EFFECTS OF EXPLOITATIVE AND EXPLORATORY R&D ON FIRM PERFORMANCE:

THE ROLE OF FIRM- AND INDUSTRY-SPECIFIC CONTINGENCIES

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ABSTRACT

Drawing from organizational learning theory, this PhD thesis explores the relationship between exploratory and exploitative R&D and firm performance and advances prior knowledge by specifying how firm- and industry-specific contingencies influence this relationship. Research on ambidexterity suggests that firms should *balance* exploratory and exploitative R&D activities for enhancing their performance (i.e. invest significantly in both activities). Yet, *exploitative R&D* (which relies on existing knowledge and old certainties and includes activities and structures that focus on efficiency) and *exploratory R&D* (which requires distant knowledge and includes activities and structures that rely on experimentation) are two antithetical activities with distinctively different knowledge requirements and outcomes. We therefore posit that *specialization* rather than ambidexterity might be more beneficial for the performance of some firms. Accordingly, in the context of R&D, we examine how *balance* versus *specialization* in exploratory R&D and exploitative R&D affect firm performance.

In the first empirical chapter, we test and make a direct comparison between specialization in either exploratory or exploitative R&D and ambidextrous R&D strategies. This chapter also identifies *whether* and *how* the returns to exploratory and exploitative R&D vary for those firms that adopt a specialization versus an ambidextrous strategy. It advances thus scholarly understanding of how certain mechanisms affect the returns from specializing in exploratory or exploitative R&D and consequently firm performance. The second empirical chapter contributes to the literature on exploration and exploitation by identifying *which* specialization strategy (exploratory or exploitative R&D) and under what *conditions* is more beneficial for firm performance. Drawing from industrial organization economics, our analysis shows that this depends on *industry orientation* (a typology we develop that captures cross-industry variations in the concentration of exploratory and exploitative R&D activities). In the third empirical chapter, we contribute to our understanding of the phenomenon by examining how firms change their specialization strategies over time. We propose that firm performance depends on the *speed* at which firms switch between specialization strategies in a given timeframe and examine how the speed of such changes affect firm performance. This chapter offers thus an explanation that accounts for performance differentials across firms that change at different speeds and in different contexts.

We test our framework and hypotheses using a longitudinal dataset of 32,537 observations. The analysis mainly supports our theoretical predictions, indicating that the effects of specialization in exploratory/exploitative R&D depend upon both firm and industry- specific dynamics that either accentuate or weaken the effects of exploratory and exploitative R&D investments.

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CHAPTER 1
INTRODUCTION

AIMS AND OBJECTIVES

Drawing mainly from organizational learning theory (March, 1991; Cyert and March, 1963; Argyris and Schön, 1978; Levinthal and March, 1993; Yelle, 1979; Cohen and Levinthal, 1990; Argyris, 2002; Huber, 1991; Fiol and Lyles, 1985; Ingram and Baum, 1997; Wang et al., 2014; Ahmed, 2003; Baum et al., 2000; Holmqvist, 2004; West and Burnes, 2000; Atuahene-Gima and Murray, 2007; Ho et al., 2015; Chiva et al., 2010) this PhD thesis applies the concepts of exploration and exploitation in the context of research and development (R&D) (D'Este, et al., 2017). Accordingly, it investigates the relationship between exploratory/exploitative R&D and firm performance and examines certain firm- and industry-specific contingencies that affect this relationship.

The organizational learning and ambidexterity literatures emphasize the role of *exploration* and *exploitation* in enhancing firm performance (Benner and Tushman, 2002; He and Wong, 2004; Cao et al. 2009, Gibson and Birkinshaw, 2004; Lubatkin et al., 2006; Wilden et al., 2018; Koryak et al., 2018; Wang et al., 2014; Junni et al., 2013). *Exploitation* largely relies on existing knowledge and old certainties, and includes activities and structures that focus on efficiency, implementation and refinement. In contrast, *exploration* requires new possibilities and distant knowledge, and includes activities and structures that rely on experimentation, new searches and discoveries (March, 1991; Gupta et al., 2006; Raisch and Birkinshaw, 2008; Dover and Dierk, 2010). This research stream hinges on the premise that organizations that want to achieve superior performance must *balance* exploration and exploitation (i.e. invest significantly in both activities) (Benner and Tushman, 2003; Levinthal and March, 1993; He and Wong, 2004; Morgan and Berthon, 2008; Tushman et al., 2010). A strategy that overrelies on exploitative activities may lead to self-destruction in the long term, mainly because at some point firms over exhaust all the possible combinations and alternatives with existing knowledge (Abernathy and Clark, 1985). Reliance also on exploitation may foster structural inertia, reducing thus firms' capacity to adapt to environmental changes and attain a good position in future markets (Atuahene-Gima, 2005; Hannan and Freeman, 1984; Uotila et al., 2009). On the other hand, a strategy that centres too much on exploration may have similarly negative performance consequences by leading to under-utilization of new ideas, by increasing the costs of experimentation or by generating a plethora of uncertain and underdeveloped ideas with excessive substitutability (March, 1991; Levinthal and March, 1993; Barney, 1991; Wernerfelt, 1984; Yelle, 1979; Kyriakopoulos and Moorman, 2004; Lockett et al., 2009).

The literature suggests that balance can be achieved in two distinct ways. More specifically, some studies emphasise the importance of organizational ambidexterity, suggesting that firms should simultaneously pursuit and excel at both knowledge exploration and exploitation by having some subunits that are more exploratory while others that are exploitative oriented (Duncan, 1976; Tushman and O'Reilly, 1996; Benner and Tushman, 2003; Gupta et al., 2006). In contrast, other studies support the view that the simultaneous pursue of the two is not necessary because short-term efficiency and long-term adaptability are inherently incompatible (Abernathy, 1985). These studies suggest that organizations can balance exploration and exploitation using a *punctuated equilibrium* approach, which rests upon the temporal shift or cycling from one activity to the other. This strategy involves periods of exploitation followed by periods of exploration (Burgelman, 2002; Gupta et al., 2006).

Although the debate on ambidexterity versus punctuated equilibrium has not yet been resolved, it is accepted in the literature that most organizations must balance exploitation and exploration using one way or another (Benner and Tushman, 2002; Feinberg and Gupta, 2004; Levinthal and March, 1993; March, 2006). However, despite the above compelling arguments, prior empirical research often shows that ambidexterity has either insignificant (Bierly and Daly, 2007) or negative effects on firm performance (Rothaermel and Alexandre, 2009; Ebben and Johnson, 2005). Furthermore, statistics from the PITEC (Technological Innovation Panel) dataset indicate that many firms do not actually balance their investments between exploratory and exploitative R&D, and they instead choose to *specialize* in one activity (i.e. invest over 66.6% of their budget in either exploratory or exploitative R&D). From the 32,537 observations that are used in this thesis, 40% of firms specialize in exploitative R&D, 31% of firms specialize in exploratory R&D, and only 29% tend to be balanced (invest between 33.3% and 66.6% in the two activities).

Prior mixed findings highlight the importance of understanding why some firms do not benefit from investing in both activities, and whether specialization (rather than ambidexterity) is more beneficial for firm performance. Although prior studies have examined the relationship between balance (or ambidexterity) and firm performance, we know very little about the relationship between specialization and firm performance. In this PhD thesis, we focus on the context of research and development (R&D) in organizations and examine how *balance* versus *specialization* in exploratory R&D and exploitative R&D influences firm performance. This study develops the premise that balance and specialization are two separate innovation strategies that are more beneficial for certain firms and contexts and less advantageous for other firms and contexts.

Accordingly, we adopt a contingency approach and seek to advance understanding of this phenomenon by examining how firm- and industry-specific factors influence the effectiveness of exploratory R&D and exploitative R&D in enhancing firm performance. To achieve this aim, this study identifies how the usefulness of *balance* versus *specialization* changes depending on the characteristics of the firm and the environment or industry in which the firm competes. To identify such firm- and industry-specific contingency factors, the thesis examines a set of research questions that are organized in three groups and empirical chapters:

Q1: Specialization in exploratory and exploitative R&D and firm performance: In the first empirical chapter of this thesis, we argue that a reason for prior mixed findings with respect to exploitation and exploration and firm performance is partly the implicit assumption of some studies that the effects of exploration and exploitation on firm performance do not differ across firms that are specialized and those that are ambidextrous. Nevertheless, exploration and exploitation involve different and incompatible processes (Chen and Katila, 2008; Benner and Tushman, 2003). Hence, the economic returns to exploratory R&D may differ for firms that specialize in exploratory R&D, and a similar argument may apply in the case of exploitative R&D. Accordingly, the first empirical chapter of this thesis examines two important research questions:

a) Is specialization in either exploratory or exploitative R&D more beneficial than an ambidextrous strategy?

b) How do the economic returns of exploratory and exploitative R&D differ for those firms that adopt a specialization versus an ambidextrous strategy?

This set of questions offers a direct comparison between specialization in exploratory and exploitative R&D and ambidextrous R&D investment strategies. To our knowledge, there are no studies that make a direct comparison between specialization and ambidexterity in the context of R&D. Hence, it remains unclear whether firms should be *ambidextrous* or *specialize*. Equally, prior research has not examined how the impact of exploratory and exploitative R&D on firm performance varies across firms that make different decisions with respect to specialization and ambidexterity. In other words, we do not know whether the effects of R&D investments differ for firms that adopt a specialized (exploratory or exploitative) versus an ambidextrous R&D investment strategy, and in which situations is more advantageous for firm performance. This chapter therefore aims at addressing these issues.

Q2: The role of industry orientation: Whereas the first empirical chapter focuses on whether firms should be *ambidextrous* or *specialize*, the second empirical chapter examines *which* specialization strategy (exploratory or exploitative) and under *what conditions* is more advantageous to the firm. Drawing from industrial organization economics (Dranove et al., 1998; Jacobides et al., 2006), we suggest that the answer to this question depends on a particular characteristic (the *orientation*) of the industry in which the firm operates. *Industry orientation* is a typology that this thesis develops to capture cross-industry regularities and variations in the concentration of the exploration and exploitation activity. According to this typology, industries may be *exploitative-oriented* (most firms in these industries specialize in exploitation but there is a low concentration of firms that specialize in exploration), or *exploratory-oriented* (they exhibit the opposite pattern), or *hybrid* (whereby firms pay similar attention to both exploitation, exploration and ambidextrous strategies).

Accordingly, this study examines how the orientation of each industry affects how beneficial specialization in exploratory or exploitative R&D is for firm performance. The analysis shows that specialization in exploitative R&D has a negative effect on performance when the firm operates in an exploitative-oriented industry. Conversely, the opposite pattern emerges with the corresponding effect on performance being positive when a firm that specializes in exploitative R&D operates in an exploratory-oriented industry. These findings explain why firms experience different returns to such strategies when the orientation of their industry varies.

Q3: Changing specialization strategies and the role of speed: As we discussed earlier, firms may choose to either invest simultaneously in both exploratory and exploitative R&D (Benner and Tushman, 2003; He and Wong, 2004) or engage in a temporal shift from one activity to the other (Burgelman, 2002; Gupta et al., 2006). In the third empirical chapter, we propose that firm performance depends not only on the way ambidexterity is achieved, but also on the *speed* at which firms change their investments from one activity to the other. To enhance our understanding of this phenomenon, we examine thus how quickly firms change from one *specialisation strategy* to another within a given timeframe, and how the speed of such change affect firm performance.

This analysis captures that some firms change from a specialized in exploitative R&D strategy to either a specialized in exploratory R&D strategy or ambidextrous strategy, whereas others change from a specialized in exploratory R&D strategy to either a specialized in exploitative R&D or ambidextrous strategy. There are also some firms that change from an ambidextrous strategy to either a specialized in exploratory R&D or exploitative R&D strategy. We propose that changing specialization strategies may enhance learning and establish new capabilities (Vermeulen and Barkema, 2001), but changing at higher speed between specialization strategies can be disruptive and harmful (Klarner and Raisch, 2013; Amburgey et al., 1990). Therefore, firms that change their specialization strategies quickly (e.g. every 1-2 years) may not benefit from their learning as those firms that change their strategy at a lower speed (e.g. every 4-5 years). In addition, the chapter examines the context under which how the negative effect of speed on firm performance could be ameliorated. This aspect of the analysis shows that that the negative effects of speed of change could be moderated (positively) when firms operate in R&D intensive industries that require firms to adapt to dynamic changes.

The unit of our analysis is the firm. To test our hypotheses and address our research objectives, we use econometric analysis and data from the *Technological Innovation Panel* (PITEC) survey.

This dataset is designed to monitor the innovation activities of Spanish firms across time. The dataset is collected and managed by the INE (which is Spain's National Statistics Institute). PITEC is a panel survey and will therefore enable us to trace not only the economic innovation expenditures of a variety of firms that operate in multiple industries, but also control for the heterogeneity in firms' decisions to invest in exploratory/exploitative R&D and their impact on firms' financial performance. PITEC reports the actual amount of money that firms invest in internal and external R&D. It therefore allows us to understand the outcome of decisions and innovation strategies employed by firms.

The information reported in PITEC is obtained from postal questionnaires. PITEC provides over 460 variables for approximately 12,000 companies. We have been granted access to a set of coordinated year-based files from 2005 to 2012. After clearing and merging the related variables of the years spanning from 2005-2012 and deleting the missing values, the final dataset includes 32,537 observations. Given that our sampled firms are clustered within industries, a *Multilevel Mixed Model* approach is adopted to test our theoretical predictions and conceptual framework (Bliese and Ployhart, 2002; Anderson, 2014; Preacher et al., 2006). This will enable us to test both the direct and contingency effect of each explanatory variable on our dependent variable (total factor productivity, TFP).

THEORETICAL CONTRIBUTIONS

This study makes a number of contributions to organization learning (March, 199; Cyert and March, 1963; Levitt and March, 1988; Nelson and Winter, 1982; Levinthal and March, 1993; Baum et al., 2000) and exploration/exploitation (or ambidexterity) literatures (O'Reilly and Tushman, 2013 for a review) by specifying how firm- and industry-specific factors influence the impact of exploratory and exploitative R&D on firm performance. We extend the discussion on ambidexterity by identifying the conditions under which specialization in either exploration or exploitation is more beneficial than the equal distribution of resources. We theorize and expect that a balanced orientation is not always the optimal strategy for superior firm performance and this balance is contingent upon different factors. Accordingly, we develop a conceptual framework that extends prior studies by showing that the usefulness of *balance* versus *specialization* changes depending on the characteristics of the firm and the environment or industry in which the firm competes. More specifically, each empirical chapter contributes to the exploration/exploitation and ambidexterity literature in the following way:

The first empirical chapter explains how and why the performance-enhancing effects of firms that specialize in explorative/exploitative R&D differ from those firms that decide to make similar investment in both explorative/exploitative R&D. It thus shows why the effectiveness of exploratory and exploitative R&D depends upon the firm's choice to pursue investments that are similar (or dissimilar) to the specialization of the firm. It thus contributes to research that examined the effects of being ambidextrous (Auh and Menguc, 2005; He and Wong, 2004; Jansen et al., 2006; Uotila et al, 2009; Venkatraman, et al., 2007; Lubatkin et al., 2006), but has not examined if and how the returns from specializing in either in exploratory and exploitative R&D might be more beneficial for firm performance, and whether those effects strengthen or weaken when firms choose to invest in activities that require knowledge that is similar to the firm's own knowledge base. Furthermore, we show that certain factors allow firms to specialize and achieve ambidexterity in the broader network when interacting with other firms (Gupta et al., 2006 Chesbrough, 2003; Cassiman and Veugelers, 2006; Chesbrough, 2006; Wassmer et al., 2017). This view contributes to organization learning theory that clarifies the different types of learning and their advantages but does not specify when different types of learning associated with exploration and exploitation are more effective in enhancing firm performance, and whether they complement or substitute each other in enhancing firm performance (March, 1991; Holmqvist, 2004; Baum et al., 2000; Levinthal and March, 1993: Casillas and Moreno-Menéndez, 2014;).

Second, drawing from industrial organization theory (Bain, 1968; Schumpeter, 2017; Porter 1979; 1990; 2000; Mason, 1939; Jacobides et al., 2006; Dranove et al., 1998;), we show how the structure of the industry with its level of competition may require a different balance towards specialization to counter-act competitors' behaviour. We thus enhance understanding of how firms should invest their resources to successfully respond to competitive conditions. This study also differs from prior studies (Benner and Tushman, 2003; Gupta et al., 2006; Jansen et al., 2006) because it emphasizes the interrelatedness of external and internal factors for determining whether balance or specialization is the most optimal solution for firm performance. Identifying the industry-specific mechanisms that make specialization more beneficial enables us to specify which specialization strategy firms should pursue and how the industry in which they operate may affect the economic returns to this strategy. We contribute thus to ambidexterity (exploitation and exploration) research that has not examined how the orientation of each industry affects the economic returns to exploration and exploitation for the focal firm.

The third empirical chapter draws from learning theory and research on temporal effects (Klarner and (Raisch, 2013; Levinthal and March 1993; Rosenkopf and Nerkar, 2001; Hashai et al., 2015; Casillas and Moreno-Menéndez, 2014; Swift, 2016), extends prior research on the exploration and exploitation literature and firm performance in two ways. First, it identifies how quickly firms should switch between specialization strategies. This enables us to understand how firms could minimize the cost of disruption associated with either quick changes (of a shorter time-length) or extreme changes (i.e., from being specialized in exploration to being specialized in exploitation strategies and vice versa) that influence firm performance. Second, it increases knowledge of how frequently firms need to shift between specialization strategies. Although the temporal effects of this issue have largely been ignored by the literature, understanding of these phenomena could help firms to use time effectively to create a source of competitive advantage (Shi et al., 2012).

MANAGERIAL IMPLICATIONS

This PhD thesis also has important implications for practice as some firms may benefit more by focusing on utilizing successfully established and tested technologies, avoiding thus the cost of experimentation, while others may benefit more by investing time and resources in exploring the potential of new ideas and technologies (March, 1991; Uotila et al., 2009; Bierly and Daly, 2007). This means that senior managers need to be aware that under certain circumstances there is no need to allocate their resources and time equally between the two activities not only because ambidexterity requires different structures and knowledge to manage it successfully but also because the usefulness of ambidexterity has some limits (Ebben and Johnson, 2005; Rothaermel and Alexandre, 2009; Amason et al., 2006; Bierly and Daly, 2007, Kyriakopoulos and Moorman, 2004). Hence, the results will help firms to 1) develop an optimal exploration/exploitation strategy that enhances their economic performance and 2) identify contingency factors that affect their performance in current and future markets (Aug and Mengue, 2005; Cao et al., 2009; Jansen et al., 2006).

Second, the results can help managers choose which specialization strategy they should follow and how the industry affects the benefits of this strategy. The typology of industry orientation can help firms decide *whether* a specialization strategy as well as *which* specialization strategy (exploration or exploitation) is more advantageous for each industry. Hence it can help them develop a better exploration/exploitation strategy that enhances performance by ensuring a better fit between the firm and its industry.

Third, the findings show that two firms that shift between specialization strategies experience different performance when they do it at different speeds and in technologically different industries. Managers should understand that when their firms quickly shift from one specialization strategy to another, they compress learning over a shorter time frame which may in turn lead to diminishing returns (Hashai et al., 2015; Dierickx and Cool, 1989). Hence, a high-speed cycling from one activity to the other might actually have adverse consequences for their performance. They should also bear in mind that the way in which speed affects their performance depends on the technological dynamism of their industry (Uotila et al., 2009; Gupta et al., 2006) Technologically dynamic industries enable firms that change their specialization strategies frequently to enhance their performance. It is thus advisable to change specialization strategies at a faster pace.

CHAPTER 2
LITERATURE REVIEW

As the determinants of exploration and exploitation (i.e. what factors may encourage firms to balance the two activities) are outside the scope of this PhD thesis, our review focuses on studies that examine how exploration and exploitation (or ambidexterity) influence firm performance. A key question addressed in this PhD thesis is whether balance (ambidexterity) or specialization is better for firm performance. This chapter thus synthesizes prior knowledge and empirical evidence about this relationship and therefore serves as a platform for conceptual development and empirical testing.

Definitions of Exploratory and Exploitative R&D

In this thesis, *exploratory R&D* is defined as creative work and research (both basic and applied) that is conducted in the firm as a way to create new ideas, accumulate new knowledge and advance understanding that may lead to something new in the firm and/or the market. By contrast, *exploitative R&D* is captured by firms' R&D expenditure on technological development that consists of the systematic work that relies mainly upon the firm's existing knowledge base and which aims at developing new features or refining existing features of products and processes. Hence, exploratory R&D requires firms to move to unknown territories and explore unfamiliar knowledge, whereas exploitative R&D requires the utilization of already tested knowledge and aims at making use of existing knowledge to create new products or refine existing ones. Hence, exploratory R&D is closer to what typically some studies in the past referred to as the "research" component (either basic or applied) of R&D, whereas exploitative R&D is closely aligned with the "development" component of R&D (March, 1991; Jansen et al., 2006; He and Wong, 2004; D'Este et al., 2017).

The above definitions are aligned with the technological innovation literature (Jansen et al., 2006; He and Wong, 2004; Smith and Tushman, 2005) and organisational learning (Rosenkopf and Nerkar, 2001; Vermeulen and Barkema, 2001; Piao and Zajac, 2016). According to this view, we should distinguish exploratory R&D and exploitative R&D by considering three dimensions: 1) their relatedness to existing knowledge, technologies and processes, 2) their relatedness to existing markets and 3) their ultimate objective. In the case of exploratory R&D, firms rely mainly upon new knowledge, and for this reason, they often engage in experimental work that may or may not consider its immediate practical application in business and market. On the other hand, exploitative R&D consists of the systematic work that relies mainly upon the firm's existing knowledge base that has been accumulated through repetition and practical experience and aims mainly at creating, refining or improving products and processes.

The proposed definitions are also in line with recent conceptualizations of exploration and exploitation that stress the importance of repetition and incremental refinement of a firm's existing products (repetitive exploitation and incremental exploitation) and *exploration* as the development of new products aimed at creating new market trajectories and domains (Piao and Zajac, 2016). These definitions emphasise the idea that the balance between exploitation and exploration lies not on the presence/absence of learning but on the types of learning that occur i.e., repetitive and incremental in exploitative R&D versus radical learning in exploratory R&D. Nevertheless, our considerations are consistent with the common consensus that the essence of exploitation is minor advances and refinements/extension of existing ideas, competences and technologies whereas the essence of exploration is search, discover and experimentation with new alternatives (March, 1991).

The definitions that we adopt for exploratory and exploitative R&D are also aligned with organizational learning theory and the work of March (1991) on knowledge exploration and exploitation. We view exploratory and exploitative R&D as two antithetical activities. While exploitative R&D largely relies on a firm's existing knowledge base, and includes activities and structures that focus on efficiency, implementation and refinement, exploratory R&D requires new possibilities and distant knowledge, and includes activities and structures that rely on experimentation, new searches and discoveries (March, 1991; Gupta et al., 2006; D'Este et al., 2017).

Disadvantages and Benefits of Exploratory and Exploitative R&D

The literature acknowledges that excessive exploration (exploratory R&D) may lead to risky experimentation, with unpredictable results and distant returns (March, 1991; Levinthal and March, 1993) that may affect the firm's cash flow (Auh and Menguc, 2005) and disrupt established routines (Mitchell and Singh, 1993; Hannan and Freeman, 1984; Abernathy and Clark 1985, Tushman and Anderson, 1986). Nevertheless, a number of other theoretical arguments suggest that exploratory R&D can improve firm performance. First, it can improve firm performance by enhancing a firm's absorptive capacity, reflected on a firm's ability to identify and internalize valuable knowledge (Cohen and Levinthal, 1990). Firms with adequate exploratory R&D, and thus absorptive capacity, function proactively and experiment with emerging opportunities (Lavie and Rosenkopf, 2006; Rothaermel and Alexandre, 2009). This means that those firms are more likely to identify potentially promising technological opportunities, make strategic decisions about what technologies to pursue, choose carefully what markets to enter and decide what innovative outputs will have the greater commercial value to exploit further (Teece, 2007). As a result, firms that engage in exploration are better able to identity evolutionary paths that translate technological opportunities into valuable outputs.

Second, exploratory R&D can help firms to enter (or even create) a new market and enhance product design (Mitchell and Singh, 1993). Firms can tap into a domain-specific knowledge as a result of exploration and experimentation, resulting in superior outcomes and new ideas and concepts that can add greater value and utility for consumers, enabling the firm not only to enter new market domains but also create new ones (He and Wong, 2004). Finally, because exploratory R&D leads to outputs (especially those that involve tacit knowledge) that are difficult to replicate, first-mover advantages from having the monopoly of a product can enhance firm performance (Atuahene-Gima and Murray, 2007).

The literature also acknowledges that excessive exploitation (investing a lot in exploitative R&D) may lead to knowledge obsolescence (Levinthal and March, 1993), foster structural inertia, (Hannan and Freeman, 1984) and cause capability rigidities (Leonard-Barton, 1992) that are often reflected in lower firm performance (Katila and Ahuja, 2002; Bierly and Daly, 2007). Yet, despite these negative effects, exploitation comes with significant benefits. First, the returns to exploitative R&D are proximate in time and more predictable (March, 1991). The dual conceptualization of exploitation as repetitive and incremental supports this line of thinking and indicates that while incremental exploitation creates better products or services, repetitive exploitation achieves efficiency gains by reducing the cost and improving quality due to repetitive engagement with the same tasks (Piao and Zajac, 2016). Regardless of the nature of exploitation (repetitive or incremental), investments in exploitative activities are likely to enhance firm performance because firms operate within their comfort zone, shifting from existing product lines to product extensions (Morgan and Berthon, 2008).

Second, as firms engage in further exploitative activities, building further confidence on areas of already established capabilities (Baum et al., 2000), making their subsequent exploitation in the same field more efficient (Levinthal and March, 1993). Hence, exploitative R&D not only creates reliability through refinement and routinization, but it can also extend the life cycle of technologies and generate a stream of sales for longer. Third, because exploitative outcomes are familiar to both the innovating firm and its customers, their commercialization is less risky (Abernathy and Clark, 1985). Finally, the economies of scale, scope and learning in exploitative strategies are high, enhancing thus firm's performance (Auh and Menguc, 2005).

Exploratory and Exploitative R&D and Firm Performance?

As explained a key question this PhD thesis explores is *how* (the mechanisms) and the context (*when*) which balance (ambidexterity) or specialization is more beneficial for firm performance. In this section thus, we synthesize prior empirical results that explore the effects of exploration, exploitation and ambidexterity on firm performance.

Despite the growing literature on exploration-exploitation, little empirical evidence confirms its effect on firm performance (Raisch and Birkinshaw, 2008; O'Reilly and Tushman, 2013 for a review). He and Wong (2004) test the ambidexterity hypothesis at the firm level in the context of technological innovation. Using data from 206 manufacturing firms, they find a positive effect of exploration and exploitation on firm performance (sales growth). Gibson and Birkinshaw (2004), based on data collected from 4,195 individuals in 41 firm units, also show that the capacity of the firm to be aligned with existing demands and be adaptable to emerging environmental changes impacts significantly its performance. Along the same lines, Lubatkin et al., (2006) indicate that that the joint pursuit of exploratory and exploitative activities affects positively the performance of small-to-medium enterprises. Similarly, a recent study considered the viability of the ambidexterity hypothesis in buyer-supplier relationships (Aoki and Wilhelm, 2017). Specifically, through the case study of Toyota Motor Corporation, the authors illustrate that the firm can be ambidextrous by simultaneously achieving mass production with exploitative focus and product development with exploratory focus, thus counteracting tendencies to overemphasise either exploration or exploitation.

By contrast, other studies find either an insignificant or even a negative effect on firm performance (Rothaermel and Alexandre, 2009; Amason et al., 2006; Ebben and Johnson, 2005). For instance, some of these studies suggest that attempts to be both efficient (exploitative-oriented) and flexible (exploratory-oriented) to customer demands impact negatively the performance of small firms (Ebben and Johnson, 2005). Other studies do not find any effect of ambidexterity on firm performance (Bierly and Daly, 2007). They suggest instead that exploration and exploitation have a differential effect on performance, showing that there is a linear and positive relationship between exploration and performance, and a concave relationship between exploitation and firm performance, indicating diminishing returns to exploitation after a point (Bierly and Daly, 2007).

The fact that some studies find a positive effect of balancing exploratory and exploitative activities (being ambidextrous) while other studies point to an insignificant or negative effect indicates that there is no universal relationship between balance (ambidexterity) and firm performance. This in turn, suggests that a number of moderating factors may influence the impact of exploration and exploitation on firm performance (Junni et al., 2013), and that the usefulness of ambidexterity might be contingent upon firm- and industry-specific idiosyncrasies. The following sections therefore review what we know about such contingencies (moderators).

FIRM-SPECIFIC MODERATING FACTORS

Although one would expect the benefits of exploratory and exploitative activities (i.e., exploratory R&D/exploitative R&D used interchangeable with the terms exploration and exploitation) to differ under different circumstances and conditions, few studies have identified what factors moderate the relationship between exploration, exploitation and firm performance. This Phd thesis classifies the moderators of this relationship into two distinct groups (*firm-specific* and *industry-specific)* that in turn, help us understand the conditions under which firms achieve superior performance outcomes.

The Role of Firm Resources and Firm Size

A firm-specific moderator of the relationship between exploration, exploitation and firm performance is *firm resources*. Firms with rich resources have the ability to both exploit and explore (Cao et al., 2009), whereas firms with scarce resources are more likely to end up worse-off from adopting a mixed strategy (Ebben and Johnson, 2005). Similarly, larger firms are more likely to have access to a larger pool of resources compared to smaller firms (Chen and Hambrick, 1995). Since the large size of the firm is often associated with abundance in resources (Cao et al., 2009), larger firms can achieve a balanced orientation more effectively, exploiting and exploring simultaneously. By contrast, smaller firms with fewer resources may be less successful when they attempt to be ambidextrous.

Reinforcing this line of thinking, Cao et al. (2009) suggests that firm performance is contingent upon the firm's size, emphasising that size is indicative of the resources a firm possesses. The importance of resources is that they can mitigate the negative effects caused on firm performance when imbalances between exploration and exploitation occur (Cao et al., 2009). For instance, over exploitation may lead to knowledge obsolescence, whereas over exploration compromises the immediate cash flow of the firm due to continuous experimentation with novelties (Teece, 1986). These risks however are less threatening for larger firms because the possession of abundant internal resources provides them with a buffer to neutralize the negative effects caused by imbalances in exploratory and exploitative activities. By contrast, smaller firms are more vulnerable and exposed to these risks because of their limited resources to cushion these risks (Cao et al., 2009).

Large firms with more resources are more capable of achieving structural separation, allowing their exploitative units to apply existing knowledge to refine characteristics of products in order to increase the efficiency of both organizational routines and products (Benner and Tushman, 2003, March, 1991), and exploratory units to deal with knowledge that is external to the firm that can potentially create breakthrough innovations (McGrath, 2001). Therefore, greater resources could secure high levels of engagement in both exploration and exploitation enhancing firm performance. By contrast, when a firm has inadequate resources to deploy, it will have to decide how much and on which activity it will invest. It is likely that either one or both will be deprived of essential resources. Hence, optimal firm performance may be contingent upon the resources that a firm possesses because those resources act as internal shock absorbers that rectify disruption

(Bourgeouis, 1981).

Similarly, the external resources to which firms have access to can moderate the relationship between exploration exploitation and firm performance (Cao et al., 2009). Drawing on theories of organisational behaviour, the authors suggest that when firms have access to abundant external resources they can more easily obtain the resources needed to carry out innovations due to their larger quantity and multiple offerings (Dess and Beard, 1984). For instance, resources such as technological knowledge and industry related information could be accessed through alliances with external parties (Powell et al., 1996; Wassmer et al., 2017). An alliance strategy is an attractive alternative to firms that focus on either exploration or exploitation. This strategic decision allows firms to enjoy the benefits of focusing on one activity without being penalised from not investing in the other (Gupta et al., 2006; Wassmer et al., 2017; Choi and McNamara, 2018). Therefore, the resources possessed by a firm and the external resources the firms have access to work in conjunction to influence its performance (Cao et al., 2009). These findings indicate that firm performance is contingent upon the availability of internal and external resources and therefore on the size of the firm.

The relationship between exploration/exploitation and firm performance may also be moderated by a firm’s organisational slack (Voss, 2008; Lavie et al., 2010; Luger et al., 2018). Consistent with the above line of thinking, firms with high levels of unabsorbed slack (defined as unutilized and ready to deploy assets; O’Reilly and Tushman, 2004) can simultaneously explore and exploit. Nevertheless, Luger et al., 2018 suggest that firms with slack resources could maintain a balance between exploration/exploitation even if this balance proves harmful for their performance. This study emphasizes that firms with slack resources can insulate themselves from the negative effects from choosing not to align (adapt) their investments with the needs of the environment, overlooking weak signals that point to adaptation strategies.

The Role of a Firm’s Market Orientation

Another firm-specific moderator of the relationship between exploration, exploitation and firm performance is the *market orientation* that the firm chooses to adopt (Kyriakopoulos and Moorman, 2004; Atuahene-Gima, 2005). Market orientation refers to the firm’s ability to predict and respond to market needs ahead of its competitors, while serving and creating value for its current and emerging customers (Kohli and Jaworski, 1990; Slater and Narver, 1999). Results from a research on 75 Dutch business units of packaged food producers reveal that strong market orientation facilitates a complementarity of both exploratory and exploitative marketing strategies, which in turn, results in better financial performance of the product (Kyriakopoulos and Moorman, 2004). By contrast, firms with weak market orientation exhibit a reduction in product financial performance.

In explaining how market orientation moderates the effects of exploration, exploitation and firm performance, the authors suggest that market-oriented firms i) are customer-led, implying that those firms are proactive to customer demands and reactive to their expectations, ii) act as a bridge that ensures that information from exploitative activities flows to relevant parts of the organization in order to be utilized, and iii) can respond to the external environment, sensing trends, and predicting competitors behaviours by interpreting incoming information (Day, 1994). Similarly, market orientation also moderates positively the relationship between exploration, exploitation and firm performance by affecting managerial choices regarding resource allocation (Atuahene-Gima, 2005). Market-oriented firms are more likely to have a closer interaction with the market, and thus greater market knowledge with which they can easily identify capability deficiencies and emerging opportunities that necessitate the investment on new capabilities. For this reason, market-oriented firms are likely to build stronger internal competences that enable them to make wiser judgments in resource allocation (Atuahene-Gima, 2005). Therefore, market-oriented firms are more sensitive to environmental cues and such sensitivity allows them to identify opportunities for enhancing their performance. These characteristics of market-oriented firms facilitate an ambidextrous orientation of both exploratory and exploitative strategies that enhances firm performance.

The Role of the Leadership Team Characteristics and Team Composition

Another firm-specific moderator of the relationship between exploration, exploitation and firm performance is the characteristics of the leadership team (Lubatkin et al., 2006). This study assessed the behavioral integration of the top management team using three dimensions: i) the level of the team's collaborative behavior, ii) the quantity and quality of information exchanged, and iii) the team's emphasis on joint decision making. The authors found support for the moderating role of the top management team's (TMTs) behavioral integration. The explanation behind these results is that behaviorally integrated TMTs act as a forum in which senior managers exchange knowledge, resolve conflicts, and create a set of shared perceptions, that facilitate firm's gravitation towards a balanced orientation (Lubatkin et al., 2006, p.652). Thus, behavioral integration allows the TMT to be sensitive to market needs by combining information and insights to develop and strengthen internal capabilities that are essential for incremental and radical innovations (Hambrick et al., 1998).

Further, a recent study on managers characteristics in promoting an exploratory/exploitative or ambidextrous orientation indicates that managers play a far more important and configurational role in adopting and promoting a specific perspective that is different from prior established design perspectives on ambidexterity (Zimmermann et al., 2018). Along the same lines, a recent study focuses on three important managerial capabilities of firms' CEOs and founders (i.e., expertise breadth, external connectivity, empowering leadership (Wang et al., 2018) in supporting temporal ambidexterity. The results indicate that these specific managerial capabilities promote ambidexterity especially in the context of young ventures. In line with the behavioural characteristics of the TMT, recent work (Koryak et al., 2018) considers the effect of TMT heterogeneity on exploration and exploitation expanding this discussion on considering the moderating role of team size in the relationship. The study concludes that team heterogeneity is beneficial in management that requires creative thinking and experimentation with new alternatives (i.e., exploratory activities)

Beyond team characteristics to either explore or exploit, other studies indicate that manager-level attributes to allocate resources and time evenly between exploratory and exploitative activities reflect their ambidextrous predispositions (O'Reilly and Tushman 2004). Although individual level characteristics that predispose either an exploratory/ exploitative or ambidextrous behaviour is beyond the scope of this thesis we believe that a network perspective on individual-ambidexterity is important in demonstrating that ambidexterity may be more viable when interacting or accessing resources that are of limited supply at the firm/Individual level.

For instance, Rogan and Mors (2014) rather than viewing the individual as a single unit that works in isolation, they conceptualize them as agents embedded in networks. This echoes the idea of Gupta et al., (2006) who view firms as units operating in a wider network of firms. The importance of these two conceptualizations that is emphasized in network theory is that the actions of firms and thus individuals working in them are shaped by those networks they are embedded in (i.e., their interactions, knowledge flows and actions of others constitute a part of this network). This consideration is important because the exploration/exploitation distribution (or behaviours at the manager level) could be moderated by the interactions, information flows, and actions of other firms in the network. Thus, network dynamics may affect the relationship between firms exploratory/exploitative or ambidextrous behaviour and activity.

The Role of the Firm's Learning Mode

Prior research has also shown that exploration and exploitation have a different effect on firm performance that is contingent upon the firm's current learning mode and it is more prominent when competition intensifies (Auh and Menguc, 2005). Specifically, the effects of exploration and exploitation on firm performance vary depending upon firms' current learning mode; namely exploratory-oriented (i.e., *prospectors*) or exploitative-oriented (i.e., *defenders*). The effect of exploration on firm performance increases for defenders when competitive pressure increases, whilst it reduces for prospectors. Therefore, exploitative-oriented firms are more likely to benefit from exploration, whereas exploratory-oriented firms from exploitation. The explanation is that prospectors' existing level of exploration is already high. Engaging therefore in greater exploratory activity will compromise the short-term profitability and cash flow of the firm (March, 1991), which is an argument that is consistent with a curvilinear-effects logic.

Exploitation however might be more beneficial to secure the firm's current income. By contrast, exploitative firms are more likely to have greater economic returns from exploratory activity as a means to achieve their differentiation. The justification is that because exploitative firms already invest more resources on exploitation, their further engagement with exploitation will only serve to neutralise competitors' actions (Auh and Menguc, 2005). Responding therefore to competitors behaviour with similar activities, such as price-cutting strategies and imitating techniques will simply provoke their replicative behaviour.

Implicit in this argument is that the performance effect of exploration and exploitation is different for exploratory and exploitative firms when competition increases. When competition intensifies, defenders should respond by skewing the balance towards exploratory activities to increase their performance. By contrast, prospectors are likely to benefit from exploitation. These findings suggest that the learning mode of the firm will impact differentially its performance and cautiously direct firms to respond differently in competitive conditions, increasing accordingly their exploratory or exploitative activities. They further indicate that the equal distribution of resources on both exploratory and exploitative activities may not always be the optimal way to achieve superior performance, pointing that under different contextual conditions (e.g., competition) and firm-idiosyncratic characteristics (i.e., learning mode), the optimal balance might necessitate an "imbalance" to improve performance.

Further, a recent study on technological acquisitions explored the moderating role of a firm's acquisition rate in the relationship between a firm's exploration or exploitation orientation and subsequent behaviour (*integrated* versus *independent* knowledge leverage behaviour; Choi and McNamara, 2018). This line of thinking indicates that acquiring firms with exploitative trajectory are likely to utilize and integrate their existing knowledge stock with that of the acquired firm as a way to make minor refinements (integrated knowledge leverage behaviour). By contrast, acquiring firms with exploratory focus often leverages the knowledge acquired through acquisitions to create a new technological trajectory (independent knowledge leverage behaviour). The authors theoretically predict and empirically test the idea that a high acquisition rate will weaken the link between the degree of exploitation and integrated knowledge leverage. In contrast, they found support for the existence of a stronger relationship between exploration and independent knowledge leverage for frequent acquirers. This study highlights that acquisition intensity by a firm can affect the relationship between exploitation or exploration orientation and knowledge leverage behaviors. Those findings once again indicate that investments in either exploration or exploitation may be determined and moderated by the firms current learning predisposition and already chosen technological trajectory.

INDUSTRY-SPECIFIC MODERATING FACTORS

The Role of Competition

At the industry level, prior studies suggest that the level of competition in an industry or environment (Matusik and Hill, 1998) moderates the relationship between exploitation, exploration and firm performance. Jansen et al. (2006) empirically test this hypothesis, showing that pursuing exploitative innovation is more beneficial for financial performance in competitive environments. In explaining their findings, the authors theorized that engaging in exploitation is beneficial when competition increases because risk-taking behaviour (i.e., exploration) can be disruptive to firms' organisational routines. For this reason, they suggest that firms are required to find ways to eliminate disruption, focusing instead on risk-aversive behaviour that seeks to create minor improvements, incremental changes and refinements on existing innovations (Matusik and Hill, 1998; Lumpkin and Dess, 2001).

The Role of Environmental and Technological Dynamism

Environmental dynamism defined as the rate of change and degree of instability of an environment (Dess and Beard, 1984) has been also found to have a moderating and differential effect on the relationship between exploration, exploitation and performance (Jansen, et al., 2006). Engaging in exploration is more effective in dynamic environments that are characterized by rapid technological changes, uncertainty and fluctuations in customer needs and demands (Jansen et al., 2006). Similarly, in industries where technological dynamism is high, exploratory activities are more profitable than exploitative activities (Uotila et al., 2009). High technological dynamism, which prior studies capture by measuring the R&D intensity (R&D over sales) of an industry has a positive moderating effect on exploratory activities and financial performance (e.g., Uotila et al., 2009). However, in industries with low and average R&D intensity, exploration has a negligible effect on firm performance (Uotila et al., 2009). These findings therefore suggest that as the R&D intensity of the industry increases so does the effect of exploration on the economic performance of the firm.

An explanation for such findings is that in dynamic environments firms are forced to constantly explore novel ideas. By contrast, less dynamic environments may not require a similarly high focus on exploration because a firm's existing stock of technologies could be used for a longer time period, allowing firms to focus instead on exploitation and risk-aversive strategies (Zahra and Ellor, 1993). Therefore, by definition in low dynamic environments the rate of new inventions, and therefore the firm's need to respond to changes is low. Bierly and Daly (2007) find empirical support for the view that exploration has a stronger impact on performance in high technological than in low technological environments in the context of small manufacturing firms.

Overall, by pointing to the moderating and differential impact of environmental dynamism on the relationship between the firm's exploratory and exploitative activity and firm performance, these results suggest that in environments with lower technological dynamism the balance between exploration and exploitation may not be ideal from the point of view of performance.

In line with the above thinking, recent studies on the exploration exploitation debate (Luger et al., 2018; Stieglitz et al. 2016) question whether firms need to move away from balancing their exploration/exploitation investments towards aligning them to meet contextual demands. Is ambidexterity a better investment option and more viable because firms learn from accumulated experience and are therefore capable to balance exploration and exploitation (O'Reilly and Tushman, 2008), or does this balance affect a firm's ability to adapt to changing technological environments?

In sum, we can make a number of observations from the above synthesis of the literature. First, prior empirical findings about the balance between exploration and exploitation and firm performance are mixed, with some studies suggesting a positive, negative or insignificant effect on firm performance. Placing similar emphasis on both exploratory and exploitative activities may not always be the optimal way to achieve superior performance. Second, prior results also emphasise the moderating role of certain firm-specific and industry-specific factors on the firm's exploration, exploitation and firm performance. Firm-specific moderators include factors such as firm resources, firm size, market orientation, learning mode and leadership team characteristics. The industry-level moderators include factors such as competition, environmental and technological dynamism. All these results about moderators imply that that the balance between exploration and exploitation (ambidexterity) matters less in certain cases (Luger et al., 2018). Another interesting idea is that firms should calibrate their exploratory/exploitative R&D investments to match dynamic environments (Posen and Levinthal, 2012; Luger et al., 2018; Uotila et al., 2009). Since environments change over time, maintaining a balance between exploration/exploitation would influence performance negatively due to misalignment between R&D investments and contextual needs (Posen and Levinthal, 2012; Luger et al., 2018). In environments characterised with incremental changes, it is more beneficial for firms to maintain their ambidexterity because their accumulated experiential learning will equip them to balance the two. Nevertheless, firms in less dynamic environments with discontinuous changes should skew the balance to prevent inertia and environmental misalignment that is likely to impact their performance negatively (Luger et al., 2018).

Further, and consistent with Luger's et al., (2018) logic that the exploration/exploitation balance should be aligned with environmental demands, other studies (Stieglitz et al. 2016; Posen et al., 2012) argue that focused orientations either towards exploration or exploitation are often associated with higher returns than balancing orientations. Specifically, and against the idea that dynamism forces firms to explore to avoid knowledge obsolescence (Uotila et al., 2009), some studies suggest that environments characterised with frequent changes often necessitate to devalue exploration and shift the balance towards exploitation and inertial practices that restrict exploration (Stieglitz et al., 2016). These results indicate once again that dynamic environments necessitate a different focus. In sum, scholars have started increasingly to indicate that environmental changes require organizations to become focused either on exploratory or exploitative activities rather than balancing the two.

Yet, although a large volume of studies focuses on the effects of balance, three key questions remain less well understood. First, we have an incomplete understanding of how specialization in exploratory R&D or exploitative R&D influences firm performance. Given that specialization may change how beneficial exploration and/or exploitation is, we also do not understand how the returns to exploratory R&D and exploitative R&D differ for firms that choose to specialize vis-à-vis those firms that invest a similar amount of effort and resources in both.

Second, irrespective of the level of competition in a given industry, the opportunities to engage in collaborative projects and knowledge sourcing depend on what the majority of firms in these industries do with respect to exploratory and exploitative R&D. For instance, the availability and nature of opportunities in an industry in which the majority of firms specialize in exploratory R&D differ from those in industries that focus on exploitative R&D. As a result, we have a rather incomplete knowledge of how the orientation of the industry in which the firm operates changes the relationship between specialization in exploratory R&D or exploitative R&D and firm performance, and in which industry settings it is more beneficial to specialize (or pursue balance), and if so in which activity they should specialize.

Third, the literature acknowledges that firms may change their exploratory R&D or exploitative R&D focus over time. However, little research has examined how firms change (i.e. what patterns they adopt when they change) and how temporal dimensions in exploratory R&D and exploitative R&D (i.e. how quickly firms change from one activity to the other) influence firm performance (Hashai et al., 2015; Klarner and Raisch, 2013; Casillas and Moreno-Menéndez, 2014). We address these questions in three separate empirical chapters in which we develop and test a set of hypotheses concerning these effects. Before doing do, however, the next chapter sets the theoretical foundation for the thesis.

Technological Diversification-Firm Performance

Our aim to examine the effects of ambidexterity and specialization can also benefit from a review of the literature on technological diversification and firm performance. Technological diversification relates to the knowledge diversity that underlines the nature of products and the way they are produced. Technological diversification requires firms to expand their technological competence into a broader range of scientific disciplines and technological domains (Granstrand and Oskarsson, 1994). Yet, such expansion is not always associated with product diversification (Granstrand et al., 1997; Gambardella and Torrisi, 1998). Technological diversification can be defined and understood as a firm's strategy for finding unexplored niches in the market to differentiate themselves from their competitor firms, since the ultimate aim of technological diversification is to achieve synergies between different technological domains (Kim et al., 2016; Pan et al., 2018).

Our review on technological diversification points to two observations. First, the theoretical arguments in the literature on technological diversification echoes the idea of investing in both exploration and exploitation (March, 1991; Koryak et al., 2018). This requires integrating new knowledge in the firm's existing knowledge base yet avoiding excessive investments in either that could lead to either technological exhaustion or costly experimentation. Secondly, although specialized and diversified firms follow a different investment strategy to enhance their performance, specialized firms can outsource their expertise and diversify their knowledge by tapping into complementary collaborative opportunities in different industries. Such opportunities help them strengthen and complement their core competences using their prior established expertise.

Empirical evidence indicates that firms often use their technology alliance portfolios drawing upon their combinative capabilities to enhance their performance (Lucena and Roper, 2016). Specifically, diversity in technology alliance portfolios allows firms to improve not only their absorptive capacity but also ambidexterity in R&D. By implication, the ability of the firm is enhanced through better exploitation of both internal and external knowledge and knowledge generated from exploration and exploitation.

The literature offers a variety of explanations about the drivers of technological diversification (Kim et al., 2016; Besanko et al., 2010; Quintana-Garcia and Benavides-Velasco, 2008). First, firms decide to diversify (intra-firm) using their technological resources and know-how with other fellow-units (Markides and Williamson, 1994) as a way to achieve synergies that accentuate their value when complement one another and aim at extending existing product lines (Besanko et al., 2010; Suzuki and Kodama, 2004). Second, firms that diversify technologically (and are therefore exploratory) are more likely to expand their absorptive capacity and technological competences, especially when their diversification focuses on areas of established expertise (related diversification) (Baum et al., 2002; Quintana-Garcia and Benavides-Velasco, 2008). Tapping into diversified areas of technological expertise of other units or firms helps the focal firm enhance its exploratory capabilities and integrate into external knowledge its routines (Cohen and Levinthal, 1990; Quintana-Garcia and Benavides-Velasco, 2008).

Although some opportunities could be identified and exploited commercially, low knowledge overlap between new and existing knowledge affects the firm's ability to capitalize on new knowledge and thus ability to generate new products. Thus, technological diversification could enhance firm performance by preventing against the natural tendency of firms to follow the same trajectory making their core rigidities into liabilities (Leonard-Barton, 1992) by taking advantage of cross-fertilization and utilization of knowledge originating from between different technologies (Suzuki and Kodama, 2004).

Therefore, technological diversification is likely to strengthen a firm's competence or exploratory/exploitative R&D and productivity especially if investments are related in the firm's chosen trajectory since building on existing areas of core technology, redeploying mainly firm core assets will ultimately expand the firm's knowledge base and enhances its performance (Klette and Kortum, 2004). Third, technologically diversified firms are more likely to reduce the risk involved in R&D and them to learn to adapt more easily in technological environments that are often characterised with dynamism, frequent changes and unpredictability. Because both exploratory R&D and exploitative R&D is uncertain due to increased risk of knowledge obsolescence and experimentation with proximate returns, firms aim at eliminating the risk by distributing their R&D resources across various technologies (Garcia-Vega, 2006; Corradini et al., 2016). This approach enables firms to develop diverse and versatile technologies by expanding their technological scope. Technological diversification is a necessity not only because of increased environmental uncertainty but primarily due to technological complexity and firm-specific architectural competence that is required to be successful (Suzuki and Kodama, 2004; Fleming and Sorenson, 2001; Leonard-Barton, 1992).

Forth, technological diversification helps firms generate revenue because they are more likely to develop products with diverse technologies and prevent technological lock-ins (Granstrand, 1998; Suzuki and Kodama, 2004) and capability rigidities (Leonard-Barton, 1992). Technological diversification may affect the firms' combinative capacity by allowing the firm to blend and infuse its existing knowledge base with new components that are likely to be used in developing new breakthrough ideas (Quintana-Garcia and Benavides-Velasco, 2008; Garcia-Vega, 2006).

Overall, the above arguments are reminiscence of the idea of balancing exploratory and exploitative R&D investments since firms that choose to diversify their technological innovations follow to some extent a path-dependant trajectory that allows them to be successful because they build on their core competencies, assets and capabilities (via related diversification) rather than totally deviate from these as often happens when firms engage in unrelated diversification.

Drawing from organizational learning theory, scholars of technological diversification emphasise the importance of maintaining consistency in the firm's knowledge base at times of firms' diversification efforts (Quintana-Garcia and Benavides-Velasco 2008). Resembling the trade-off between exploration and exploitation (March 1991; Fleming 2001), finding the right balance between the need to diversify technological efforts and the need to use and exploit the firm's existing knowledge base that is underlined by specific technological skills is important for both large and small-size firms (Corradini et al., 2016). Especially smaller firms that often engage in search depth and technological specialisation will enable them to be successful from their R&D investments by maintaining a narrow focus on their activities (or chosen technological areas; Corradini et al., 2016).

Theoretical predictions suggest that the trade-off between specialisation and technological diversification will be in favour of specialised firms in technologically turbulent environments characterised by abundancy in technological opportunities (Benner and Tushman, 2003). Some studies suggest that when exploration investments are risky, resource demanding, have unpredictable returns and require complex knowledge recombination, firms are more likely to follow a technologically specialized trajectory (Toh and Kim, 2013). Some studies suggest that the higher the rate of patenting activity in technologically intense environments, the lower the chances to explore the possibilities that arise from inter-sectoral technological recombination because of time and resource limitations especially in the context of small firms (Corradini et al. 2016; Stuart and Podolny, 1996; Fleming and Sorenson, 2001). As a result, this reduces the opportunities for engaging in exploration and experimentation of new research domains away from the current technological trajectory and capabilities. Thus, specialisation in exploitation may be more beneficial since firms exploit mainly internal competencies that have built across time and along an already tested technological trajectory (Kogut and Zander 1992; Corradini et al. 2016).

Interestingly, Kim et al., (2016) explore the contingent role of core-technology competence in the relationship between technological diversification and firm performance (growth). In line with the arguments that support the ambidexterity hypothesis, the authors argue in favour of the duality of characteristics of a firm's core-technology competence. They suggest that competence in (core) domain knowledge i.e., build on existing knowledge integrating simultaneously new knowledge elements as well as architectural knowledge on R&D enhances firm performance. The first attribute that could characterise ambidextrous firms increases the chances of commercializing technologies by combining value of existing and new knowledge generated from technological diversification. The second attribute, architectural competence in R&D which typically refers to a firm's ability to identify explore and integrate new knowledge elements utilizing and translating technological opportunities originating from diverse fields of technology captures firms with greater investments in exploratory R&D. Therefore, firms with low core-technology competence are likely to face challenges when choose to diversify technological especially with unrelated technological fields that require the integration of diverse and unfamiliar knowledge (Kim et al., 2016). By contrast, firms with greater core-technology capacity are better equipped to control technological complexity and identify evolutionary paths and opportunities that arise from diverse technological fields. Those ideas are in line with ambidextrous investments, indicating that insufficient and excessive technological diversification can be destructive for firm growth (Quintana-Garcıa and Benavides-Velasco, 2008). The authors conclude that a firm's core technological competences affects the commercial returns to technological diversification (Kim et al., 2016).

Consistent with the idea of balancing exploration and exploitation, studies on technological diversification suggest that searching for new knowledge elements expands the firm's knowledge base by allowing distinctive combinations to be made (Fleming, 2001; Katila and Ahuja, 2002). Yet, high levels of knowledge deviation and technological diversification may destruct the desired balance and combination between exploitation and exploration (March, 1991; Levinthal and March, 1993). Hence, one may conclude that such imbalance in technological diversification could be distractive to the firm's capacity and competitive position by affecting knowledge generation, assimilation and utilization (Quintana-Garcıa and Benavides-Velasco, 2008).

CHAPTER 3
THEORETICAL BACKGROUND

To address the research objectives of this PhD thesis, we draw on *organizational learning theory* that has been most widely used in the exploration and exploitation literature (Levitt and March, 1988; Huber, 1991; Cyert and March, 1963; Huber, 1991; Fiol and Lyles, 1985; Wang and Ahmed, 2003; Levinthal and March, 1993) and *industrial organization economics* (Bain, 1968; Mason, 1939; Schumpeter, 2017; Porter 1979; 1990; 2000). The justification for choosing these two theories is twofold. First, they fit well the phenomena of interest and the objectives of the thesis to focus on how specialization in exploratory and exploitative R&D affects firm performance, and how the external environment (industry) might change this relationship. Second, because organizational learning theory focuses on learning processes within the firm whereas industrial organization economics is a theory of the environment (industry), the two theories play a complementary role in explaining the relationship between exploratory R&D, exploitative R&D and firm performance. Such complementarities also assist us in identifying factors and conditions that moderate this relationship.

In the next sections, we review these two theories and the key concepts that are employed in the next chapters of this thesis. In addition, we review the *resource-based view (RBV)* of the firm (Barney, 1991; Wernerfelt, 1984) that attributes performance differentials to firms' idiosyncratic resources (e.g. technology). In addition to the RBV theory, we assess the concept of *organizational dynamic capabilities* (Teece, 1994; Teece et al, 2007; Teece and Pisano, 1994) and its relevance to the exploration exploitation context. The dynamic capabilities concept suggests how well a firm utilises its available inputs (e.g. knowledge predisposition and strengths) to create specific outputs and products and respond timely to changing industry circumstances (Dutta et al., 2005; Teece, 1994). Both the RBV and the concept of dynamic capabilities will act complementary to our two main theories (*organizational learning theory* and *industrial organization economics*) in better explaining how both firm- and industry-specific characteristics affect the usefulness of balance and specialization and, in turn, the effects of exploratory and exploitative R&D on firm performance.

Organizational Learning Theory-Mechanisms of learning

In the context of organizational learning theory, *organizational learning* refers to the process of creating, retaining, and transferring knowledge within an organization (Cyert and March, 1963; Levitt and March, 1988; Huber, 1991; Fiol and Lyles, 1985; Wang and Ahmed, 2003; Levinthal and March, 1993). This perspective of learning views firms as information processing systems that develop, infer, circulate, and store information within the organisational boundaries (Cyert and March, 1963; Huber, 1991). Thus, important components to enhance firm knowledge that could in turn affect firm performance is knowledge acquisition through information distribution and interpretation and storage of this information in a firm's memory.

Firms in their search and effort to acquire knowledge, distribute such knowledge across firm units, translate and integrate such knowledge into their routines to enhance firm performance have two choices (West and Burnes, 2000). The first choice is to act as learning entities of a closed system in which learning is a private matter that is restricted within firm boundaries. The second choice is for firms to act as learning entities of an open system where learning is the result of inter-organisational learning and interaction between individual firms and the context where they operate. Knowledge acquisition therefore and translation into beneficial learning occurs both within and outside organisational boundaries (Wang and Ahmed, 2003).

Therefore, organisational learning occurs and is the result of a firm's effort to obtain knowledge from different agents (i.e., knowledge from intra-organisational units, other inter-organisational firms and the environment), disseminate such knowledge within its units, manipulate it to fit its purpose and implement it to its routines to achieve better performance outcomes (Fiol and Lyles, 1985). Organisational knowledge is stored in the form of experience and reflected in personal capabilities of those working in the firm, reflecting to some extent the absorptive capability of organisations. As firms accumulate experience, they further add to their expertise (i.e., result of their specialization and narrowing of their focus when engaging in either exploratory and exploitative R&D), contributing thus to revenue generation and firm performance.

Apart from learning within organisational boundaries, learning theories admit that the environment where the firm competes and operates contributes to its learning process including its behaviour and choices a firm pursues. In organisational environments, the learning context such as the structure of an industry is a significant contributing factor to the firm's learning potential (Wang and Ahmed, 2003). The inclusion of the industrial context explicitly indicates the need for firms to engage in various modes of learning (both *single-loop* and *double-loop* learning as well as *adaptive* and *generative learning* to sustain their competitive advantage and expertise (Argyris and Schon, 1978; Morgan and Berthon, 2008; Argyris, 1976; Bierly and Daly, 2007).

Indeed, current organisational learning practices involve single and double-loop level learning. In a single-loop learning, firms change their actions based on the difference between the desired and actual output (Argyris, 1976). A single-loop learning is often related with the ability of the firm to detect errors and rectify them in its attempt to sustain quality control (Argyris and Schon, 1978; Argyris, 1976). Similarly, firms utilize their adaptive learning to create minor refinements and incremental changes to their innovations. By contrast, *double-loop* learning is classified as a higher level of learning because of its proactive nature that enables firms to act proactively by preventing errors to occur at first place. Similarly, in *generative learning*, firms create ideas as a result of risk-taking action to produce breakthrough outputs (Morgan and Berthon, 2008).

Some studies also suggest that firms learn by engaging either in *local* (i.e., search for knowledge that exhibits some degree of similarity to the firm's own knowledge base) versus *distant* (knowledge that is different to what the firms knows; March and Simon, 1958; Rosenkopf and Almeida, 2003; Rosenkopf and Nerkar, 2001). The search for distant versus local search is partly determined on the desired outcome. For instance, if firms aim at creating quality through minor improvements on existing products/processes and services they need to learn through local search and build further expertise in a specific domain (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). By contrast, engaging in distant search (Baum et al., 2000) to enhance learning better fit the aim of entering or even shaping new industries and markets (Rosenkopf and Nerkar, 2001; He and Wong, 2004). Regardless however of the type of the learning mechanism the firms need to engage to meet their objectives, we suggest that firms always learn but the value of each learning mechanism is different in different contexts and conditions and thus learning has the potential to accentuate its value in certain contexts and weakens in others.

Organizational Learning Theory in the context of Specialization

A key premise in organizational learning theory is that organizations are able to learn through experience (inferences from past activities) that can subsequently be used to develop conceptual maps to interpret such experience and make it useful (Levitt and March, 1988; Huber, 1991). Experience is therefore the driving force that contributes to the understanding of a process. In organizational learning theory, firms are conceptualized as learning entities that are able to make inferences from past activities and incorporate these into new organizational routines (i.e., rules, procedures and strategies through which organizations operate; Levitt and March, 1988).

Organizations therefore become more competitive over time as they gain experience and learn. Learning through direct experience help firms create and accumulate beneficial knowledge that induces greater efficiency due to the repetitive execution of the same set of activities which in turn enhances firm performance (Huber, 1991). This type of learning (*experiential learning*) therefore enables organizations to develop capabilities either in the form of exploitation or exploration (March 1999; Holmqvist, 2004). It allows firms to become better at those routines they repeat successfully and less capable in activities and processes they do irregularly. This self-reinforcing nature of learning makes firms prone to maintain their current focus and trajectory (i.e. specialise in either activity; March 1999).

Organizational learning theory is particularly relevant in explaining how specialization in either exploratory or exploitative R&D may enhance firm performance by enabling firms to firstly build capabilities in areas of established competence and secondly, by engaging in different types of knowledge search (so called local or distant). In the context of exploratory and exploitative R&D, firms learn by engaging in *local search* (i.e., search for knowledge that exhibits technological and geographical similarity to that of the firm's own knowledge stock) and *distant search* (i.e., use new knowledge that is often distant to their own existing knowledge/technological base; Rosenkopf and Almeida, 2003). According to organizational learning theory and the literature on exploration and exploitation, firms have to decide on how best to allocate their attention, time and resources between exploring new knowledge and routines and exploiting existing knowledge and established routines (March, 1991; Levinthal and March, 1993; Baum et al., 2000). Firms often search for solutions, ideas and technologies that have already used successfully in the past, replicating therefore their past behavior (Cyert and March, 1963; Nelson and Winter, 1982; Levitt and March, 1988).

In the context of specialization, although firms are uncertain about the rewards of a given activity, with repetitive execution of certain activities and processes, they accumulate experience and confidence, diminish unpredictability and strengthen their capabilities. Success breeds further success as organizations repeat such activities and processes as it is more rewarding to repeat a prior action, rather than actions for which they have limited knowledge, experience and understanding (Levitt and March, 1988; Baum et al., 2000). This echoes the idea that as a process or activity becomes standardized, and as techniques are learned, the time required to accomplish it declines while the quality of executing the task improves (March, 1991). In other words, enhanced performance from specialization is facilitated by concentrating efforts in areas of already established capabilities (Baum et al., 2000). This further increases the likelihood of firms to improve their operations and perfect their organisational routines gaining further greater operational functionality and achieve efficiency gains.

Exploratory and Exploitative R&D in the context of Organizational Learning Theory

Organizational learning theory also helps us gain a better understanding of what exploratory R&D and exploitative R&D conceptually and practically represent by considering: 1) what type of learning occurs in each activity, and 2) what is the aim and possible output of engaging in either exploratory R&D and exploitative R&D.

Prior research suggests that exploitation (and therefore exploitative R&D) builds on the firm's existing knowledge base, whereas exploration stretches beyond its current knowledge stock and requires new knowledge and searches (Uotila et al., 2009; Atuahene-Gima and Murray, 2007; Bierly and Daly, 2007; Gupta et al., 2006; Blindenbach-Driessen and Ende, 2014; Benner and Tushman, 2002). The justification is that exploitative R&D aims at creating minor improvements and advances in existing components, whereas exploratory R&D requires a shift towards a different technological trajectory. For this reason, exploitative R&D requires local search (i.e., search for knowledge that exhibits technological similarity to that of the firm's own knowledge stock) in order to build competence and gain expertise in a specific domain (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). Exploratory R&D on the other hand, requires distant search (Baum et al., 2000) that often necessitates that firms move beyond technological boundaries (Rosenkopf and Nerkar, 2001) and enter new domains (He and Wong, 2004).

Furthermore, exploratory R&D is aligned with *double-loop learning* (Argyris and Schon, 1978) and *generative learning* (Senge, 1990) in order to create new ways of doing things in the light of experience (Argyris, 1976). In generative learning, firms generate ideas as a result of risk-taking action (Morgan and Berthon, 2008). Consequently, in exploratory R&D, firms have to engage in a different, more sophisticated ways to produce breakthrough ideas.

By contrast, exploitative R&D requires *single loop* and *adaptive* learning in order to create improvements or create new features for existing products and processes. Searching for ideas and alternatives in close proximity enhances the existing knowledge stock and experiential learning, yet in an incremental rather than radical way (Yelle, 1979). Exploitative R&D differs from exploratory R&D because it often requires adaptive learning to create refinements on products and processes, whereas the exploratory R&D requires firms to engage in generative learning through experimentation with novelties and risk-taking action with new alternatives. Therefore, revolutionary changes are likely to be the output of exploratory R&D, whereas evolutionary and incremental changes are likely to be the output of exploitative R&D (Bierly and Daly, 2007).

Furthermore, because firm performance is a joint function of the potential returns from a given activity and the firm's own capabilities, firms enhance their performance as they accumulate more experience (Levinthal and March, 1993; Gaur and Lu, 2007). It is well accepted in organizational learning theory that searching for new directions where skills have to be developed from scratch reduces the speed with which existing skills could be improved. It is also accepted that building capabilities with existing activities make the search of entirely new ways less attractive (Levitt and March, 1988). In other words, capabilities' improvement when undertaking an activity increases the likelihood of returns for engaging in that activity (Argyris and Schon 1978; Sydow et al., 2009). These two premises in organizational learning theory (the cumulative effects of both *experiential learning* and *competence building*) suggest that investment decisions are often guided by organisations' prior experience. Therefore, the more competent the firm is in a specific activity, the greater the likelihood in enhancing its performance by increasing effort in this activity.

Industrial Organization Economics

Industrial organisation economics theory will help us address the set of research questions and hypotheses concerning how industry factors affect the impact of exploratory and exploitative R&D on firm performance. Research on industrial organization economics has focused on how firm performance is influenced by industry-specific characteristics such as *competition, barriers to entry, industry concentration, product differentiation* and *the price elasticity of demand* (Bain, 1968; Mason, 1939; Schumpeter, 2017; Porter, 2000). Within industrial organization economics, there are 5 distinct, but interrelated, paradigms that aim at explaining performance differences across firms (Conner, 1991): 1) the Structure-Conduct-Performance view, 2) the Schumpeterian view, 3) the Chicago approach, 4) the transaction costs approach and 5) the Neo-Classical Perfect Competition view. The key logic behind each paradigm, including the conceptualization of firms, the main assumptions of each paradigm and how performance differential arise across firms are summarized in Table 1. Because this PhD thesis focuses on two of these paradigms to address its research objectives, the following paragraphs discuss the Structure-Conduct-Performance (SCP) paradigm and the Schumpeterian view.

The Structure-Conduct-Performance (SCP) paradigm attributes variations in performance across firms to an industry's configuration (Mason, 1953; Bain, 1968). It suggests that the structure of the industry determines a firm's behaviour (conduct), its chosen strategy and, in turn, its performance. The SCP paradigm rests on the notion that the firms' main strategic objective is to achieve monopoly power and set product prices, and that this objective is achieved by either driving competitors out of the market or by colluding with other firms (Weiss, 1979; McWilliams and Smart, 1993; Barney, 1986, Porter, 1981; Conner, 1991). This implies that firms that want to achieve superior performance should dominate and control a large share of the market (Bain, 1968; Mason, 1953; Conner, 1991). In this sense, innovation can help a firm to implement a strategy that will gradually make the firm one of the few providers (or even the only provider) of a set of products or services (Conner, 1991). Therefore, the motivation for the firm according to the Structure-Conduct-Performance paradigm is to prevent other firms to gain monolpoly power by driving certain firms out of business. Product differentiation through an innovation and higher entry barriers are seen as two fundamental ways for a firm to reach such position in a given industry (Comanor and Wilson, 1974).

Reinforcing this line of thinking, Schumpeter (1950) suggested that firms should enhance their competitive position and firm performance not through price competition but by creating innovations that make rivals movements and products obsolete (Conner, 1991). According to this view, firms are conceptualized as entities that continuously seek new ways of competing. For this reason, they need to develop revolutionary ideas (which can be achieved through exploratory

R&D) or to refine the features of existing products (which can be achieved through exploitative R&D) to establish greater market share and power. Competition therefore forces firms to innovate and upgrade continuously to prevent technological obsolescence.

Drawing therefore upon the SCP paradigm and the Schumpeterian view on how performance differentials across firms arise, we develop hypotheses about potential moderators that can be identified at the industry level predicting and testing empirically how the effects of exploratory R&D and exploitative R&D on firm performance differ depending on industry characteristics.

Table 1 – Theories of the Firm in IO (Industrial Economics)

	Conceptualisation of the Firm	Assumptions	Performance differentials
Neoclassical Theory	**Input Combiners**: Firms work together to produce a product. This joint production occurs by combining labour and capital	a) Easy and same access to resources (technology), b) access to symmetrical information, c) mobility of resources	No above normal returns occur because of firm homogeneity
Structure-Conduct-Performance	**Output Restrainers**: Firms restrict output generated by other firms by a) gaining monopolistic position by driving other firms out of business or by b) colluding with other firms with the objective to control prices and/or output	Firm heterogeneity that is reflected on monopoly power (industry concentration)	Above normal returns exist because of a) different industry characteristics (e.g. industry concentration) and b) within industry differences in the market power of each firm.
Schumpeterian theory	**Seek new ways to compete:** Firms engage in radical innovation to produce breakthroughs as a way to exercise monopoly and limit competition by making competitors' inventions obsolete	Market power provides firms with the resources to engage in radical innovation	Performance differentials exist because firms use innovation (radical) to find new ways of competing
The Chicago approach	**Seekers of Efficiency**: Firms outperform competitors because they are better (efficient) in both product production and distribution. Effective firm collusions are rare due to costly monitoring and enforcement.	a) Firm heterogeneity due to differences in inputs, b) the role of new entrants causes the efficiency differentials across established firms.	Short-term performance differentials exist and arise from the exploitation of current (not new) innovations. Yet, imitative entry will erode long-term performance differentials (profits).
Transaction costs theory	**Avoiders of the Cost**: Firms are trying to economise by keeping the cost of transaction of market exchange lower or equal than the cost of producing something internally	Firm heterogeneity arises due to differences in firms' ability to minimise cost.	Performance differentials exist when firms act as avoiders of cost throughout an exchange in market. Transaction cost will be higher when a) asset specificity (dependence) is high, b) when the number of actors is small (interdependency), c) when complete (contingent) contracts is difficult to be written and enforced to specify actors' behaviour.

The Resource-based View (RBV) of the Firm

As noted earlier, the RBV will help us better develop and support the reasoning for certain hypotheses that consider how firm-specific characteristics affect the usefulness of balance and specialization and, in turn, the effects of exploratory and exploitative R&D on firm performance. Firms vary in their performance because of the different resources and assets they possess (Barney, 1991; 2001). However, not all resources could be translated into valuable outputs. A firm's strength lies in its ability to deploy the appropriate resources to conceive and implement appropriate strategies that enhance its performance (Wernerfelt, 1984). For instance, complementarity in resources could lead to different performance outcomes (Dierickx and Cool, 1989).

The importance and distinctiveness of complementarity in assets is that their value accentuates when employed together (Teece, 1986). An established expanded network could act as a complementary asset that enables firms to accelerate their performance outputs by sensing market trends and needs. Similarly, collaborations and strategic alliances may be important in accessing complementary assets (Lockett and Thompson, 2001; Lockett et al., 2009). Thus, performance differentials across firms may derive from differences in firms' efforts to access complementary resources that are important for the acquisition of new and valuable knowledge.

The complementarity and interconnectedness of resources may prevent rivals to replicate firm resources (Teece, 1986). The difficulty in imitating these resources derives not only from their limited mobility (specific to the firm), but also utility to other firms. For this reason, firms with complementary resources are more likely to be perform better because they exhibit heterogeneity in both resources and capability in deploying them that is difficult to imitate. Because internal organizational resources are finite and exhaustive, tapping into diverse and complementary knowledge resources of other firms could affect positively a firm's performance (Lavie, 2006).

The possession of complementary resources that are likely to be rare and valuable, can also give firms positional advantages and increase their ability to employ strategies that lead to product differentiation. In the resource-based view, firms can obtain superior performance not only because they possess difficult to copy resources assets, but because they are able to overcome organisational resource constrains by tapping into assets and knowledge of external firms. By implication, above normal profits based on the resource view derives from the fact that firms employ heterogeneous resources to create an output that is highly differentiated from alternative ones (Conner, 1991). In other words, product differentiation is the result of the distinctiveness in resources employed to produce the specific output.

Therefore, the resource-based view of the firm emphasises the importance of identifying inputs that are more likely to be translated into profitable outputs and retain and exploit those characteristics that make these inputs unique (Conner, 1991). The idea of complementarity in resources is highly relevant in explaining performance differentials across specialized firms. For instance, consider two firms that specialize in the same activity (let’s say exploratory R&D), yet they operate in a differently- oriented industry and thus the returns to their specialization activity differ. Put simply, the effects of firms that specialize in exploratory R&D may be stronger (attenuate) in specific industries where the output of exploratory ideas has more chances to be utilized (complemented) by exploitative firms and vice versa.

Limitations of the RBV theory and its extension of the Dynamic Capabilities Framework

Despite the importance of the RBV theory in explaining performance differentials across firms that are attributed to the specific heterogeneous and often path-dependent and difficult to clone assets that a firm possesses, the theory has been criticized as conceptually vague and tautological (Mosakowski and Mc Kelvey, 1997). Those criticisms derive from the simple observation that although the RBV theory outlines which resources can lead to sustainable competitive advantage (i.e., better performance outcomes), it offers little explanation about the mechanisms by which those resources can be transformed into strategic assets. More importantly however, it has been criticized on the grounds of its feasibility especially in dynamic industry environments (D'Aveni and Ravenscraft, 1994)

Dynamic Organisational Capabilities

Another framework that is also relevant in theorizing and explaining why the effects of specializing in exploratory or exploitative R&D on firm performance differ across differently-oriented industries is that of *dynamic capabilities* (defined as a firm’s capacity to employ and adapt existing competences and expertise to achieve compatibility with the technological environment, Teece, 1994). Dynamic capability requires the firm’s ability to explore and exploit by recognizing technological opportunities and maintaining its competitiveness through combining, integrating and reconfiguring its intangible assets, such as its tacit knowledge and expertise (i.e., specialization) to match the need of the external industry (Teece et al., 1997; Teece, 2007). This framework thus identifies which capabilities (i.e., its strengths on exploratory or exploitative activities, and which combinations of these capabilities (resource configuration) could trigger better performance outcomes (Teece et al., 1997). Organisational capabilities therefore are all those internal and external competences that are employed effectively to rapidly changing environments such as those of R&D intensive industries. They can be conceptualized as the efficiency with which a firm utilises its available inputs to create specific outputs and products and respond timely to changing industry circumstances (Dutta et al., 2005; Teece, 1994). A capability to be dynamic needs to carry two important properties; *technical* and *evolutionary* fitness (Helfat et al., 2007). Technical fitness refers to how well the capability enables a firm to sustain its living, whereas evolutionary fitness refers to how well the capability enables a firm to make its living. Dynamic capabilities therefore assist firms not only in adapting to the environment (industry), but also in achieving evolutionary fitness by shaping the environment. For instance, by creating better quality strategic alliances and collaborative agreements/opportunities in some industries than in others. Furthermore, organizational capability is defined as a set of high-level routines that when in operation have the potential of producing significant outputs (Winter, 2003). Routine is a learned behavior that is highly patterned. Its success is attributed to its learning through repetition. Repetitive execution of the same activities and tasks (i.e. specialization) enables firms to comprehend in greater detail and precision the processes required to develop effective routines (Eisenhardt and Martin 2000). This idea echoes that of organizational learning theory and its emphasis on the firm's experiential learning and competence building through repetition in achieving better performance outcomes.

The concept of dynamic capabilities resonates the definitions given by other authors. For instance, dynamic capabilities are defined as *combinative capabilities*, which encompass the ability of firms to synthesise and apply existing and assimilated knowledge to generate new knowledge (Kogut and Zander, 1992). Similarly, dynamic capabilities can be equated with *architectural competence* (Henderson and Cockburn, 1994) or simple *capabilities* (Amit and Shoemaker, 1993). More importantly however, dynamic capabilities are organizational and strategic sequences that above all require resource integration, restructuring and mainly reconfiguration to achieve transformation of resource inputs into valuable outputs (Teece et al., 1997). Although in our thesis, we have not tested empirically the existence of dynamic capabilities, since their conceptual definition due to their tacit element appears less concrete, our analysis implicitly suggest that the routines specified in product development, expertise and experiential knowledge to revenue-producing products and services might capture the essence of the dynamic capability concept (Clark and Fujimoto, 1991). Building on that, we argue that specialized firms that mainly focus on building a routine that is highly repetitive in nature are likely to possess valuable dynamic capabilities that could potentially enable them to use their expertise to restructure their resources to fit industry needs and thus achieve superior performance outcomes. The idea of dynamic capabilities thus is relevant for our research enquiry because it will enhance understanding on which and how knowledge-related capabilities (exploration or exploitation) and in which industries attenuate or weaken their value and what are the underlying mechanisms that will enable firms to utilize their expertise and capabilities (i.e., specialization) to respond to different industrial contexts.

Determinants of Firms' Dynamic Capabilities

Three set of factors (namely *firm processes*, *firm position*, and *firm path*) has been suggested as critical to a firm's formation of dynamic capabilities. Specifically, the first factor refers to *organisational processes.* This factor encapsulates the idea that the competitive advantage of a firm might lies with the way things are carried out in the firm (i.e., routines) and its general practice of learning and knowledge acquisition (Teece et al., 1997). These organizational routines reflect patterns of current practice and learning behavior that affect the formation of a firms' dynamic capabilities repertoire. *Firm position* is another factor that shapes and determines the outcome of dynamic capabilities. This factor implies that the present position of the firm in terms of its current technological endowments, equipment, complementary assets and relationships with suppliers and external parties are all essential in helping firms to build their distinctive competence and capability. Finally, the firm's chosen or inherited *path* that is partly defined by the available strategic alternatives and opportunities, found for instance in some industry contexts, constitutes part of its dynamic capabilities (Teece and Pisano, 1994). Accordingly, a firm's organizational routines, which are the cumulative efforts of highly patterned activities based on repetition, are shaped by the specific assets firms possess which have been predetermined by the firms already chosen trajectory. Therefore, the firm's processes, position and chosen trajectory collectively reflect and encompass its capabilities. The distinctiveness of these bound-to-the firm capabilities is that they have to be built (Teece and Pisano, 1994).

Traits of Dynamic Capabilities

The capacity of the firm to identify the value of environmental opportunity is critical capability in defining its performance. However, because knowledge is cumulative and largely consequential in nature, learning is dependent upon the level of the firm's current learning stock (Kogut and Zander, 1992). By implication, the ability of a firm to recognize not only the value of external novel information, acquire and integrate it into its routines, but also from its ability to exploit it towards commercial ends is vital to its capabilities (Cohen and Levinthal, 1990). This capability is a firm's absorptive capacity that necessitates for its successful application the synthesis of existing and new knowledge (Kogut and Zander, 1992). It depends thus from its prior knowledge stock, diversity of background and overlap between prior and new knowledge. This capability requires skills such as scanning, updating, creating, and interpreting information at both local and distant proximity (Teece, 2007; Nelson and Winter, 1982). It necessitates the creation of internal knowledge and the exploitation of the knowledge that has been accumulated by others. With respect to technological innovation, R&D activity may be thought as a form of search for novel products and processes. However, when a firm's knowledge creation relies heavily on in its-house R&D, overlooking the potential of exploring new possibilities by tapping into external knowledge, its performance potential will ultimately be compromised. In fast-paced and exploratory-oriented environments a large portion of technological innovations often yields from exploring external sources (e.g., collaborators). In the context of exploration and exploitation, this implies that the effect of specializing in either exploratory or exploitative R&D is partly dependent on the availability of knowledge sourcing and external collaboration of the industry where the firm has chosen to operate and compete.

Access to information is a prerequisite in identifying technological opportunities. The ability to recognize their value and potential however depends partly on the existing knowledge and learning capacities of the firm. It involves interpreting skills in translating and integrating this information to the firm's objectives. Thus, acquisition and assimilation of this knowledge to match specific objectives is just the first step. The second step involves filtering the information and identifying its commercial potential. This task involves scanning and monitoring internal and external technological opportunities (Teece, 2007). For instance, a firm that seeks to sustain and upgrade its output should sense potentially promising technological opportunities, make strategic decisions about what technologies to pursue, choose carefully what industries segments to target and decide what outputs will have the greater commercial value to exploit further (Teece, 2007).

Integration is another critical trait of dynamic capability. The ability of the firm to integrate external activities and technologies into its established routines and processes is a core element of its dynamic capability repertoire (Teece and Pisano, 1994). The way a firm integrates its routines has a significant effect on its performance output (Clark and Fujimoto, 1991). The importance of the idea that capability is embedded in the ways of integrating and coordinating routines is explained by the way that firms respond to changes in the environment.

In highly volatile environments, it makes sense to acknowledge the value in the ability to identify the need to reconfigure and restructure the set of assets that a firm has on its disposal to achieve the required transformation (Amit and Schoemaker, 1992). The ability to reconfigure and transform is a learned skill and its application requires that the firm acknowledges the most critical assets and is willing to discard those that are less relevant to meet its objectives.

Briefly, the dynamic capabilities concept reflects the capacity of the firm to employ its internal and external assets in a way efficient to increase its output. Capabilities indicate how good a firm is in combining efficiently a number of resources to accomplish a certain objective (Amit and Schoemaker, 1993). The dynamic capabilities of the firm are hard to articulate explicitly because they are captured in a firm's high-performance routines, and they are embedded in its processes. They are an intermediate step between inputs and outputs that induce transformation (Dutta et al., 2005). One can only see the resources that a firm uses to produce specific outputs, but he can only speculate on the capabilities employed in converting one to the other (Dutta, et. al., 2005). Capabilities are determined by the way things are carried out in the firms, its position, and its history and chosen trajectory. Their distinctive characteristics that make them immune to replication are that they require time to be built and are not tradable in the market. Finally, a firm's absorptive capacity, its ability to identify the need to reconfigure and restructure the set of its existing assets, integrate external activities and technologies into its established routines and its ability to coordinate its routines are just but a few core elements of the dynamic capabilities.

Therefore, we could argue that a specialized firm's capability, which is determined to some extent by its absorptive capacity to identity evolutionary paths, could be strengthened in those contexts (industries) where the value of its expertise accentuates. In other words, in those industries where the knowledge and specialization of the firm could be utilized to produce something of a greater utility.

CHAPTER 4: METHODS AND DATA

Epistemological Underpinnings

We adopt a positivist approach to the phenomenon of knowledge exploration and exploitation. We therefore subscribe to the view that there is an objective reality to the interpretation of the phenomenon under study. For this reason, we use quantitative methodologies and regression analysis to examine the effect of each independent variable on the dependent. According to the positivist approach, any knowledge claims that we make should be supported through quantifiable data and validated through statistical analysis (Benton and Craib, 2010). Therefore, the synthesis of logic and empiricism holds great promise in establishing legitimate knowledge claims. For this reason, our approach values verifiability (testability) as the most objective criterion to differentiate analytic from speculative knowledge (Caldwell, 2010).

For these reasons, we do not attach personal values or feelings to understanding the factors that affect firms' decisions to invest in exploratory or exploitative activities. Yet, the objectivist approach and reliance on quantifiable data that are based purely on numbers and frequencies does not necessarily reject subjective interpretations. We acknowledge that what we consider facts in our study (e.g. investment decision of firms) could be theory impregnated, meaning that what we see as researchers can be affected by theory. Consistent with Kuhn (1970) we believe that inductivist and falsificationist approaches to research are not entirely correct because they view as legitimate knowledge (science) the progressive accumulation of facts to confirm various hypotheses and theories (Benton and Craib, 2010). We acknowledge thus that it is highly likely that even factual information (numerical data) observations are not entirely value free and objective but it can be affected by our theoretical presuppositions (Benton and Craib, 2010; Kuhn, 1970). This implies that although, for instance, we monitor and report how much firms invest on exploration and exploitation using numerical data, we are trying to theorise based on the literature the conditions underpinning firms' decisions. Therefore, we study firms' decisions to invest in either exploratory and exploitative R&D and we do it as much as possible objectively using over 32,537 observations and numerical data (the actual money firms' report).

METHOD

To address the research objectives of this thesis, we need to have sufficiently high variation in both firm- and industry-specific factors. A large number of observations are required to identify inter-firm differences in exploration and exploitation and how such variations influence firm performance. A quantitative approach is more appropriate for addressing the research objectives of this thesis for three reasons. First, regression analysis will enable us to establish not only *causality,* but also the directionality of the relevant relationships (Bryman, 2008) and place greater confidence in our research results (statistical significance captured in p values). Although the use of qualitative analysis (e.g., case studies or semi-structured interviews) is particularly useful for better understanding the processes underlying exploration and exploitation, such analysis will not enable us to identify and measure the causal effects of such differences and identify variations across firms and time.

Second, another objective in our study is to obtain a representative sample in order to apply our research results to other firms with similar characteristics. This means that qualitative approaches to the study of exploration and exploitation are less appropriate because it would be less likely and feasible to obtain a representative sample to draw conclusions that can be generalized. Another benefit concerns the length of the time period. Although qualitative analysis may enable us to ask managers about their investments in exploration and exploitation in prior years, their responses are likely to be less reliable because of memory restrictions. Therefore, because one of our main objectives is to describe variation across firms and observe their economic evolution over time, a structured instrument such as surveys organized by the national institute of statistics and a probabilistic sample would be more appropriate in mapping the overall trend.

DATA SOURCES AND SAMPLE

This PhD thesis employs data from PITEC (Technological Innovation Panel dataset), which is a longitudinal dataset that is co-managed by the Spanish National Statistics Institute (INE), the Spanish Foundation for Science and Technology (FECYT), and the Foundation for Technical Innovation (COTEC). Spain constitutes of big and small-to-medium enterprises, and the majority of them engage in R&D. Specifically, PITEC accounts for 86% of all firms with 200 or more employees, and a sample of firms with intramural R&D expenditure that accounts for 56% of all firms engaged in in-house R&D, according to data from the Research Business Directory (DIRID). The cross-sectional dimension of the panel data not only reduces multicollinearity problems among explanatory variables, but also increases the degrees of freedom and variability across firms (Baltagi et al., 2005). Therefore, the nature of panel data allows us to obtain a more accurate and efficient estimation of the effect of each independent on our dependent. PITEC also comprises of firms that operate in various industries with low (furniture, recycling), medium (aeronautic space construction) and high technological intensity (chemical and pharmaceutical). Thus, PITEC and Spain provide an appropriate setting for testing our framework and proposed hypotheses and consider how firm-specific idiosyncrasies and industry factors influence the relationship between exploration/exploitation and firms' performance and innovativeness.

PITEC resembles in structure and objectives the Community Innovation Survey (CIS). It includes firm-level anonymized data that monitor the economic evolution and technological activities of firms in Spain. The information reported in PITEC is collected through several postal questionnaires. The companies are selected from national surveys conducted by the National Institute of Statistics in the field of innovation: "Survey on Technological Innovation in Companies and Statistics on R&D (http://icono.fecyt.es/pitec/Paginas/por_que.aspx). We have been granted access to a set of coordinated year-based files from 2003 to 2012. Similar to other Community Innovation Survey (CIS), there is high reliability in the reported data because the survey is administered every two years by the National Statistics Institute (INE) in Spain and sent to firms that are obliged to respond. As a result, over a 90% response rate is achieved.

PITEC is an appropriate source of data for this thesis for several reasons. First, rather than just providing an aggregate measure of R&D, it is a very detailed innovation survey that reports variables that are essential for identifying how much firms invest in exploratory versus exploitative R&D, providing a detailed breakdown of the distribution of R&D expenditure across exploratory activities (basic and applied research) and exploitative activities (technological development). Second, there is high reliability in the reported data because this is not a self-administered survey, but it is instead administered and managed by the National Statistics Institute (INE) after consulting a group of academics and researchers. Third, PITEC follows the same firms across time allowing us to trace the innovative activity of those firms and investigate with greater accuracy their economic evolution, changes over time, and heterogeneity in their decisions, especially those concerning investments in exploratory and exploitative activities. Fourth, the dataset also reports the R&D services that firms purchase from the market.

Our analysis focuses on firms with more than 10 employees. We avoided focusing on particularly small firms because they do not report (or do not conduct) exploratory and exploitative R&D systematically and this may bias the results for all other firms. Instead of focusing on a single industry (Rothaermel, 2001; Rothaermel and Alexandre, 2009; He and Wong, 2004), we have chosen to examine 56 industries to increase variability in our data and be able to test how certain hypothesized effects differ across groups of industries. The use of this multi-industry sample will enable us to test not only the direct effect of exploratory and exploitative R&D investments on a firm performance, but also the interacting effect of investing heavily in one activity (specialization strategies) when a firm operates in differently oriented industries (exploratory/ exploitative-oriented or hybrid industries). The initial sample consisted of 41,196 firm-year observations that had information on exploratory and exploitative R&D investments. However**,** after deleting missing observations and firms that had less than four years of information, the final sample resulted in an unbalanced panel sample of 32,537 observations (5697 firms) over the 2003-2012 period.

Advantages of Longitudinal Panel Data

Panel data better capture the dynamics of adjustment (Baltagi et al., 2005; Baltagi, 2001). This means that the longitudinal aspect of PITEC survey allows us to take a dynamic perspective on the study of exploration and exploitation. Studies using cross-section data cannot estimate the effect of each variable across time, but they can only make estimations at a certain point in time. Using panel, we will be able to estimate the investment decisions of firms at different points in time. Furthermore, because panel data include a time dimension we would be able to control for the performance and investment decisions of firms in prior years.

Using panel data allows us to control for firm heterogeneity (Pindado et al., 2012). Using information across firms and across time, we are able to control for such unobserved heterogeneity. For instance, firms may differ in decisions to invest in exploration or exploration. Some firms may be more exploratory- or exploitative- oriented and this propensity may change over time because of various external or internal factors. Therefore, entering firm-specific variables into our specified model, will allow us to obtain more accurate estimation effects, controlling for firm variations.

Panel data also provide us with a viable solution to problems of endogeneity. Endogeneity can arise because there is reverse causality in the model and the dependent variable might influence some independent variables (Wooldridge et al., 2002). In our study, for example, it is possible that firms with superior performance engage in ambidextrous strategies due to greater access to resources (both internal and externa) and vice versa (Cao et al., 2009) Thus, the use of longitudinal data will enable us to construct instrumental variables to mitigate problems that arise from endogeneity (Pindado et al., 2012).

MEASURES

In addition to the following sub-sections that describe in detail how the measures employed in the study were constructed, Table 1 in Appendix 1 at the end of the thesis provides a brief description of the main variables used in this study.

DEPENDENT VARIABLE

Following the literature on R&D and performance (Audretsch and Feldman, 1996; Adams and Jaffe, 1996; Feinberg and Majumdar, 2001; Fey and Birkinshaw, 2005), we capture firm performance by constructing a measure of *total factor productivity (TFP)*. TFP is an appropriate measure for our study mainly for three reasons: First, TFP accounts not only for the sales of products and services of firms, but also for two key inputs; namely the firm's labour (number of employees) and capital (tangible assets). Because industries vary in the inputs they use, a few studies also consider the cost of intermediate inputs when estimating TFP (Kafouros et al., 2008; Kafouros et al., 2018). Although data on intermediate inputs are not available in the dataset, we tried to address cross-industry variations by using multi-level estimators that are nested in each industry. Second, the TFP measure reflects the fact that R&D investment leads not only to the development of new products but also to new process innovations that might enhance firm productivity by leading to higher efficiency and to the better allocation of resources. Finally, while other measures of firm performance such as profitability are very volatile and often take negative values, total factor productivity remains relatively stable to market fluctuations, exchange rate variations, transfer pricing, accounting standards and the treatment of royalties (Buckley, 1996).

Following common practice (e.g. Adams and Jaffe, 1996; Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b; Kafouros et al., 2018), we operationalize each firm's productivity performance by estimating a 'residual' that captures increases in firm output that cannot be explained by firm inputs. This residual is the outcome of a function where the nominator is a firm's *output* (firm sales) and the denominator include the two key firm inputs: *labour* (the number of employees) and *capital* (tangible assets). As TFP captures a firm's ability to generate sales while controlling for the inputs that a firm uses to achieve that level of output, it avoids biases associated with the fact that different outputs may exhibit different economies of scale (Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b). The estimation of TFP is based on the fact that productivity is the intermediate transformation capacity level between inputs and outputs and thus reflects a firm' ability to transform and generate value from a given number of inputs (Dutta et al., 2005). To be consistent with prior studies and given that economic relationships are rarely linear, we transform the TFP measure in its logarithmic form (Van Beveren, 2012; Qingwang and Junxue, 2005).

Finally, we should acknowledge that productivity (Griliches, 1979; 1998; Cassiman et al., 2010) and sales growth (He and Wong, 2004; Venkatraman et al., 2007) have been used widely in the literature of exploration and exploitation. However, prior studies have also used various dependent variables, including measures of profitability such as *ROE and ROA,* (Aug and Mengue, 2005), innovativeness (Ahuja and Katila, 2001), and market-based indicators such as *Tobin's Q* (Uotila et al., 2009; DeCarolis and Deeds, 1999) and subjective measures of firm performance based of manager's perceptions regarding firm's sales growth, profit growth, market share growth and operational efficiency (Cao et al., 2009; Lubatkin et al., 2006; Gibson and Birkinshaw, 2004). Given that we have available the actual R&D expenditure (in money) of firms, we avoided using measures that rely on perceptions (which in addition are not available longitudinally). Similarly, because of insufficient data availability we also could not use measures of profitability.

Estimating TFP

To estimate total factor productivity (TFP) for each firm (i) at time (t), we need to consider the relationship between certain firm inputs X and firm outputs Y. This is a standard practice employed in the literature (Griliches, 1998; Kafouros et al., 2018). This practice is a production function or a transformation of the Cobb-Douglas model that considers both *labour* (the number of employees) and *capital* (tangible assets) as inputs (see equation 1). To estimate total factor productivity (TFP), we firstly estimated the production function and secondly estimated the residual TFP of this production function. This residual reflects variations in a firm's output (sales) that cannot be explained by variations in the inputs (Temouri et al., 2008; Smarzynska Javorcik, 2004). In the estimation, we also included industry and year dummy variables to account for industry-specific idiosyncrasies and changes over time (Kafouros et al., 2018). The following equation represents the total output (Y) as a function capital input (K), labour input (L) and residual ε.

$$Y_{\mathrm{it}} = K_{\mathrm{it}} + L_{\mathrm{it}} + T_{\mathrm{t}} + \mathrm{I}_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \quad (1)$$

The letter *Y* represents the total input of a firm as a function of total factor productivity (A), *capital input* (K) which is measured at tangible asset, and *labour input* (L) which is measured as number of employees (Smarzynska Javorcik, 2004). T and I refers to year and industry dummies, respectively. The ε is residual of this equation (Temouri et al., 2008), which reflects TFP.

KEY INDEPENDENT VARIABLES

Exploratory and Exploitative R&D investments

Prior research has used various ways to measure exploratory and exploitative activities. For instance, in the context of patent analyses, exploration was measured as *search scope*, which characterized the tendency of firms to cite different patents. Exploitation is such studies was measured as *search depth*, indicative of firms' propensity to cite existing patents frequently (Katila and Ahuja, 2002). We did not use patent data to measure exploration and exploitation (Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001) firstly because the survey questionnaire reported only limited information on the number of patents they file and secondly because the propensity to file innovations varies across industries (Cockburn and Griliches, 1987).

The degree to which firm's search behavior crosses both technological and organizational boundaries has also been suggested in the literature (Rosenkopf and Nerkar 2001), while other studies (e.g. Bierly and Chakrabarti, 1996) aligned radical and incremental innovations with exploitation and exploration, respectively. However, we did not use these measures because exploration and exploitation may be associated with radical and incremental innovative outputs, but they differ conceptually given that they refer to activities (rather than an actual output). In addition, it may be possible for a radical innovation to be based on the combination of existing knowledge and technologies.

To develop measures for our key independent variables, we rely on established practice in the ambidexterity literature (Jansen et al., 2006; He and Wong, 2004; Smith and Tushman, 2005), the organizational learning literature (Rosenkopf and Nerkar, 2001; Vassolo et al., 2004; Vermeulen and Barkema, 2001; D'Este et al., 2017), the definition proposed in March's (1991) seminal work and the definitions of R&D (OECD, 2002). *Exploitative R&D* consists of the systematic work that relies mainly upon the firm's existing technological and knowledge base and aims mainly at developing and/or creating new features or refining/improving existing features of products and processes, extending therefore the life cycle, market fit and effectiveness of innovations. By contrast, when firms engage/invest in *explorative R&D,* firms have to conduct entirely new research (which can be basic or applied), accumulate new knowledge, and often engage in experimental work without necessarily considering its immediate practical application. Yet, the ideas developed when engaging in exploratory R&D are more likely to lead to new and/or different outputs.

The PITEC survey provides us with a direct measure of exploratory and exploitative R&D that is consistent with the established measurement of R&D innovation activities (OECD, 2002). PITEC reports R&D investment into its distribution in exploratory and exploitative R&D. Consistent with established literature (March, 1991; Jansen et al., 2006; He and Wong, 2004; D'Este et al., 2017) and the definition provided in the PITEC survey, R&D exploration consists of the creative work and research (both basic and applied) that is conducted as a way to accumulate new knowledge that may lead to something new in the firm and/or the market. By contrast, exploitation is captured by firms' R&D expenditure on technological development that consists of the systematic work that relies mainly upon the firm's existing knowledge base that has been accumulated through repetition and practical experience that aim at refining or improving substantially existing products and processes.

The above line of thinking is consistent with recent work that contends that R&D is a heterogeneous activity (D'Este et al 2017; Czarnitzki et al., 2011; Bargegil and Lopez, 2014), and it should not be aggregated. This line of thinking is also consistent with the recent studies that equate the "Research" component of R&D with exploration, and the "Development" component of R&D with exploitative activities (D'Este et al., 2017; Shift, 2016). As noted earlier, the *Research* component incorporates both basic and applied elements, whereas the *Development* component incorporates the refinement and improvement of existing products and processes.

Basic research is experimental or theoretical work in nature that aims at creating and generating knowledge not necessarily with a particular application (OECD, 2002), e.g. to find certain combinations of materials that may hold electric charge for longer. Applied research on the other hand aims at knowledge generation with practical applications (OECD, 2002), e.g. to use a combination of materials that leads to a new generation of batteries. In other words, exploitative R&D makes use of the extant knowledge that often emerges from the exploratory R&D (research phase) and is aimed at improving existing products, services devices and materials (OECD, 2002). The description of R&D (OECD, 2002; D'Este et al., 2017) echoes March's (1991) terminology and relates the "exploration of new possibilities," with the basic and applied research component, whereas the "exploitation of old certainties" is associated with the developmental component.

Therefore, as in recent work (D'Este et al., 2017), we measure exploratory R&D using the expenditure (i.e. internal R&D budget) that the firm spends annually on research and exploratory activities (both basic and applied). We then divide the resulting figure with the number of employees to normalize the measure for the size of the firm, and as in the TFP measure, we transform it into its logarithm (Qingwang and Junxue, 2005; Van Beveren, 2012). Similarly, we measure exploitative R&D using the investment made in exploitative R&D (i.e. technological development). This measure is again divided by the number of employees to normalize it for firm size and it is expressed in its logarithmic form (Van Beveren, 2012). Given that these data are reported annually in the database, both exploratory and exploitative R&D measures are time-variant, enabling us to observe the distribution of one over the other and how they change from year to year.

Firm Specialization in Exploratory and Exploitative R&D vs Ambidextrous Firms.

Following previous studies (He and Wong, 2004; Cao et al., 2009), we use the absolute difference in percentage between firms' expenditure on exploratory and exploitative R&D. Building on the definition that specialization is a strategy by which firms limit the scope of their activities, we classify a firm as specialized in one activity when it spends over 66.6% of its internal R&D budget on either exploration or exploitation. This means that a firm's investment in one of the two activities is at least two times higher than its investment in the other activity.

We measure firms' specialization in exploratory and exploitative R&D investments using two different ways. The first measure is a year-specific measure of specialization that reflects what the firms does in a given year. This variable is time-variant because a firm could specialize in exploratory R&D in one year (i.e. they spend over 66.6% of their internal R&D budget on exploration), but in the next year it may spend over 66.6% of its budget on exploitation.

Further, the theory and hypotheses discussed in certain chapters of this thesis do not concern what a firm does in one year but instead they are about the overall specialization strategy of the firm (their strategy over several years that the firms exist in the dataset). As discussed in the theoretical background of the thesis, cycling between the two activities from one year to the other (i.e. specializing in exploratory R&D in one year and then specializing in exploitative R&D in the next year is just a way of achieving ambidexterity (i.e., through temporal cycling or punctuated equilibrium). We also developed a second measure of specialization that captures the overall strategy of the firm. Accordingly, each firm is categorized in one of the following three groups (using three dummy variables): specialization in exploratory R&D (the average investment in exploration is higher than 66.6%), specialization in exploitative R&D (the average investment in exploitation is higher than 66.6%), and ambidextrous (the percentage of their budget spent on either is between 33.3% and 66.6%).

Exploratory-Oriented, Exploitative-Oriented and Hybrid Industries

To test the hypotheses concerning the role of industry orientation, we classify each industry in one of the following groups: *exploratory-oriented, exploitative-oriented* and *hybrid industries*. Based on prior studies (He and Wong, 2004; Cao et al., 2009) and in line with the way in which we estimated specialization at the firm level, we estimated how many firms specialize and in which activity in each industry (i.e. we identified where the concentration of firm is) and consider the absolute difference between such concentration in identifying the industry's orientation. Initially, we identified the number of firms in each industry that had over 66.6% of their internal R&D budget spent on exploratory or exploitative activities (i.e., firms that are specialized), and how many firms were ambidextrous in each industry. Table 1 reports the concentration of firms across industries. The letters R, T, and H next to the industry sector indicate the orientation of the industry i.e., *Exploratory* and *Exploitative-oriented*, and *Hybrid* industries, respectively).

We subsequently estimated the absolute difference between firms that specialized in each activity (refer to the last column in Table 1). The mean value of the absolute difference (which is 20%) was used to classify each industry, depending on whether this deviation was higher or lower that 20%. The pharmaceutical sector (Industry Code 12) is highly specialized in exploratory R&D as it exhibits an absolute difference of 37% (54% exploration and only 17% exploitation). At the other end of the spectrum, an industry that is highly specialized in exploitative R&D includes the telecommunication services sector (Industry Code 42) that exhibits an absolute difference of 47% (17% exploration and 64% exploitation). When industries are not classified as oriented on either exploratory or exploitative R&D (i.e., with less than 20% mean value between specialised in exploration and exploitation R&D firms) such as industry code 20 (refer to the last column in Table 1), fall into the category of hybrid industries. Based on this categorization, we created dummy variables, one for industries that are oriented in exploratory R&D, one for industries that are oriented in exploitative R&D and one for industries that are hybrid.

Table 1 –Industry Concentration based on R&D investments (R, T, and H next to the industry indicate exploratory and exploitative oriented, and Hybrid)

Industry Name	Industry Code	Firms that specialize in exploratory R&D	Firms that specialize in exploitative R&D	Ambidextrous Firms	Total number of firms	Firms that specialize in exploratory R&D in %	Ambidextrous Firms in %	Firms that specialize in exploitative R&D in %	Absolute difference between specialization in exploratory and exploitative R&D (%)
Agriculture - R	0	274	143	144	561	49%	26%	25%	23%
Extractive - R	1	88	35	37	160	55%	23%	22%	33%
Food and Drink - H	2	1,166	784	818	2,768	42%	30%	28%	14%
Tobacco - H	3	11	13	2	26	42%	8%	50%	8%
Textiles - H	4	375	384	221	980	38%	23%	39%	1%
Clothing - H	5	55	74	28	157	35%	18%	47%	12%
Leather and Footwear - H	6	79	72	57	208	38%	27%	35%	3%
Wood & Cork- H	7	115	110	63	288	40%	22%	38%	2%
Paper - H	8	129	113	115	357	36%	32%	32%	4%
Publishing, Graphic Arts & Reproduction - H	9	97	139	90	326	30%	28%	43%	13%
Coking Petroleum Refining - H	10	12	7	21	40	30%	53%	18%	13%
Chemicals - R	11	1,576	816	1,013	3,405	46%	30%	24%	22%

Pharmaceutical Products - R	12	586	182	317	1,085	54%	29%	17%	37%
Rubber and Plastic - H	13	445	646	315	1,406	32%	22%	46%	14%
Ceramic Wall and Floor Tiles - H	14	76	69	31	176	43%	18%	39%	4%
Non-Metallic Minerals - H	15	346	317	309	972	36%	32%	33%	3%
Ferrous Metallurgical Products - H	16	145	227	104	476	30%	22%	48%	17%
Non-Ferrous Metallurgical Products - T	17	59	149	95	303	19%	31%	49%	30%
Metallic Products - T	18	518	1,030	495	2,043	25%	24%	50%	25%
Machinery and Mechanical Equipment - T	19	783	1,858	1,060	3,701	21%	29%	50%	29%
Office Machines and Computing Equipment- H	20	21	13	43	77	27%	56%	17%	10%
Electrical Machinery and Materials - T	21	341	682	412	1,435	24%	29%	48%	24%
Electronic Components - T	22	65	164	132	361	18%	37%	45%	27%
Radio, TV& Commun. Devices - T	23	128	303	185	616	21%	30%	49%	28%
Medical Precision and Optical Instruments - T	24	270	511	392	1,173	23%	33%	44%	21%
Motor Vehicles - T	25	233	598	291	1,122	21%	26%	53%	33%

Shipbuilding - T	26	26	66	34	126	21%	27%	52%	32%
Aircraft and spacecraft Manufacturing - T	27	11	70	41	122	9%	34%	57%	48%
Transport Materials - T	28	27	93	53	173	16%	31%	54%	38%
Furniture - H	29	221	273	143	637	35%	22%	43%	8%
Toys and Games - T	30	18	46	13	77	23%	17%	60%	36%
Manufactured Goods - H	31	53	75	45	173	31%	26%	43%	13%
Recycling - H	32	21	30	45	96	22%	47%	31%	9%
Production and distribution of Electricity, Gas & Water- H	33	92	94	119	305	30%	39%	31%	1%
Construction - H	34	221	343	308	872	25%	35%	39%	14%
Sale and Repair of Motor Vehicles - T	35	5	30	4	39	13%	10%	77%	64%
Wholesale Trading - H	36	497	559	346	1,402	35%	25%	40%	4%
Retail Trading - T	37	33	72	50	155	21%	32%	46%	25%
Hotel Industry - R	38	34	21	9	64	53%	14%	33%	20%
Transport - H	39	44	54	25	123	36%	20%	44%	8%
Activities linked to Transport &Travel - T	40	21	45	25	91	23%	27%	49%	26%

Postal & Mail Activities - H	41	2	2	0	4	50%	0%	50%	0%
Telecommunication Services - T	42	46	175	54	275	17%	20%	64%	47%
Financial Intermediation - T	43	138	283	101	522	26%	19%	54%	28%
Real Estate Activities - H	44	33	36	12	81	41%	15%	44%	4%
Machinery and Equipment - T	45	7	31	8	46	15%	17%	67%	52%
Software - T	46	351	1,312	647	2,310	15%	28%	57%	42%
Computing Activities - T	47	87	411	177	675	13%	26%	61%	48%
Research & Development	48	660	226	681	1,567	42%	43%	14%	28%
Technical Services in Architecture - T	49	346	740	480	1,566	22%	31%	47%	25%
Trials and Technical Analysis - H	50	163	171	190	524	31%	36%	33%	2%
Business Activities - H	51	215	344	201	760	28%	26%	45%	17%
Education - H	52	35	45	37	117	30%	32%	38%	9%
Film &Video Activities - H	53	13	21	25	59	22%	42%	36%	14%
Radio &TV activities - T	54	13	37	8	58	22%	14%	64%	41%

Specialized Firms in Exploitative/Exploratory-oriented and Hybrid Industries

We created 9 separate variables based on a 3X3 table. For instance, firms that specialize in exploratory R&D and operate in exploratory, hybrid and exploitative-oriented industries are in the corresponding Cells 1, 2 and 3 of Table 2 below. Firms that specialize in exploitative R&D and operate in an exploratory-, hybrid- and exploitative-oriented industry belong respectively to Cells 7, 8, and 9 of the table. Similarly, firms that are ambidextrous and operate in exploratory-, hybrid- and exploitative-oriented industries belong to corresponding Cells 4, 5 and 6 of the Table 2.

Table 2: The nine dummies that correspond to specialized firms in oriented industries

		Industry orientation		
		Exploitative Oriented	Hybrid Industries	Exploratory Oriented
Firms Specialization Strategy	Firms Specialize in Exploitative R&D	Cell 1	Cell 2	Cell 3
	Ambidextrous Firms	Cell 4	Cell 5	Cell 6
	Firms Specialize in Exploratory R&D	Cell 7	Cell 8	Cell 9

Patterns of Change in Exploratory and Exploitative R&D

In addition to the above measures, we also identified seven distinct strategic patterns that firms follow with respect to their specialization strategy. The first three patterns focus on firms that do not change their specialization strategy over time, whereas the remaining four patterns concern situations in which firms change their specialization strategy from one activity (e.g. exploratory R&D) to another (e.g., exploitative R&D)

Regarding the first three patterns, as noted earlier, they involve firms that do not change their specialization strategy over time, i.e. they remain specialized in the same activity for all the years. The three patterns include: a) *firms that* remain *specialized in exploratory R&D, b) firms that* remain *specialized in exploitative R&D* and *c)* firms that remain *simultaneously ambidextrous* (i.e. they spend a similar amount of money on both activities). To be consistent with the definition that specialization is a strategy by which firms limit the scope of their activities, we classify a firm as specialized in exploration or exploitation when it spends over 66.6 % of its internal R&D budget on either exploratory or exploitative R&D for all the observable years in the dataset.

This classification ensures that firms do not change their chosen specialization strategy and thus they remain specialized every year and throughout the sampled years. For instance, Firm A spends 75% of its innovation budget on exploratory R&D and the remaining 25% on exploitation R&D in year t. Next year (t+1), the same firm spends 85% on exploratory R&D and the remaining 15% on exploitation R&D. Although this firm has increased its spending on explorative R&D, it has not changed its specialization strategy.

Further, there is a third pattern in the dataset in which firms remain c) *simultaneously ambidextrous'*. Building on the definition of ambidexterity, we classify ambidextrous firms those that synchronously make similar investments on both exploratory and exploitative R&D every year and throughout the sampled years in the dataset, (the cut-off points are between 33.3% and 66.6%). Examples of ambidextrous firms include firms that spent 50% on exploratory R&D and 50% on exploitative R&D, or 60% on exploratory R&D and 40% exploitative R&D). Simultaneous ambidexterity also requires *structural* ambidexterity (i.e., physical separation between exploration and exploitation units) (O'Reilly and Tushman, 2008). For this reason, it is less viable for resource-constrained (often smaller-size) firms. Further, there are cases where firms operate in stable environments such as service industries where balancing exploitative and exploratory R&D is not a necessity (Chen and Katila, 2008; Goosen, et al., 2012; McIver et al, 2010; O'Reilly and Tushman, 2013).

Firms also change among three dominant patterns i.e., a) *specialized in exploratory R&D*, b) *specialized in exploitative R&D*, and c) *simultaneous ambidextrous*. Those firms may change either regularly (i.e., annually) or irregularly (i.e., every two, three, four years and so on).

Regardless of the frequency of change those firms predominantly change (cycle) between

exploitative R&D, exploratory R&D, and ambidextrous R&D investments. We have identified that those firms are more likely to cycle between six different patterns in their R&D investments. A) exploitative R&D firms either become ambidextrous R&D or exploratory R&D firms. B) ambidextrous R&D firms either become exploitative or exploratory R&D, and C) exploratory R&D firms either become exploitative or ambidextrous R&D firms. Thus, the directionality of change is from A=>B or A=>C, B=>C or B=>A and C=>A or C=>B. or (A=>B and C=>B, A=>C, C=>A and B=>A, B=>C).
For instance, Firm A is simultaneous ambidextrous (i.e., with R&D distribution 50% on exploratory and exploitative R&D in year t. Next year (t+1), the same firm decides to spend more on exploratory R&D with distribution 80% 20%. And in the third year (t+3), the same firm may decide to reverse its investments towards exploitative R&D with distribution 70% 30%. This means that this firm cycles between investments 3 times for the last three years.

CONTROL VARIABLES

Industry Competition

As competition can affect firm performance, we control for such effects. We used two different measures of competition. First, we measured competition using the number of intra-industry competitors at the 2-digit level. However, because this measure does not capture the market share of firms and whether few firms control most of the market, we also estimated a measure of competition that relies on the Herfindahl Index. The Herfindahl Index is widely used in the literature and it is accepted in various studies as a good and appropriate indicator of industry concentration (Kafouros and Aliyev 2016; Wu and Xia, 2016). Herfindahl index is estimated as the sum of squared market shares of firms in the industry. Hence, it is calculated as $CI_j = 1 - \sum_{i=1}^{n} s_{ij}^2$, where s_{ij} is the market share of firm i in industry j and therefore it takes values between 0 and 1. A higher level of the Herfindahl Index suggests that there is a lower concentration level within an industry, which reflects lower levels of competition. We therefore use the inverse value of the Herfindahl Index (i.e. 1- Herfindahl index) so that a higher value reflects higher levels of competition.

Tangible Assets

Following prior studies (Auh and Menguc, 2005; Jansen et al., 2006; Lubatkin et al., 2006), we control for *firm's tangible assets.* The literature has emphasized the importance of resource constrains and difficulties in changing resources when environments change (Hannan and Freeman, 1984; Tushman et al., 1985). Some firms have more physical capital such as buildings and equipment that may affect firm performance. We measure this variable by using the firm's gross investment in tangible assets (expressed in logs). We should also note that tangible assets partly control for firm size. I did not measure firm size using the number of employees as used in some prior studies (He and Wong, 2004; Jansen et al., 2006) because I use the number of employees to normalize other variables for size effects.

Newly Created Firms

Controlling for firm age is important as well-established firms may perform better than entrant firms due to their accumulated experiential learning (Jansen et al., 2006). Such experiential learning that is partially captured in the number of years the firm operates may influence firm performance. Consistent with prior studies (Kafouros et al, 2015; Cao et al., 2009), controlling for firm age enables us to capture heterogeneity between well-established and newly founded firms. Furthermore, firm age has been associated with established and difficult to change institutional routines and norms that stimulate inertial behaviour affecting thus firm performance (Tushman and Romanelli, 1985). We control for *newly created firms* using a dummy variable that takes the value of 1 if a firm is newly created (i.e., in the last 4 years; Laursen and Salter, 2006). An alternative operationalization of firm age is the number of years since the firm's foundation (Lubatkin et al., 2006). However, due to a large number of missing observations, we were not able to use this measure.

International Sales

Firm performance is also affected by whether a firm sells its products and services nationally or internationally. A firm's market is associated with firm's growth and expansion that could also be affected by its linkage with global markets (He and Wong, 2004). Further, selling in international markets has been associated with international competitiveness and access to new knowledge and market information (Cassiman and Veugelers, 2006). To control for such differences, we include in our model a dummy variable that takes the value of 1 for firms that sell their products internationally.

Affiliated Firms

Groups can help their affiliated firms by transferring knowledge, resources, skills and capabilities. As a result, firms that are affiliated to groups may be able to achieve higher performance than firms that operate alone (Khanna and Palepu, 1997). We control for the fact that some firms belong to a group (affiliated business) whereas others do not, using a dummy variable that takes the value of 1 for affiliated firms.

Protection

Consistent with prior studies (Vega-Jurado, 2008; Laursen and Salter, 2006; 2014), we consider the variety of mechanisms that firms use to protect their inventions. We draw on the responses of firms to the question in the survey on whether the firms actually apply for any legal mechanism to protect their inventions. We consider whether in reality firms use those mechanisms rather than their perception of importance about their use. In PITEC, firms indicate whether they use four different types of protection namely *patents, utility models, trademarks* and *copyrights*. We use the sum of each firm's response on the use of these four types of legal mechanisms for the protection of their inventions. Firms that score higher on a scale of 0-4 was used as an indicator that this firm utilizes a wider array of legal protection mechanisms to protect its inventions compared with their low-score counterparts. We also use the logarithmic value of the variable to maintain consistency in the modelling.

Industry's R&D intensity

We control for the industry's R&D intensity using the industry's total R&D expenditure divided by total industry sales (Uotila et al., 2009). In environments with high levels of R&D spending, technological opportunities are more abundant than in environments with lower R&D spending (Zahra, 1996a; Zahra, 1996b). These opportunities may influence firm performance (Baysinger and Hoskisson, 1989).

High Technological Firms

Given that high-tech firms are qualitatively different from low-tech firms, we develop a dummy variable that takes the value of 1 when a firm belongs to high-tech industries. The construction of this variable is based on the OECD classification given in COTEC Report (1997) as cited in Bayona Sáez and Arribas (2002). High-tech industries refer to sectors such as chemicals, pharmaceutical, computing, electronics, electrical, communication, and medical devices and optical instruments. By contrast, medium and low-tech industries include sectors such as textiles, furniture, leather, rubber and plastic (Table 2 in Appendix 1).

Time Effects and Industry Dummies

We control for time effects by incorporating year dummies (that equals 1 if associated with the corresponding year) to account for differences in economic trends and business cycles over years (Belderbos et al., 2010). In models that are not nested in industries (i.e. when they are not multi-level), we also include industry dummies in our model to account for the different industry characteristics and variations in their nature, both technological and economic.

ESTIMATION METHOD

Given that firms in our sample are clustered within industries, a *Multilevel Mixed Model* approach, which is often also referred to as *Hierarchical Linear regression* is appropriate for estimating the coefficients of interest (Bliese and Ployhart, 2002; Preacher et al., 2006; Anderson, 2014). Unlike traditional panel data estimators, we use a multilevel analysis with mixed effects, which as the name suggests it considers both Fixed Effects (FE) and Random Effects (RE) and specify the model to produce results that are nested in each industry and id (firm). By nesting the effects within each firm (id) the analysis has the additional benefit of producing an estimator that is very close to FE (because it estimates the effects separately for each firm), and it has the additional benefit of estimating coefficients for each industry separately. Although we consider using FE models, the fact that we expected the effects of specialization strategies and exploration/exploitation investment to vary a lot depending on the industry made the Fixed Effect estimator less appropriate to reveal variability at both industry and firm level (Wooldridge, 2002; Preacher et al., 2006; Anderson, 2014). Thus, our chosen Multilevel Mixed Effect estimator allows us to explicitly specify the estimation with complicated clustering patterns near models while relies on the assumption of independence of error terms, which may be violated when firms are clustered in various industries (Hox et al., 2017; Preacher et al., 2006; Anderson, 2014).

We also considered using alternative methods for estimating our empirical model. Initially, we considered running our model using ordinary least squares (OLS) regression following practice of established studies (e.g., He and Wong, 2004; Jansen et al., 2005). However, OLS regression often yields biased coefficients and it is not suitable for treating endogeneity (Blundell and Bond, 2000). Endogeneity problem often arises from unobserved heterogeneity due to omitted variable problems, errors in measurement, simultaneity problems and general discrepancy between true variables and their proxies. This often happens when the chosen variables are not strictly exogenous, but they correlate somehow with the error term in our specified model (Pindado et al., 2012). As for the simultaneity problem (reverse causality) often occurs when TFP and explanatory variables are correlated somehow. Yet, instead of explanatory variables causing some change in TFP, it goes the other way. In our case, this implies that the error term of the production function will affect the choice of inputs factors, and for this reason an association will be detected between the error terms and our chosen key explanatory variables (Blundell and Bond, 2000). Subsequently, we avoided using OLS estimates because of the high possibility of obtaining biased coefficients in estimating TFP.

Similarly, we also considered using Fixed effects (FE) and Random effects (RE) models for analysing our dataset. The use of Fixed effects (within group estimator) was not appropriate in our study because when running the regressions, we could not get coefficients of the time-invariant variables (including the specialization variable, ambidexterity and industry-orientation).

Our choice not to use FE estimator was also validated using the Hausman and Mundlak test (Cameron and Trivedi, 2009; Mundlak, 1978) which confirmed that RE models are more suitable than FE for our study. Please, note that we also experimented with the RE estimator for testing the hypotheses of Chapter 6 and obtained consistency across the results). Yet, we decided that Multilevel mixed effect is more appropriate estimator for the purpose of our study for the reasons we explained earlier on.

We also followed established studies on ambidexterity (e.g., Uotila et al., 2009) and used the generalized least squares (GLS) estimator as alternative estimator to our main Multilevel Mixed Model estimator. This approach would validate and establish that our results are not a product of a specific estimator (Wooldridge, 2000; Blundell and Bond, 2000).

As mentioned, despite the fact that our data is longitudinal (which as mentioned controlled for individual heterogeneity; Pindado et al., 2012), and that we run the results using also GLS models, we still had concerns that endogeneity might be an issue in our study. As we explained the endogeneity problem might occur because our dependent (TFP) affects some of the explanatory variables (Pindado et al., 2012). In the context of exploration and exploitation, it is that firms that specialize in ambidexterity may be endogenous to firm performance (TFP). Thus, in our models, the issue of endogeneity might occur when, for instance, ambidextrous firms may be better performing firms. To mitigate this problem, we followed common practice and used as instrumental variables the explanatory variables lagged (Pindado et al., 2012). Specifically, we followed established studies on ambidexterity (e.g., Uotila et al., 2009) and used the Arelano-Bond GMM estimator (Arellano and Bond, 1991; Wooldridge, 2001; Hansen, 2010; Roodman, 2006). As explained, the GMM estimation method uses the lagged values of the explanatory variables as main instruments and it is often adopted as a sufficient solution to endogeneity issues because these lagged variables are interrelated with the regressors they instrument (Pindado et al., 2012; Uotila et al., 2009; Arellano and Bond, 1991). However, the Hansen (1982) test of instruments validity indicated that the fit of the instruments is not good, which the regression provides statistically insignificant results for the variables which are dummies (which is expected given that dummies do not vary a lot over time).

We finally attempted to address the issue of endogeneity using the two-stage least squares (2SLS) estimator but as explained the effectiveness of this approach depends on finding appropriate and using valid instruments (Bollen et al., 2007). Specifically, the process involves two stages. In the first stage we found two variables that are uncorrelated with the error term in order to predict a proxy for our potentially endogenous regressor. In the second stage, we use the predicted value to estimate our linear regression model (Wooldridge, 2002). The choice of these two variables were driven and justified by theoretical arguments in the literature on ambidexterity (Ebben and

Johnson, 2005 Cao et al., 2009; Chen and Hambrick, 1995) We used thus *firm age* and *number of employees* as instruments and consider the possibility that they are endogenously determined to ambidextrous firms. The theoretical justification is that resource abundant firms can exploit and explore (Cao et al., 2009; Ebben and Johnson, 2005). Equally, larger size firms have access to external munificent environments or are resource rich internally that allows them to be ambidextrous (Chen and Hambrick, 1995). In addition, we performed a post estimation test to ensure that the variables we chose are exogenous. The results from both the Durbin statistic and Wu-Hausman had very small values (Durbin (score) chi2(1) = 452.738 (p = 0.0000) and Wu-Hausman F (1,29802) = 459.675 (p = 0.0000) (Wooldridge, 2002). We also test our odel for overidentification. The p values of both Sargan (score) chi2(1) =1.68566(p = 0.1942) and Basmann chi2(1) = 1.68558 (p = 0.1942) were large, suggesting that the choice of these two instrumental variables is valid, and our model is correctly specified. Subsequently, the results from the tests are indicative that endogeneity is not a problem in our analysis.

The Empirical Model

As mentioned, the first step before running our regression analysis was to follow established studies and estimate the productivity function (Equation 1) to identify differentials in TFP across firms of various industries operating in Spain (Kafouros et al., 2018; Temouri et al., 2008). In the second step we introduced the model including our key explanatory variables and controls (Equation 2 below). Our specified model included not only firm-specific variables but also industry-specific variables that all together account for variations in productivity of our sampled firms. We also followed common practice and included the logarithmic transformation of variables to allow interpretation of the results (Qingwang and Junxue, 2005; Van Beveren, 2012). Our approach follows established methodology and the model is the following (Temouri et al., 2008):

$$Y_{it} = b0j + b1X1_{it} + b2X2_{it} + b3X3_{it} + b4X4_{it} + b5X5_{it} + b6X6_{it} + b7X7_{ij} + b8X8_{it} + b9X9_{ij} + b10X10_{it} + e_{it} \quad (2)$$

Where Y_{it} refers to our dependent variable (TFP) for an individual firm $_{(i)}$ in time $_{(t)}$ and industry $_{(j)}$. The X variables represent our key explanatory and control variables. Specifically,

X1 represents investments in exploratory R&D

X2 represents investments in exploitative R&D

X3 represents the tangible resources

X4 represents the international sales of firms

X5 represents those firms that belong to a business group

X6 is the inverse Herfindahl Index

X7 represents the number of legal mechanisms firm use to protect their inventions,

X8 represents the industry intensity

X9 represents the age of firms

X10 represents firms that operate in high-technology industries

In our model we further included industry and time dummies which we omit here for simplification. The e_{it} indicates the error term.

CHAPTER 5

SPECIALIZATION IN EXPLORATORY AND EXPLOITATIVE R&D: CONSEQUENCES FOR FIRM PERFORMANCE

ABSTRACT
This chapter contributes to organizational learning theory and to research on exploration and exploitation by enhancing understanding of 1) whether specializing in either exploratory or exploitative R&D is more beneficial than an ambidextrous strategy, and 2) whether the returns to exploratory and exploitative R&D differ for those firms that adopt a specialization strategy versus those firms that are ambidextrous. Our empirical analysis of a longitudinal dataset of 32,537 observations indicates that for firms that specialize in exploratory R&D, the positive effects of such an exploratory R&D activity are stronger than the effects of exploitative R&D activity on firm performance. By contrast, for firms that specialize in exploitative R&D, the positive effects of such an exploratory R&D activity are weaker than the effects of exploitative R&D activity on firm performance. Our study therefore joins the discussion on ambidexterity by advancing the debate on whether firms should be *ambidextrous* or *specialize* in either of these two activities and contributes to organisational learning theory by explaining the mechanisms under which the effects of exploratory and exploitative R&D become weaker or strengthen depending upon the firm's choice to pursue investments that are similar or deviate to their current specialization strategy and knowledge trajectory.

KEYWORDS: *exploratory R&D, exploitative R&D, specialization strategies, ambidexterity*

INTRODUCTION

The organizational learning theory and the innovation literature have long recognized the importance of investing in *exploration* and *exploitation* for enhancing firm performance (Benner and Tushman, 2002; He and Wong, 2004; Cao et al. 2009, Gibson and Birkinshaw, 2004; Lubatkin et al., 2006). However, these two types of activities involve a distinctively different knowledge base, different structures, processes and may lead to dissimilar performance outcomes. Applying the concepts of exploration and exploitation in the context of R&D, we expect investments in exploratory R&D to be unpredictable because firms are required to experiment with unfamiliar knowledge. Yet, these investments could lead to knowledge creation, breakthrough ideas and new opportunities (Gupta et al., 2006; Belderbos et al., 2010). By contrast, investments in exploitative R&D yield more predictable returns because firms leverage their current knowledge stock to standardize organizational routines and improve efficiency.

Work on organizational learning emphasizes the benefits of ambidexterity and suggests that firms should make similar investments in both exploratory and exploitative activities (He and Wong, 2004; Gibson and Birkinshaw, 2004; Lubatkin et al., 2006; Katila and Ahuja, 2002; Venkatraman et al., 2007). However, although an ambidextrous strategy comes with certain advantages (Auh and Menguc, 2005; Ahuja and Lampert, 2001; Leonard-Barton, 1992), many prior empirical studies show that ambidexterity has either insignificant (Bierly and Daly, 2007) or even negative effects on firm performance (Rothaermel and Alexandre, 2009; Ebben and Johnson, 2005). Such inconsistency in prior empirical findings points to the value of understanding why some firms do not benefit from investing in both activities, and whether specialization (rather than ambidexterity) is actually more beneficial for firm performance.

We address this gap in our understanding by arguing that a reason for prior mixed findings in the literature is partly the implicit assumption of some studies that the effects of exploration and exploitation on firm performance does not differ across firms that are specialized and those that are ambidextrous. However, because exploration and exploitation involve different and incompatible processes, it may be the case that the economic returns to exploratory R&D may differ for firms that specialize in exploratory R&D. A similar argument may apply in the case of exploitative R&D.

Our analysis in this chapter advances the above issue by offering a direct comparison between specialization in exploratory and exploitative R&D versus ambidextrous R&D investment strategies. To our knowledge, there are no studies that explicitly make a direct comparison between specialization and ambidexterity in the context of R&D. It therefore remains unclear in the literature whether firms should be *ambidextrous* or *specialize* (invest the vast majority of their time and resources in either exploratory or exploitative R&D). Equally, prior studies have not explicitly investigated how the impact of exploratory and exploitative R&D on firm performance varies across firms that make different decisions with respect to specialization and ambidexterity. In other words, it is less well-understood whether the effects of R&D investments differ for firms that adopt a specialized (exploratory or exploitative) versus an ambidextrous R&D strategy and in which situations is more advantageous for firm performance.

This first empirical chapter of this PhD thesis thus empirically test two important research questions: **a)** is specialization in either exploratory or exploitative R&D strategy more beneficial than an ambidextrous strategy? and **b)** how the economic returns of exploratory and exploitative R&D differ for those firms that adopt a specialization versus an ambidextrous strategy? Although the extant literature recognizes that the distribution between exploratory and exploitative R&D is contingent upon different industry dynamics, including technological dynamism and competition (Auh and Menguc, 2005; Jansen, et al., 2005; Uotila et., 2009), and firm idiosyncrasies, including firms resources and size (Cao et al., 2009; Ebben and Johnson, 2005; Luger et al., 2018), we have a limited understanding of the mechanisms that make specialization in exploratory or exploitative R&D a better strategic option compared to ambidexterity in enhancing firm performance.

The current chapter advances scholarly understanding of how certain mechanisms might influence the effectiveness of specializing in exploratory or exploitative R&D and thus firm performance. Drawing from organizational learning theory (Cyert and March, 1963; Levitt and March, 1988; March, 1991; Baum et al., 2000; Levinthal and March, 1993), we argue that a specialized strategy might be more beneficial over an ambidextrous one for firm performance for two reasons. First, because specialized firms limit the scope of their activities, they gradually accumulate experiential learning that is utilized to strengthen their ability to produce a product/service more proficiently (Capon et al., 1988; Calderini and Scellato, 2005). Second, because specialized firms carry on building competence in areas of already established competence and expertise, they gradually enhance their performance by eliminating errors when repeating subsequent similar investments (Levitt and March, 1988; Baum et al., 2000; Holmqvist, 2004).

Accordingly, we develop a conceptual framework that clarifies the mechanisms that make specialization more beneficial than the joint pursuit of both. We expect that specialized in exploratory/exploitative R&D to be more effective in enhancing firm performance because firms by learning to use and reuse their existing exploratory or exploitative knowledge they gradually strengthen the skills required to perfect certain organisational tasks, achieve thus ultimately efficiency gains (Baum et al., 2000). Building on this reasoning, we examine a set of hypotheses that aim at clarifying the above relationships.

Our analysis of a longitudinal dataset of 32,537 observations supports this reasoning, indicating that not only specialization in exploratory/exploitative R&D has a positive direct effect on firm performance, but also that this effect is stronger for those firm that choose to make investments that are similar to their existing knowledge trajectory. Exploratory R&D investments have a stronger positive effect on the performance of those firms that specialize in exploratory R&D, whereas exploitative R&D investments have a stronger positive effect on the performance of those firms that specialize in exploitative R&D. Conversely, the opposite pattern emerges with the corresponding effect of exploratory R&D on firm performance being weaker when a firm specializes in exploitative R&D. The importance of the differential effect on firm performance depends upon the firms' current investment strategy and learning predisposition indicating that firms may experience different returns to their specialization strategy when they decide to make investments that are different to their current knowledge and learning trajectory.

Our study seeks to make a number of contributions. First, it develops a conceptual framework that explains how and why the performance-enhancing effects of firms that specialize in explorative/exploitative R&D differ from those firms that decide to jointly pursue both R&D investments. Second, it helps us understand why the effectiveness of exploratory and exploitative R&D depends upon the firm's choice to pursue investments that are similar to the specialization of the firm. As such, it contributes to exploitation and exploration research that has considered the effects of being ambidextrous (Auh and Menguc, 2005; He and Wong, 2004; Jansen et al., 2006; Uotila et al., 2009; Venkatraman, et al., 2006; Lubatkin et al., 2006), but has not examined if and how the returns from specializing in either in exploratory and exploitative R&D might be more beneficial for firm performance, and whether those effects accentuate or weaken when firms choose to invest in activities that require knowledge that is similar to the firm's existing knowledge base.

Third, our analysis suggests that specialization is a more effective way in enhancing firm performance. This theoretical position does not contradict the notion of ambidexterity. Yet, it extends this notion by suggesting that there may be dynamics either in the environment or firm-specific factors that may allow firms to carry on building on what they are endowed to do well (i.e. specialize) and achieve ambidexterity in the broader network when interacting with other firms (Gupta et al., 2006; Stettner and Lavie, 2014). This is consistent with the idea that although balancing the conflicting demands that exploration and exploitation entail including conflicting routines, negative transfer, and limited specialization, these imbalances can be offset by exploring in one mode (e.g., through collaborations) and exploiting in another (e.g., exploiting internally firm's own knowledge base; Stettner and Lavie; 2014).

As such, this view contributes to organization learning theory that clarifies the different types of learning and their advantages but does not sufficiently specify when different types of learning associated with exploration and exploitation are more effective in enhancing firm performance, and whether they complement or substitute each other in enhancing firm performance.

THEORETICAL BACKGROUND

Organizational Learning Theory

The overarching theoretical lens that is used in this chapter (as well as in the rest of this PhD thesis) is organizational learning theory (Levinthal and March, 1993; Wang and Ahmed, 2003 (Levitt and March, 1988; Huber, 1991; Cyert and March, 1963; Huber, 1991; Fiol and Lyles, 1985). One of the basic premises of organizational learning theory is that firms use their experience gained through practice to develop conceptual frameworks in order to interpret such experience (Levitt and March, 1988; Huber, 1991). Accumulated experience serves as a learning mechanism helping firms to undertake various processes. Firms as learning entities make inferences from their experience, incorporating their experiential learning into *organizational routines* (Levitt and March, 1988). Over time, firms become competent on specific routines because of their accumulated experience and repetitive use of the same knowledge. Experiential learning enables firms to strengthen their competence either in the form of knowledge exploitation or exploration (Holmqvist, 2004; March, 1991). Further, experiential learning enables firms to accumulate knowledge that is valuable for enhancing performance and for executing a set of activities (Huber, 1991). This self-reinforcing nature of learning may encourage some firms to maintain their current focus and trajectory (i.e. specialise in either activity) to achieve superior firm performance. Organizational learning theory is therefore particularly relevant in explaining how exploratory and exploitative R&D investments and how specialization in either of these two types of R&D research activities may lead to different performance outcomes.

Since firm performance is a joint function of the potential returns from a given activity and the exhibited competence of a firm at it, organizations are likely to enhance their performance as they accumulate more experience (Baum et al., 2000). It is well accepted in organizational learning theory that searching for new directions where skills have to be developed from scratch reduces the speed with which existing skills could be improved (Holmqvist, 2004). Further, competence building with existing activities make the search of entirely new activities less attractive (Levitt and March, 1988; Kim and Miner, 2007). Subsequently, increases in competence when undertaking an activity increases the likelihood of returns for engaging in that activity (Argyris and Schon 1978; Gupta et al., 2006). These two premises in organizational learning theory (the cumulative effects of both experiential learning and competence building) suggest that investment decisions are often guided by organisations' experience with them, and thus the more competent and endowed the organization is with a specific activity, the greater the likelihood in succeeding with it and thus enhancing its performance.

Exploratory R&D and Exploitative R&D

Drawing from the organizational learning literature (Levinthal and March, 1993; Wang and Ahmed, 2003; Levitt and March, 1988; Huber, 1991; Cyert and March, 1963; Huber, 1991; Fiol and Lyles, 1985) and March's (1991) seminal work, we suggest that when firms invest in exploitative R&D they engage in local search looking for knowledge that is similar to that of their own knowledge stock aiming at gaining efficiency in production and execution of tasks (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). By contrast, when firms invest in exploratory R&D, they engage in distant search looking and experimenting with knowledge dissimilar to that of their own knowledge stock (Gupta et al., 2006; Baum et al., 2000; He and Wong, 2004). Investments thus in exploitative R&D enhance firm performance mainly because firms strengthen their existing competencies and skills and achieve economies of scale and scope maintaining their overall efficiency in production (Baum et al., 2000; Morgan and Berthon, 2008; Auh and Menguc, 2005). On the other hand, investments in exploratory R&D enhance firm performance mainly because firms strengthen their ability to identify ways to become efficient (Lavie and Rosenkopf, 2006; Rothaermel and Alexandre, 2009) by pursuing new technological trajectories (Teece, 2007) and combine knowledge from different areas that could lead to breakthrough ideas and ways of creating products/processes (He and Wong, 2004).

HYPOTHESES

Exploratory R&D and Firm Performance

Although we acknowledge that exploratory R&D is experimental in nature (Levinthal and March, 1993) and may disrupt a firm's organisational routines (Mitchell and Singh, 1993; Hannan and Freeman, 1984), we expect exploratory R&D investments to increase firm performance for the following reasons.

First, exploratory R&D strengthens firms' ability to search for new knowledge that in turn expands their existing knowledge base (Vermeulen and Barkema, 2001). Searching for new knowledge areas exposes firms to knowledge that is different to the knowledge that already resides within their organization and in the industry they compete (Henderson and Clark, 1990). This broadening in search scope revitalizes a firm's knowledge base because new knowledge elements blend in to infuse firms with fresh ideas and combinations (Vermeulen and Barkema, 2001). Knowledge heterogeneity and experimentation with new alternatives unlocks further novel thinking (Wu and Shanley, 2009), enhancing experimentation, knowledge generation and therefore firm performance. New knowledge also helps firms avoid capability rigidities (Leonard-Barton, 1995) knowledge obsolescence (Levinthal and March, 1993) and structural inertia

(Hannan and Freeman, 1984). Once again, this leads to stronger firm performance.

Second, in line with the above arguments, another view suggests that exploratory R&D strengthen a firm's ability to search for knowledge that is sufficiently *distant* to that of the firm, i.e. to go beyond its own technological trajectories (Benner and Tushman, 2002; Rosenkopf and Nerkar, 2001). Seeking for distant knowledge is likely not only to complement a firm's existing knowledge stock (Rosenkopf and Nerkar, 2001) but also reduces competency traps (i.e. cases in which firms gravitate towards areas of already established competencies; Leonard-Barton, 1995), knowledge overlap and replication of prior practices (Baum et al., 2000; Vermeulen and Barkema, 2001). These in turn, help the firm undertake current and new tasks and enhance firm performance.

Third, investments in exploratory R&D are likely to accelerate a firm's generative learning and stimulate a new stream of ideas and develop entirely different technologies. By definition, exploratory R&D stimulates a firm's *generative learning* (Morgan and Berthon, 2008; Jerez-Gomez, 2005; Senge, 1990; Argyris and Schon, 1978; Argyris, 1976). The proactive nature of exploratory R&D stimulates risk-taking behavior and facilitates the generation of novel ideas (Morgan and Berthon, 2008). Experimentation with new ideas could change the utility and application of knowledge elements, creating a mindset that encourages a continuous stream of new ideas (Lee et al., 2012). As a result, generative learning can unsettle an existing technological trajectory (Gatignon et al., 2002) by inviting firms to question their existing knowledge and understanding (Subramaniam and Youndt, 2005). Hence, experimentation with novel ideas can help the firm to move beyond adaptive learning (which only helps at refining existing products) and engage into generative learning that further enhances exploration.

Fourth, exploratory R&D is likely to enhance a firm's absorptive capacity (i.e., a firm's ability to identify, internalize and exploit commercially valuable knowledge; Cohen and Levinthal, 1990). Firms with adequate exploratory activity function proactively and experiment with emerging opportunities (Lavie and Rosenkopf, 2006; Rothaermel and Alexandre, 2009). This means that those firms are more likely to sense potentially promising technological opportunities, make strategic decisions about what technologies to pursue, choose carefully what markets to enter and decide what innovative outputs will have the greater commercial value to exploit further (Teece, 2007). As a result, firms that engage in exploratory R&D are better able to identity evolutionary paths that translate technological opportunities into valuable outputs. Accordingly, we introduce the following hypothesis that serves as the starting point for our analysis:

H1a: *Investment in exploratory R&D has a positive direct effect on firm performance.*

Exploitative R&D and firm performance

Exploitative R&D is likely to enhance firm performance for a number of reasons. First, when firms invest in exploitative R&D, they often engage in local search and look for knowledge that exhibits technological and geographical similarity to that of their own knowledge (Baum et al., 2000; Rosenkopf and Almeida, 2003). In exploitative R&D, firms often exploit knowledge that has been used successfully in the past, searching for opportunities with knowledge similarity to that of their own, and building additional expertise in their chosen domain (Rosenkopf and Nerkar, 2001). Searching in areas of established competence not only is less resource-intense, but also reduces unpredictability because firms mainly replicate past behavior (Levitt and March, 1988; Nelson and Winter, 1982; Baum et al., 2000) and accumulate knowledge through repetition and experiential learning.

Once the utilization of existing knowledge is repeated, it becomes routinized and refined through informed experience (Baum et al., 2000). Firms make inferences from their experiential learning that is coded into organisational rules that allows them to work more efficiently in similar tasks (Holmqvist, 2004). The focus on the same task and accumulated expertise in a firm's chosen domain allows them to build capabilities that contribute towards greater effectiveness of exploitation (Rosenkopf and Nerkar, 2001). Therefore, experiential learning improves investments in exploitative activities because the generation of experiential rules is directly used by the firm to refine products and processes (Dodgson, 1993; Holmqvist, 2004), which in turn enhances firm performance by ensuring that there is a constant stream of revenue. Repetition also enhances the firm's knowledge of how to do it better next time, and therefore leads to improvements in execution.

Second, investments in exploitative R&D strengthens the firm's ability to build on its existing knowledge base (March, 1991). Because exploitative R&D investments rely on the firm's chosen technological trajectory (Baum, et al., 2000) they require little diversity and variety in the firm's existing knowledge base. Hence, there is a lower need for firms to cross organizational and technological boundaries (Rosenkopf and Nerkar, 2001). This enables firms to operate within their comfort zone and remain efficient by shifting from existing product lines to product extensions. Efficiency and flexibility in firms' operations derive mainly from knowledge that has been gained in the firm's already chosen technological and organizational trajectory since its purpose is mainly to extend the life cycle of current products and services (Morgan and Berthon, 2008). Furthermore, there are significant economies of scale, scope and learning in exploitative strategies, enhancing once again firm profitability (Auh and Menguc, 2005). In summary, the knowledge gained in the firm's chosen trajectory helps the firm make incremental changes to existing products and processes, which in turn increases the effectiveness of a firm's investments in exploitative activities.

Third, exploitative R&D investments can be enhanced by adaptive learning (Auh and Menguc, 2005) that occurs as a by-product of experience and repetition. As noted earlier, adaptive learning involves an iterative process and refers to changes and refinements (Tyre and Von Hippel, 1997; Schilling et al., 2003) that create changes to improve output (Fiol and Lyles, 1985). This implies that exploitative R&D investments aims at refining and adapting existing product innovations to markets' current needs (Benner and Tushman, 2003). Its main purpose is that firms learn to do minor refinements to existing products and processes. Adaptive learning therefore is the type of learning (i.e., survival learning) by which firms exploit or even copy existing knowledge (Senge, 1990). As firms make changes to prior errors they accumulate experience, enhancing gradually their adaptive learning. They learn from their mistakes and make adaptations to satisfy existing customers' needs. As adaptive learning leads to improvements and refinements in existing products and processes, it increases efficiency in undertaking further exploitative tasks and enhances overall firm performance. Accordingly, we introduce a second hypothesis that also serves (together with H1a) as the starting point for our analysis:

H1b: *Investment in exploitative R&D has a positive direct effect on firm performance.*

The interaction between Explorative R&D and Exploitative R&D

A natural question that follows from Hypotheses 1a and 1b is whether explorative R&D and exploitative R&D complement or substitute each other in increasing firm performance. If there are synergies between the two activities, then they will increase the effectiveness of each other in improving firm performance and in this case their joint interaction effect is expected to be positive. By contrast, if they involve competing processes that do not improve the processes of the other activity, their joint interaction effect is expected to be negative. We should acknowledge that an overarching argument in the literature is that there is a key advantage when firms engage simultaneously in both exploratory and exploitative R&D (He and Wong, 2004; Lavie et al., 2010; Dover and Dierk, 2010; O'Reilly and Tushman, 2013; Junni et al., 2013) because the ideas that are generated by the exploratory R&D team can be used by the exploitative R&D team. Although this view points to a complementary relationship (He and Wong, 2004; Hess and Rothaermel, 2011), a number of other arguments suggest that they do not benefit each other (Markides et al., 2013; Turner et al., 2013; Junni et al., 2013).

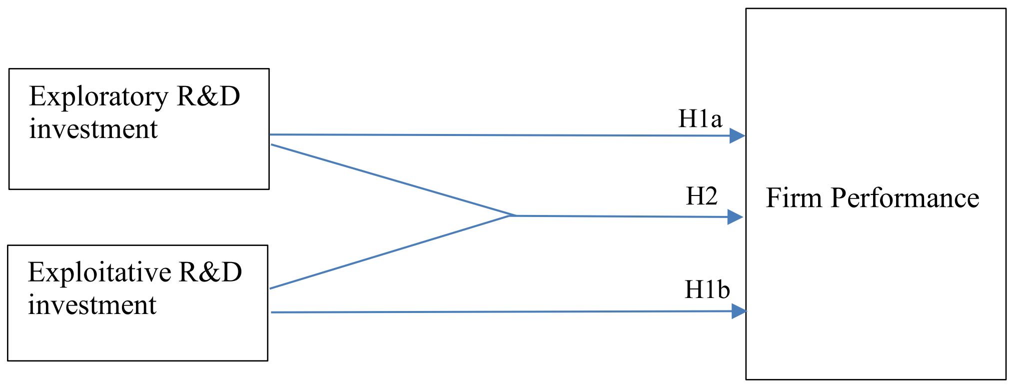
Drawing on theoretical knowledge from organizational learning theory, we expect that exploratory R&D and exploitative R&D are antithetical learning mechanisms and involve different activities, processes and tasks (Duncan, 1976; March, 1991; Baum et al., 2000; Holmqvist, 2004; Simsek, 2009; Turner et al., 2013). In addition, whereas exploitative R&D aims at refinement and efficiency, exploratory R&D focuses on experimentation (Gupta et al., 2006). The different demands and processes of the two activities means that they require different knowledge, searches, expertise and scientists. This means that the personnel that specializes in one of the two activities is less familiar with the other activity and it is less likely to be able to contribute and add value to it.

Similarly, it is less likely that the members of staff who focus on exploratory R&D will be competent in engaging in exploitative R&D given that the two activities require different knowledge, capabilities, learning (single vs. double-loop learning) and organizational structures and culture (Tushman et al., 2010; Wang and Rafiq, 2014). Given that R&D exploration and R&D exploitation are by definition two different types of investment (Markides, 2013; Turner et al., 2013; Martini et al., 2013; Stettner and Lavie, 2014), we also expect that they will compete for financial resources in the firm. This implies that for a given level of resources, when investment in one activity increases, investment in the other activity will have to decrease. This may create tension between teams and once again it may lead to situations that are not synergetic.

In summary, based on the notion that R&D exploration and R&D exploitation require not only different but also incompatible types of learning, processes, expertise and members of staff, we expect such incompatibility to affect the returns to each activity and therefore their joint moderating effect on firm performance (Figure 1 summarizes these relationships). We therefore introduce the following hypothesis about their joint moderating effect:

H2: *The joint moderating effect of exploratory R&D and exploitative R&D on firm performance is negative.*

Figure 1 – Exploratory R&D, Exploitative R&D and Firm Performance



The role of Specialization in Exploratory and Exploitative R&D

We define *specialization as* a strategy by which firms invest more time and resources in either exploratory or exploitative R&D, aiming at becoming very competent in this activity in order to gain efficiency within the overall system (Gupta et al., 2006). We expect *specialization* strategy to come with efficiency gains that make it more advantageous than an *ambidextrous* strategy (i.e., invest in both exploratory and exploitative R&D to a similar extent). More specifically, the literature on ambidexterity suggests that firms have to balance their investments because exploitation will secure a firm's current cash flow, whereas exploration will ensure the generation of new ideas and a position in future markets (Benner and Tushman, 2003; Gibson and Birkinshaw; 2004; Lubatkin et al., 2006; O'Reilly and Tushman, 2013). Although certain conditions may require firms to engage in both (Koryak et al., 2018; Cao et al., 2009; Uotila et al., 2009; Jansen et al., 2006), there might be significant benefits for firms that can specialize in either one (Wernerfelt and Montgomery, 1988).

First, a specialized in exploratory or exploitative R&D strategy could lead to greater returns to a given set of activities because a firm strengthens its ability to undertake a certain set of tasks more efficiently as it accumulates experiential learning faster in areas of familiar knowledge and prior established expertise (Baum et al., 2000; Koryak et al., 2018). A specialized firm increases its ability and competence in producing a product or service more proficiently. Such proficiency derives mainly from the repetitive execution and engagement with the same activities (Hanks and Chandler, 1994).

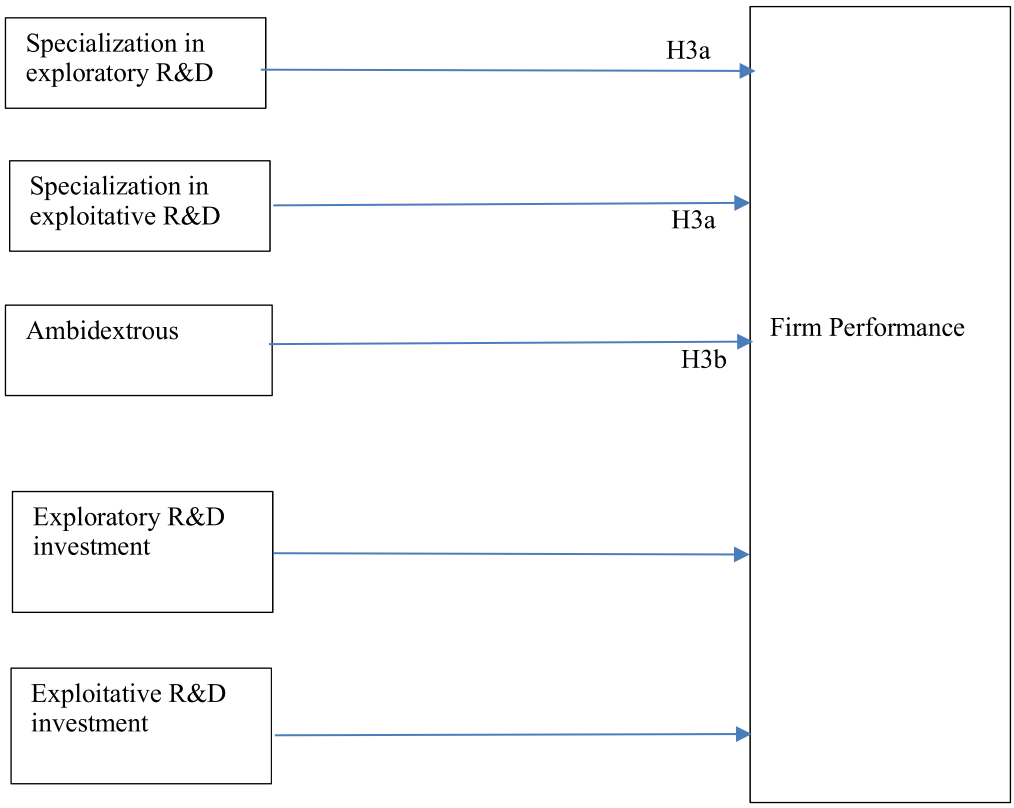
Second, specialization may enhance firm performance by leading to efficiency gains. Efficiency gains derive mainly from the fact that firms carry on building competence on areas of already established competence. With the repetitive execution of the same tasks and processes, firms accumulate experience and confidence, diminish unpredictability and strengthen their capabilities (Baum et al., 2000; Holmqvist, 2004; Rosenkopf and Nerkar, 2001; Morgan and Berthon, 2008; Argyris, 1976; Bierly and Daly, 2007). By inference, when firms invest in either exploratory or exploitative R&D, they strengthen their skills required to undertake such specific investments, diminish errors in execution of processes involved in those activities and perfect the execution of processes involved in these activities.

Efficiency gains are more likely to occur from prior repeated actions rather than actions for which firms have limited knowledge, experience and understanding (Levitt and March, 1988; Baum et al., 2000; Rothaermel and Deeds, 2004). This echoes the idea that when a process or activity becomes standardized, the time required to accomplish it reduces while the quality of executing such activity improves (March, 1991; Casillas and Moreno-Menéndez, 2014). In the context of exploratory or exploitative R&D, firms learn to use and reuse their existing exploratory or exploitative knowledge strengthening the required skills involved to perfect organisational tasks to achieve such efficiency gains. By contrast, firms that are ambidextrous will not benefit from the above efficiency gains and performance advantages. Accordingly, we introduce the following two hypotheses (Figure 2 summarizes these relationships):

H3a: *Specialization in either exploratory R&D or exploitative R&D has a positive effect on firm performance.*

H3b: *Pursuing exploratory R&D and exploitative R&D simultaneously and to a similar extent (ambidextrous strategy) has a negative effect on firm performance.*

Figure 2 – Effects of specialization in exploratory and exploitative R&D



How do the effects of Exploratory and Exploitative R&D differ for Firms that pursue a Specialization Strategy?

We further investigate whether the effects of exploratory and exploitative R&D on firm performance differ for firms that choose to specialize in either activity. For several reasons, we hypothesize that the positive effects of exploratory R&D on firm performance are stronger for firms that specialize in exploration and weaker for firms that specialize in exploitation. Equally, we expect the positive effects of exploitative R&D on firm performance to be stronger for firms that specialize in exploitation and weaker for firms that specialize in exploration. Our argumentation relies on the premise that the effectiveness of exploratory and exploitative R&D in enhancing firm performance depends on the similarity between the knowledge that is needed for the activity and the knowledge base in which the firm specializes. Our argument is consistent with the idea that increases in knowledge overlap causes improvements in a firm's absorptive capacity and therefore increases the likelihood of a firm to create value from knowledge similarity than dissimilarity (Sears and Hoetker, 2014). Therefore, higher similarity leads to efficiencies and therefore to higher performance.

Drawing on organizational learning theory (Levitt and March, 1988; Huber, 1991; March, 1991), we develop the view that the effectiveness of exploratory and exploitative R&D in enhancing firm performance depends on the firm's ability to carry on building on its existing knowledge base. According to this view, exploratory and exploitative R&D are more likely to lead to further advancement when undertaken in the firm's already established knowledge base and technological trajectory due to similarities with its current knowledge stock and expertise (Baum, et al., 2000). Hence, exploratory R&D investments are expected to be particularly advantageous for performance when firms specialize in exploration activities (similarly, exploitative R&D investments are more advantageous for firms that specialize in exploitation activities).

When there is knowledge overlap between exploratory or exploitative R&D activities and the firm's knowledge base, there is no need for the firm to cross its technological boundaries and this may strengthen its expertise (Rosenkopf and Nerkar, 2001). Knowledge similarity and overlap between a firm's current knowledge base and area of specialization enables a firm to further strengthen its skills and enhance its expertise because it operates within its comfort zone by remaining efficient through repeating tasks and undertaking activities the firm already knows and is familiar with (Sears and Hoetker, 2014).

Efficiency in firm's operations derive mainly from knowledge accumulation in familiar tasks, processes and activities. This may enable the firm to avoid errors in execution and engagement of activities required in either exploratory or exploitative R&D investments. Therefore, as knowledge accumulates and is compatible with the firm's current trajectory and knowledge predisposition it enhances the firm's established expertise and ability to undertake subsequent (similar) investments more successfully (March 1999; Holmqvist, 2004; Rosenkopf, and Nerkar, 2001).

Second, the strengthening effect of investing in exploratory or exploitative R&D activities that align with the firm's specialization could also be explained by the notion of absorptive capacity. Because a firm's absorptive capacity depends largely on the overlap between prior and new knowledge (Cohen and Levinthal, 1990; Sears and Hoetker, 2014; Volderba et al., 2010), the greater the knowledge overlap between exploratory and exploitative R&D and firm's knowledge base the better the knowledge assimilation and utilisation the firm could gain from undertaking activities of similar nature. By contrast, the low degree of knowledge overlap between a specialization strategy and the firm's current knowledge is likely to weaken a firm's absorptive capacity. When firms invest in R&D activities that are unrelated to those undertaking currently, they will have to develop or modify their knowledge base to accommodate the knowledge requirements of the new R&D investment. Although this may still be beneficial in many respects, it may be less efficient than conducting activities that fall within the firm's specialization sphere.

Therefore, the higher the degree of relatedness in knowledge base between the existing and current R&D investments the more likely is to facilitate knowledge assimilation and successful application of new elements into the firm's current routines, strengthening its performance (Cohen and Levinthal, 1990; Zahra and George, 2002; Lane et al., 2006; Choi and McNamara, 2018). Consistent with this line of thinking, studies on technological acquisitions (Choi and McNamara, 2018) suggest that acquirer firms exhibit *integrated knowledge leverage* when they merge, combine and assimilate the acquired knowledge into their existing knowledge base using both knowledge inputs to enhance firm performance. Investment in explorative or exploitative activities that deviates from what the firm is currently doing is likely to disrupt certain organizational routines, structures and processes increasing the cost when trying to experiment with novel and unfamiliar ideas and technological opportunities (Dierickx and Cool, 1989; Zollo and Winter, 2002). This once again will bear negative consequences for the firm's performance and efficiency. Accordingly, we introduce the following two hypotheses (Figure 3 summarizes these relationships):

H4: *For firms that specialize in R&D exploration, the positive effects of exploratory R&D investment on firm performance are stronger than the effects of exploitative R&D investment on firm performance.*

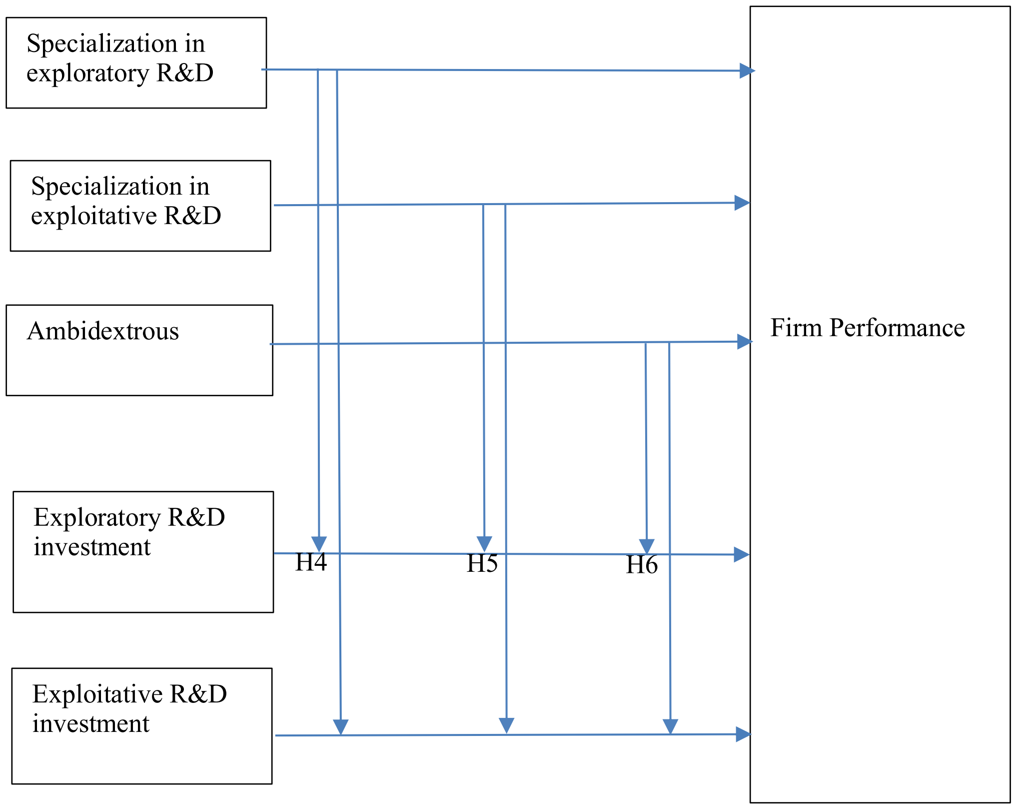
H5: *For firms that specialize in R&D exploitation, the positive effects of exploratory R&D investment on firm performance are weaker than the effects of exploitative R&D investment on firm performance.*

How do the effects of Exploratory and Exploitative R&D differ for Firms that pursue an Ambidextrous Strategy?

Given that being ambidextrous requires firms to make similar investment in both exploratory and exploitative R&D, firms are familiar to a similar extent with the processes and activities required for exploratory and exploitative R&D. As such, we expect the returns to exploratory and exploitative R&D to be similar for firms that choose to be ambidextrous (rather than specialized). Ambidextrous firms that choose to engage in both activities have to acquire and integrate new knowledge into their organisational routines, but also utilize and develop different capabilities and skills to those that are habitually use (Turner et al., 2013; Gibson and Birkinshaw, 2004; Koryak et al., 2018). This in turn builds their competence into advancing their know-how in order to gain greater expertise and insights relevant to their specific investments (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). Given that the firm chooses to pursue both exploratory and exploitative R&D, the accumulation of new skills and capabilities associated with the two activities are likely to be the same. For this reason, we expect the returns to those investments to be similar (Figure 3 summarizes this relationship). Building on the above views, we introduce the following hypothesis:

H6: *For firms that pursue an ambidextrous strategy, the effects of exploratory R&D investment on firm performance are similar with the effects of exploitative R&D investment on firm performance.*

Figure 3 – Interaction effects of specialization



DATA AND METHODS

The Data and Methods used in this study are described in greater detail in the Method Section of Chapter 4 of this PhD thesis.

Sample

To test the hypotheses, we need firm-level longitudinal data as the effects of exploration activities take time to materialize (March, 1991) and exploratory competencies require time to accumulate and strengthen (Rhee and Kim, 2014). We collect data from a national innovation survey that is designed to monitor the economic development and technological activities of Spanish firms. Similar to the Community Innovation Survey (CIS) in other countries, there is high reliability in the reported data because the survey is administered every two years by the National Statistics Institute (INE) in Spain and sent to firms that are legally obliged to respond (Armando and Mendi, 2018; D'Estee et al., 2017). As a result, over 90% response rate is achieved. This dataset is appropriate for testing our hypotheses because it provides a detailed breakdown of the distribution of R&D expenditure by type (exploitative and exploratory R&D). Our analysis focuses on firms with more than 10 employees. Instead of focusing on a single industry (Rothaermel, 2001; He and Wong, 2004), we examine 56 industries to increase variability in our data and test the effects of specialization in industries with different orientation. The initial sample consisted of 41,196 firm-year observations that had information on exploratory and exploitative investments. However**,** after deleting missing and ambiguous observations, and firms that had less than four years of information, the final sample resulted in an unbalanced panel of 32,527 observations (5567 firms) over the 2003-2012 period.

DEPENDENT VARIABLE

Following common practice and the literature on R&D (Kafouros et al., 2018; Adams and Jaffe, 1996; Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b), we measure firm performance by estimating its productivity performance (TFP). As explained in detail in Chapter 4, the choice of TFP as our dependent variable was based on three reasons. First, TFP considers the firm's outputs (i.e., sales both from products and services) but also inputs i.e., the firm's investment in labour (reflected in number of employees) and tangible assets (or capital). Thus, TFP reflects the ability of the firm to make sales while controlling for the cost of inputs that a firm utilizes to achieve a certain level of output. By implication, TFP measures avoid biases that often derive from the fact that different outputs may exhibit different economies of scale (Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b). Second, TFP reflects that R&D investments could lead to both product and process innovations. This implies that although the development of new products could affect a firm's sales, process innovations may influence the firm's cost or modify its labour capital and thus enhance its productivity by leading to efficiency gains due to better allocation of resources. Third, while other measures such as firm profitability are unstable and often take negative values, productivity measures remain stable regardless of fluctuations in the market, variations of exchange rate, and accounting standards (Buckley, 1996).

In estimating TFP, we estimate a 'residual'. This residual (with nominator the firm's *output* (firm sales) and denominator the firm's inputs (labour and capital) reflects variations in firm output that cannot be explained by variations in firm inputs. The estimation of TFP (is given in Equation 1 in Chapter 4) and as explained, it reflects the intermediate capacity of inputs into outputs which reflects the firm' proficiency in generating value from specific input. Since economic relationships are rarely linear and to ease the interpretation of our results, we followed standard methodology and transform the TFP measure in its logarithmic form (Van Beveren, 2012; Qingwang and Junxue, 2005).

INDEPENDENT VARIABLES

Firms' Exploitative and Exploratory R&D

Consistent with prior research (D'Este et al., 2017; March, 1991; Jansen et al., 2006; He and Wong, 2004; Shift, 2016) and the survey's definitions (PITEC), exploration consists of the *creative basic & applied research* conducted by firms in order to develop new knowledge that aims at creating something new to business and market. By contrast, exploitation consists of the *systematic technological development* that relies upon the firm's existing knowledge that has been accumulated through repetition and practical experience that aims at refining or improving substantially existing products and processes. As explained in detail in Chapter 4, firms in the survey report the distribution of their current R&D expenditure by type of research. Accordingly, we measure exploration using the log of each firm's annual investment in exploratory/experimental research activities (once again, we divide it by the number of employees to normalize for firm size). Similarly, we measure exploitation using the log of each firm's annual investment in exploitative activities (normalized for firm size).

Firms' Specialization in Exploratory, Exploitative R&D and Ambidexterity (for the convenience of the examiners, we have reproduced this section from Chapter 4. Nevertheless, for greater details on operationalization of variables please refer to Chapter 4)

Following previous studies (He and Wong, 2004; Cao et al., 2009) we use the absolute (percentage) difference between firms' expenditure on exploratory and exploitative activities. Building on the definition that specialization is a strategy by which firms limit the scope of their activities, we classify a firm as specialized in one activity when it spends over 66.6% of its internal R&D budget on either exploration or exploitation. This means that a firm's investment in one of the two activities is at least two times higher than its investment in the other activity. In operationalising the specialization in exploratory and exploitative R&D variables we used two different approaches. First, we use is a year-specific measure of specialization that reflects what the firms does in a given year. This variable is time-variant because a firm could specialize in exploratory R&D in one year but not in the next year. Second, we estimate the average percentage of each firm's budget spent on exploratory and exploitative R&D throughout the sampled years. This classification ensures that a firm remains specialized in one activity over a long period of time (rather than for just 2-3 years). We accordingly create two variables, one for specialization in exploration and one for specialization in exploitation, that take the value of 1 when a firm specializes in one of the two activities (and 0 otherwise). Further, when the percentage of the firm's budget is thus between 33.3% and 66.6%, these firms were categorized as firms with ambidextrous investments (i.e., ambidextrous firms).

CONTROL VARIABLES

We further control for various firm- and industry-specific factors that may affect firm performance. First, we control for each firm's *tangible resources* (Auh and Menguc, 2005; Jansen et al., 2006; Lubatkin et al., 2006), measured as the log of each firm's gross investment in tangible resources in each year. This may account for the difficulties that resource-constrained firms encounter in different industrial environments (Hannan and Freeman, 1984; Tushman et al., 1985). Second, we control for *newly created* firms using a dummy variable that takes the value of 1 if a firm is newly created (Laursen and Salter, 2006). This variable may affect firm performance by influencing a firm's ability to find collaborators, establish itself in an industry and accumulate different types of knowledge.

Third, we control for each firm's *international sales* (dummy variable that takes the value of 1 for firms that sell their products abroad) because a firm's market expansion is associated with its growth (He and Wong, 2004), international competitiveness and access to new market knowledge (Cassiman and Veugelers, 2006). Fourth, we control for *affiliated firms* using a dummy variable that takes the value of 1 for firms that are affiliated to groups (Khanna and Palepu, 1997; Blindenbach-Driessen and Ende, 2014) and may therefore enjoy certain advantages that enhance their performance. Fifth, given that a firm's appropriability strategy may affect its performance (Laursen and Salter, 2006; 2014), we control for the mechanism that each firm uses to protect its inventions (Vega-Jurado et al., 2008). These mechanisms include the use of four *protection* mechanisms (patents, utility models, trademarks and copyrights. This variable therefore ranges from 0 to 4, depending on how many of these mechanisms each firm employs.

However, firm performance can also be affected by industry-specific attributes. We control for industry's intensity of *competition* operationalized using the number of 2-digit intra-industry competitors (Jansen et al., 2006) because in highly competitive industries firms are forced to improve operational efficiency (Matusik and Hill, 1998) and avoid risk-taking behavior (Miller and Friesen, 1983; Auh and Menguc, 2005) or experiment with novelties to avoid obsolescence (Uotila et al., 2009). Because this measure does not capture the market share of firms and whether few firms control most of the market, we also estimated Herfindahl Index (the results from the regressions of this chapter Herfindahl Index as a measure of competition). As explained in the general method section of this thesis, Herfindahl Index (HI) is an appropriate measure of industry concentration (Kafouros and Aliyev 2016; Wu et al. 2016). We estimated HI by summing of squared market shares of firms in the industry. It is thus calculated as $CI_j = 1 - \sum_{i=1}^{n} s_{ij}^2$, where s_{ij} is the market share of firm i in industry j and therefore it takes values between 0 and 1. The higher the value of Herfindahl Index the lower the concentration level within an industry, reflective thus of low levels of competition. We therefore use the inverse value of the Herfindahl Index (i.e. 1- Herfindahl Index) so that a higher value indicates high levels of competition.

We control for *time effects* by including in the model year dummies (that equals 1 that corresponds to specific year) to account for differences in economic trends over years (Belderbos et al., 2010). In models that are not nested in industries (i.e. when they are not multi-level), we also include industry dummies in our model to account for the different industry characteristics and variations in their nature, both technological and economic. Further, we include in the model a binary variable that represents those firms that operate in high-technological industries. As explained in the method section of this thesis, in constructing this variable we use the OECD classification (given in COTEC Report 1997 cited in Bayona Sáez and Arribas, 2002). *High-tech industries* refer to sectors such as chemicals, pharmaceutical, computing, electronics, electrical, communication, and medical devices and optical instruments. By contrast, medium and low-tech industries include sectors such as textiles, furniture, leather, rubber and plastic (taking the value of 1 when firms operate in high tech industries and 0 otherwise). We also control for the *industry's R&D intensity* using the industry's total R&D expenditure divided by total industry sales (Uotila et al., 2009) because in environments with high levels of R&D spending, there are abundancy of technological opportunities than in environments with lower R&D spending (Zahra, 1996). These opportunities may influence firm performance (Baysinger and Hoskisson, 1989). Finally, when using GLS as an alternative estimator, we included *industry dummies* in our model to control for technological and economic variations.

ESTIMATION METHOD (Since the estimation method remains the same across the three empirical chapters of this thesis, we have reproduced below a cut-down version for the convenience of examiners. Please refer to the method section of Chapter 4 for greater details and reasoning for our choice)

As explained in Chapter 4, given that our sampled firms are clustered within industries, a *Multilevel Mixed Model* approach was better suited for estimating TFP (Bliese and Ployhart, 2002; Preacher et al., 2006; Anderson, 2014; Pindado et al., 2012). As explained the choice of Multilevel Mixed estimator was driven by two factors: First, in contrast to traditional panel data estimators, multilevel analysis with mixed effects considers both FE and RE effects. Second, the model is specified at different levels, meaning that it produces coefficients that are nested in each industry and firm. Third, by nesting the effects within each firm the analysis has the additional benefit of producing an estimator that is very close to FE since it estimates the effects separately for each firm and industry separately (Wooldridge, 2000; Blundell and Bond, 2000). Although as we explained, we experimented with other estimators such as FE and RE, the fact that we expected the effects of specialization strategies and exploration/exploitation investment to vary a lot depending on the industry made this estimator less appropriate to reveal variability at both industry and firm level. Thus, our chosen estimator allows us to explicitly specify the estimation with complicated clustering patterns near models while relies on the assumption of independence of error terms, which may be violated when firms are clustered in various industries (Hox et al., 2017; Anderson, 2014; Preacher et al., 2006). As a robustness check, we also used alternative estimators to establish consistency across our results, including the generalized least squares (GLS) estimator which is appropriate when using longitudinal data (Wooldridge, 2000; Blundell and Bond, 2000).

As discussed in detail in Chapter 4 of the PhD thesis, we followed established practice and specified our model (refer to equation 2) (Temouri et al., 2008). We also transform the variables in their logarithmic form to ease the interpretation of our findings (Qingwang and Junxue, 2005; Van Beveren, 2012). However, in equation 2 for testing the hypotheses of Chapter 5, we also added the specialization variables and interaction terms.

RESULTS

Table 1 presents the descriptive statistics and correlations of the variables used in the model and Table 2 reports the regression results. Consistent with prior studies, we mean-centered those variables that were included in the interactions to mitigate potential problems with multicollinearity (Cao et al., 2009; He and Wong, 2004; Lin et al., 2012). We also estimated VIF (Variance Inflation Factor) to avoid multicollinearity in the variables chosen (Wooldridge, 2001; Hansen, 2010). The maximum VIF obtained in any of the models for substantive variables was significantly below the cut-off of 2 for regression models (O'Brien, 2007; Lin et al., 2012). Specifically, the highest VIF we obtained from our analysis was 1.55 with average 1.15. Thus, since VIF is considerably lower than the critical value, we rule out the potential bias in our coefficients due to multicollinearity.

Table 1 – Descriptive statistics and correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Total Factor Productivity	1.000													
2	Specialization in Exploratory R&D	0.015	1.000												
3	Specialization in Exploitative R&D	0.001	-0.544	1.000											
4	Specialization in ambidexterity	-0.016	-0.427	-0.527	1.000										
5	Exploratory R&D	-0.042	0.477	-0.822	0.403	1.000									
6	Exploitative R&D	-0.066	-0.791	0.464	0.302	-0.202	1.000								
7	Tangible Assets	0.227	0.013	-0.036	0.025	0.085	0.044	1.000							
8	International Sales	0.246	0.004	-0.023	0.021	0.025	0.003	0.069	1.000						
9	Affiliated Firms	0.355	-0.020	0.012	0.007	-0.032	-0.013	0.094	0.106	1.000					
10	Industry Competition	0.071	0.057	-0.069	0.016	0.062	-0.040	0.039	0.153	-0.016	1.000				
11	Protection	0.144	-0.003	-0.036	0.042	0.053	0.020	0.083	0.166	0.143	0.102	1.000			
12	Industry's R&D intensity	-0.316	0.035	-0.100	0.072	0.244	0.149	0.028	-0.062	-0.096	0.038	0.024	1.000		
13	Newly Created Firms	-0.055	-0.007	-0.007	0.014	0.030	0.031	0.018	-0.051	-0.007	-0.006	-0.021	0.050	1.000	
14	High Technological Firms	0.157	0.065	-0.079	0.020	0.130	0.005	0.027	0.137	0.037	0.177	0.093	-0.087	-0.014	1.000
	Mean	0.066	0.306	0.401	0.292	4389	4917	8.786m	0.770	0.465	0.925	-3.863	0.070	0.005	0.219
	Std. Dev.	0.841	0.461	0.490	0.455	20822	17295	86.8m	0.421	0.499	0.088	3.541	0.198	0.073	0.413
	Min	-3.812	0.000	0.000	0.000	0.000	0.001	29.000	0.000	0.000	0.000	-6.908	0.001	0.000	0.000
	Max	3.660	1.000	1.000	1.000	2371429	1489540	3bn	1.000	1.000	0.988	1.386	8.726	1.000	1.000

Table 2 – Regression results (Mixed Multilevel Model)

	Model 1			Model 2			Model 3		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1a: Exploratory R&D				0.007***	0.001	0.000	0.029***	0.007	0.000
H1b: Exploitative R&D				0.007***	0.001	0.000	0.029***	0.007	0.000
H2: Exploratory R&D X Exploitative R&D							-0.003***	0.001	0.001
H3a: Specialization in Exploratory R&D									
H3a: Specialization in Exploitative R&D									
H3b: Specialization in Ambidexterity									
Tangible Assets	-0.002	0.004	0.629	-0.003	0.004	0.416	-0.0037	0.004	0.382
International Sales	0.036*	0.015	0.017	0.035*	0.016	0.022	0.035*	0.015	0.023
Affiliated Firms	0.123***	0.016	0.000	0.124***	0.016	0.000	0.125***	0.016	0.000
Industry Competition	0.274†	0.152	0.071	0.269†	0.151	0.075	0.268†	0.151	0.075
Protection	0.004**	0.002	0.008	0.003*	0.002	0.012	0.003*	0.002	0.011
Industry's R&D intensity	-0.205†	0.107	0.055	-0.212*	0.105	0.043	-0.219*	0.105	0.037
Newly Created Firms	-0.305***	0.080	0.000	-0.309***	0.080	0.000	-0.307***	0.080	0.000
High Technological Firms	0.067	0.115	0.560	0.051	0.116	0.658	0.042	0.115	0.718
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.204	0.128	0.112	-0.266*	0.130	0.040	-0.418**	0.134	0.002
Industry Variance	0.2588	0.0684		0.2622	0.0682		0.2621	0.0683	
Firm Variance	0.4973	0.0437		0.4965	0.0437		0.4951	0.0435	
Residual Variance	0.1266	0.0148		0.1264	0.0148		0.1262	0.0148	
Wald chi2 (18-20)	175.92	P>	0.000	233.720	P>	0.000	266.860	P>	0.000
Number of observations	32527			32527			32527		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

Table 2 – Regression results (cont.) (Mixed Multilevel Model)

	Model 4	Model 5	Model 6	Model 7

	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1a: Exploratory R&D	0.005***	0.001	0.000	0.011***	0.002	0.000	0.010***	0.002	0.000	0.009***	0.003	0.000
H1b: Exploitative R&D	0.013***	0.003	0.000	0.006***	0.002	0.000	0.010***	0.002	0.000	0.012***	0.003	0.000
H2: Exploratory R&D X Exploitative R&D												
H3a: Specialization in Exploratory R&D	0.057**	0.022	0.008							0.052*	0.022	0.015
H3a: Specialization in Exploitative R&D				0.035*	0.015	0.016				0.028†	0.015	0.053
H3b: Specialization in Ambidexterity							-0.041**	0.014	0.003	0.000	(omitted)	
Tangible Assets	-0.004	0.004	0.376	-0.004	0.004	0.392	-0.004	0.004	0.357	-0.004	0.004	0.361
International Sales	0.035*	0.016	0.023	0.035*	0.016	0.022	0.035*	0.016	0.023	0.035*	0.016	0.023
Affiliated Firms	0.124***	0.016	0.000	0.124***	0.017	0.000	0.125***	0.017	0.000	0.124***	0.016	0.000
Industry Competition	0.267†	0.151	0.075	0.268†	0.151	0.075	0.268†	0.149	0.073	0.266*	0.150	0.076
Protection	0.003*	0.002	0.015	0.003*	0.002	0.014	0.003*	0.002	0.016	0.003*	0.002	0.015
Industry's R&D intensity	-0.216*	0.105	0.039	-0.214*	0.105	0.041	-0.216*	0.105	0.039	-0.217*	0.105	0.038
Newly Created Firms	-0.308***	0.080	0.000	-0.309***	0.080	0.000	-0.307***	0.080	0.000	-0.308***	0.080	0.000
High Technological Firms	0.047	0.116	0.686	0.047	0.116	0.689	0.052	0.115	0.653	0.046	0.116	0.693
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.305*	0.135	0.024	-0.294*	0.134	0.028	-0.283*	0.131	0.031	-0.321*	0.138	0.020
Industry Variance	0.0009	0.0007		0.0009	0.0010		0.0017	0.0019		0.0009	0.0007	
Firm Variance	0.4965	0.0437		0.4961	0.0437		0.4958	0.0435		0.4962	0.0437	
Residual Variance	0.1262	0.0148		0.1263	0.0148		0.1262	0.0148		0.1262	0.0148	
Wald chi2 (18-20)	220.08	P>	0.000	268.920	P>	0.000	236.62	P>	0.000	267.710	P>	0.000
Number of observations	32527			32527			32527			32527		

Table 2 – Regression results (cont.) (Mixed Multilevel Model)	**Model 8**			**Model 9**			**Model 10**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
Exploratory R&D	0.005***	0.001	0.000	0.005***	0.001	0.000	0.011***	0.003	0.000
Exploitative R&D	0.011***	0.003	0.000	0.019***	0.004	0.000	0.006***	0.001	0.000
Specialization in Exploratory R&D	-0.110	0.058	0.057	0.103***	0.029	0.000			
Specialization in Exploitative R&D							0.021	0.050	0.675
Specialization in Ambidexterity									
H4: Specialization in Exploratory R&D X Exploratory R&D	0.020**	0.007	0.003						
H4: Specialization in Exploratory R&D X Exploitative R&D				-0.007†	0.004	0.069			
H5: Specialization in Exploitative R&D X Exploitative R&D							0.002	0.006	0.750
H5: Specialization in Exploitative R&D X Exploratory R&D									
H6: Specialization in Ambidexterity X Exploratory R&D									
H6: Specialization in Ambidexterity X Exploitative R&D									
Tangible Assets	-0.0039	0.004	0.348	-0.004	0.004	0.351	-0.004	0.004	0.388
International Sales	0.035*	0.016	0.024	0.035*	0.016	0.022	0.035*	0.016	0.022
Affiliated Firms	0.124***	0.016	0.000	0.125***	0.016	0.000	0.124***	0.017	0.000
Industry Competition	0.266†	0.151	0.078	0.266*	0.150	0.075	0.267†	0.150	0.075
Protection	0.003*	0.002	0.015	0.003*	0.002	0.015	0.003***	0.002	0.013
Industry's R&D intensity	-0.221*	0.102	0.030	-0.216*	0.105	0.039	-0.214*	0.105	0.041
Newly Created Firms	-0.308***	0.079	0.000	-0.308***	0.080	0.000	-0.309***	0.080	0.000
High Technological Firms	0.045	0.116	0.696	0.045	0.116	0.701	0.049	0.116	0.671
Time Effects									
Constant	-0.280*	0.135	0.037	-0.343**	0.133	0.010	-0.288*	0.134	0.031
Industry Variance	0.0014	0.0006		0.0014	0.0006		0.0000	0.0000	
Firm Variance	0.4961	0.0436		0.4961	0.0437		0.4962	0.0437	
Residual Variance	0.1261	0.0148		0.1262	0.0148				
Wald chi2 (18-20)	237.27	P>	0.000	225.060	P>	0.000	281.090	P>	0.000
Number of observations	32527			32527			32527		

Table 2 – Regression results (cont.) (Mixed Multilevel Model)

	Model 11			**Model 12**			**Model 13**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
Exploratory R&D	0.028***	0.006	0.000	0.009***	0.002	0.000	0.009***	0.002	0.000
Exploitative R&D	0.006***	0.001	0.000	0.010***	0.002	0.000	0.010***	0.002	0.000
Specialization in Exploratory R&D									
Specialization in Exploitative R&D	0.179***	0.045	0.000						
Specialization in Ambidexterity				-0.109**	0.041	0.008	-0.110*	0.038	0.004
H4: Specialization in Exploratory R&D X Exploratory R&D									
H4: Specialization in Exploratory R&D X Exploitative R&D									
H5: Specialization in Exploitative R&D X Exploitative R&D									
H5: Specialization in Exploitative R&D X Exploratory R&D	-0.021***	0.006	0.000						
H6: Specialization in Ambidexterity X Exploratory R&D				0.009†	0.006	0.087			
H6: Specialization in Ambidexterity X Exploitative R&D							0.009†	0.005	0.068
Tangible Assets	-0.004	0.004	0.313	-0.004	0.004	0.341	-0.004	0.004	0.341
International Sales	0.035*	0.016	0.024	0.035*	0.016	0.022	0.035*	0.016	0.023
Affiliated Firms	0.125***	0.017	0.000	0.125***	0.017	0.000	0.125***	0.017	0.000
Industry Competition	0.260†	0.150	0.082	0.266†	0.149	0.074	0.265*	0.149	0.075
Protection	0.003*	0.002	0.012	0.004	0.002	0.016	0.003*	0.002	0.016
Industry's R&D intensity	-0.218*	0.102	0.033	-0.215*	0.105	0.040	-0.215*	0.105	0.040
Newly Created Firms	-0.308***	0.079	0.000	-0.307***	0.080	0.000	-0.307***	0.080	0.000
High Technological Firms	0.044	0.116	0.701	0.052	0.115	0.652	0.052	0.115	0.652
Time Effects									
Constant	-0.410**	0.139	0.003	-0.275*	0.131	0.036	-0.274*	0.132	0.038
Industry Variance	0.000	0.000		0.0017	0.0018		0.0017	0.0018	
Firm Variance	0.496	0.049		0.4959	0.0435		0.4959	0.0435	
Residual Variance	0.126	0.015		0.1262	0.0148		0.1262	0.0148	
Wald chi2 (18-20)	272.030	0.139	0.003	229.260	P>	0.000	234.32	P>	0.000
Number of observations	32527			32527			32527		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

Model 1 is our basic model and includes only the control variables. We test the performance effects of exploratory and exploitative R&D investments on firm performance (TFP) in Model 2. This corresponds to H1a which suggests that investments in exploratory R&D has a positive direct effect on firm performance and H1b which predicts that investments in exploitative R&D have a positive direct effect on firm performance. These effects are positive and statistically significant at 0.1% level, indicating that investment in exploratory and exploitative R&D enhances firm performance. Hence, these results support H1a and H1b.

Model 3 tests the interaction effects between exploratory R&D and exploitative R&D on firm performance. It therefore tests the validity of H2a that postulates that the joint moderating effect of exploratory R&D and exploitative R&D on firm performance is negative. The results of the analysis indicate that these effects on firm performance (TFP) are negative and statistically significant at the 0.1% level. Therefore, these results support H2. They also support the notion that the two activities do not involve compatible processes and they do not necessarily increase the effects of each other on firm performance.

Models 4-7 test whether the effect of being specialized in either exploratory R&D or exploitative R&D is more advantageous than being ambidextrous. These effects tests H3a (which states that specialization in either exploratory R&D or exploitative R&D has a positive effect on firm performance) and H3b (which suggests that pursuing exploratory R&D and exploitative R&D simultaneously and to a similar extent (ambidextrous strategy) has a negative effect on firm performance). These results show that although the performance effects of specialization in exploratory R&D and exploitative R&D are positive, the effects of being ambidextrous are negative. Therefore, it seems that being specialized in either activity is more beneficial for firm performance than being ambidextrous.

Models 8 and 9 test H4 according to which '*for firms that specialize in R&D exploration, the positive effects of exploratory R&D investment on firm performance are stronger than the effects of exploitative R&D investment on firm performance*'. The interaction effects of exploratory R&D and specialization in explorative R&D are positive at the 1% level, while the interaction effects of exploitative R&D are negative at the 10% level, supporting therefore our theoretical prediction.

Models 10 and 11 test H5. This hypothesis predicts that '*for firms that specialize in exploitative R&D, the positive effects of exploratory R&D investment on firm performance are weaker than the effects of exploitative R&D investment on firm performance*'. Our analysis indicates that the interaction effects between exploratory R&D and specialization in exploitation are negative at the 0.1% level, while the interaction effects between exploitative R&D and specialization in exploitation are positive (but statistically insignificant), partly supporting our theoretical prediction stated in H5.

Finally, Models 12 and 13 test H6. This hypothesis explores whether the effects of exploratory

R&D and exploitative R&D investment differ for firms that are ambidextrous. According to H6, '*for firms that pursue an ambidextrous strategy, the effects of exploratory R&D investment on firm performance are similar with the effects of exploitative R&D investment on firm performance'.* The results indicate that the interaction effects of both exploratory R&D and exploitative R&D are similar and positive at the 10% level, thus supporting Hypothesis 6.

ROBUSTNESS CHECKS AND ADDITIONAL ANALYSIS

Results using Alternative Estimators

To check the robustness of the above results to alternative estimation methods, we also used Generalized Least Squares (GLS) as an alternative estimator to Multilevel Mixed Model (Wooldridge, 2001; Hansen, 2010). The new results using the GLS estimator are reported in Table 3. Overall, the majority of the hypotheses are supported. Specifically, the results in Model 2 indicate that the direct effects of both exploratory R&D and exploitative R&D on firm performance are positive and statistically significant at the 0.1% level, supporting thus H1a and H1b. Model 3 shows that the interaction between exploratory and exploitative R&D on firm performance is negative and statistically significant at the 0.1% level. Thus, Hypothesis 2 is also supported with the GLS estimator. Models 4-7 indicate that while specialization in exploratory and exploitative R&D has a positive effect on firm performance (at 1% and 5% level of significance, respectively), being ambidextrous has a negative effect on firm performance (at 1% level), supporting H3a and H3b.

Models 8 and 9 support H4, indicating that the interaction effects of exploratory R&D are positive at the 1% level, while the interaction effects of exploitative R&D are negative at the 10% level. Those findings give support to the idea that for firms that specialize in exploratory R&D, the effects of engaging in the same activity (i.e., exploratory R&D) are stronger than the effects of engaging in the opposite activity (i.e., exploitative R&D) on firm performance. Models 10 and 11 indicate that for firms that specialize in exploitation R&D, the effects of exploratory R&D investment are negative at the 0.1% level, while the effects of exploitative R&D are positive but statistically insignificant (i.e., H5 is partly supported). Models 12 and 13 indicate that the interaction effects of both exploratory and exploitative R&D (an ambidextrous strategy) are similar and positive at the 10% level, supporting thus H6.

Overall, the results are in favour of a specialization over an ambidextrous strategy, indicating that specialized in exploratory R&D firms may benefit from exploratory R&D investments, whereas specialized in exploitative R&D firms may benefit from exploitative R&D investments.

Table 3*:* Regression Results (using GLS, RE)	Model 1 Coef.	S.E	P	Model 2 Coef.	S.E	P	Model 3 Coef.	S.E	P
H1a: Exploratory R&D				0.007***	0.001	0.000	0.029***	0.005	0.000
H1b: Exploitative R&D				0.007***	0.002	0.000	0.029***	0.005	0.000
H2: Exploratory R&D X Exploitative R&D							-0.003***	0.001	0.000
H3a: Specialization in Exploratory R&D									
H3a: Specialization in Exploitative R&D									
H3b: Specialization in Ambidexterity									
Tangible Assets	-0.002	0.003	0.579	-0.003	0.003	0.306	-0.003	0.003	0.259
International Sales	0.039**	0.014	0.004	0.038**	0.014	0.005	0.03**	0.014	0.005
Affiliated Firms	0.131***	0.014	0.000	0.132***	0.014	0.000	0.133***	0.014	0.000
Industry Competition	0.293*	0.128	0.022	0.287*	0.129	0.026	0.287*	0.129	0.025
Protection	0.004*	0.001	0.004	0.004*	0.001	0.007	0.004**	0.001	0.006
Industry's R&D	-0.197†	0.101	0.052	-0.204*	0.100	0.041	-0.213*	0.100	0.034
Newly Created Firms	-0.307***	0.092	0.001	-0.310***	0.092	0.001	-0.309***	0.092	0.001
High Tech. Firms	0.068	0.122	0.579	0.062	0.123	0.612	0.061	0.122	0.617
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Industry Dummies	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.539***	0.167	0.001	-0.614***	0.168	0.000	-0.777***	0.171	0.000
Wald chi2/F statistic (70-73)	12432	P>	0.000	12457	P>	0.000	12519	P>	0.000
R squared	0.3333			0.335			0.337		
Number of observations	32527			32527			32527		
Number of firms	5567			5567			5567		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

Table 3: Regression Results, cont. (using GLS, RE)	**Model 4**			**Model 5**			**Model 6**			**Model 7**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1a: Exploratory R&D	0.005***	0.001	0.000	0.011***	0.002	0.000	0.010***	0.002	0.000	0.009***	0.002	0.000
H1b: Exploitative R&D	0.013***	0.003	0.000	0.006***	0.002	0.000	0.010***	0.002	0.000	0.012***	0.003	0.000
H2: Exploratory R&D X Exploitative R&D												
H3a: Specialization in Exploratory R&D	0.050***	0.016	0.001							0.045*	0.016	0.004
H3a: Specialization in Exploitative R&D				0.036*	0.017	0.027				0.029†	0.017	0.082
H3b: Specialization in Ambidexterity							-0.037***	0.011	0.001		(omitted)	
Tangible Assets	-0.003	0.003	0.259	-0.0032	0.003	0.276	-0.003	0.003	0.243	-0.0034	0.003	0.242
International Sales	0.038**	0.014	0.005	0.038**	0.014	0.005	0.038**	0.014	0.005	0.038**	0.014	0.005
Affiliated Firms	0.132***	0.014	0.000	0.132***	0.014	0.000	0.132***	0.014	0.000	0.132***	0.014	0.000
Industry Competition	0.285*	0.129	0.027	0.285*	0.129	0.027	0.283*	0.129	0.028	0.283*	0.129	0.028
Protection	0.003**	0.001	0.008	0.003**	0.001	0.008	0.003**	0.001	0.008	0.003**	0.001	0.008
Industry's R&D intensity	-0.206*	0.100	0.038	-0.206*	0.100	0.039	-0.208*	0.100	0.037	-0.208*	0.100	0.037
Newly Created Firms	-0.310***	0.092	0.001	-0.311***	0.092	0.001	-0.310***	0.092	0.001	-0.310***	0.092	0.001
High Technological Firms	0.066	0.123	0.593	0.061	0.123	0.619	0.064	0.123	0.605	0.064	0.123	0.600
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Industry Dummies	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.655***	0.167	0.000	-0.640***	0.168	0.000	-0.634***	0.167	0.000	-0.672***	0.168	0.000
Wald chi2/F statistic (73)	12474	P>	0.000	12475	P>	0.000	12478	P>	0.000	12492	P>	0.000
R squared	0.335			0.335			0.335			0.335		
Number of observations	32527			32527			32527			32527		
Number of firms	5567			5567			5567			5567		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10**

Table 3: Regression Results, cont. (using GLS, RE)	**Model 8**			**Model 9**			**Model 10**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
Exploratory R&D	0.005***	0.001	0.000	0.005***	0.001	0.000	0.011***	0.003	0.000
Exploitative R&D	0.011***	0.003	0.000	0.019***	0.004	0.000	0.006***	0.002	0.000
Special. Explor.R&D	0.099†	0.053	0.060	0.099**	0.033	0.003			
Special. Exploit. R&D							0.021	0.046	0.650
Special. Ambid.									
H4: Specialization in Exploratory R&D X Exploratory R&D	0.017**	0.006	0.005						
H4: Specialization in Exploratory R&D X Exploitative R&D				-0.007**	0.005	0.098			
H5: Specialization in Exploitative R&D X Exploitative R&D							0.002	0.005	0.726
H5: Specialization in Exploitative R&D X Exploratory R&D									
H6: Specialization in Ambidexterity X Exploratory R&D									
H6: Specialization in Ambidexterity X Exploitative R&D									
Tangible Assets	-0.003	0.003	0.227	-0.003	0.003	0.232	-0.003	0.003	0.274
International Sales	0.038**	0.014	0.005	0.038**	0.014	0.005	0.038**	0.014	0.005
Affiliated Firms	0.132***	0.014	0.000	0.132***	0.014	0.000	0.132***	0.014	0.000
Industry Competition	0.284*	0.129	0.028	0.284*	0.129	0.028	0.285*	0.129	0.027
Protection	0.003**	0.001	0.008	0.003***	0.001	0.008	0.003**	0.001	0.008
Industry's R&D intensity	-0.211	0.098	0.031	-0.207*	0.100	0.038	-0.206*	0.100	0.039
Newly Created Firms	-0.310	0.091	0.001	-0.310***	0.092	0.001	-0.311***	0.092	0.001
High Technological Firms	0.067	0.123	0.583	0.064	0.123	0.605	0.061	0.123	0.620
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Industry Dummies	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.635***	0.167	0.000	-0.695***	0.168	0.000	-0.637***	0.168	0.000
Wald chi2/F statistic (74)	12485***	P>	0.000	12471***	P>	0.000	12480***	P>	0.000
R squared	0.335			0.335			0.335		
Number of observations	32527			32527			32527		
Number of firms (n)	5567			5567			5567		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10**

Table 3: Regression Results, cont. (using GLS, RE)	**Model 11**			**Model 12**			**Model 13**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
Exploratory R&D	0.029***	0.005	0.000	0.009***	0.002	0.000	0.009***	0.002	0.000
Exploitative R&D	0.006***	0.002	0.000	0.010***	0.002	0.000	0.010***	0.002	0.000
Special. Explor.R&D									
Special. Exploit. R&D	0.181***	0.038	0.000						
Special. Ambid.				-0.099*	0.047	0.033	-0.101*	0.044	0.02
H4: Specialization in Exploratory R&D X Exploratory R&D									
H4: Specialization in Exploratory R&D X Exploitative R&D									
H5: Specialization in Exploitative R&D X Exploitative R&D									
H5: Specialization in Exploitative R&D X Exploratory R&D	-0.022***	0.005	0.000						
H6: Specialization in Ambidexterity X Exploratory R&D				0.009	0.006	0.187			
H6: Specialization in Ambidexterity X Exploitative R&D							0.009	0.006	0.143
Tangible Assets	-0.004	0.003	0.188	-0.004	0.003	0.228	-0.004	0.003	0.227
International Sales	0.038**	0.014	0.005	0.038**	0.014	0.005	0.038**	0.014	0.005
Affiliated Firms	0.133***	0.014	0.000	0.132***	0.014	0.000	0.132***	0.014	0
Industry Competition	0.278*	0.129	0.031	0.281*	0.129	0.029	0.280*	0.129	0.03
Protection	0.003**	0.001	0.008	0.003**	0.001	0.008	0.003**	0.001	0.008
Industry’s R&D intensity	-0.210*	0.098	0.032	-0.207*	0.1	0.037	-0.207*	0.1	0.037
Newly Created Firms	-0.310***	0.092	0.001	-0.310***	0.092	0.001	-0.310***	0.092	0.001
High Technological Firms	0.065	0.123	0.596	0.063	0.123	0.606	0.063	0.123	0.606
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Industry Dummies	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.766***	0.17	0	-0.626***	0.168	0	-0.625***	0.168	0
Wald chi2/F statistic (74)	12516***	P>	0	12491***	P>	0	12490***	P>	0
R squared	0.3352			0.335			0.3353		
Number of observations	32527			32527			32527		
Number of firms (n)	5567			5567			5567		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10**

The Role of Time Lags

The results reported in the previous tables rely on exploratory and exploitative R&D measures that are not lagged. To examine the sensitivity of the hypothesized findings to changes in the lag structure of the exploratory and exploitative R&D measures, we estimated new variables using 1- and 2-year lags to allow for the fact that exploratory and exploitative R&D may take a few years to affect the performance of firms. We then estimated the key models after replacing the initial measures with the lagged ones. This analysis showed that the effects of exploratory and exploitative R&D on firm performance became statistically insignificant. This result implies that exploratory and exploitative R&D generate performance effects rather quickly. Although this result is to some extent surprising, it can be justified by the fact that the firms of the sample undertake exploratory and/or exploitative R&D for several years and therefore there is a stream of output associated not only with a given year but also with previous years.

Differences across High-Tech and Low-Tech Industries

The results presented in the above tables rely on the full sample. I further examine how the hypothesised effects differ across firms that operate in high-tech and low-tech industries. In doing so, I split the sample into those firms that are classified (according to COTEC Report 1997 cited in Bayona Sáez and Arribas, 2002) as firms operating in high-tech industries (such as chemicals, pharmaceutical, computing, electronics, electrical, communication, medical devices and optical instruments) and low-tech industries (such as textiles, furniture, leather, rubber and plastic). I then estimated all the models for those two sub-samples separately. Overall, the results exhibit consistency across high- and low-tech firms and yield a pattern that is almost identical to the results for the full sample.

Specifically, *Hypothesis 1* is confirmed for firms in both high- and low-tech industries (with the only exception being that the effects of exploitative R&D on firm performance for high-tech firms loses its statistical significance). Similarly, the results for *Hypothesis 2* yield similar coefficients (even though the statistical significance changes from 1% to 5% for those firms that operate in high-tech industries). Likewise, *Hypothesis 3* is also supported for both high- and low- tech firms, suggesting once again that there are no significant differences across the two sub-samples (with the only exception being that the level of significance for firms that specialize in exploratory and exploitative R&D is now at 10% from 5% and that those firms that specialize in exploratory R&D become statistically insignificant). Likewise, *Hypothesis 4* is also confirmed for both high- and low- tech firms (even though the statistical significance changes from 1% to 5% only for those firms that specialize in exploratory R&D and invest in exploitative R&D and operate in high tech industries, and from 10% to no significant effects for those firms that operate in low-tech industries.

Hypothesis 5 however is not supported for firms in high tech industries. It appears that it does not support our theoretical prediction that the effects of exploitative R&D are stronger and positive for those firms that specialize in exploitative R&D. Precisely, the effects of specializing in exploitative R&D for those firms that invest in exploitative R&D are negative, yet the level of significance is at 10% and not significant for those firms operating in low-tech industries. Nevertheless, our theoretical prediction that the effects of specializing in exploitative R&D and invest in exploratory R&D is supported for firms operating both in high and low-tech industries (with the only exception being that the level of significance is from 0.1% to 1%).

Finally, *Hypothesis 6* is also supported, and the level of significance improves from 10% to 1% for firms in high-tech industries, but loses its significance for firms in low-tech industries, yet the directionality of the relationship remains the same (i.e., positive). As for ambidextrous firms the effects of exploitative R&D for ambidextrous are stronger and positive, providing thus further support for the hypothesized effects and the level of significance improves from 10% to 1% for firms in high-tech industries, but it loses its significance for firms in low- tech industries, yet the directionality of the relationship remains the same (i.e., positive).

Outliers

We also tested whether the hypothesised effects hold after removing the outliers from the dataset. In doing so, we created the standardised residuals variable and remove from the dataset those cases that were over 3 and less than -3 standard deviations (Howell, 1998; Miller 1991). The final sample were reduced from n=32,527 to n=32,077. Overall, the hypothesised effects were consistent and often improved their significant levels with the exception of hypothesis 6. Specifically, hypothesis 4 which tested the theoretical prediction that for firms that specialize in exploratory R&D, the effects of exploratory R&D investments on firm performance are stronger than the effects of exploitative R&D investment on firm performance improved its significance level from 10% to 0.1%. The same pattern emerged for hypothesis 5. For hypothesis 5, when we treated the dataset for outliers and tested our theoretical prediction that for specialized in exploitative R&D firms the effects of exploitative R&D on firm performance, the statistical significance of the results was improved. Nevertheless, the results for hypothesis 6 for which we predicted similar returns from exploratory and exploitative R&D for ambidextrous firms lost its significance from 10%.

Results for Firms in Manufacturing Industries

We further investigated whether the hypothesised effects hold only for manufacturing firms including those firms that operate in service industries (i.e. industry codes 36; 37; 38; 43; 44; 49; 50; 51; 52; 53; 54; 55). The final sample excluding those firms is estimated at n=27341. Overall, the hypothesised effects were confirmed, exhibiting consistency across the full sample and by excluding those firms that operate in service industries. Specifically, *Hypothesis 1* which suggests that investment in exploratory/exploitative R&D has a positive direct effect on firm performance is also supported and is statistically significant at 0.1% level.

Hypothesis 2 tests the interaction effect of exploratory R&D and exploitative R&D. Specifically, pursuing exploratory R&D and exploitative R&D simultaneously and to a similar extent (ambidextrous strategy) has a negative effect on firm performance is confirmed (the only difference being that it loses its significance from 0.1% to 10%.

Similarly*, Hypothesis 3* which indicates that specialization in either exploratory R&D or exploitative R&D is more advantageous than being ambidextrous is also supported (the only difference being that it loses its significance from 1% to 5% for firms that specialize in exploratory R&D, and from 5% to 10 % for firms that specialize in exploitative R&D, and for ambidextrous firms from 0.1% to 1% level of significance).

Hypothesis 4 which indicates that when specializing in exploratory R&D, the effects of exploratory R&D investment on firm performance are stronger than the effects of exploitative R&D investment on firm performance is partly supported. Although the directionality of the relationship is confirmed, the hypothesised effects of exploratory R&D investment for firms that specialize in exploratory R&D do not reach statistical significance. Yet, the hypothesised effects of exploratory R&D investment for firms that specialize in exploitative R&D are supported.

Also, the results for *Hypothesis 5,* which theoretically predict that for firms that specialize in exploitative R&D, the positive effects of exploratory R&D investment on firm performance are weaker than the effects of exploitative R&D investment on firm performance, are consistent with those obtained when running the regressions for the full sample (i.e., they partly support our theoretical prediction) and yet the directionality of the hypothesized relationships remains as stated in our initial predictions.

Finally, *Hypothesis 6,* which tests whether the effects of exploratory R&D and exploitative R&D investment differ for firms with ambidextrous R&D investments, were also confirmed. This hypothesis not only is supported but improved its statistically significance from 1% level to 0.1%.

Transition Probability Matrices (TPM)

TPM discloses information about the probability of firms changing status i.e., the specialization strategy across years. Overall, the results from the analysis indicate that there is less than 25% (ranging from 11% to 25%) chance for firms in our sample to change specialization strategy from one year to the next. Specifically, the rows in Tables 4a, b, c reflect the initial values, and the columns reflect the final values. In Table 4a, each year, 88.85% of the firms that do not specialize in exploratory R&D in the data remained specialized in exploratory R&D in the next year; the remaining 11.15% became specialized in exploratory R&D. Although those that specialize in exploratory R&D had only a 25.36% chance of not specializing in R&D in each year, those firms that specialize in exploratory R&D had 74.64% chance of remaining specialized in the trajectory they had chosen. Similarly, In Table 4b the chances of firms that specialize in exploitative R&D to change strategy from one year to the next is only 13.52% and 19.26% for those firms that specialize in exploitative R&D. The same pattern is observed for ambidextrous firms (Table 4c). There is only a 10.11% chance that not ambidextrous firms change their strategy to from one year to the next and 25.59% chance for a firm that is ambidextrous to become either exploitative or exploratory the next year. Overall, the firms in our sample exhibit less chances to change their strategy, they are more likely to carry on doing what they currently do in terms of their exploratory and exploitative activities.

Table 4a - Transition Probability Matrices (TPM) For Exploratory Firms

	Firms that do not specialize in Exploratory R&D (%)	Firms that specialize in Exploratory R&D (%)
Do not specialize in Exploratory R&D	88.85	11.15
Specialize in Exploratory R&D	25.36	74.64
Total	69.24	30.76

Table 4b - Transition Probability Matrices (TPM) For Exploitative Firms

	Do not Specialize in Exploitative R&D (%)	Specialize in Exploitative R&D (%)
Do not specialize in Exploitative R&D	86.48	13.52
Specialize in Exploitative R&D	19.26	80.74
Total	59.48	40.52

Table 4c - Transition Probability Matrices (TPM) For Ambidextrous Firms

	No Ambidextrous Firms (%)	Ambidextrous Firms %
Not Ambidextrous Firms	89.89	10.11
Ambidextrous Firms	25.59	74.41
Total	71.28	28.72

Curvilinear Effects

In the previous models, the implicit assumption was made that the effects of exploratory and exploitative R&D on firm performance were linear. This implied that the higher the firm's investment in exploratory and exploitative R&D is, the stronger the positive effects on performance will be. However, both exploratory and exploitative R&D are associated with various advantages and disadvantages that may be more pronounced in lower or higher levels of investment. Subsequently, the effects of exploratory and exploitative R&D on performance might curvilinear. For example, they may follow a U-shape or an inverted U-shape pattern. In order to examine whether such effects are curvilinear, the main models were re-estimated after including squared terms of exploratory and exploitative R&D. Table 5 reports the results for the full sample of firms. As we can observe, the squared terms are in both models statistically insignificant. They do not therefore support the notion of curvilinear effects.

Although the above results do not support the curvilinear effects for the full sample, it may be argued that the pattern of the effects of exploratory and exploitative R&D on firm performance may differ for firms that specialize in one of the two activities. According to the reasoning that was discussed in the theoretical section of the chapter, we expect the effects of exploratory R&D on firm performance to decline more slowly for firms that specialize in exploration, while the effects of exploitative R&D on firm performance should decline more slowly for firms that specialize in exploitation. To explore whether this is the case and whether the curvilinear effects differ between firms that specialize in exploration and those that specialize in exploitation, the models with squared terms were re-estimated for each sub-group of firms separately (i.e. for firms that specialize in exploration and firms that specialize in exploitation).

Table 5 also reports the additional results whereas Figures 4a, 4b, 5a and 5b depict the marginal effects for each subgroup and activity separately. These reveal an interesting pattern of results that shows that the effects differ. Although many of the terms are still statistically insignificant, it is interesting that in the case of firms that specialize in exploration, the effects are steeper for exploratory R&D but much flatter for exploitative R&D. However, the opposite occurs in the case of firms that specialize in exploration, i.e. the effects are steeper for exploitative R&D and flatter for exploratory R&D. To compare the effects more directly, we have also graphically depicted them in Figures 6a and 6b. Overall, these graphical representations of the analysis support the view that specialization in one activity increases the returns to this activity by enhancing efficiency, but not those of the other activity.

Table 5: Regression Results for curvilinear effects

	Full sample						Firms that specialize in Exploratory R&D (9,820 obs)						Firms that specialize in Exploitative R&D (12,876 obs)					
	1			2			3			4			5			6		
	Coeff	se	sig	Coeff	se	sig	Coeff	se	sig	Coeff	se	sig	Coeff	se	sig	Coeff	se	sig
Explorative R&D	0.003	0.003	0.267	0.005	0.001	0.000	0.071	0.034	0.037	0.030	0.010	0.003	0.008	0.007	0.230	0.002	0.003	0.545
Exploitative R&D	0.008	0.001	0.000	0.005	0.003	0.094	0.007	0.005	0.134	0.005	0.012	0.654	0.025	0.008	0.001	0.105	0.032	0.001
Explorative R&D - Squared	0.000	0.000	0.374				-0.003	0.002	0.175				-0.001	0.001	0.322			
Exploitative R&D - Squared				0.000	0.000	0.371				0.000	0.002	0.896				-0.005	0.002	0.009
Tangible Assets	-0.010	0.003	0.000	-0.010	0.003	0.000	-0.007	0.004	0.086	-0.007	0.004	0.069	-0.009	0.004	0.015	-0.008	0.004	0.026
International Sales	0.035	0.011	0.002	0.035	0.011	0.002	0.041	0.022	0.060	0.042	0.022	0.061	0.069	0.019	0.000	0.069	0.019	0.000
Affiliated Firms	0.110	0.014	0.000	0.110	0.014	0.000	0.166	0.019	0.000	0.165	0.019	0.000	0.141	0.023	0.000	0.142	0.023	0.000
Industry Competition	0.253	0.142	0.075	0.254	0.142	0.074	0.429	0.234	0.066	0.430	0.234	0.066	0.113	0.110	0.306	0.098	0.110	0.375
Protection	0.003	0.002	0.054	0.003	0.002	0.054	0.005	0.003	0.161	0.005	0.003	0.183	0.006	0.002	0.003	0.006	0.002	0.003
Industry's R&D intensity	-0.183	0.092	0.047	-0.182	0.092	0.049	-0.308	0.147	0.037	-0.311	0.143	0.030	-0.764	0.221	0.001	-0.762	0.217	0.000
Newly Created Firms	-0.183	0.036	0.000	-0.183	0.036	0.000	-0.215	0.099	0.030	-0.218	0.101	0.030	-0.099	0.067	0.138	-0.098	0.067	0.142
High Technological Firms	0.064	0.117	0.581	0.064	0.117	0.582	0.103	0.112	0.358	0.104	0.113	0.359	0.083	0.105	0.427	0.081	0.104	0.435
Time Effects	inc.			inc.			inc.			inc.			inc.			inc.		
Constant	-0.190	0.137	0.165	-0.189	0.136	0.165	-0.732	0.225	0.001	-0.585	0.231	0.011	-0.219	0.124	0.077	-0.514	0.177	0.004

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10**

Figure 4a - Marginal effects of exploratory R&D for firms that specialize in exploratory R&D

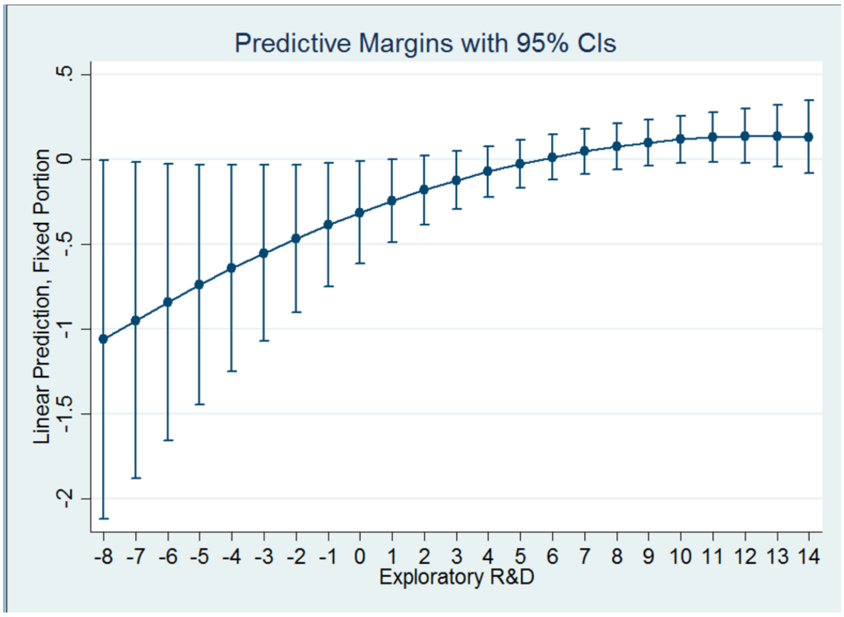


Figure 4b - Marginal effects of exploitative R&D for firms that specialize in exploratory R&D

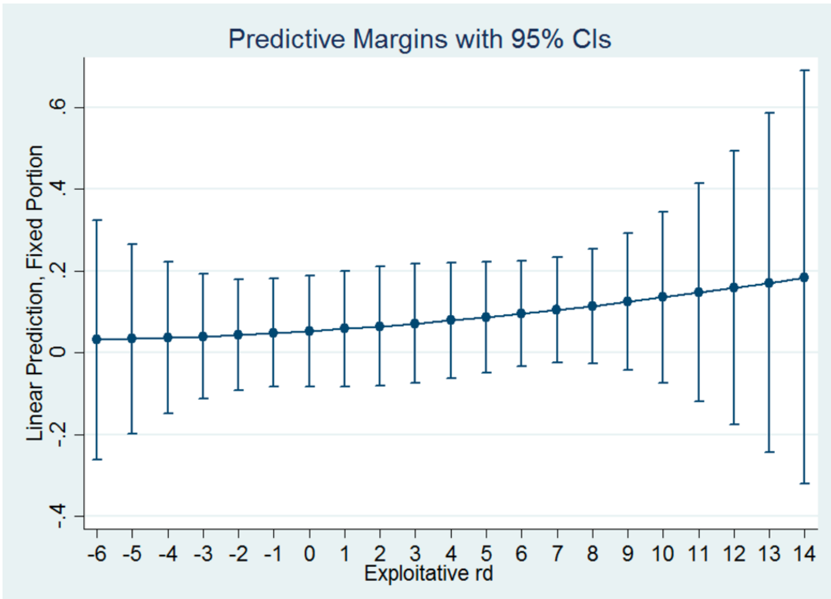


Figure 5a - Marginal effects of exploratory R&D for firms that specialize in exploitative R&D

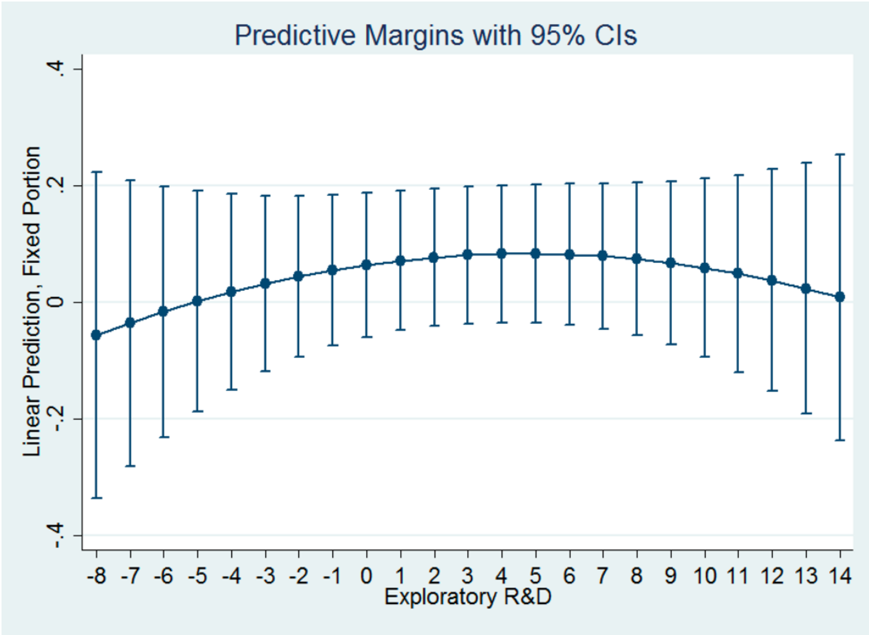


Figure 5b - Marginal effects of exploitative R&D for firms that specialize in exploitative R&D

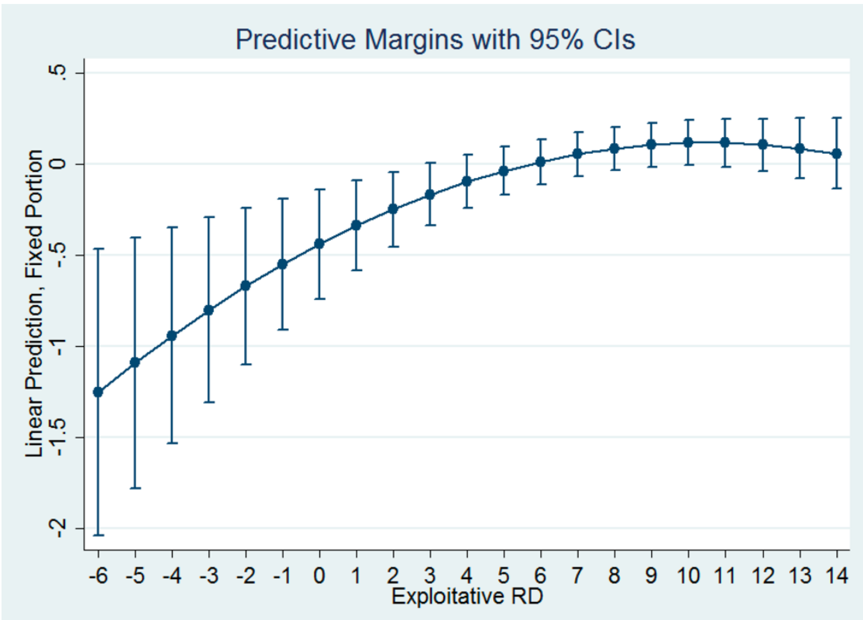


Figure 6a - Effects of R&D exploration squared for firms that specialize in different strategies

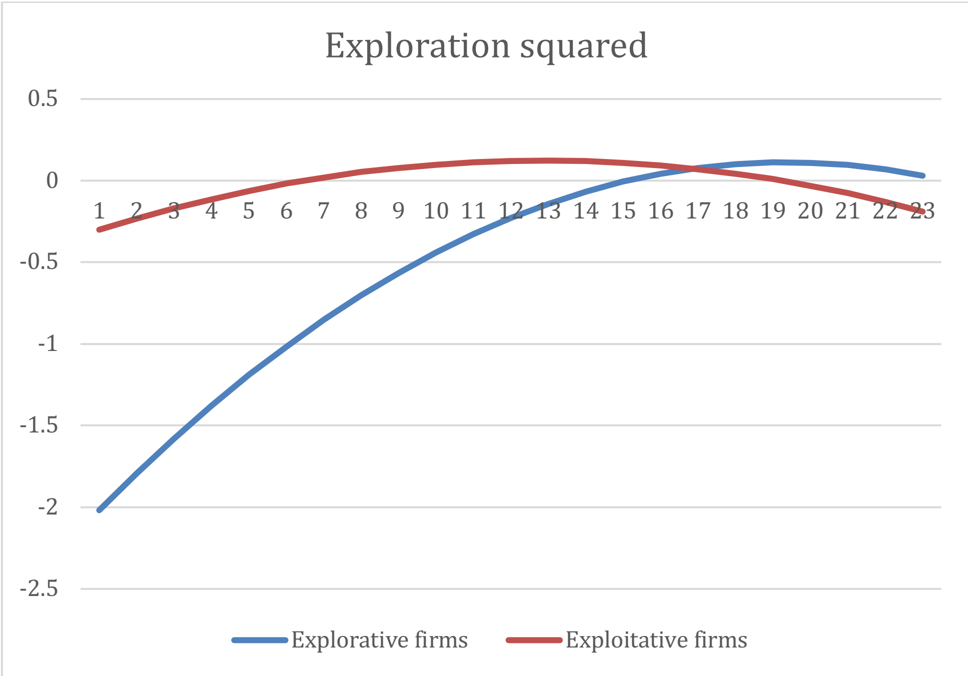
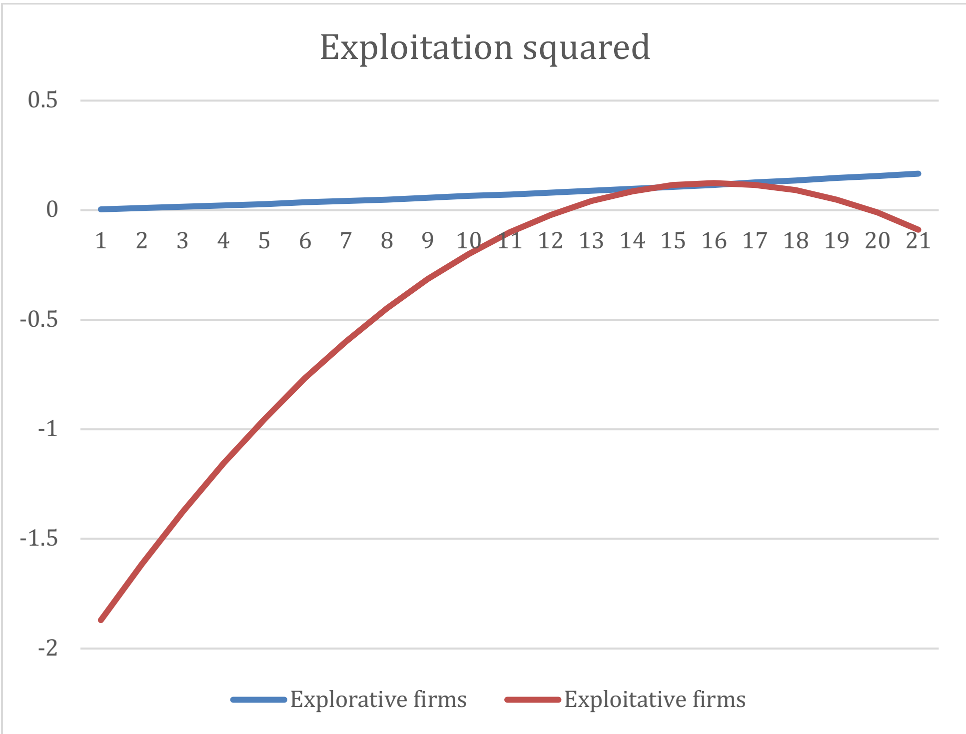


Figure 6b -Effects of R&D exploitation squared for firms that specialize in different strategies



Patterns in Specialization: The effects of Constant Specialization

We have also examined how firms that remain specialized in one activity every year (or remained simultaneously ambidextrous every year) without changing their strategy perform. We term this pattern as “constant specialization”. As noted in the General Methodological Chapter of this thesis, there are three distinct patterns of firms in our dataset that adopt a *constant specialization strategy* (i.e., do not change their specialization strategy throughout their life in the dataset).

These patterns include a) *firms that* remain *specialized in exploratory R&D, b) firms that* remain *specialized in exploitative R&D* and *c)* firms that remain *simultaneously ambidextrous* (i.e. they spend a similar amount of money and resources on both activities). As already discussed, since specialization is a strategy by which firms limit the scope of their activities, we classify a firm as specialized in exploratory or exploitative R&D when this firm spends over 66.6 % of its internal R&D budget on either exploring new technologies or exploiting existing ones. The results from the regression analysis (Table 6) indicate that the effects of remaining constantly specialized on firm performance are statistically insignificant except for those firms that specialize in Exploratory R&D and invest in similar exploratory R&D activities (see Model 4 in Table 6 below).

Table 6: Regression Results for the effects of Constant Specialization on Firm Performance

	Model 1			**Model 2**			**Model 3**		
	Coef.	S. E	P	Coef.	S. E	P	Coef.	S. E	P
Exploratory R&D	0.007***	0.001	0.000	0.007***	0.001	0.000	0.007	0.001	0.000
Exploitative R&D	0.007***	0.001	0.000	0.007***	0.001	0.000	0.008	0.001	0.000
Constant specialization in Exploration	0.016	0.045	0.719						
Constant specialization in Exploitation				0.034	0.035	0.328			
Constant Ambidexterity							-0.007	0.046	0.885
Tangible Assets	-0.003	0.004	0.415	-0.003	0.004	0.412	-0.003	0.004	0.416
International Sales	0.036	0.016	0.022	0.035	0.016	0.022	0.035	0.016	0.022
Affiliated Firms	0.125	0.017	0.000	0.124	0.017	0.000	0.125	0.016	0.000
Ind. Competition	0.269	0.151	0.075	0.270	0.151	0.074	0.269	0.151	0.075
Protection	0.004	0.002	0.013	0.004	0.002	0.013	0.004	0.002	0.012
Industry's R&D	-0.212	0.105	0.043	-0.212	0.105	0.043	-0.213	0.105	0.043
Newly Created	-0.310	0.080	0.000	-0.309	0.080	0.000	-0.309	0.080	0.000
High Tech. Firms	0.034	0.112	0.760	0.056	0.117	0.634	0.051	0.116	0.658
Time Effects	Inc	Inc	Inc	Inc	Inc	Inc	Inc	Inc	Inc
Constant	-0.267	0.129	0.038	-0.276	0.131	0.035	-0.267	0.130	0.040
Ind.Variance	0.032	0.019	0.010	0.014	0.010	0.003	0.000	0.000	0.000
Firm Variance	0.494	0.043	0.416	0.494	0.044	0.416	0.497	0.044	0.418
Residual Variance	0.126	0.015	0.100	0.126	0.015	0.100	0.126	0.015	0.100
Wald chi2 (19)	240.250	P>	0.000	279.390	P>	0.000	246.940	P>	0.000
Number of observations	32527			32527			32527		

$*p < 0.05$; $**p < 0.01$; $***p < 0.001$; †$p < 0.10$

Table 6: Regression Results for the effects from Constant Specialization on Firm Performance (cont.)	**Model 4**			**Model 5**			**Model 6**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
Exploratory R&D	0.007	0.001	0.000	0.007	0.001	0.000	0.007	0.001	0.000
Exploitative R&D	0.007	0.001	0.000	0.007	0.001	0.000	0.007	0.001	0.000
Constant specialization in Exploration	-0.193	0.118	0.102	-0.008	0.052	0.874			
Constant specialization in Exploitation							-0.095	0.089	0.284
Constant Ambidexterity									
Constant specialization in Exploration X Exploratory R&D	**0.026†**	0.015	0.087						
Constant specialization in Exploration X Exploitative R&D				0.009	0.008	0.265			
Constant specialization in Exploitation X Exploitative R&D							0.016	0.011	0.157
Constant specialization in Exploitation X Explorative R&D									
Constant Ambidexterity X Explorative R&D									
Constant Ambidexterity X Exploitative R&D									
Tangible Assets	-0.004	0.004	0.398	-0.003	0.004	0.412	-0.004	0.004	0.398
International Sales	0.036	0.016	0.022	0.035	0.016	0.023	0.035	0.016	0.022
Affiliated Firms	0.125	0.017	0.000	0.125	0.016	0.000	0.124	0.017	0.000
Industry Competition	0.268	0.151	0.076	0.269	0.151	0.075	0.272	0.151	0.072
Protection	0.004	0.002	0.014	0.004	0.002	0.014	0.004	0.002	0.012
Industry's R&D intensity	-0.211	0.104	0.043	-0.212	0.105	0.043	-0.212	0.105	0.044
Newly Created Firms	-0.312	0.080	0.000	-0.310	0.080	0.000	-0.308	0.080	0.000
High Technological Firms	0.033	0.112	0.771	0.034	0.112	0.759	0.054	0.117	0.642
Time Effects	Incl	Incl	Incl	Incl	Incl	Incl	Incl	Incl	Incl
Constant	-0.259	0.129	0.044	-0.261	0.127	0.039	-0.269	0.130	0.039

Ind. Variance	0.034	0.019	0.012	0.034	0.019	0.011	0.013	0.010	0.003
Firm Variance	0.493	0.043	0.416	0.494	0.043	0.416	0.494	0.044	0.416
Residual Variance	0.126	0.015	0.100	0.126	0.015	0.100	0.126	0.015	0.100
Wald chi2 (19-20)	245.400	P>	0.000	282.750	P>	0.000	278.700	P>	0.000
Number of observations	**32527**			**32527**			**32527**		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

Table 6: Regression Results for the effects from Constant Specialization on Firm Performance (cont.)

	Model 7			**Model 8**			**Model 9**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
Exploratory R&D	0.008	0.001	0.000	0.007	0.001	0.000	0.007	0.001	0.000
Exploitative R&D	0.008	0.001	0.000	0.008	0.001	0.000	0.008	0.001	0.000
Constant specialization in Exploration									
Constant specialization in Exploitation	0.036	0.038	0.349						
Constant Ambidexterity				-0.202	0.220	0.360	-0.278	0.210	0.186
Constant specialization in Exploration X Exploratory R&D									
Constant specialization in Exploration X Exploitative R&D									
Constant specialization in Exploitation X Exploitative R&D									
Constant specialization in Exploitation X Explorative R&D	-0.001	0.005	0.888						
Constant Ambidexterity X Explorative R&D				0.024	0.025	0.324			

Constant Ambidexterity X Exploitative R&D							0.034	0.023	0.144
Tangible Assets	-0.003	0.004	0.412	-0.003	0.004	0.404	-0.003	0.004	0.399
International Sales	0.035	0.016	0.023	0.036	0.015	0.022	0.036	0.015	0.021
Affiliated Firms	0.124	0.017	0.000	0.125	0.016	0.000	0.125	0.016	0.000
Industry Competition	0.270	0.151	0.074	0.268	0.151	0.076	0.266	0.151	0.078
Protection	0.004	0.002	0.012	0.004	0.002	0.012	0.004	0.002	0.012
Industry's R&D intensity	-0.213	0.105	0.043	-0.212	0.105	0.043	-0.212	0.105	0.043
Newly Created Firms	-0.309	0.080	0.000	-0.309	0.080	0.000	-0.309	0.080	0.000
High Technological Firms	0.056	0.117	0.634	0.052	0.116	0.657	0.052	0.116	0.657
Time Effects	Incl	Incl	Incl	Incl	Incl	Incl	Incl	Incl	Incl
Constant	-0.277	0.131	0.035	-0.264	0.129	0.041	-0.261	0.129	0.043
Ind. Variance	0.014	0.010	0.003	0.263	0.068	0.158	0.263	0.068	0.158
Firm Variance	0.494	0.044	0.416	0.496	0.044	0.418	0.496	0.044	0.418
Residual Variance	0.126	0.015	0.100	0.126	0.015	0.100	0.126	0.015	0.100
Wald chi2 (19-20)	280.210	P>	0.000	242.670	P>	0.000	242.710	P>	0.000
Number of observations	**32527**			**32527**			**32527**		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

Results using Split Analysis

Although the correlation between specialization strategies and exploratory/exploitative R&D is not particularly high, we have further tested Hypotheses 4 and 5 using split analysis rather than moderated regression analysis (interactions). Hypothesis 4 suggested that for firms that specialize in exploratory R&D, the positive effects of exploratory R&D investment on firm performance are stronger than the effects of exploitative R&D investment on firm performance. Hypothesis 5 suggested that for firms that specialize in exploitative R&D, the effects of exploratory R&D investment on firm performance are weaker than the effects of exploitative R&D investment on firm performance. To test these hypotheses using split analysis, we re-run the main model separately for groups of firms that specialize in exploratory R&D and groups of firms that specialize in exploitative R&D.

Table 7 reports the new results. The results confirm H4 and H5 and the hypothesised effects are consistent with those results when running the regressions on the sub-samples. The theoretical prediction that the effect of exploitative R&D on firm performance is stronger for those firms that specialize in exploitative R&D is confirmed in Model 1 (whereas exploratory R&D is not significant). A similar pattern is also observed when firms specialize in exploratory R&D with its effects being stronger for specialized in exploratory R&D firms (whereas the effects of exploitative R&D are not significant in Model 2).

Table 7: Regression Results using Split Analysis for firms with Different Specialization

	Specialize Exploitative R&D			**Specialize Explorative R&D**			**Ambidextrous**		
	Model 1			**Model 2**			**Model 3**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
Exploratory R&D	0.001	0.003	**0.769**	0.034*	0.014	0.017	0.035**	0.011	0.002
Exploitative R&D	0.025**	0.009	0.005	0.008	0.006	**0.192**	0.012	0.010	0.216
Tangible Assets	0.003	0.006	0.571	-0.004	0.003	0.227	-0.007	0.008	0.418
International Sales	0.084***	0.023	0.000	0.027	0.029	0.345	0.039	0.026	0.138
Affiliated Firms	0.154***	0.027	0.000	0.186***	0.028	0.000	0.226***	0.029	0.000
Industry Competition	0.297**	0.115	0.010	0.342	0.268	0.202	0.069	0.148	0.641
Protection	0.005**	0.002	0.003	0.006†	0.004	0.089	0.004*	0.002	0.024
Industry's R&D intensity	-0.647***	0.186	0.001	-0.352†	0.171	0.039	-0.450**	0.174	0.010
Newly Created Firms	-0.196**	0.072	0.007	-0.292†	0.153	0.055	-0.328**	0.121	0.007
High Technological Firms	0.025	0.107	0.815	0.104	0.118	0.381	-0.009	0.137	0.945
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.471***	0.139	0.001	-0.558*	0.230	0.015	-0.377*	0.154	0.014
Industry Variance	0.179	0.035		0.2517	0.0531		0.2641	0.0619	
Firm Variance	0.490	0.045		0.5285	0.0520		0.4753	0.0539	
Residual Variance	0.1091	0.0155		0.1161	0.0216		0.1111	0.0158	
Wald chi2 (18-20)	672.63	P>	0.000	254.750	P>	0.000	266.860	P>	0.000
Number of observations	13040			9996			9491		

DISCUSSION AND CONCLUSION

Theoretical Contributions

Prior studies have considered the advantages of exploration and exploitation and the performance effects of being ambidextrous (Cao et al., 2009; Ebben and Johnson, 2005; Junni et al., 2013; Gibson and Birkinshaw, 2004; Dover and Dierk, 2010; Turner et al., 2013; Martini et al., 2013). Despite prior contributions, the literature has not explicitly made a direct comparison between ambidextrous and specialization strategies. Therefore, it remains unclear which strategy (ambidexterity or specialization) is more beneficial for firm performance. The literature has also made the implicit assumption that the returns to exploration and exploitation are similar for ambidextrous and specialized firms. However, it may well be the case that specialization may change the extent to which exploratory and exploitative R&D investments influence firm performance.

This chapter contributes to organization learning and ambidexterity literatures (Argyris, and Schön, 1978; Atuahene-Gima, and Murray, 2007; Levinthal and March, 1993; Tushman et al., 2010; O'Reilly, and Tushman, 2013) by addressing the above issues. The value of the chapter lies in a) *specifying* how specialization in exploratory and exploitative R&D directly affects the performance of the firm and b) *identifying* how the effects of exploratory and exploitative R&D on firm performance differ for firms that adopt a specialization versus an ambidextrous strategy. From the point of view of organizational learning theory, this analysis advances our understanding of this subject by explaining why the effectiveness of exploratory and exploitative R&D on performance is affected by the firm's choice to invest in activities that require knowledge that is similar with (or different from) the firm's current knowledge base and specialization choice.

In this chapter, we developed a reasoning that explains why firms are on average better-off when they specialize in either exploratory R&D or exploitative R&D, rather than when they make a similar amount of investment in both exploratory and exploitative R&D (i.e., being ambidextrous). We theorize that specialization improves firm performance because firms build up their expertise by repeating and investing over and over again in the same tasks, processes and activities (Levitt and March, 1988; 1965; Argyris and Schon, 1978; Hedberg, 1981; Cyert and March, 1963). This enables them to accumulate experiential learning and to decrease the likelihood of doing errors in subsequent similar investments. We advance prior thinking by showing that the effects of specializing in either exploratory or exploitative R&D on firm performance might be stronger and positive compared to an ambidextrous strategy. Our reasoning indicates that the experiential learning that the firm gains when it engages in either exploratory or exploitative R&D contributes to strengthening its ability to perform competently related processes and activities (Cohen and Levinthal, 1990; Volderba et al., 2010; Sears and Hoetker, 2014; Casillas and Moreno-Menéndez, 2014).

Our theoretical contribution is threefold. First, we extend theoretical knowledge on exploration and exploitation (March, 1991; Tushman and O'Reilly, 1996; O'Reilly and Tushman, 2013) by showing how specializing in either of these two activities in the context of R&D affects firm performance. Drawing from organizational learning theory and on the role of experiential learning in competence building we argue that the accumulation of experiential learning enables firms to build competence either in the form of exploitation or exploration (March 1999; Holmqvist, 2004; Baum et al., 2000; Casillas and Moreno-Menéndez, 2014). Such competence allows firms to become proficient at activities they undertake regularly. Learning through direct experience helps firms to accumulate beneficial knowledge that could easily be incorporated into their routines, affecting thus subsequent engagement with similar investments strengthening further their expertise on their chosen R&D investments. This reasoning helps us explain why specialization is beneficial.

Second, we contribute to the ambidexterity-firm performance debate by making a direct comparison between ambidextrous and specialization strategies and by hypothesizing that the effects of exploratory and exploitative R&D on firm performance differ for firms that pursue a specialization versus an ambidextrous strategy. Drawing on organizational learning theory (Cyert and March, 1963; Nelson and Winter, 1982; Levitt and March, 1988; March, 1991; Levinthal and March, 1993; Baum et al., 2000; Fiol and Lyles, 1985; Wang and Ahmed, 2003), we suggest that specializing in either exploratory or exploitative R&D is likely to affect firm performance positively for two main reasons. Specialization limits the scope of the firm's activities while strengthening its competence in areas of prior established competence. Specialization also enables firms to exploit and build on their current knowledge with no need to engage in distant search or cross its own technological boundaries (Rosenkopf and Almeida, 2003; Rosenkopf, and Nerkar, 2001). Consequently, specialized firms could replicate past behaviour, utilize what they already know and use ideas and technologies that have been tested successfully in the past (Cyert and March, 1963; Nelson and Winter, 1982; Levitt and March, 1988). Those firms thus enhance their performance compared to those firms that invest in both and run the risk of performing less well at both, given the differential knowledge-base and structures that are required to make similar investments in both exploratory and exploitative R&D (March, 1991; Lubatkin et al., 2006; Junni et al., 2013).

Third, we contribute to organisational learning theory. The theory explains the importance of different learning mechanisms (i.e., *double-loop*/*generative* learning which is often equated with exploratory knowledge and single loop/*adaptive* learning which reflects exploitative knowledge; Argyris and Schon, 1978; Morgan and Berthon, 2008; Argyris, 1976). It also recognizes that different types of learning matter for firm performance (March, 1991; Levinthal and March, 1993; Baum et al., 2000; Casillas and Moreno-Menéndez, 2014; Holmqvist, 2004). However, organisational learning theory does not explicitly clarify the conditions under which their value and therefore their effects on performance may accentuate or weaken. In the context of exploratory and exploitative R&D, our results show that there is a performance-enhancing effect when there is knowledge similarity between current R&D investments and a firm's existing knowledge base. By contrast, we show that there is a performance-weakening effect when there is knowledge dissimilarity between current R&D investments and a firm's knowledge base.

Managerial Implications

Because our findings are related with R&D investments they have practical implications for managerial decision. Precisely, as our study explains why and how specializing in either exploratory or exploitative R&D is more beneficial than making simultaneous investments in both exploratory and exploitative R&D, it can help managers to develop an optimal exploratory/exploitative R&D investment strategy. Importantly however, our analysis could help managers to understand why limiting the scope of their investments and corresponding activities is likely to enhance their firm performance.

Since our analysis is in favour of specializing strategies and our results are suggestive that exploratory and exploitative strategies that focuses on investing over 66.6% of their R&D budget in either exploring new ideas and technologies (exploratory R&D) or exploiting (exploitative R&D) existing ones may be more beneficial than ambidextrous one. Investments for which firms follow the same technological trajectory, underpinned by the same knowledge base they are currently undertake, utilising therefore and building upon their existing knowledge stock are more likely to enhance their firm performance. The firm-enhancing effect of those strategies often derives from the fact that those firms repetitively engage with the same investments, and thus they are more likely to strengthen their competence and expertise on the tasks and activities they undertake regularly. Further, because specialized firms narrow the focus of their activities, often replicating prior successful behaviour, they minimize this way the likelihood of doing errors in subsequent similar investments.

Further, our analysis suggests that the equal distribution between exploratory and exploitative R&D is not always the most optimal strategy for enhancing firm performance. For this reason, our results could assist managerial decisions on how to make a better distribution in their resources, given the fact that exploratory and exploitative R&D are distinctively different activities, and thus require different physical structures, knowledge base and personnel to manage them successfully. Importantly however, since our findings are in favour of specialization strategies, they could assist managers in understanding the importance of accumulating experiential learning in strengthening their expertise and ultimately their firm's revenue.

Limitations and Future Research

Our findings are subject to a number of limitations, some of which may provide opportunities for future research. First, although we used a multi-industry context to test our hypotheses and increase sample heterogeneity, our empirical analysis of the Spanish dataset is for a single country and thus our findings may apply only to those firms with similar attributes to that of the Spanish firms. For instance, there are differences in the innovation systems of different members of the OECD countries (Bayona Sáez and Arribas, 2002). Those differences are more prominent across countries of the European Union, Japan and the USA (OECD, 2000). Although Spain belongs in countries of the European Union, the Spanish innovation system is distinct from that of other countries mainly because R&D expenditure in Spain is below average compared to that of other European countries (Eurostat statistics, 2016). Despite this distinctive characteristic of Spanish firms, we would expect the effects of specialization to accentuate (be more positive and stronger) if R&D expenditure was higher in Spain and Spanish firms had to operate in a more stimulating environment like that of the rest of the European countries (European Commission, 2000). Future research thus may build on our study using firms from different countries of varied innovation system and explore whether the R&D expenditure of a country matters for the returns to specialization.

Second, although our longitudinal analysis and the choice of different estimators, we try to minimize the omitted variable problem and endogeneity issues, in the absence of appropriate instrumental variables we suggest caution in indicating causal relationships (Wooldridge, 2002). Third, although in the robustness section of our analysis we tested whether the patterns of constant specialization and constant ambidexterity affect differently firm performance (no significant results found), it would be interesting to explore *whether* and *how* these different patterns of specialization e.g., *sequential specialization* (i.e., change from being specialized in one activity in year t to becoming either ambidextrous or specialized in the other activity in year t+1) versus *focused specialization* (those firms that persistently specialize for many years) differ in countries with strong and weak appropriability regimes (IPR). For instance, we would expect the effects of sequential specialization on firm performance to be stronger than the effects of *focused specialization* in industries with weak protection because greater access to knowledge leakage (Kafouros and Forsans, 2012; Ho and Wang, 2015) and thus abundance of knowledge will allow firms with *sequential specialization* strategies to exploit easier ideas developed by other competitor firms and explore (experiment) by being exposed to new technologies and opportunities.

Third, we demonstrated how a firm's specialization strategy had different returns depending on whether the firm specializes in exploratory/exploitative R&D or is ambidextrous. Nevertheless, we do not consider how firm resources (tangible or tacit) might interact with specialization strategies to affect firm performance. Since larger-size firms have abundance of resources (Ebben and Johnson, 2005; Cao et al., 2009), and greater access to a larger pool of specialist knowledge (Chen and Hambrick, 1995), we would expect that a specialization strategy may be more viable and beneficial compared to an ambidextrous strategy, given the differential knowledge base and structure required to undertake exploratory and exploitative R&D activities.

CHAPTER 6
THE VALUE OF SPECIALIZATION STRATEGIES ACROSS INDUSTRIES

ABSTRACT

Although prior research has identified the benefits of being *ambidextrous* (i.e. of pursuing both knowledge exploration and exploitation), two strategically important questions remain unanswered. First, are there certain conditions in the industry in which the focal firm operates that make *specialization* in either exploration or exploitation more beneficial than ambidexterity? Second, in cases in which specialization is beneficial, which specialization strategy (exploratory or exploitative) and under what conditions is more advantageous to the firm? In this study, we address the above questions by examining how firm performance is influenced by specialization in exploration or exploitation. We posit that the answer to these questions depends on a particular industry characteristic (*industry orientation*). We argue that industry orientation affects the availability, value and transaction costs of accessing of collaborative opportunities and, in turn, influences how beneficial an exploratory or exploitative specialization strategy is for the firm. To test our framework, we develop a typology of industry orientation that captures cross-industry regularities and variations in the concentration of the exploration and exploitation activity. Our empirical analysis of 32,537 firms shows that pursuing an exploitation strategy affects negatively performance when firms operate in an exploitative-oriented industry. Conversely, pursuing an exploitation strategy affects positively performance when firms operate in a hybrid or in an exploratory-orientated industry. Our analysis shows that two firms that adopt the same specialization strategy may experience different effects on their performance when the orientation of their industry varies, implying that certain industry dynamics make it possible to achieve ambidexterity at the industry level.

KEYWORDS: *exploration, exploitation, specialization, industry orientation*

INTRODUCTION

Knowledge exploitation and exploration have long been identified as essential innovation activities in achieving firm competitiveness (March, 1991; Chen and Katila, 2008; Auh and Menguc, 2005; Koryak et al., 2018; Junni, et al., 2013). Knowledge exploitation enables firms to leverage existing knowledge to refine products and services, standardize processes and improve efficiency, whereas knowledge exploration involves distant search and experimentation activities that help firms generate new ideas, knowledge and discoveries (Gupta et al., 2006; Belderbos et al., 2010; Turner et al., 2013; Chang et al., 2009). Prior research has focused on the advantages of pursuing *both* exploitation and exploration (Benner and Tushman, 2002; He and Wong, 2004; Morgan and Berthon, 2008; Martini et al., 2013; Tushman et al., 2010; Koryak et al., 2018). This strategy is achieved either by making a similar investment in both activities every year, or by engaging in 'temporal cycling' whereby the firm switches between exploration and exploitation every one or two years.

Such a balanced strategy may assist firms in improving efficiency and generating rents (Auh and Menguc, 2005) while avoiding getting trapped in outdated technologies (Ahuja and Lampert, 2001; Leonard-Barton, 1992; Jansen et al., 2006). Conversely, other studies show that engaging in both activities has an insignificant (Bierly and Daly, 2007; Venkatraman et al., 2007) or even a negative effect on firm performance (Rothaermel and Alexandre, 2009; Ebben and Johnson, 2005; Lavie et al., 2011) because the knowledge and processes needed to undertake the two activities are incompatible (Rosenkopf and Nerkar, 2001; Lubatkin et al., 2006; Floyd and Lane, 2000). As such, not only there is an ongoing debate of whether firms should be *ambidextrous* (invest in both activities) or *specialize* (invest the vast majority of their time and resources in either exploration or exploitation over a long period of time), but it is also less well understood which specialization strategy (exploratory or exploitative) and in which situations is more advantageous for firm performance.

Such conflicting findings prompt the need to conduct research aimed at identifying the boundary conditions under which exploration and exploitation lead to superior performance. One research avenue for enhancing understanding of such conditions is to examine the industry context in which firms specialize and conceptualize how it may facilitate or impede certain exploration and exploitation processes and, in turn, influence their effects of firm performance. As prior research suggests, a given strategy or asset by itself is not useful unless it can be applied to a specific context (Sirmon et al., 2008), emphasizing the value of advancing research that has begun to examine the context in which exploration and exploitation is conducted (Auh and Menguc, 2005; Uotila et al., 2009).

To understand why exploration or exploitation are more beneficial in certain contexts than in others, we develop a typology of *industry orientation* that conceptualizes cross-industry regularities and variations in the concentration of the exploration and exploitation activity. According to this typology, industries may be *exploitative-oriented* (whereby most firms in these industries specialize in exploitation and only few firms specialize in exploration), *exploratory-oriented* (they exhibit the opposite pattern), or *hybrid* (approximately the same percentage of firms specialize in exploratory and exploitative R&D and are ambidextrous. Drawing from industrial organization economics (Bain, 1968; Porter, 2000; McGahan and Porter, 1997; Dranove et al., 1998; Jacobides et al., 2006), we contend that industry orientation affects three key factors that in turn influence how beneficial an exploratory or exploitative specialization strategy is. First, industry orientation affects the *availability* of collaborative and knowledge-sourcing opportunities that firms are exposed to. It therefore makes the pool of potentially complementary opportunities in the market to be numerous and important in some industries, but scarcer and less significant in other industries. Second, the level of availability in turn affects the difficulty and *transaction costs* of accessing opportunities and expertise from the market. The higher the availability in a given industry is, the lower the difficulty and transaction costs of accessing these opportunities will be. Third, industry orientation affects how *valuable* these opportunities are by influencing the similarity (or overlap) between the explorative or exploitative activities that a firm undertakes and those offered by other firms in the industry. A higher degree of such similarity makes external opportunities redundant and decreases their marginal value.

Building on this reasoning, we examine how the relationship between specialization in exploration or exploitation and firm performance is influenced by the orientation of the industry in which a firm operates. Accordingly, we develop a conceptual framework that clarifies the mechanisms that make specialization more beneficial in a given industry context. Given that firms that choose to specialize may focus on either exploration or exploitation, our analysis helps us understand which specialization strategy (exploratory or exploitative) is more advantageous and in which industry contexts. We expect specialization over a given time timeframe to be more effective in enhancing firm performance when the industry in which the firm operates is characterized by a higher availability of collaborative and knowledge sourcing opportunities that complement the firm's internal innovation activities. These environments enable firms that specialize in one activity (e.g. exploitation) to use external markets in their industry to access expertise and opportunities related to the activity they do not pursuit (e.g. exploration), thus increasing their performance (Chesbrough, 2003; Gupta et al., 2006; Lichtenthaler and Lichtenthaler, 2009; Cassiman and Veugelers, 2006; Chesbrough, 2006).

Our analysis of a longitudinal dataset of 32,537 observations supports this reasoning, indicating that the adoption of specialization in exploitation has a negative effect on performance when the firm operates in an exploitative-oriented industry that presents fewer and less valuable external opportunities for complementing its internal activities. Conversely, the opposite pattern emerges with the corresponding effect on performance being positive when a firm that specializes in exploitation operates in a hybrid or exploratory-oriented industry. The importance of differentiating industry contexts in this manner lies in showing that firms that adopt a similar specialization strategy in exploration or exploitation may experience different returns to specialization when the orientation of their industry differs.

Our study seeks to make a number of contributions. First, it develops a new typology for industry contexts and a conceptual framework that together explain how and why the performance-enhancing effects of exploration and exploitation vary across industries. Second, it helps us understand which specialization strategy firms should pursue and how certain context-specific characteristics should determine the effectiveness of these strategies. As such, it contributes to exploitation and exploration research that has considered the role of the environment (Auh and Menguc, 2005; Jansen et al., 2006; Thornhill and White, 2007; Uotila et al., 2009) but has not examined how the orientation of each industry affects the returns to exploration and exploitation for the focal firm. Our analysis also implies that although some firms maintain a specialization strategy over time, certain industry dynamics make it possible to achieve ambidexterity at the industry level, whereby some firms specialize in exploration and other firms specialize in exploitation (Gupta et al., 2006; Cassiman and Veugelers, 2006; Chesbrough, 2006). This theoretical position does not necessarily contradict the logic of ambidexterity; yet it extends this notion from the context of a single firm to the context of the broader industry.

THEORETICAL BACKGROUND

Exploration, Exploitation and Organizational learning

Within the organizational learning literature (Cyert and March, 1963; Levitt and March, 1988; Huber, 1991; Fiol and Lyles, 1985; Wang and Ahmed, 2003; Levinthal and March, 1993), it has been established that although knowledge exploration and exploitation can be complementary in enhancing firm performance, they involve different processes and activities and therefore compete for resources within firms (March, 1991; Gupta et al., 2006; Wilden et al., 2018; Koryak et al., 2018; Junni et al., 2013). Exploitation relies on a firm's existing knowledge base. It requires local search and, as an activity, focuses on efficiency (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). Exploration requires distant knowledge and experimentation (March, 1991; Gupta et al., 2006; Baum et al., 2000; He and Wong, 2004; Wilden et al., 2018; Koryak et al., 2018; Junni et al., 2013). Exploration and exploitation also differ in terms of learning. Double-loop and generative learning in exploration enables firms to generate a stream of ideas (Argyris and Schon, 1978; Morgan and Berthon, 2008; Chiva et al., 2010), whereas single loop adaptive learning in exploitation facilitates incremental changes to existing products and processes (Argyris, 1976; 2002).

Exploitation improves performance by helping firms strengthen established competencies, extend the life cycles of their products, achieve economies of scale and scope, and sustain rent generation (Baum et al., 2000; Morgan and Berthon, 2008; Auh and Menguc, 2005). Because exploitation focuses on products familiar to both the innovating firm and its customers, it is also less risky and has predictable returns (Abernathy and Clark, 1985). On the other hand, exploration affects firm performance by helping firms to identify opportunities (Cohen and Levinthal, 1990; Zahra and George, 2002; Lane et al., 2006; Lavie and Rosenkopf, 2006; Rothaermel and Alexandre, 2009), pursuit new technological trajectories (Teece, 2007) and combine knowledge from different domains that may result in the creation of entirely new markets (He and Wong, 2004; Sears and Hoetker, 2014) and first-mover advantages (Atuahene-Gima and Murray, 2007).

Although some firms invest time, effort and resources in both exploration and exploitation (Gibson and Birkinshaw; 2004; O'Reilly and Tushman, 2013; Uotila et al., 2009; Wilden et al., 2018), other firms adopt a specialization strategy (and sustain this over time). In this study, we define *specialization* as a strategy by which firms limit the scope of their activities and invest the vast majority of their resources, time and effort in either exploitation or exploration for a long period of time. Specialization provides two significant advantages (Wernerfelt and Montgomery, 1988; Brusoni et al., 2001; Calderini and Scelato, 2005; Romer, 1987). First, it increases the efficiency with which firms perform a set of explorative or exploitative activities. Such efficiency gains result from the repetition in execution and the accumulated expertise and experiential knowledge gained by focusing on specific tasks (Hanks and Chandler, 1994; Holmqvist, 2004; Cassillas and Moreno- Moreno-Menéndez, 2014). Second, specialization can increase the returns to certain activities by enabling firms to perform such activities at a lower marginal cost and risk. Lower marginal cost and higher returns are the result of becoming better in undertaking certain activities because learning pertaining to these activities accumulates faster in areas of established expertise (Hanks and Chandler, 1994; Baum et al., 2000; Holmqvist, 2004).

As firms operate in a broader network of organizations (Gupta et al., 2006; Lavie et al., 2010; Rothaermel and Deeds, 2004), some firms may specialize in activities they are endowed to do well and use the market to transact and exchange outputs, skills and expertise with firms that perform well in other activities. As noted earlier, this view implies that although balance between exploration and exploitation may not be achieved within the firm, it is achieved at the market or industry level. Access to the market is facilitated by three key mechanisms. First, firms may engage in formal collaboration, such as alliances and joint ventures, or simply acquire technology. Second, they may engage in knowledge sourcing or license technologies and inputs from other organizations. Finally, firms can engage in informal collaboration or exploit external knowledge spillovers (involuntary leakage of knowledge) (Chesbrough, 2003; Laursen and Salter, 2006; Issakson et al., 2016).

Industrial Organization and the Role of the Industry

Prior studies have largely focused on how firms can (internally) balance exploration and exploitation (Raich et al., 2009; Uotila et al., 2009; Junni et al., 2013 for a review) and what are the consequences for their performance (He and Wong, 2004; Birkinshaw, and Gupta, 2013; Markides, 2013; O'Reilly and Tushman, 2013 for a review). However, with few notable exceptions (Jansen et al., 2006; Auh and Menguc, 2005; Luger et al., 2018), prior studies paid little attention to how the environment or industry in which the firm operates may make specialization in one of these activities more beneficial and change its effect on firm performance. For this reason, it is important to consider how industrial organization theory enhances our understanding of the phenomenon. Specifically, industrial organization theory explains performance variations across firms based on the structural characteristics of the industries they operate (Bain, 1968; Mason, 1953; Schumpeter, 1950; McGahan, and Porter, 1997; Rumelt, 1991). It suggests that the structure of the industry determines a firm's behavior (conduct), its chosen strategy and, in turn, its performance. Empirical evidence confirms the importance of industry effects (Wernerfelt and Montgomery, 1988; Rummelt, 1991; Kamasak, 2011; Lee et al., 2001; Markides, 1999). Industry structure accounts for 19% and 30% of the aggregate variance in firm profitability (McGahan and Porter, 1997; McGahan, 1999).

Two branches of the IO theory, namely neoclassical theory and transaction cost theory are particularly useful in explaining why some firms may choose to specialize in either exploration or exploitation and why they may perform well even when they do not balance internally the two activities (Conner, 1991). The neoclassical theory conceptualizes firms as “input combiners” (Alchian and Demsetz, 1972). In short, it suggests that because a firm’s performance depends on the combination of various inputs, we have to consider how the industry in which the firm operates influences the availability of external markets as well as the likelihood and effectiveness of collaborations. In a similar manner, transaction-cost thinking focuses on how certain characteristics of the industry influence the opportunities as well as the cost that firms face for using the market and transact (exchange) with other organizations (Williamson, 1981; Coase, 1992; Geyskens et al., 2006; Baldwin, 2007; Stoelhorst and Raaij, 2004).

Typology of Industry Orientation

Although specialization has certain advantages, we expect its effectiveness in enhancing firm performance to differ considerably across industries. Building on industrial organization economics (Alchian and Demsetz, 1972; Stoelhorst and Raaij, 2004), we argue that such variations are driven by contextual industry factors and, in particular, by the *availability* of collaborative and knowledge-sourcing opportunities as well as the difficulty and *transaction costs* of accessing such opportunities from the market (Jarillo, 1989; Williamson, 1981; Coase, 1992).

These variations, in turn, influence the likelihood and effectiveness of collaboration, knowledge sourcing, the exchange between organizations and, subsequently, the *value* of such opportunities. With few notable exceptions (Jansen et al., 2006; Auh and Menguc, 2005; Luger et al., 2018), prior studies paid little attention to how a firm's industry influences the effect of specialization and its performance. Certain characteristics or regularities in industries affect firm performance (Bain, 1968; Mason, 1939) by determining how effective a firm's chosen strategy is in a particular context (McGahan and Porter, 1997; McGahan, 1999; Wernerfelt and Montgomery, 1988; Kamasak, 2011; Rumelt, 1991; Markides, 1999). Our typology of industry orientation captures the regularities of exploratory and exploitative R&D across industries. The development of this typology rests upon research that points to differences in the architecture of industries (Jacobides et al., 2006; Jacobides and Billinger, 2006; Pisano and Teece, 2007) and to the existence of strategic groups within industries (Dranove et al., 1998; Peteraf and Shanley, 1997; Porter, 1979; Thomas and Venkatraman, 1988; McGee and Thomas, 1996; DeSarbo and Grewal, 2008). Each industry has a distinct architecture that provides the contours for its members to interact and try to minimize transaction costs (Jacobides et al., 2006). These contours lead to the formation of groups of firms that share path-dependent research strategies, invest in similar technologies and are bound by a similar scope of commitments (Porter, 1979; Thomas and Venkatraman, 1988; McGee and Thomas, 1996; DeSarbo and Grewal, 2008). As such, some firms can compete in an industry by providing activities and outputs that complement those of the majority of rival firms, and by using these to gain competitive advantages (Jacobides et al., 2006 Schmiedeberg, 2008) or create alliances to influence the industry's trajectory (Rosenkopf and Tushman, 1998; Lavie et al., 2011; Rosenkopf and Schilling, 2007; Lavie and Rosenkopf, 2006).

To capture such differences in the exploration and exploitation strategies of firms, our typology of industry orientation is based on two key dimensions: 1) the *concentration* (number) of firms that specialize in either exploration or exploitation within each industry, and 2) the main *strategic intent* (objective) of those firms to either refine existing products and processes (i.e. exploit) or invent something entirely new (explore). Based on these criteria and as noted earlier, we distinguish industries into *exploitative-oriented, exploratory-oriented* and *hybrid*. Exploitative-oriented industries are characterized by a large number of firms that specialize in exploitation, whereas the concentration of firms that specialize in exploration is low. By contrast, exploratory-oriented industries exhibit the opposite trend. In hybrid industries, approximately the same percentage of firms specialize in exploratory and exploitative R&D and are ambidextrous.

The Competitive and Comparative Advantages of Specialization

Applying these two branches of the IO theory to the exploration-exploitation literature is important because they enable us to explain why certain industries enable firms to be successful even when they specialize in only one activity. They also point to the significant benefits and advantages of specialization. More specifically, the literature on ambidexterity suggests that firms have to balance their investments because exploitation will secure a firm's current cash flow, whereas exploration will ensure the generation of new ideas and a position in future markets (Benner and Tushman, 2003; Gibson and Birkinshaw; 2004; Lubatkin et al., 2006; O'Reilly and Tushman, 2013). Although certain conditions may require firms to engage in both (Cao et al., 2009; Uotila et al., 2009; Jansen et al., 2006), there might be significant benefits for firms that specialize in either one (Wernerfelt and Montgomery, 1988; Romer, 1987).

Specialization is a strategy by which firms limit the scope of their activities and outputs in order to benefit from efficiency within the overall system (Rumer, 1987; Gupta et al., 2006). A specialization strategy provides the firm with two significant advantages. First, a firm that specializes in one activity increases its ability to produce a specific output or perform a set of activities more efficiently. Such efficiencies are accomplished because of the repetition in execution, accumulated expertise and experiential knowledge gained by engaging in a specific task (Hanks and Chandler, 1994; Romer, 1987; Brusoni et al., 2001; Calderini and Scelato, 2005). The adoption of specialization strategies is largely justified by contextual factors, such as environmental and technological complexity in the industry in which the firm operates (Burns and Stalker, 1961; Brusoni et al., 2001). Such factors as well as the availability of external markets and the ease of accessing the market also affects the extent of specialization in a firm (Jarillo, 1989; Watson, 2007). For instance, being able to establish strategic alliances may allow a firm to access resources and expertise that the firm does not possess internally (Hans and Gaylen, 1994; He and Wang, 2015; Lavie and Rosenkopf, 2006).

Second, specialization leads to higher returns to a given set of activities by increasing a firm's ability to perform such activities at a lower marginal cost and risk compared to other firms. Lower marginal costs and higher returns are both the result of being better in undertaking a specific set of activities because experiential learning pertaining to *that* activity accumulates faster in areas of prior or established expertise (Baum et al., 2000; Holmqvist, 2004; Chiva et al., 2010). Although lower marginal costs and higher returns are sources of competitive advantage, specialization is also the fundamental mechanism underlying the comparative advantages associated with the use of the market (Ricardo, 1817). Applying the principle of comparative advantage in our context implies that because firms do not have to be self-sustained entities, they can enhance their performance by focusing on activities they are endowed to do well (e.g. exploration) and exchange their outputs and expertise to firms that are superior in performing other activities (e.g. exploitation). Firms thus that adopt a specialized innovation strategy instead of balancing their exploratory and exploitative activities can still be successful if they operate in an industry where there are greater opportunities to internalize what they are competent to produce themselves and acquire either formally (e.g., through licensing or patent acquisition) or informally (e.g., through unintended positive knowledge externalities) what they need from the industry market (Buckley and Ghauri, 2015; Buckley, 2016; Chesbrough, 2003; Choi and McNamara, 2018)

Market Mechanisms that Firms use for Intra-industry Collaboration and Knowledge Sourcing

Firms use different mechanisms to access the market (Chesbrough, 2003; 2006; Laursen and Salter, 2006) and complement their exploitative or exploratory activities. These mechanisms include 1) formal collaborative alliances, joint ventures, and mergers & acquisitions 2) knowledge sourcing and licensing and 3) informal collaboration and interaction, and involuntary knowledge leakage or spillovers.

Alliances involve voluntary knowledge exchange and collaboration (Gulati, 1998; Yamakawa et al., 2011). They are used as means for exploring new prospects and exploiting existing knowledge (Koza and Lewin, 1998; Lavie and Rosenkopf, 2006). Firms may form exploration alliances with other firms in order to discover new ideas, opportunities and technologies, build new competencies (Koza and Lewin, 1998; Dittrich and Duysters, 2007) and pursue exploitation alliances to leverage existing firm resources and competences by sourcing complementary assets (Rothaermel and Deeds, 2004). Regardless of whether firms expand their existing network of alliances by adding new partners or reinforcing their existing alliance network by interacting with prior partners (Podolny, 1994), they aim at eliminating environmental uncertainty and technological complexity, but also at accelerating knowledge diffusion and achieving cost-efficiency (Chesbrough, 2003; Beckmann, 2006). Strategic alliances thus allow firms to assemble partners' resources to explore and exploit internal and external resources (Yamakawa et al., 2011). Similarly, joint ventures provide firms with opportunities to pool capital and expertise (Kogut and Zander, 1992; 1993), and control environmental changes by shifting the risks to outsiders (Yiu and Makino, 2002). Similarly, acquisition is another way to obtain technological know-how and advance technical capabilities (Ahuja and Katila, 2001; Phene et al., 2012). More importantly however, via acquisitions firm-bound advantages are often fuse with the assets of the acquired firm to effectively improve firm performance because of their attenuated combined value (Ahuja and Katila, 2001). Likewise, firms seek to overcome pressures for balancing exploratory and exploitative activities by engaging in mergers. Firms choose to merge with firms of a comparable knowledge base in achieving synergies and facilitating exploitation activities (Phene et al., 2012). By contrast, other firms choose to merge with firms of a dissimilar knowledge base to reconfigure their existing businesses and change their strategic intent (Capron et al., 1998).

Knowledge sourcing through contracting out research is also another channel that firms use to outsource their specialized knowledge (Powel et al., 1996). The realization that it is no longer required to have exclusive, proprietary ownership of a technology, but licensing its proprietary rights give specialized in exploration firms more chances to get their ideas and technologies exploited by others. The technological know-how needed to advance drugs is complicated, and the competencies involved testing them and putting them into the market similarly complex that no single firm could guarantee that promising exploratory ideas will be successful. For instance, the highly exploratory biotech firm, FIT BIOTECH, developed the Gene Transport Unit (GTU) technology to be used in DNA vaccines and gene therapy (http://www.fitbiotech.com/fit-biotech/). Despite the value of this technology, its application will be limited if the FIT BIOTECH firm did not choose to license its proprietary GTU technology to pharmaceutical firms for the development of the next generation of medical treatments with a need for cost effective, safer and efficacious drugs. Firms that specialize in exploration thus need to find ways to accelerate the pace of their ideas, technologies and discoveries in order to reach successful application and commercialization. Operating therefore in industries where other firms can leverage a firm's exploratory investments is vital for helping those ideas to pass onto the stage of implementation. Firms could also benefit from informal networks that are often formed for knowledge sharing rather than organizational interaction (Granovetter, 1983; Hansen, 1999). Since informal networks do not require formal contractual agreements to access knowledge, knowledge leakages are greater and thus firms could benefit from accessing this knowledge. Similarly, firms could benefit from localized knowledge spill overs. For instance, investments in R&D by firms and Universities spill over unintentionally to other firms for exploitation (Jaffe, 1989; Acs et al., 1992; 1994; Issakson et al., 2016). Finally, network research acknowledges the extent to which knowledge (tacit) is embedded in informal knowledge sharing among firms (Cooke and Morgan, 1993), confirming the importance of organisational linkages for knowledge flows (Piore and Sabel, 1984; Drifield et al., 2016) emphasizing that network embeddedness increases the frequency of social interactions and exchanges across firms. Hence, the existence of both knowledge-seeking and knowledge-creating firms in an industry is likely to give specialized in either exploratory or exploitative R&D firms greater prospects to use the market.

HYPOTHESES

To explain how the performance of specialized firms is affected by the orientation of the industry in which they operate, we focus on how variations in the concentration of the exploration and exploitation activity across industries affects a) the availability, b) value of collaborative and knowledge sourcing opportunities across industries and c) the difficulty and transaction costs of accessing these collaborative and knowledge-sourcing opportunities which in turn determines which specialization strategy (exploratory or exploitative) is more advantageous for firm performance. In the cells of Table 1, we summarize the nine possible combinations of firms' specialization strategy (vertical axis) and industry orientation (horizontal axis). Table 1 also summarizes the key differences that each combination exhibits in terms of opportunities, value added and transaction costs. The next sections develop a hypothesis for each of these nine combinations (cells).

Table 1: Specialization strategies and industry orientation

Firms Specialization Strategy	Exploitative-oriented industry	Hybrid industry	Exploratory-oriented industry
Specialization in exploitation strategy	***Cell 1 (-)*** (1) Low availability of exploration-specific collaborative opportunities and assets (2) High difficulty and transaction costs in accessing/acquiring such opportunities and assets (3) Exploitation-specific assets exhibit low value added	***Cell 2 (+)*** (1) Good availability of exploration-specific collaborative opportunities and assets (2) Moderate difficulty and transaction costs in accessing/acquiring such opportunities and assets (3) Exploitation-specific assets exhibit moderate value added	***Cell 3 (+)*** (1) High availability of exploration-specific collaborative opportunities and assets (2) Low difficulty and transaction costs in accessing/acquiring such opportunities and assets (3) Exploration-specific assets exhibit high value added
Ambidextrous Firms	***Cell 4 (-)*** (1) High availability of exploitation-specific collaborative opportunities and assets but Low availability of exploration-specific collaborative opportunities and assets (2) Exploitation-specific assets exhibit less value added	***Cell 5 (+)*** (1) Good availability of exploration-specific collaborative opportunities and assets (2) Moderate difficulty and transaction costs in accessing/acquiring such opportunities and assets (3) Exploitation-specific assets exhibit moderate value added	***Cell 6 (-)*** (1) High availability of exploration-specific collaborative opportunities and assets but low availability of exploitation-specific collaborative opportunities and assets (2) Exploitation-specific assets exhibit less value added
Specialization in exploration strategy	***Cell 7 (+)*** (1) High availability of exploitation-specific collaborative opportunities and assets (2) Low difficulty and transaction costs in accessing/acquiring such opportunities and assets (3) Exploitation-specific assets exhibit high value added	***Cell 8 (+)*** (1) Good availability of exploitation-specific collaborative opportunities and assets (2) Moderate difficulty and transaction costs in accessing/acquiring such opportunities and assets (3) Exploitation-specific assets exhibit moderate value added	***Cell 9 (-)*** (1) Low availability of exploitation-specific collaborative opportunities and assets (2) High difficulty and transaction costs in accessing/acquiring such opportunities and assets (3) Exploration-specific assets exhibit low value added

Industry orientation

Pursuing a Specialization in Exploitative R&D strategy in Exploitative-Oriented Industries (cell 1)

Due to the abovementioned mechanisms pertaining to the availability, transaction costs and value of collaborative and knowledge sourcing opportunities, we expect specialization in exploitation to have a negative effect on performance when the focal firm operates in an exploitative-oriented industry. First, industrial organization theory views firms as input combiners (Conner, 1991; Bain, 1968; Mason, 1939). In our context, firms may find advantageous to specialize in exploitation as long as it is possible and efficient to use the market to collaborate and/or source knowledge, expertise and inputs. When firms that specialize in exploitation operate in exploitative-oriented industries, they are exposed to a limited number of exploration-specific opportunities (Kogut and Zander, 1992; Jacobides et al., 2006). Limited availability, in turn, impedes the focal firm's ability to find new ideas to explore, decreasing therefore the marginal returns to its specialization in exploitation strategy. This reasoning is consistent with the notion that firms that are exposed to expertise that is similar to their own (Henderson and Clark, 1990) cannot broaden their horizons (Vermeulen and Barkema, 2001; Wu and Shanley, 2009).

Second, in such industries, the limited number of firms that specialize in exploration slows down the generative learning of firms that specialize in exploitation (Morgan and Berthon, 2008; Auh and Menguc, 2005; Argyris and Schon, 1978) and decreases the likelihood of changing the scope of their activities, locking them within the same exploitative trajectory (Nelson and Winter, 1982; O'Reilly and Tushman, 2013; Zahra and George, 2002). When explorative opportunities are limited, and firms have to over-utilize existing ideas (Atuahene-Gima, 2005; Uotila et al., 2009), they face higher difficulties in identifying and establishing collaborative and knowledge sourcing agreements. The limited number of explorative firms in such industries also increases their bargaining power. Hence, in such situations, not only the transaction costs of accessing the market are likely to be higher for firms that specialize in exploitation (Coase, 1992; Williamson, 1981; Geyskens et al., 2006) but also the terms of such agreements are likely to be less favourable for these firms, resulting once again in diminishing returns to exploitation.

Third, the knowledge, expertise and outputs of firms that specialize in exploitation may easily become redundant in exploitative-oriented industries because many other firms also specialize in exploitation. A high degree of similarity in knowledge, orientation, objectives and outputs of firms that specialize in exploitation erodes their uniqueness, may inhibit creativity (Baum et al., 2000) and may therefore decrease the value of these outputs. This argument is consistent with prior research that shows that the value of technological investments declines when firms make similar investments or focus on similar offerings (Vassolo et al., 2004; Wassmer et al., 2010; Belderbos and Zou, 2009). This in turn, decreases the effects of their exploitative activities on performance. Accordingly, we expect specialization in exploitation to be less beneficial in exploitative-oriented industries:

H1 (cell 1)*: The pursuit of a specialization in exploitation strategy has a negative effect on performance when the firm operates in an exploitative-oriented industry*

Pursuing a specialization in exploratory R&D strategy in exploratory-oriented industries (cell 9)

Due the abovementioned mechanisms, we further expect specialization in exploration to be a less beneficial strategy when the focal firm operates in an exploratory-oriented industry. First, although inter-firm performance variations are driven by firms' ability to achieve differentiation (Bain, 1968; Mason, 1939; Conner, 1991; Comanor and Wilson, 1974), the clear majority of firms in exploratory-oriented industries engage in the development of new ideas and technologies. Due to the lower number of firms that specialize in exploitation in such industries, exploratory firms have fewer opportunities to use the market and find formal and informal means of collaboration in order to ensure that their ideas will get exploited. As the low likelihood of accessing exploitative-specific opportunities increase the difficulty and transaction costs of using the market, the returns to exploratory specialization strategies will decrease in exploratory-oriented industries.

Second, although exploratory-oriented industries are characterized by the abundance of technological opportunities and ideas (Uotila et al., 2009; Zahra, 1996), the nature of these industries makes new ideas and technologies to become obsolete quickly (Sorensen and Stuart, 2000). Although the high concentration of exploratory firms contributes to an industry's knowledge reservoir, the marginal value and usefulness of each additional idea added to this pool is decreasing due to the large number of ideas that exist. In such situations, the knowledge and outputs of firms that specialize in exploration are likely to have a decreasing effect on their performance because many of these ideas do not get exploited. Reinforcing this premise, prior research found decreasing returns when firms that operate in dynamic industries focus intensively on exploratory activities (Uotila et al., 2009).

Third, homogeneity in knowledge resources increases the likelihood of creating substitutable outputs (Barney, 1991; 2001; Aug and Mengue, 2005) that in turn become less valuable. A specialization in exploration strategy is less beneficial when pursued in exploratory-oriented industries because the high availability of ideas in these markets increases their substitutability (Levinthal and March, 1993; Kyriakopoulos and Moorman, 2004). Although exploratory firms do not possess exactly the same knowledge resources, they often use equivalent knowledge, technologies and components to compete (Barney, 1991; Dierickx and Cool, 1989). As a result, the likelihood of creating substitutable outputs to that of competitors is higher. In such cases, their actions are likely to be counteracted by similar competitive behavior (Aug and Mengue, 2005), thus decreasing the returns to specialization in exploration. Hence:

H2 (cell 9): *The pursuit of a specialization in exploration strategy has a negative effect on performance when the firm operates in an exploratory-oriented industry*

Pursuing a specialization in exploitation (exploration) strategy in hybrid and exploratory-oriented (exploitative-oriented) industries (cells 2-3 & 7-8)

Although hybrid and exploratory-oriented industries differ in the availability of exploitation-specific factors, they both feature high availability of exploration-specific opportunities. Building on the logic of previous hypotheses, we expect firms in such industries to be more effective in taking advantage of collaborative and knowledge sourcing opportunities from the market to enhance their performance (Conner, 1991; Bain, 1968; Mason, 1939). In hybrid and exploratory-oriented industries, the greater availability of exploratory-specific knowledge and expertise means that firms that specialize in exploitation have more opportunities to use the market (Vermeulen and Barkema, 2001; Kogut and Zander, 1992), increasing the returns to exploitative specialization strategies.

Second, in hybrid and exploratory-oriented industries the easier access to exploratory knowledge, ideas and expertise enables exploitative firms to reduce costs by internalizing exploitation-specific functions while acquiring ideas from the market (Williamson, 1981). Transaction cost logic also suggests that the structure of hybrid and exploratory-oriented industries offsets the negative consequences of specializing in one innovation strategy at the expense of the other by allowing firms to source ideas more easily as bargaining power in such situations is not high. A richer set and greater availability of opportunities decreases the transaction costs of accessing expertise and collaborative agreements, increasing thus the effects of exploitation on performance.

Third, exploitative firms that operate in hybrid and exploratory-oriented industries are more likely to accelerate their generative learning because they are exposed to a large volume of ideas (Cohen and Levinthal, 1990; Kogut and Zander, 1993; Morgan and Berthon, 2008). Firms that specialize in exploitation may acquire new knowledge (Koza and Lewin, 1998; Koryak et al., 2018) while firms that specialize in exploration have better chances of getting their ideas exploited (Junni et al., 2013). In such situations, firms come together to explore new opportunities (Gupta et al., 2006; Baum et al., 2000), exploit technologies and confront an industry's uncertainties (Ozcan and Eisenhardt, 2009; Anderson and Tushman, 2001). Additionally, in hybrid and exploratory-oriented industries, the knowledge base and outputs of firms are more likely to be diverse and are therefore less likely to become redundant and substitutable (Belderbos and Zou, 2009; Zhao, 2006; Yang et al., 2014). Accordingly, we expect specialization in exploitation to have greater returns in hybrid and exploratory-oriented industries:

H3a&b (cells 2-3): *The pursuit of a specialization in exploitation strategy has a positive effect on performance when the firm operates* ***a)*** *in a hybrid industry or* ***b)*** *in an exploratory-oriented industry.*

Applying the same logic, we expect specialization in exploratory R&D to be more beneficial when the focal firm operates in a hybrid or an exploitative-oriented industry. First, hybrid- and exploitative-oriented industries feature high availability of exploitation-specific knowledge and skills and therefore provide firms that specialize in exploratory R&D with a richer set of opportunities to get their ideas exploited in the market. Second, the establishment of collaborative agreements is easier to occur but also the transaction costs associated with the collaboration are likely to be lower given the high number of firms that possess complementary to exploration expertise. Third, for the reasons discussed earlier, such industry dynamics may also accelerate learning within organizations and make collaborative agreements more valuable due to synergies and complementarities. Finally, the ideas and technologies developed by exploratory firms will face lower competition in hybrid and exploitative-oriented industries. Hence, specialization in exploratory R&D is likely to be more advantageous in hybrid and exploitative-oriented industries:

H4a&b (cells 7 & 8): *The pursuit of a specialization in exploration strategy has a positive effect on performance when the firm operates* ***a)*** *in a hybrid industry or* ***b)*** *in an exploitative-oriented industry.*

Pursuing an ambidextrous strategy in hybrid, exploratory-oriented and exploitative-oriented industries (cells 4, 5 & 6)

The next set of hypotheses concerns those firms that are ambidextrous and operate in different industries. Hybrid industries feature similar availability of exploration- and exploitation-specific R&D opportunities. About a third of firms in those industries make similar investments in *both* exploratory and exploitative R&D, about a third specializes in exploratory R&D and the remaining third specializes in exploitative R&D.

For a number of reasons, I expect the pursuit of an ambidextrous strategy to have a positive effect on performance when the firm operates in a hybrid industry. First, the diversity of both exploratory and exploitative-specific knowledge, expertise and capabilities in hybrid industries helps ambidextrous firms to identify collaborative opportunities while inducing low to moderate difficulty and transaction costs in accessing such opportunities. These conditions therefore increase the likelihood of getting firms' exploratory ideas utilized and commercialized, while accelerating their ability to produce new knowledge and technologies.

Hybrid industries can also offer ambidextrous firms more chances to come together to either explore new technologies (Gupta et al., 2006; Cassiman and Veugeulers, 2006; Hess and Rothaermel, 2011) or exploit existing ones to respond to industry uncertainty (Ozcan and Eisenhardt, 2009; Anderson and Tushman, 2001; Banergee and Siebert, 2017). Exploitative and exploratory-specific collaborative agreements are easier to occur in hybrid industries and the transaction costs associated with those are likely to be lower given the high number of firms that possess skills and knowledge that could complement (rather than substitute) both exploration- and exploitation-specific needs. Furthermore, ambidextrous firms in hybrid industries have better chances to accelerate their adaptive and generative learning by making a better use of collaborative agreements to accentuate their own knowledge base due to complementary synergic skills between receiver and receptor firms (Cohen and Levinthal, 1990; Kogut and Zander, 1993; Argyris, 1976; Morgan and Berthon, 2008; Hess and Rothaermel, 2011; Ho and Wang, 2015). Once again, this suggests that ambidextrous strategy is likely to influence firm performance positively when the firm operates in a hybrid industry.

By contrast, I expect that being ambidextrous and operate in a highly-specialized industries (either exploratory or exploitative-oriented) will have negative consequences for firm performance. The theoretical justification for this expectation relies on the notion that the value of the ideas and outputs of an ambidextrous firm are likely to be partially redundant or be less valuable in industries that are oriented towards one particular direction (Belderbos and Zou, 2009; Zhao, 2006; Li and Chi, 2013). First, the ideas, technologies and knowledge developed by specialized firms are likely to be ahead of those ideas and knowledge that an ambidextrous firm can produce and offer in specialized industries. Therefore, their value is likely to be limited due to their restricted utility in those industries (Vassolo et al., 2004; Belderbos and Zou, 2009; Yang et al., 2014).

Furthermore, in hybrid industries the knowledge base and outputs of specialized in exploratory R&D firms are more likely to be dissimilar and distinct from specialized in exploitative R&D firms (Brusoni et al., 2001). Specialization is such environments therefore is difficult to compete when firms are ambidextrous and therefore the ideas and outputs of ambidextrous firms are likely to become either redundant or substitutable by expert knowledge. Accordingly, competing in highly-specialized industries will impact negatively the performance of ambidextrous firms. Based on the above discussion, I introduce the following hypotheses:

H5a&b (cells 4, 5 & 6): *The pursuit of an ambidextrous strategy* ***(a)*** *has a positive effect on performance when the firm operates in a hybrid industry, but* ***(b)*** *a negative effect on performance when the firm operates in either an exploitative-oriented or explorative-oriented industry.*

DATA AND METHODS

(For the convenience of the examiners, we have reproduced the data and methods sections from other chapters of this PhD. thesis. However, for greater details please refer to the Method section of Chapter 4 of the thesis).

Sample

To test the hypotheses, we need firm-level longitudinal data as the effects of exploration activities take time to materialize (March, 1991). We collect data from a national innovation survey that is designed to monitor the economic development and technological activities of Spanish firms. Similar to the Community Innovation Survey (CIS) in other countries, there is high reliability in the reported data because the survey is administered every two years by the National Statistics Institute (INE) in Spain and sent to firms that are legally obliged to respond. As a result, over 90% response rate is achieved. This dataset is appropriate for testing our hypotheses because it provides a detailed breakdown of the distribution of R&D expenditure by type (exploitative and exploratory R&D). Our analysis focuses on firms with more than 10 employees. Instead of focusing on a single industry (Rothaermel, 2001; He and Wong, 2004), we examine 56 industries to increase variability in our data and test the effects of specialization in industries with different orientation. The initial sample consisted of 41,196 firm-year observations that had information on exploratory and exploitative investments. However**,** after deleting missing and ambiguous observations, and firms that had less than four years of information, the final sample resulted in an unbalanced panel of 32,527 observations (5567 firms) over the 2003-2012 period.

DEPENDENT VARIABLE

As explained in greater detail in chapter 4, we follow common practice (e.g. Adams and Jaffe, 1996; Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b), and operationalize each firm's productivity performance by estimating a 'residual' that captures increases in firm output that cannot be explained by firm inputs. This residual is the outcome of a function where the nominator is a firm's *output* (firm sales) and the denominator include the two key firm inputs: labour (the number of employees) and capital (tangible assets). As TFP captures a firm's ability to generate sales while controlling for the inputs that a firm uses to achieve that level of output, it avoids biases associated with the fact that different outputs may exhibit different economies of scale (Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b). The estimation of TFP is given in equation 1 in Chapter 4 and it is based on the fact that productivity is the intermediate transformation capacity level between inputs and outputs and thus reflects a firm' ability to transform and generate value from a given number of inputs. To be consistent with prior studies and given that economic relationships are rarely linear, we transform the TFP measure in its logarithmic form (Van Beveren, 2012; Qingwang and Junxue, 2005).

INDEPENDENT VARIABLES

Firms' Exploitative and Exploratory R&D

Consistent with prior research (March, 1991; Jansen et al., 2006; He and Wong, 2004) and the survey's definitions, exploration consists of the *creative basic & applied research* conducted by firms in order to develop new knowledge that aims at creating something new to business and market. By contrast, exploitation consists of the *systematic technological development* that relies upon the firm's existing knowledge that has been accumulated through repetition and practical experience that aims at refining or improving substantially existing products and processes. Firms in the survey report the distribution of their current R&D expenditure by type of research. Accordingly, we measure exploration using the log of each firm's annual investment in exploratory/experimental research activities (once again, we divide it by the number of employees to normalize for firm size). Similarly, we measure exploitation using the log of each firm's annual investment in exploitative activities (normalized for firm size).

Firms' Specialization in Exploratory and Exploitative R&D

Following previous studies (He and Wong, 2004; Cao et al., 2009) we use the absolute (percentage) difference between firms' expenditure on exploratory and exploitative activities. Building on the definition that specialization is a strategy by which firms limit the scope of their activities, we classify a firm as specialized in one activity when it spends over 66.6% of its internal R&D budget on either exploration or exploitation. This means that a firm's investment in one of the two activities is at least two times higher than its investment in the other activity. In operationalising the specialization in exploratory and exploitative R&D variables we used two different approaches. First, we use is a year-specific measure of specialization that reflects what the firms does in a given year. This variable is time-variant because a firm could specialize in exploratory R&D in one year but not in the next year. Second, we estimate the average percentage of each firm's budget spent on exploratory and exploitative R&D throughout the sampled years. This classification ensures that a firm remains specialized in one activity over a long period of time (rather than for just 2-3 years). We accordingly create two variables, one for specialization in exploration and one for specialization in exploitation, that take the value of 1 when a firm specializes in one of the two activities (and 0 otherwise). Further, when the percentage of the firm's budget is thus between 33.3% and 66.6%, these firms were categorized as firms with ambidextrous investments (i.e., ambidextrous firms).

Hybrid, Exploitative- and Exploratory-Oriented Industries

In line with the way we estimated specialization at the firm level, we consider the absolute difference between exploration and exploitation in identifying the industry's specialization. We first identified for each year separately the number of specialized firms in each industry that spend over 66.6% of their internal R&D budget on either exploratory or exploitative activities and estimated the percentage of these firms over each industry' total number of firms. Secondly, we estimated for each industry the absolute difference between the percentage of firms that specialize in exploration and those that specialize in exploitation. We finally estimated that the absolute difference for the 56 industries of our sample was on average 20% and used this value to distinguish industries that were oriented towards one of the two activities (i.e. those that exceeded

20%) from other industries that were less oriented towards one activity (i.e. hybrid industries, please refer to Table 1 of Chapter 4).

For example, only 17% of firms in the telecommunication sector specialized in exploration while 64% of firms specialized in exploitation. As this industry exhibits an absolute difference of 47%, it was classified as an exploitation-oriented industry. Other exploitation-oriented industries include sectors such as machinery, mechanical equipment, electrical, motor vehicles and computing. At the other end of the spectrum, 54% of firms in the pharmaceutical industry specialized in exploration and only 17% of firms specialized in exploitation. We thus classified this industry as exploratory-oriented. Other exploratory-oriented industries in our sample include the extractive, health-related and chemicals sectors. Industries that were not oriented towards exploitation or exploration (e.g. electricity, textiles, petroleum refining and minerals) fell into the hybrid industries (Table 1 of Chapter 4). Based on this categorization, we create three variables that take the value of 1 when an industry is hybrid or oriented towards exploitation or exploration (and 0 otherwise). On average, exploitative-oriented industries are characterized by a high concentration of firms that specialize in exploitation (51%) and only 21% of firms specialize in exploration. By contrast, exploratory-oriented industries have a high concentration of firms (47%) that specialize in exploration and only 21% of firms in such industries specialize in exploitation. In hybrid industries, approximately the same percentage of firms specialize either in exploratory and exploitative R&D and are ambidextrous (refer to descriptive statistics of Table 1 in Appendix 2). This distinction is also reflected on the spending on exploration and exploitation. In exploitative-oriented industries, spending on exploitative R&D strategies is approximately three times higher than the corresponding spending on exploration. By contrast, spending on exploration in exploratory-oriented industries is double compared to that on exploitation, whereas investment in exploration and exploitation is similar in hybrid industries (Table 1, Appendix 2).

Specialized Firms operating in Hybrid, Exploitative- and Exploratory-Oriented Industries

To test our hypotheses, we needed to create variables that capture that firms that specialize in exploitation or exploration may operate in hybrid, exploitative- or exploratory-oriented industries. As Table 1 of Chapter 4 exhibits, there are 9 different combinations (i.e. each cell represents one of the nine possible combinations in this 3x3 table). For example, firms that specialize in exploitation and operate in an exploitative-oriented industry are represented by Cell 1, whereas those that specialize in exploitation and operate in a hybrid or exploratory-oriented industries belong to Cell 2 and Cell 3, respectively. Similarly, ambidextrous firms that operate in exploitative-, hybrid and exploratory-oriented industries are represented by Cells 4, 5, 6 respectively of the 3x3 table. Specialized in exploration firms that operate in exploitative-oriented, hybrid or exploratory-oriented industries fall into Cell 4, Cell 5 and Cell 6, respectively. Based on this taxonomy, we create nine dummy variables that take the value of 1 when a firm belongs to one of these nine cells (and 0 otherwise).

CONTROL VARIABLES

We further control for various firm- and industry-specific factors that may affect firm performance. First, we control for each firm's *tangible resources* (Auh and Menguc, 2005; Jansen et al., 2006; Lubatkin et al., 2006), measured as the log of each firm's gross investment in tangible resources in each year. This may account for the difficulties that resource-constrained firms encounter in different industrial environments (Hannan and Freeman, 1984; Tushman et al., 1985). Second, we control for *newly created* firms using a dummy variable that takes the value of 1 if a firm is newly created (Laursen and Salter, 2006). This variable may affect firm performance by influencing a firm's ability to find collaborators, establish itself in an industry and accumulate different types of knowledge.

Third, we control for each firm's *international sales* (dummy variable that takes the value of 1 for firms that sell their products abroad) because a firm's market expansion is associated with its growth (He and Wong, 2004), international competitiveness and access to new market knowledge (Cassiman and Veugelers, 2006). Fourth, we control for *affiliated firms* using a dummy variable that takes the value of 1 for firms that are affiliated to groups (Khanna and Palepu, 1997; Blindenbach-Driessen and Ende, 2014) and may therefore enjoy certain advantages that enhance their performance. Fifth, given that a firm's appropriability strategy may affect its performance (Laursen and Salter, 2006; 2014), we control for the mechanism that each firm uses to protect its inventions (Vega-Jurado et al., 2008). These mechanisms include the use of four *protection* mechanisms (patents, utility models, trademarks and copyrights. This variable therefore ranges from 0 to 4, depending on how many of these mechanisms each firm employs.

However, firm performance can also be affected by industry-specific attributes. We control for industry's intensity of *competition* operationalized using the number of 2-digit intra-industry competitors (Jansen et al., 2006) because in highly competitive industries firms are forced to improve operational efficiency (Matusik and Hill, 1998) and avoid risk-taking behavior (Miller and Friesen, 1983; Auh and Menguc, 2005) or experiment with novelties to avoid obsolescence (Uotila et al., 2009). Because this measure does not capture the market share of firms and whether few firms control most of the market, we also estimated Herfindahl Index (the results from the regressions of this chapter Herfindahl Index as a measure of competition). As explained in the general method section of this thesis, Herfindahl Index is widely accepted in various studies as an appropriate measure of industry concentration (Kafouros and Aliyev 2016; Wu et al. 2016). We estimated by summing of squared market shares of firms in the industry. It is thus calculated as $CI_j = 1 - \sum_{i=1}^{n} s_{ij}^2$, where s_{ij} is the market share of firm i in industry j and therefore it takes values between 0 and 1. A higher value of the Herfindahl Index indicates lower concentration level within an industry, and thus low levels of competition. We therefore use the inverse value of the Herfindahl Index (i.e. 1- Herfindahl index) so that a higher value indicates high levels of competition.

We control for *time effects* by including in the model year dummies (that equals 1 that corresponds to specific year) to account for differences in economic trends over years (Belderbos et al., 2010). In models that are not nested in industries (i.e. when they are not multi-level), we also include industry dummies in our model to account for the different industry characteristics and variations in their nature, both technological and economic. Further, we include in the model a binary variable that represents those firms that operate in high-technological industries. As explained in the method section of this thesis, in constructing this variable we use the OECD classification given in COTEC Report 1997 cited in Bayona Sáez and Arribas (2002). *High-tech industries* refer to sectors such as chemicals, pharmaceutical, computing, electronics, electrical, communication, and medical devices and optical instruments. By contrast, medium and low-tech industries include sectors such as textiles, furniture, leather, rubber and plastic (taking the value of 1 when firms operate in high tech industries and 0 otherwise). Finally, we control for the *industry's R&D intensity* using the industry's total R&D expenditure divided by total industry sales (Uotila et al., 2009) because in environments with high levels of R&D spending, there are abundancy of technological opportunities than in environments with lower R&D spending (Zahra, 1996). These opportunities may influence firm performance (Baysinger and Hoskisson, 1989).

ESTIMATION METHOD (As explained in prior empirical chapters, since the estimation method remains the same across the three empirical chapters of this thesis, we have reproduced below a cut-down version for the convenience of examiners. Please refer to the method section of Chapter 4 for greater details and reasoning for our choice)

As explained in Chapter 4, given that our sampled firms are clustered within industries, a *Multilevel Mixed Model* approach was better suited for estimating TFP (Bliese and Ployhart, 2002; Preacher et al., 2006; Anderson, 2014; Pindado et al., 2012). As explained the choice of Multilevel Mixed estimator was driven by two factors: First, in contrast to traditional panel data estimators, multilevel analysis with mixed effects considers both FE and RE effects. Second, the model is specified at different levels, meaning that it produces coefficients that are nested in each industry and firm. Third, by nesting the effects within each firm the analysis has the additional benefit of producing an estimator that is very close to FE since it estimates the effects separately for each firm and industry separately (Wooldridge, 2000; Blundell and Bond, 2000). Although as we explained, we experimented with other estimators such as FE and RE, the fact that we expected the effects of specialization strategies and exploration/exploitation investment to vary a lot depending on the industry made this estimator less appropriate to reveal variability at both industry and firm level. Thus, our chosen estimator allows us to explicitly specify the estimation with complicated clustering patterns near models while relies on the assumption of independence of error terms, which may be violated when firms are clustered in various industries (Hox et al., 2017; Anderson, 2014; Preacher et al., 2006). As a robustness check, we also used alternative estimators to establish consistency across our results, including the generalized least squares (GLS) estimator which is appropriate when using longitudinal data (Wooldridge, 2000; Blundell and Bond, 2000).

As discussed in detail in Chapter 4 of the PhD thesis, we followed established practice and specified our model (refer to equation 2) (Temouri et al., 2008). We also transform the variables in their logarithmic form to ease the interpretation of our findings (Qingwang and Junxue, 2005; Van Beveren, 2012). However, in equation 2 for testing the hypotheses of Chapter 6, we also added apart from the specialization variables at firm level, the variables regarding the orientation of the industry.

RESULTS

Table 3 presents descriptive statistics and correlations for the model's variables (Table 1 in Appendix 2 at the end of the chapter provides further descriptive statistics depending on the orientation of the industry). The maximum VIF value obtained in any of the models was below the cut-off point of 2 (O'Brien, 2007; Lin et al., 2012). The highest VIF value we obtained from our analysis was 1.73 with average 1.21. Table 4 reports the regression results using Multilevel Mixed Effects Model *(Hierarchical Linear Model)* with results that are nested both in each industry *and* firm (Bliese et al., 2002). Unlike traditional panel data, this estimator has the additional benefit of producing coefficients that are very close to FE estimators. Model 1 is the baseline model. Model 2 introduces variables that test how firm performance (TFP) is influenced when firms that specialize in exploitative R&D operate in a exploitative-oriented industry (cell 1), how performance is affected when ambidextrous firms compete in exploitative-oriented (cell 4) and exploratory-oriented industries (cell 6) respectively, and how firm performance is affected when firms that specialize in exploratory R&D operate in an equally exploratory-oriented industry (cell 9). Model 3 tests the corresponding effects for firms that specialize in exploitative R&D and operate in hybrid (cell 2) and exploratory-oriented industries (cell 3), the performance effects for firms that are ambidextrous and operate in an equally hybrid industry (cell 5) and whether those effects change for firms that specialize in exploratory R&D and compete in an exploitative-oriented (cell 7) hybrid industry (cell 8). In the first three models, the operationalization of the specialization variable relies on a year-specific estimation (i.e., it is measured every year).

In Models 4 and 5, the specialization variable is based on average-specific estimation (i.e., it is measured as the average of all the years of the sample for each firm)). Accordingly, Model 4 tests how firm performance is affected when firms that specialize in exploitative R&D operate in a similarly exploitative-oriented industry (cell 1), how performance is affected when ambidextrous firms compete in exploitative-oriented (cell 4) and exploratory-oriented industries (cell 6) respectively, and how firm performance is affected when firms that specialize in exploratory R&D operate in an equally exploratory-oriented industry (cell 9). Model 5 reports the corresponding effect on firm performance for the remaining cells, i.e., the corresponding effects for firms that specialize in exploitative R&D and operate in hybrid (cell 2) and exploratory-oriented industries (cell 3), the performance effects for firms that are ambidextrous and operate in an equally hybrid industry (cell 5) and whether those effects change for firms that specialize in exploratory R&D and compete in a exploitative-oriented (cell 7) hybrid industry (cell 8).

Table 3- Descriptive Statistics and Correlations

	Variable	1	2	3	4	5	6	7	8	9	10
1	Total Factor Productivity	1.000									
2	Exploitative Firms in Exploitative industries	-0.036	1.000								
3	Exploitative Firms in Hybrid Industries	0.077	-0.121	1.000							
4	Exploitative Firms in Exploratory Industries	-0.041	-0.103	-0.121	1.000						
5	Ambidextrous Firms in Exploitative Industries	-0.044	-0.082	-0.097	-0.082	1.000					
6	Ambidextrous Firms in Hybrid Industries	0.068	-0.106	-0.124	-0.106	-0.085	1.000				
7	Ambidextrous Firms in Exploratory Industries	-0.048	-0.122	-0.143	-0.121	-0.097	-0.125	1.000			
8	Exploratory Firms in Exploitative Industries	0.013	-0.067	-0.079	-0.067	-0.054	-0.069	-0.079	1.000		
9	Exploratory Firms in Hybrid Industries	0.064	-0.126	-0.147	-0.125	-0.100	-0.129	-0.148	-0.082	1.000	
10	Exploratory Firms in Exploratory Industries	-0.049	-0.175	-0.206	-0.175	-0.140	-0.180	-0.207	-0.114	-0.214	1.000
11	Exploratory R&D	-0.050	0.288	0.216	0.240	0.215	0.157	0.248	-0.174	-0.452	-0.517
12	Exploitative R&D	-0.059	-0.308	-0.532	-0.364	0.169	0.098	0.198	0.145	0.170	0.352
13	Tangible Assets	0.207	0.041	0.028	-0.054	0.051	0.055	-0.053	0.040	0.021	-0.080
14	International Sales	0.240	-0.004	0.009	0.001	0.007	-0.007	0.022	-0.014	0.008	-0.021
15	Affiliated Firms	0.328	0.004	-0.007	-0.039	0.009	0.028	-0.021	-0.003	0.009	0.015
16	Industry Competition	0.055	0.114	-0.027	0.002	0.101	-0.040	-0.016	0.075	-0.056	-0.066
17	Protection	0.131	0.035	-0.020	-0.017	0.045	0.016	0.008	-0.002	-0.022	-0.022
18	Industry's R&D intensity	-0.301	0.218	-0.095	-0.050	0.300	-0.082	-0.053	0.093	-0.101	-0.077
19	Newly Created Firms	-0.066	-0.001	-0.008	-0.006	0.021	-0.013	0.016	0.007	-0.006	-0.004
20	High Tech. Firms	0.142	0.309	-0.193	0.010	0.220	-0.163	0.019	0.210	-0.202	-0.032
	Mean	0.059	0.093	0.124	0.093	0.062	0.098	0.125	0.042	0.133	0.229
	Std. Dev.	0.937	0.291	0.330	0.290	0.241	0.297	0.331	0.201	0.339	0.420
	Min	-11.01611	0	0	0	0	0	0	0	0	0
	Max	5.528801	1	1	1	1	1	1	1	1	1

Table 3- Descriptive Statistics and Correlations (cont.)

	Variable	11	12	13	14	15	16	17	18	19	20
1	Total Factor Productivity										
2	Exploitative Firms in Exploitative industries										
3	Exploitative Firms in Hybrid Industries										
4	Exploitative Firms in Exploratory Industries										
5	Ambidextrous Firms in Exploitative Industries										
6	Ambidextrous Firms in Hybrid Industries										
7	Ambidextrous Firms in Exploratory Industries										
8	Exploratory Firms in Exploitative Industries										
9	Exploratory Firms in Hybrid Industries										
10	Exploratory Firms in Exploratory Industries										
11	Exploratory R&D	1.000									
12	Exploitative R&D	-0.221	1.000								
13	Tangible Assets	0.086	0.046	1.000							
14	International Sales	0.020	0.003	0.069	1.000						
15	Affiliated Firms	-0.031	0.003	0.091	0.102	1.000					
16	Industry Competition	0.056	-0.041	0.038	0.146	-0.015	1.000				
17	Protection	0.054	0.023	0.082	0.171	0.141	0.104	1.000			
18	Industry’s R&D intensity	0.239	0.138	0.028	-0.067	-0.082	0.039	0.018	1.000		
19	Newly Created Firms	0.028	0.033	0.021	-0.052	-0.002	-0.003	-0.018	0.052	1.000	
20	High Tech. Firms	0.129	0.005	0.027	0.134	0.031	0.170	0.092	-0.082	-0.013	1.000
	Mean	4281	4790	7463471	0.755	0.449	0.924	-3.978	0.068	0.006	0.215
	Std. Dev.	19806	16427	79900000	0.430	0.497	0.089	3.520	0.192	0.074	0.411
	Min	0	0	0	0	0	0	-6.90775	0.0006376	0	0
	Max	2371429	1489540	3.00E+09	1	1	0.9877058	1.386294	8.725727	1	1

Table 4 - Regression Results (Multilevel Mixed Model)

	year-specific specialization						average-specific specialization								
	Model 1			**Model 2**			**Model 3**			**Model 4**			**Model 5**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1: Specialized in exploitation firms in exploitative-oriented industries (Cell 1)				-0.055*	0.028	0.047				-0.357***	0.074	0.000			
H2: Specialized in exploration firms in exploratory-oriented industries (Cell 9)				-0.033†	0.017	0.052				-0.233***	0.027	0.000			
H3a: Specialized in exploitation firms in hybrid industries (Cell 2)							0.409***	0.039	0.000				0.427***	0.045	0.000
H3b: Specialized in exploitation firms in exploratory-oriented industries (Cell 3)							0.024	0.019	0.206				0.022	0.043	0.590
H4a: Specialized in exploration firms in hybrid industries (Cell 8)							0.363***	0.034	0.000				0.339***	0.042	0.000
H4b: Specialized in exploration firms in exploitative-oriented industries (Cell 7)							0.006	0.026	0.816				0.013	0.064	0.843
H5b: Ambidextrous firms in exploitative-oriented industries (Cell 4)				-0.074**	0.029	0.010				-0.298***	0.082	0.000			
H5a: Ambidextrous firms in hybrid industries (Cell 5)							0.357***	0.036	0.000				0.354***	0.045	0.000

H5b: Ambidextrous firms in exploratory-oriented industries (Cell 6)				-0.044**	0.017	0.008				-0.296***	0.034	0.000			
Exploratory R&D	0.007***	0.001	0.000	0.005***	0.002	0.001	0.004*	0.002	0.012	0.005***	0.001	0.000	0.005***	0.001	0.000
Exploitative R&D	0.007***	0.001	0.000	0.006***	0.002	0.001	0.008***	0.002	0.000	0.005***	0.002	0.001	0.005***	0.002	0.000
Tangible Assets	-0.003	0.004	0.416	-0.001	0.003	0.796	-0.001	0.003	0.689	-0.001	0.003	0.796	-0.001	0.003	0.727
International Sales	0.035*	0.016	0.022	0.051***	0.014	0.000	0.049†	0.014	0.000	0.050***	0.014	0.000	0.049***	0.014	0.000
Affiliated Firms	0.124***	0.016	0.000	0.129***	0.015	0.000	0.129***	0.015	0.000	0.130***	0.015	0.000	0.130***	0.015	0.000
Industry Competition	0.269†	0.151	0.075	0.334**	0.112	0.003	0.335**	0.111	0.003	0.334**	0.111	0.003	0.334**	0.111	0.003
Protection	0.003*	0.002	0.012	0.004**	0.002	0.003	0.004**	0.002	0.003	0.004**	0.002	0.002	0.004**	0.002	0.003
Industry’s R&D intensity	-0.212*	0.105	0.043	-0.572*	0.242	0.018	-0.525*	0.217	0.016	-0.529*	0.231	0.022	-0.523*	0.219	0.017
Newly Created Firms	-0.309***	0.080	0.000	-0.300***	0.091	0.001	-0.302***	0.091	0.001	-0.302***	0.091	0.001	-0.302***	0.091	0.001
High Technological Firms	0.051	0.116	0.658	0.267***	0.030	0.000	0.415***	0.033	0.000	0.365***	0.042	0.000	0.412***	0.034	0.000
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.266*	0.130	0.040	-0.417***	0.106	0.000	-0.618***	0.106	0.000	-0.307**	0.107	0.004	-0.599***	0.107	0.000
Industry Variance	0.2622	0.0682													
Firm Variance	0.4965	0.0437		0.0235	0.6255		0.0229	0.6508		0.658	0.023		0.650	0.023	
Residual Variance	0.1264	0.0148		0.1270	0.0067		0.0067	0.1268		0.127	0.007		0.127	0.007	
Wald chi2 (22-23)	233***	P>	0.000	310***	P>	0.000	600***	P>	0.000	490***	P>	0.000	609***	P>	0.000
Number of observations	32527			32527			32527			32527	-	-	32527	-	-

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

n=5567

The results in Models 2 and 4 indicate that a specialization in exploitation strategy has a negative effect on firm performance when firms operate in exploitative-oriented industries. The results therefore corroborate H1. The results yield a similar pattern when the opposite case is considered. According to Models 3 and 4, a specialization in exploration strategy has a negative effect on firm performance when firms operate in exploratory-oriented industries. They therefore provide empirical support to H2 and to the theoretical prediction that certain advantages become partially redundant when they are offered by several other firms in the same industry.

Models 3 and 5 test the hypothesized effects of H3a and H3b. The pursue of a specialization in exploitation strategy enhances firm performance when firms compete in hybrid industries, thus providing support for H3a. Despite our expectations, the corresponding effects of this specialization strategy appear to be statistically insignificant when firms operate in exploratory oriented industries. Hence H3b is not supported. A similar pattern in the results (Models 3 and 5) emerges when we consider the effects of a specialization in exploration strategy. This strategy makes a positive contribution to firm performance when firms operate in hybrid industries. Hence, H4a is supported. However, we do not find support for H4b that suggests that pursuing a specialization in exploration strategy is beneficial when firms compete in exploitative-oriented industries.

Furthermore, Models 2-5 allow us to test H5a&b. These hypotheses state that "the pursue of an ambidextrous strategy has **a)** a positive effect on performance when the firm operates in a hybrid industry but **b)** a negative effect on performance when the firm operates in either an exploitative-oriented or explorative-oriented industry". The results in Models 2-5 fully support these predictions. Specifically, in Models 2 and 4, the coefficients for the relevant hypotheses are negative when firms that are ambidextrous operate in either in either exploitative-oriented or explorative-oriented industries. By contrast, in Models 3 and 5, the corresponding coefficients are positive when firms that are ambidextrous operate in hybrid industries.

Overall, the results suggest that firm strategies are less beneficial when firms operate in industries that exhibit an orientation that is similar to their own specialization strategy. However, a specialization strategy in either exploration or exploitation appears to be advantageous for firms that compete in hybrid industries. Although we got statistically insignificant results when we seek to find support that specialized firms benefit from operating in industries with an orientation that is dissimilar to their own strategy, the results overall suggest that the comparative advantages of specialization strategies are more prominent when they complement the orientation of the industry.

ROBUSTNESS CHECKS AND ADDITIONAL ANALYSES

Alternative Estimators

First, to check the robustness of the above results to alternative estimation methods, we rerun the models using the Generalized Least Squares (GLS) estimator as an alternative estimator to Multilevel Mixed Model. Table 5 reports the new results for both year-specific and average-specific measures (the latter measure classifies specialized firms those that spend over 66.6% of their internal R&D budget on either exploratory or exploitative R&D). The new results for the hypothesized effects are similar with those reported in Table 4. Specifically, all the hypotheses are confirmed with the exception of H3b and H4b which do not give a statistically significant coefficient (H3b and H4b were also not confirmed in Table 4 that used Multilevel Mixed Model).
Second, we examined the sensitivity of the results to changes in the operationalization of the firm specialization variable. Rather than categorizing as specialized firms those that spend over 66.6% of their internal R&D budget on either exploratory or exploitative R&D, we experimented with the value of 75%. This change has resulted in findings that were consistent with those reported in Table 4. It therefore seems that by changing the cut-off point of specialization does not lead to significant changes in the results.
Thirdly, we conducted a similar robustness analysis after changing the operationalization of industries' classification. Specifically, rather than using the number of firms (i.e. concentration) in each industry to classify the orientation of the industry, we used an alternative industry classification that is based on the overall investment in exploration and exploitation within each industry. We accordingly categorize industries as exploitative- or exploratory-oriented when they spend over 66.66% of their internal R&D budget on either of these two activities. For one more time, the new results using this classification led to similar effects for the hypotheses as those reported in Table 4.

Outliers

Further, we also examined whether the hypothesised effects are supported after eliminating from the dataset the outliers. In doing so, we created the standardised residuals variable and eliminate from the dataset those firms that were over 3 and less than -3 standard deviations. The final sample were reduced from n=32,527 to n=32,077. Overall, the hypothesised effects were consistent with the only exception being that cell 9 from 10% level of significance (for the time-variant specialization) lost its significance, yet the directionality of the relationship remained qualitatively the same. And cell 4 reduced its significance from 1% to 5% when tested with the outliers removed from the dataset.

Table 5 - Regression Results (GLS Estimator)

	Year-specific Specialization									Average-specific Specialization					
	Model 1			**Model 2**			**Model 3**			**Model 4**			**Model 5**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1: Specialized in exploitation firms in exploitative-oriented industries (Cell 1)							-0.059*	0.030	0.048				-0.343***	0.076	0.000
H2: Specialized in exploration firms in exploratory-oriented industries (Cell 9)							-0.042*	0.017	0.013				-0.231***	0.027	0.000
H3a: Specialized in exploitation firms in hybrid industries (Cell 2)				0.402***	0.039	0.000				0.419***	0.045	0.000			
H3b: Specialized in exploitation firms in exploratory-oriented industries (Cell 3)				0.024	0.019	0.221				0.021	0.043	0.620			
H4a: Specialized in exploration firms in hybrid industries (Cell 8)				0.355***	0.034	0.000				0.332***	0.043	0.000			
H4b: Specialized in exploration firms in exploitative-oriented industries (Cell 7)				0.006	0.026	0.806				0.019	0.064	0.764			
H5b: Ambidextrous firms in exploitative-oriented industries (Cell 4)							-0.076*	0.030	0.012				-0.282***	0.084	0.001
H5a: Ambidextrous firms in hybrid industries (Cell 5)				0.350***	0.037	0.000				0.347***	0.045	0.000			

H5b: Ambidextrous firms in exploratory-oriented industries (Cell 6)							-0.051**	0.017	0.002				-0.292***	0.034	0.000
Exploratory R&D	0.007***	0.001	0.000	0.004	0.002	0.024	0.005**	0.002	0.003	0.004***	0.001	0.001	0.004***	0.001	0.000
Exploitative R&D	0.007***	0.002	0.000	0.008***	0.002	0.000	0.005**	0.002	0.002	0.005***	0.002	0.001	0.004**	0.002	0.003
Tangible Assets	-0.003	0.003	0.306	0.001	0.003	0.859	0.001	0.003	0.683	0.001	0.003	0.824	0.001	0.003	0.722
International Sales	0.038**	0.014	0.005	0.060***	0.014	0.000	0.064***	0.014	0.000	0.060***	0.014	0.000	0.062***	0.014	0.000
Affiliated Firms	0.132***	0.014	0.000	0.148***	0.014	0.000	0.151	0.015	0.000	0.149***	0.014	0.000	0.149***	0.015	0.000
Industry Competition	0.287*	0.129	0.026	0.339**	0.109	0.002	0.337**	0.110	0.002	0.337**	0.110	0.002	0.337**	0.109	0.002
Protection	0.004*	0.001	0.007	0.005**	0.002	0.001	0.005***	0.002	0.001	0.005***	0.002	0.001	0.005***	0.002	0.000
Industry's R&D	-0.204*	0.100	0.041	-0.572**	0.225	0.011	-0.630*	0.253	0.013	-0.570*	0.227	0.012	-0.582*	0.243	0.016
Newly Created Firms	-0.310***	0.092	0.001	-0.304**	0.091	0.001	-0.303***	0.092	0.001	-0.305***	0.091	0.001	-0.304***	0.091	0.001
High Tech. Firms	0.062	0.123	0.612	0.408***	0.034	0.000	0.263***	0.030	0.000	0.404***	0.034	0.000	0.355***	0.043	0.000
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Industry Dummies	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.614***	0.168	0.000	-0.635***	0.105	0.000	-0.436***	0.104	0.000	-0.617***	0.105	0.000	-0.329***	0.105	0.002
Wald chi2/F statistic (70-73)	12457	P>	0.000	649	P>	0.000	649	P>	0.000	658.000	P>	0.000	540	P>	0.000
R squared	0.335			0.1851			0.191			0.1854			0.181		
Number of observations	32527						32527			32527			32527		
Number of firms	5567						5567			5567			5567		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

DISCUSSION AND CONCLUSION

Theoretical Contributions

Prior studies have considered the advantages of exploration and exploitation and emphasized the importance of pursuing both activities (Cao et al., 2009; Ebben and Johnson, 2005). Despite prior contributions, the literature has overlooked the role that external markets play in determining the returns to exploration and exploitation. As such, the question "which specialization strategy (exploratory or exploitative) and under what conditions is more advantageous to the firm?" has not been addressed sufficiently. Building on the premise that firms may use the market to balance the need to explore and exploit (Gupta et al., 2006), we contend that the returns to a specialization in exploitation or exploration strategy depend on a particular characteristic (the *orientation*) of the industry in which the firm operates. The empirical analysis of 32,537 observations supports our theoretical predictions and contributes to the exploration/exploitation literature in a number of ways.

First, our analysis contributes to the literature on exploration and exploitation by specifying how the benefits of adopting exploratory and exploitative specialization strategies vary across industries with different orientation. As the effects of exploration and exploitation strategies on firm performance are not uniform, two firms might adopt a similar strategy but experience very different returns because of differences in the concentration of explorative- and exploitative-oriented firms in their industry. Our analysis further complements prior studies that focused on the firm's own characteristics by showing that the firm's choice to invest in exploration and/or exploitation is driven by industry orientation that in turn influences 1) the availability of collaborative and knowledge-sourcing opportunities that firms are exposed to, 2) the difficulty and transaction costs of accessing such opportunities and expertise from the industry and 3) the value of these opportunities.

Second, work on organizational learning and innovation emphasizes the importance of ambidexterity, suggesting that firms should pursuit exploration and exploitation (Duncan 1976; Benner and Tushman, 2003; He and Wong, 2004; Levinthal and March, 1993; March, 2006; Morgan and Berthon, 2008). In developing a new typology that captures the orientation of firms in each industry, our study contributes to the ambidexterity-firm performance debate by showing that specialization, rather than ambidexterity, is particularly advantageous in certain industries. Exploratory-oriented, exploitative-oriented and hybrid industries affect differently the opportunities that specialized firms have for complementing their operations and activities using the market. Our typology of industry orientation, therefore, helps us enhance understanding of how firms should distribute their efforts and investments across exploration and exploitation in order enhance their performance based on the orientation of the industry they operate.

Our approach differs from prior studies in exploration and exploitation (Benner and Tushman, 2003; Gupta et al., 2006; Jansen et al., 2006) by considering the interrelatedness between the focal firm's specialization strategy and the specialization strategies of firms in an industry. This explains why although some firms maintain a specialization strategy, industry dynamics make it possible to achieve ambidexterity at the industry level. Our approach therefore enables us to consider why certain industries may be more beneficial to specialized firms. It explains why some specialized firms perform poorly when they operate in industries with a similar orientation to that of the firm's own specialization strategy, whereas others enhance their performance in industries where there are more opportunities to engage in collaborative and knowledge sourcing opportunities that are complementary to the firm's own specialization.

Managerial Implications

Because our findings explain why specialized firms perform differently in industries with different orientation, they have practical implications for managerial decisions. First, as our study identifies the industry-specific mechanisms that make specialization more beneficial, it can help managers understand which specialization strategy their firms should pursue and how the industry in which they operate affects the returns and therefore the choice of this strategy. For instance, a specialization in exploitation strategy decreases performance when the firm operates in an exploitative-oriented industry that exhibits fewer opportunities for complementing its own activities. Conversely, the corresponding effect on performance can be positive when a firm that specializes in exploitation operates in a hybrid or exploratory-oriented industry. Although these findings do not contradict the premise that balance between exploration and exploitation is beneficial for enhancing firm performance, they suggest that a firm's specialization strategies can enhance firm performance if their output complements industry's needs. Second, our findings reinforce the view that firms may be in a more advantageous position if they invest in activities that are more likely to produce outputs that are less substitutable in the industry. Our typology of industry orientation can help firms decide whether a specialization strategy as well as *which* specialization strategy (exploration or exploitation) is more beneficial for a given concentration of firms that engage in similar activities or complementary activities. Managers thus can develop an optimal exploration/exploitation strategy that enhances performance by ensuring a better fit between their firm's expertise and industry's needs.

Limitations and Future Research

Our findings have some limitations, some of which may stimulate future research especially on the contingent role of the environment in the relationship between exploratory/exploitative R&D and firm performance. First, for testing our hypotheses concerning the effects of specialization in exploratory- exploitative-oriented and hybrid industries, we use firms operating in a single country but operating in multiple-industry sectors (both firms operating in high and low-tech industries) to increase sample heterogeneity. Nevertheless, we acknowledge that the generalizability of our results may be confined to those firms with similar characteristics to those of Spanish firms. For instance, one distinctive attribute of Spanish firms is that R&D expenditure in Spain is below average compared to that of other European countries (Eurostat statistics, 2016). Subsequently, other research may consider replicating and extending our results using a variety of counties of various degrees of institutional development (Kafouros and Aliyev, 2016; Chari and Banalieva, 2014; Chari and David, 2012). We would expect the effects of specialization to be stronger and more positive in countries with strong institutional development since collaborative agreements between firms that explore, and exploitative industries can formally be shaped, and sanctions imposed, and contract enforcement is strong (Powel et al., 1996). For instance, licensing the proprietary rights of a technology is often encouraged in countries with strong institutional development. This in turn, can give specialized firms (in exploration) more opportunities to form collaborative agreements to get their ideas and technologies exploited by others and specialized firms (in exploitation) the chance to infuse their knowledge base with new ideas.

Further, we empirically tested and confirmed the differential returns to a specialization strategy in exploratory exploitative and hybrid industries. Yet, we did not explore how the degree of institutional development in various countries could interfere and affect the returns to a specialization versus an ambidextrous strategy. For instance, based on studies (Kafouros and Aliyev, 2016) we would expect that countries that undergo major institutional transformations to affect differently the returns to a specialized versus and ambidextrous strategy. Specifically, our theoretical prediction is that specialized firms will benefit to a greater extent in countries that are not under transitional period and institutional reform because the transaction costs of using the industry market is low (Chari and Banalieva, 2014; Williamson, 2000; Kafouros and Aliyev, 2016), encouraging thus specialized firms to engage easier in formal collaborative agreements and share the proprietary rights of their technologies with other firms of different specialization. Nevertheless, we would expect that institutional development will have less significant impact (negligible effect) on the returns to ambidextrous firms since those firms often explore and exploit themselves, relying less on using the industry to complement their activities.

Third, we tested our theoretical predictions, arguing that specialized in exploration firms engage in formal and informal collaborations with other firms from the *same* industry in order to get their technologies exploited, or exploit the ideas of other firms. Our predictions could be tested in the context of *inter*-industry collaboration because firms often have to cross their own technological boundaries and reach for knowledge that resides in other industries to produce better solutions (Rosenkopf and Nerkar, 2001; Belderbos et al., 2010) and achieve complementarities in research capabilities (Mindruta, 2013).

CHAPTER 7
PERFORMANCE EFFECTS OF SPEED OF CHANGE BETWEEN SPECIALIZATION STRATEGIES

ABSTRACT

The literature on exploration and exploitation stresses the importance of pursuing both activities (i.e., achieve organizational ambidexterity) for enhancing organizational performance. However, firm performance depends not only on which activity is pursued, but also on the *speed* (i.e. how quickly) at which firms change their investments from one activity to the other. To enhance our understanding of this phenomenon, we examine how quickly firms change from one specialization strategy to another within a given timeframe, and how variations in the speed of such change affect firm performance. First, we show that changing between specialization strategies at high speed has a negative effect on the performance of the firm, mainly because the firm's learning is compressed within a shorter timeframe. Second, the adverse effects of speed of change become more augmented as the size of the innovation department increases. However, these negative effects of speed may decrease (or even become positive) for firms that operate in R&D-intensive industries. These findings indicate that although high-speed changes affect negatively firm performance, in technologically dynamic environments firms benefit from changing specialization strategies at higher speed.

Keywords: exploration, exploitation, specialization, speed of change; industry R&D intensity

INTRODUCTION

Prior research has long established the link between exploration/exploitation and firm performance (Venkatraman, et al., 2006; Auh and Menguc, 2005; Cao et al, 2009; Gibson and Birkinshaw, 2004; Junni et al., 2011; Koryak et al., 2018; O'Reilly and Tushman, 2013). It has stressed the benefits of investing in both exploration and exploitation (He and Wong, 2004; Lubatkin, et al, 2006; Raisch et al., 2009) and suggested that firms may achieve this by engaging in a temporal shift (or cycling) from one activity to the other (Burgelman, 2002; Gupta et al., 2006). However, firm performance depends not only on what activity firms are choosing to pursue, but also on the *speed* (i.e. how quickly) at which firms change their investments from one activity to the other. To enhance our understanding of this phenomenon, we examine how quickly firms change from one *specialisation strategy* to another within a given timeframe, and how variations in the speed of change affect firm performance. Firms may change between three *specialization strategies* (i.e., *specialized in exploratory R&D, specialized in exploitative R&D and ambidextrous*). Some firms change from a specialized in exploitative R&D strategy to either a specialized in exploratory R&D strategy or ambidextrous strategy, whereas others change from a specialized in exploratory R&D strategy to either a specialized in exploitative R&D strategy or ambidextrous strategy. There are also firms that change from an ambidextrous strategy to either a specialized in exploratory R&D or exploitative R&D strategy.

we argue that changing specialization strategies may enhance learning and establish new capabilities (Vermeulen and Barkema, 2001; Casillas et al., 2014; Hashai et al., 2015). However, changing quickly between specialization strategies can be disruptive and harmful for firm performance (Levitt and March, 1988; Klarner and Raisch, 2013; Amburgey, 1990; Vermeulen and Barkema, 2002). The theoretical basis for this prediction is the organizational learning theory, and particularly the notion of time compression diseconomies. This notion suggests that when experiential learning is compacted over a short timeframe, it becomes less beneficial than learning that is spread over a longer period of time (Levinthal and March, 1993; Dierickx and Cool, 1989; García-García et al., 2017). Hence, since experience requires time to accumulate and organizational routines require repetitive execution to become efficient (March, 1991; Baum et al., 2000, Holmqvist, 2004), firms that quickly alternate between specialization strategies are less likely to apply their learning experience into establishing an efficient organizational routine (Schilling et al., 2003). Therefore, firms that change their specialization strategies quickly (e.g. every 1-2 years) may not benefit from their learning as those firms that change their strategy at a lower speed (e.g. every 4-5 years). Furthermore, we examine how certain contingencies associated with the size of the firm's innovation department and the R&D intensity of its industry may change the effect of speed on firm performance.

This chapter extends prior research on the exploration and exploitation literature and firm performance in two ways. First, it extends such research by identifying how quickly firms should switch between specialization strategies. It also specifies how firms could minimize the disadvantages of disruption associated with either quick changes (of a shorter time-length) or extreme changes (i.e., from being specialized in exploration to being specialized in exploitation strategies and vice versa) that may inhibit their performance. Second, knowledge of how frequently firms need to shift between specialization strategies could help them to use time effectively to create a source of competitive advantage (Shi et al., 2012).

The analysis shows that high-speed changes in specialization strategies are negatively associated with firm performance mainly because firms find it difficult to change and put in application the different elements of knowledge that specialized strategies require. This occurs because of time compression diseconomies and limitations in their absorptive capacity (Hashai et al., 2015; Garcia-Canal et., 2002). Our analysis also indicates that that the negative effects of speed of change could be moderated when firms operate in R&D intensive industries because in R&D intensive industries firms are required to adapt to dynamic environmental changes to minimize both knowledge and skill obsolescence. Shifting therefore at high speed between specialization strategies may be less adverse if it is to keep up with industry changes (Uotila et al., 2009; Kessler and Chakrabarti,1996). Overall, the findings suggest that two firms may shift between specialization strategies but experience different performance outcomes because they have chosen to do it at different speeds and in technologically different industries.

THEORETICAL FRAMEWORK AND HYPOTHESES

Organizational Learning and Specialization Strategies

Organizational learning comprises of exploitative activities and processes through which firms rely on experience and focused attention (Levinthal and March, 1993) to create refinements and increase production, as well as exploratory activities and processes through which firms rely on variability in experience and experimentation (Holmqvist, 2004). Drawing from organizational learning theory (Fiol and Lyles, 1985; Huber, 1991; Levitt and March, 1988; Argyris, 2002; Wang and Ahmed, 2003; March, 1991) we subscribe to the view that knowledge exploitation and knowledge exploration are two antithetical activities, each of which requires different learning and knowledge base (Wilden et al., 2018). When firms specialize in either exploitation and ambidextrous strategies, they have to engage in repetitive activity to improve firm efficiency, whereas when firms specialize exploration activities they experiment with distant knowledge that often deviates from their existing knowledge base (March, 1991; Gupta et al., 2006). Hence, specialization in exploitative R&D mainly utilizes the firm's existing know-how (March, 1991; Gupta et al., 2006), whereas specialization in exploratory R&D requires new knowledge, capabilities and skills (March and Simon, 1958; Weick, 1979). This important difference implies that each specialization strategy involves different types of knowledge, requires different structures and necessitates different activities that often force firms to work beyond their comfort zone and their established competencies.

Regardless of the different knowledge and activity requirements, firms that choose to specialize are forced to acquire and use new knowledge, and different capabilities and skills to those that they already possess and build competence if it is to gain some expertise (Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). However, the acquisition and application of those new skills, capabilities and knowledge that exploration and exploitation require are likely to be constrained when firms have to switch quickly between specialization strategies. This implies that a firm needs time and repetitive execution of the same task to establish routines and accumulate expertise in one activity in order to become more efficient. Time is therefore of essence because firm efficiencies are often achieved because of the repetition in execution, accumulated expertise and experiential knowledge gained by engaging in a specific task (Hanks and Chandler, 1994). Higher returns therefore often result from accumulated experiential learning gained by engaging with a specific specialization strategy, because experience can be translated faster into beneficial learning in areas of established expertise and tested competence (Baum et al., 2000; Holmqvist, 2004; Kim and Miner, 2007).

Organizational learning theory offers an important explanation which justifies the pursuit of stability in both organizational structures and activities (Haveman, 1993). As firms gain experience in engaging with specific activities and tasks, they build up their expertise in areas of chosen competence that makes them prone to repeat the same actions than shifting to a novel procedure or technology (Levitt and March, 1988; 1965; Argyris and Schon, 1978; Hedberg, 1981). This implies that learning that accumulates with experience requires time. However, frequent alternations between specialization strategies decreases a firm's ability to perform competently specific tasks compared to those firms that undertake the same task and activities for longer timeframes.

Speed of Change and Firm Performance

Drawing from organization learning theory and research on temporal effects (Vermeulen and Barkema, 2002; Laamanen and Keil, 2008; Klarner and Raisch, 2013; Levinthal and March 1993; Rosenkopf and Nerkar, 2001; Hashai et al., 2015; Casillas and Moreno-Menéndez, 2014), we examine how the speed at which firms change from one of the three specialization strategies (exploitative R&D, exploratory R&D and ambidextrous) to another influences their performance.

Although shifting from one specialization strategy to another has certain benefits because it enables firms to both exploit and explore and avoid competency traps, we contend that when these changes occur at higher speed, they negatively affect firm performance through the following mechanisms.

First, when firms decide to shift from one specialization strategy to another, they will need to undertake substantial structural changes (Jansen et al., 2009). For instance, when a firm changes from a specialised in exploitative R&D strategy to an exploratory R&D strategy, it may need to change its existing configuration by either replacing their exploitative with exploratory units or by physically separating them (Christensen, 1998; Blindenbach-Driessen and Ende, 2014). The main justification is that specialized exploratory units need to be small and decentralized and with loose processes to pursue disruptive innovation and experimentation, whereas specialized exploitative units need to be large with well-defined processes to focus on repetitive execution and production (Benner and Tushman, 2003; Tushman and O'Reilly, 1996). These structural changes are necessary to facilitate temporal shifts between specialization strategies (Gupta et al., 2006). Yet, the establishment of a new business configuration, the engagement with new activities and knowledge processes and overall the founding of an effective organizational routine often requires time to reach refinement and sophistication (Nelson and Winter, 1982).

Because there are limits to adapting to new occurrences and structures (Hannan and Freeman, 1984), fast speed changes between specialization strategies are likely to leave the firm with unsuitable structures and often unprepared to deal with the different requirements of a new specialization strategy (Vermeulen and Barkema, 2002). Economies of learning are likely to be limited at initial stages of establishing a new business configuration. This affects not only the firm's adaptation and efficiency, but also causes maladjustment and disruption to its existing business (Hannan and Freeman, 1984).

Let us consider, for instance, team composition. It has been suggested that team composition reflects the orientation (i.e., specialization) of the firm (Beckman, 2006). In our context, when firms decide to redistribute their investments from exploitative to exploratory ones, they will need to change the composition of their team to accommodate an exploratory mindset. The main justification is that founding teams whose members have a diverse working experience, prior working for the firm, are more likely to have unique ideas and contacts that encourage the engagement with exploratory activities, whereas those employees who have worked in the same firm for most of their lives have a common language and shared understanding that often encourages the engagement with exploitative activities (Beckman, 2006; Smith and Tushman, 2005; Jansen et al., 2008). In the case of a significant change between specialization strategies, a reconfiguration of the existing business model that involves a restructuring of the firm's teams may be necessary to support the new specialization strategy.

Similarly, a recent study reveals how teams could be composed a way to achieve balanced inventions (Wang et al., 2017). The findings indicate that moderate size teams and with moderate experience with inventions are more likely to develop balanced inventions of exploration and exploitation. Both studies indicate that when firms change specialization strategies, they often need to alter the composition of the team including team experience and size in order to cultivate a direction that supports the firm's specialization strategy (Wang et al., 2017).

Our discussion so far indicates that although change between specialisation strategies ultimately enable firms to become adaptive entities to market needs, it is only after enough time has passed for the firm to rectify problems associated with the disruption of its existing business (Amburgey, 1993). Since successful adaptation to new configurations requires time but also new skills and capabilities (Hannan and Freeman, 1984; Child and Kieser, 1981; Klarner, and Raisch, 2013), fast changes between specialization strategies are likely to harm those firms whose skills and capabilities cannot be shifted quickly to new technologies and knowledge requirements (Dosi, 1982; Tushman and Anderson, 1986), affecting its performance negatively. By contrast, firms that change at a lower speed and therefore less frequently are more persistent in their focus, engaging with the same activity for longer periods of time. The familiarity of a given set of routines enables those firms that change less often their specialization strategy to accumulate expertise and enhance the efficiency of a given specialization strategy with subsequent positive effects for firm performance (Rosenkopf and Nerkar, 2001).

Second, when firms change specialization strategies at high speed, they are constrained by time compression diseconomies (Dierickx and Cool, 1989). The time compression diseconomies concept suggests that when learning is compacted over a short timeframe, it is less beneficial than learning that is spread over a longer period of time (Levinthal and March, 1981; Dierickx and Cool, 1989). The same mechanism of time compression diseconomies applies to our context. When a firm changes its specialization strategy quickly (e.g. every year), it may not accumulate the same stock of knowledge as those firms that change their strategy at a lower speed (say, every four years). As learning cannot be compressed in time, quick changes between specialization strategies will contribute less to the stock of the firm's knowledge (Dierickx and Cool, 1989; Vermeulen and Barkema, 2002).

As a result, those firms that quickly seek to reach a given level of knowledge stock when this stock could be reached proportionally over a longer timeframe are likely to face diminishing returns to certain activities (Dierickx and Cool, 1989; Hashai et al., 2015) because a short time requires an increase in the capabilities of the team (and consequently managerial staff) than does a longer timeframe. For instance, learning that comes too quickly gives rise to managerial overload (Eisenhardt and Martin, 2000) and cost (Hashai et al., 2015). The associated managerial overload and cost may be related to managers additional need to use a stream of either exploratory units to pursue new ideas or exploitative units to exploit the potential of their exploratory ideas, as well as other supporting managerial resources, such as administrative staff, legal and financial consultants. The need to accommodate these additional requirements when switching to a new specialization strategy is likely to put a strain on existing resources affecting thus the business flow often reflected in a firm's poor sales.

Third, quick changes imply shorter time for firms to translate their collective experience into effective routines, beneficial learning and outcomes (Levitt and March, 1988; Levinthal and March, 1993; Vermeulen and Barkema, 2002). Experience requires time to accumulate and organizational routines require repetitive execution to become efficient (March, 1981). Hence, firms that quickly alternate between specialization strategies are less likely to apply their learning and experience into establishing a proficient organizational routine that gives structure to their activities and increase their efficiency. This is consistent with organization theory which suggests that periods of adjustment which firms are subject to less frequent changes are important for organizational routines to emerge (Klarner and Raisch, 2013). This argument is reinforced by the fact that firms often transfer and apply experiential knowledge gained from a previous situation to a new one unsuccessfully (March and Levitt, 1988; Nadolska and Barkema, 2007; Choi and McNamara, 2018) when they have little time to evaluate and decide which routines could be utilized successfully. In our context, firms that engage in high speed changes often transfer inappropriately context-specific knowledge that is gained through their experience with a specialization strategy into a new specialization strategy. Yet, those firms often fail to reconsider the effectiveness of their prior routines and retain those that increase their efficiency and production affecting therefore their performance negatively (Finkelstein and Haleblian, 2002; Ingram and Baum, 1997; Baum and Ingram, 1998). One possible explanation is that prior experiences are often hetereogeneous to translate and utilize them in another context (Choi and McNamara, 2018), preventing the firm from making inferences and transferring them to create efficient routines. From a learning point of view, we could identify three factors that often inhibit the ability of the firm to learn and utilize effectively the learning in creating efficient operational routines when the speed of change between specialization strategies is high. First, specialized firms require time and effort to realize the learning demands of a new specialization strategy. Second firms learning and absorptive capacity that is compacted in shorter timeframe restricts its ability to learn effectively from prior experiences. Third, heterogeneity in experiences prevent firms from effectively applying their learning into the context of a new specialization strategy (Choi and McNamara, 2018)

Finally, the negative effect of high-speed change on a firm's performance can also be explained by the notion of absorptive capacity (Shift, 2016). Absorptive capacity predicts that the ability of a firm to acquire, integrate into its routines and exploit to commercial ends new knowledge elements depends largely on the overlap between prior and new knowledge (Cohen and Levinthal, 1990; Lane et al., 2006). Nevertheless, the firm by investing in exploratory R&D does not necessarily benefit from new knowledge (Cohen and Levinthal, 1989, 1990) because it needs to be able to identify commercially valuable knowledge. This implies that the low degree of knowledge overlap between specialization strategies limits the firm's absorptive capacity. When firms change their specialization strategy quickly, they have to expand or alter their knowledge base to accommodate the knowledge requirements of the new specialization strategy. The low degree of relatedness in knowledge base between the existing and new specialization strategy is likely to prevent quick knowledge assimilation and successful application (Cohen and Levinthal, 1990; Zahra and George, 2002; Volderba et al., 2010). Because changing quickly from a new specialization strategy and adapting to its organizational routines, structures and processes require increased absorptive capacity, adaptation efforts and costs increase (Dierickx and Cool, 1989; Zollo and Winter, 2002) with negative consequences for the efficiency of a given strategy and subsequently for the overall performance of the firm. Accordingly:
H1*: The higher the speed of change amongst a firm's specialization strategies, the more negative its effect on firm performance.*

Extreme Changes in Specialization Strategies

Change is broadly defined in the literature as alterations in the configuration or structure of organizations (Rajagopalan and Spreitzer, 1996; Van de Ven and Poole, 1995). Such changes, which typically involve resource redeployment, can be either moderate (first-order) or extreme (second-order), thus requiring adaptive or transformative alterations respectively (Bartunek and Moch, 1987). In our context, some firms may make moderate changes to their specialization strategy. For instance, they may change from an exploitative R&D (or exploratory R&D) specialization strategy to an ambidextrous strategy. Such changes involve smaller adjustments to existing operations and organizational routines (i.e., repetitive patterns of activity; Nelson and Winter, 1982). By contrast, other firms undertake extreme changes from one year to another and shift their exploratory specialization strategy to an exploitative one (or vice versa). Such changes involve substantial departures from existing organizational routines and activities (Van de Ven and Poole, 1995; Pettigrew et al., 2001; Shift, 2016). For instance, changing from exploitative R&D to exploratory R&D is proved to be harmful for firm performance (Shift, 2016). It is possible that changes in specialization strategies require substantial changes associated not only with personnel and training changes but also behavioral changes as well as organizational reconfiguration (i.e., re-arrangement aiming at retention, deletion and addition of new elements; Karim and Mitchell, 2000). For instance, a recent study suggests that the exploratory or exploitative mind set of a team is also affected by emotions (Hakonson et al., 2016). Drawing from theories of emotion, the authors indicate that team decision-making to explore a new routine is affected by positive and optimistic emotions that broaden the novelty of individuals' thoughts and actions, whereas negative and pessimistic emotions cultivate an exploitive mindset characterised with risk aversion tendency to exploit existing routines. This study exemplifies the fact that extreme changes in specialization strategies may also require changes at the behavioural level of the team in order to nurture successfully the new specialization strategy.

We hypothesize that extreme changes in specialization strategy have a stronger negative effect on firm performance compared to moderate changes for the following reasons.

First, the success of change depends on the redeployment of tangible and intangible assets, such as knowledge stock, organizational routines and experienced personnel, in the new specialization strategy and in the routines and configurations that this particular specialization strategy requires (Mitchell and Singh, 1993; Anand and Singh, 1997; Karim and Capron, 2016). Firms that pursue moderate changes in specialization that do not significantly depart from their prior activities and focus, they can partly redeploy their assets and build on existing expertise. Conversely, firms that pursue extreme changes in specialization that require entirely different processes, routines and expertise from their current focus and trajectory, are less likely to redeploy their assets (March, 1991). Since the knowledge stock that forms the basis of organizational routines decays with disuse or even with occasional use (Hannah and Freeman, 1984), those firms that change their specialization strategy significantly will need to reinvest in those skills that have learned in the past as well as invest in learning new skills to keep up with the demands of the new specialization strategy. From a learning point of view, firms that pursue moderate changes in their specialization strategy are likely to learn more effectively because they operate in areas in which their existing knowledge has greater utility and function (Dierickx and Cool, 1989; Kogut and Zander, 1992; Sears and Hoetker, 2014). In such cases, there is higher degree of knowledge and asset overlap between the two specialization strategies, assisting firms in improving their performance.

Second, extreme changes affect negatively firm performance because they make firms liable to their newness (Rajagopalan and Spreitzer, 1997; Parastuty et al., 2015; Hannah and Freeman, 1984). Since major organizational reconfiguration sets the liability of newness clock back to zero (Amburgey, 1993), those firms that undertake extreme changes are less experienced with the routines of a specialization strategy, affecting thus negatively their reliability and accountability. Firms often exhibit high reliability and accountability when their organizational activities are highly routinized and reproducible, and that organizational performance is contingent upon its members possessing a range of organizational capabilities such as specialized knowledge of the chosen strategy and tacit understanding of its operation (Hannan and Freeman, 1984; Amburgey, 1993). Consequently, firms that make extreme changes in their strategy are likely to be less reliable and accountable not only because the routines of an exploratory specialized strategy will be less reproducible in an exploitative specialization strategy, but because there is a temporal pattern of learning investments by a firm's personnel from one specialization strategy to another (Hannan and Freeman, 1984). Further, since the collective returns to learning investments will take time to be realized and materialized, the firm's efficiency and thus revenue are likely to be affected negatively, at least at initial stages of transition to a new specialization strategy.

Further, moderate changes in firms' strategy and small shifts in their orientation allow firms to rectify their mistakes and oversights. Proponents of incrementalism have emphasized the advantages of making moderate, gradual changes in organizations (Cyert and March, 1963; Starbuck et al., 1978), suggesting that unnecessary risks can be lowered by nurturing small disruptions and small reorientations (Hedberg et al., 1976; Hedberg, 1981). Consequently, firms that make moderate changes in their strategic orientation and objectives are likely to outperform those firms that undergo extreme changes because they can rectify errors caused by small swifts between specialization strategies.

Third, an extreme change in a firm's specialization strategy does not favour the existing business because it requires a reconfiguration of the whole business model, which in turn can cause significant disruption to the firm's existing business. This is consistent with the idea of adaptive strategy (Miles et al., 1978; Tyre and Von Hippel, 1997), concluding that when changes are not consistent with the current identity, focus and orientation of the firm will ultimately be rejected. Consider the extreme change in specialization strategy that the RCA (Radio Corporation of America Company) in the mid 1950's. The semiconductor firm was initially thriving on its specialized in exploitation strategy, investing heavenly on the development of the vacuum tubes (i.e., a device used to intensify electronic signals) invention (Tushman and O'Reilly, 1996). Following a period of relative certainty and efficiency, the firm decided to make an extreme change in its specialization shifting its focus from exploiting the vacuum tubes technology to exploring a new technology, i.e., the transistor). Such an extreme change in the firm's focus and technological trajectory proved that it cannibalized the profits from the vacuum tube business, forcing the firm to fail in its new specialization strategy (Tushman and O'Reilly, 1996). Concerns such as how to effectively organize the new specialization strategy, less experience with the new technology, restricted re-deploabilty of existing personnel, greater knowledge deviation from the firm's existing knowledge base as well as co-specialized managerial capacity made the firm less prepared to deal with the requirements of the new specialization strategy. Forth, moderate changes have not only economic benefits associated with risk reduction, but also cognitive advantages. For instance, small structural adjustments cause less opposition and conflict; they are more reversible and cheaper than extreme changes. Further, small structural changes put less strain on the cognitive capacities of the managers since they do not require extensive periods of analysis to figure out appropriate solutions (Miller and Friesen, 1982). Similarly, moderate changes may be less harmful for a firm's revenue when employees feel that their interests are not threatened, and their current skills are not outdated in the new specialization strategy. Evidently, firms that undergo a phase of significant change, employees often experience stress because of the realization that their former skills are likely to become invalid and less valuable in the new setting (Schabracq and Cooper, 1998). This uncertainty is experienced to a lesser degree by employees undergoing moderate changes because they typically perceive sufficient continuity to anticipate and discern the direction of change (Van de Ven and Poole, 1995 Karim and Mitchell, 2000; Graetz, et al., 2006). Further, in case of extreme changes, employees may lose their commitment and loyalty to their firm, affecting thus the way they undertake and perform their work tasks (Becker, 1992, Becker et al., 1996; Burnes, 2004). Thus, although individuals learn and adapt to new roles and circumstances differently, extreme changes are likely to cognitively affect firms' employees regardless of their expertise and learning capacity because different skills and behaviors are required when engaging in specialization strategies that require different learning capacities (i.e., new knowledge elements and generative learning versus existing/already tested knowledge and adaptive learning; Tyre and Von Hippel, 1997) and skills (i.e., refinement versus experimentation) to engage competently. Accordingly, we expect the following:

H2*: Extreme changes in firms' specialization strategy will have a more negative effect on their performance compared to moderate changes.*

The Size of the Firm's Innovation Department

Although quick changes between specialization strategies affect negatively firm performance, we further hypothesize that this effect is more negative for firms that possess a larger innovation department than for firms with a smaller innovation department. We therefore expect the size of the firm's innovation department to negatively moderate the relationship between speed and firm performance. We argue that inertial forces are stronger when the size of the innovation department is larger (Hannan and Freeman, 1984; Amburgey et al., 1990) because size affects the organization of the innovation department. Although larger size is positively associated with resource munificence, it also increases the levels of bureaucracy, requires stronger administrative coordination and may lead to organizational instability (Baker and Cullen, 1993). For these reasons, larger innovation departments could be less effective in implementing changes than their smaller-size counterparts, which may increase the negative effects of speed on firm performance.

First, larger size leads to inertia that is triggered by the gradual loss of a firm's operational flexibility (Hannan and Freeman, 1984; Kellyand Amburgey, 1991). The loss of operational flexibility arises because when firms change specialization strategies quickly, they need to spend considerable time on reorganizing core aspects of their structure. Hence, the existing structures and personnel of the exploitative innovation department must be replaced by exploratory-oriented structures and personnel. Larger firms may decentralize the decision-making process, but such decentralization requires standardization of procedures, formalization of operations and effective integration mechanisms to link organizational subunits (Child, 1972; Lawrence and Lorsch, 1967; Haveman, 1993). This increases bureaucracy and due to the higher demands in managing bureaucracy, we expect that the negative effect of speed on firm performance to be stronger when a firm's innovation department is larger in size.

Furthermore, a large-size innovation department is more complex than smaller-size counterparts because a large number of personnel need to change their scope of their operations when shifting from one specialization strategy to the other. During this transition, firms with large size innovation departments may have for some period a mix of older and newer structures as well as exploratory and exploitative aims. This may confuse organizational action, personnel roles and relationships among firm members and give rise to organizational conflicts (Hannan and Freeman, 1984). The necessity of this structural transformation, i.e., disassembling one structure and building a new one increases organizational instability. As larger size innovation departments are more strongly affected by organizational instability, they are less adaptable to high speed changes, with negative consequences for firm performance.

Second, firm size may impact the formal organization of a firm (Haveman, 1993; Baker and Cullen, 1993) because larger size requires high levels of administrative reorganization (Blau, 1970; Baker and Cullen, 1993). The necessity of administrative reorganization in larger innovation departments adds complexity to a firm's structure by inducing disputes, and communication and coordination problems (Blau, 1970). Larger firms exhibit greater formalization in communication, task differentiation, and decentralization of authority (Haveman, 1993). For instance, the ability of personnel to conduct direct interactions diminishes as personnel increases (Graicunas, 1933). Employees in larger groups have to use formal forms of communication and interaction, which is likely to lead to fragmentation and subsequent differentiation of authority (Haveman, 1993). As the number of employees increases, the higher the scale of operations and activities that have to take place concurrently, and a greater level of control, coordination and attention is required (Haveman, 1993).

Third, as size is often associated with age (Baker and Cullen, 1993), larger firms are more likely to have habitually established rules and routines, and investments in fixed equipment that complicate decisions to change practices. Larger size makes adaptation difficult because institutionalized rules and formal structures are more developed and harder to change (Adizes, 1979). Interruption of organizational routines when shifting from one specialization strategy to another quickly is more pronounced in larger innovation departments because norms and rules are deeply embedded in established routines (Di Maggio and Powel, 1984; Amburgey, 1993; Hannan and Freeman, 1984). Hence, shifting specialization strategies affects the performance of large innovation departments to a greater extent because knowledge about its operations and activities is habitually embedded in norms and in the behavior of a large number of employees. Based on the above discussion, we introduce the following hypothesis:

H3: *The effects of speed of change on firm performance will be more negative for firms with a larger innovation department than for firms with a smaller size innovation department.*

The role of R&D Intensive Industries

In the previous section, we theorize that shifting at high speed between specialization strategies has a negative effect on the performance of the firm. However, we also argue that the effects of speed of change on firm performance could be moderated positively when firms operate in R&D intensive industries. Technologically dynamic environments are characterized by high *volatility* (i.e., high rate of change) and *unpredictability* (i.e., uncertainty) that necessitates that firms respond quickly (high speed) to keep up with frequent changes (Zahra, 1996; Schilkes, 2014). We therefore expect R&D intensive industries to positively moderate the effects of speed on firm performance because munificence in technological opportunities allows firms to benefit from quick changes (Uotila et al., 2009, Audretsch and Feldmann, 1996; Ito and Pucik, 1993; Baysinger and Hoskisson, 1989). A number of theoretical reasons supports this view.

First, the unpredictability and high rate of change in R&D intensive industries make the effects from specializing in exploratory and exploitative R&D equally important for different reasons. Firms in technologically dynamic industries focus on knowledge generation to avoid obsolescence and maintain competitive advantage (Schumpeter, 1942; 1950; Zahra and Das, 1993). Firms' rational response to maintain their competitive edge is not only to create new knowledge but also abort after utilizing very quickly their newly developed technologies and ideas and replace them with new ones in a process of creative destruction in order to keep up with frequent technological changes and achieve market differentiation. Hence, in technologically dynamic industries firms are encouraged to quickly swift from searching for distant and unfamiliar knowledge to achieve such differentiation (Zahra and Das, 1993; Schumpeter, 1950; Bierly and Daly, 2007; Uotila et al., 2009; Zahra, 1996), to maintaining their existing competence and expertise so that they will be able to exploit existing technologies and ideas.

The demands of those environments force firms not only to learn faster and translate their collective experience into organizational routines but also develop new skills and utilize existing skills and capacity to enhance their performance. Adaptation of those firms into those environments means that those firms progressively adapt and learn how to swift easier between specialization strategies. Hence, R&D intensive environments not only necessitate but also enable firms to learn how to adapt smoother making oscillation at high speed between specializing in exploratory and exploitative R&D easier to employ, offsetting therefore the negative effects of speed of change on firm performance.

Second, firms in R&D intensive industries are exposed to an environment with abundance of technological opportunities and high industry growth (Aldrich 1979; Zahra, 1993). The abundance of such technological opportunities may require firms to change strategies at faster speed in order to develop new skills and competences in emerging areas and therefore stay ahead of their competitors. A higher speed may also assist firms to avoid outdated practices, which is particularly important in R&D intensive industries in which current technologies, knowledge and skills become redundant quickly (Sorensen and Stuart, 2000). Failure to change strategies and develop new skills means that the firm may remain good at performing tasks and routines that are gradually less valued by the market. Therefore, shifting between specialisation strategies at a higher speed may have a less negative effect on firm performance in R&D intensive industries that require firms to adapt to frequent changes, minimise knowledge and skill obsolescence and keep up with demands for technological progress. Hence, the negative effects of speed of change could be moderated for firms operating in R&D intensive industries.

Third, technologically dynamic industries are fast-changing and knowledge-abundant environments where new technologies introduced at higher rates than less dynamic industries (Uotila et al., 2009; Zahra, 1996). As a result, the high levels of exploratory and exploitative R&D activities enable firms to have more opportunities not only for knowledge creation and technology generation but also utilization of existing ones. Since firms act as input combiners (Conner, 1991), the higher availability of knowledge and opportunities in those industries will help them to find more ideas to exploit, increasing therefore the returns to exploitative R&D activities (Kogut and Zander, 1992; Jacobides et al., 2006).

This reasoning is in line with the premise of Posen and Levinthal (2012) that an appropriate firm response in fast-changing environments is the utilization of existing technological opportunities. Hence, the level of technological dynamism in an industry enhances the effects of exploitation on firm performance because it accentuates the value and usefulness of exploiting the existing pool of knowledge. Further, such knowledge-triggering environments could offer firms more chances to engage successfully in exploratory R&D and increase the impact of exploratory R&D on firm performance. Therefore, firms in those dynamically-changing industries have not only better opportunities to both exploit the ideas and knowledge developed by other firms and explore new ones (Kafouros and Buckley, 2008), but quickly swift between specializing in exploratory and exploitative R&D activities alleviating therefore the negative effects of high-speed changes on firm performance. Forth, in R&D intensive industries, there is strong competition and frequent changes due to technological progress (Miller and Friesen, 1982; Zahra, 1996). Technological intensity creates opportunities for a firm within its industry and in markets outside its traditional scope, which may help the firm benefit from faster pace between specialisation strategies by exploiting opportunities in the chosen technological trajectory and exploring prospects in new markets (Zahra and Ellor, 1993). Subsequently, a higher speed of change may be less negative for firms in R&D intensive industries because firms in such environments must meet demands associated with high rates of technological progress, and because they must engage in business renewal more often (Uotila et al., 2009).

Fifth, firms that operate in technologically dynamic industries have more chances to accelerate their generative and adaptive learning (Kogut and Zander, 1993). Our reasoning suggests that firms' generative and adaptive learning accentuates in technologically dynamic industries because firms are not only exposed to new knowledge elements that expand their existing knowledge and horizons (Koza and Lewin, 1998), but also because they learn in order to create refinements on products and services created by others making therefore the swift at high speed between specialization strategies easier to employ in R&D intensive industries. Accordingly, we introduce the following hypothesis:

***H4**: The effects of speed of change on firm performance will be less negative (or even positive) in R&D intensive industries than in less R&D intensive industries.*

DATA AND METHODS

As explained, the data and methods section are mainly a reproduction from other Chapters of this PhD thesis. However, for more details on the operationalization of these variables, please refer to the Method Section (Chapter 4) of the thesis.

DEPENDENT VARIABLE

Following common practice and the literature on R&D (Kafouros et al., 2018; Adams and Jaffe, 1996; Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b), we measure firm performance by estimating its productivity performance (TFP). As explained in detail in Chapter 4, the choice of TFP as our dependent variable was based on three reasons. First, TFP considers the firm's outputs (i.e., sales both from products and services) but also inputs i.e., the firm's investment in labour (reflected in number of employees) and tangible assets (or capital). Thus, TFP reflects the ability of the firm to make sales while controlling for the cost of inputs that a firm utilizes to achieve a certain level of output. By implication, TFP measures avoid biases that often derive from the fact that different outputs may exhibit different economies of scale (Kafouros and Aliyev, 2016a; Kafouros and Aliyev, 2016b). Second, TFP reflects that R&D investments could lead to both product and process innovations. This implies that although the development of new products could affect a firm's sales, process innovations may influence the firm's cost or modify its labour capital and thus enhance its productivity by leading to efficiency gains due to better allocation of resources. Third, while other measures such as firm profitability are unstable and often take negative values, productivity measures remain stable regardless of fluctuations in the market, variations of exchange rate, and accounting standards (Buckley, 1996).

In estimating TFP we estimate a 'residual'. This residual (with nominator the firm's *output* (firm sales) and denominator the firm's inputs (labour and capital) reflects increases in firm output that cannot be explained by firm inputs (Kafouros et al., 2018). The estimation of TFP (is given in Equation 1 in Chapter 4) and as explained, it reflects the intermediate capacity of inputs into outputs which reflects the firm' proficiency in generating value from specific input. Since economic relationships are rarely linear and two ease the interpretation of our results, we followed standard methodology and transform the TFP measure in its logarithmic form (Van Beveren, 2012; Qingwang and Junxue, 2005).

INDEPENDENT VARIABLES

Firms' Exploitative and Exploratory R&D

Consistent with prior research (D'Este et al., 2017; March, 1991; Jansen et al., 2006; He and Wong, 2004; Piao and Zajac, 2016) and the survey's definitions (PITEC), exploration consists of the *creative basic & applied research* conducted by firms in order to develop new knowledge that aims at creating something new to business and market. By contrast, exploitation consists of the *systematic technological development* that relies upon the firm's existing knowledge that has been accumulated through repetition and practical experience that aims at refining or improving substantially existing products and processes. As explained in detail in Chapter 4, firms in the survey report the distribution of their current R&D expenditure by type of research. Accordingly, we measure exploration using the log of each firm's annual investment in exploratory/experimental research activities (once again, we divide it by the number of employees to normalize for firm size). Similarly, we measure exploitation using the log of each firm's annual investment in exploitative activities (normalized for firm size).

Firms' Specialization in Exploratory, Exploitative R&D and Ambidexterity

Following previous studies (He and Wong, 2004; Cao et al., 2009) we use the absolute (percentage) difference between firms' expenditure on exploratory and exploitative activities. Building on the definition that specialization is a strategy by which firms limit the scope of their activities, we classify a firm as specialized in one activity when it spends over 66.6% of its internal R&D budget on either exploration or exploitation. This means that a firm's investment in one of the two activities is at least two times higher than its investment in the other activity. In operationalising the specialization in exploratory and exploitative R&D variables we used two different approaches. First, we use is a year-specific measure of specialization that reflects what the firms does in a given year. This variable is time-variant because a firm could specialize in exploratory R&D in one year but not in the next year. Second, we estimate the average percentage of each firm's budget spent on exploratory and exploitative R&D throughout the sampled years. This classification ensures that a firm remains specialized in one activity over a long period of time (rather than for just 2-3 years). We accordingly create two variables, one for specialization in exploration and one for specialization in exploitation, that take the value of 1 when a firm specializes in one of the two activities (and 0 otherwise). Further, when the percentage of the firm's budget is thus between 33.3% and 66.6%, these firms were categorized as firms with ambidextrous investments (i.e., ambidextrous firms).

Speed of Change

We first classified each firm as either specialized in exploitation or specialized in exploration or operates in an ambidextrous mode. Change in each specialization strategy occurs when in a given year a firm switches its specialization strategy from one mode to another. For instance, a firm that specializes in exploitation may change its strategy and become specialized in exploration. Consistent with prior studies (Hashai et al. 2015; Vermeulen and Barkema, 2002; Laamanen and Keil, 2008) we operationalize the speed of change between the different specialization strategies as the average number that a firm change within a given timeframe (in our case, the overall number of years that the firm exists in the dataset). For instance, when a firm changes its specialization strategy two times within an 8-year period, its average speed of change will be 0.25 per year (i.e. a complete change will occur on average every four years). Similarly, when a firm changes its specialization strategy four times within an 8-year period, its average speed of change will be 0.50 per year (i.e. a complete change will occur on average every two years). In the former case, the speed of the change in the firm's strategy will be lower compared to that of the latter case. Our operationalization of speed therefore considers the temporal distance or gap between changes (Homburg and Bucerius, 2005).

Extreme Changes

To capture those firms that decided to change completely their specialization strategy, we created a dummy variable that takes the value of 1 for those firms that changed their specialization strategy from exploratory to exploitative R&D and vice versa, and 0 when firms change to an ambidextrous strategy to indicate moderate change in their strategy as opposed to extreme change.

Size of R&D Department

To operationalize the size of a firm's R&D department, we consider the number of internal R&D staff. Our dataset provides us with a direct measure of this variable. We then transformed it into its log to reduce the skewness of the size distribution.

CONTROL VARIABLES

We further control for various firm- and industry-specific factors that may affect firm performance. First, we control for each firm's *tangible resources* (Auh and Menguc, 2005; Jansen et al., 2006; Lubatkin et al., 2006), measured as the log of each firm's gross investment in tangible resources in each year. This may account for the difficulties that resource-constrained firms encounter in different industrial environments (Hannan and Freeman, 1984; Tushman et al., 1985). Second, we control for *newly created* firms using a dummy variable that takes the value of 1 if a firm is newly created (Laursen and Salter, 2006). This variable may affect firm performance by influencing a firm's ability to find collaborators, establish itself in an industry and accumulate different types of knowledge.

Third, we control for each firm's *international sales* (dummy variable that takes the value of 1 for firms that sell their products abroad) because a firm's market expansion is associated with its growth (He and Wong, 2004), international competitiveness and access to new market knowledge (Cassiman and Veugelers, 2006). Fourth, we control for *affiliated firms* using a dummy variable that takes the value of 1 for firms that are affiliated to groups (Khanna and Palepu, 1997; Blindenbach-Driessen and Ende, 2014) and may therefore enjoy certain advantages that enhance their performance. Fifth, given that a firm's appropriability strategy may affect its performance (Laursen and Salter, 2006;

2014), we control for the mechanism that each firm uses to protect its inventions (Vega-Jurado et al., 2008). These mechanisms include the use of four *protection* mechanisms (patents, utility models, trademarks and copyrights. This variable therefore ranges from 0 to 4, depending on how many of these mechanisms each firm employs.

However, firm performance can also be affected by industry-specific attributes. We control for industry's intensity of *competition* operationalized using the number of 2-digit intra-industry competitors (Jansen et al., 2006) because in highly competitive industries firms are forced to improve operational efficiency (Matusik and Hill, 1998) and avoid risk-taking behavior (Miller and Friesen, 1983; Auh and Menguc, 2005) or experiment with novelties to avoid obsolescence (Uotila et al., 2009). Because this measure does not capture the market share of firms and whether few firms control most of the market, we also estimated Herfindahl Index (the results from the regressions of this chapter Herfindahl Index as a measure of competition). As explained in the general method section of this thesis, Herfindahl Index (HI) is an appropriate measure of industry concentration (Kafouros and Aliyev 2016; Wu et al. 2016). We estimated HI by summing of squared market shares of firms in the industry. It is thus calculated as $CI_j = 1 - \sum_{i=1}^{n} s_{ij}^2$, where s_{ij} is the market share of firm i in industry j and therefore it takes values between 0 and 1. The higher the value of Herfindahl Index the lower the concentration level within an industry, reflective thus of low levels of competition. We therefore use the inverse value of the Herfindahl Index (i.e. 1- Herfindahl Index) so that a higher value indicates high levels of competition.

We control for *time effects* by including in the model year dummies (that equals 1 that corresponds to specific year) to account for differences in economic trends over years (Belderbos et al., 2010). In models that are not nested in industries (i.e. when they are not multi-level), we also include industry dummies in our model to account for the different industry characteristics and variations in their nature, both technological and economic. Further, we include in the model a binary variable that represents those firms that operate in high-technological industries. As explained in the method section of this thesis, in constructing this variable we use the OECD classification (given in COTEC Report 1997 cited in Bayona Sáez and Arribas, 2002). *High-tech industries* refer to sectors such as chemicals, pharmaceutical, computing, electronics, electrical, communication, and medical devices and optical instruments. By contrast, medium and low-tech industries include sectors such as textiles, furniture, leather, rubber and plastic (taking the value of 1 when firms operate in high tech industries and 0 otherwise). We also control for the *industry's R&D intensity* using the industry's total R&D expenditure divided by total industry sales (Uotila et al., 2009) because in environments with high levels of R&D spending, there are abundancy of technological opportunities than in environments with lower R&D spending (Zahra, 1996). These opportunities may influence firm performance

(Baysinger and Hoskisson, 1989). Finally, when using GLS as an alternative estimator, we included *industry dummies* in our model to control for technological and economic variations.

ESTIMATION METHOD (Since the estimation method remains the same across the three empirical chapters of this thesis, we have reproduced below a cut-down version for the convenience of examiners. Please refer to the method section of Chapter 4 for greater details and reasoning on the choice of the estimation method)

As explained in Chapter 4, given that our sampled firms are clustered within industries, a *Multilevel Mixed Model* approach was better suited for estimating TFP (Bliese and Ployhart, 2002; Preacher et al., 2006; Anderson, 2014; Pindado et al., 2012). As explained the choice of Multilevel Mixed estimator was driven by two factors: First, in contrast to traditional panel data estimators, multilevel analysis with mixed effects considers both FE and RE effects. Second, the model is specified at different levels, meaning that it produces coefficients that are nested in each industry and firm. Third, by nesting the effects within each firm the analysis has the additional benefit of producing an estimator that is very close to FE since it estimates the effects separately for each firm and industry separately (Wooldridge, 2000; Blundell and Bond, 2000). Although as we explained, we experimented with other estimators such as FE and RE, the fact that we expected the effects of specialization strategies and exploration/exploitation investment to vary a lot depending on the industry made these estimators less appropriate to reveal variability at both industry and firm level. Thus, our chosen estimator allows us to explicitly specify the estimation with complicated clustering patterns near models while relies on the assumption of independence of error terms, which may be violated when firms are clustered in various industries (Hox et al., 2017; Anderson, 2014; Preacher et al., 2006). As a robustness check, we also used alternative estimators to establish consistency across our results, including the generalized least squares (GLS) estimator which is appropriate when using longitudinal data (Wooldridge, 2000; Blundell and Bond, 2000).

As discussed in detail in Chapter 4, we followed established practice and specified our model (refer to equation 2) (Temouri et al., 2008). We also transform the variables in their logarithmic form to ease the interpretation of our findings (Qingwang and Junxue, 2005; Van Beveren, 2012). However, in equation 2 for testing the hypotheses of Chapter 7, we also added the variables of *speed of change*, *extreme changes*, *size of innovation department*, *industry R&D intensity* and their interactions with the speed of change.

RESULTS

Table 1 presents the descriptive statistics and correlations for the key variables while Table 2 reports the regression results using the Multilevel Mixed Effect Model. We also examined the possibility of multicollinearity in our chosen variables. The maximum VIF value obtained in any of the models was significantly below the cut-off point of 2 (O'Brien, 2007; Lin et al., 2012). The highest VIF value we obtained from the analysis was 1.55 with average 1.19. Hence, the possibility of getting biased coefficients because of multicollinearity in the chosen variables is low.

To estimate the results, we use Multilevel Mixed Effects Model and specify the model to produce results that are nested both in each industry and firm (Bliese et al., 2002). As explained, unlike traditional panel data our chosen estimator has the additional benefit of producing coefficients that are close to FE estimator and produces coefficients for each firm and industry separately (Pindado et al., 2012). Model 1 is a baseline model for firm performance (measured as TFP). Model 2 tests the direct effect of *speed of change*, whereas Model 3 presents the direct effect of *extreme changes* on firm performance. Model 4 includes simultaneously both these direct effects. Model 5 presents the results of the interaction between speed of change and size of the firm's Innovation Department. Model 6 tests the interaction between speed of change and industry's R&D intensity (technological dynamism). In model 7, we test both the direct and interaction effects of all the specified hypotheses on firm performance.

Models 2 and 3 test the hypothesized effects of H1 and H2. They test and provide support of the idea that the speed of change between specialization strategies and the extreme changes from specializing in exploratory R&D strategy to a specialized in exploitative R&D strategy (and vice versa) affect negatively firm performance. The results are consistent when both direct effects are tested simultaneously (but the coefficient of extreme changes loses slightly its statistical significance from 5% to 10% level). The results suggest that high speed and thus frequent changes between specialization strategies affect adversely a firm's revenue. As explained in the theoretical background of Chapter 7, when firms cycle quickly between specialization strategies, their experience (experiential learning) is compressed in time and thus less likely to be translated into beneficial learning that will help them to establish effective organizational routines to enhance their performance (Hashai et al., 2015; Klarner and Raisch, 2013; Dierickx and Cool, 1989)

Model 5 tests the first interaction (Speed of Change X size of innovation Department) and the results confirm Hypothesis 3. They indicate that the negative effects of speed of change become augmented as the size of innovation department becomes larger. This result supports the view that inertial forces, bureaucracy and administrative coordination are likely to be more prominent in bigger-size firms

(Hannan and Freeman, 1984; Baker and Cullen, 1993) that prevent them from switching between exploratory and exploitative R&D. Model 6 supports Hypothesis 4, suggesting that although (on average) high speed among specialization strategies harms a firm's performance, its negative effects turn into positive in R&D intensive industries because technological opportunities are abundant in those environments and firms are likely to find it easier to switch amongst specialization strategies. Model 7 (which is the full models provides support for the above results.

Overall, the results suggest that firms that change specialization strategies very quickly, they are negatively affected in terms of performance. The negative effects of speed of change are more pronounced when the innovation department increases in size. Interestingly, the effects of speed on firm performance are ameliorated by the R&D intensity of the industry, suggesting that although fast speed changes between specialization strategies affect negatively firm performance, those effects become positive when firms operate in technologically dynamic industries.

Table 1: Descriptive Statistics and Correlations

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Total Factor Productivity	1													
Exploratory R&D	-0.074	1												
Exploitative R&D	-0.065	0.2815	1											
Tangible Assets	0.2074	0.0849	0.0874	1										
International Sales	0.2395	-0.023	-0.0301	0.0691	1									
Affiliated Firms	0.3276	-0.009	-0.0001	0.0909	0.11	1								
Industry Competition	0.0552	-0.0209	-0.0592	0.0376	0.15	-0.02	1							
Protection	0.1307	0.0162	0.0034	0.0822	0.17	0.143	0.105	1						
Industry's R&D intensity	-0.301	0.2823	0.2049	0.0283	-0.07	-0.1	0.04	0.0244	1					
Newly Created Firms	-0.066	0.0327	0.0413	0.0208	-0.05	-0.01	-0	-0.021	0.0519	1				
High Tech. Firms	0.1418	-0.0023	-0.0249	0.0267	0.14	0.037	0.178	0.0946	-0.088	-0.012	1			
Size of Innovation Department	0.1077	0.2869	0.3401	0.0957	0.04	0.121	-0.06	0.0728	0.0776	-0.003	-0.0003	1		
Speed	-0.037	-0.028	-0.0368	-0.019	-0.05	-0.08	0.008	-0.081	-0.075	0.006	-0.0465	-0.0589	1	
Extreme Changes	-0.006	-0.0093	-0.0164	-0.006	-0.01	-0.01	0.006	-0.024	-0.033	-0.01	0.0003	-0.0179	0.25	1
Mean	0.059	4281	4790	8.160	0.755	0.449	0.924	-3.978	0.068	0.006	0.215	2147288	0.215	0.068
Std. Dev.	0.937	19806	16427	1.734	0.430	0.497	0.089	3.520	0.192	0.074	0.411	13300000	0.198	0.252
Min	-11.016	0	0	-2.313	0.000	0.000	0.000	-6.908	0.001	0.000	0.000	879	0.000	0.000
Max	5.529	2371429	1489540	16.341	1.000	1.000	0.988	1.386	8.726	1.000	1.000	500000000	0.857	1.000

Table 2 Regressions (Multilevel Mixed Model)

	Model 1			**Model 2**			**Model 3**			**Model 4**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1: Speed of change				-0.149***	0.044	0.001				-0.143**	0.045	0.002
H2: Extreme changes							-0.020*	0.010	0.039	-0.018†	0.010	0.062
H3: Speed of change X Size of Innovation Department.												
H4: Speed of change X Industry R&D intensity												
Size of Innovation Department	0.021***	0.005	0.000	0.021***	0.005	0.000	0.022***	0.005	0.000	0.022***	0.005	0.000
Exploratory R&D	0.003**	0.001	0.003	0.004**	0.001	0.002	0.003**	0.001	0.004	0.004	0.001	0.002
Exploitative R&D	0.004*	0.002	0.018	0.004*	0.002	0.016	0.003*	0.002	0.026	0.004*	0.002	0.022
Tangible Assets	-0.005	0.004	0.245	-0.005	0.004	0.247	-0.005	0.004	0.247	-0.005	0.004	0.249
International Sales	0.033*	0.015	0.030	0.032*	0.015	0.031	0.033*	0.015	0.029	0.033*	0.015	0.030
Affiliated Firms	0.120***	0.017	0.000	0.119***	0.017	0.000	0.121***	0.017	0.000	0.120***	0.017	0.000
Industry Competition	0.268†	0.147	0.068	0.268†	0.147	0.068	0.268†	0.147	0.068	0.268†	0.147	0.069
Protection	0.003*	0.002	0.027	0.003*	0.002	0.031	0.003*	0.002	0.028	0.003*	0.002	0.031
Industry’s R&D intensity	-0.219*	0.101	0.031	-0.218*	0.102	0.032	-0.217*	0.102	0.033	-0.216*	0.102	0.033
Newly Created Firms	-0.308***	0.080	0.000	-0.308***	0.080	0.000	-0.308***	0.080	0.000	-0.308***	0.080	0.000
High Technological Firms	0.051	0.114	0.658	0.045	0.114	0.690	0.051	0.114	0.656	0.046	0.114	0.687
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.495***	0.133	0.000	-0.454***	0.131	0.001	-0.497***	0.133	0.000	-0.457***	0.131	0.000
Industry Variance	0.257	0.065		0.257	0.0646		0.2571	0.0650		0.2566	0.0646	
Firm Variance	0.4879	0.0437		0.4874	0.0437		0.4876	0.0437		0.4872	0.0437	
Residual Variance	0.1266	0.0149		0.1266	0.0149		0.1266	0.0149		0.1266	0.0149	
Wald chi2 (19-22)	234.23	P>	0.000		P>	0.000	231.68	P>	0.000	241.690	P>	0.000
Number of observations	32527			32527			32527			32527		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

Table 2 cont. Regressions (Multilevel Mixed Model)	**Model 5**			**Model 6**			**Model 7**		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1: Speed of change	-0.151***	0.047	0.001	-0.018†	0.010	0.061	-0.146**	0.048	0.002
H2: Extreme changes	-0.018†	0.010	0.065	-0.137**	0.047	0.003	-0.018†	0.010	0.065
H3: Speed of change X Size of Innovation Department.	-0.025†	0.015	0.089				-0.029*	0.015	0.040
H4: Speed of change X Industry R&D intensity				0.479*	0.241	0.047	0.499*	0.242	0.040
Size of Innovation Department	0.022***	0.005	0.000	0.021***	0.005	0.000	0.022***	0.005	0.000
Exploratory R&D	0.004**	0.001	0.002	0.003**	0.001	0.003	0.004**	0.001	0.002
Exploitative R&D	0.004*	0.002	0.017	0.004*	0.002	0.020	0.004*	0.002	0.015
Tangible Assets	-0.005	0.004	0.251	-0.005	0.004	0.239	-0.005	0.004	0.240
International Sales	0.033*	0.015	0.030	0.032*	0.015	0.032	0.032*	0.015	0.033
Affiliated Firms	0.120***	0.017	0.000	0.120***	0.017	0.000	0.120***	0.017	0.000
Industry Competition	0.266†	0.147	0.069	0.285*	0.146	0.050	0.284*	0.145	0.050
Protection	0.003*	0.002	0.031	0.003*	0.002	0.037	0.003*	0.002	0.037
Industry's R&D intensity	-0.209*	0.104	0.045	-0.376***	0.108	0.000	-0.374***	0.108	0.001
Newly Created Firms	-0.308***	0.080	0.000	-0.304***	0.080	0.000	-0.303***	0.080	0.000
High Technological Firms	0.046	0.114	0.688	0.046	0.112	0.683	0.046	0.112	0.683
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	
Constant	-0.462***	0.131	0.000	-0.461***	0.128	0.000	-0.466***	0.128	0.000
Industry Variance	0.2566	0.0643		0.2462	0.0618		0.2459	0.0613	
Firm Variance	0.4867	0.0437		0.4875	0.0437		0.4869	0.0437	
Residual Variance	0.1266	0.0149		0.1265	0.0149		0.1265	0.0149	
Wald chi2 (19-23)	239.3	P>	0.000	288.960	P>	0.000	287.73	P>	
Number of observations	32527			32527			32527		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

ROBUSTNESS CHECKS AND ADDITIONAL ANALYSIS

Results using Alternative Estimators

As a robustness check, we used alternative estimators. We found that the generalized least squares (GLS) estimator was also appropriate when using longitudinal data (Hanse, 1982; 2010; Wooldridge, 2001). We considered empirical reasons in choosing Random Effects (RE) versus Fixed Effects (FE) estimators. Empirically, the fixed effect model was not appropriate for testing our hypotheses because important variables such as the *speed of the change* is a time-invariant variable (based on averages throughout the firm's years of operation). Additionally, the Fixed Effects (FE) estimator was not appropriate for testing the effects of binary variables such as the *extreme changes* variable we used in our empirical model. Table 3 reports the regression results using the GLS estimator. Overall, the hypothesised effects are supported and in some cases the statistical significance of our results was improved. Specifically, when running the GLS regression *Hypothesis 2,* which states that extreme changes between specialization strategies affect negatively the performance of the firms improved its statistically significance from 10% to 5%. However, *Hypothesis 3,* which tests the interaction between speed and the size of innovation department reduces its significance from 5% to 10% level.

Treatment for Outliers

We further explored whether the hypothesised effects are supported when removing from the dataset the outliers. As in prior empirical chapters of this PhD thesis, we used the standardised residuals variable and delete from the dataset those cases that were over 3 and less than -3 standard deviations. The final sample were reduced from n=32,527 to n=32,077. Overall, the hypothesised effects were consistent both when using the full sample and the sample with the outliers excluded which further supports the fact that the coefficients we obtained were not biased to sample specifications.

Results for Manufacturing Industries

We further investigated whether the hypothesised effects hold only for manufacturing firms including those firms that operate in service industries (i.e. industry codes 36; 37; 38; 43; 44; 49; 50; 51; 52; 53; 54; 55). The final sample excluding those firms is estimated at n=25,434. Model 2 tests *Hypothesis 1* which examines the direct effects of speed of change on firm's performance is fully confirmed for manufacturing firms. Model 3 tests *Hypothesis 2* which indicates that extreme changes between specialization strategies affect negatively firm performance did not reach statistically significance for manufacturing firms. When testing both speed and extreme changes into model 4 again although speed kept its significance, extreme changes did not.

Hypothesis 3 which tests the interaction effect of speed and size of innovation department is also supported for manufacturing firms. Model 6 tests *Hypothesis 4* which explores that the interaction effect of speed of change and industry R&D intensity is not supported. In the final model (model 7) when adding all direct and interaction effects into the model the results were partly supported. Precisely, the hypothesised effects were confirmed for both hypotheses 1 and 3 of which the former improved its significance from 1% to 0.1%. Hypotheses 1 and 4 were not supported, yet the directionality of the relationship remained the same.

	Model 1			**Model 2**			**Model 3**			**Model 4**		
Table 3 – Regression Results using the GLS Estimator	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	
H1: Speed of change				-0.145**	0.047	0.002				-0.138**	0.047	0.003
H2: Extreme changes							-0.021*	0.010	0.029	-0.019*	0.010	0.047
H3: Speed of change X Size of Innovation Department.												
H4: Speed of change X Industry R&D intensity												
Size of Innovation Department	0.024***	0.005	0.000	0.023***	0.005	0.000	0.024***	0.005	0.000	0.024***	0.005	0.000
Exploratory R&D	0.003*	0.002	0.019	0.003*	0.002	0.014	0.003*	0.002	0.025	0.003*	0.002	0.019
Exploitative R&D	0.003*	0.002	0.024	0.003*	0.002	0.021	0.003*	0.002	0.035	0.003*	0.002	0.030
Tangible Assets	-0.004	0.003	0.109	-0.004	0.003	0.111	-0.004	0.003	0.110	-0.005	0.003	0.112
International Sales	0.0363**	0.014	0.008	0.035**	0.014	0.009	0.036**	0.014	0.008	0.036**	0.014	0.009
Affiliated Firms	0.127***	0.014	0.000	0.126***	0.014	0.000	0.128***	0.014	0.000	0.127***	0.014	0.000
Industry Competition	0.286*	0.129	0.027	0.286*	0.129	0.026	0.286*	0.129	0.026	0.286*	0.129	0.026
Protection	0.003*	0.001	0.019	0.003*	0.001	0.022	0.003*	0.001	0.019	0.003*	0.001	0.022
Industry’s R&D	-0.211*	0.097	0.029	-0.211*	0.097	0.029	-0.209*	0.097	0.031	-0.209*	0.097	0.031
Newly Created Firms	-0.309***	0.092	0.001	-0.309***	0.092	0.001	-0.310***	0.092	0.001	-0.310***	0.092	0.001
High Tech. Firms	0.062	0.122	0.611	0.058	0.122	0.634	0.062	0.122	0.611	0.058	0.122	0.633
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Industry Dummies	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.850***	0.169	0.000	-0.809***	0.170	0.000	-0.852***	0.169	0.000	-0.812***	0.170	0.000
Wald chi2/F statistic (73-74)	12792.3	P>	0.000	12849.8	P>	0.000	12816.89	P>	0.000	12870.2	P>	
R squared	0.3452			0.346			0.346			0.3462		
Number of observations	32527			32527			32527			32527		
Number of firms	**5567**			**5567**			**5567**			**5567**		

Table 3: cont. Regression Results using the GLS Estimator	Model 5			Model 6			Model 7		
	Coef.	S.E	P	Coef.	S.E	P	Coef.	S.E	P
H1: Speed of change	-0.147**	0.048	0.002	-0.133**	0.048	0.005	-0.142**	0.048	0.003
H2: Extreme changes	-0.019*	0.010	0.050	-0.019*	0.010	0.046	-0.019*	0.010	0.049
H3: Speed of change X Size of Innovation Department.	-0.027	0.017	0.109				-0.031†	0.017	0.069
H4: Speed of change X Industry R&D intensity				0.442*	0.194	0.022	0.464*	0.195	0.017
Size of Innovation Department	0.024***	0.005	0.000	0.023***	0.005	0.000	0.024***	0.005	0.000
Exploratory R&D	0.003**	0.002	0.017	0.003*	0.002	0.020	0.003*	0.002	0.017
Exploitative R&D	0.003*	0.002	0.025	0.003*	0.002	0.029	0.003*	0.002	0.023
Tangible Assets	-0.004	0.003	0.113	-0.004	0.003	0.106	-0.004	0.003	0.107
International Sales	0.036**	0.014	0.009	0.035**	0.014	0.009	0.035**	0.014	0.010
Affiliated Firms	0.126***	0.014	0.000	0.127***	0.014	0.000	0.127***	0.014	0.000
Industry Competition	0.284*	0.129	0.027	0.3020*	0.130	0.020	0.300*	0.129	0.020
Protection	0.003*	0.001	0.022	0.003*	0.001	0.026	0.003*	0.001	0.026
Industry's R&D	-0.201*	0.099	0.041	-0.356***	0.099	0.000	-0.353***	0.099	0.000
Newly Created Firms	-0.309***	0.092	0.001	-0.306***	0.092	0.001	-0.3056***	0.092	0.001
High Tech. Firms	0.057	0.122	0.641	0.060	0.122	0.621	0.059	0.122	0.630
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Industry Dummies	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.815***	0.170	0.000	-0.817***	0.171	0.000	-0.819***	0.171	0.000
Wald chi2/F statistic (76-77)	12887	P>	0.000	12869.9	P>	0.000	12889.10	P>	0.000
R squared	0.3467			0.346			0.347		
Number of observations	32527			32527			32527		
Number of firms	5567			5567			5567		

***p < 0.05; **p < 0.01; ***p < 0.001; †p < 0.10.**

DISCUSSION AND CONCLUSION

Theoretical Contributions and Implications

The exploration and exploitation literature has considered the performance advantages of investing in exploration and exploitation (Cao et al., 2009; Ebben and Johnson, 2005; Wilden et al., 2018; Koryak et al., 2018) but has not paid attention to how the speed of changing between specialization strategies might affect performance and how the firm's context might affect the relationship between speed and performance. Therefore, the question "what is the performance effect of speed of change between specialization strategies, and under what conditions is more advantageous to the firm?" has not been addressed.

This chapter contributes to research on exploration and exploitation (Markides, 2013; Martini et al., 2013; Tushman et al., 2010; O'Reilly and Tushman, 2013; Raisch et al., 2009; Chen and Katila, 2008) and ambidexterity literature (D'Este et al., 2017; Cassiman and Veugelers, 2006; Atuahene-Gima, and Murray, 2007; Levinthal and March, 1993) by explaining how higher speed of changes in a firm's specialization strategy has a negative effect on its performance. Drawing from organizational learning theory (Dierickx and Cool, 1989; Cyert and March, 1963). Levinthal and March, 1993; Holmqvist, 2004; Tyre and Von Hippel, 1997; Schilling et al., 2003; Kim and Miner, 2007) we contend that higher speed and therefore quick transitions between a firm's exploratory/exploitative R&D compromises its learning and therefore it is less likely to help the firm establish efficient organizational routines to enhance its performance (Levitt and March, 1988; Klarner and Raisch, 2013; Dierickx and Cool, 1989). The proposed justification relies on the fact that shorter experience with a specific strategy cannot easily be translated into beneficial learning, putting strain on the firm's absorptive capacity (Vermeulen and Barkema, 2002; Cohen and Leventhal, 1990; Hashai et al., 2015; Casillas and Moreno-Menéndez, 2014).

Therefore, although it is often presumed that firms should change rapidly from one specialization strategy to the other to avoid knowledge obsolescence and capability rigidity (Teece, 2007; Atuahene-Gima, 2005), we found that fast alterations in strategies impact negatively firm performance (Klarner and Raisch, 2013; Vermeulen and Barkema, 2002). This finding contributes to the exploration and exploitation literature by showing at which speed firms need to change their investment decisions in order to create a source of competitive advantage (Uotila et al., 2009; Gupta et al., 2006). In doing so, the chapter offers an explanation that accounts for variations in firm performance when firms decide to change their specialization strategies at different speeds and in different contexts. The findings suggest that firms experience different performance outcomes not only because they change between specializing in exploratory/exploitative R&D at different speeds but also because they have different characteristics (size of innovation department) and operate in different industries (high and low R&D intensity). This finding advances the exploration/exploitation literature by showing that the effects of speed at which firms change their specialization strategy on firm performance are contingent upon different industry environments.

A key insight that the analysis is that although higher speed affects negatively a firm's performance, these negative effects turn into positive effects when firms operate in R&D-intensive industries. Because R&D intensive industries are characterized by the need for technological progress, faster changes between exploratory/exploitative strategies are more beneficial because they enable firms to invest in activities that are becoming more valuable in their industry (Sorensen and Stuart, 2000; Zahra, 1993). The findings contribute to understanding the relationship between technological dynamism and a specialization strategy (Uotila et al., 2009; Gupta et al., 2006; Zahra, 1996). Ignoring that the effects of speed might vary in different contexts could be a major shortcoming in understanding that fast-pace changes between exploratory/exploitative R&D strategies could increase rather than compromise a firm's performance in technologically dynamic industries that require firms to respond quickly to frequent technological changes (Miller and Friesen, 1982; Zahra, 1996).

Furthermore, we show that the adverse effects of speed are even more negative as the size of the firm's innovation department increases. In larger innovation departments, inertial forces are stronger (Hannan and Freeman, 1984; Rajagopalan and Spreitzer, 1997; Parastuty et al., 2015; Amburgey et al., 1990) and the levels of bureaucracy and administrative coordination further increase (Baker and Cullen, 1993). Consequently, larger innovation departments may find more difficult to change their exploratory and exploitative R&D strategies. They may also be less effective in implementing changes because they face higher organizational instability than their smaller-size counterparts (Hannan and Freeman, 1984). Another insight from the empirical analysis indicates that extreme changes in the firm's specialization strategy impact negatively its performance. From a learning point of view, although moderate changes in specialization allows firms to redeploy their assets and build on existing expertise, enhancing their learning (Dierickx and Cool, 1989; Kogut and Zander, 1992), extreme changes require entirely different processes, routines and expertise from the current focus and trajectory (March, 1991; Wilden et al., 2018) and they are more likely to put overload and demands on the firm's existing knowledge stock and basis. These findings contribute to organizational learning theory, emphasizing the importance of accumulated experience (Dierickx and Cool, 1989; Baum et al., 2000; Holmqvist, 2004) by explaining why some firms that change exploratory/exploitative R&D strategies faster alleviate the negative effects of experiential learning that is compressed in time.

These results, together with the findings about the role of industry help us understand why two firms that change their specialization in exploratory/exploitative R&D at the same speed may exhibit different performance outcomes because they operate in different industries and because the size of their innovation department differs. The findings about R&D intensive industries also challenge the view that fast-paced changes in strategy affect negatively firm performance

(Vermeulen and Barkema, 2002). It appears that in technologically dynamic environments, firms are exposed to an abundance of technological opportunities that may make it easier to switch at faster speed between exploratory and exploitative R&D (Cohen and Levinthal, 1990; Zahra and George, 2002).

MANAGERIAL IMPLICATIONS

The findings have a number of practical implications. First, managers should understand that due to time compression diseconomies (Dierickx and Cool, 1989), firms that quickly shift from one specialization strategy to another compress learning over a shorter time frame which may in turn lead to diminishing returns (Hashai et al., 2015). Higher speed also requires an increase in managerial capabilities and it is likely to put a strain on a firm's existing resources (Eisenhardt and Martin, 2000; Hashai et al., 2015). Hence, managers should keep in mind that even in cases in which ambidexterity is beneficial, a high-speed cycling from one activity to the other might actually have adverse consequences for their performance. Managers should control how frequently they change their specialization strategies and seek to minimize managerial cost and avoid overload that may compromise rent generation. As the management of time is subject to managerial control (Ancona et al., 2001), our findings could help managers to use time effectively to create a source of competitive advantage (Shi et al., 2012).

Second, managers should bear in mind that the way in which the speed of changing specialization strategies affects their performance depends on the technological dynamism of the industry in which their firm competes. R&D intensive industries enable firms that change their specialization strategies frequently to enhance their performance. It is therefore advisable for such firms to change specialization strategies at a faster pace. This may enable firms in such industries to keep up with the industry's changes and exploit opportunities for technological progress. Conversely, for those firms operating in industries that exhibit lower levels of technological dynamism, it is advisable to change their specialization strategies less frequently.

Third, managers should be aware that the negative effect of speed on a firm's performance accentuates for those firms with larger innovation departments than for those with smaller innovation departments. The key managerial implication of this finding is that firms with larger innovation departments should limit their speed as it has a particularly negative effect on performance mainly because size could increase organizational instability and could affect organizational operations (Hannan and Freeman, 1984; Baker and Cullen, 1993).

Managers need to be cautious that some loss of their firm's operational flexibility will occur throughout the transition to a new specialization strategy because a large number of personnel need to change the scope of their operations when shifting from one specialization strategy to the other. Furthermore, as the size of the innovation department increases, greater managerial control, coordination and attention is required for speedy changes (Haveman, 1993; Baker and Cullen, 1993; Lubatkin et al., 2006). In such situations, managers will have to spend considerable time on reorganizing core aspects of their firm's structure, coordinating their employees' actions and maintaining control by formalizing their operations (Child, 1972), taking managers' attention away from rent generation.

Forth, managers should understand that firms that make extreme changes in their specialization strategies (i.e. shift their exploratory specialization strategy to an exploitative one or vice versa) may decrease their performance to a greater extent than those firms that make moderate changes (i.e., from being specialized in exploration/exploitation to being ambidextrous and vice versa). Managers should be aware that when they invest in activities that involve a substantial departure from their firm's current activities and organizational routines, they need to direct more time, resources and skills towards a reconfiguration of the business and this may cause significant disruption (Karim and Mitchell, 2000; Van de Ven and Poole, 1995). For example, concerns may arise on how effectively to organize an efficient routine for the new specialization strategy which may be exacerbated by the fact that the firm is likely to have limited experience with it and the existed personnel restricted re-deployability in the new business. Thus, by identifying how quickly firms should switch between specialization strategies and understanding what type of changes (extreme vs moderate) they should pursue, managers can minimize disruption that could inhibit their ability to generate revenues.

LIMITATIONS AND FUTURE RESEARCH

Our results are subject to a number of limitations, some of which may provide promising avenues for future research. First, although we used a large sample of firms that compete in different industry contexts, all those firms located in Spain. Therefore, our results are more applicable to Spanish firms and to firms that exhibit similar characteristics to Spanish firm. To examine whether our theoretical predictions and empirical findings hold for other countries, future studies should consider conducting a similar analysis for different countries or adopt a multi-country research design.

Second, we tested our theoretical predictions, arguing that faster speed of change between specialization strategies affects negatively firm performance (as measured by a firm's ability to generate sales). Future research can extend our theoretical predictions by considering how speed affects firms' ability to innovate. As sales and innovation are determined by different factors, the results might be different. For instance, it might well be the case that although speed has a negative effect on firm sales, it may be beneficial for innovation because it enables firms to discover and absorb new technologies quickly. Such differences might be more profound in technologically dynamic industries in which the risk of knowledge obsolescence is higher (Sorensen and Stuart, 2000; Uotila et al., 2009) and firms should innovate quickly to deal with short product life cycles.

Third, our analysis considered certain firm-specific and environment-specific contingencies that influence the effects of the speed of change on firm performance. For instance, we have shown that the effects of speed are more negative for those firms with larger innovation departments. Conversely, we found that the effects of speed are positively moderated by the level of technological dynamism in an industry. Although this examination has shown that the effects of speed may vary, a valuable avenue for future research would be to consider other factors and contingencies, either firm-specific or environment-specific, that might affect the role of speed. For instance, from the point of view of firm-specific characteristics, future studies may consider characteristics, such as the age of the firm, could interact with speed to affect firm performance. Fast pace changes can be disruptive to a firm's established routines (Hannan and Freeman, 1984; 1987). Hence, although older firms survive long enough and rebuild new routines (Amburgey, 1993), speed might affect the performance of older organizations to a greater extent.

Similarly, from the point of view of environmental contingencies, one of the characteristics of Spain is that its R&D intensity is below the average of other European countries (Eurostat statistics, 2016). This might affect how fast firms can change from one specialization strategy to the other. R&D intensity is a strong indicator of innovative output (Deeds, 2001). Hence, firms in countries with greater R&D intensity and shorter product life cycles may need to change faster between specialization strategies compared to countries with low R&D intensity and prolonged product life cycles. Future research may extend the current study by using countries with different R&D intensities.

CHAPTER 8
CONCLUDING REMARKS

DISCUSSION AND CONCLUSIONS

This study sets out to explore the performance effects of *knowledge exploitation* (often equated with efficiency, implementation and refinement) and *knowledge exploration* (often equated with experimentation, new searches and discoveries; Duncan, 1976; March, 1991; Gupta et al., 2006; Raisch and Birkinshaw, 2008; Dover and Dierk, 2010) in the context of R&D (D'Este, et al., 2017). Accordingly, the study draws from organizational learning theory (March, 1991; Cyert and March, 1963; Argyris and Schön, 1978; Levinthal and March, 1993; Yelle, 1979; Cohen and Levinthal, 1990; Argyris, 2002; Huber, 1991; Fiol and Lyles, 1985; Ingram and Baum, 1997; Wang and Ahmed, 2003) and examines the effects of exploratory and exploitative R&D on firm performance and shows how these effects are contingent upon certain firm- and industry-specific factors (Ebben and Johnson, 2005; Uotila et al., 2009).

Prior studies emphasise the importance for firms to be *ambidextrous* by balancing (i.e., making similar investments) both exploratory and exploitative R&D activities (He and Wong, 2004; Cao et al., 2009; Ebben and Johnson, 2005; Venkatraman, et al., 2006; Auh and Menguc, 2005; Gibson and Birkinshaw, 2004; Wilden et al., 2018; Koryak et al., 2018). We suggest that, from the point of view of performance, being ambidextrous might not be the most optimal choice in all contexts (Bierly and Daly, 2007; Rothaermel and Alexandre, 2009; Ebben and Johnson, 2005; Kyriakopoulos and Moorman, 2004; Auh and Menguc, 2005; Cao et al, 2009). Accordingly, we advance the concept of *specialization* (Hanks and Chandler, 1994; Romer, 1987; Brusoni et al., 2001; Calderini and Scelato, 2005) and explore how *balance* versus *specialization* in exploratory and exploitative R&D affects firm performance under certain contingencies.

Although prior research has examined the relationship between ambidexterity (or balance) and firm performance, research on the relationship between specialization and firm performance is limited. For this reason, it remains unclear whether firms should be *ambidextrous* or *specialize* in either exploratory or exploitative R&D and how their decision might change in different industry environments and contexts. We therefore adopt a contingency approach and enhance understanding of this phenomenon by examining how firm- and industry-specific factors influence the effectiveness of exploratory R&D and exploitative R&D on firm performance. We argue that balance and specialization are two distinct strategies that are more beneficial for some firms and contexts and less valuable for other firms that operate in different contexts. This study thus identifies, tests empirically and theorises on the mechanisms that explain the usefulness of *balance* versus *specialization* for different firms and in different industry contexts. To identify such firm- and industry-specific idiosyncrasies, this thesis explored three set of research questions that were organized in three separate empirical chapters:

In the **first empirical chapter** of this PhD thesis we examined two important research questions:

a) Is specialization in either exploratory or exploitative R&D more beneficial than an ambidextrous strategy?

b) How the economic returns of exploratory and exploitative R&D differ for those firms that adopt a specialization versus an ambidextrous strategy?

Whereas the first empirical chapter focused on *whether* firms should be *ambidextrous* or *specialize* (Wilden et al., 2018), the second empirical chapter examined which specialization strategy (exploratory or exploitative R&D; Dranove et al., 1998; Jacobides et al., 2006) and under what *conditions* is more valuable for enhancing firm performance. In the **second empirical chapter** of this PhD thesis we examined:

a) How *the orientation of the industry* (i.e., *exploratory-oriented, exploitative-oriented and hybrid*) affect the impact of exploratory and exploitative R&D on firm performance?

Finally, in the **third empirical chapter** of this PhD thesis we examined:

a) How the *speed of change* between specialization strategies influence the usefulness of balance and specialization, and in turn, the effects of exploratory and exploitative R&D on firm performance?"

b) Are there any conditions under which the effects of *speed* (hypothesized negative) could change?

Since the theories, hypotheses, methodology and empirical results have been discussed in detail throughout this PhD thesis, the next section briefly summarises the theories we draw upon and synthesises the empirical findings.

THEORIES EMPLOYED & EMPIRICAL FINDINGS

For answering the first set of questions, we draw on organizational learning theory (March, 1991; Cyert and March, 1963; Argyris and Schön, 1978; Levinthal and March, 1993; Yelle, 1979; Cohen and Levinthal, 1990; Argyris, 2002; Huber, 1991) arguing in favour of the positive effects of a specialized strategy (over an ambidextrous) on firm performance. Our justification is based on two important considerations. First, since by definition specialization requires focused attention, specialized firms by limiting the scope of their R&D activities, they gradually accumulate experiential knowledge that is utilized to strengthen their capacity to work proficiently on those R&D tasks that engage frequently (Romer, 1987; Hanks and Chandler, 1994; Brusoni et al., 2001; Holmqvist, 2004). Second, specialized firms build competence in areas of already established expertise (Baum et al., 2000). As a result, when specialized firms repeat those R&D activities that require similar knowledge base to their current knowledge trajectory and predisposition, they often eliminate errors in subsequent executions (Cohen, and Levinthal, 1990; Lane et al., 2006). We therefore argue that specialized firms build on what their existing knowledge base without the need to look for unfamiliar knowledge or cross organizational or technological boundaries (Romer, 1987; Hanks and Chandler, 1994; Brusoni et al., 2001). They can fully exploit their current expertise replicating prior successful ideas.

By contrast, ambidextrous firms are running the risk of being mediocre at both exploratory and exploitative R&D given the differential knowledge base and structures they require (Lubatkin et al., 2006, March, 1991; Blindenbach-Driessen and Ende, 2014). The performance-enhancing effects of specialization (either in exploratory/exploitative R&D) derive from firms' ability to learn to use and reuse their existing knowledge stock (exploratory or exploitative). This in turn, strengthens their capacity to perfect the execution of those R&D activities that repeat frequently, achieving thus greater efficiency, productivity and expertise (Baum et al., 2000; Ebben and Johnson, 2005).

Building on this reasoning, in the first empirical chapter of the thesis, we examine a set of hypotheses about the relationship between specialization in exploratory/exploitative R&D and firm performance. The empirical analysis of 32,537 observations largely supports our theoretical predictions. Precisely the results show that exploratory R&D investments have a stronger positive effect on the performance of those firms that specialize in exploratory R&D, whereas exploitative R&D investments have a stronger positive effect on the performance of those firms that specialize in exploitative R&D. Conversely, the opposite pattern emerges with the corresponding effect of exploratory R&D on firm performance being weaker when a firm specializes in exploitative R&D.

For answering the second set of questions nested in the orientation of industry typology, we rely on *organizational learning theory* that has been most widely used in the exploration and exploitation literature (Levitt and March, 1988; Huber, 1991; Cyert and March, 1963; Huber, 1991; Fiol and Lyles, 1985; Wang and Ahmed, 2003; Levinthal and March, 1993) but we also employ *industrial organization economics* (Bain, 1968; Mason, 1939; Schumpeter, 2017; Porter 1979; 1990; 2000). We build on the notion that firms can adopt a specialization strategy, and yet achieve ambidexterity complementing their activities and accentuating the value of their expertise and knowledge using the industry (Gupta et al., 2006; Hess and Rothaermel, 2011; Chesbrough, 2006). Without contradicting the notion of ambidexterity, we extend it from the context of firm to the context of the wider industry (Gupta et al., 2006; Cassiman and Veugelers, 2006).

Specifically, we contend that the returns to specialization depend upon the *orientation* of the industry where firm competes. To this end, we develop a typology of industry orientation (Bain, 1968; Porter, 2000; McGahan and Porter, 1997; Dranove et al., 1998; Jacobides et al., 2006) that captures regularities and variations in the concentration of exploratory/exploitative R&D activities.

This typology clarifies *which* specialization strategy and *how* the returns to a specialization strategy differ for those firms that operate in *exploratory-oriented, exploitative-oriented* and *hybrid* industries. We argue that differently-oriented industries account for performance differentials across firms because they affect differently the opportunities that specialized firms have in complementing their activities using the industry. We suggest three mechanisms that could change the industry dynamics between specialized firms and industries and thus the returns to a specialization strategy **a)** the *availability* of collaborative and knowledge-sourcing opportunities that firms are exposed in differently oriented industries **b)** the *transaction costs* of accessing opportunities and expertise from the industry and **c)** the *knowledge similarity* between firm's explorative/exploitative activities and that of the industry's (Cassiman. and Veugelers, 2006; Buckley, and Ghauri, 2015; Williamson, 1981; Geyskens et al., 2006; Sears and Hoetker, 2014).

The empirical analysis of 32,537 observations mainly supports our theoretical predictions. It shows that the effects of specializing in exploitative R&D are negative for firm performance when firms compete in an equally exploitative-oriented industry. Equally, the effects of specializing in exploitative R&D are positive for firm performance when firms compete in a hybrid or in an exploratory-orientated industry. Our findings suggest that the returns to a specialization strategy become stronger and positive when firms operate in industries that are differently-oriented to the firms' current investment strategy and learning predisposition. The main justification is that a firm's offerings and activities (exploratory or exploitative) are more valuable when they complement rather than substitute industry's activities (Chesbrough, 2003; 2006; Cassiman and Veugelers, 2006; Vassolo et al., 2004; Buckley and Casson, 1976).

For answering the third set of questions, we draw again on organizational learning theory and particularly the notion of *time compression diseconomies (*Dierickx and Cool, 1989) and studies on temporal dimensions (Hashai et al., 2015; Klarner and Raisch, 2013; Casillas and Moreno-Menéndez, 2014) to argue that firms that quickly alternate between specialization strategies are less likely to apply their learning experience into establishing efficient organizational routines because their experiential learning is compacted over a short timeframe (Levinthal and March, 1993; Dierickx and Cool, 1989). Therefore, firms that change their specialization strategies quickly may not benefit from their learning as those firms that change their strategy at a lower speed.

The analysis of 32,537 multi-industry Spanish firms shows that fast-speed changes in specialization strategies are negatively associated with firm performance. Our theoretical justification lies on the fact that firms find it difficult to change and put in application the different elements of knowledge that specialized strategies require due to time-compression diseconomies and limitations in their absorptive capacity (Hashai et al., 2015; Zahra and George, 2002; Chen and Katila, 2008; Blindenbach-Driessen and Ende, 2014; Casillas, and Moreno-Menéndez, 2014). Interestingly, the negative effects of speed of change could be ameliorated (moderated positively) when firms compete in R&D intensive industries. Our justification is based on the nature of dynamic industries. The abundance of knowledge in those environments make it easier for firms to generate not only new knowledge but also leverage existing knowledge allowing them to cycle and switch easier between specialization strategies (Zahra and Das, 1993; Schumpeter, 1950; Bierly and Daly, 2007; Uotila et al., 2009; Zahra, 1996).

THEORETICAL CONTRIBUTIONS

The study makes a number of theoretical contributions. It contributes to organization learning theory (Cyert and March, 1963; Nelson and Winter, 1982; Levitt and March, 1988; March, 1991; Levinthal and March, 1993; Baum et al., 2000) and to the ambidexterity (exploration/exploitation) literature (Tushman et al., 2010; O'Reilly and Tushman, 2013) by identifying how *firm idiosyncrasies* and *industry dynamics* affect the returns to exploratory and exploitative R&D. Specifically, it adds to the ambidexterity debate and its effect on firm performance (Birkinshaw and Gupta, 2013; Wang and Rafiq, 2014) by specifying the boundary conditions of ambidexterity, theorizing and empirically testing the idea that *specialization* (rather than ambidexterity) might be a more advantageous investment strategy for enhancing firm performance when certain conditions are met.

Our analysis also adds to organizational learning theory by identifying that the effectiveness of a learning mechanism (exploratory and exploitative R&D) in enhancing firm performance accentuates when a firm chooses to invest in activities with similar knowledge to that of the firm's specialization strategy. We advance scholarly knowledge on exploration and exploitation a) by explaining *how and why* the effects of exploratory and exploitative R&D on firm performance differ for firms that adopt a specialization versus an ambidextrous strategy and b) by specifying the mechanisms that explain why some firms (on average) may be better off to specialize in either exploratory or exploitative R&D rather than being ambidextrous, emphasising the importance of *experiential learning* and *competence building* when engaging with either exploratory or exploitative R&D activities (Baum et al., 2000; Holmqvist, 2004; Brusoni et al., 2001; Levitt and March, 1988; 1965; Argyris and Schon, 1978; Hedberg, 1981; Chiva, and Alegre, 2010). More precisely, each empirical chapter of this study contributes to organization learning and ambidexterity literature in the following ways:

First, although extant research on knowledge exploration and exploitation justifies the reasons for firms to be ambidextrous for enhancing their performance (Cao et al., 2009; Ebben and Johnson, 2005; Koryak et al., 2018; Lubatkin et al., 2006), it has overlooked the boundary conditions of ambidexterity and whether firm *specialization (*rather than ambidexterity) might be a better investment option for some firms and in specific contexts. To our knowledge, the exploration/exploitation literature has not explicitly made any direct comparison between ambidextrous and specialization strategies. For this reason, there is ambiguity about the effects of ambidexterity versus specialization strategies and the conditions under which their effectiveness on firm performance augments or weakens. The literature has also made the implicit assumption that the returns to exploratory and exploitative activities are similar for both ambidextrous and specialized firms (Markides, 2013). However, the returns to specialization strategies may depend upon the choice of firms to invest further in either exploratory or exploitative R&D.

Second, we contribute to organisational learning theory (March, 1991; Levinthal and March, 1993; Argyris and Schon, 1978; Morgan and Berthon, 2008; Argyris, 1976; Chiva et al., 2010) by clarifying the importance of different learning mechanisms (exploration or exploitation) and in what contexts they matter the most for enhancing firm performance. Specifically, organisational learning theory explains the importance of different types of learning mechanisms (i.e., *single* versus *double-loop* learning, *adaptive* versus *generative* learning), their objectives (efficiency versus discovery), their knowledge requirements (new versus existing knowledge stock), and their possible performance outcomes (short-term versus long-term gains). However, it does not explain the conditions under which the value of such learning mechanisms accentuates or diminishes. In the context of exploratory and exploitative R&D, our results show that that there is a performance-enhancing effect when there is knowledge similarity between existing R&D investments and a firm's existing knowledge base, whereas there is a performance-weakening effect when there is knowledge dissimilarity between current R&D investments and a firm's knowledge stock (Choi and McNamara, 2018).

Third, our study contributes to the ambidexterity-firm performance debate (Duncan 1976; Benner and Tushman, 2003; He and Wong, 2004; Levinthal and March, 1993; March, 2006; Morgan and Berthon, 2008) and extends the ambidexterity discussion by shedding light on moderators. With only few exceptions (Aug and Mengue, 2005; Jansen et al., 2006; Benner and Tushman, 2003; Luger et al., 2018), prior research has overlooked the role that external industries play in affecting the returns to exploratory and exploitative activities. We address this gap in our knowledge by theorizing how the effects of specializing in exploratory/exploitative R&D are contingent upon the orientation of the industry in which the firm competes. We advance thinking on ambidexterity by explaining how differently-oriented industries (i.e., *exploratory, exploitative or hybrid*) affect the returns to specialization strategies. Our theoretical reasoning suggests that certain dynamics in *exploratory, exploitative and hybrid* industries shape differently the *availability* of certain collaborations, determine the *transaction costs* of accessing those collaborative opportunities and the *value* of these opportunities that is mainly affected by knowledge similarity between the explorative or exploitative activities and those offered by other firms in those industries.

Another important contribution of the study is the typology of industry orientation, which explains why two firms that adopt the same specialization strategy exhibit different performance outcomes. Studies on industrial organisation economics often presume (and thus operationalize) competition with the number of intra-industry firms (Porter, 2000; McGahan, 1999). Thus, the established assumption is that the higher the number of intra-industry firms, the greater the intensity of competition. Our typology challenges the way we think about and operationalize competition. The analysis shows that what matters in an industry is the nature of R&D activities the majority of firms engage rather than the number of firms operating in those industries. In doing so, this study explains why is it that some specialized firms perform poorly when they operate in industries with a similar orientation to that of the firm's own specialization strategy, whereas others enhance their performance in industries that complement the firm's own specialization strategy. The opportunities to engage in collaborative agreements, knowledge sourcing and accessing expertise differ across differently-oriented industries, affecting the returns to exploratory and exploitative R&D activities.

We advance theoretical understanding of this issue by showing that depending on the orientation of an industry, some industries may present greater opportunities for complementing the activities of specialized firms. Our approach is distinct from prior studies (Benner and Tushman, 2003; Gupta et al., 2006; Jansen et al., 2006) because it considers the interrelatedness between the focal firm's specialization strategy and the specialization strategies that the majority of firms engage in an industry. This explains why although some firms maintain a specialization strategy, yet industry dynamics enable them to achieve ambidexterity at the industry level (Gupta et al., 2006). Although our positioning does not necessarily contradict the ambidexterity logic, it adds to this notion by linking together the context of a single firm to the context of the industry.

The literature has also considered that ambidexterity could be achieved: a) either by *simultaneously* having firm subunits that explore and others that exploit (Benner and Tushman, 2003; He and Wong, 2004; Tushman and O'Reilly, 1996) b) or by *temporarily shifting* from one activity to the other (Burgelman, 2002; Gupta et al., 2006). Yet, it paid no attention to how the speed of change between the two specialization strategies might influence firm performance and whether the firm's industrial context might affect the relationship between speed and performance. Thus, the question "what the effect of speed of change between specialization strategies is (exploratory/exploitative and hybrid) and under what conditions is more advantageous to the firm?" has not been explored in depth yet. In doing so, we offer a more comprehensive view of the factors that account for variations in firm performance when firms decide to change their specialization strategies at different speeds and in different contexts. Precisely, we explain why is it that two firms may shift between specialization strategies yet experience different performance outcomes because they have chosen to do it at different speeds and in different technologically dynamic industries.

Our findings add to the ambidexterity literature by showing at which speed firms need to change their investment decisions in order to create a source of competitive advantage (Uotila et al., 2009; Gupta et al., 2006). Our findings could help firms to minimize the cost of disruption associated with either quick changes (of a shorter time-length) or extreme changes (i.e., from being specialized in exploratory R&D to being specialized in exploitative R&D and vice versa) that may inhibit their ability to generate revenue.

Finally, our findings show that quick changes in specialization strategy enhances performance when the industry where the firm operates is technologically dynamic (R&D intense). The findings contribute to understanding the interaction between industry technological dynamism and a specialization strategy (Uotila et al., 2009; Gupta et al., 2006). Ignoring that the effects of speed might vary in different contexts could be a major shortcoming in understanding that fast-pace changes between exploration/exploitation strategies could increase rather than compromise a firm's performance in technologically dynamic industries. For this reason, firms in such industries may have to alternate quickly between specialization strategies in order to adapt to frequent technological changes (Miller and Friesen, 1982; Zahra, 1996).

MANAGERIAL IMPLICATIONS

Since our study explores the effects of exploratory and exploitative R&D on firm performance, the findings have practical implications for managers. From a performance point of view, it seems that specializing in either exploratory or exploitative R&D may be a better investment option than being ambidextrous under certain industry-specific attributes such as the orientation of the industry and the R&D intensity of the industry where firms compete, and firm-specific characteristics such as the speed at which firms choose to change between specialization strategies (Hashai et al., 2015; Klarner and Raisch, 2013; Hannan and Freeman, 1984; Kelly and Amburgey, 1991).

This is important because not all firms can be ambidextrous (especially resource-constrained and small-size firms (Cao et al., 2009; Ebben and Johnson, 2005)), and because ambidexterity is not beneficial in all contexts (Auh and Menguc, 2005). Our findings therefore suggest that firms do not necessarily need to balance their exploratory and exploitative R&D as this may result in being mediocre at both (Lubatkin et al., 2006, March, 1991; Blindenbach-Driessen and Ende, 2014). It seems that firms are better off when investing in R&D activities (either exploratory or exploitative) that exhibit knowledge similarity to the firm's current focus and trajectory, utilising thus and build upon their current knowledge pool (Sears and Hoetker, 2014). Firm managers should realise that by engaging repetitively in the same R&D (exploratory or exploitative) firms are likely to strengthen their capabilities and skills involved with the specific R&D and thus add further to their expertise mainly because they will be able to replicate prior successful behaviour, decreasing the possibility of doing errors in subsequent tasks. Managers can exploit their existing knowledge pool, use already tested and successful ideas and replicate past activities offering the industry what they are endowed to do well and getting from the industry what they are less competent to do by themselves to enhance their firm performance (Buckley, and Ghauri, 2015; Buckley, 2016; Schmiedeberg, 2008).

Furthermore, the analysis indicates that the equal distribution between exploratory and exploitative R&D is not always the most optimal strategy for improving firm performance (Auh and Menguc, 2005; Ebben and Johnson, 2005; Kyriakopoulos and Moorman, 2004). They could assist managers in reconsidering whether an equal distribution of their R&D activities could fulfil their firm objectives. Not only because an equal distribution requires different physical structures, but also because they require managerial capacity and knowledge of both exploratory and exploitative R&D to manage them successfully (Blindenbach-Driessen and Ende, 2014).

Our findings also show to managers that the orientation of the industry affects the returns to a specialized activity. The results can help managers decide how to distribute their R&D budget to enhance the performance of their firm. Importantly, the results could help managers appreciate why reducing the scope of their activities and tasks is likely to improve firm performance (Romer, 1987; Hanks, and Chandler, 1994; Brusoni et al., 2001; Holmqvist, 2004). Since the findings indicate that differently-oriented industries affect differently the returns to a specializing activity, they could potentially assist managers in distributing their R&D budget towards either exploratory or exploitative activities. In doing so, managers have to consider that they are better off when they offer their firm's expertise in industries with orientation different to their own specialization because in such industries it is more likely that their activities will complement industries' needs and therefore the marginal value of their offerings will not be easily redundant by competitors' offerings (Rothaermel, 2001; Cassiman and Veugelers, 2006; Chesbrough, 2006; Vassolo et al., 2004; Schmiedeberg, 2008).

Specifically, managers will be able to understand which investment decision they should pursuit depending on the offerings, availability of knowledge, the transaction cost (i.e., internalize some activities versus buy them from the market) of the industry where their firm competes (Jacobides and Billinger, 2006; Hess and Rothaermel, 2011). Therefore, they will be able to make informed decisions that will help firm performance. For instance, our analysis indicates that a specialization in exploitation strategy decreases performance when the firm operates in a similarly exploitative-oriented industry where the majority of firms undertake similar activities to those of the focal firm, limiting therefore opportunities for complementing its own activities (Rothaermel, 2001). By contrast, when a firm specializes in exploitation and operates in a hybrid or exploratory-oriented industry, it is likely that there will be more chances for the firm to either collaborate or source knowledge to complement its activities.

Although these findings do not contradict the premise that balance between exploration and exploitation is beneficial for enhancing firm performance (He and Wong, 2004; Lubatkin et al., 2006; Koryak et al. 2018), they suggest that a firm's specialization strategy can enhance firm performance if it complements industry's needs. Our findings reinforce the idea that firms benefit when they invest in activities that are more likely to produce products and services that are different to industry' s offerings mainly because their value is less likely to be redundant (Vassolo et al., 2004; Karim and Capron, 2016). Our typology of industry orientation can help firms decide whether a specialization strategy as well as *which* specialization strategy (exploration or exploitation) is more advantageous for a given concentration of firms that engage in either similar or complementary activities. This can help managers develop an optimal exploration/exploitation strategy that enhances performance by ensuring a better fit between the firm and its industry's offerings.

Further, our analysis indicates that shifting quickly between specialization strategies affects firm performance negatively (Hashai et al., 2015; Shi et al., 2012) and such negative effects exacerbate a) when the firm decides to make an extreme change shifting for instance from exploration to exploitation investments and vice versa. Yet, high-speed changes between specialization strategies are beneficial for firms operating in R&D intensive environments. These findings have a number of managerial implications.

Our findings also suggest that managers should avoid shifting very quickly (within one or two years) their investment decisions because this way the learning of their firm will be compressed within a short time-frame, which in turn, may lead to decreasing returns. As exploration and exploitation require different knowledge, operational structures and processes to be successful, managers should be cautious that the choice to alternate between investment decisions is likely not only to put a strain on a firm's existing resources, but also on managerial capabilities. As the management of time is subject to managerial control (Ancona, Goodman, Lawrence, and Tushman, 2001), our findings could help managers to use time effectively to create a source of competitive advantage (Shi et al., 2012). Consequently, managers should control how frequently they change their specialization strategies in order to minimize disruption to established operational routines, managerial and resource cost in order to avoid overload that is likely to limit rent generation especially at initial stages until a task becomes efficient through its repetitive execution (Hannan and Freeman, 1984; Amburgey et al., 1990)

Furthermore, the findings show that the negative effects of speed on firm performance turn into positive when firms compete in industries with intense R&D expenditure. The results from prior research indicate that in technologically dynamic environments, exploration is more beneficial for performance since firms are required to constantly generate new knowledge to avoid outdated practises and knowledge obsolescence and at the same time exploit knowledge that has accumulated in such knowledge abundant environments (Uotila et al., 2009; Banerjee and Siebert, 2017). Our results implicitly provide support for this contention suggesting that firms in such industries have to keep up with its frequent changes and exploit opportunities for technological progress at frequent intervals. Hence, findings could assist managers when their firms operate in industries with low levels of technological dynamism to change their specialization strategies less frequently while those managers with firms operating in industries with high levels of technological dynamism to cycle between the two specialization strategies more often.

Managers should be aware that the size of their R&D department has an effect on the performance of their firm when they decide for instance to change quickly their exploration investments to exploitation investments and vice versa. Our results suggest that the negative effect of speed on a firm's performance exacerbates for those firms that own larger innovation departments than for those with smaller innovation departments. Consistent with prior research which shows that size increases organizational instability and changes to large size firms affect its operations (Hannan and Freeman, 1984; Baker and Cullen, 1993), we suggest that the bigger the size of the innovation department the greater the disruption to already established operational routines. Thus, we would advise managers with large innovation departments to avoid making fast-paced changes to their specialization strategies it is expected that some loss of their firm's operational flexibility will occur throughout the transition to a new specialization strategy because a large number of personnel need to change the scope of their operations when shifting from one specialization strategy to the other. Furthermore, as the size of the innovation department increases, it requires greater managerial control and coordination skills. For instance, managers will have to spend considerable time on reorganizing core aspects of their firm's structure, coordinating their employees' actions and maintaining control by formalizing their operations (Child, 1972). All these logistics and practicalities are likely to take managers' attention from their firm's rent generation.

Managers should acknowledge that shifting their exploratory specialization strategy to an exploitative strategy or vice versa, i.e., make an extreme shift to their investments they may put at risk their firm performance to a greater extent compared to making a moderate shift (i.e., from being specialized in exploration/exploitation to being ambidextrous and vice versa). Exploration and exploitation activities require not only different knowledge base, but also resources, time to materialize, and changes in operational structures in order to succeed. Consequently, the workload for both employees and managers is likely to be significant if the firm's current activities and organizational routines deviate from existing practices. If this is the case, then managers may need to direct their time and monetary resources. They should also develop their skills to reconfigure a business model that is likely to disrupt the firm's established routines until managers have accumulated experiential knowledge on how to run it smoothly (Karim and Mitchell, 2000; Van de Ven and Poole, 1995). For instance, limited experience with a specific investment strategy and restricted redeployability of the existed personnel in the new business may cause less smoothly operational system (Karim et al., 2016). Overall, our findings could help managers not only to identify how quickly firms should switch between specialization strategies but also understand that extreme changes in their investment may cause disruption that could prevent the firm to generate its revenue.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Our findings exhibit a number of limitations that could potentially trigger some future research. First, although we used a multi-industry context to test our hypotheses, the generalizability of our results is limited to those firms with similar attributes to that of Spanish firms and context. For instance, the R&D expenditure in Spain is below average compared to that of the other European countries (Eurostat statistics, 2016). Subsequently, future studies could test our theoretical predictions in contexts of different development and innovation infrastructure. For instance, future studies could examine whether and how the effects of specialization versus ambidextrous strategies affect firm performance in emerging and well-developed countries where institutional norms play a crucial role in legitimizing the firm's activities (DiMaggio and Powell, 1984).

Second, we argue that firms that specialize in exploratory R&D have more opportunities to engage in collaborations (formal and informal) with other firms from the same industry in order to either exploit their own technologies or utilize the ideas of other firms. As firms often reach for knowledge that is beyond their own technological and firm boundaries to produce better solutions (Belderbos et al., 2010; Rosenkopf and Nerkar, 2001) and achieve complementarities in research capabilities (Mindruta, 2013; Cassiman and Veugelers, 2006), future research can explore our predictions in the context of inter-industry collaborations.

Third, although we examined how the returns from a firm's specialization strategy are influenced by industry orientation, we did not consider how other contextual factors such as the institutional development of a country or other industry dynamics, such as the intellectual property rights (IPR) protection of the industry, could interact with specialization strategies to affect firm performance. As the legal framework is less important when firms use complex designs, secrecy, complementary assets and tacit knowledge to protect their inventions (Thomä and Bizer, 2013), we expect that IPR protection will have a strong effect on the performance of firms that specialize in exploitation, rather than exploration. In addition, although strong appropriability regimes enable firms to protect their inventions (Teece, 1986), weak appropriability regimes lead to positive externalities and knowledge leakage (Kafouros and Forsans, 2012). Consequently, we would expect that in industries with weak protection, firms that specialize in exploitative R&D will have more opportunities to exploit the ideas and technologies developed by their rivals.

Forth, we found that quick changes between specialization strategies affect negatively firm economic performance. Future research could test and develop a conceptual framework that considers how speed of change affects firms' ability to innovate. Since sales and innovation are both reflective of a firms' performance, yet they are affected by different factors, it might be possible that the results may vary. Therefore, although high speed might impact firm sales negatively mainly because it is disruptive to a firm's established routines, its effect might be positive for innovation. As quick changes allow for expansion in knowledge capacity and prevent capability rigidity (Teece, 2007 Atuahene-Gima, 2005), we would expect the effect of speed of change on innovation (or innovative thinking and creativity) to be positive. Such differences might be more pronounced in technologically dynamic industries which are threatened from technology obsolescence (Sorensen and Stuart, 2000; Uotila et al., 2009) and firms are forced to constantly innovate to keep up with frequent changes and short product life cycle.

Fifth, our analysis considered certain firm- and environment-specific contingencies that could affect the relationship between specialization strategies and firm performance. Future studies could consider other contingencies that might affect this relationship. For instance, from the point of view of firm-specific contingencies, future studies may explore how the age of the firm could interact with the speed of change between specialization strategies to affect firm performance. We would expect that older organizations might be affected the most because their routines are highly institutionalised and thus the speed of change will cause major disruptions to their operations (Hannan and Freeman, 1984). Nevertheless, some studies suggest that older firms survive long enough to rebuild new routines and discard those that make them less efficient with their operations (Amburgey, 1993; 1987). Therefore, the speed of change between specialization strategies is likely to be less distractive to their daily operations.

Finally, from the point of view of environment, future research may extend the current study by examining how different industry dynamics might affect the relationship between specialization strategies and firm performance. For instance, firms in highly competitive environments are often forced to produce new technologies and generate a constant stream of new ideas (Schumpeter, 1942; 1950; Zahra and Das, 1993). This suggests that the effect of specialization in exploitative R&D on firm performance will be negative. Yet, a counter argument suggests that because in highly competitive environments, firms often abandon quickly technologies and replace them with new ones (creative destruction*)*, the effects of specializing in exploitative R&D on firm performance are stronger and more positive than the effects of specializing in exploratory R&D due to positive externalities (Kafouros and Buckley, 2008).

APPENDIX 1

Table 1: Operationalization of variables used in this study

Variables	Definitions
Total factor productivity (TFP)	Log (firm sales/Labour+Capital)
Exploratory R&D	Log (internal R&D expenditure to Basic & Applied research/number of employees)
Exploitative R&D	Log (internal R&D expenditure to Technological Development/ number of employees)
Industry Competition	inverse value of the Herfindahl Index
Tangible Assets	Log (gross investment in tangible resources in the last two years
Newly Created Firms	Binary variable that takes 1 if a firm is created in the last 4 years
International Sales	a binary that takes the value of 1 for firms sell their products at international markets
Affiliated Firms	Binary that takes the value of 1 for firms that belong to a group (affiliated business)
Protection	Log (sum of 4 types of legal mechanisms for protection, i.e., patents, utility models, trademarks and copyrights)
Year Dummies (2003-2012)	Each dummy equals 1 if associated with the corresponding year.
Industry Dummies	Dummy that equals 1 for each corresponding industry.
Firms' specialization in exploratory/exploitative R&D	Time-variant binary that takes the value of 1 when a firm spends over 66.6% of its budget on either exploratory or exploitative R&D).
Ambidextrous Firms	Time-variant binary that takes the value of 1 when a firm spends between 33.33% and 66.66% of its budget on both exploratory and exploitative R&D).
Exploratory/Exploitative-Oriented Industries	The median value of 20 is used to split the industries into their orientation.
Hybrid industries	Binary variable that takes the value of 1 for industries that did not fall into an oriented category
Speed of change	Years of a firm's life in the dataset/number of changes in investment decisions
Extreme Changes	Binary that takes the value of 1 for firms that swift from exploratory R&D to exploitative R&D and vice versa
Size of innovation Department	Log (the number of internal R&D staff of the firm)
Industry R&D Intensity	Industry's total R&D expenditure / total industry sales
Constant Specialization in Exploratory R&D	Invest in Exploratory R&D for all the observable years in the dataset
Constant Specialization in Exploitative R&D	Invest in Exploitative R&D for all the observable years in the dataset
Constant Specialization in Ambidexterity	Make similar investments on both Exploitative and Exploratory R&D for all the observable years in the dataset

Table 2: OECD classification contained in the COTEC Report 1997 (source: Bayona Sáez and Arribas (2002).

High technological intensity
Chemicals and pharmaceutical products Office machinery and computer equipment Electrical machinery and material
Electronic components
Radio and TV apparatus and communications Medical, precision and optical instruments
Medium technological intensity
Rubber and plastic materials Mechanical machinery and equipment Motor vehicles
Marine construction
Aeronautics and space construction Other transport material
Low technological intensity
Extraction, cooking plants and petrol refining
Food, drinks and tobacco
Textiles, clothing and footwear
Timber and cork (excluding furniture)
Furniture
Other manufacturing activities
Recycling
Paper, publishing, graphic arts and reproduction Non-metallic mineral products
Ferrous and non-ferrous metal products
Metal products (excluding machinery and equipment) Electricity, gas and water production and distribution

APPENDIX 2

Descriptive statistics regarding exploratory, exploitative and hybrid industries

Table 1 reports the descriptive statistics for different industries. As this table shows, not all industries are similar in the extent and in the way they choose to invest in exploratory and exploitative R&D. Some industries are characterized by a large number of firms that specialize in exploitative R&D (*i.e., exploitative-oriented industries*), whereas others exhibit a preference in exploratory R&D *(i.e., exploratory-oriented industries*). In addition, there are some industries namely *hybrid industries* that are more balanced in this distribution i.e., make similar investments between exploratory and exploitative R&D.

Table 1: Additional Descriptive Statistics

	Exploratory-oriented Industries			Hybrid Industries			Exploitative-oriented Industries		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Exploration / Internal R&D expenditure	7482	63%	29%	13474	49%	31%	16989	35%	28%
Exploitation / Internal R&D expenditure	7482	37%	29%	13474	51%	31%	16989	65%	28%
Investment in Exploration	7482	1,333,949.00 €	4,631,013.00 €	13474	290,328.20 €	1,131,020.00 €	16989	416,606.40 €	4,283,753.00 €
Investment in Exploitation	7482	773,922.30 €	4,240,810.00 €	13474	299,173.70 €	1,013,528.00 €	16989	1,057,136.00 €	8,048,603.00 €
Number of Inter-industry competitors	7482	285	148	13474	172	128	16989	268	171
Tangible Resources	7482	2,952,391 €	20,900,000 €	13474	10,100,000 €	93,000,000 €	16989	7,383,461.00 €	84,800,000.00 €
Purchase knowledge from Companies (% of total innovation expenditure)	7482	26%	40%	13474	24%	40%	16989	26%	42%
Purchase knowledge from Universities/Research Institutes (% of total innovation expenditure)	7482	23%	39%	13474	19%	37%	16989	16%	35%
Remuneration of R&D staff	7482	30,567.70 €	19,263.15 €	13474	26,316.37 €	59,814.14 €	16989	30,776.08 €	39,645.56 €
Number of legal mechanisms to protect inventions (patents, utility models, trademarks and copyrights)	7482	1	1	13474	1	1	16989	1	1
Firm Sales per Employee (euro)	7482	230,706 €	309,809 €	13474	293,044 €	617,907 €	16989	200,129.30 €	532,837.20 €
Sales from innovative products per Employee (euro)	7482	113,589 €	253,724 €	13474	153,885 €	391,663 €	16989	103,266.20 €	345,465.70 €
Number of registered patents	6711	2	11	12129	1	3	15211	1	11
Firm R&D Intensity (Firms total innovation expenditure/ firm sales)	7482	11.19%	20.85%	13474	5.13%	10.55%	16989	8.73%	13.70%

Industry R&D Intensity Industry total innovation expenditure/ industry sales)	7482	22%	38%	13474	2%	8%	16989	4%	4%
Total Industry Innovation Expenditure	7482	521,000,000.00 €	428,000,000.00 €	13474	120,000,000 €	96,600,000 €	16989	333,000,000 €	290,000,000 €
Firm Innovation Expenditure	7482	2,953,375.00 €	10,400,000.00 €	13474	959,357 €	2,865,030 €	16989	2,734,435 €	18,400,000 €
Market share	7482	1%	4%	13474	2%	10%	16989	14%	212%
International Sales	7482	11,900,000,000 €	8,140,000,000 €	13474	11,700,000,000 €	10,900,000,000 €	16989	12,000,000,000 €	14,400,000,000 €
Year of Establishment	7013	1981	20	12059	1979	21	15517	1983	20
Internal R&D	7482	2,107,145 €	7,297,451 €	13474	589,264 €	1,721,307 €	16989	1,473,184 €	10,300,000 €
External R&D	7482	579,254 €	3,852,254 €	13474	133,351 €	784,000 €	16989	474,161 €	5,844,528 €
% of firms in High Technology Industries	7482	60%	49%	13474	1%	8%	16989	21%	41%
% of firms that Operate Internationally	7482	75%	43%	13474	76%	43%	16989	75%	43%
% of firms that are Affiliated to business group	7482	46%	50%	13474	46%	50%	16989	44%	50%
Number of Firm Employees	7482	226	1046	13474	340	1241	16989	356	1720
% of firms that Specialize in Exploration firm (over 66.6% time- variant special)	7482	47%	50%	13474	35%	48%	16989	21%	41%
% of firms that Specialize in Exploitation Firms (over 66.6%)	7482	21%	41%	13474	37%	48%	16989	51%	50%
% of Ambidextrous Firms	7482	31%	46%	13474	28%	45%	16989	28%	45%

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