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Human capital and innovation: the importance of the optimal organizational task structure

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ABSTRACT

Management literature has identified high-skilled human capital as a crucial dimension of innovation processes at the firm level. In this study, we introduce an alternative view of human capital based on the tasks that firms' workers perform. We propose a measure of cognitive analytical and interpersonal tasks: the degree of abstractism. We argue that the level of abstractism of a firm has an effect on a firm's propensity to innovate and on its product innovation performance. We hypothesize that while the degree of abstractism has a linear positive relationship with the propensity to innovate, the relationship between abstractism and product innovation performance follows an inverted u-shaped relationship. We find partial support to our hypotheses using data from more than six thousand Portuguese firms. We discuss how these results change our understanding of the relationship between human capital and innovation at the firm level.

1. Introduction

Innovation is considered to be a source of competitive advantage (Banbury and Mitchell, 1995; Tushman and O'Reilley, 1996). Research on innovation management has focused its attention on finding the conditions that determine the success of innovation activities and the environmental factors that influence how firms innovate (e.g., Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Klingebiel and Rammer, 2013). Innovation scholars have given attention to a variety of strategic factors that potentially affect the success of innovation activities, as trade-offs and complementarities between internal and external R&D activities (e.g., Cassiman and Veugelers, 2006), knowledge outsourcing decisions (e.g., Demirbag and Glaister, 2010; Weigelt, 2009) or cooperation agreements (e.g., Grimpe and Kaiser, 2010; de Faria et al., 2010). Researchers have also stressed the role of human capital in explaining how firms successfully translate innovation inputs into innovation outputs (e.g., Faems and Subramanian, 2013). However, limited attention has been devoted to the impact that recent changes on firms' workforce due to technological change (e.g., Hilton, 2008; Colbert et al., 2016; Wegman et al., 2016) may have on how firms organize their innovation activities and transform innovation inputs into innovation outputs. We aim to address this gap by studying firms' innovation processes from a task-based perspective. We propose task measures that allow the assessment of the organizational task structure that maximizes the propensity of a firm to innovate and its product innovation performance.

The task approach appeared in economic literature linked to the concept of technological change and, in particular, to automation of routine tasks. Automation of routine tasks has been pointed out as a source for changes in firms' workforce composition over the last decades (Autor et al., 2003; Acemoglu and Autor, 2011). The so-called routinization hypothesis builds on the idea that codifiable repetitive work can be executed, not just by human labor, but also by computers and computer-driven machines. Moreover, it argues that as the cost of computing capacity declines over time, firms have an incentive to substitute human labor for computers. This incentive is amplified by the complementarity between high-skilled personnel and technology. As a consequence, firms are dichotomously shifting towards more cognitive task focused structures or more flexible physical task-oriented, whilst firms that perform mostly repetitive work are having problems in adapting their activities (Fonseca et al., 2018b).

Using a task framework, we theorize on how and why different task organizations (i.e., how firms organize their activities) can influence the returns of firms' innovation processes. Our approach assumes that

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firms organize their activities in a series of tasks with the aim of more efficiently transform inputs into outputs. In line with the task-based literature, we consider three types of task activities: abstract, manual and routine (Autor et al., 2003; Acemoglu and Autor, 2011; Fonseca et al., 2018b). Abstract are mainly cognitive analytical and interpersonal task activities, while manual are non-cognitive tasks that require flexibility. Routine are centered on repetitive tasks, those that can be performed by following a set of instructions and, thus can be coded and performed by a machine. The combination of firms' tasks results into distinct organizational task structures. Following the task framework provided by the literature, we theorize on how firms' task intensity affects innovation activities.

We propose a measure of intensity of abstract activities conducted within firms – the degree of abstractism. We claim that abstract activities have a different nature than manual and routine tasks. Employees conducting abstract tasks are mainly engaged in cognitive and knowledge-intensive activities. Creative thinking is at the core of abstract tasks, especially when comparing with manual and routine (Bartel and Lichtenberg, 1987; Autor et al., 2003). Despite having different characteristics, both routine and manual tasks are linked to less knowledge-intensive activities such as repetitive work or work requiring physical dexterity (Autor et al., 2003). Therefore, we posit that firms with different degrees of abstractism will also have a different set of competencies and resources. We theorize that abstractism influences firm-level innovation processes at two levels. Firstly, we hypothesize a positive linear relationship between the level of abstractism of the activities of a firm and its propensity to develop new to the market innovations. Secondly, we predict an inverted u-shaped relationship between the degree of abstractism and a firm's product innovation performance. That is, we predict that a firm's level of abstractism influences its probability to innovate and innovation performance in different manners. We explain this dissimilarity with the fact that different steps of the innovation process require different competences and resources (Henderson and Cockburn, 1994; Danneels, 2002). More precisely, we claim that the factors explaining why a firm develops an innovation are different from the ones explaining what makes it a successful innovator. The decision to develop innovation activities is mainly dependent on a firm's organizational creativeness and knowledge conversion capabilities (Danneels, 2002; Anderson et al., 2014), while a firm's innovation performance is determined by how effectively it can translate innovation activities into market success. A firm can frequently develop innovations and still fail to obtain market success. Likewise, a firm can have difficulties starting innovation projects and still be very efficient in the commercialization stage.

We use data from three consecutive waves of the Portuguese Community Innovation Survey (CIS 2008, CIS 2010, CIS 2012) supplemented by a linked employer–employee dataset to test our hypotheses. We empirically test the twofold nature of the effect of the degree of abstractism on firm-level innovation. By estimating a two-equation model using a Heckman procedure, we find that innovation performance is maximized at an intermediate value of the degree of abstractism (approximately 46% and 54% for our sample, depending on the level of newness of the innovation activities). That is, firms that have higher innovation performance are the ones that combine both abstract and non-abstract tasks. However, we only find partial support to our hypothesis that the propensity to innovate is maximized by increasing the degree of abstractism. Despite finding a positive and significant relationship between the degree of abstractism and the propensity to introduce products that are new to the market, the hypothesis is not supported when we use a more strict definition of innovation: propensity to introduce products that are new to the world.

Given the simultaneity of the innovation processes (Thornhill, 2006), we show indications that firms face a potential trade-off when defining their degree of abstractism: to maximize their propensity to innovate they need high levels of abstractism, whilst for maximizing performance intermediate levels of abstractism are optimal. Our results expand existing knowledge on how human capital influences the innovation process (e.g., Faems and Subramanian, 2013). In particular, by identifying the above-described trade-off, we show that different skills and tasks are required for different phases of the innovation process. Our findings suggest that the optimization of the innovation process is related to different organizational challenges. For the first phase, a more abstract organizational form enables a firm to foster cognitive activities and consequently to increase organizational creativity. In a second phase, a balance between abstract and non-abstract leads a firm to a superior market performance associated with innovative products.

This paper is organized as follows. We provide the theoretical grounds and develop the hypotheses in Section 2. Section 3 describes the data and the empirical approach. The descriptive statistics and the results are described in Sections 4 and 5 respectively. In Section 7 we discuss the results and conclude in Section 8.

2. Theoretical framework and hypotheses

2.1. Automation of routine tasks

The effects of automation of routine work processes have been mainly studied in the labor economics field, in the context of technological change affecting labor markets. Whilst its effects are acknowledged by management literature (e.g., Hilton, 2008; Colbert et al., 2016; Wegman et al., 2016), limited attention has been given by management scholars to these phenomena. A model based on tasks upsurges as a theory to describe the role of computers or computer-aid machines as substitutes for humans in certain tasks or as complementarity tools to human activities in others (Autor et al., 2003). Scholars using a task-based approach conceptualize the workplace as a collection of task activities put together to achieve a desired output (Autor et al., 2003) and typically group these tasks into three main categories: abstract, routine and manual.

Abstract tasks are non-routine cognitive tasks involving analytical skills and/or interpersonal skills (Autor et al., 2003; Fonseca et al., 2018a). Typical activities include data analysis, creative thinking, coaching, directing or maintaining interpersonal relationships; all activities related to problem-solving, managing or carrying out complex communications. Abstract tasks are the core, for example, of how engineering, managerial or medical jobs are currently conducted. Contrary to abstract tasks, routine tasks are based on routine content that can be executed by following a set of instructions and can therefore be codified into a computer program.[1]

At the core of routine tasks is accurateness, repeatability, repetitive motion or the ability to follow the pace established by an equipment (Autor et al., 2003; Fonseca et al., 2018a). Routine tasks are particularly intensive in jobs like office clerk, salesperson, machine operator or assembling jobs. Manual tasks are non-cognitive and non-routine, requiring flexibility and physical dexterity. Most manual tasks activities are conceptually simple, but because of its high variability cannot be coded into a computer and therefore cannot be routinized. Those tasks are mostly associated with physical jobs, in particular those that require spatial orientation, manual dexterity, equipment operation or hands on the tools. Examples of occupations that currently have a high manual intensity include construction workers, cleaners, drivers or welders.[2]

[1] For the sake of simplicity we do not distinguish between routine cognitive and routine non-cognitive (routine manual). Technology is a substitute for both types of routine tasks; the main difference relies on the use of repetitive cognitive skills, which is mainly relevant when looking at task transitions which is not the focus of our study. Thus, we are confident that bundling together both types of routine tasks does not imply an oversimplification of the problem that we want to study.

[2] The boundaries between routine and manual tasks evolve in line with the development of artificial intelligence. The evolution of artificial intelligence

Extant literature gives indication that these three kinds of tasks are differently affected by the introduction of automation technologies. Whereas manual tasks are not directly affected by technology adoption as most activities require levels of flexibility and dexterity that current technology cannot provide yet (Acemoglu and Autor, 2011), empirical evidence shows that automation influences both routine and abstract tasks. Though, the influence is dissimilar in its nature. Routine intensive jobs can potentially be substituted by computers or computer aided-machines, whereas abstract jobs exhibit complementarities with automation technologies (Autor et al., 2003; Acemoglu and Autor, 2011).[3]

The rising pace of automation is leading to a decline in the number of firms organizing their activities around routine tasks, hand-in-hand with an increase in the number of highly abstract firms (Fonseca et al., 2018b). Firms focused on routine tasks in the past may have had to adapt to technological change by upgrading their technology and restructuring their activities to become more focused on other tasks, contingent on the net benefit each combination of technology and human resources within the firm.

Autor et al. (2003) and Fonseca et al. (2018b) provide the foundations for a novel approach to the firm's internal structure. Employing a task-based approach that relies on the actual activities performed by workers allows obtaining metrics of human capital at the organization level that go beyond traditional measures as workers' education. The resource-based view of the firm emphasizes that firms' internal resources and internal organization (e.g., how firms pool and structure their human capital and respective interrelationships) are important drivers to achieve competitive advantage (Barney, 1991; Wernerfelt, 1984; Barney and Wright, 1998). Consequently, adopting a task-based view allows us to disentangle the relationships that are typically attributed to human capital as a broad concept.

While innovation management literature acknowledges the association between human capital characteristics and innovation performance (e.g., Faems and Subramanian, 2013), most studies bundle human capital together with other measures, such as R&D activities, into proxies to firms' absorptive capacity (e.g., Veugelers, 1997; Grimpe and Sofka, 2009). Human capital plays a major role in absorptive capacity development, but its strategic importance goes beyond just being a component of it, as the literature on strategic human capital emphasizes (e.g., Chadwick and Dabu, 2009). We contribute to this literature by applying a task-based approach to understand the relationship between organizational structure, innovation propensity and innovation performance. We argue that differentiating firms according to their task distribution allows for a more precise assessment of the capabilities of a firm than classical measures of human capital like the level of education of the workforce. Reducing human capital to the educational dimension only allows the assessment of a firm's potential to create knowledge and does not allow differentiating firms according to the way they organize their human capital towards the creation of value.

2.2. Task-based approach

The foundation of the task approach relies on seminal work of Autor et al. (2003), which dissects workplace's activities into tasks. Underlying their approach is the relationship between technology and firms' activities: computers and computer aided-machines (automation technologies) are a substitute for routine tasks and a complement for non-routine cognitive (abstract) tasks. Tasks are built on the activities performed by firms' employees, in particular their occupations. Thus, tasks are not grounded on traditional firms' characteristic such as industry, firm size, technological intensity or employees' education, despite associations between those can emerge ex post. For example, it is not surprising that firms with high levels of abstract intensive tasks tend to be more concentrated in engineering or consultancy, or have high technological intensity. Yet, this is a result rather than an imposition of the task approach, since no such structure is imposed ex ante. Due to differences in business models and technological intensity, it is possible to find within the same industry firms with high levels of abstract tasks and firms which tasks are mainly routine. With the introduction of automation technologies (and the decreasing relative price of capital), tasks associated with clerical jobs tend to be automated, which consequently will lead firms to shift towards more abstract tasks.

Another important dimension of the task approach is how it differs and complements education as a human capital measure. Naturally, employees performing highly abstract activities are more likely to hold a college degree. Yet, by construction, tasks are not directly related to formal education, but to the actual activities performed within the firm and consequently of its strategy. For example, in a country with high education attainment, most managers will hold a college degree, while in a low education attainment country they will not. Both are abstract workers and execute similar complex tasks, despite their differences in educational levels. The task approach captures this nuanced view, which is not identifiable if we limit our classification of human capital to traditional education attainment, adding an extra layer of information about human capital and technological ability of the firm (Autor et al., 2003; Fonseca et al., 2018a).

Most literature on innovation management has given special attention to firms' R&D activities, patent activity or cooperation strategies (e.g., Li et al., 2008; Klingebiel and Rammer, 2013; Noseleit and de Faria, 2013; Kim et al., 2016). However, the importance of human capital has been less investigated. With some exceptions like Faems and Subramanian (2013), which investigates the importance and substitutability of human capital diversity, recent studies mainly use human capital as a control (a stylized positive relationship) or as a proxy of absorptive capacity (e.g., Kneller and Stevens, 2006; Escribano et al., 2009; Grimpe and Sofka, 2009). Conversely, recognizing human capital as a strategic resource that needs to be correctly allocated can yield important results, as innovation activities depend greatly on the knowledge and expertise of employees (Youndt et al., 1996). By unbundling human capital into actual task activities performed by employees within firms we will propose a novel approach in innovation management studies.

Innovation activities are often described as a vehicle to expand market share and achieve long-term competitive advantage (Damanpour, 1991; Banbury and Mitchell, 1995; Grimpe and Sofka, 2009). We look at two dimensions of the innovation process: propensity to introduce new products and product innovation performance. We claim that these two dimensions are linked to different firm-level mechanisms. The propensity to introduce new products is mainly dependent on how firms can leverage their human capital to generate organizational capabilities that enable innovation to take place (Chen and Huang, 2009). Product innovation performance is dependent on the ability of firms to translate the investments made in innovation activities into revenues. That is, innovation propensity is associated with firms' organizational creativity and technological competences, whereas innovation performance is dependent on firm's market

(*footnote continued*)
allows for the codification of more complex tasks and transforms some traditionally manual tasks into routine ones. An illustrative example is the development of self-driving cars that is giving an indication that driving will evolve from a manual task to a routine one. This trend led us to the decision to focus our attention on the degree of abstractism and not to explore the distinction between routine and manual tasks. Current developments on artificial intelligence will further rewire this relationship, has automation of some more cognitive tasks will be possible in the future (Frey and Osborne, 2017). However, for the period under analysis is safe to assume that the implementation of automation technologies has been empirically observed to substitute routine jobs (Acemoglu and Autor, 2011; Goos et al., 2014; Fonseca et al., 2018a).

[3] The complementarity between abstract workers (high-skilled) and technology has been described exhaustively in labor economics literature (e.g., Krueger, 1993; Goldin and Katz, 1998; Krusell et al., 2000; Autor et al., 2003; Acemoglu and Autor, 2011).

competences (e.g., Anderson et al., 2014).

The propensity of a firm to conduct innovation activities is often associated to particular characteristics that indicate the potential capability to create and implement new ideas, like R&D intensity, firm size or employees' education (Huiban and Bouhsina, 1998; Galende and de la Fuente, 2003). Yet, existing literature gives limited attention to firms' diversity in terms of workplace activities and reduces the human capital dimension to levels of education or to the share of employees who are scientists or engineers (e.g., Sofka et al., 2014; Grimpe and Kaiser, 2010). Consequently, it fails to describe the combination of activities actually performed in the workplace. Adopting a task-based approach helps to overcome this limitation.

2.3. Hypotheses

As discussed above, the main objective of our study is to understand how a firm's task distribution influences two dimensions of its innovation process: propensity to introduce new products and product innovation performance. We argue that, despite being interconnected, the propensity to innovate and the innovate performance require different capabilities from a firm. The propensity to innovate is more closely linked to organizational creativity and knowledge transformation mechanisms (Amabile, 1996; Anderson et al., 2014), while innovation performance is related with firm's ability to transform an innovation into a commercial success.

The process of developing an innovation requires organizational creativity and therefore it is dependent on the creativity of the firm's workforce. Creativity is an antecedent of innovation, since it is tied to the generation of novel and useful ideas, and it feeds the innovation process (Scott and Bruce, 1994; Amabile, 1996; Baer, 2012; Anderson et al., 2014). Innovation is then the result of idea generation, together with its implementation, and consequently a function of creativity in both individual and group dimensions (Anderson et al., 2014). Idea generation is an individual cognitive process (Mumford and Gustafson, 1988) grounded on employees' cognitive characteristics such as ability, skills, and knowledge, together with individual traits such as personality (Woodman et al., 1993; Anderson et al., 2014).

Following Ford (1996), we consider that firms' employees are grouped into two competing activities: to be creative or to conduct routine and manual actions. Routine and manual actions are related with the execution of repetitive work or non-cognitive work that demands flexibility, or a combination of both. Routine and manual activities executed in a repetitive and habitual fashion do not motivate employees to generate ideas (Perrow, 1970; Baer, 2012). Consequently, we claim that the contribution of routine and manual tasks to the propensity to innovate is neutral as routine and manual employees are not associated with the generation of ideas that potentially lead to new products.

Cognitive activities are at the core of abstract tasks: employees performing abstract activities are, by definition, concentrated in cognitive analytical activities, such as analyzing and interpreting data and information, thinking creatively; and in cognitive interpersonal activities as coaching, guiding, motivating subordinates or forming and keeping the relationship with stakeholders. Thus, by fostering abstract activities, firms increase their potential to engage in a creative path and make use of employees' creativity skills, which can be translated into idea generation and its subsequent transformation into new products. By increasing the degree of abstractism – the intensity of abstract tasks activities conducted by a firm – firms become more focused on non-routine cognitive intensive tasks and consequently increase their knowledge conversion capability. This capability is propelled by abstract employees because of their cognitive capacities that can combine and recombine existing knowledge leading to innovation (Glynn, 1996; Nonaka and von Krogh, 2009). Since creativity dependents on the flow of new ideas (Frese et al., 1999), we argue that by increasing their degree of abstractism, firms increase the creative process and consequently its propensity to develop innovations. We expect that the effect is linear since the cumulativeness of individual cognitive tasks is non-detrimental to new ideas generation, and consequently innovation development depends linearly on the number and quality of ideas (Baer, 2012). We hypothesize:

Hypothesis H1. A firm's propensity to introduce new products (product innovation propensity) is positively affected by its degree of abstractism.

Innovation performance measures the success of innovation activities (Kim et al., 2016), and is intertwined with a firm's propensity to innovate. Existing literature assumes that the existence of this dependency implies that the determinants driving innovation performance are similar to the ones explaining innovation propensity (Thornhill, 2006): investments in R&D activities, firm's age and size and the level of education of the workforce (e.g., Hagedoorn and Cloodt, 2003; Thornhill, 2006; Grimpe and Kaiser, 2010; Faems and Subramanian, 2013). This assumption may be over-simplistic since it does not take into consideration the task distribution within a firm. We claim that the task balance needed to maximize innovation propensity is different from the one needed to maximize innovation performance. A firm's innovation propensity is associated with its organizational creativity and technological competences, whereas innovation performance is dependent on its market competences (e.g., Anderson et al., 2014).

Although the decision to start product innovation projects – innovation propensity – and the development and commercialization of new products – innovation output – happen in parallel (Thornhill, 2006) and firms often combine the screening for new ideas and their implementation (Hart et al., 2003; Schmidt et al., 2009; Markham and Lee, 2013), different competencies are needed to maximize innovation propensity and innovation performance. Creativity and idea generation are the main factors influencing a firm's propensity to innovate (George, 2007; Baer, 2012), while innovation performance can only be maximized if a firm has market-oriented competencies (Danneels, 2002). These market-oriented competencies are linked to a wider set of skills and tasks, ranging from abstract to non-abstract. A wider task distribution is necessary to integrate both customer competencies and technological competencies (Henderson and Cockburn, 1994), since both cognitive and non-cognitive tasks are linked to those competencies. Market competences are therefore associated with the integration of abstract and non-abstract tasks in inter-functional teams that are by turn associated with market success (Atuahene-Gima, 1996).

In contrast with Hypothesis H1, in which we predict that the propensity to innovate has a linear positive relationship with the degree of abstractism, we claim that the relationship between abstractism and innovation performance is curvilinear. Notwithstanding abstract tasks been important for innovation performance, by simply hiring more abstract employees, the execution of non-routine cognitive tasks increases, yet it also implies a decrease in the proportion of non-abstract tasks conducted within the firm (assuming a fixed number of employees). We argue that maximizing innovation performance requires a combination of both cognitive and non-cognitive tasks put together to maximize customer and technological competencies, and consequently achieve innovation performance success. Therefore, we expect an inverted u-shaped relationship between the degree of abstractism of a firm and its innovation performance.

Our argument that both cognitive and non-cognitive tasks are important for a firm to maximize its innovation performance follows the similar logic than the one used to explain why the absorptive capacity of an organization is not only dependent on the absorptive capacity of individual members but also on a firm's internal organization. As Cohen and Levinthal (1990) argue, while individual members' contributions are important, the ability to transform those into absorptive capacity requires an organization capability to incorporate and enhance individual contributions. We apply the same reasoning by arguing that an organizational capability that integrates both technological and customer competences and fosters the contributions of both abstract and non-abstract task is required for converting an innovation into a revenue stream. By balancing cognitive analytical and interpersonal (e.g., complex thinking and leadership) along with routine and manual tasks (e.g., sales, operations or administrative activities) firms can leverage their market competences and align the motivations, abilities and skills inherent to each type of worker so that an optimal level of innovation performance can be reached.

Balancing abstract and non-abstract tasks implies that an optimal mix between abstract and non-abstract tasks exists. That is, the relationship between the degree of abstractism and innovation performance follows an inverted u-shape form: an increase in the degree of abstractism is associated with a more than proportional increase in innovation performance, until it reaches an optimal (non-trivial) point. Increasing the degree of abstractism beyond the optimal point results in a decrease in innovation performance as the firm becomes saturated with abstract tasks and, consequently, less manual and routine tasks are performed within the firm. We argue that a balance between the two groups of tasks (abstract and non-abstract) is necessary since market performance can only be maximized if firms combine activities tied to abstract tasks, like planning and adaptation of products to markets, with non-abstract activities, like market screening and sales activities (Atuahene-Gima, 1996). Balancing the two kinds of activities is then necessary to achieve the optimal innovation performance; too much of either tasks results in suboptimal innovation performance levels. Therefore, we hypothesize:

Hypothesis H2. There is an inverted u-shaped relationship between the degree of abstractism and product innovation performance.

3. Methods

3.1. Data

We use data from three waves of the Portuguese version of the European Community Innovation Survey (CIS) to test our hypotheses. The CIS is widely used in innovation management research (e.g., Laursen and Salter, 2006; de Faria and Sofka, 2010; Grimpe and Kaiser, 2010; de Faria et al., 2010; Klingebiel and Rammer, 2013; Sofka et al., 2018) and is developed under the guiding principles of the Oslo Manual (OECD and Eurostat, 2005). Each wave of the data includes information on innovation activities for a 3-year window. Thus we hold information about innovation activities for three consecutive periods 2006–2008, 2008–2010 and 2010–2012. Although the CIS is very rich in what concerns innovation activities, it lacks the information required to apply a task approach. To overcome this challenge, we supplement the CIS with information from the linked employer–employee dataset *Quadros de Pessoal* (QP) created by the Portuguese Ministry of Labour in the 1980s.

The use of QP is crucial since it provides information on all firms' employees occupations, which we use to construct the task measures. We have yearly information for the whole period covered by the three CIS waves (2006–2012). The firm identification number allows us to match the two surveys rendering detailed information on firms' innovation activities, innovation performance, internal organization and personnel. Also, the survey allows the construction of more refined measures of educational attainment, firms' number of employees, firms' age and firms' share of foreign equity.

After matching the two databases and without losing any observation from the CIS, we follow Grimpe and Kaiser (2010) by restricting the population of interest to firms that introduced product (and service) innovations.

3.2. Variables

3.2.1. Dependent variables

Since we look at two different dimensions of the innovation process (propensity to innovate and innovation performance), we rely on two sets of dependent variables to test our hypotheses. The first dependent variable measures the probability of a firm to innovate, which we operationalized as a binary variable that equals one when firms innovate and zero otherwise. We explore different definitions of innovation, by defining it as products that are new to the national market where the firm operates or as products that are new to the world. The second dependent variable is the innovation performance measured by the logarithm of sales of innovative products, which we deflate using last wave-year GDP deflators. The measurement of sales from innovative product follows the definition of the first stage variable (new to the market). As pointed out by Grimpe and Kaiser (2010), new product sales, being an innovation output measure, constitute a more accurate measure of innovation performance than typically used measures like patents or R&D expenditures. We opted to use the absolute value of sales associated to product innovations rather than its share since it allows to capture the size of the firm and consequently leads to more robust estimation models (e.g., Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Grimpe and Kaiser, 2010).

3.2.2. Independent variables – task measures

To empirically test our hypotheses, we resort on task measures that describe the workplace into abstract, routine and manual task activities. For creating the task measures we follow the conversion of Fonseca et al. (2018a) on how specific occupations are linked to particular tasks. The measures are constructed by making use of the O*NET database descriptors, which capture the activities that workers perform in their occupations.[4] In Table A1, we summarize the mapping linking tasks to occupations for ISCO 88, 2-digit level occupational codification. In the end, by looking at the main occupation of an employee, we are able to classify her task in the firm. That is, each employee is classified into abstract, routine or manual, and, by turn, the computation of the firm's task shares of employees in each task is straightforward: for each firm, there are abstract, manual and routine task shares and their sum is unitary.

Contrary to Fonseca et al. (2018b), which groups firms based on tasks, we take continuous measures. We use this approach as we are interested in how the degree of abstractism influences the combination of tasks that maximize the innovative performance, that is, how can the activities executed by firms be optimally combined to achieve successful innovation. For our models, we use the share of abstract employees to create the measure of the degree of abstractism to gauge the influence of analytical and complex interpersonal skills (abstract) on innovation.

3.2.3. Control variables

We control for several other factors that can influence innovation performance. First, we control for the share of college workers in firms' workforce since it is expected that high-skilled employees contribute positively to the innovation output (e.g., de Faria and Sofka, 2010; Grimpe and Kaiser, 2010).[5]

[4] The Occupational Information Network (O*NET) database is the main project of the U.S. Department of Labor's O*NET program. The dataset contains complex information at occupational level regarding the work activities and tasks.

[5] By construction, tasks are not tied to education. However, a natural concern may rise as we expect an association between some occupations and individuals' educational attainment. Since tasks are built on occupations, it may be the case that education could measure alone similar activities. Therefore, multicollinearity problems could emerge when including both the tasks and education variables. However, this is not the case for our sample as the VIF

The literature emphasizes the role of firms' absorptive capacity on both the decision to innovate and on innovation performance (Cohen and Levinthal, 1989, 1990). Absorptive capacity, defined as the capacity to acquire, assimilate, transform and apply knowledge (Zahra and George, 2002), enables firms to tap into the external knowledge and recombine it with its knowledge. Absorptive capacity has been associated with firms' R&D activities in the spirit of Cohen and Levinthal (1990) and, more recently, human capital (e.g., Kneller and Stevens, 2006; Zhang et al., 2007; Escribano et al., 2009; Grimpe and Sofka, 2009). In line with the extant literature, we include the deflated R&D expenditures in our models. Zahra and George (2002) suggest that firms' experience can affect its innovation performance; to account for that we include firms' age as a measure of its accumulated experience.

Following de Faria and Sofka (2010), we add controls for explorative and exploitative innovation activities (March, 1991). The sustainable equilibrium between exploitation and exploration leads firms to be successful competing in both short and long-term (McNamara and Baden-Fuller, 2007). Thus, we include exploration and exploitation continuous indexes constructs that are independent of each other. We construct the indexes from 4-point Likert scale questions in CIS, which we sum and divide by its maximum. Exploration measures are associated with developing new markets and new products, whereas exploitation is defined as seeking improvements in quality and flexibility, reducing labor and operational costs, and reducing costs of resources.[6]

Furthermore, we include the logarithm of the number of employees to account for benefits from economies of scale and scope on innovation (Henderson and Cockburn, 1994). To control for the level of firms' internationalization, we include the share of foreign-owned equity. We control for industries by grouping them according to industry technological and knowledge intensity, following the OECD and Eurostat's classification of high to low-tech manufacturing and into knowledge and less knowledge-intensive services (Hatzichronoglou, 1997). The inclusion of this control allows distinguishing firms according to their industry and to proxy the technological intensity of firms. Finally, CIS wave-year dummies are included to control for the economic cycle.

3.3. Econometric model

We used two intertwined dependent variables to test our hypotheses: the decision to innovate and product innovation performance. It is clear that the decision to innovate (first step) determines whether we observe product innovation performance (second step): when a firm decides not to innovate, there is no performance to be measured. Therefore, not taking into account the interrelationship of the two steps in the estimation would produce potentially biased results. To overcome such potential problem, we employ a Heckman's selection model, in which before estimating the product innovation performance model (the outcome equation), we consider the decision to engage in product innovation (the selection equation). For the set of innovative firms, both equations are estimated simultaneously by maximum likelihood, which overcomes the concerns of simultaneity between the two raised by Thornhill (2006).[7]

The interrelationship between the variables measuring product innovation performance and the decision to innovate leads to an identification problem. To overcome this, we include an identification variable (an exclusion restriction): the engagement in process innovation. Process innovation is defined in CIS as "the implementation of new or significantly improved production process, distribution method or supporting activity". Process innovation is usually associated with the decision to product innovate since complementarities arise from the simultaneous pursuit of both product and process innovation (Martinez-Ros, 1999; Reichstein and Salter, 2006). Conversely, process innovation does not directly increase the turnover of a product that is new to the market, as process innovations relate to efficiency and cost reductions (Utterback and Abernathy, 1975; Damanpour and Gopalakrishnan, 2001). Therefore, using process innovation as an exclusion restriction solves the identification problem raised by a simultaneous estimation of both equations. In this way, we do not need to rely on the functional form to identify the model.

Formally, let *innov* be decision to engage in product innovation (binary) and *perform* be the continuous variable that measures the logarithm of the corresponding innovation performance. The first step of the model can be written as:

$$\text{innov}_i^* = z_i'\gamma + u_i \tag{1}$$

where innovation propensity $innov^*$ is a latent variable that is dependent on the vector z that contains the independent variables previously described and the identification variable, conducting process innovation, and u is the error term with $u \sim N(0, 1)$. The observed variable is the decision to innovate *innov* that takes the value 1 when $\text{innov}_i^* > 0$ and zero otherwise.

Innovation performance is the second step in our model and it is conditional on the first step. We formally write:

$$\text{perform}_i = x_i'\beta + e_i \quad \text{if} \, \text{innov}_i = 1 \tag{2}$$

where the innovation performance $perform_i$ is explained by the vector x that is the same as z excluding the process innovation variable, and e is the error term with $e \sim N(0, \sigma)$. Eq. (2) is only observed if $innov_i = 1$, that is, a selection towards firms that engaged in product innovation activities. The model allows the correlation between the error term in both equations, $\rho = corr(u, e)$, to be different from zero. If we reject the null hypothesis that $\rho = 0$, then there is a selection effect that would bias the results of the innovation performance equation, in case we ignore the first step of the model. The covariates also include the quadratic terms for the abstract task share. The quadratic term is employed to empirically test Hypothesis H2, that is, the inverted u-shaped relationship between the degree of abstractism and the innovation performance. We further follow Lind and Mehlum (2009) and Haans et al. (2015) to formally test for a u-shaped relationship, providing the necessary robustness checks.

4. Descriptive Statistics

Table 1 includes the correlation matrix, means and standard deviations of the variables included in the empirical analysis. Our final sample consists of 11,970 firms, 3,469 of which have introduced an innovation. The table shows that the share of abstract employees is on average relatively low (about 22%), and that the variance among firms is relatively large. The abstract share is positively correlated with the education measure, which comes up from the fact that many abstract workers have a college degree. It is important to note that we do not assume such relationship in our classification, as abstract workers are

(*footnote continued*)
values indicate (lower than 3.05).

[6] Exploration and exploitation measures are constructed using the CIS variables on strategies for reaching enterprise's goals. For exploration we use "increase range of goods or services" and "enter new markets or increase market share" for CIS 2010 and "introducing new or significantly improved goods or services", "developing new markets within Europe" and "developing new markets outside Europe" for CIS 2012. For exploitation we use "improve quality of goods or services", "reduce labor costs per unit output", "reduce material and energy costs per unit output" for CIS 2010 and "Increasing flexibility/responsiveness of your organization", "reducing in-house costs of operation" and "reducing costs of purchased materials, components or services" for CIS 2012. For each case, we sum the scores and divide by the theoretical maximum to construct the index.

[7] For a discussion of the Heckman's selection model see Cameron and Trivedi, 2005, Section 16.5.

Table 1
Correlation table and descriptives statistics.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	Innov. Perform. (log)	1.00															
(2)	Abstract (share)	0.12***	1.00														
(3)	R&D (log)	0.31***	0.22***	1.00													
(4)	No. employees (log)	0.51***	−0.04*	0.40***	1.00												
(5)	Age (log)	0.13***	−0.22***	0.03*	0.28***	1.00											
(6)	Foreign equity (%)	0.21***	0.04*	0.08***	0.31***	0.05**	1.00										
(7)	Exploration	0.07***	0.08***	0.24***	0.10***	0.01	−0.00	1.00									
(8)	Exploitation	0.17***	−0.11***	0.10***	0.16***	0.08***	0.04**	0.26***	1.00								
(9)	College education (%)	0.15***	0.78***	0.23***	0.02*	-0.23***	0.09***	0.09***	−0.14***	1.00							
(10)	Process innovation (d)	0.05**	−0.03*	0.19***	0.10***	−0.02*	0.01*	0.13***	0.15***	−0.03*	1.00						
(11)	High-tech manuf	0.07***	0.06***	0.09***	0.08***	0.01*	0.09***	0.05**	0.02*	0.04*	0.04*	1.00					
(12)	Med-high-tech manuf	0.09***	−0.09***	0.10***	0.06***	0.10***	0.10***	0.06**	0.08***	−0.13***	0.05**	−0.07***	1.00				
(13)	Med-low-tech manuf	−0.06***	−0.18***	−0.03*	−0.07***	0.05**	−0.07***	0.03*	0.05**	−0.22***	0.02*	−0.08***	−0.20***	1.00			
(14)	KIS	−0.00	0.60***	0.08***	−0.06**	−0.21***	0.00	0.03*	−0.15***	0.64***	−0.02*	−0.09***	−0.21***	−0.26***	1.00		
(15)	LKIS	−0.03*	−0.10***	−0.11***	−0.05**	0.00	0.03*	−0.13***	−0.06***	−0.06***	−0.13***	−0.07***	−0.17***	−0.22***	−0.22***	1.00	
(16)	Other industries	0.02*	−0.00	0.01*	0.02*	−0.08***	−0.02*	−0.03*	0.01	0.01	−0.00	−0.04*	−0.10***	−0.13***	−0.13***	−0.11***	1.00
	Mean	16.08	0.22	4.81	3.69	2.76	0.09	0.63	0.73	16.76	0.44	0.02	0.10	0.21	0.16	0.22	0.08
	Standard deviation	3.09	0.26	7.38	1.21	0.87	0.28	0.31	0.25	22.11	0.50	0.13	0.30	0.41	0.37	0.41	0.28

Notes: The mean–variance inflation factor (VIF) is 1.6 and the maximum is 3.0. (d) refers to dummy variable. Number of observations is 11,970.
*5% significant, **1% significant, ***0.1% significant.

identified just by their tasks and not by their education level. It is also evident that the Knowledge Intensive Services (KIS) rely more on Abstract workers than other industries. On average, the firms in our sample have about 40 employees (3.69 log points), have 9% of foreign-equity in their capital structure, and approximately 44% have introduced process innovations.

Table 1 also shows the mean–variance inflation factors (VIF) for the sample. The mean value of the VIF is 1.6, and its maximum value does not exceed 3.0, values that are below the commonly accepted critical values (Brauer and Wiersema, 2012). Moreover, the correlation matrix does not reveal indications of possible multicollinearity as all correlation values fall below 0.7, except for education and the abstract share that have a correlation of 0.78. The correlation between education and abstract is moderately high, yet given the high variance found in those variables and the absence of high VIF, we infer that it does not raise concerns in estimating our empirical models.[8] In any case, in our econometric models, a high correlation between the two variables can decrease the precision of our estimates, consequently reinforcing the validity of any significant results obtained.

5. Results

We estimate the two steps of the model simultaneously using a maximum likelihood procedure. Table 2 presents the results of the first step – the propensity to introduce new products. The results show that the independence between the two equations is rejected (the LR test rejects $\rho = 0$ at the 1% level for all models), confirming our assumption that both steps are correlated. In Models 1.1 and 2.1, we estimate the propensity to innovate using only the control variables, varying the definition of innovation. For the first model, we consider innovation when a firm introduces products that are new to the market where it operates. The second model restricts that definition to products that are not only new to the market where the firm is present but that are also new to the world. We argue that the second definition is closer to measure the newness of an innovation.

The results from both models show a positive relationship between the measures of R&D expenses, education and exploration strategy and the dependent variables significant at the 0.1% level. Moreover, and in line with our expectations, the exploitation variable has a significant and negative effect on the propensity to develop products that are new to the market or to the world. Process innovation, the identification variable, is positively significant at the 0.1% level. We omit controls of the technological and knowledge intensity of the firms from the tables for the sake of brevity. Those controls are reasonably consistent along the several models and confirm the positive relationship between the innovation process, mainly innovation performance, and firms' technology intensity.

In the subsequent models, we include the task measure in the form of shares. Models 3.1 and 4.1 contain the linear relationship as hypothesized in H1.[9] Model 3.1 corresponds to the broader definition of innovation as used in Model 1.1, whereas in Model 4.1 we narrow down the definition of innovation as in Model 2.1. The results do not fully support Hypothesis H1, that is, we do not find a robust positive relationship between the propensity to innovate and the degree of abstractism (measured by the abstract share). While Model 3.1 provides an indication that the effect is significant (at 5% level), the non-significant findings from Model 4.1 leads us to conclude that our sample does not provide sufficient evidence to support Hypothesis H1.

[8] We present an alternative specification in our robustness checks table excluding the education variable and the results are in line with our main model specification.

[9] We have estimated Models 3.1 and 4.1 including a squared term for abstract for testing a u-shaped relationship at the first step and we did not find any support for this alternative relationship. See more details in Section 6.

Table 2
Marginal effect for the innovation propensity (first step)

	Model 1.1	Model 2.1	Model 3.1	Model 4.1
Abstract (share)			0.047*	0.018
			(0.021)	(0.014)
Process innovation (d)	0.130***	0.044***	0.130***	0.044***
	(0.008)	(0.005)	(0.008)	(0.005)
log R&D	0.011***	0.003***	0.011***	0.003***
	(0.001)	(0.000)	(0.001)	(0.000)
log No. employees	0.012***	0.017***	0.013***	0.017***
	(0.003)	(0.002)	(0.003)	(0.002)
log Age	0.008	−0.005	0.008	−0.005
	(0.004)	(0.003)	(0.004)	(0.003)
Foreign equity (%)	0.032*	0.018*	0.033*	0.019**
	(0.013)	(0.007)	(0.013)	(0.007)
Exploration	0.304***	0.129***	0.303***	0.130***
	(0.014)	(0.012)	(0.014)	(0.012)
Exploitation	−0.062***	−0.049***	−0.062***	−0.049***
	(0.017)	(0.012)	(0.017)	(0.012)
College (%)	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
chi2	11044.8	471.7	11196.3	477.4
log likelihood	−11856.7	−2514.8	−11841.6	−2511.7
ρ	−0.669***	−0.136	−0.657***	−0.161
	(0.089)	(0.232)	(0.090)	(0.230)
No. Observations	11,970	8,674	11,970	8,674
Innov. definition (dep. var.)	Market	Global	Market	Global

Results from a two equation selection Heckman model estimated simultaneously using maximum likelihood. All regressions include industry dummies for the technological and knowledge intensity (OECD/Eurostat classification) and CIS wave-year dummies. Marginal effect computed at the means. (d) dummy variable. Standard errors in parentheses. The dependent variable is a binary variable that equals one when firms innovate and zero otherwise. Innovation definition is *market* when the firm introduced a new product to the national market where the firm operates or *global* when firm introduced products that are new to the world. *Global* is not available in CIS 2006.
*5% significant, **1% significant, ***0.1% significant.

The innovation performance results (second step) are summarized in Table 3. Contrasting with the results from the first step, we find that foreign equity to be highly significant (0.1% level) and positive in the second step. The coefficients associated with R&D and college education are overall not significant, despite being significant at the 5% level in some of the specifications.

The primary variable of interest, the abstract share, is included in Models 3.2 and 4.2 in the quadratic form. As in the previous step, we define innovation in Models 1.2 and 3.2 in broader terms – innovation new to the market where the firm operates – and limiting it to innovation new to the world market in Models 2.2 and 4.2. Since some variables are not available in CIS 2006, we cannot use this wave for estimating Models 2.2 and 4.2. The results for the broader definition of innovation (Model 3.2) show that there is an inverted u-shaped relationship between the degree of abstractism (abstract share) and innovation performance, supporting Hypothesis H2 – the relationship is highly significant (at 0.1% level) for both the linear and the squared abstract share. The effect remains positive when we use the restricted definition of innovation (Model 4.2), and it is significant at the 5% level. We justify the drop in the significance level to the relatively small pool of firms that develop a new to the world innovation. When using the latter definition of innovation, the sample drops to about one six of the original 3469 innovative firms, not only because of the reduced number of firms introducing world innovation but also because the variable that defines it is not available in CIS 2006.

For each model, the optimal degree of abstractism can be calculated through the derivative ($-\hat{\beta}_1/2\hat{\beta}_2$, with $\hat{\beta}_1$ and $\hat{\beta}_2$ being the coefficients associated with the linear and quadratic terms of the abstract share, respectively). For Model 3.2 the innovation performance is maximized with a degree of abstractism of 46%, while the maximum is attained at 54% in the case of Model 4.2. In Fig. 1, we plot the estimated u-shaped

Table 3
Regression results for the innovation performance (second step)

	Model 1.2	Model 2.2	Model 3.2	Model 4.2
Abstract (share)			1.540***	1.874*
			(0.342)	(0.899)
Abstract (share) squared			−1.685***	−1.739*
			(0.346)	(0.860)
log R&D	−0.009	0.032*	−0.010	0.029*
	(0.005)	(0.013)	(0.005)	(0.012)
log No. employees	0.896***	0.917***	0.888***	0.905***
	(0.023)	(0.068)	(0.023)	(0.068)
log Age	−0.071*	−0.109	−0.089**	−0.127
	(0.031)	(0.076)	(0.031)	(0.076)
Foreign equity (%)	0.600***	0.650***	0.583***	0.654***
	(0.085)	(0.176)	(0.085)	(0.176)
Exploration	−0.515***	−0.388	−0.504**	−0.432
	(0.154)	(0.497)	(0.155)	(0.494)
Exploitation	0.274*	0.461	0.263*	0.445
	(0.120)	(0.322)	(0.119)	(0.321)
College (%)	0.004**	0.002	0.004*	0.001
	(0.001)	(0.004)	(0.002)	(0.004)
Constant	11.124***	14.809***	10.989***	14.715***
	(0.322)	(1.130)	(0.328)	(1.130)
chi2	11044.8	471.8	11196.3	477.4
log likelihood	−11856.8	−2514.8	−11841.6	−2511.7
No. Observations (2nd step)	3,469	578	3,469	578
Innov. definition (dep. var.)	Market	Global	Market	Global

Results from a two equation selection Heckman model estimated simultaneously using maximum likelihood. The dependent variable is the log sales of innovative products. All regressions include industry dummies for the technological and knowledge intensity (OECD/Eurostat classification) and CIS wave-year dummies. Innovation definition is *market* when the firm introduced a new product to the national market where the firm operates or *global* when firm introduced products that are new to the world. *Global* is not available in CIS 2006. (d) dummy variable. Standard errors in parentheses.
*5% significant, **1% significant, ***0.1% significant.

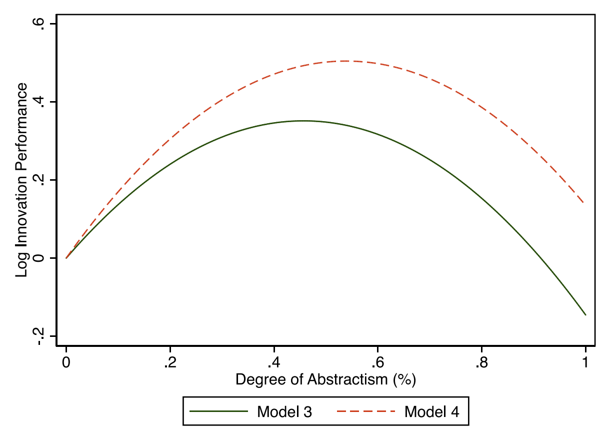

Fig. 1. Degree of abstractism's effect on innovation performance. Marginal effects of the share of Abstract employees on log sales of innovative products computed from two equation selection Heckman. The coefficients plotted correspond to Models 3 and 4 (see Tables 2 and 3 for more details). The degree of abstractism that maximizes the curves is 46% for Model 3 and 54% for Model 4.

curves for the two models. The figure clearly shows the non-linear behavior of innovation performance when the degree of abstractism increases, increasing until the optimal point and decreasing after that.

We further conduct robustness checks in order to corroborate the inverted u-shape relationship between the degree of abstractism and innovation performance. We start with the test proposed by Lind and Mehlum (2009), which in our case tests the following condition:

$$\hat{\beta}_1 + 2\hat{\beta}_2 X_l < 0 < 2\hat{\beta}_1 + \hat{\beta}_2 X_h \tag{3}$$

where X_l and X_h represent the minimum and maximum values observed in the data for the abstract share. We statistically test for the inequality for Models 3 and 4. The tests support the inverted u-shape relationship at the 1% significance level for Model 3 and at 5% significance level for Model 4. As suggested by Haans et al. (2015), we also add a cubic term to account for an alternative functional form. Including the cubic term yield not significant results (at 1% level) in both models. We further split the sample into two parts: firms that are below and above the maximum point of the curve. We then estimate the model separately for both subsamples and excluding the quadratic term. The estimates for the abstract share are significant and in line with the u-shaped hypothesis: positive for the firms below the maximum and negative for firms above the maximum.[10]

6. Robustness checks

To assess the robustness of our findings, we ran several additional model specifications (see Table 4). We start by addressing the high correlation (0.78) found between the education variable and the abstract share variables. While the VIFs do not indicate a multicollinearity concern, we checked if the exclusion of the college share covariate affects our main findings. The results summarized in Table 4 as Models 5 and 6 correspond to an alternative specification to Models 3 and 4, where we exclude the education measurement. This robustness check shows that our findings are not driven by the inclusion of the education variable since the coefficients hold a similar magnitude and precision. Moreover, these results give additional support to our theoretical assumption that the variable abstract share is measuring an additional dimension that is not captured by variables measuring the educational level of the employees of a firm.

In Models 7 and 8, we test a u-shaped relationship in the first step between the decision to innovate and the degree of abstractism. As theorized, the results do not support the u-shaped link between the two constructs. The results for the second step remain in line with the u-shaped hypothesis, corroborating our previous findings.

In the last robustness check shown in the table (Model 9) we tested if our results are specifically related to innovation activities or if they also hold for imitation activities. To do so, we used an alternative definition of our dependent variables (first and second stages) where we also take into consideration the imitation activities of firms: we differentiate between firms that developed products new at least to the firm and firms that kept their product portfolio unchanged (no product innovation). As expected, when we consider this broader dependent variable the results are not in line with our hypotheses. We additionally explore the robustness of the primary independent variable (abstract share) by using different operationalizations of the control group, in particular by including the share of routine or manual tasks. The results for the abstract share variable remain stable: the changes in the optimal level for the share of abstract do not exceed 13 percentage points when compared to the baseline specification, Model 3.2 (the results are available upon request). All in all, the robustness checks conducted give support to our theoretical reasoning relating tasks structure to innovation activities since the mechanisms driving our hypotheses are related to innovation but not imitation activities.

7. Discussion

By considering the tasks developed by employees within a firm, this study brings new light to the understanding of the relationship between human capital and innovation activities at the firm level. We complement classical measures of human capital, such as education, by conceptualizing the organization of the firm towards tasks. This novel approach builds on how firm's activities are organized and it allows a more accurate assessment of firms' innovation capabilities. By using a task approach, we investigate how the degree of abstractism (measured by the share of abstract employees) influences both the firm's propensity to innovate and the firm's innovation performance. In line with our predictions, we empirically find an inverted u-shaped relationship between the degree of abstractism and innovation performance. Our results indicate that the optimal degree of abstractism for optimizing innovation performance is approximately 46% when the product is new to the national market where the firm operates and 54% when the product is new to the world, thus increasing its degree over those thresholds is detrimental for innovation performance. Furthermore, the magnitude of these effects alone should not be overlooked as an increase in the degree of abstractism from 20% to 40% leads to 11% increase in sales in the case of a product new to the national market. Surprisingly, we do not find robust support for our prediction that an increase in the degree of abstractism is associated with an increase in the propensity to develop innovations when we consider the stricter definition of innovation as products new worldwide. However, the results give an indication that the two steps of the innovation process have different optima in terms of task distribution and lead us to believe that firms face a trade-off when deciding the task structure of its workforce.

The trade-off arises from the distinct role that the degree of abstractism assumes for each step of the product innovation process. The innovation process can be divided into two parts: the first is related to

Table 4
Robustness checks

	Model 5	Model 6	Model 7	Model 8	Model 9
Main equation (second step)					
Abstract (share)	1.738***	1.910*	1.768***	1.968*	1.968
	(0.335)	(0.888)	(0.356)	(0.910)	(1.208)
Abstract (share) squared	−1.659**	−1.717*	−1.946***	−1.840*	−2.427
	(0.346)	(0.860)	(0.364)	(0.880)	(1.248)
College (%)			0.004*	0.001	0.018**
			(0.002)	(0.004)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes
No. Observations (2nd step)	3,469	578	3,469	578	6,208
Selection equation marginal effects (first step)					
Abstract (share)	0.086***	0.049***	−0.058	−0.035	−0.016
	(0.017)	(0.011)	(0.051)	(0.034)	(0.022)
Abstract (share) squared			0.121*	0.057	
			(0.053)	(0.034)	
College (%)			0.001***	0.001***	0.001**
			(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes
ρ	−0.624***	−0.156	−0.660***	−0.159	−0.473***
	(0.094)	(0.225)	(0.090)	(0.236)	(0.046)
chi2	11266.0	469.9	11194.1	482.5	1336.7
log likelihood	−11854.4	−2518.6	−11839.0	−2510.3	−26570.4
No. Observations	11,970	8,674	11,970	8,674	11,970
Innov. definition	Market	Global	Market	Global	Firm + Mkt

Results from a two equation selection Heckman model estimated simultaneously using maximum likelihood. The dependent variable is a binary variable that equals one when firms innovate and zero otherwise in the first step and the log sales of innovative products in the second step. Marginal effect computed at the means in the first step. Controls are log R&D expenditures, log no. of employees, log age, foreign equity (%), and exploration and exploitation indexes. All regressions include industry dummies for the technological and knowledge intensity (OECD/Eurostat classification) and CIS wave-year dummies. Innovation definition is *market* when the firm introduced a new product to the national market where the firm operates or *global* when firm introduced products that are new to the world. *Global* is not available in CIS 2006. (d) dummy variable. Standard errors in parentheses.

*5% significant, **1% significant, ***0.1% significant.

[10] For sake of brevity we do not report these results in the paper, yet they can be provided upon request.

creating the product, in which organizational creativity and technological competences are required; and, the second, associated with the commercialization of the product, is dependent on more market-oriented capabilities, like marketing (Grant, 1991; Song and Parry, 1997; Cooper, 2001; Anderson et al., 2014). Since the degree of abstractism gauges the intensity of cognitive activities that the firm performs, it captures the potential of idea generation and consequently organizational creativity. Because the first phase of the innovation process relates with creating, integrating and recombining resources (Danneels, 2002), we claim that the more abstract activities a firm conducts the higher its propensity to innovate will be.

In the second stage of the innovation process which success is measured by innovation performance, market-oriented competences that are present in both abstract and non-abstract tasks, like the evaluation of consumer behavior, and distribution, sales and communication capabilities, are essential (Danneels, 2002). For example, crafting the strategic marketing plan is an abstract task, whereas sales activities are mainly non-abstract tasks. Firms use their integration capabilities for combining the resources associated with customer and technological competencies (Henderson and Cockburn, 1994), which translates into a combination of both abstract and non-abstract tasks. Our results show that the relationship between abstractism and innovation performance is non-linear; it is an inverted u-shape, which implies that there is an optimal combination of abstract and non-abstract task activities where both are different from zero. Hence, an increase their degree of abstractism above a certain threshold (46% and 54% for our data), is associated with a decrease in sales of the new products. Given the simultaneity of the two stages of the innovation process, our findings reveal partial support for a potential trade-off faced by firms when defining their optimal degree of abstractism: the degree of abstractism should be maximized in order to optimize the propensity to innovate while the optimization of innovation performance is obtained when a firm balances both abstract and non-abstract tasks.

By using a novel approach based on tasks, this study contributes to our understanding of how human capital influences innovation activities at the firm level (e.g., Faems and Subramanian, 2013). The trade-off that we uncover makes clear that different types of skills and tasks are required during different phases of the innovation process. Our findings suggest that the maximization of each innovation phase is related to different organizational challenges. Innovation propensity is mainly associated with cognitive activities that increase organizational creativity while maximizing innovation performance requires a balance between abstract and non-abstract activities.

Our results also provide some interesting insights on how the level of newness of a firm's products innovation activities may affect the level of abstractism that maximizes innovation performance. We find that firms that only develop products that are new to the market where they operate maximize their innovation performance with a degree of abstractism of 46%, while firms that develop new to the world products maximize their innovation performance with a degree of abstractism of 54%. We explain this relationship between the level of newness of the innovation activities and the optimal level of abstractism with the fact that global innovations require more creativity and flexibility that are associated with abstract tasks.

While established assumptions could lead managers to opt for a highly abstract workforce as a way to maximize innovation output, our findings show that this decision, while optimizing innovation propensity, may be sub-optimal in terms of innovation performance. Managers should be aware of the tensions and trade-offs that a workforce with a high degree of abstractism may originate if the two stages of the innovation process are intertwined. The optimal organizational form depends on the phase of the innovation that the firm is: a highly abstract form might be preferred for maximizing the propensity to innovate, but an organizational form balancing abstract and non-abstract tasks is optimal for converting innovation activities into market success.

7.1. Limitations and future research

In this study, we adopt a firm-level approach to understand how the degree of abstractism influences the innovation outputs. The trade-off found suggests that firms should adopt some form of organizational separation. Organizational separation seems to be essential for simultaneously maximizing both innovation propensity and innovation performance. However, identifying such optimal structure is beyond the scope of this study and represents an interesting avenue for future research. We believe that studies exploring forms of organizational separation that can mitigate the inherent tensions in the innovation process; or that enable the simultaneous optimization both dimensions simultaneously can push forward the knowledge on how firms should be organized to innovate successfully.

Although the survey data used is very rich, it also comes with limitations in what concerns exploring specific research paths that would enrich our understanding of the relationship between the task structure of a firm's workforce and its innovation performance. First, our results could be complemented by studies that would measure task distribution at the individual level rather than at the occupational level. Second, since firms can dynamically adjust to the environment, future studies should explore which particular circumstances can lead firms to make changes in their task structure. Third, because our data do not allow us to make definitive causal statements on the relationships that we study, future research could use field experimental data, or larger panel data that allow to model these structural relationships more precisely. Finally, future research could investigate our theoretical claims with an alternative innovation performance variable, like patent activity. More specifically, it would be interesting to explore the effect of task distribution on patent activity in industries and countries with highest patent propensity.

8. Conclusion

We have opened a new research line in innovation management research: the task approach. We have established the connection between tasks and innovation at the firm level by investigating how the degree of abstractism can influence the propensity to innovate and innovation performance. We contribute to the existing literature by theorizing on a twofold relationship of the degree of abstractism: a linear positive contribution to the propensity to innovate, together with an inverted u-shaped relationship with innovation performance. Our results show that the optimal innovation performance takes place when firms balance their degree of abstractism but only provide limited evidence on the linear relationship between the degree of abstractism and the propensity to innovate. Despite not providing full support to our hypotheses, the results give strong indications that firms face challenges when planning their innovation activities. Since the innovation process occurs simultaneously, the relationship is paradoxical: the degree of abstract has two optima contingent on the phase of the innovation process that the firm is on, yet those processes are interrelated. This suggests that firms should consider the tensions and trade-offs inherent to the innovation process between the two abstractism's optima and find a balance between the two. Our findings suggest that some form of organizational separation could lead to a maximization of two interlinked innovation processes.

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The information, views and opinions expressed in this article are those of the authors and do not necessarily reflect the official opinion of the institutions that the authors belong.

Appendix A

Table A1

Table A1
O*NET descriptor and scale type by task

Abstract	
12+13	Small enterprises &corporate managers
21	Physical, mathematical and eng. science prof.
22	Life science and health professionals
23	Teaching professionals
24	Other professionals
31	Physical and eng. science associate prof.
32	Life science and health associate prof.
33	Teaching associate professionals
Routine	
34	Other associate professionals
41	Office clerks
42	Customer services clerks
52	Models, salespersons and demonstrators
73	Precision, handicraft, print. and rel. trades work.
74	Other craft and related trades workers
81	Stationary-plant and related operators
82	Machine operators and assemblers
Manual	
51	Personal and protective services workers
71	Extraction and building trades workers
72	Metal, machinery and related trades workers
83	Drivers and mobile-plant operators
91	Sales and services elementary occupations
93	Laborers in mining, const., manuf. and transp.

Notes: Occupational codes are ISCO-88. Adapted from Fonseca et al. (2018b). To construct the categories, O*NET measures are aggregated into task intensity indexes using principal components and then attributed to ISCO 2-digits occupations using U.S. employment data and a detailed cross-walk. Task allocation is based on the most intensive task in a given occupation.

References

Acemoglu, D., Autor, D.H., 2011. Skills, tasks and technologies: implications for employment and earnings. In: Ashenfelter, O., Card, D.E. (Eds.), Handbook of Labor Economics. Elsevier Inc., Amsterdam, pp. 1043–1171.
Amabile, T.M., 1996. Creativity in context. Westview, Boulder, CO.
Anderson, N., Potočnik, K., Zhou, J., 2014. Innovation and Creativity In Organizations. J. Manage. 40 (5), 1297–1333.
Atuahene-Gima, K., 1996. Market orientation and innovation. J. Bus. Res. 35 (2), 93–103.
Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118 (4), 1279–1333.
Baer, M., 2012. Putting creativity to work: the implementation of creative ideas in organizations. Acad. Manage. J. 55 (5), 1102–1119.
Banbury, C.M., Mitchell, W., 1995. The effect of introducing important incremental innovations on market share and business survival. Strat. Manage. J. 16 (S1), 161–182.
Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manage. 17 (1), 99–120.
Barney, J., Wright, P.M., 1998. On becoming a strategic partner: the role of human resources in gaining competitive advantage. Hum. Resour. Manage. 37 (1), 31–46.
Bartel, A.P., Lichtenberg, F.R., 1987. The comparative advantage of educated workers in implementing new technology. Rev. Econ. Stat. 69 (1), 1–12.
Brauer, M.F., Wiersema, M.F., 2012. Industry divestiture waves: how a firm's position influences investor returns. Acad. Manage. J. 55 (6), 1472–1492.
Cameron, A.C., Trivedi, P., 2005. Microeconometrics: methods and applications. Cambridge University Press, New York.
Cassiman, B., Veugelers, R., 2006. In search of complementarity in innovation strategy: internal R&D and External Knowledge Acquisition. Manage. Sci. 52 (1), 68–82.
Chadwick, C., Dabu, A., 2009. Human resources, human resource management, and the competitive advantage of firms: toward a more comprehensive model of causal linkages. Organ. Sci. 20 (1), 253–272.
Chen, C.-J., Huang, J.-W., 2009. Strategic human resource practices and innovation performance — the mediating role of knowledge management capacity. J. Bus. Res. 62 (1), 104–114.
Cohen, W.M., Levinthal, D.A., 1989. Innovation and learning: the two faces of R&D. Econ. J. 99 (397), 569–596.
Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35 (1), 128–152.
Colbert, A., Yee, N., George, G., 2016. The digital workforce and the workplace of the future. Acad. Manage. J. 59 (3), 731–739.
Cooper, R.G., 2001. Winning at New Products. Accelerating the Process from Idea to Launch. Perseus Books, Cambridge, MA.
Damanpour, F., 1991. Organizational innovation: a meta-analysis of effects of determinants and moderators. Acad. Manage. J. 34 (3), 555–590.
Damanpour, F., Gopalakrishnan, S., 2001. The dynamics of the adoption of product and process innovations in organizations. J. Manage. Stud. 38 (1), 45–65.
Danneels, E., 2002. The dynamics of product innovation and firm competences. Strat. Manage. J. 23 (12), 1095–1121.
de Faria, P., Sofka, W., 2010. Knowledge protection strategies of multinational firms–a cross-country comparison. Res. Pol. 39 (7), 956–968.
de Faria, P., Lima, F., Santos, R., 2010. Cooperation in innovation activities: the importance of partners. Res. Pol. 39 (8), 1082–1092.
Demirbag, M., Glaister, K.W., 2010. Factors determining offshore location choice for R&D projects: a comparative study of developed and emerging regions. J. Manage. Stud. 47 (8), 1534–1560.
Escribano, A., Fosfuri, A., Tribó, J.A., 2009. Managing external knowledge flows: the moderating role of absorptive capacity. Res. Pol. 38 (1), 96–105.
Faems, D., Subramanian, A.M., 2013. R&D manpower and technological performance: the impact of demographic and task-related diversity. Res. Pol. 42 (9), 1624–1633.
Fonseca, T., Lima, F., Pereira, S.C., 2018a. Job polarization, technological change and routinization: evidence for Portugal. Labour Econ. 51, 317–339.
Fonseca, T., Lima, F., Pereira, S.C., 2018b. Understanding productivity dynamics: a task taxonomy approach. Res. Pol. 47 (1), 289–304.
Ford, C.M., 1996. A theory of individual creative action in multiple social domains. Acad. Manage. Rev. 21 (4), 1112–1141.
Frese, M., Teng, E., Wijnen, C.J.D., 1999. Helping to improve suggestion systems: predictors of making suggestions in companies. J. Organ. Behav. 20 (7), 1139–1155.
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. 114, 254–280.
Galende, J., de la Fuente, J.M., 2003. Internal factors determining a firm's innovative

behaviour. Res. Pol. 32 (5), 715–736.
George, J.M., 2007. Creativity in organizations. Acad. Manage. Ann. 1 (1), 439–477.
Glynn, M.A., 1996. Innovative genius: a framework for relating individual and organizational intelligences to innovation. Acad. Manage. Rev. 21 (4), 1081–1111.
Goldin, C., Katz, L.F., 1998. The origins of technology–skill complementarity. Q. J. Econ. 113 (3), 693–732.
Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. 104 (8), 2509–2526.
Grant, R.M., 1991. The resource-based theory of competitive advantage: implications for strategy formulation. Calif. Manage. Rev. 33 (3), 114–135.
Grimpe, C., Kaiser, U., 2010. Balancing internal and external knowledge acquisition: the gains and pains from R&D outsourcing. J. Manage. Stud. 47 (8), 1483–1509.
Grimpe, C., Sofka, W., 2009. Search patterns and absorptive capacity: low- and high-technology sectors in European countries. Res. Pol. 38 (3), 495–506.
Haans, R.F.J., Pieters, C., He, Z.-L., 2015. Thinking about U: theorizing and testing U- and inverted U-shaped relationships in strategy research. Strat. Manage. J. 37 (7), 1177–1195.
Hagedoorn, J., Cloodt, M., 2003. Measuring innovative performance: is there an advantage in using multiple indicators? Res. Pol. 32 (8), 1365–1379.
Hart, S., Hultink, E.J., Tzokas, N., Commandeur, H.R., 2003. Industrial companies' evaluation criteria in new product development gates. J. Prod. Innov. Manage. 20 (1), 22–36.
Hatzichronoglou, T., 1997. Revision of the high-technology sector and product classification. OECD Science, Technology and Industry Working Papers 1997/02. OECD Publishing.
Henderson, R., Cockburn, I., 1994. Measuring core competence? Evidence from the pharmaceutical industry. Strat. Manage. J. 15 (S1), 63–84.
Hilton, M., 2008. Skills for work in the 21st century: what does the research tell us? Acad. Manage. Perspect. 22 (4), 63–78.
Huiban, J.-P., Bouhsina, Z., 1998. Innovation and the quality of labour factor: an empirical investigation. Small Bus. Econ. 10 (4), 389–400.
Kim, B., Kim E, Miller, D.J., Mahoney, J.T., 2016. The impact of the timing of patents on innovation performance. Res. Pol. 45 (4), 914–928.
Klingebiel, R., Rammer, C., 2013. Resource allocation strategy for innovation portfolio management. Strat. Manage. J. 35 (2), 246–268.
Kneller, R., Stevens, P.A., 2006. Frontier technology and absorptive capacity: evidence from OECD manufacturing industries. Oxf. Bull. Econ. Stat. 68 (1), 1–21.
Krueger, A.B., 1993. How computers have changed the wage structure: evidence from microdata, 1984–1989. Q. J. Econ. 108 (1), 33–60.
Krusell, P., Ohanian, L.E., Ríos-Rull, J.-V., 2000. Capital-skill complementarity and inequality: a macroeconomic analysis. Econometrica 68 (5), 1029–1053.
Laursen, K., Salter, A., 2006. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. Strat. Manage. J. 27 (2), 131–150.
Li, D., Eden, L., Hitt, M.A., Ireland, R.D., 2008. Friends, acquaintances, or strangers? Partner selection in R&D alliances. Acad. Manage. J. 51 (2), 315–334.
Lind, J.T., Mehlum, H., 2009. With or without u? The appropriate test for a U-shaped relationship. Oxf. Bull. Econ. Stat. 72 (1), 109–118.
March, J.G., 1991. Exploration and exploitation in organizational learning. Organ. Sci. 2 (1), 71–87.
Markham, S.K., Lee, H., 2013. Product Development and Management Association's 2012 Comparative Performance Assessment study. J. Prod. Innov. Manage. 30 (3), 408–429.
Martinez-Ros, E., 1999. Explaining the decisions to carry out product and process innovations: the Spanish case. J. High Technol. Manage. 10, 223–242.
McNamara, P., Baden-Fuller, C., 2007. Shareholder returns and the exploration–exploitation dilemma: R&D announcements by biotechnology firms. Res. Pol. 36 (4), 548–565.
Mumford, M.D., Gustafson, S.B., 1988. Creativity syndrome: integration, application, and innovation. Psychol. Bull. 103 (1), 27–43.
Nonaka, I., von Krogh, G., 2009. Perspective—tacit knowledge and knowledge conversion: controversy and advancement in organizational knowledge creation theory. Organ. Sci. 20 (3), 635–652.
Noseleit, F., de Faria, P., 2013. Complementarities of internal R&D and alliances with different partner types. J. Bus. Res. 66 (10), 2000–2006.
OECD, Eurostat, 2005. Oslo manual. The Measurement of Scientific and Technological Activities. OECD Publishing.
Perrow, C., 1970. Organizational analysis: a sociological view. Brooks/Cole, Belmont, CA.
Reichstein, T., Salter, A., 2006. Investigating the sources of process innovation among UK manufacturing firms. Ind. Corp. Change 15 (4), 653–682.
Schmidt, J.B., Sarangee, K.R., Montoya, M.M., 2009. Exploring new product development project review practices. J. Prod. Innov. Manage. 26 (5), 520–535.
Scott, S.G., Bruce, R.A., 1994. Determinants of innovative behavior: a path model of individual innovation in the workplace. Acad. Manage. J. 37 (3), 580–607.
Sofka, W., Shehu, E., de Faria, P., 2014. Multinational subsidiary knowledge protection—do mandates and clusters matter? Res. Pol. 43 (8), 1320–1333.
Sofka, W., de Faria, P., Shehu, E., 2018. Protecting knowledge—how legal requirements to reveal information affect the importance of secrecy. Res. Pol. 47 (3), 558–572.
Song, X.M., Parry, M.E., 1997. The determinants of Japanese new product successes. J. Marketing Res. 34 (1), 64–76.
Thornhill, S., 2006. Knowledge, innovation and firm performance in high- and low-technology regimes. J. Bus. Vent. 21 (5), 687–703.
Tushman, M., O'Reilley III, M.A., 1996. Ambidextrous organizations: managing evolutionary and revolutionary change. Calif. Manage. Rev. 38 (4), 8–30.
Utterback, J.M., Abernathy, W.J., 1975. A dynamic model of process and product innovation. Omega 3 (6), 639–656.
Veugelers, R., 1997. Internal R &D expenditures and external technology sourcing. Res. Pol. 26 (3), 303–315.
Wegman, L.A., Hoffman, B.J., Carter, N.T., Twenge, J.M., Guenole, N., 2016. Placing job characteristics in context: cross-temporal meta-analysis of changes in job characteristics since 1975. J. Manage. 20 (10), 1–35.
Weigelt, C., 2009. The impact of outsourcing new technologies on integrative capabilities and performance. Strat. Manage. J. 30 (6), 595–616.
Wernerfelt, B., 1984. A resource-based view of the firm. Strat. Manage. J. 5 (2), 171–180.
Woodman, R.W., Sawyer, J.E., Griffin, R.W., 1993. Toward a theory of organizational creativity. Acad. Manage. Rev. 18 (2), 293–321.
Youndt, M.A., Snell, S.A., Dean, J.W., Lepak, D.P., 1996. Human resource management, manufacturing strategy, and firm performance. Acad. Manage. J. 39 (4), 836–866.
Zahra, S.A., George, G., 2002. Absorptive capacity: a review, reconceptualization, and extension. Acad. Manage. Rev. 27 (2), 185–203.
Zhang, J., Baden-Fuller, C., Mangematin, V., 2007. Technological knowledge base, R&D organization structure and alliance formation: evidence from the biopharmaceutical industry. Res. Pol. 36 (4), 515–528.