PITEC), which provides extensive information about 4,114 firms during the period 2005–2016 (40,256 firm-year observations), our focus extends beyond the direction and dimension of the impact of knowledge on radical innovation. We also aim to test potential heterogeneities in the relationship to capture the granularity of knowledge generation and innovation processes.

The findings reveal the role of several firm characteristics in shaping knowledge, namely the firms with the largest human capital, productivity, and exports being the prominent generators of internal knowledge. Their less competitive counterparts tend to depend more on external knowledge. This dichotomy carries fundamental implications for the effects of knowledge on the intensity of radical innovations, as only internal knowledge provides the differentiating traits that enable a firm to diverge from its competition and develop more technologically-intensive innovations. Thus, our evidence suggests that generating knowledge from internal sources is the key strategy to foster radical innovations.

Regarding heterogeneous effects, the outcomes demonstrate the decreasing marginal returns from knowledge, with the initial efforts directed towards knowledge generation providing the strongest effects. Furthermore, mature firms are the main beneficiaries of internal knowledge generation, and over a longer period. Their experience, structure, and stability provide differentiating traits that facilitate the effective capture and integration of knowledge into their organization.

The academic contribution of this study is multidimensional. From a conceptual point of view, the outcomes provide evidence for the prevalence of Schumpeter's Mark II. Our intuition suggests the technological dominance of incumbent firms over the transformative potential of young firms due to the larger and more persistent returns that the former obtains from the generation of knowledge. Additionally, from a methodological perspective, we complement previous studies by analysing the knowledge-innovation relationship in depth from a systematic perspective, identifying the profile of knowledge generators to better understand the forces driving the relationship and applying a dynamic perspective that captures the cumulative nature of innovation activities. This increases the robustness of the analysis.

In addition to its contribution to the literature on innovation economics, this research provides relevant insights for policymakers. Besides providing regulation and environments for the open transference of knowledge between firms, the development of mechanisms for fostering internal R&D investment and the continuous improvement of product lines foster the development of the most efficient paths towards, and beyond, the technological frontier.

The structure of the chapter is the following. Section 4.2 presents a literature review analysing the seminal contributions related to innovation patterns, knowledge generation, and other key concepts, as well as the definition of the hypotheses. Section 4.3 describes the database, and the variables introduced in the econometric analysis. Section 4.4 explains the modelling structure. Section 4.5 shows the results obtained and their explanation. Finally, Section 4.6 discusses and concludes the research.

4.2. Literature review

4.2.1. Schumpeterian patterns of innovation

The dichotomy between creative destruction and creative accumulation emerges from the examination of two different contexts. Firstly, in *The Theory of Economic Development* (Schumpeter, 1934) the focus is set on the classical industrial structure of late nineteenth-century Europe, characterized by great technological discontinuities and numerous small firms. Here, the entrepreneur is identified as the key driver of technological change and progress, generating wealth through the development of innovation. Secondly, *Capitalism, Socialism and Democracy* (Schumpeter, 1942) draws inspiration from the features of the American industry during the early twentieth century, dominated by large firms leading innovation through substantial R&D investments and specialized personnel. These firms, with their accumulated knowledge and solid market position, create entry barriers to new entrepreneurs and small firms, establishing themselves as the dominant organisations (Bell and Pavitt, 1993; Pavitt, 1999; Malerba and Orsenigo, 1995).

Based on these ideas, Freeman et al. (1982) identify two models. Mark I defends the thesis that in periods of economic turbulence, new and small firms emerge contesting market shares through the development of innovative ideas which crystallize into radical innovations (Tushman and Anderson, 1986; Henderson and Clark, 1990; Simonetti, 1996; Freeman and Louca, 2001; Perez and Canino, 2009). Mark II suggests that innovation and technical changes are rooted in cumulative learning processes and path-dependent patterns mainly characteristic of well-established firms, resulting in the persistent development of innovation activities (Dosi, 1982; Nelson and Winter, 1982; Antonelli, 1997).

The innovation patterns particular to each mark are respectively labelled as widening and deepening (Malerba and Orsenigo, 1995). Widening patterns are related to continuously growing innovation bases, thanks to the entrance of new firms and innovations, leading to an erosion of competitive and technological advantages of established firms. Deepening patterns are characterized by the dominance of firms innovating continuously through the accumulation of technological capabilities, which crystallize in R&D investment and the development of incremental innovations (Grant, 2000; Santamaría et al., 2009).

The debate on which pattern dominates in specific contexts refers directly to the structural characteristics of innovation environments. For instance, while widening patterns prevail in technologically intensive sectors due to the continuous entrance of new technologies and firms, deepening patterns dominate low-tech industries, in which mature and large firms will always have an advantage (Malerba and Orsenigo, 1995; Breschi et al., 2000; Cefis et al., 2020). However, contemporary interpretations propose a synthesis, arguing that successful innovation strategies tend to combine both patterns. Incremental innovations provide a solid knowledge base to develop more novel ideas in further steps, reducing the risks associated with the innovation processes. Additionally, radical innovations complement and must pair with incremental innovations to allow a firm to maintain its competitive advantage (Tushman and O'Reilly, 1996; Kanter, 2006; Farjoun, 2010; Acemoglu et al., 2022). The relationship between the two patterns is grounded in their complementarity, deepening patterns being based on the cumulative nature of innovation, thus becoming a useful tool for consistent knowledge generation. And, in the latter stages, this integrates into a firm's behaviour and manifests itself in more complex innovations and a better organisation.

4.2.2. Developing capabilities and knowledge

Developing deepening and widening strategies has significant implications on knowledge development, especially the ones related to firm performance and innovation (March, 1991). Depending on their situation, firms might engage in organisational exploration, searching for new knowledge, adopting new technologies, or generating new and radical innovations. Otherwise, they may exploit their current knowledge, refining it and addressing their market segment more effectively (Levinthal and March, 1993).

Despite both exploration and exploitation being subject to constraints and competition for resources, firms with extensive capabilities integrate and balance both strategies (O'Reilly and Tushman, 2013). This ambidexterity encompasses multiple dimensions within and outside a firm, enabling the parallel development of different business processes (Gibson and Birkinshaw, 2004) and, in the long term providing an increased performance.

To increase their success probability by being adaptable to different technological contexts, firms should develop mechanisms to build their knowledge stock, via internal procedures or absorbing it from external sources (Stieglitz and Heine, 2007), thus increasing competitiveness in a knowledge-based economy (Tseng and Goo, 2005).

Although knowledge and capacity building are constructs falling within a plethora of definitions and measures, in general, they separate into two streams. The internal generation of knowledge is a creative process based on skills and experience generated fundamentally by R&D investment and internal problem-solving (Grant, 2000; Smith et al., 2005). Whereas reliance on external sources depends on absorptive capabilities, in other words, how easily a firm can learn from interacting directly or indirectly with other actors (Cohen and Levinthal, 1990).

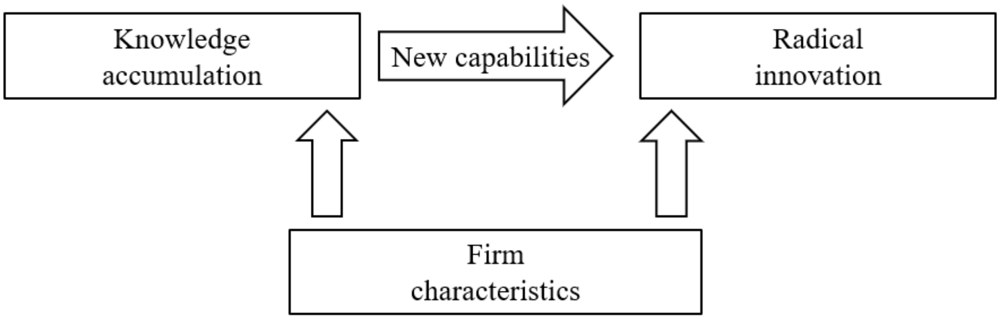
According to Grigoriou and Rothaermel (2017), external sources of knowledge are imperfect substitutes for internal knowledge sourcing, although they do provide access to new knowledge that previously was inaccessible. However, this does not negate complementary strategies that simultaneously incorporate internal and external knowledge. Therefore, a relevant, and often overlooked, question arises as to which firm profile is most likely to generate, or depend, on each type of knowledge.

4.2.3. The effects of knowledge on radical innovations

To enhance productivity and innovation, knowledge must be reconverted and integrated into a firm's culture, crystallizing into new capabilities, and allowing the development of more sophisticated innovations (Kogut and Zander, 1992; Bierly et al., 2009). Figure 2.1 shows a diagram of this process which falls within the dynamic capability paradigm (Cepeda and Vera, 2007; Teece, 2007). According to the intuitions of the theory, firms with larger knowledge stocks are more likely to adopt strategies that increase their innovation performance. To understand this more effectively, one must interpret innovation itself as an outcome of knowledge, driven by apprenticeship, creativity, experience, experimentation, and problem-solving (Smith et al., 2005).

In recent years, a new stream of empirical evidence related to the formation of knowledge and innovation has revitalized the debate on creative destruction and knowledge accumulation patterns. Applying Structural Equation Models, Forés and Camisón (2016) analyse the correlations between activities related to the internal formation of knowledge, the absorptive capacity of firms and the introduction of incremental and radical innovations, finding a positive association between all the elements. This idea complements the findings of Delgado-Verde et al. (2016) that, expanding the perspective of knowledge, uncover strong relationships between the volume of intangible capital and the development of radical innovations.

Figure 4.1. Knowledge accumulation to radical innovations diagram.



Although both approaches are relevant and rich in their contribution, they lack the implementation of dynamic effects and are limited by the nature and size of their data.[13] Innovation, as a cumulative and path-dependent process, is highly driven by past behaviours, transforming a firm's capabilities. For this reason, the study of knowledge and innovation from the perspective of the continuous and persistent development of the two provides an increased level of robustness to the analysis and enriches the contribution (Triguero and Córcoles, 2013). Based on this approach, we propose the following hypothesis:

[13] The studies mentioned above are conducted using relatively small samples with less than 2,000 observations.

H1: The continuous generation of internal knowledge and the absorption of external knowledge have positive effects on the intensity of radical innovations.

Despite the benefits of the two sources of knowledge to the development of radical innovations, evidence indicates that competitiveness is based on a set of processes and a culture that integrates resources to accomplish strategic objectives (Kogut and Zander, 1992; Grant, 2000). The better-performing firms are more likely to be intensive in terms of skills, expertise, and knowledge (Zander and Kogut, 1995). The accessibility of external knowledge is contingent on the degree of innovation openness and knowledge sharing. Which, if not properly managed, leads to knowledge leaking. Becoming particularly determinantal to the development of radical innovations (Ritala et al., 2018).

Consequently, internal knowledge, inherently private, provides increased effects on radical innovations. Enabling firms to generate differential capabilities, gaining a competitive edge. Therefore, we propose the following:

H2: The knowledge generated from internal sources has stronger effects than external knowledge on the development of radical innovations.

Nevertheless, treating knowledge as a homogenously distributed factor of radical innovations across firms and sectors of activity is, at best, an oversimplification, as it ignores the granularity of the knowledge a firm needs according to their profile and the characteristics of their activity. Along these lines, we focus on two sources of heterogenous effects, the knowledge needs of sectors based on their technological intensity, and the differences in recombinant capabilities between mature and young firms.

Addressing, firstly, the characteristics of each sector, one must consider their structural factors. According to Pavitt's taxonomy, manufacturing sectors can be divided according to their characteristics and technological intensity into four groups: *i)* in scale-intensive sectors large firms dominate the production of basic materials and consumer durables; *ii)* supplier-dominated sectors are associated with traditional manufactures; *iii)* science-based sectors are composed by high-tech firms devoted mainly to the development of science; *iv)* specialized-suppliers focus on the production of specialized or high-tech technologies (Pavitt, 1984; Bogliacino and Pianta, 2016).

This clustering shows that the effects of knowledge on the development of radical innovations are more relevant to high-tech sectors, rather than low-tech, as the products they produce are more complex and subject to increasing evolution and change. Consequently:

> *H3:* The generation of knowledge to develop radical innovations is more relevant in high-tech sectors.

In addition to the technological characteristics of sectors, firms might exploit knowledge differently depending on their experience. There are, however, opposing views in the literature regarding this. One school defends the tenet that mature firms are more likely to take profit from knowledge accumulation, and more effectively, to generate more complex innovations, when their performance is below aspiration (Eggers and Kaul, 2018). However, if their economic returns match the aspiration, then, they do not have sufficient incentives to build upon their knowledge base and generate more complex innovations. The alternative school views novelty and creativity as characterizing the development of radical innovations. Consequently, young firms have a comparative advantage in this context, as they are more flexible and present a greater innovation potential (Schneider and Veugelers, 2010; Carayannopoulos, 2017; Veugelers et al., 2019).

There is a clear gap in the literature regarding the heterogeneous returns of knowledge in reference to firm age. In this paper, we propose a complementary view based on the inherent competitive forces of both mature and young firms. According to evidence, the development of innovation activities is riskier for young firms than it is for mature firms (this group tends to design more stable strategies) (Coad et al., 2016). Additionally, through experience, mature firms embody a set of capabilities that improve their performance (Gkypali et al., 2015). The accumulated learning of mature firms allows for a better exploitation of all knowledge. They can better scrutinize and implement this resource (Petruzzelli et al., 2018).

Alternatively, since young firms tend to have fewer resources to fall back on, evidence suggests that, if properly absorbed into the firm, external sources of knowledge are useful for boosting innovation performance (Protogerou et al., 2017). As previously explained, external knowledge serves as an imperfect substitute for internal knowledge, providing coverage of the gaps that firms with limited knowledge generation potential could not address with solely their internal resources. Thus, recovering the intuitions directed towards the role of competitive capabilities and knowledge we propose the following:

H4a: Mature firms obtain more returns from all sources of knowledge.

H4b: For young firms, external knowledge provides more returns.

4.3. Data and descriptive statistics

4.3.1. The database

The Spanish Technological Innovation Panel (PITEC) offers comprehensive insights into the innovative behaviour of over 12,000 firms from 2003 to 2016. The data was compiled by the Spanish National Institute of Statistics (INE) with the support of the Spanish Foundation for Science and Technology (FECYT). The surveying methodology and definitions adhere to the Oslo Manual guidelines (OECD and Eurostat, 1997; OECD and Eurostat, 2005), ensuring international comparability and serving as an input to other Community Innovation Surveys.

PITEC, widely employed by applied economists, stands out as a robust tool to analyse a firm's innovative behaviour from a multitude of perspectives, the width and depth of the panel establish itself as a robust tool to capture the complex interlinks in the development of innovation activities, and with the potential to keep adding value our understanding of all these processes.

To maintain data consistency and a relatively balanced dataset to avoid biases in the dynamic panel data methods, we apply two minor filters to the original data. Firstly, since some relevant variables were not introduced in the first two waves, and a considerable number of firms were not incorporated into the panel, we decided to limit the period to 2005–2016. Secondly, firms must appear, during at least four consecutive years in the sample to be considered; this filter is introduced to avoid unbalancedness problems with the econometric strategy. As a result, we obtain an unbalanced panel constituted of 40,255 firm-year observations across 4,114 firms.

4.3.2. Descriptive statistics

In this research, the variables are categorized into different sets. The first set relates to the proxies of internal and external knowledge. On the one hand, internal knowledge generation focuses on internal R&D investment and continuous product improvement, which materializes into incremental innovations. According to Baum et al. (2017), firms developing R&D and innovation simultaneously present a set of capabilities that differentiates them from the others, while simultaneously avoiding endogenous effects from the separate modelling of R&D and innovation. Note that the generation of internal knowledge identifies firms conducting internal R&D and incremental innovations simultaneously during the same period.

Table 4.1. Definition of the variables.

Variables	Type	Definition
Dependent variables		
$K^{Internal}$	B	1 if the firm invests in internal R&D and introduces at least one incremental innovation during the same period; 0 otherwise.
$K^{External}$	B	1 if the firm invests in external R&D and cooperates with other actors during the same period; 0 otherwise.
rad_int	C	Sales due to radical innovations, measured per employee.
Firm characteristics		
Age	D	Firm age.
Size	D	Number of employees.
Human capital	C	Share of employees with higher education.
Productivity	C	Sales per employee.
Export intensity	C	Exports per employee.
Physical investment	C	Investment in tangible assets per employee.
Public financing	B	1 if the firm receives public financing; 0 otherwise.
Parent	B	1 if the firm is the parent firm of a group; otherwise.
Subsidiary	B	1 if the firm belongs to a group and is a subsidiary; 0 otherwise.
Sector-specific controls		
Scale-intensive	B	Firms producing basic materials or consumer durables.
Supplier-dominated	B	Firms associated with traditional manufacturers.
Science-based	B	Firms operating in high-tech sectors conducting a considerable amount of R&D and innovation.
Specialized-suppliers	B	Firms producing specialized or high-tech technologies.

B refers to binary variables, C to continuous variables, and D to discrete variables.

On the other hand, the absorption of external knowledge is proxied through the acquisition of external R&D and cooperation with other agents, public or private. Following Forés and Camisón (2016), these two variables are the main determinants of absorptive capabilities and reflect with precision the needs of external knowledge. Although additional information could be introduced in this external dimension, PITEC does not provide sufficient information regarding additional sources of external knowledge.

Secondly, radical innovation development and intensity are computed using information regarding whether innovations are new to the market, and the weight of these innovations on the total sales during a fiscal year. Despite the relative subjectivity of these variables, several authors use them, and they appear to provide consistent intuitions (Arvanitis et al., 2015; Tojeiro-Rivero et al., 2019).[14]

Thirdly, to test our proposed hypotheses, we need to identify a set of exogenous variables that address performance and additional firm characteristics, as proxies of what drives a firm's competitiveness. According to evidence, innovation, trade, and productivity form a system that follows two distinct patterns. Self-selection (Melitz, 2003) explains that, mainly, the most productive firms are the ones conducting successful innovations and addressing international markets effectively. Therefore, these two fields are dominated by the most effective firms. Alternatively, De Loecker (2007) shows that, besides self-selection effects, firms in international trade develop additional capabilities that help them boost their innovation performance and productivity. Consequently, as an outcome of the two patterns, we interpret productivity (sales per employee) and export intensity (exports per employee) as relevant determinants of competitive capabilities.

In addition to these performance indicators, firm size (number of employees) and human capital (share of employees with higher education) define other inherent capabilities that have the potential to improve knowledge and innovation. Other characteristics relevant to the analysis are firm age, testing heterogeneous effects of knowledge, physical investment, public financing, and status within a group. Finally, the technological characteristics of sectors are grouped according to Pavitt's taxonomy. Table 4.1 presents the definitions of all the variables.

[14] Despite not every innovation new to the market necessarily qualifies as radical, we follow the interpretation that they primarily hinge on novel and differential ideas, which set them apart from the notion of incremental innovation.

Table 4.2. Description of the variables

Variables	All firms	$K^{Internal}$	$K^{External}$	Radical
Dependent variables				
$K^{Internal}$	0.363 (0.481)	1.000 (0.000)	0.627 (0.484)	0.547 (0.498)
$K^{External}$	0.167 (0.373)	0.289 (0.453)	1.000 (0.000)	0.280 (0.449)
rad_int (thou. Euros)	22.979 (137.632)	29.277 (173.426)	36.825 (121.498)	70.665 (234.278)
Firm characteristics				
Age	30.904 (19.155)	32.443 (20.426)	33.723 (21.260)	31.873 (20.551)
Size	180.846 (520.028)	232.149 (652.397)	350.794 (520.028)	254.680 (729.971)
Human capital	0.192 (0.190)	0.223 (0.191)	0.245 (0.209)	0.228 (0.204)
Productivity (thou. Euros)	255.510 (410.847)	266.585 (389.821)	305.442 (409.907)	267.588 (431.316)
Export intensity (thou. Euros)	80.429 (202.220)	92.597 (204.708)	107.320 (176.617)	89.019 (214.033)
Physical investment (thou. Euros)	11.180 (95.800)	12.030 (60.238)	14.761 (67.972)	11.984 (46.906)
Public financing	0.327 (0.469)	0.492 (0.500)	0.722 (0.448)	0.485 (0.500)
Parent	0.080 (0.271)	0.117 (0.321)	0.139 (0.346)	0.107 (0.310)
Subsidiary	0.353 (0.478)	0.393 (0.488)	0.497 (0.500)	0.383 (0.486)
Sector-specific controls				
Scale-intensive	0.279 (0.448)	0.252 (0.434)	0.301 (0.459)	0.245 (0.430)
Supplier-dominated	0.349 (0.477)	0.267 (0.443)	0.370 (0.444)	0.301 (0.459)
Science-based	0.150 (0.357)	0.205 (0.403)	0.205 (0.404)	0.168 (0.374)
Specialized-suppliers	0.223 (0.416)	0.276 (0.447)	0.224 (0.417)	0.285 (0.451)

N (firm-year observations) = 40,256; n (firms) = 4,114. All values show Mean (Std. Err.)

Table 4.2 describes the variables, providing the information for the full sample and subsamples of internal knowledge, generators, external knowledge acquirers, and radical innovators. Approximately one-third of the firms in the whole sample generate knowledge internally (36.3%), while about half acquire it externally (16.7%). Regarding the complementarities between internal and external sources of knowledge, most internal generators do not complement their knowledge with external sources (only 28.9% of them exhibit this behaviour). However, most firms acquiring external knowledge simultaneously develop internal knowledge (62.7%). This points towards a non-bidirectional relationship between the two variables, as external sources of knowledge appear to be more related to internal knowledge than the opposite relationship.

Among radical innovators, most of them generate knowledge internally (54.7%) while half acquire it externally (28%). Note that despite the differences not being statistically significant, on average, the knowledge generators seem to be bigger firms, with relatively more human capital, being more productive, and more prone to address internal markets. These patterns will be consistently tested in our econometric modelling.

4.4. Methodology

To comprehensively examine dynamic knowledge generation processes and their impact on the intensity of radical innovation we propose a multi-step framework. The first step involves capturing the determinants of persistent internal or external knowledge generation. The second step assesses the influence of knowledge on the intensity of radical innovations. This approach endogenizes the relationship between knowledge generation and radical innovation development.

In a dynamic framework, the relationship between present and past activities might be represented as:

$$K_{i,t}^{m} = \gamma K_{i,t-1}^{m} + \beta X_{i,t-1} + \varepsilon_i + u_{i,t} \text{ (4.1)}$$

where $K_{i,t}^{m}$ is the likelihood of generating knowledge in the present for each category $m = \{internal, external\}$; $K_{i,t-1}^{m}$ represents whether a firm was conducting these activities in the previous period, determined by γ; β is a vector of parameters defining the effects of the covariates $X_{i,t}$; ε_i are individual-specific and time-invariant error terms; and $u_{i,t} \sim iid\ N(0, \sigma_u^2)$ are serially independent error terms.

However, this approach is severely biased by unobserved heterogeneity and correlations between the error terms and the covariates, as well as correlations across periods. According to Chamberlain (1984) and Mundlak (1978), the correlation between the individual-specific, time-invariant terms and the covariates can be allowed under the relationship $\varepsilon_i = c\bar{X}_i + \alpha_i$, assuming that $\alpha_i \sim iid\ N(0, \sigma_\alpha^2)$. Nevertheless, the errors $v_{i,t} = \alpha_i + u_{i,t}$ are still correlated across periods in the following manner:

$$\rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2} \text{ (4.2)}$$

To solve this issue, we follow Wooldridge's (2005) approach, where he proposes an alternative Conditional Maximum Likelihood estimator based on the exogeneity of the initial conditions, where the relationship between time-invariant errors and the initial condition is expressed as:

$$\alpha_i = b_0 + b_1 K_{i,1}^m + \zeta_i (4.3)$$

where b_0 introduces firm heterogeneity, b_1 is the effect of the initial condition $K_{i,1}^m$, and ζ_i are additional individual specific error terms. Consequently, the expression we will use to determine the persistence of knowledge is specified as:

$$K_{i,t}^m = b_0 + \gamma K_{i,t-1}^m + b_1 K_{i,1}^m + \beta X_{i,t-1} + c\bar{X}_i + \zeta_i + u_{i,t} \quad (4.4)$$

Note that Equation (4.4) approaches the likelihood of being a generator of knowledge since $K_{i,t}^m$ is a binary variable. Thus, the model follows a probabilistic function and is estimated through maximum likelihood. Ideally, the unobserved heterogeneity b_0 should be treated as fixed-effects. However, theory shows that, when applying maximum likelihood in finite samples, the estimator fixed-effects provides bias of order $O(T-1)$. Consequently, using random-effects must be the option considered to estimate this dynamic probabilistic model.

Once this is determined, we build a proxy to quantify the degree of persistence in the generation of knowledge, to differentiate long-term generators from relatively recent ones. In this regard, we build a new count variable $Count\_K_{i,t}^m$ in the following manner:

$$Count\_K_{i,t}^m \begin{cases} Count\_K_{i,t-1}^m + 1 \; if \; K_{i,t}^m = 1 \\ 0 \; if \; K_{i,t}^m = 0 \end{cases} \quad (4.5)$$

This construct allows us the capture more deeply the transformation of knowledge in new capabilities that will generate, in return, an increased radicalness in the innovation activity. To capture this innovation dimension, we measure the intensity of radical innovations as a function of past radical innovations, to capture dynamic feedback and persistence, knowledge, and the set of firm characteristics. However, the intensity of radical innovations presents an accumulation of zeros on the left extreme, this feature is controlled by applying censored models:

$$rad\_int_{i,t}^* \begin{cases} rad\_int_{i,t} \; if \; rad\_int_{i,t} > 0 \\ 0 \; if \; rad\_int_{i,t} = 0 \end{cases} \quad (4.6)$$

Where $rad\_int_{i,t}$ is the intensity of radical innovations and $rad\_int^{*}_{i,t}$ is its estimated value under the structure:

$$rad\_int^{*}_{i,t} = c_0 + \delta rad\_inn_{i,t-1} + c_1 rad\_inn_{i,1} + \theta_1 Count\_K^{m}_{i,t-1} + \theta_2 X_{i,t-1} + d\bar{X}_i + \mu_i + w_{i,t} \quad (4.7)$$

Where c_0 are firm-specific fixed-effects, c_1 and d solve the biases of the estimation of dynamic models, imposing the initial condition and average effects respectively; θ_k are vectors of parameters; μ_i and $w_{i,t}$ are error terms. As Wooldridge (2005) explains, the corrections conducted in Equation (4.4) provide robust outcomes for Tobit models.

Additional specifications to be added to the econometric structure itself are the transformation of all continuous and discrete variables to logarithms, to increase the normality of the data. We also introduce sector-fixed effects and time-fixed effects to control for homogeneous behaviours across the sample.

The methodology presented assumes a certain degree of endogeneity, inherent to the cumulative development of knowledge and innovation. While this constitutes a limitation, the dynamic framework presented aims to establish a robust structure of causality to analyse the principal associations between the determinants of knowledge, the effects of knowledge on radical innovations, and the identification of heterogeneous effects.

4.5. Regression outcomes

4.5.1. Knowledge generation and its effects on radical innovations

This section presents and develops the outcomes obtained from the modelling. In a preliminary step, we explore the determinants of a firm's persistence in knowledge generation, setting the stage for the correct understanding of its subsequent effects on the intensity of radical innovations. Table 4.3 presents the regression outcomes of Equation (4.4).

Examining, firstly, the dynamic dimension of the model, both internal and external sources of knowledge exhibit strong path dependence, as evidenced by their reliance on past behaviour and the significance of the initial condition. This underscores the cumulative nature of knowledge and innovation activities, in line with established principles in the field of innovation economics (Pavitt, 1986; Dosi, 1988). Certain patterns emerge consistently between internal and external sources of knowledge. Young firms display a higher likelihood of being persistent knowledge generators, most likely due to their heightened knowledge need, as compared to mature firms with established knowledge stocks. Firm size also emerges as a significant factor, with larger firms demonstrating the improved capacity for consistent knowledge development, as well as physical and public investment contributing to material resources.

Beyond these commonalities, the determination of internal knowledge involves additional dimensions compared to the absorption of external knowledge, such as presenting higher volumes of human capital, productivity, and export intensity. In contrast to their strong positive association with internal knowledge generation, these variables show no significant impact on the external absorption of knowledge. This posits the divergent knowledge needs and generation potential of firms with distinct characteristics, being the firms with more skills and performance the prominent generators of internal knowledge.

Out of the 40,256 observations, the estimator correctly predicts 84% of the real present values of internal knowledge ($K^{Internal}$) and 90% of the real present values of external knowledge ($K^{External}$).[15] However, a notable pattern emerges in the discrepancies between the estimation and the real values. While the errors of the first specification are distributed in a relatively homogeneous manner across generators and non-generators of knowledge, the estimator tends to underestimate firms with greater capabilities of acquiring external knowledge, displaying a greater efficiency in addressing firms with lower human capital, productivity, and exports. This leads to a reduction in the number of firms concurrently involved in internal and external knowledge activities.

Transforming the outcomes into continuous values according to Equation (4.5), on average, firms tend to generate internal knowledge persistently during 1.264 consecutive years (with a standard deviation of 2.37), while external knowledge absorption spans during 0.45 consecutive years (with a standard deviation of 1.53). Developing this idea further, internal knowledge demands more extensive efforts and investment, resulting in a larger persistence in its development.

The next step in the modelling structure involves computing the effects of both internal and external sources on the intensity of radical innovations, considering the path-dependent and dynamic nature of the innovation process. Table 4.4 provides the outcomes

[15] Table 4A.1 shows the distribution of the real and estimated values.

of the censored regression for internal sources, in the first column, and external sources, in the second column.

Table 4.3. Dynamic random-effects probit for the persistent generation of knowledge.

Variable	(1) Internal	(2) External
K^{m}_{t-1}	1.465***	1.336***
	(0.022)	(0.029)
Age$_{t-1}$ (Logs)	-0.147**	-0.198**
	(0.067)	(0.081)
Size $_{t-1}$ (Logs)	0.162***	0.115***
	(0.036)	(0.044)
Human capital $_{t-1}$	0.224***	0.074
	(0.083)	(0.099)
Productivity $_{t-1}$ (Logs)	0.055**	0.016
	(0.027)	(0.033)
Export intensity $_{t-1}$ (Logs)	0.008***	0.001
	(0.003)	(0.004)
Physical investment $_{t-1}$ (Logs)	0.010***	0.010**
	(0.003)	(0.004)
Public financing $_{t-1}$	0.049**	0.113***
	(0.025)	(0.029)
Parent	0.095**	0.102**
	(0.044)	(0.049)
Subsidiary	-0.017	0.153***
	(0.031)	(0.035)
Scale-Intensive	0.008	0.028
	(0.035)	(0.039)
Specialized-suppliers	0.255***	-0.044
	(0.036)	(0.043)
Science-based	0.307***	0.134***
	(0.042)	(0.048)
Initial condition	0.558*** (0.030)	0.535*** (0.038)
Average effects	Yes	
Time dummies	Yes	
rho	0.249 (0.012)	0.225 (0.014)
Observations	40,255	
Firms	4,114	
Wald test for non-zero slopes	9,755.22***	7,027.32***
LR test for no correlation	607.99***	368.18***

*p<0.1; **p<0.05; ***p<0.01. Firms not belonging to a group are the base outcome of group dummies. Supplier-dominated is the base outcome of sector dummies.

Again, the dynamic dimension consistently shows the path-dependent patterns in the development of radical innovations, in terms of the first lag and the initial condition. The effects of knowledge, however, diverge greatly across the two specifications. Internal knowledge offers a positive and significant impact on the intensity of radical innovation. Specifically, for each one-percent increase in internal knowledge building, the weight of radical innovations on total sales increases by 0.384%. On the contrary, the effect of external knowledge appears to be non-significant. We attribute this to a smaller coefficient value and an increase in its standard error. Recall that the previous estimator isolated firms absorbing solely external knowledge, providing a clearer separation of the effects from both sources and limiting complementary effects between the two.

To understand, why internal knowledge yields a positive effect while external knowledge has a neutral impact, it is crucial to recognize that the analysis focuses on the most technologically intense innovations new not only to the firm but to the entire market. Consequently, the development of these innovations requires more intensive knowledge building.

Thinking more deeply into the nature of external knowledge, its availability to a wider range of firms and the need for efficient transmission channels imply less complexity. Therefore, external knowledge fails to provide differential capabilities that allow a firm to gain technological edges over the others. However, internal sources of knowledge do generate these differentiating characteristics. Being private and harder to transmit to other organisations, it arises from more complex competitive needs aimed at addressing substantial internal needs or improving a firm's market position.

Despite the divergence in the effects of each source, the results do not reject the need for external knowledge, motivated by a lack of capabilities, nor the complementarities between the internal and external knowledge sources. The intuition, however, remarks the greater relevance of internal knowledge in the generation of more complex innovations, with an increased degree of novelty.

These findings partially confirm hypothesis *H1*, finding a significant association between internal knowledge and radical innovations, but not for external sources of knowledge. Nevertheless, this relationship provides robust intuitions for *H2*, highlighting the relevance of firm characteristics, recalling the dominant profile in the identification of knowledge needs and the development of internal knowledge presented in Table 4.3, and its robust effect on the development of innovation shown in Table 4.4.

Table 4.4. Dynamic fixed-effects Tobit for the intensity of radical innovations.

Variable	(1) Internal	(2) External
rad_int$_{t-1}$ (Logs)	1.359*** (0.011)	1.373*** (0.013)
Count_ K^{m}_{t-1} (Logs)	0.384*** (0.050)	-0.064 (0.075)
Age $_{t-1}$ (Logs)	-0.095 (0.496)	-0.383 (0.497)
Size $_{t-1}$ (Logs)	0.948*** (0.212)	1.098*** (0.213)
Human capital $_{t-1}$	0.918* (0.498)	1.015** (0.499)
Productivity $_{t-1}$ (Logs)	0.322* (0.168)	0.339** (0.169)
Export intensity $_{t-1}$ (Logs)	-0.014 (0.017)	-0.005 (0.017)
Physical investment $_{t-1}$ (Logs)	0.112*** (0.018)	0.127*** (0.018)
Public financing $_{t-1}$	1.108*** (0.153)	1.156*** (0.153)
Parent	-0.109 (0.206)	0.138 (0.206)
Subsidiary	-0.044 (0.139)	-0.034 (0.139)
Scale-Intensive	-0.464*** (0.145)	-0.397*** (0.145)
Specialized-suppliers	0.632*** (0.148)	0.943*** (0.147)
Science-based	-0.209 (0.175)	0.219 (0.173)
Initial condition	0.138*** (0.011)	0.158*** (0.011)
Average effects	Yes	
Time dummies	Yes	
Observations	40,255	
Firms	4,114	
Uncensored	12,571	
Censored	27,684	
Log. Likelihood	-53,297.32	-53,414.516
Wald test for non-zero slopes	16,043.03***	15,963.61***

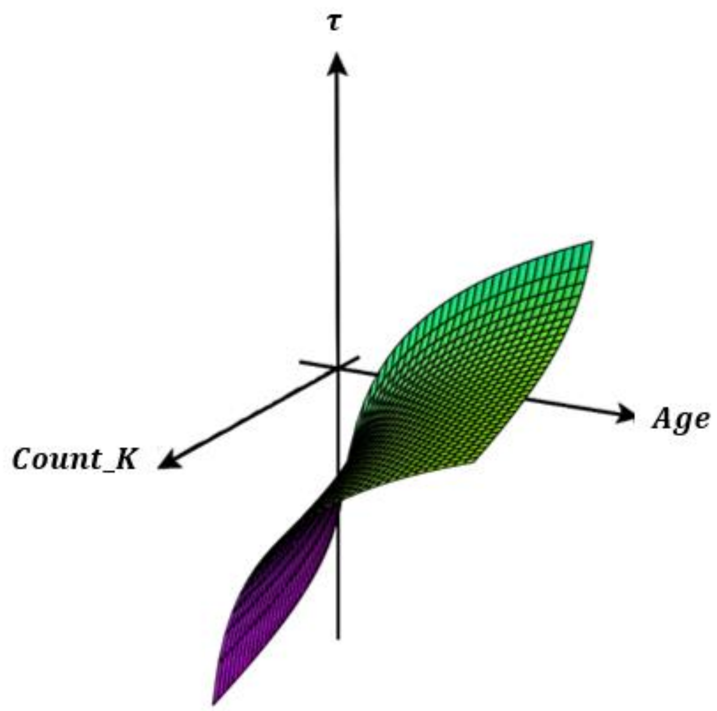
*p<0.1; **p<0.05; ***p<0.01. Firms not belonging to a group are the base outcome of group dummies. Supplier-dominated is the base outcome of sector dummies.

4.5.2. Firm age and sector heterogeneities

In the baseline outcomes, the effects of internal knowledge on the intensity of radical innovations are positive. However, one might expect heterogeneities across different firm groups. According to the intuition presented in Section 4.2.3., we identify firm age and the technological intensity of each sector as the main sources of divergences in the results. To account for this, we run additional specifications introducing, first, an interaction between knowledge and firm age[16] for the complete sample and, second, similar specifications but differentiating two subsamples: one addressing firms in high-tech sectors (science-based and specialized-suppliers) and other firms in low-tech sectors (supplier-dominated and scale-intensive). Table 4.5 shows the outcomes of these additional regressions.

Addressing differences between high-tech and low-tech sectors, the average impact of internal knowledge in high-tech sectors is slightly higher than in low-tech ones. However, considering the standard error of the effects, the difference between the two coefficients is not significant.[17] In the case of the interaction between knowledge and age, there are again no significant differences, overall leading to a clear rejection of hypothesis *H3*.

Figure 4.2. Representation of the marginal effects of the interaction between knowledge and firm age.



Source: Developed by the authors using CalcPlot3D

[16] The interaction is specified as: $-1.036 \cdot \ln(Count\_K) -0.629 \cdot \ln(Age) + 0.728 \cdot \ln(Count\_K \times Age)$.
[17] We applied the test of seemingly unrelated samples $Z = (\tau_H - \tau_L)/\sqrt{\sigma_H \sigma_L}, Z \sim N(0,1)$, which for the variable *Count_K* provides a value of 1.017, not significant at traditional confidence levels.

Table 4.5. Dynamic fixed-effects Tobit for the intensity of radical innovations across sector clusters.

	Sample				**High-tech**				**Low-tech**			
Variable	**(1) Internal**		**(2) External**		**(1) Internal**		**(2) External**		**(1) Internal**		**(2) External**	
rad_int_{t-1}	1.359***	1.357***	1.373***	1.373***	1.231***	1.231***	1.239***	1.239***	1.455***	1.452***	1.473***	1.474***
	(0.011)	(0.013)	(0.013)	(0.013)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
$Count\_K^{m}_{t-1}$	0.384***	-1.036***	-0.064	-0.195	0.438***	-0.758**	-0.052	-0.072	0.328***	-1.156***	-0.060	-0.353
(Logs)	(0.050)	(0.212)	(0.075)	(0.303)	(0.068)	(0.295)	(0.103)	(0.420)	(0.071)	(0.306)	(0.108)	(0.435)
Age_{t-1} (Logs)	-0.095	-0.629	-0.383	-0.399	-0.017	-0.549	-0.339	-0.342	-0.145	-0.654	-0.379	-0.410
	(0.496)	(0.501)	(0.497)	(0.498)	(0.727)	(0.736)	(0.728)	(0.731)	(0.681)	(0.687)	(0.682)	(0.634)
$Count\_K^{m}_{t-1}$ x		0.728***		0.066		0.620***		0.010		0.751***		0.145
Age (Logs)		(0.105)		(0.147)		(0.149)		(0.206)		(0.151)		(0.209)
Initial condition	0.138***	0.138***	0.158***	0.158***	0.168***	0.168***	0.175***	0.175***	0.113***	0.114***	0.148***	0.148***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Control variables	Yes											
Average effects	Yes											
Time dummies	Yes											
Observations	40,255				15,007				25,248			
Firms	4,114				1,554				2,560			
Uncensored	12,571				5,721				6,850			
Censored	27,684				9,286				18,398			
Log. Likelihood	-53,297.32	-53,273.52	-53,414.52	-51,414.42	-23,509.22	-23,500.54	-23,556.35	-23,556.35	-29,709.32	-29,696.93	-29,781.56	-29,781.32
Wald test for non-zero slopes	16,043.03***	16,053.93***	15,963.61***	15,963.92***	6,732.49***	6,737.83***	6,701.35***	6,701.39***	8,997.97***	9,004.65***	8,943.11***	8,943.31***

*p<0.1; **p<0.05; ***p<0.01. Firms not belonging to a group are the base outcome of group dummies. Supplier-dominated is the base outcome of sector dummies.

Contrary to the analysis of sector-based heterogeneities, the interaction between internal knowledge and firm age introduces an increased degree of complexity in the interpretation of the marginal gains from knowledge accumulation. To visualize this information, Figure 2.2 presents the hyperplane of the marginal effects of the interaction.[18]

We should highlight the observed decreasing marginal returns from knowledge. The initial years of persistent knowledge generation contribute the most to the intensity of radical innovations, this then decreases gradually. Additionally, firms experience different returns from knowledge in terms of intensity and duration.

In this regard, firms benefit comparatively more from the initial effects and the persistent generation of knowledge, as they obtain positive returns over a more extended period. To demonstrate this, we isolate the plane $\tau = 0$ as follows:

$$-1.036 \cdot \ln(Count_K) - 0.629 \cdot \ln(Age) + 0.728 \cdot \ln(Count_K \times Age) = 0 \; (4.8)$$

Solving this equation provides the last year of knowledge generation that yields positive gains about firm age.

$$Count\_K = e^{0.321 \cdot \ln(Age)} (4.9)$$

On average mature firms possess more established practices, a solid organisational structure, better market positions, and extensive experience across various dimensions. These elements collectively constitute a fraction of a firm's implicit knowledge. This derivative of knowledge, unmeasurable with the available information, acts as an amplifier of the observed internal sources, leading towards a better and longer-lasting use of knowledge for the development of complex innovations. This evidence provides additional insights to the literature and aligns with hypothesis *H4a.* Neither in this case, does external knowledge present significant effects. Consequently, no effects are benefiting young firms, leading to the rejection of hypothesis *H4b.*

4.6. Discussion and conclusions

This chapter contributes to an ongoing research strand exploring the complementary linkages between knowledge generation and radical innovations. Existing approaches

[18] Note that, despite not having a significant effect, the effect of the logarithm of age is shown to not distort the representation of the marginal effects.

often focus on specific triggers of innovation such as interrelations between organisations, market dynamics, capabilities, and other sources of knowledge building (Beck et al., 2016; Delgado-Verde et al., 2016; Forés and Camisón, 2016; Cefis et al., 2020; González-Sánchez et al., 2020). Despite their valuable contribution, they frequently overlook the cumulative and path-dependent nature inherent in knowledge and innovation processes. Addressing this gap, our study employs a multi-step methodology based on dynamic panel models to unravel the profile of internal and external knowledge generators, as well as assess the impact of this knowledge generation on the intensity of radical innovations.

The insights obtained from the Spanish Technological Innovation Panel (PITEC) capture the innovative behaviour (or lack of it) of 4,114 Spanish firms over the period 2005–2016, providing a total of 40,256 firm-year observations, and the outcomes gathered fall within three main strands. First, internal knowledge generators exhibit better performance and a more skilled labour force than firms absorbing external knowledge, presenting a superior endowment of human capital, productivity, and export intensity. Consequently, a more dynamic competitive environment drives these firms, incentivizing internal R&D investments and the continuous improvement of product lines.

Secondly, as the generation of internal knowledge is motivated by these enhanced characteristics, its impact on the intensity of radical innovations is significant, greatly enhancing a firm’s innovative potential. While this does not deny the need for external knowledge, nor its role as a potential complement of internal knowledge, the results underscore that internal sources of knowledge provide the distinctive traits that allow a firm to differentiate itself from its competitors and foster new product development. According to our reasoning, the mechanism triggering this differentiation lies in the divergent complexity and accessibility of internal knowledge relative to its external counterpart, being the latter simpler and easier to transmit, it does not provide differential traits as effectively.

Thirdly, the effects of knowledge on radical innovation development are far from homogenous. While we do not observe significant differences across high-tech and low-tech sectors, strong heterogeneities emerge based on firm age. As the implicit knowledge of mature firms is boosted by their experience, structured organisation, established market position, and other dynamics, they obtain the largest marginal gains from the persistent generation of knowledge, and over a more extended period. This enables them to build a more robust knowledge stock and achieve greater success in developing radical innovations. From a theoretical point of view, these results provide a derivative based on firm age that backs the coexistence of Schumpeter Marks I and II. However, there is a prevalence of the second, as incumbent firms dominate markets and innovation due to their extensive investments in R&D, which drive innovation extensively (Schumpeter, 1942; Freeman et al., 1982). This sets a relevant research question for future developments regarding the transitioning patterns that transform entrant firms from being agents driven by novelty and creativity towards leveraging innovation from the accumulation of skills and expertise, becoming solidly established in a determined market niche.

From a policy perspective, open innovation systems, in which knowledge can be transferred easily, should complement additional policies strategically target internal sources of knowledge, such as internal R&D as, despite their effects being mostly confined to a particular firm, they drive more complex innovations in the long term, thus allowing the organisation to transition towards the technological frontier. The development or improvement of soft instruments, such as grants, subsidies, or tax credits, related to knowledge-intensive activities should provide better incentives to generate new knowledge, enriching innovation systems with a continuous stream of knowledge and capabilities. Within a strategic knowledge-sharing system, this will provide spillover effects boosting the performance of other actors and limiting knowledge leaking.

Finally, while this research sheds light on a relevant aspect of the knowledge-innovation nexus, it is not without limitations. These originate mainly from the subjectivity of the dependent variables, as knowledge itself is a conceptual construct and might fall within different definitions, and the measure of the intensity of radical innovations is identified by the firm itself, which might lead to an overestimation of a firm’s innovative potential and might cause certain biases (Mairesse and Mohnen, 2010). Future research lines stemming from this article should aim at exploring measures of internal and external knowledge, including additional dimensions, improved quantification, and deeper insights.

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4.8. Appendix 4A

Table 4A.1. Distribution of the real and estimated values from Equation (4.4).

	Internal			External	
	0	**1**		**0**	**1**
0	22,842	2,805	**0**	32,375	1,158
1	3,624	10,985	**1**	2,843	3,880

The rows indicate the real values and the columns the estimated ones.

Table 4A.2. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) rad_int	1.000														
(2) $K^{Internal}$	0.250	1.000													
(3) $K^{External}$	0.204	0.254	1.000												
(4) Age	0.002	0.028	0.040	1.000											
(5) Size	0.127	0.177	0.219	0.297	1.000										
(6) Human capital	0.132	0.117	0.120	-0.101	-0.171	1.000									
(7) Productivity	0.098	0.093	0.120	0.135	0.315	0.077	1.000								
(8) Export intensity	0.120	0.201	0.152	0.190	0.271	0.119	0.325	1.000							
(9) Physical investment	0.145	0.188	0.183	0.056	0.308	0.060	0.277	0.235	1.000						
(10) Public financing	0.227	0.261	0.371	0.003	0.166	0.155	0.080	0.134	0.222	1.000					
(11) Parent	0.065	0.103	0.099	0.098	0.203	0.058	0.109	0.087	0.092	0.102	1.000				
(12) Subsidiary	0.050	0.061	0.134	0.058	0.451	-0.005	0.291	0.161	0.187	0.047	-0.210	1.000			
(13) Scale intensive	-0.046	-0.042	0.023	0.022	0.173	-0.111	0.190	-0.002	0.097	-0.003	0.041	0.069	1.000		
(14) Specialized suppliers	0.106	0.093	0.003	-0.051	-0.144	0.159	-0.125	0.042	-0.086	0.052	-0.022	-0.070	-0.333	1.000	
(15) Science-based	0.032	0.119	0.070	0.033	0.007	0.213	0.138	0.093	0.079	0.027	0.017	0.068	-0.255	-0.222	1.000

Chapter 5:

Concluding remarks and future research

5.1. Concluding remarks and policy implications

This dissertation takes a comprehensive and systematic view on innovation processes. The motivation is to investigate the drivers that foster innovation and its persistence with a view to offering policy intuitions to technologically moderate countries, such as Spain, that would allow them to enhance their technological capabilities. In a context of transformative change due to rapid technological advancements and contemporary social and environmental challenges, the topics addressed gain significance in devising effective tools to mitigate negative economic shocks and leverage scientific and technological advances.

The thesis investigates the drivers of innovation from three complementary perspectives, each constituting an independent section but sharing a common interest within the paradigm of the Schumpeterian understanding of innovation, evolutionary economics, and dynamic capabilities. It commences with a cross-sectional analysis of the association between debt financing and innovation across a sample of European manufacturers, subsequently narrowing its focus on the degree of innovation persistence, variability, and knowledge dynamics for a sample of Spanish firms.

Going into more detail, Chapter 2 delves into the interpretation of innovation as an uncertain and resource-intensive strategy, underscoring the pivotal role of efficient financial markets in generating active business dynamics (Beck and Demirguc-Kunt, 2006; Lv and Xiong, 2023). By differentiating working capital and physical investment, addressing short-term and long-term resources respectively, the chapter aims at scrutinizing the non-linear effect of debt financing on the development of innovation activities and productivity.

Debt financing is a financial determinant of a firm’s innovative behaviour, as it serves as a tool to surpass financial barriers that hamper the development of innovation (Gilmore et al., 2013; García-Quevedo et al., 2018). However, debt also generates obligations in the shape of stricter objectives, requirements and transparency that might moderate creativity and innovation (Christensen et al., 2008; Shi et al., 2019). Building on this research line, we complement and expand recent findings intending to examine the boundaries of debt acquisition (Ang et al., 2019; Li et al., 2021), searching for the critical point that delimits the maximum returns from debt, as well as the complementarities between working capital and physical investment.

The baseline outcomes reveal a convex relationship between debt acquisition and innovation, in which the marginal gains from debt diminish for each additional unit, reaching different maximums depending on whether the results and imputed on working capital or physical investment. Additionally, there are strong complementary effects between working capital and physical investment. The underlying mechanism behind these complementarities hinges on the role of working capital as an adjustment tool for short-term resources to cope with unexpected shocks when undertaking long-term investments (Ding et al., 2013). Despite the relevance of working capital in the short-term, firms tend to underfinance this resource, this being a structural problem underlying the design of investment plans. Identifying long-term needs is considerably easier than anticipating future short-term needs (Deloof, 2003), leading to a suboptimal design of investment plans.

Finally, testing heterogeneous effects we observe different behaviours across firms operating in low-tech or high-tech sectors, as well as across young and mature firms. On the one hand, while firms in low-tech sectors focus their investments towards increasing productivity, leaving the innovative dimension on a second plane, firms in low-tech develop strategies in addressing innovation activities. On the other hand, young firms rely greatly on physical investment and the complementarities between physical investment and working capital. Alternatively, mature firms develop complex investment activities leveraging all dimensions simultaneously.

Chapter 3 reinterprets the analysis of innovation persistence. Understanding the dynamics of innovation processes as a combination of true state persistence, the path-dependent patterns of innovation, and spurious state persistence, the effect of characteristics internal or external to the firm (Altuzarra, 2017), we disentangle the effects of learning-by-exporting (De Loecker, 2007), differentiating its temporal and spatial dimensions (Segarra-Blasco et al., 2022).

Dividing the sample into five categories depending on the degree of innovation persistence, we find a consistent and positive effect of the temporal dimension on being a persistent R&D investor or innovator. Regarding the spatial dimension, the results are considerably more heterogeneous. Exporting solely to markets inside the European Union (EU) encourages transitioning events towards R&D innovation. Exporting only outside the EU increases the likelihood of all innovator groups except for the most persistent one, which is predominantly determined by firms exporting simultaneously inside and outside the EU.

Analysing the changes in the innovation status individually, we observe that experienced exporters addressing markets inside and outside the EU have fewer incentives to stop or start innovation activities. This suggests that R&D investors or innovators exporting extensively in terms of experience and markets addressed have no incentive to abandon their behaviour. Neither have non-innovative exporters incentives to start R&D or innovation, as they already have an established international situation and do not perceive the potential benefits from innovation as sufficient to risk their stable situation.

Alternatively, while markets outside the EU discourage the abandonment of innovation activities, exporting to EU markets has no significant impact. The insights we draw about these findings are related to the incentives that each market provides, being the EU a relatively safer environment good for transitioning events but does not provide sufficient competitive incentives for developing sustained R&D or innovation strategies.

Chapter 4 is based on the dynamic study of innovation, linking the continuous generation of internal and external knowledge with the development of radical innovations. Conceptually, the related study tests the complementarities between two innovation patterns identified in the evolutionary understanding of innovation. Malerba and Orsenigo (1995) explain, on the one hand, widening patterns as continuously growing technological bases due to the entrance of radical innovations to the market. On the other hand, deepening patterns relate to a deep understanding of a specific technology, developing extensive R&D and incremental innovations.

From a managerial perspective, exploration and exploitation strategies are based on similar intuitions. Organisational exploration aims at the development of new technologies and exploitation related to the continuous improvement of processes or products (Gilsing and Nooteboom, 2006). Therefore, this chapter understands knowledge as an intangible asset mainly related to exploitation activities, but which has the potential to provide new capabilities for the development of more new and complex ideas, which might crystallize into innovations new to the market.

The topic is addressed in three steps. Firstly, we examine the determinants of the continuous generation of internal knowledge or the adoption of external knowledge. In this regard, we find that firms with more skills, productivity, and export intensity are the most prominent generators of internal knowledge. However external knowledge acts as an imperfect substitute for internal knowledge (Grigoriou and Rothaermel, 2017), providing otherwise inaccessible capabilities to firms less intensive in these key elements.

Secondly, imputing the effects of each source of knowledge on the intensity of radical innovations, the results suggest that only internal knowledge provides the differential capabilities that allow firms to develop these innovations. Analysing this finding in greater depth, we find that external knowledge is available to a larger set of firms and is comparatively less complex than internal knowledge for effective transmission. Consequently, external knowledge fails to provide the specific capabilities to develop completely new innovations.

Thirdly, when exploring heterogeneous effects, we find that mature firms obtain larger initial marginal gains from knowledge. Moreover, the gains from knowledge tend to persist over a more prolonged time span for mature firms, as their increased experience provides a larger stock of implicit knowledge that allows for better incorporation of knowledge into a firm's activities and culture.

Several conclusions may be drawn from the subjects addressed in this dissertation. Firstly, the distribution of short-term and long-term resources is relevant in determining the innovative profile of firms. Specifically, the acquisition of working capital and physical investment from financial markets is based on decreasing marginal returns obtained from debt financing and the complementary interlinkages between working capital and physical investment. An incorrect provision of short-term needs in the design of investment plans leads to inefficient investments (Deloof, 2003). This pattern is present in our findings, showing the tendency to under-leverage working capital and over-leverage physical investment.

This raises a concern about improving the efficiency of investment design. To tackle this issue, firms must strengthen their short-term needs provision by better anticipating internal and external business cycles that force them to increase their working capital stock to absorb negative shocks. Besides managerial implications, policymakers also play a significant role in the better design of investment plans. If the under-funding of working capital is a systematic pattern of a specific country, the design of credit lines from public institutions targeting short-term resources with relatively lower interest rates should provide increased incentives for their acquisition. An example of a similar tool designed to cover working capital needs was, for instance, the public guarantees of the Spanish Official Credit Institute (ICO) credit lines offered during the COVID-19 lockdowns. Although that case was exceptional, tools providing similar incentives to firms would improve their investment plans.

Secondly, learning-by-exporting patterns are fundamental not only for deriving innovation activities during a determined period but also for persistent development. Nevertheless, the effects of learning-by-exporting are not homogeneous. As a development of our insights, firms should match their foreign market strategies and their innovation plans and expectations. For non-innovative firms developing innovation activities, EU markets provide a safer competitive environment to accomplish their objective and gain expertise in terms of innovation and market expansions. However, experienced R&D investors and innovators require stronger competitive incentives to maintain persistence in their behaviour, thus, they are extensive exporters, addressing markets inside and outside the EU.

Promoting competitiveness in the design of strategic exporting plans should be the main target for policymakers. For Spanish firms with nascent ideas or innovation projects, policymakers should encourage them to address markets with a similar culture and legal framework to guarantee a moderate degree of competition to develop and consolidate their innovation more effectively. To help in maintaining persistent innovative behaviours, firms should be encouraged to undertake wider trade ventures, in which firms address EU and foreign markets simultaneously. In this context, EU markets provide a solid backing for a firm’s operations and wider markets provide increased incentives for the continuous development of R&D and the improvement of processes and products.

Thirdly, we derive additional learning patterns originating from the development of knowledge-intensive activities such as internal and external R&D, incremental innovation, and cooperation, obtaining proxies for the internal or external acquisition of knowledge. The predominant firm profile differs in each knowledge source, firms with larger human capital and performance being the main generators of internal knowledge, while external knowledge serves as an imperfect substitute for other firms. Additionally, incumbent firms, with more experience and better-established positions find larger gains, in volume and time prolongation, from the continuous generation of internal knowledge.

Based on our observations, we differentiate two topics of interest for policymakers. On the one hand, from the heterogeneous determination and effects of knowledge, the results provide insights for the efficient design of innovation systems. Exploiting the role of networks, communities, and linkages, firms benefit from open innovation systems using a wide range of external actors and sources (Laursen and Salter, 2006). However, this generates a trade-off between knowledge appropriability and sharing that might limit a firm's participation in open systems or the radicalness of its innovations (Laursen and Salter, 2014).

To guarantee a consistent stream of knowledge entering innovation systems policymakers should encourage the development of internal innovation activities intensive in knowledge through soft tools. Besides providing benefits to a particular firm, if knowledge leaks are minimized, this generation of new knowledge and the development of new products would have spillover effects on the rest of the economy, benefiting a broader range of actors.

On the other hand, the differential effects of knowledge across young and mature firms set a conceptual challenge regarding the nature of competitiveness and technological dominance. Despite the results suggest the prevalence of Schumpeter's Mark II, in which incumbents dominate the development of innovation, entrant firms also obtain positive and significant effects from the accumulation of knowledge on the development of radical innovations, suggesting an overlapping of Mark I and II, in which the second is established as the dominant tendency.

Reconsidering the author himself, Schumpeter (1947) poses an extremely relevant question for his readers (although later authors mostly overlook this.) He questions the diminishing relevance of the entrepreneur as creative destruction patterns stabilize. New firms have a comparative advantage in perceiving new opportunities beyond established practices and behaviours. However, they must surpass market barriers and social resistance to change, as well as surmount technical and skills barriers for the correct development of their ideas. If an entrant firm is capable of coping with these challenges, it will establish itself in a determined market niche, in which its novelty will depend greatly on the radicalness and disruptiveness of the technologies developed. Consequently, in later stages, the previous entrant firms driven by entrepreneurial performance will become an established part of the latter market structures, an incumbent.

At this point, one might expect the cycle to repeat itself in some sort of recurrent equilibrium-disruption-equilibrium business pattern. Nevertheless, and as our results suggest, incumbent firms play a key role in the development of radical products and the introduction of innovative technologies. Following Antonelli (2015), established firms have strong incentives to defend their positions and to preserve their technological and organisational conditions. However, our findings contribute to this discussion by showing how established firms take part in the adaptative nature of the markets by themselves developing radical innovations, in which they might not have a relative advantage in terms of creativity, but where their expertise, skills, and resources act as a counterbalance.

Innovation is an endogenous process, depending on firm characteristics and on the characteristics of the environment in which it operates. The role of the policymaker in this environment is specific, given the heterogeneous gains of knowledge and in the development of innovation, they can choose whether to provide tools for young firms with larger creativity but lower chances of success, which will result in an increased in competitiveness due to the entrance of new firms. Or they may focus on mature firms, which contribute with their greater stocks of tangible and intangible capital, that might develop more complex innovations in exchange for less dynamic markets.

5.2. Limitations and future research lines

The topics explored in this thesis represent initial steps towards the development of future ideas aiming at better understanding the nature and dynamics inherent in innovation processes. While the ideas presented are a work in progress, and subject to ongoing refinement, it is crucial to be aware of and acknowledge certain limitations that underscore the need for further investigation. The primary constraints are related to the subjective interpretation of innovation in the data sources utilized, aspects such as the degree of radicality or innovativeness might be biased due to a firm's interpretation of its innovative behaviour.

In Chapter 2 the cross-sectional nature of the data and the sample specificity limits the dynamic analysis of the effects of debt acquisition and the complementarities between working capital and physical investment to a contemporaneous analysis of the research questions analysed. In Chapters 3 and 4, despite observing a relatively extended period (2005 to 2016), PITEC lacks renewed information concerning the innovative behaviour in firms during recent years. Additionally, we acknowledge a relative degree of endogeneity in the modelling structures presented, these being strictly tied to the dynamic nature of innovation.

Despite these limitations, we offer a broad, systematic, and consistent view of the determinants of innovation, its persistence, and dynamic effects, confirming elements previously identified in the literature and we detail them with additional precision or contribute new dimensions to their better understanding. Since we intend this research project to be a first step into the development of additional research, we propose several topics to be addressed in the future with an increased level of detail.

From Chapter 2, we identify the need for a robust theorization of the combined effects of working capital and physical investment on a firm's innovative behaviour, with a complete and detailed explanation of the behavioural mechanisms playing a significant role in the process. Acquiring panel data with extensive information on a firm's financial dimensions would facilitate a more in-depth analysis of dynamic effects and long-term trends. Shifting the focus of attention from debt financing to other external sources of capital such as capital markets, would introduce another relevant dimension to the analysis of the trade-offs between the internal/external acquisition trade-off.

Building on the outcomes obtained from Chapter 3, a more detailed disaggregation of the spatial dimension of learning-by-exporting with would provide greater granularity to the analysis of its spatial dimensions. Developing a dynamic system that endogenizes both trade and innovation would establish a framework for jointly examining self-selection patterns and learning effects, as well as exploring the potential bilateral relationship between trade and innovation.

Finally, from Chapter 4, which is the richest in terms of conceptual foundations and implications, we suggest several dimensions to be addressed in future developments. Focusing on the nature of knowledge, future research projects might add additional proxies of internal or external knowledge generation, such as the direct acquisition of knowledge, process innovation, or disaggregating the distinct types of cooperation. Generating an index of knowledge accumulation or analysing in depth the complementarities between internal and external knowledge would also provide relevant contributions to the literature. Alternatively, exploring a firm's transition from entrepreneurial dynamics to incumbent behaviours is an interesting topic to address. More specifically determining which patterns or characteristics foster the transition towards either an adoption of protectionist practices or towards a consistently and dynamic innovative behaviour is of considerable interest.

Although acknowledging the need for further work to develop the research lines opened in this thesis, the current exploration of topics ranging from the impact of debt financing on innovation to the dynamics of innovation persistence and the role of knowledge ready contribute significantly to the understanding of the drivers of innovation. Overall, the findings emphasize the importance of a nuanced understanding of short-term and long-term resources, the significance of learning-by-exporting patterns, and the heterogeneous effects of knowledge across young and mature firms. They provide valuable managerial and policy implications to strategically approach innovation, enhancing the technological capabilities needed to foster competitiveness and providing tools for efficiently tackling contemporaneous challenges.

5.3. References

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