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Shifting back and forth: How does the temporal cycling between exploratory and exploitative R&D influence firm performance?

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ABSTRACT

Research on ambidexterity has established that many firms engage in temporal cycling between exploratory and exploitative activities, but it has not examined how quickly firms engage in temporal cycling and how this decision affects their performance. We enhance understanding of this phenomenon by examining how the *speed* at which innovative firms choose to cycle between exploratory and exploitative R&D influences their performance. We also examine contingencies that affect this relationship. Our longitudinal multi-level analysis of 32,527 observations shows that high-speed temporal cycling decreases firm performance by increasing time compression diseconomies in learning. However, we also show that this relationship is firm- and context-specific. Although high-speed cycling harms firms with large-scale R&D operations, it benefits firms that operate in technologically dynamic industries. Our study shifts the discussion from how much firms invest in exploration and exploitation to how quickly they change their focus from one activity to the other.

Keywords: exploration, exploitation, R&D, organizational learning, speed.

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1. Introduction

Despite the antithetical nature of exploration and exploitation (Auh & Menguc, 2005; Boumgarden, Nickerson, & Zenger, 2012; Raisch, Hargrave & Van de Ven, 2018), prior research underscores the importance of being *ambidextrous* for strengthening a firm's performance and competitive advantages (Raisch, Birkinshaw, Probst & Tushman, 2009; Junni, Sarala, Taras & Tarba, 2013; Balboni, Bortoluzzi, Pugliese & Tracogna, 2019; Jansen, Kostopoulos, Mihalache & Papalexandris, 2016). Some firms achieve ambidexterity by spending a similar amount of time and resources on exploration and exploitation simultaneously (this is often termed as simultaneous ambidexterity; Benner & Tushman, 2003). Other firms become ambidextrous by shifting back and forth between the two activities (this is termed as temporal ambidexterity; Burgelman, 2002; Gupta, Smith & Shalley, 2006; Wang, Luo, Maksimov, Sun & Celly, 2019; Simsek, Heavey, Veiga, & Souder, 2009). The latter strategy involves a temporal cycling in which firms focus almost exclusively on one activity first before focusing on the other (Venkatraman, Lee & Iyer, 2007).

Cycling between the two activities can be particularly beneficial (Sabherwal, Hirschheim, & Goles, 2001; Uotila, 2017; Venkatraman et al., 2007). It can help firms avoid competency and failure traps (Simsek et al., 2009; Sigglekow & Levinthal, 2003), deal with resource scarcity and managerial overload (Ebben & Johnson, 2005; Hashai, Kafouros & Buckley, 2018; Boumgarden et al., 2012), manage periods of change and stability (Klarner & Raisch, 2013) and improve their competitiveness (Tushman & O'Reilly, 1996; Sabherwal et al., 2001). However, temporal cycling can also be challenging because the organisational structures, incentives and culture that promote exploration differ from those that promote exploitation (Boumgarden et al., 2012). Hence, cycling between the two activities requires significant changes in routines, practices and resource allocation (Simsek et al., 2009).

Although temporal ambidexterity has attracted attention for its potential to overcome the need to pursue (or balance) these two antithetical activities simultaneously (Simsek et al., 2009; Boumgarden et al., 2012), prior research has not examined how quickly firms engage in temporal cycling and how this strategic decision influences their performance. For instance, while many firms choose to cycle between exploration and exploitation very quickly (e.g. every 1-2 years; Gersick, 1994; Venkatraman et al., 2007), other firms choose to cycle less frequently (e.g. every 4-5 years; Boumgarden et al., 2012). We address this gap in our understanding by examining how the performance of innovative firms is influenced by the *speed* at which they choose to cycle between a strategy that is exclusively (or almost exclusively) focused on exploratory R&D to a strategy that is exclusively (or almost exclusively) focused on exploitative R&D, and vice versa. The theoretical significance of examining the performance consequences of speed of temporal cycling lies in the fact that although two firms may seem equally ambidextrous (Wang et al., 2019), they may achieve different performance because they have chosen to cycle between exploration and exploitation at different speeds.

Drawing on organizational learning (March, 1991; Levinthal & March, 1993; Baum, Li & Usher, 2000; Holmqvist, 2004; Levitt & March, 1988) and organizational ecology (Hannan & Freeman, 1984), we argue that a firm's experiential learning is subject to time compression diseconomies (Dierickx & Cool, 1989). When temporal cycling between exploratory and exploitative R&D occurs at a higher speed, the usefulness of experiential learning decreases because knowledge requires time to accumulate and organizational routines require repetitive execution to become efficient (Baum et al., 2000, Holmqvist, 2004). We therefore expect firms that alternate between exploratory and exploitative R&D very quickly to become less effective in integrating their learning into organizational routines (Schilling, Vidal, Ployhart & Marangoni, 2003; Lavie, Kang & Rosenkopf, 2011) and to experience negative effects on their performance (Stieglitz, Knudsen & Becker, 2016).

Furthermore, prior studies suggest that the usefulness of ambidexterity is contingent on firm-specific or contextual factors such as firm resources, firm age, market share, environmental dynamism and competition (Junni, Sarala, Taras, & Tarba, 2013; Balboni et al., 2019; Jansen et al., 2016; Uotila et al., 2009; Venkatraman et al., 2007). Although these studies do not examine the effects of speed, they highlight the importance of considering such contingencies and call for research on the moderating role of organizational variables and environment (Simsek et al., 2009). Motivated by these studies, we examine how the relationship between the speed of temporal cycling and firm performance is affected by two key contingencies (namely, the scale of the firm's R&D operations and the R&D intensity of the industry in which the firm operates). Although these are not the only contingencies worth examining, we choose to focus on these factors because of their theoretical relevance in determining whether high-speed cycling is required, easily implemented and beneficial. Specifically, the scale of R&D operations can influence the effects of speed by affecting organizational inertia and the resources that firms spend on switching from exploitative to exploratory R&D (and vice versa). On the other hand, R&D intensity in an industry determines how dynamic the firm's external environment is and how quickly the firm must respond to changes (Schilkes, 2014; Lee, Sambamurthy, Lim & Wei, 2015).

By examining the performance effects of speed of temporal cycling and the contingencies that influence these effects, we make two distinct theoretical contributions. First, we advance understanding of the relationship between exploration, exploitation and firm performance (He & Wong, 2004; Raisch et al., 2009; Balboni et al., 2019) by showing that firm performance is determined not only by whether firms engage in temporal cycling (Simsek et al., 2009; Venkatraman et al., 2007), but also by how quickly firms choose to cycle between exploratory and exploitative R&D. In this respect, the analysis shows that high-speed temporal cycling is on average negatively associated with firm performance (Lee et al., 2015; Stieglitz et al., 2016).

Second, we identify contingencies that influence how the speed of temporal cycling affects firm performance. Although prior research suggests that the speed of engaging in new initiatives has adverse consequences for firm performance (Laamanen & Keil, 2008), we show that R&D intensity in an industry moderates positively the negative effects of speed of cycling as firms in such environments need to implement quick changes to minimize knowledge obsolescence (Uotila, Maul, Keil & Zahra, 2009; Uotila, 2017). By contrast, we show that firms with large-scale R&D operations cannot cope well with quick changes. As a result, the negative effects of speed of temporal cycling on firm performance become stronger.

2. Theory and hypotheses

2.1. Theoretical Background

Organizational learning theory suggests that individuals and firms make inferences from their experience (Levinthal & March, 1993; Huber, 1991). Inferences lead to conceptual maps that translate experience into knowledge and learning that facilitates the creation of efficient *routines* (i.e., rules, procedures and strategies around which firms are constructed and operate; Levitt & March, 1988). Experience is therefore a driving force in advancing the understanding of routines. Learning through direct experience (*experiential learning*) helps firms create and accumulate knowledge that induces greater efficiency due to the repetitive execution of the same set of activities (Huber, 1991). Experiential learning also enables organizations to develop exploitative and exploratory capabilities (Cyert & March, 1963; Holmqvist, 2004) and become better at those routines they repeat frequently and less capable in those they do irregularly.

Although firms learn from exploratory and exploitative activities, they have to overcome the challenge of dealing with inconsistent routines (Ebben & Johnson, 2005) when they invest in both (March, 1991, Levinthal & March, 1993; Baum et al., 2002). Such inconsistency arises due to different knowledge-specific requirements of exploration and exploitation (Kim, Song & Nerkar, 2012). Exploitative R&D involves the use of existing knowledge to refine and improve existing products and processes (Gupta et al., 2006; Holmqvist, 2004; Tyre & Von Hippel, 1997; Limaj & Bernroider, 2019). In exploitative R&D, firms learn through local search and experiential refinement to become more efficient in executing routines (Rosenkopf & Nerkar, 2001; Rosenkopf & Almeida, 2003). By contrast, in exploratory R&D, firms find new ways of performing routines (Morgan & Berthon, 2008). It necessitates search and experimentation with distant knowledge that deviates from the firm's existing knowledge stock, aiming at generating new ideas and technologies (Baum et al., 2002; Turner, Swart & Maylor, 2013). Although both exploratory and exploitative R&D are needed to sustain superior performance, the different types of learning and routines that are required for exploration and exploitation create trade-offs (Kim et al., 2012; Wang et al., 2019; Raisch et al., 2018; Lavie et al., 2011).

Organizational learning is also influenced differently when firms engage in temporal cycling and when they go through periods of stability. Temporal cycling between exploration and exploitation prevents firms' predisposition to overexploit at the expense of exploration, and vice versa (Uotila, 2017; Lampert & Kim, 2018). Temporal cycling helps firms avoid becoming liable to their own competencies that may become liabilities over time (Levinthal & March, 1993; Wang et al., 2019) and lead to inertial practices (Hannan & Freeman, 1984). Cycling between exploitative and exploratory R&D also prevents firms from getting trapped into a single mode of learning that may restrict their adaptability to changing environments (Benner & Tushman, 2003; Teece, 2007; Simsek et al., 2009). By contrast, other scholars suggest that firms need periods of stability as these enable firms to convert their experiences into beneficial learning and establish efficient routines (Eisenhardt & Martin, 2000; Hashai et al., 2018). As firms gain experience, they build up expertise that predisposes them to engage in the same activities, rather than shifting their focus to new ones (Levinthal & March, 1981, 1993; Levitt & March, 1988).

As efficiency gains depend on the repetitive execution of the same tasks over time (Baum et al., 2000; Huber, 1991; Uotila, 2017), organizational learning theory postulates that firms need sufficient time to translate their experience into learning (Levitt & March, 1988; Holmqvist, 2004). Frequent changes between exploratory and exploitative R&D may decrease a firm's ability to perform specific tasks competently compared to firms that undertake the same activities within a longer timeframe. This view is consistent with a central tenet in organizational ecology theory (Hannan & Freeman, 1984) that suggests that firms are subject to strong inertial forces and find it challenging to make frequent and radical changes. The theory emphasizes that learning and structural inertia must be considered in a dynamic context. In some situations, organizations may change continuously only to find that their environment has also changed, and that it now requires a new organizational configuration (Hannan, Polos & Carroll, 2003).

Firms that choose to shift from exploratory to exploitative R&D (and vice versa) have to acquire and use new and different knowledge, capabilities and skills to those they already possess (Rosenkopf & Nerkar, 2001; Rosenkopf & Almeida, 2003). However, the establishment of new and effective routines requires time (Hannan et al., 2003; Nelson & Winter, 1982; Wang et., al., 2019). As a result, experiential learning that is compacted in a short timeframe becomes less beneficial than learning that is spread over a longer period of time (Levinthal & March, 1993; Dierickx & Cool, 1989).

In such situations, firms may face *time compression diseconomies*, which refers to the challenges and costs incurred by firms seeking to accumulate quickly a stock of assets when this stock could be accumulated over a longer duration (Dierickx & Cool, 1989; Hashai et al., 2018). In the context of organizational learning, time compression diseconomies kick in when firms try to learn new routines within a short timeframe. Learning that is compressed in time makes firms liable to their newness (Rajagopalan & Spreitzer, 1997; Parastuty, Schwarz, Breitenecker & Harms, 2015; Wang et al., 2019) and increases the difficulty of establishing and reproducing routines in a reliable manner (Hannan & Freeman, 1984; Lavie et al., 2011). Hence, compressing learning within a limited timeframe decreases the likelihood of improving firm operations and of perfecting organisational routines, decreasing therefore the rate of efficiency gains. By contrast, firms that allow sufficient time to learn routines are more likely to turn experiential leaning into useful applications and routines (Cyert & March, 1963; Hedberg, 1981; Vermeulen & Barkema, 2002; Klarner & Raisch, 2013). This point highlights the idea that organizations need sufficient time to accomplish certain activities at a given quality level. Hence, superior performance is facilitated by concentrating efforts in a given area for sufficient time (Baum et al., 2000).

2.2 Speed of Temporal Cycling and Firm Performance

Although the temporal cycling between exploratory and exploitative R&D can help firms adapt and develop new capabilities (Barnett & Freeman, 2001; Vermeulen & Barkema, 2002; Klarner & Raisch, 2013), we contend that cycling at high speeds decreases firm performance. Drawing on organizational learning (Levitt & March, 1988; Holmqvist, 2004; Cyert & March, 1963; Baum et al., 2002) and organizational ecology (Hannan & Freeman, 1984), we expect high-speed cycling to inhibit the firm’s ability to learn and use its knowledge effectively. Our logic focuses on four causal mechanisms that concern: 1) the direct effect of high-speed cycling on a firm's existing products, markets and relations; 2) the role of time compression diseconomies (Dierickx & Cool, 1989); 3) the context-specificity and applicability of experiential learning (Baum et al., 2002 Holmqvist, 2004; Levinthal & March, 1993); and 4) the role of prior learning (absorptive capacity) (Volderba, Foss and Lyles, 2010; Zahra & George, 2002; Cohen & Levinthal, 1990).

Starting from the first causal mechanism, high-speed organizational changes direct managerial attention from performance-enhancing tasks to how to manage such changes (Hannan et al., 2003). Hence, shifting quickly from exploratory to exploitative R&D (or vice versa) diverts managers attention from improving organizational efficiency and performance to predicting the fate of the new structure. Opportunities for new products and services are overlooked, the generation of such products and services gets disrupted or becomes less efficient, and relations with customers are left unattended. Frequent changes also require new routines and a new workforce with different capabilities and skills (Barnett & Freeman, 2001). They lead to a cascade of other changes, affect relationships with external firms and increase the need for new relational ties. In such situations, the firm's existing products, markets and relations suffer from limited organizational attention. As these problems accentuate at higher speed, they decrease firm performance.

Second, firms that cycle at high speed are constrained by time compression diseconomies because they are forced to learn within a restricted timeframe (Dierickx & Cool, 1989). As learning cannot be compressed in time, we expect high-speed cycling to make a limited contribution to the firm's learning and performance (Vermeulen & Barkema, 2002). Learning very quickly gives rise to managerial overload (Eisenhardt & Martin, 2000; Wang et al., 2019), increases organizational costs and requires additional managerial attention and commitment (Hashai et al., 2018; Boumgarden et al., 2012). The need to accommodate these additional demands puts a strain on the firm's existing resources, decreasing therefore firm performance (Stieglitz et al., 2016; Ebben & Johnson, 2005).

Consistent with this view, work on organizational ecology emphasizes that the process of abandoning one structure and adopting another makes organizational action unstable and more complicated (Hannan et al., 2003). Hence, shifting between different structures at higher speeds reduces firms' reliability (their ability to produce products and services with small variance in their quality; Hannan & Freeman, 1984). This view effectively suggests that when firms have limited experience and less efficient routines in place, they find it difficult to deal with reorganization. As a result, 'liability of newness' sets back their operations and decreases reliability (Hannan & Freeman, 1984). By contrast, firms that engage in the same activity for longer time periods become familiar with a given set of routines, accumulate expertise in a specific area and enhance the efficiency of exploratory or exploitative activities. This reasoning is consistent with the premise that learning at lower speed is more likely to lead to the accumulation of greater knowledge in the long run (March, 1991). As learning that is well distributed across time is more beneficial than knowledge that is compacted in a short timeframe (Dierickx & Cool, 1989), lower speed of cycling allows firms to absorb and utilise knowledge more efficiently.

Third, shifting back and forth quickly between exploratory and exploitative R&D decreases the usefulness of prior knowledge, as well as the applicability and transferability of prior learning into other contexts (Levinthal & March, 1993). When such changes occur frequently, firms have little time to translate experiential learning into effective routines and outcomes (Levitt & March, 1988; Vermeulen & Barkema, 2002). Experience requires time to accumulate and organizational routines require repetitive execution to mature (Levinthal & March, 1993; Holmqvist, 2004). Firms that quickly alternate between exploratory and exploitative R&D are less able to integrate their learning and experience in organizational routines that enhance performance. This view is consistent with work that suggests that periods of adjustment in which firms are subject to less frequent changes are important for organizational routines to emerge (Klarner & Raisch, 2013; Stieglitz et al., 2016). This reasoning suggests that firms apply experiential knowledge to a new situation less successfully (Nadolska & Barkema, 2007; Choi & McNamara, 2018) when they have little time to evaluate which routines to retain and how these should be employed. Hence, high-speed cycling limits firms' ability to transfer and apply effectively prior knowledge about exploratory routines to exploitative routines and vice versa.

Finally, high-speed cycling decreases firm performance (Stieglitz et al., 2016) by stretching the firm's absorptive capacity (Volderba et al., 2010; Swift, 2016). Absorptive capacity largely depends on the overlap between prior and new knowledge (Lane, Koka, & Pathak, 2006). When firms change from exploratory and exploitative R&D quickly, they need to alter their knowledge and learning to accommodate the requirements of the new activity (Solís-Molina, Hernández-Espallardo & Rodríguez-Orejuela, 2018). The low degree of relatedness between exploratory to exploitative routines prevents knowledge assimilation and application (Zahra & George, 2002; Volderba et al., 2010). Because shifting back and forth quickly from exploratory to exploitative R&D and adapting to new organizational routines and structures puts strain on the firm's absorptive capacity, we expect adaptation efforts and costs to increase (Zollo & Winter, 2002; Boumgarden et al., 2012) with negative consequences for firm performance. Hence:

> ***H1****: A higher speed of temporal cycling between exploratory and exploitative R&D decreases firm performance.*

2.3 The Scale of R&D Operations

Hannan and Freeman (1984) further emphasized that an important challenge that organizations face concerns the responsiveness of the structure to changes. This point effectively involves the question of how quickly and easily firms can be reorganized. For instance, prior research suggests that mixing strategies that require different organization is not beneficial for many firms (Ebben & Johnson, 2005). Although we expect the speed of temporal cycling (on average) to decrease firm performance, we further hypothesize that these negative effects become more pronounced for firms with a larger scale of R&D operations than for firms with a smaller scale of R&D operations (i.e., we expect the scale of R&D operations to moderate negatively the relationship between the speed of temporal cycling and firm performance).

First, the scale of R&D operations affects how R&D as an activity is organized and governed. A larger scale increases inertial forces and makes the quick implementation of changes difficult and challenging (Hannan & Freeman, 1984; Amburgey, Kelly & Barnett, 1990). Although firms with large-scale R&D operations benefit from resource munificence (Ebben & Johnson, 2005), their decentralized operations require coordination (Baker & Cullen, 1993) and lead to bureaucracy. Large-scale R&D operations increase the number of routines that must be changed quickly and therefore the disadvantages of temporal cycling at high-speed. They also require stronger administrative reorganization (Baker & Cullen, 1993; Blindenbach-Driessen & Van den Ende, 2014) particularly when changes occur frequently, giving rise to complexity, disputes and communication problems (Blau, 1970). In such situations, firms spend considerable time and resources on reorganizing their structures and on replacing exploitative routines with exploratory ones (and vice versa). Hence, large-scale R&D operations increase time compression diseconomies and decrease firms' ability to implement the quick changes that high-speed temporal cycling requires.

Second, when the scale of R&D is large, a large number of R&D personnel needs to change its scope (Beckman, 2006). When these transitions occur quickly, changing the mindset of large R&D units becomes more difficult and firms may be left with a mix of exploratory and exploitative routines for some period (Vermeulen & Barkema, 2002). This may confuse organizational action, personnel roles and relationships among staff members and give rise to organizational conflicts (Hannan & Freeman, 1984; Hannan et al., 2003). Such structural transformations (i.e., disassembling one structure and building a new one) also increase organizational instability (Baker & Cullen, 1993). Further, when large-scale operations and activities have to take place concurrently, the level of control, coordination and attention that is required increases (Haveman, 1993; Barnett & Freeman, 2001). As firms with large-scale R&D operations are more strongly affected by organizational instability, they are less able to adapt to high-speed changes with negative consequences for firm performance.

Third, firms with larger R&D operations have habitually established routines (Baker & Cullen, 1993; Di Maggio & Powel, 1984) and investments in fixed equipment that complicate the decision to change quickly. High-speed temporal cycling becomes more challenging because institutionalized formal structures are more developed and harder to change (Amburgey et al., 1990). Interruption of organizational routines when shifting from exploitative to exploratory R&D (and vice versa) quickly is more pronounced in larger R&D units because norms and rules are deeply embedded in established routines (Di Maggio & Powel, 1984; Hannan & Freeman, 1984). Hence, as knowledge about the firm's operations and activities is habitually embedded in such norms, we expect a higher speed of temporal cycling to decrease firm performance more strongly when the scale of R&D operations is larger than when it is smaller:

H2*: The negative effects of the speed of temporal cycling between exploratory and exploitative R&D on firm performance will be stronger for firms with a larger scale of R&D operations than for firms with a smaller scale.*

2.4. The role of R&D Intensive Industries

Another central issue identified by Hannan and Freeman (1984) concerns the temporal pattern of changes in key environments and, more specifically, how quickly such changes occur. Building on this tenet, the next part of our framework focuses on the industrial context in which the firm operates. Specifically, we contend that the negative effects of speed of temporal cycling on firm performance are weaker when firms operate in R&D intensive industries than when they operate in industries that are less R&D intensive. Several theoretical reasons support this view.

First, R&D intensive industries are technologically dynamic (Schilke, 2014). Their context is characterized by high volatility, changes in technological trajectories, frequent introduction of new discoveries and quick depreciation of existing ones (Posen & Levinthal, 2012; Luger, Raisch & Schimmer, 2018). Due to the nature of these industries, firms not only must engage in exploratory R&D to generate new ideas (Zahra & Das, 1993), but also in exploitative R&D to exploit these ideas quickly. Given that new knowledge and technologies in dynamic industries become obsolete quickly (Schumpeter, 1942), firms have to abandon their newly developed technologies and ideas and replace them with new ones (Sorensen & Stuart, 2000). This necessitates firms to cycle between exploratory and exploitative R&D quickly. In such situations, although high-speed temporal cycling is still challenging, we expect its negative effects on firm performance to be weaker because it helps firms respond quickly and keep up with environmental changes (Schilkes, 2014).

Second, the above logic is in line with the premise put forward by Posen and Levinthal (2012) that an appropriate firm response in dynamic environments is the exploitation of existing opportunities. However, such dynamic environments also offer opportunities to increase the returns to exploratory R&D because firms are exposed to new knowledge and ideas (Koza & Lewin, 1998) that accelerate their learning (Kogut & Zander, 1993). Subsequently, firms in dynamic industries can identify better opportunities to exploit existing ideas but also explore new ones (Kafouros & Forsans, 2012) by shifting quickly between exploratory and exploitative R&D while partly avoiding the negative effects of high-speed cycling on firm performance. The above reasoning is also reinforced by the view that technologically dynamic environments require firms to learn faster and develop new skills.

Furthermore, firms in R&D intensive industries are exposed to an environment that is characterized by abundant technological opportunities (Zahra, 1993; Uotila et al., 2009). As technologies evolve quickly, firms need to develop new competences in emerging areas (Battisti, Beynon, Pickernell & Deakins, 2019). As such, shifting from exploratory to exploitative R&D at a higher speed has a less negative effect on firm performance in R&D intensive industries that require firms to adapt to frequent changes, minimise knowledge obsolescence, keep up with new demands and technological breakthroughs, and engage in business renewal more often (Uotila et al., 2009). This premise does not necessarily suggest that such practice is equally viable or equally beneficial for all firms. For instance, limitations in management expertise and resources may make some firms to be less effective in dealing with external environmental changes (Ebben & Johnson, 2005). However, despite the challenges associated with inconsistent configurations, we expect the negative effects of speed to be weaker in technologically dynamic industries. Accordingly, we introduce the following hypothesis:

H3*: The negative effects of the speed of temporal cycling between exploratory and exploitative R&D on firm performance will be weaker in R&D intensive industries than in less R&D intensive industries.*

3. Data and methods

3.1. Sample

To test the hypotheses, we collected firm-level longitudinal data from PITEC (Technological Innovation Panel). PITEC is designed to monitor the economic development and technological activities of Spanish firms (i.e., similar to the Community Innovation Survey, CIS). There is high reliability in the reported data because PITEC is a large-scale survey that is administered every two years by the National Statistics Institute (INE), the Foundation for Science and Technology (FECYT), and the Foundation for Technical Innovation (COTEC) 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 and R&D. Firms are legally obliged to respond and, as a result, over 90% response rate is achieved, reducing therefore concerns about selection bias in the sample. This dataset is appropriate for testing the hypotheses because it provides a breakdown of the type of R&D (exploitative and exploratory) (e.g., D'Este, Marzucchi, & Rentocchini, 2017; Czarnitzki et al., 2011; Armand & Mendi, 2018). Our analysis focuses on firms with more than 10 employees that reported information for over four years (this is needed to trace changes over time). Instead of focusing on a single industry (Rothaermel & Alexandre, 2009; He & Wong, 2004), we examine 56 industries (mainly manufacturing but also some in services) to increase variability in our data. The final sample includes an unbalanced panel of 32,527 firm-year observations (5567 firms) over the 2003-2012 period.

3.2 Dependent Variable

Following prior studies on R&D and performance (Fey & Birkinshaw, 2005; Kafouros, Wang, Mavroudi, Hong & Katsikeas, 2018; Adams & Jaffe, 1996), we capture firm performance by constructing a measure of *total factor productivity (TFP) (*Qingwang & Junxue, 2005; Van Beveren, 2012*)*. The benefits of productivity performance over other performance measures have been documented in the literature. First, TFP accounts not only for firm sales from products and services but also for various inputs and resources that firms use, such as labour and capital. It therefore reflects how effective the firm is in achieving a certain level of output (sales) from a given level of inputs (labour and capital). As such, the measure is effective in capturing variations in firm output that cannot be explained by variations in firm inputs.

Second, TFP captures the different benefits of investing in R&D (Kafouros et al., 2018). For instance, R&D could lead both to product and process innovations. Although new product introductions affect firm sales, process innovations enhance productivity by leading to efficiency gains due to the better allocation of resources. TFP reflects both changes. Third, while financial measures of performance such as firm profitability are volatile and take negative values, TFP cannot be easily manipulated and it is less affected by market fluctuations, exchange rates and differences in accounting standards (Buckley, 1996).

To estimate TFP for each firm (i) at time (t), we consider the relationship between certain firm inputs X and firm outputs Y. This is a standard practice employed in the R&D literature (Adams & Jaffe, 1996; Kafouros & Aliyev, 2016; Kafouros et al., 2018). It relies on a function that considers both *labour* (the number of employees) and *capital* (tangible assets) as inputs (see equation 1). To estimate total factor productivity (TFP), we estimated the production function and its residual (TFP). This residual reflects variations in a firm's output (sales) that cannot be explained by variations in firm inputs (Temouri, Driffield & Higón, 2008; Smarzynska Javorcik, 2004). 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 & Aliyev, 2016). The following equation represents the total output (Y) as a function capital input (K), labour input (L) and residual ε.

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

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 refer to year and industry dummies, respectively; ε is the residual of this equation (Temouri et al., 2008), which reflects TFP.

3.3. Independent Variables

3.3.1. Exploratory and exploitative R&D

In constructing measures for exploratory and exploitative R&D, we took into consideration both the definition of R&D (OECD, 2005) and the conceptual definitions of what constitutes exploratory and exploitative activities (March, 1991). To operationalize these measures, we used a number of survey items from the PITEC database that provide direct measures of exploratory and exploitative R&D by capturing each firm's annual investment in those activities. As such, PITEC allows us to distinguish investments by type of R&D activities.

Specifically, PITEC is capturing firms' investment in *exploratory R&D* by asking firms to report their annual R&D investment in basic research that "consists of experimental or theoretical work that is mainly undertaken to obtain new knowledge on the essentials of observable phenomena and facts, without considering giving them any particular application or use whatsoever" and/or investment in applied research that "consists of the original work carried out to acquire new knowledge; however, it is mainly directed towards a specific practical objective".

To capture firms' investment in *exploitative R&D,* PITEC asks firms to report their annual R&D investment in experimental development that "consists of systematic work based on existing knowledge, obtained from the research and/or practical experience, aimed at the production of new materials, products or devices; at the establishment of new processes, systems and services, or at the substantial improvement of those already existing".

Our measures of *exploratory* and *exploitative R&D* are consistent with prior empirical research (D'Este et al., 2017; Czarnitzki et al., 2011; Barge-Gil & Lopéz, 2014, 2015) as well as with the established conceptual definition in the literature that distinguishes between the aim of creating entirely "new" knowledge and systematic work aimed at refining or improving existing products and processes using the firm's "existing" knowledge base (March, 1991; He and Wong, 2004; D'Este et al., 2017).

Based on the above survey items, our operationalization uses each firm's actual (annual) investment in those activities. We divide each firm's investment in those activities with the number of firm employees to normalize the figures for firm size (D'Este et al., 2017). We also transform these measures into their logarithm to normalize their range and improve the interpretation of the results (Qingwang and Junxue, 2005; Van Beveren, 2012). Given that information on such investments is reported annually, the exploratory and exploitative R&D measures are time variant. This is particularly important for the research design of the study because it enables us not only to observe the annual distribution between these two types of activities but also whether and how they change from year to year.

3.3.2 Speed of Temporal Cycling

Drawing from studies on temporal effects (Hashai et al., 2018; Vermeulen & Barkema, 2002), we operationalize the speed of temporal cycling between exploratory and exploitative R&D as the number of times that a firm changes its focus from one activity to the other in a given period of time (in our case, the entire period that the firm exists in the dataset). For instance, when a firm cycles two times within an 8-year period, its average speed of cycling is 0.25 per year (i.e. a complete change occurs on average every four years). When a firm cycles four times within an 8-year period, its average speed of cycling is 0.50 per year (i.e. a complete change occurs on average every two years). In the former case, the speed of the firm's cycling is lower compared to that of the latter case. Our operationalization of speed therefore considers the temporal distance or gap when cycling between the different activities (Homburg & Bucerius, 2005). Some firms are exclusively or almost exclusively focused on one activity (e.g. they spend 80%, 90% or even 100% of their budget on exploratory R&D) before they exclusively or almost exclusively focus on the other activity (e.g. exploitative R&D). However, other firms are ambidextrous. In a given year, they may spend 50 or 60% of their budget on one activity and the rest of it on the other activity. Our measure also captures such firms.

3.3.3 Scale of R&D Operations and Industry R&D Intensity

To operationalize the scale of each firm's R&D operations, we use the annual innovation expenditure of the firm. Consistent with prior studies, we calculate industry's R&D intensity using the industry's total R&D expenditure divided by the industry's total sales (Uotila et al., 2009; Zahra, 1996). Following common practice, both variables were transformed using logs to maintain consistency in the empirical model and help the interpretation of the results (Qingwang and Junxue, 2005; Van Beveren, 2012).

3.4 Control Variables

We control for various firm- and industry-specific factors that may affect firm performance. First, we control for each *firm's tangible assets* using the log each firm's investment in tangible resources (Lubatkin, Simsek, Ling & Veiga, 2006; Jansen, Tempelaar, Van den Bosch & Volberda, 2009). This may account for the difficulties that resource-constrained firms encounter in different industrial environments (Hannan & Freeman, 1984; Tushman, Virany, & Romanelli, 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 & 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). International expansion is associated with firm growth (He & Wong, 2004), international competitiveness and access to new market knowledge (Cassiman & 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 (Blindenbach-Driessen & Ende, 2014) as these firms enjoy certain advantages that may enhance performance. Fifth, given that a firm's appropriability strategy may affect its performance (Laursen & Salter, 2006; 2014), we control for the mechanisms that each firm uses to protect its inventions (Vega-Jurado, Gutiérrez-Gracia, Fernández-de-Lucio & Manjarrés-Henríquez, 2008). These mechanisms include the use of four *protection* mechanisms (patents, utility models, trademarks and copyrights). This variable ranges from 0 to 4, depending on how many of these mechanisms each firm employs. We also use the logarithmic value of the variable to maintain consistency in the modelling. Next, we created a dummy variable that takes the value of 1 when firms undertake *extreme changes* and shift from exploratory to exploitative R&D or vice versa, and 0 when firms undertake moderate changes, cycling from exploitative (or exploratory) R&D to ambidexterity or vice versa. We controlled for extreme changes in temporal cycling because while moderate changes typically involve adaptive alterations and smaller adjustments to existing routines, extreme changes involve substantial departures from existing organizational routines.

Firm performance can also be affected by industry-specific attributes. One way to control for *competition* in each industry is to use the number of 2-digit intra-industry competitors (Jansen et al., 2009). In highly competitive industries, firms are forced to improve operational efficiency (Matusik & Hill, 1998) and avoid risk-taking behavior (Miller & Friesen, 1982; Auh & 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 estimated the Herfindahl Index (HI) as a measure of industry concentration (Kafouros & Aliyev 2016). The higher the value of Herfindahl Index the lower the concentration level within an industry, which reflects a lower level of competition. We therefore use the inverse value of the Herfindahl Index (i.e. 1- Herfindahl Index). Hence, a higher value indicates high levels of competition. The model also includes a dummy variable that represents firms that operate in high-tech industries (based on the OECD classification), such as pharmaceutical, computing and electronics. Finally, we control for *time effects* by including year dummies in the model.

3.5 Estimation Method

Given that our sampled firms are clustered within industries, a *Multilevel Mixed Model* approach is better suited for estimating TFP (Bliese & Ployhart, 2002; Preacher, Curran & Bauer, 2006; Anderson, 2014). The choice of Multilevel Mixed estimator was driven by three reasons. First, the Multilevel Mixed Model approach is specified at different levels of analysis that enables us to produce coefficients that are nested in each industry and firm. This is particularly important in our analysis that includes several industries that may exhibit differences in how quickly they cycle between exploratory and exploitative R&D. Second, in contrast to traditional panel data estimators that typically focus on FE (Fixed Effects) or RE (Random Effects), multilevel analysis with mixed effects considers both FE and RE effects.

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 for each firm (and within each industry) separately (Wooldridge, 2000; Blundell & Bond, 2000).

Although we experimented with other estimators such as FE and RE, the fact that we expected the effects of exploratory and exploitative R&D to vary a lot depending on the industry made these estimators less appropriate to reveal variability at industry and firm level. Thus, our chosen estimator allows us to explicitly specify the estimation with complicated clustering patterns while relying on the assumption of independence of error terms, which may be violated when firms are clustered in various industries (Anderson, 2014; Preacher et al., 2006).

4. Results

Table 1 presents the descriptive statistics and correlations. Table 2 reports the regression results using the Multilevel Mixed Effect estimator. We specify the model to produce results that are nested both in each industry and firm (Bliese & Ployhart, 2002). The maximum value of the variance inflation factor (VIF) in any of the models was below the cut-off point of 2, suggesting that the possibility of multicollinearity is low. Model 1 is a baseline model. Model 2 tests the direct effect of speed of temporal cycling. Models 3 and 4 introduce the interaction between speed and the scale of R&D operations; and between speed and industry's R&D intensity. Model 5 is a full model that includes all the direct and interaction terms.

Most of the control variables have a positive and statistically significant effect on firm performance, which is consistent with prior theoretical expectations. Two variables (*tangible assets* and *high-tech firms*) yield statistically insignificant effects, while *industry R&D intensity, newly created firm* and *extreme changes* appear to influence firm performance negatively in most of the models (with few exceptions). From these results, it is worth noting that extreme changes from exploratory to exploitative R&D and vice versa exhibit a negative effect. This result can be explained by the fact that such changes involve substantial alterations to existing routines and significant departures from existing organizational routines. As such, extreme changes have adverse consequences for firm performance.

Model 2 provides support for Hypothesis 1, indicating that the speed of temporal cycling between exploratory and exploitative R&D decreases firm performance. This result remains consistent (but differs in its significance level) across Models 3 to 5. Overall, it supports the premise that when firms cycle quickly between activities, their experiential learning is compressed in time and it is less likely to be translated into beneficial outcomes and effective organizational routines (Hashai et al., 2018; Klarner & Raisch, 2013). Models 3 and 5 corroborate Hypothesis 2 (although the level of significance is lower in Model 3 than in Model 5). The results indicate that the negative effects of speed of change become stronger as the scale of R&D operations increases.

The results in Models 4 and 5 are partly in line with our expectations in Hypothesis 3. Interestingly, the positive coefficient of the interaction term is much higher than the negative coefficient of the direct effect of speed. This result suggests that although (on average) high-speed has adverse effects on firm performance, its negative effects turn into positive in R&D intensive industries. It therefore supports the logic that because technological opportunities are abundant in dynamic environments, firms benefit from cycling quickly between exploratory and exploitative R&D.

Furthermore, we conducted a number of robustness checks and additional analyses. First, although the Multilevel Mixed estimator is the most appropriate approach for our multi-industry analysis, we also explored whether our results are robust to alternative panel-data estimators that are not nested in the industry and firm levels. Specifically, we re-estimated all the models using the generalized least squares (GLS) estimator. This is an appropriate estimator for longitudinal data (Wooldridge, 2001; Blundell & Bond, 2000). Overall, the new results suggest that all the hypothesised effects are supported with the exception of Hypothesis 2 which is less strongly supported (the R^2 value was 0.35).

Second, R&D investments might be endogenous (Hamilton & Nickerson, 2003). To address potential endogeneity, we followed common practice and re-estimated the models using the two-stage least squares (2SLS) approach (Hamilton & Nickerson, 2003; Certo, Busenbark, Woo & Semadeni, 2016). This approach uses instruments that are uncorrelated with the error term to proxy the potentially endogenous regressors (i.e., R&D investments) in the first stage. It then employs the predicted values to estimate the model in the second stage (Wooldridge, 2002). We use three instrumental variables: number of industry competitors; industry sales and total industry's innovation expenditure. The rationale behind the selection of these instruments is that although they may influence exploratory and exploitative R&D investments, they are not directly associated with the error term as these three variables are exogenously determined by market, regulatory and other institutional forces (Hamilton & Nickerson, 2003). A post estimation analysis confirmed that the chosen instruments are not weak. The new results from the 2SLS approach are qualitatively similar to the results obtained from the multilevel mixed estimator, providing strong support to the hypotheses (with the only exception being that the interaction between speed and R&D scale lost its statistical significance; yet its directionality remained the same).

Third, drawing from prior studies (Auh & Menguc, 2005; He & Wong, 2004; Venkatraman et al., 2007), we used a firm's sales as an alternative measure of performance (after normalizing for firm size using the number of employees). As economic relationships are rarely linear, we used the logarithm of the measure (Wang, Shrestha, Robertson & Pokhrel, 2012). The hypothesised effects were consistent with our initial analysis. Furthermore, although we employed a logarithmic specification, we re-estimated the model after removing outliers from the dataset (we delete cases that were over 3 and less than -3 standard deviations). The sample reduced from 32,527 to 32,077 observations but all the hypothesised effects were consistent with the results reported earlier.

Fourth, our analysis assumes that the direct performance effects of speed are linear. Nevertheless, such effects might change beyond (or below) a certain threshold and may take a curvilinear form (i.e., a U-shaped or inverted U-shaped relationship). Following usual practice, we squared the relevant term (speed) and re-estimated the models. The results indicate that the effects of speed are linear, confirming that on average high-speed cycling decreases firm performance.

We have also conducted an additional analysis using the size of the firm (operationalized as the number of employees), rather than that of R&D operations, as potential moderator of speed and firm performance. The new results indicate that the interaction term between speed and size was not statistically significant. We also experimented with the firm's tangible assets as an alternative measure of firm size (Lubatkin et al., 2006) and once again the interaction term between firm size and speed was statistically insignificant. A justification for these results is that cycling involves changes in exploratory and exploitative R&D, and it does not necessarily require all the functions and departments of the entire firm to change.

Finally, our sample includes both manufacturing and services industries. Although this is not necessarily a problem given that we employed the Multilevel Mixed Effect estimator, we investigated whether the hypothesised effects hold for manufacturing firms only (n=25,434). Once again, the hypotheses were supported (however, the coefficient of Hypothesis 3 remained similar in its directionality but lost its statistical significance).

5. Discussion and conclusions

5.1 Theoretical Contributions and Conclusions

The literature on exploration and exploitation has considered the performance implications of simultaneous ambidexterity (O'Reilly & Tushman, 2013; Junni et al., 2013; Luger et al., 2018). It has suggested (Boumgarden et al., 2012; Gupta et al., 2006; Gonzaleza & Massaroli de Melo, 2018) that achieving ambidexterity through cycling may be a good alternative that can help firms manage resource (Ebben & Johnson, 2005) and managerial demands (Simsek et al., 2009). However, prior research has largely ignored how the *speed* of cycling between exploratory and exploitative R&D affects firm performance and what contingencies influence this relationship. This limits our understanding of when a higher speed of cycling is beneficial and when it is not. By capturing temporal variations, our analysis helps us explain why two ambidextrous firms that make similar investments in exploration and exploitation differ in their performance because they cycle between such activities at different speeds. Accordingly, the study makes a number of theoretical contributions.

First, it contributes to research on exploration and exploitation (Auh & Menguc, 2005; Uotila et al., 2009; O'Reilly & Tushman, 2013) and ambidexterity (Simsek et al., 2009; He & Wong, 2004) by shifting the discussion from how much firms invest in exploration and exploitation (Raisch et al., 2009; Luger et al., 2018) to how quickly they change their focus from one activity to the other. This kind of inquiry offers a new explanation as to why innovative firms differ in their performance. It shows that ignoring the role of temporal dimensions (Simsek et al., 2009; Boumgarden et al., 2012), such as that of speed, could be a significant shortcoming in advancing theory.

To this end, our study contributes to organizational learning theory that focuses on the benefits of exploration and exploitation (March,1991; Raisch et al., 2009; Wang et al., 2019) without explicitly addressing how the speed of shifting from one activity to the other affects learning. Drawing from the notion of time compression diseconomies (Dierickx & Cool, 1989), we show that although engaging in both activities might be beneficial, high-speed cycling strains the firm's absorptive capacity (Vermeulen & Barkema, 2002; Raisch et al., 2018) and influences how effectively organizations learn (Klarner & Raisch, 2013; Baum et al., 2002). It therefore decreases firm performance in certain contexts, particularly when cognitive constrains prevent firms from pursuing exploration and exploitation simultaneously (Solís-Molina et al., 2018).

A second contribution to organizational learning theory and to the literature on temporal cycling (Venkatraman et al., 2007; Simsek et al., 2009; Boumgarden et al., 2012) lies in identifying contingencies that either offset or strengthen the inherent disadvantages of high-speed cycling and in turn how it influences firm performance. The first contingency we identify concerns the industry context in which the firm operates. Specifically, we show that the negative effects of speed depend on how R&D-intensive the firm's industry is. Interestingly, as the positive interaction term between speed and R&D-intensity is higher than the negative direct effect of speed, the results suggest that cycling quickly becomes advantageous in highly dynamic environments.

This finding helps us understand how the effects of organizational learning differ across industry contexts. Our analysis implies that firms in dynamic contexts are better able to overcome challenges associated with time compression diseconomies and in turn benefit from high-speed cycling. This finding stands in contrast to the established notion that speed has adverse consequences for firm performance (Hashai et al., 2018). Furthermore, our study contributes to studies that examine whether dynamic environments necessitate exploratory investments or exploitative investments (Uotila et al., 2009; Posen & Levinthal, 2012; Stieglitz et al., 2016; Uotila, 2017) by showing that the nature of R&D-intensive environments makes cycling at high speed an essential requirement and a better strategy.

Thirdly, we show that while speed is beneficial in R&D-intensive contexts, firms that possess large R&D departments cannot easily cope with quick changes. As a result, the adverse effects of speed are greater for firms with large scale R&D operations (Parastuty et al., 2015; Amburgey et al., 1990; Lavie et al., 2011). Although large-scale R&D operations benefit from resource munificence, they increase bureaucracy and make coordination more difficult (Baker & Cullen, 1993). They also increase organizational instability and inertial forces (Hannan & Freeman, 1984), making new routines difficult to emerge. These findings contribute to organizational learning theory by clarifying that although scale in R&D may yield economies in learning, it comes with disadvantages that make high-speed cycling between activities particularly challenging and less beneficial (Dierickx & Cool, 1989; Baum et al., 2000; Holmqvist, 2004; Lavie et al., 2011).

5.2 Managerial Implications

As temporal cycling and more generally the management of time are seen as sources of competitive advantage (Shi, Sun, & Prescott, 2012), our findings could help managers understand when they should cycle between exploratory and exploitative R&D quickly and when they should not (Laureiro-Martínez et al., 2015). First, firm strategies should take into consideration that due to time compression diseconomies, changing quickly between exploratory and exploitative R&D may, on average, compromise organizational learning, increase coordination challenges and result in diminishing returns. Spending considerable time on reorganizing their structure and coordinating different functions seems to be taking their attention away from rent generation. Managers should be aware that higher speed of cycling requires additional managerial capacity and may put a strain on a firm's existing resources (Hashai et al., 2018). They should therefore first carefully evaluate whether they have the organisational resources and managerial capabilities to do so. If a firm's environmental context requires frequent shifts between exploration and exploitation, managers should plan in advance and direct more time and resources to meet the different requirements of the two activities.

Second, firm strategies should take into consideration that technological dynamism in the industrial context in which firms operate determines how beneficial high-speed cycling is for firm performance. Therefore, managers must align the speed of switching back and forth between exploration and exploitation with their industry context. In dynamic R&D-intensive industries, firms are better off cycling between exploratory and exploitative R&D at higher speeds. Conversely, as the life cycle of technologies is longer in less R&D-intensive contexts, cycling less frequently appears to be a better strategy for enhancing firm performance (Posen & Levinthal, 2012; Stieglitz et al., 2016). As this timeframe can have a significant effect on firm performance (Van Looy, Martens & Debackere, 2005), the speed of cycling should match the life cycle of technologies.

Third, managers should be aware that the negative effect of high-speed cycling on firm performance accentuates for firms with large-scale R&D operations. As larger scale often leads to organizational inertia, managers should consider that quick changes may result in losing operational flexibility. As the scale of operation increases, greater managerial control, coordination and attention are required to succeed in the new strategy. Hence, when firms with large scale R&D operations change the scope of their operations very often, the associated challenges and costs will likely decrease firm performance. Given the negative consequences and inertial disadvantages of having very large R&D departments, some firms choose to engage in R&D alliances, create spin off companies or partly outsource their technological development.

5.3 Limitations and future research

Our analysis comes with a number of limitations, some of which could open avenues for future research. First, given our focus on a single country, we were not able to examine how cross-country contingencies influence the effects of speed. For instance, it would be useful to examine how our theoretical predictions vary across emerging and developed countries. Differences in institutional norms, intellectual property protection and market-supporting institutions in these countries may change the way firms operate and the difficulty of cycling between activities by accessing external markets for ideas and technologies. Second, future research should consider how other contextual factors and industry contingencies influence the effects of speed of cycling on firm performance. For instance, market share and competition (Venkatraman et al., 2007) could determine the speed of cycling given that less competitive environments may allow longer periods of exploitation and less frequent cycling. Focusing on firm-specific factors (e.g. firm age, characteristics of top managers, CEO tenure; Simsek, 2007) may also allow future research to connect the determinants of exploratory and exploitative activities with their consequences. For instance, younger firms are liable to their newness (Rajagopalan and Spreitzer, 1997) and have less institutionalized routines, which in turn can affect the ease with which they can make frequent changes.

Furthermore, future research could examine how the speed of cycling affects firm performance in the context of alliances. Alliances can help firms gain access to exploration and exploitation specific knowledge and technologies (Wassmer, & Madhok, 2017) and therefore serve as an alternative to cycling between exploration and exploitation activities. Firms can avoid being penalised for focusing (internally) on one activity and capture the benefits of ambidexterity by engaging with a wider firm network (Gupta et al., 2006). Although prior research has examined what type of alliances enhance firm performance (Lavie et al., 2011; Rothaermel and Deeds, 2004), little research has considered how frequently firms engage in alliances and how this practice affects the speed of cycling.

Finally, future research could examine how the speed of cycling affects not only firm performance, but also various dimensions of firm innovativeness such as the volume and quality of patents and sales from new products. Although high-speed cycling may on average decrease firm performance, this finding does not imply that high-speed cycling would have an equally negative effect on firms' innovative capacity. For instance, the effects of high-speed cycling might be positive for the firm's innovativeness and patenting activity by encouraging knowledge expansion and preventing capability rigidity (Teece, 2007; Atuahene-Gima & Murray, 2007). Hence, considering the consequences of such temporal dimensions for measures of innovativeness would be a useful avenue for advancing the field.

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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														
2. Exploratory R&D	-0.05***													
3. Exploitative R&D	-0.06***	-0.20***												
4. Tangible Assets	0.21***	0.08***	0.046***											
5. International Sales	0.24***	0.02***	0.01	0.07***										
6. Affiliated Firms	0.33***	-0.03***	-0.01	0.09***	0.10***									
7. Industry Competition	0.06***	0.06***	-0.04***	0.04***	0.16***	-0.02**								
8. Protection	0.13***	0.05***	0.02***	0.08***	0.17***	0.14***	0.10***							
9. Industry's R&D intensity	-0.30***	0.24***	0.15***	0.03***	-0.06***	-0.10***	0.04***	0.02***						
10. Newly Created Firms	-0.07***	0.03***	0.03***	0.02***	-0.05***	-0.01	-0.00	-0.02***	0.05***					
11. High-Tech Firms	0.14***	0.13***	0.01	0.03***	0.14***	0.04***	0.18***	0.09***	-0.09***	-0.01*				
12. Scale of R&D Operations.	0.16***	0.28***	0.31***	0.23***	0.09***	0.34***	-0.06***	0.22***	0.23***	0.01	0.06***			
13. Speed	-0.04***	0.03***	-0.05***	-0.02***	-0.05***	-0.08***	0.01	-0.08***	-0.07***	0.01	-0.05***	-0.16***		
14. Extreme Changes	-0.01	-0.05***	-0.09***	-0.01	-0.01	-0.01	0.01	-0.02***	-0.03***	-0.01	0.00	-0.06***	0.25***	
Mean	0.06	5.46	6.11	8.16	0.77	0.47	0.92	-3.88	0.07	0.01	0.22	12.91	0.21	0.06
Std. Dev.	0.94	3.46	3.22	1.73	0.43	0.50	0.09	3.54	0.20	0.08	0.41	1.60	0.20	0.25
Min	-11.02	-8.29	-6.88	-2.31	0	0	0	-6.91	0.00	0	0	6.78	0	0
Max	5.53	14.68	14.21	16.34	1	1	0.99	1.39	8.73	1	1	20.03	0.86	1

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

Table 2 –Regression Results (Multi-level Mixed Effects; dependent variable = firm performance, TFP)

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.	S.E	Coef.	S.E	Coef.	S.E	Coef.	S.E	Coef.	S.E
H1: Speed of temporal cycling			-0.143**	0.045	-0.151***	0.047	-0.018†	0.01	-0.146**	0.048
H2: Speed of cycling X Scale of R&D Operations					-0.025†	0.015			-0.029*	0.015
H3: Speed of cycling X Industry R&D intensity							0.479*	0.241	0.499*	0.242
Scale of R&D Operations (log)	0.022***	0.005	0.022***	0.005	0.022***	0.005	0.021***	0.005	0.022***	0.005
Exploratory R&D (log)	0.003**	0.001	0.004	0.001	0.004**	0.001	0.003**	0.001	0.004**	0.001
Exploitative R&D (log)	0.003*	0.002	0.004*	0.002	0.004*	0.002	0.004*	0.002	0.004*	0.002
Tangible Assets (log)	-0.005	0.004	-0.005	0.004	-0.005	0.004	-0.005	0.004	-0.005	0.004
International Sales	0.033*	0.015	0.033*	0.015	0.033*	0.015	0.032*	0.015	0.032*	0.015
Affiliated Firms	0.121***	0.017	0.120***	0.017	0.120***	0.017	0.120***	0.017	0.120***	0.017
Industry Competition	0.268†	0.147	0.268†	0.147	0.266†	0.147	0.285*	0.146	0.284*	0.145
Protection (log)	0.003*	0.002	0.003*	0.002	0.003*	0.002	0.003*	0.002	0.003*	0.002
Industry R&D intensity (log)	-0.217*	0.102	-0.216*	0.102	-0.209*	0.104	-0.376***	0.108	-0.374***	0.108
Newly Created Firms	-0.308***	0.08	-0.308***	0.08	-0.308***	0.08	-0.304***	0.08	-0.303***	0.08
High Technological Firms	0.051	0.114	0.046	0.114	0.046	0.114	0.046	0.112	0.046	0.112
Extreme changes	-0.020*	0.01	-0.018†	0.01	-0.018†	0.01	-0.137**	0.047	-0.018†	0.01
Time Effects	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	-0.497***	0.133	-0.457***	0.131	-0.462***	0.131	-0.461***	0.128	-0.466***	0.128
Industry Variance	0.2571	0.065	0.2566	0.0646	0.2566	0.0643	0.2462	0.0618	0.2459	0.0613
Firm Variance	0.4876	0.0437	0.4872	0.0437	0.4867	0.0437	0.4875	0.0437	0.4869	0.0437
Residual Variance	0.1266	0.0149	0.1266	0.0149	0.1266	0.0149	0.1265	0.0149	0.1265	0.0149
Wald chi^2	231.68	P>	241.69	P>	239.3	P>	288.96	P>	287.73	P>
Number of observations	32527		32527		32527		32527		32527	

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