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Abstract

This paper studies the relationship between the use of management control systems and different types of innovation (product and process), considering innovation contexts (high-tech versus low-tech sectors). We develop and test our hypotheses based on a large sample of Spanish manufacturing firms and find that input controls have a positive association only with process innovation in both innovation contexts. Behavior controls have similar effects on both types of innovation outcomes for high-tech firms, while they have stronger positive associations with process than with product innovation for low-tech firms. Output controls are equally relevant for product and process innovation in both contexts.

Keywords: Management control systems; product innovation; process innovation; sector characteristics; panel data.

1. Introduction

The simultaneous attainment of innovative results and the enforcement of control practices are two sometimes contradictory yet essential targets for contemporary businesses. Management control systems (henceforth MCS) are increasingly found to be pertinent management tools in innovative businesses, as existing theoretical arguments and empirical evidence indicate that the presence of MCS can actually assist in the management of activities leading to innovation (Adler & Chen, 2011; Bisbe & Malagueño, 2009, 2015; Bisbe & Otley, 2004; Cardinal, 2001; Chenhall, 2003; Davila, 2000; Davila, Foster, & Li, 2009a; Ferreira, Moulang, & Hendro, 2010; Henri, 2006; Revellino & Mouritsen, 2009; Ylinen & Gullkvist, 2014). Notwithstanding such progress, further research on the relationship between MCS and innovation is still in demand, as so far such a relationship is found to be neither direct nor straightforward (Chenhall & Moers, 2015; Davila, Foster, & Oyon, 2009b). In response to such demand this paper aims to explore in more detail the functions of MCS (i) for different types of innovation and (ii) in different innovation contexts.

Prior work has emphasized that different types of innovation call for different mechanisms of control (Bedford, 2015; Chenhall & Moers, 2015; Davila, 2000; Davila et al., 2009b; Van de Ven, Polley, Garud, & Venkataraman, 1999). The innovation literature has separated innovations either with respect to their degree of novelty (incremental or radical) or with respect to the type of change they embody (product or process) (Tidd, Bessant, & Pavitt, 2009). While the first type of distinction and its links to corporate strategic orientation has been treated by extant research (Bedford, 2015; Dekker & van den Abbeele, 2010; Stouthuysen, Slabbinck, & Roodhooft, 2017; Ylinen & Gullkvist, 2014), the second distinction has remained less explored. Management accounting literature has advanced in understanding the role of MCS for product innovation (Bisbe & Malagueño, 2009, 2015; Bisbe & Otley, 2004; Davila et al. 2009a, among several others), yet process innovation has remained out of focus.

Product and process innovations differ in their determinants and implementation patterns (Utterback & Abernathy, 1975), present distinct knowledge requirements (Gopalakrishnan, Bierly, & Kessler, 1999) and relate differently to creativity and uncertainty (Çokpekin & Knudsen, 2012; Frishammar, Florén, & Wincent, 2011). Hence, insights from studies of product innovation may not be directly applicable to process innovation (Damanpour, 2010; Stadler, 2011). This allows us to argue that the role and function of MCS differ for each one, a theoretical premise that we further develop in this work. By doing so we respond to the demand for studies analyzing the role of MCS for other than product innovations (Chenhall & Moers, 2015) and contribute to this line of research by exploring how and why product and process innovation relate differently to MCS.

In addition, considering that firms do not operate in isolation and that the patterns of innovation and related strategies, decisions and results are sector driven (Becheikh, Landry, & Amara, 2006; Heidenreich, 2009; Pavitt, 1984; Reichstein & Salter, 2006; Tidd et al., 2009), we expect the relationship between MCS and innovation outcomes to be context-specific, too. In fact, contingency theory in management accounting literature confirms that the function and role of MCS varies according to the context within which firms operate (Chenhall, 2007; Otley, 2016) and encourages further research in this direction. Combining these insights and demands, the core research question this work addresses is how MCS relate to product and process innovation in distinct contexts.

Previous research has argued for the benefits of combining different types of controls within a single business (Cardinal, Sitkin, & Long, 2004; Chenhall, 2003; Kreutzer, Walter, & Cardinal, 2015; Stouthuysen et al., 2017) and has moved towards broader definitions of MCS (Malmi & Brown, 2008). To address our research question, we take such insights on board and use the input-behavior-output control trichotomy relying on prior work. Rockness and Shields (1984) show how this combination of controls is appropriate for research and development (R&D) activities, Cardinal (2001) highlights the fit of such controls due to their ability to capture not only the content but also the temporal location of innovation activities, and Akroyd and Maguire (2011) confirm the appropriateness of this trichology for new product development.

We empirically execute our study through a quantitative research design study based on a large dataset. Such an approach allows for a robust multifactor analysis, assists in better understanding the relationship between MCS and innovation in a continuum and sheds more light on the manner in which these two managerial challenges become intertwined.

Our findings show that input controls have a significant and positive association only with process innovation for both high- and low-tech firms. In terms of behavior controls, we find them to be similarly beneficial for product and process innovation in high-tech industries and to have a stronger positive association with process than product innovation in low-tech industries. Output controls turn out to have similar positive associations with both product and process innovations in both innovation contexts. Such results add to prior work on MCS and product innovation (Bedford, 2015; Bisbe & Malagueño, 2009, 2015; Bisbe & Otley, 2004; Cardinal, 2001; Davila et al., 2009a; Stouthuysen et al., 2017; Ylinen & Gullkvist, 2014), by showing evidence about the positive relationship between MCS and process innovation, a critical source of organization efficiency (Das & Joshi, 2012). In addition, they contribute to contingency theory in the management accounting literature (Chenhall, 2007; Otley, 2016), by investigating different roles of MCS on the two innovation outcomes in distinct contexts (high-tech versus low-tech sectors).

The remainder of this paper is structured as follows: Section 2 draws the theory links between MCS and different innovation outcomes and contexts. Section 3 discusses how input, behavior and output controls relate to product and process innovation within different innovation contexts, and develops the ensuing hypothesis. Section 4 explains the methodologies and data used for this study and section 5 reports our results. Section 6 discusses our findings and concludes.

2. The Role of MCS for Innovation

Prior research has established the positive influence of MCS on innovation by paying special attention to their role in facilitating creativity and/or assisting in the reduction of uncertainty through their impact on knowledge and information (Bisbe & Malagueño, 2009; Bisbe & Otley, 2004; Chenhall & Moers, 2015; Davila, 2000; Davila et al., 2009b; Henri, 2006; Jørgensen & Messner, 2009; Ylinen & Gullkvist, 2014). In the majority, such endeavors have so far concentrated on some of the attributes and functions of innovation (e.g. creativity and knowledge creation) or have approached innovation as a lump process.

Aiming to enrich this line of research, we explore the idea that while creativity and innovation are closely intertwined, they still remain distinct constructs, with the former describing the generation of novel ideas and the latter requiring the conversion of such ideas into new and commercially successful products, services, or ways of doing things (Amabile, 1996; Baer, 2012; Georgdottir & Getz, 2004; Oldham & Cummings, 1996; Shalley & Zhou, 2008; West, 2002; West & Farr, 1990; Woodman, Sawyer, & Griffin, 1993). This means that MCS are not only relevant for the ignition stage of innovation, rather they remain significant for the follow up stages of the process, such as the implementation and commercialization of new ideas (Bisbe & Malagueño, 2015).

Building upon this, here we take closer look at the variety of functions that MCS can perform in distinct phases of the innovation process from its commencement to its conclusion.

In a delineative model, innovation managers need to (i) search for opportunities that may lead to innovation, (ii) select the opportunities that are feasible as well as the necessary resources, (iii) implement the selected projects, (iv) monitor their outcomes and redefine them if conditions change, and (v) capture the benefits of successfully implemented projects (Tidd et al., 2009). Information and knowledge are key in making and facilitating the respective decisions; scanning for opportunities requires resources that allow managers to gather and interpret information and signals that lie outside the organization. Next comes the incorporation of new knowledge and information in explicit targets and the operationalization of the latter via knowledge sharing, exchanging and integrating. Finally, appropriating the benefits of executed innovation projects is linked to learning from past experience, evaluating past practices and feeding information and knowledge back into the innovation process. Extant literature shows how MCS can fulfil such requirements by aiding the generation and deployment of knowledge (Bisbe & Malagueño, 2015), assisting the provision and exchange of information (Simons, 1995; Davila, 2000), facilitating learning processes (Merchant & Otley, 2006) and promoting knowledge integration (Ditillo, 2004; Jørgensen & Messner, 2009).

These distinct knowledge-intensive tasks require the development and implementation of more than one control mechanism to serve the innovation process from the inception of new ideas all the way to their commercialization. Previous empirical research on the relationship between MCS and innovation has been mostly based on the application of Simons' (1995) levers of control framework to analyze the drivers of adoption and use of control systems under different strategic orientations and modes of management

(Bedford, 2015; Bisbe & Malagueño, 2009, 2015; Bisbe & Otley, 2004). Here we place our emphasis on the influence of already selected sets of controls for the outcome of the innovation process and hence direct our attention to examine the attribute of the innovation process that is controlled. To this end, we draw on the *input-behavior-output* control trichotomy proposed and used by Akroyd and Maguire (2011), Cardinal (2001), and Rockness and Shields (1984).

Input controls assist the management of resources related to innovation (Akroyd & Maguire, 2011; Cardinal, 2001; Poskela & Martinsuo, 2009; Rockness & Shields, 1984). They are significant for organizations that depend on creativity and have been mostly linked to personnel selection and training activities (Abernethy & Brownell, 1997; Grabner & Speckbacher, 2016; Merchant, 1985; Rockness & Shields, 1984). Innovation scholars view personnel selection as a means of skill acquisition in organizations (Leiponen, 2005), while training activities have been found to improve the firms' innovation capabilities (Cohen & Levinthal, 1990; Hidalgo & Albors, 2008). Given that much of the technological and market knowledge that underpins innovation is often tacit and idiosyncratic (Utterback & Afuah, 2000), a commitment to the development of human capital through training programs is critical for innovation (Freel, 2005). Consequently, input controls are important vehicles for knowledge production, acquisition and transformation; activities that facilitate the innovative process.

Behavior controls refer to mechanisms monitoring the tasks related to the implementation of innovative projects and determining how knowledge is coordinated, distributed and shared within the organization. These more bureaucratic mechanisms regulate activities that convert inputs into outputs by establishing formalized procedures and rules, job descriptions and operational routines (Abernethy & Brownell, 1997; Cardinal, 2001; Cardinal et al., 2004; Kirsch, 1996). The use of behavior controls commonly implies a high level of understanding by the organization regarding the required resources, the appropriate behaviors and sequence of events during the transformation process (Abernethy & Brownell, 1997; Eisenhardt, 1985; Ouchi, 1979; Rockeness & Shields, 1984; Snell, 1992). Acknowledging the intrinsic uncertainty of innovation-related activities, in this work, behavior controls mostly refer to the execution stage of the innovation process that involves the assimilation, application and coordination of new knowledge.

Finally, *output* controls regulate outcomes and results. They specify the targeted outputs and thereby assist managers in evaluating whether outputs align well with the desired goals, and establish rewards (Cardinal, 2001; Eisenhardt, 1985; Merchant, 1985; Ouchi, 1979; Snell, 1992). Here, *output* controls incorporate the means of predicting, measuring and evaluating the results of the innovation process. They bridge the last with the initial stage of the innovation process as they define the targets against which results are evaluated and feedback information that is relevant for the reigniting of the innovation process. Output controls embody codified information in a systematic and non-exclusive manner and hence reduce uncertainty by allowing cross-temporal comparisons and providing feedback information when targets are underachieved or missed (Green & Welsh, 1988). Their connection to strategy means that the they help alleviate a potential lack of direction, allow autonomy and can address motivational problems (Merchant & Van der Stede, 2012). Figure 1 summarizes the relevance of the *input-behavior-output* control trichotomy across the innovation process.

[Insert Figure 1 near here]

We expect that the manner in which MCS influence innovation will not be uniform between distinct innovation outcomes (product and process innovation) and across different innovation contexts (high- and low-tech sectors[1]). Literature on innovation and technological change has emphasized that the determinants of product and process innovation as well as the contexts within which they develop are different (Cohen & Klepper, 1996; Damanpour & Gopalakrishnan, 2001; Ettlie & Reza, 1992; Gopalakrishnan et al., 1999; Pavitt, 1984; Reichstein & Salter, 2006; Tidd et al., 2009). Such differences are worthy of further exploration and to this end, we next proceed to discuss how the idiosyncrasies of product and process innovation and sectoral characteristics influence the relationship between MCS and innovation.

2.1 Different Innovation Outcomes

Innovativeness is the capability of a firm to develop and commercialize new products and processes (Damanpour & Gopalakrishnan, 2001; Garcia & Calantone, 2002). Product and process innovations capture different types of changes taking place within an organization. Product innovation refers to a new technology, artefact, service or combination introduced to meet user or market needs (Tidd et al., 2009; Utterback & Abernathy, 1975) and process innovation is defined as new elements or processes

[1] We follow the OECD's classification of manufacturing industries. According to OECD (2005, 2011), two indicators of technology intensity are used in the classification: i) R&D expenditures divided by value added; and ii) R&D expenditures divided by production. Then, the division of manufacturing industries into high-technology, medium-high-technology, medium-low-technology and low-technology groups was made after ranking the industries according to their average over 1991–1999 against aggregate 12 OECD countries' R&D intensities. As in previous research (Heidenreich, 2009; Santamaría, Nieto, & Barge-Gil, 2009; among several others), we combine low-tech and medium-low-tech industries under the label of low-tech industries; and we join high-tech and medium-high-tech industries under the label of high-tech industries. Usually, low-tech industries are those with an average R&D intensity lower than 0.9% (textiles, food products, tobacco and wood, among others) and those (medium-low-tech) with an average R&D intensity of between 0.9% and 3% (rubber and plastic products, coke, refined petroleum products, basic metals, among others). High-tech industries are those (medium-high-tech) with an average R&D intensity between 3% and 5% (electrical machinery, motor vehicles, railroad and transport equipment, machinery, among others) and those (high-tech) with an average R&D intensity higher than 5% (aircraft and spacecraft, pharmaceuticals, office machinery, radio, TV, medical, precision and optical instruments, among others).

introduced into an organization's production or service operations (Reichstein & Salter, 2006; Tidd et al., 2009; Utterback & Abernathy, 1975).

The decision to pursue product or process innovation is driven by different objectives and abides by distinct strategies. Product innovation aims at meeting customer demands, entering new markets and increasing revenues in the short-medium-term, while process innovation targets longer term objectives such as efficiency improvement and cost-saving (Boer & During, 2001; Das & Joshi, 2012). As such, product innovation is a more market-driven decision that largely depends on introducing novelty to the market and while process innovation is more oriented towards interfirm problem-solving. Such differences translate into distinct knowledge requirements, with product innovation requiring information by multiple, largely external to the firm, sources and process innovation drawing more on knowledge that is firm-specific, sourced primarily by the firms' employees (Ettlie & Reza, 1992) and suppliers (Reichstein & Salter, 2006; von Hippel, 1988).

Prior research has used the concepts of codifiability (or tacitness), completeness, and complexity (Gopalakrishnan et al., 1999; Turner & Makhija, 2006) to account for the particularities of product and process innovation with regards to their knowledge content and requirements. Knowledge associated with product innovation is relatively more codified than that used for process innovation (Stadler, 2011). Product innovators are required to clearly assimilate customers' needs into the design and manufacture of new products (Ettlie, Bridges, & O'Keefe, 1984), hence, the knowledge content of product innovation needs to be more observable, better understood and articulated and transferred easier (Kogut & Zander, 1992; Makhija & Ganesh, 1997). In contrast, knowledge contained in process innovations is more tacit and cumulative, and thus more "sticky" and difficult to observe, measure and express (Makhija & Ganesh, 1997; Nonaka & Takeuchi, 1995).

Completeness refers to the degree to which the knowledge is sufficient and available (Turner & Makhija, 2006) for decision-making and tends to increase the more iterative and programmed decision making (Gresov, 1990). The fact that technology and product life cycles are increasingly shortened and that product innovation is sourced from multiple agents with expressed preferences, leads us to infer that the generation of product innovations is based on more incomplete information than that of process innovation. While process innovation is more serendipitous and enters decision-making processes less frequently the tasks it involves are more routinized and repetitive, as long as coordination is achieved, its knowledge completeness should be higher than product innovation.

Finally, complexity here refers to the amount of information, the level of sophistication, and its interrelatedness (Galunic & Rodan, 1998; Gopalakrishnan et al., 1999). Extant research suggests that product innovations are easier to understand and are less complex due to their higher degree of observability; attributes that actually ease the external sourcing of information (Von Hippel, 1988). In turn, the generation of a new idea related to process innovation requires the understanding of how the sophisticated systems of the specific organization work, a characteristic that increases not only the degree of uniqueness but also the complexity. Process innovation is also more systemic as it impacts the overall process of changing inputs into outputs and usually involves a large aggregate of equipment, people, and social systems (Gopalakrishnan et al., 1999; Tornatzky & Fleischer, 1990). The distributed yet interrelated nature of knowledge required for process innovation builds more 'causal ambiguity' in the organizational system (Lippman & Rumelt, 1982) and explains why process innovation is relatively more complex than product innovation (Gopalakrishnan et al., 1999) and why uncertainty takes longer to resolve in process innovation projects than in product innovation projects (Frishammar et al., 2011).

Such insights allow us to suggest that the particularities of product and process innovation and ensuing implications for their management influence the way the two innovation types relate to control. More specifically, we infer that while input controls would serve both product and process innovation, their benefits are expected to be more pronounced for process innovation due to its more tacit and cumulative nature (Hidalgo & Albors, 2008). This distinctive characteristic of process innovation combined with the idea that behavior controls are more appropriate for more routinized tasks (Merchant & Van der Stede, 2012), lead us to suggest that, overall, behavioral controls are more relevant for process than product innovation. Such an idea is also supported by the fact that uncertainty takes longer to resolve in process innovation projects (Frishammar et al., 2011) and that planning and standardization activities are found to assist towards this end (Das & Joshi, 2012). However, the role of such practices for new product development is less obvious as the design and enforcement of guidelines reduces the likelihood of behavior deviation (Weick, 1979) and may consequently stifle creativity, thus decreasing the potential for product innovation. Finally, constructing and communicating innovation targets for distinct groups and units promotes both product and process innovation. Coherent and specific targets facilitate both types of innovation as they provide a clear sense of direction and project vision (Leonard-Barton, 1995; Tidd et al., 2009). Hence, we would expect outcome controls to be equally relevant for product and process innovation.

Product and process innovation presents differences in all contexts but contextual characteristics will influence the way product and process innovation relate to MCS. We next discuss the contextual attributes that may affect such a relationship.

2.2 Different innovation contexts

The context, and particularly the type of industrial sector, is a key factor to consider in the study of innovation and its patterns. Extant research argues that the nature of innovation can often be sector-driven (Castellacci, 2008) due the fact that different sectors are characterized by distinct objectives and forms of managing innovation (Becheikh et al., 2006; Heidenreich, 2009; Pavitt, 1984; Reichstein & Salter, 2006; Tidd et al., 2009). As the rate, outcome and organization of innovative activities differ greatly across sectors (Malerba, 2002, 2005), we expect that industry particularities will influence the mechanisms of control related to innovation management.

Indeed, the relevance of contextual factors for the function, effectiveness and design of MCS has long been recognized by management accounting scholars (see Chenhall, 2007, for an extensive review). Williams and Seaman (2001) show how the type of industrial sector and the level of competition and centralization influence the design and evolution of MCS and argue against the non-discriminatory generalization of control practices. So far, contingency theorizing in MCS research has highlighted the relevance of environmental uncertainty and complexity, the technological regime and the strategy of the firm. More specifically, contexts characterized by higher levels of environmental and task uncertainty are argued to require more open, externally focused and non-financial types of MCS (Chenhall, 2007). In a similar logic, informal, personnel and broad scope controls seem to be more suitable in technological regimes characterized by technological interdependence. Finally, broad scope controls are a better fit with differentiation strategies while more traditional or formal controls suit cost leadership strategies better (Chenhall, 2007, p. 173). Embracing the recent demand for more research in this field (Otley, 2016), here we distinguish between high- and low-technology sectors and examine how the idiosyncrasies of these distinct innovation contexts may impinge upon the role of MCS for innovation outcomes.

High- and low-technology settings present several differences that may bear consequences for the development and functioning of MCS. To begin with, high- and low-tech sectors present distinct levels of technological and market *uncertainty.* Technological uncertainty is sourced by the ambiguity with regards to the functions and expected performance of new technologies (Davidow, 1986) and affects the development and implementation of novel ideas. Market uncertainty arises due to customers' concerns regarding the new product or process and its ability to meet their needs and reflects the possible adoption hesitation from the market as a whole (Levy, 1998; Moriarty & Kosnik, 1989). In comparison to low-technology settings, high-technology settings entail higher market and technological uncertainty and present more intense competitive conditions (Barlow & Sarin, 2003). In high-tech contexts, the frequency of technology and market disruptions is higher and the speed of obsolescence is more rapid (Davidow, 1986; Moore, 1993). This requires managers to make fast decisions even if based on incomplete information, suggesting that the information gathering and processing functions served by MCS are of great importance.

In addition, high- and low-tech sectors differ with respect to the dominating *strategy* pursued by firms. In high-tech industries, the ability of firms to adapt and survive depends on the continuous introduction of new products, while in low-tech settings survival depends mostly on the ability of firms to change and improve their production processes (Cefis & Marsili, 2011). Namely differentiation strategies are more commonplace in high-tech sectors whereas cost efficiency strategies dominate in low-tech sectors. Past research suggests that the selection of strategy affects its implementation and hence the type of control chosen (Govindarajan, 1988; Govindarajan & Fisher, 1990).

Relatedly, the decision-making styles are distinct in the two contexts (Covin, Slevin, & Heeley, 2001) and so is the *organization of innovation activities*. Prior work has shown that while in high-tech sectors innovation is mostly attached to formally structured R&D activities (Santamaría et al., 2009), in low-tech sectors innovation relies mostly on non R&D activities such as learning-by-doing and learning-by-using (Hirsch-Kreinsen, 2008; Trott & Simms, 2017). Such differences are linked to unequal degrees of task complexity and interdependence within and outside the firm. In high-tech industries the innovative activities of firms are embedded in complex business ecosystems offering novel products and services (Gulati, 1995), thus activity and task interdependence with other firms are quite pronounced. On the one hand, such a structure allows for synergies and collaboration. On the other, it places boundaries on firms' technological choices that then become driven by technical advancements and innovations of the established system (Mohr, 2001). Therefore, although market demands undoubtedly play a decisive role for innovation in this context, the innovations of high-tech firms are inevitably more technology-oriented than those of low-tech enterprises (Tunzelmann & Acha, 2005).

These structural characteristics suggest that the *knowledge stock and distribution* differ between the two settings as well. Innovation in low-tech industries involves the application of high-tech components into existing products and production processes (Robertson, Smith, & von Tunzelmann, 2009), hence their orientation is largely driven by the technological achievements of high-tech firms. High-tech industries are then considered to be "innovation suppliers" that produce and diffuse new knowledge and low-tech sectors become "users of innovation" that receive and integrate novel knowledge

(Brusoni, Prencipe, & Pavitt, 2001; Brusoni, 2005; Hauknes & Knell, 2009). This suggests that the actions required for knowledge production, acquisition and integration are distinct between the two contexts. High-tech sectors are by definition populated by more skilled and specialized personnel whereas the skill requirements for employees in low-tech sectors are lower and less diverse. Recent empirical evidence confirms that training activities are more relevant for innovation in low-tech industries while ensuring the employment of high-skilled workers would be more essential for firms operating in high-tech industries (Barge-Gil, Nieto, & Santamaría, 2011). Finally, the two contexts differ with respect to the *degree of novelty* of innovation. Empirical research confirms that low-tech firms are more prone to develop incremental innovations than high-tech ones (Hirsch-Kreinsen, 2008) and that bears consequences for the appropriateness of different types of controls as exploration and exploitation place distinct control requirements on firms (Bedford, 2015).

Overall, we have argued that high- and low-tech sectors differ in terms of the degree of uncertainty, common business strategy, organization of innovation activities, knowledge stock and distribution， as well as the type of innovations they tend to pursue. Such differences are expected to alter the role of input, behavior and output control for product and process innovation processes and are shown in Figure 2. Combining such insights we next turn to develop the ensuing hypotheses.

[Insert Figure 2 near here]

3. Hypothesis Development

3.1 Input controls

Input controls play a critical role for the search and selection of opportunities and resources, due to their function for new knowledge production and acquisition. These controls are relevant in both high- and low-tech sectors and have been found to positively relate to both radical and incremental innovation (Cardinal, 2001). Prior work finds them appropriate for tasks entailing high cognitional complexity (Ditillo, 2004), as in high-tech contexts, but also confirms their suitability in contexts where knowledge is fine grained, partly tacit and difficult to codify, as in low-tech sectors (Ditillo, 2012). Aiming to fine grain the role of input controls for innovation, here we argue that input controls serve different objectives in high- and low-tech sectors as the relevant strategies, opportunities and sourcing of innovation in the two contexts are distinct.

High-tech companies most commonly follow differentiation strategies leading to product innovations while low-tech companies pursue more cost efficiency strategies that are linked to process innovation (Hirsch-Kreinsen, 2008; Trott & Simms, 2017). Hence, the portfolio of innovative projects differs between the two contexts and managers are expected to tailor the selection and development of human resources to the type of innovation outcome pursued. In addition, as aforementioned, high- and low-tech sectors differ in the way they organize innovation activities, with the former relying on formal research and development tasks and the latter focusing more on technology adaptation and learning by doing. Then, in high-tech sectors, input controls become adjusted to serve the identification of resources that are suitable for R&D activities leading to product innovation, and in low-tech sectors these controls assist the development of skills for technology adaptation and learning by doing/using leading to process innovation. Overall, the fact that the two sectors specialize in the pursuit of distinct innovation outcomes suggests that managers design input controls accordingly. Such insights lead us to the following hypotheses:

Hypothesis 1a: Input controls in high-tech industries have a stronger positive association with product than with process innovation

Hypothesis 1b: Input controls in low-tech industries have a stronger positive association with process than with product innovation

3.2 Behavior controls

Behavior controls facilitate the execution stage of the innovation process by assisting firms in assimilating and transforming knowledge according to their objectives and coordinating the related activities. High-tech sectors are characterized by high degrees of market and technology uncertainty and such characteristics are found to reduce the usefulness of process formalization (Poskela & Martinsuo, 2009) and to render the use of behavior controls as less appropriate (Eisenhardt, 1985). At the same time, the diversity of knowledge and the high variety and interdependence of tasks performed in high-tech sectors weaken the managers' ability to accurately allocate responsibility for performance to specific tasks and such conditions stifle the effectiveness of behavior controls (Abernethy & Brownell, 1997; Ouchi, 1979; Rockness & Shields, 1984). Finally, the standardized and bureaucratic nature of behavior controls seems to be contradictory to the path-breaking objective of innovations pursued in high-tech sectors, hence we do not expect behavior controls to be valuable in these contexts.

The insights presented previously led us to infer that the execution stage of innovation in low-tech industries is more predictable and structured than in high-tech industries and that the more routinized nature of tasks in low-tech sectors allows for the implementation of some form of standardization. Prior research suggests that staging processes (Cooper, 1994) and programming techniques (Gassmann, Sandmeier, & Wecht, 2006) can facilitate the assimilation of knowledge. The greater need for the assimilation of external knowledge that characterizes the low-tech environments (Robertson et al., 2009) justifies the relevance of behavior controls in these contexts. In addition, the dominance of cost efficiency strategies in such sectors comes hand in hand with task routinization and acquiring process engineering skills and implies high task programmability (Govindarajan & Fisher, 1990), all of which are attributes that increase the usefulness of behavior controls (Abernethy & Brownell, 1997; Ouchi, 1979; Rockness & Shields, 1984).

Low-tech firms allow high-tech ideas to gain practical applicability and accelerate the diffusion of new technologies across sectors (Robertson & Patel, 2007) and such activities are especially evident for process innovation (Kirner, Kinkel, & Jaeger, 2009; Trott & Simms, 2017). As previously argued, process innovation is more systemic than product innovation, and hence, in greater need of coordination and knowledge integration, two attributes that further enhance the usefulness of behavior controls (Ditillo, 2012). Finally, as process innovation is overall more incremental than product innovation and presents higher programmability and iteration of tasks, we expect it to benefit more from the use of behavior controls. Such insights are incorporated in the following hypotheses:

Hypothesis 2a: Behavior controls in high-tech industries have no effect on either product or process innovation

Hypothesis 2b: Behavior controls in low-tech industries have a stronger positive association with process than with product innovation

3.3 Output controls

Output controls bridge the last with the initial stage of the innovation process. They define the targets against which results are evaluated and feed information back to the process. Output controls are particularly useful in focusing and redefining the innovation strategy, hence their function and effectiveness is interrelated with the strategic choices of the firm (Govindarajan & Fisher, 1990; Henry, 2006; Snell, 1992).

In high-tech contexts, the conditions of intense competition and shorter product life cycles call for more frequent target setting and evaluation of results, hence output controls become indispensable for any type of innovation. The design and development of output controls requires different members of the organization to share their past experience and future visions and incorporates the result of knowledge exchanges in specific metrics. This process involves the sharing and codification of tacit knowledge, increases the availability of information and makes knowledge complexity more manageable. The high level of technological and market uncertainty intensifies the need to scan, evaluate and structure the shared and comparable opportunities and targets, yet compromises the effectiveness of output controls as it reduces the level of outcome measurability (Ouchi, 1979; Rockness & Shields, 1984). Research shows that the more uncertain the market and technology environment the less appropriate the output-based controls are, and that such controls may lead to reduced risk-taking behavior (Cardinal, 2001; Poskela & Martinsuo, 2009) that is necessary for innovation. Nevertheless, in recent developments the techniques and metrics used to capture the value of innovation are found to assist the target setting and facilitate the evaluation of innovation projects (Georghiou, Cassingena, Keenan, Miles, & Popper, 2008; Rinne, 2004). Hence, we suggest that a proper design of output controls in high-tech industries is both desirable and attainable and can facilitate both types of innovation.

Firms operating in low-tech contexts tend to pursue cost-efficiency strategies that imply incremental interventions in routinized tasks. Strategic decisions are driven by cost information that is highly observable and measurable, hence output controls are a good fit (Govindarajan & Fisher, 1990). The "specialization" of low-tech sectors in process innovation and the high technical complexity that this involves, call for mechanisms that allow for a coordinated and systematic transmission of technical knowledge. Ditillo

(2004) finds that output (or result) controls serve such functions and assist in setting objectives and monitoring achievements. Process innovation relies more on technological knowledge while product innovation combines technological and market knowledge, hence we expect that the benefits of outcome controls in low-tech sectors are more pronounced for process innovation. Finally, as strategies and targets need to be consistent with the business environment, managers in low-tech sectors will develop output controls that capture information regarding process innovation, whereas output controls in high-tech sectors will focus more on knowledge that is relevant to achieve product innovation (Cefis & Marsili, 2011). Such insights lead us to the following hypotheses:

Hypothesis 3a: Output controls in high-tech industries have positive associations with both product and process innovation.

Hypothesis 3b: Output controls in low-tech industries have a stronger positive association with process than product innovation.

4. Data and Methods

4.1 Sample and Data

The reliance on well-established types of MCS and the specific objective of this study to account for the multiplicity of factors that are relevant to the innovation process both within and outside the organizations under study, leads us to focus on scope rather than depth and to rely on secondary sources. The desire to link internal decisions with the surrounding organizational conditions and to search for patterns of associations between different controls and distinct innovation outcomes, requires the reliance on a large data set that allows for generalization.

To this end, our empirical analysis is based on archival data collected through the Spanish Business Strategies Survey (SBSS), a secondary survey database compiled by the Spanish Ministry of Finance and Public Administrations and the Public Enterprise Foundation.[2] This annual firm-level panel data represents small/medium-sized enterprises (SME) (with employee numbers ranging from 10 to 200), and large firms (with more than 200 employees). SMEs dominate the sample and are selected through a random stratified sample according to firm size and industry classification, while large firms are surveyed on a census basis.[3] The empirical analysis is based on an unbalanced panel of firms with information available for the period 2001–2007. The sample contains 2,267 unique firms (4,167 firm-year observations).

Such an approach grants us access to large-scale evidence of the issue under study: it overcomes the idiosyncratic characteristics of firms (through the use of control variables) and provides different sets of proxies for each type of MCS, while still leaving room to identify patterns of behavior and permit some degree of categorization and generalization.

The benefits of data availability, high external validity, sample size and the generalizability of results from the use of publicly available data are typically accompanied by a trade-off with respect to construct validity. As in Gallemore and Labro (2015), we attempt to address the latter by: (i) carefully selecting multiple proxies for each type of control mechanism that is well-defined in extant literature, (ii) verifying that prior research confirms the relevance of our proxies and the controls proposed, and (iii)

[2] Many researchers have used the same database to study innovation, finance, human resources, etc. Their works have been published in top journals: https://www.fundacionsepi.es/investigacion/esee/en/sesee_articulos.asp.
[3]The survey's detailed questionnaire is available at http://www.fundacionsepi.es/investigacion/esee/en/svariables/indice2.asp.

testing that all our proxies are positively correlated with one another (reported later in Table 1).

The SBSS includes a wide and interesting set of variables related to Spanish firms operating in all manufacturing industries within the NACE-Rev.1 classification, such as firms' innovation activities and inputs (i.e. R&D effort, external collaboration agreements), environmental factors (sector, the degree of competition in product markets), and firm characteristics (size, leverage, internationalization). The availability of such non-conventional information on business activity and innovation orientation allows us to study the role of MCS for innovation while controlling for other determining factors of innovation outcomes at firm-level. The actual questionnaire items for the measures of innovation outcomes and MCS are available in Appendix A.

4.2 Variables and Methodology

4.2.1 Dependent Variables

In order to identify how MCS affect firms' innovativeness, we measure different innovation types using two dependent dummy variables. *Product innovation* takes a value of 1 when the firm introduces completely new products *or* products to the market with important modifications *or* products with new functions resulting from innovation *or* products with changes in their design, presentation, materials or composition at year t; and 0 otherwise. *Process innovation* takes the value 1 when the firm has introduced some significant modification in the production process, such as the instigation of machines with new technologies or new methods of organization, or both, at year t; and 0 otherwise.

4.2.2 Independent Variables

In selecting our independent variables, we sought to identify several proxies for the three types of controls according to their theoretical definitions discussed in section 2. Every proxy captures a different conceptual facet (but does not necessarily share a common theoretical foundation) of the corresponding type of MCS (Bedford & Speklé, 2018). As in Davila (2005) and Davila, Foster, and Jia (2015), we construct an index for each type of control system, which is the sum of multiple proxies of every control mechanism, and we use these indexes as our main independent variables. Such composite indicators allow us to empirically test the aggregate effect of a combination of constituent elements measuring distinct aspects of MCS, and to maximize the predictive capacity and parsimony of our model (Bollen, 2011; Bollen & Diamantopoulos, 2015). These types of indicators are suitable for many researches in management accounting (Bedford & Speklé, 2018). Similar to other management accounting instruments, MCS are control mechanisms intentionally designed by individuals within an organization, which are formed by mixtures of elementary components and can be better measured by composite indicators (Bedford & Speklé, 2018; Henseler, 2017).[4]

Respectively, input controls assist the management of resources related to innovation and are usually linked to personnel selection and training activities (Abernethy & Brownell, 1997; Cardinal, 2001; Grabner & Speckbacher, 2016; Merchant, 1985; Rockness & Shields, 1984). Hence, we include the availability of human capital resources through both hiring skilled personnel (*Skilled personnel*) to capture skill acquisition and incorporation (Leiponen, 2005), and financial resources spent on training programs (*Training*) to capture the increase in human capital and innovation capabilities (Cohen & Levinthal, 1990; Hidalgo & Albors, 2008). *Skilled personnel* is a dummy variable equal

[4] We construct indexes for different types of MCS, rather than use individual proxies, as the main independent variables. According to Henseler (2017), if the goodness of fit of the model is not significantly worse, the composite indicators should be preferred over individual indicators based on the criterion of parsimony. Comparing the statistics of the estimated models of Table 4 (index effects) and that of Table 7 (individual indicator effects), we find that it is suitable to use composite indicators in our study. However, some authors raise concerns about the use of composite indicators due to the potential loss of information and suggest the use of individual indicators (Howell, Breivik, & Wilcox, 2007).

to 1 if the firm hires graduate engineers or employees with professional experience in R&D activities, and 0 otherwise. *Training* is the total amount of the annual external training costs of a firm. Since one is a dummy and the other a continuous variable, we first standardize the two proxies of input controls and then calculate an index, *Input control index*, as a sum of the standardized proxies.[5] Hence, *Input control index* is a continuous variable and a higher *Input control index* is a result of using more input controls in terms of both number of controls or higher values in the continuous input control proxy.

Behavior controls refer to the mechanisms that monitor and regulate the execution of innovation projects by establishing rules, procedures, and operational routines (Abernethy & Brownell, 1997; Cardinal, 2001; Kirsch, 1996). We use five items to construct the proxy of these types of controls. The explicit planning of innovation activities, such as guidelines, stage gate systems, resources allocation, budgets, etc., facilitates the operationalization and allocation of inputs required for innovation and thereby assists in avoiding delays, costs and uncertainty linked to the implementation of projects. *Planning of innovation activities* takes the value 1 if the firm has developed a plan of innovation activities; and 0 otherwise. Quality control and standardization helps different business units to develop and share a common understanding of the appropriate behavior during the process of converting inputs into outputs (Abernethy & Brownell, 1997; Cardinal, 2001; Rockness & Shields, 1984). *Quality control* is equal to 1 if the firm carries out or contracts quality control and standardization activities, and 0 otherwise. Activities undertaken to adopt and deploy innovative technologies are also grouped under behavior controls because they facilitate the acquisition of external technologies and the transformation such technologies into new processes and products development. This is

[5] The *Input control index* can be negative because of the standardization of each proxy.

captured by *Tech assimilation*, which has the value 1 if the firm has carried out or contracted services to assimilate imported technologies, and 0 otherwise. The existence of an internal committee/department and external consulting for technology and innovation processes in the firm are the last two items of behavior control and capture the acquisition and assimilation of external knowledge that can assist in the codification and application of knowledge. The existence of experts is essential for innovation as they facilitate cross-functional and cross-unit communication within the organization and the interchange of opinions and brainstorming, all of which enhances firms' innovative potential (Lawrence & Lorsch, 1967). Experts and technical consultants become highly pertinent in converting inventions into innovations as these key individuals (or teams) can provide critical knowledge and communicate new beliefs and culture throughout the organization (Tidd et al., 2009). The variable *Committee* is equal to 1 if the firm has a technological or R&D committee, and 0 otherwise. *External consulting* takes the value of 1 if the firm uses external advisors and/or experts to gain information about technology, and 0 otherwise. The *Behavior control index* is the sum of the previously mentioned behavior control proxies. Since the five proxies of behavior controls are dummy variables, the *Behavior control index* is a count variable with a scale from 0 to 5; higher values capture the use of more types of behavior controls.

Finally, output controls regulate outcomes and results. Specifically, output controls define the desired results by setting up goals, evaluating whether outputs align well with the desired goals, and rewarding (punishing) successful (failed) goal attainment[6] (Cardinal, 2001; Eisenhardt, 1985; Merchant, 1985; Ouchi, 1979; Snell, 1992). The index of outcome controls is composed of three items: (i) the use of indicators for innovation

[6] Our database allows us to capture the target setting and evaluation functions of output controls, however it remains constrained in offering valid proxies for rewarding mechanisms. Hence, the latter remain beyond the scope of the current analysis.

results (*Indicators of innovation results*), (ii) mechanisms of the evaluation of the prospect of technology change (*Tech evaluation*), and (iii) use of market research or commercialization services for new products (*Market research*). As in Akroyd and Maguire (2011) we link output control to the collection and analysis of information, and the monitoring and evaluation of key indicators. Indicators of innovation results embody the targets that firms aspire to achieve but also serve as reference points for the evaluation of the actual outputs. *Indicators of innovation results* is a dummy variable that takes the value 1 when the firm has made use of indicators of innovation outcomes in its decision-making processes, and 0 otherwise. The composition and update of output controls requires the continuous acquisition of information related to the targets sought (Turner & Makhija, 2006). An innovation is invention accompanied by commercial transactions (Freeman & Soete, 2000; Porter, 1990), the relevant information with regards to the desired outcomes combined relates to technological and market trends. The mechanisms for the collection and systematization of such information form part of the output control set. Mechanisms capturing and evaluating the prospect of technological change help to identify whether the desired technological outcome is achieved or not. *Tech Evaluation* is a dummy variable that takes a value of 1 if the firm has evaluated technological alternatives or assessed the prospects of technical change, and 0 otherwise. In turn, market research activities evaluate the possibilities of the successful commercialization of new products and inform managers about practices and product characteristics that are sought by the market. *Market Research* is equal to 1 if the firm indicates that it has performed or contracted market studies and marketing services for the commercialization of new products, and 0 otherwise. We construct *Output control index* as the sum of the three proxies of output controls. Similar to the previous index, *Output control index* is also a count variable from 0 to 3. A higher *Output control index* means the use of more output controls.

4.2.3 Control Variables

In addition to the MCS measures, and in order to observe the cleanest possible effect of MCS, we include firm and environment characteristics in the regressions to account for other factors that might influence firms' innovation outcomes.

First, we control for other firm activities that might drive innovation results. *R&D intensity* measures the internal R&D expenditures scaled by total sales. The external R&D activities are captured by the variable *Collaboration*. It is 1 if the firm performs innovation activities via technological agreements with other firms or research organizations, and 0 otherwise. More R&D activities increase the probability of successful innovation outcomes. Besides R&D activities, firms also carry out non-R&D activities to increase innovation outcomes (Barge-Gil et al., 2011). *Design* is a dummy variable with a value of 1 when the firm has performed design activities, such as architectural, fashion, interior, graphic, industrial and engineering design; and 0 otherwise. *Automation* is a dummy variable taking the value 1 if the firm uses automatic machines, robots or computer-aided design/computer-aided manufacturing, and 0 otherwise.

Second, we consider the role of firms' characteristics. We control for *Firm size,* one of the most important determinants of the innovation activities of the firm (Becheikh et al., 2006; Cohen & Klepper, 1996), measured by the natural logarithm of sales. Capital structure captures firms' financial constraints (Chen & Miller, 2007) and is measured by the equity-to-debt ratio, scaled by multiplying the ratio by 1/100 (*Leverage*). We account for firms' innovation incentives for international market competition (Galende & de la Fuente, 2003; Veugelers & Cassiman, 1999) and use export intensity (*Export*) as a control variable, measured by the ratio of the firm's sales in foreign markets to total sales.

Third, we control for market and environmental factors that might influence the innovation outcomes (Santamaría, Nieto, & Barge-Gil, 2010). *Market share* (the firms' share in its main market) is used to measure product market competition that affects the necessity of undertaking innovation activities (Schumpeter, 1942). In addition, we control for both client pressure and supplier pressure to capture the product and factor market characteristics. According to Cuervo-Cazurra and Un (2007), firms with concentrated clients need to keep updating their technological capabilities in order to avoid the defection of clients to competitors with superior technologies. It is the percentage of sales to the firm's three largest clients (*Client concentration*). Similarly, *Supplier concentration* is calculated as a percentage of total purchases from the three main suppliers. *Market share, Client concentration* and *Supplier concentration* are all scaled by multiplying the original numbers by 1/100.[7] Veugelers and Cassiman (1999) find that the incentives to innovate depend on the extent to which the results from innovation activities can be appropriated or easily diffused within or across industries. Hence, *Appropriability* is the ratio of the total number of patents per industry to the total number of patenting firms in that industry. In addition, firms with higher growth opportunity are expected to innovate more. Following Huergo (2006), we include a measure of the growth of market demand in the regressions. It is a dummy variable *Expansion*, which is 1 when the firm has claimed that its main market is expanding, and 0 otherwise. The year fixed effect is controlled in all regressions. Definitions of the variables are listed in Appendix B.

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[7] We also scale *Leverage*, *Market share, Client concentration* and *Supplier concentration* by taking natural logarithms. The regression results remain the same.

4.2.4 Methodology

Due to the binary character of the dependent variables, and in order to model the simultaneous generation of product and process innovations, we use bivariate probit estimations to study our hypotheses.[8] Such an approach is suitable for our research objectives for several reasons. First, the usual multinomial models assume that the innovation decisions are strict substitutes (which is not the case for at least 9% of our sample), whereas the bivariate approach allows for modelling simultaneous innovation outcomes. Second, unlike univariate probit models, the bivariate probit model allows us to incorporate a certain correlation structure for the unobservable factors related to different innovation outcomes. In particular, the model considers the correlations among errors instead of assuming them to be zero or constant (Belderbos, Carree, Diederen, Lokshin, & Veugelers, 2004). Third, a related advantage of this cross-equation structure of errors is that the specification of the equations (i.e. the independent variables) can vary across dependent variables. Lastly, but most importantly for this study, we can compare the influence of our independent variables on different innovation outcomes (Santamaría, Nieto, & Miles, 2012).

We estimate our hypotheses using bivariate probit models based on two subsamples that are different in technological opportunity and innovation contexts: high-tech versus low-tech firms. Following the OECD classification of manufacturing industries, we first identify firms belonging to high-tech industries (*High*); medium-high-tech industries (*Medium High*); medium-low-tech industries (*Medium Low*) and low-tech industries (*Low*). In order to test the relationship between MCS and innovation outcomes in different

[8] Our sample is a panel dataset. Hence, we also use a random-effect panel probit model, by controlling for firm characteristics and year effect, as a robustness check of our results. The results remain the same. They are available upon request.

contexts, we classify firms in the high-tech sectors as those belonging to both high-tech and medium-high-tech industries, while firms in the low-tech sectors as those from medium-low-tech and low-tech industries.

4.3 Descriptive Statistics

Table 1 reports the descriptive statistics and correlations of the main independent and control variables based on the full sample. The mean of input control index, the behavior control index, and the output control index is around -0.094, 1.184, and 0.643, respectively. [9] We conduct an analysis of the variance inflation factor (VIF) and confirm that the concern of a multicollinearity problem in the regressions is mitigated as individual VIF values are lower than 10 and average VIF values are lower than six (Neter, Wasserman, & Kutner, 1989).[10]

[Insert Table 1 near here]

Table 2 provides further information regarding the sample structure. We report the number of observations that have different innovation outcomes and MCS, for both full sample and subsamples separating firms of high-tech and low-tech sectors. In terms of innovation outcomes, around 15% of the observations in the full sample claim to have product innovation and 29% process innovation. About 9% of the sample have both product and process innovations. Comparing the innovation outcomes for the two

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[9] We show the summary statistics of the full sample in Table 1 to provide a general pattern of our sample, even though the main estimations are based on the subsamples of different innovation contexts (high-tech vs. low-tech). The summary statistics of the two subsamples are untabulated. For high-tech (low-tech) firms, the mean of input control index, the behaviour control index, and the output control index is 0.349 (-0.330), 1.560 (0.983), and 0.846 (0.534), respectively.

[10] One concern of using composite indicators is high multicollinearity among the proxies. Following Bedford and Speklé (2018) and Henseler, Hubona, and Ray (2016), we examine the multicollinearity of the composite proxies for each type of MCS. In untabulated results, the individual VIF values of proxies for the three types of MCS in our samples are lower than 3 and the average VIF values are lower than 1.9. Hence, the multicollinearity of composed indicators is not a concern of this study. These results also indicate that each proxy with at least 70% of its total variance is not shared with the other proxies of the same type of MCS, which further confirms the use of composite indicators (Bedford & Speklé, 2018).

subsamples, we find that it is always more frequent that both high-tech and low-tech sectors apply process innovation than product innovation. Furthermore, Table 2 indicates that firms in high-tech sectors are more innovative than those in low-tech sectors with regard to both product and process innovations. Approximately 22% of high-tech firms, compared to 11% of low-tech firms, achieve product innovation. With respect to process innovation, around 34% of high-tech firms undertake process innovation, while 27% of low-tech firms show successful process innovation. The same trend continues if we look at firms that have both product and process innovations.

Moreover, Table 2 shows that behavior controls are the most commonly used innovation-related control mechanism, followed by input controls and output controls. Around 21% of our full sample use one innovation-related control; 18% use two controls; 28% of firms implement all three types of MCS. Comparing the two subsamples, we find that it is more common for high-tech firms to use innovation-related MCS than those in low-tech sectors. In addition, it seems that high-tech firms are more active in using all three types of controls than low-tech firms are.

[Insert Table 2 near here]

As we are interested in MCS and their effects on different innovation outcomes, the univariate comparison between firms with only product and those with only process innovation (Table 3) offers some initial insights regarding the behavioral patterns of innovative firms and highlights some differences between product and process innovation.

[Insert Table 3 near here]

More specifically, we find that all three controls are commonplace for both innovation outcomes in high-tech sectors. However, comparing between innovation outcomes, they are more tightly coupled with product innovation, especially according to the behavior and output control indexes for low-tech firms.

5. Empirical Results

Keeping these general characteristics in mind (tables 2 and 3), we now turn to the presentation and description of the empirical results on the relationship between MCS and innovation. We test how distinct types of controls are associated with the two innovation outcomes, by considering such a relationship in different innovation contexts.

Table 4 presents the bivariate probit estimation results capturing the relationship between the use of different types of MCS and innovation outcomes by splitting samples into high-tech and low-tech sectors. As discussed in section 4.2.4, we classify firms in the high-tech sectors as those belonging to both high-tech and medium-high-tech industries, while firms in the low-tech sectors as those from medium-low-tech and low-tech industries. Columns (1) and (2) state the results for the subsample of high-tech firms, and those of low-tech firms are indicated in columns (3) and (4). In order to further test whether the effects of MCS differ for the two types of innovation outcomes, we carry out Wald tests to examine whether the coefficients of MCS are statistically different for product and process innovations in Table 5.

[Insert tables 4 and 5 near here]

For high-tech sectors, *Input control index* has a positive and statistically significant association only with process innovation. An increase of one unit in the index is associated with an average increase in the probability of successful process innovation of 1.3 percentage points.[11] The positive relationship is statistically significant at the 10%

[11] This is the average marginal effect of *Input control index* on innovation outcomes. To save space, the average marginal effects of all independent variables for all regressions are untabulated but they are available upon request. For the discussion of the remainder of the paper, we use the average marginal effects

level. The results of Table 5 imply that the coefficients of input controls for the two innovation outcomes are not statistically different. Similarly, for firms in low-tech sectors, the input control index also has a statistically significant relationship only with process innovation. One more unit in the input control index is correlated with 2.4 percentage points more in the probability of successful process innovation (significant at 1%). Moreover, comparing the coefficients of the input control index on different innovation outcomes, we find that the coefficient on the process innovation is larger than that on the product innovation. Such a difference is statistically significant at a 10% level (Table 5). These results support Hypothesis 1b but not Hypothesis 1a.

According to tables 4 and 5, we find that the use of behavior controls have similar positive relationships with both product innovation and process innovation for high-tech firms. Increasing one unit of the *Behavior control index* is correlated with a higher probability of successful product innovation of 2.0 percentage points (statistically significant at 5%), and that of process innovation of 4.4 percentage points (statistically significant at 1%). For the firms of low-tech sectors, a one-unit increase in the *Behavior control index* is correlated with a higher success probability of product innovation of 1.5 percentage points (statistically significant at 1%), while it is associated with an increase in the probability of having successful process innovation of 5.5 percentage points (statistically significant at 1%). According to the Wald test, the positive correlation is stronger for process innovation than for product innovation for low-tech firms. Therefore, Hypothesis 2b is supported but Hypothesis 2a is not.

Moreover, *Output control index* is positively associated with the two innovation outcomes, and such positive relationships are statistically significantly at 1% for both

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of independent variables.

settings. For high-tech sectors, increasing *Output control index* by one unit is associated with 5.5 percentage points for the probability of successful product innovation, and 5.6 percentage points for that of successful process innovation. Similarly, firms in the low-tech sectors that use one more unit of the output controls have a 2.0 percentage points increase in the probability of product innovation and a 5.1 percentage points increase in that of process innovation. However, the coefficients are not statistically different for product vs. process innovations, as shown in Table 5. These results indicate that Hypothesis 3a is supported while Hypothesis 3b is not. The overall results for all our hypotheses are summarized in Table 6.

[Insert Table 6 near here]

6. Discussion and Conclusions

The management accounting literature has established the positive association of MCS with innovation and this paper extends this line of inquiry. Overall, the results of this study confirm the relevance and importance of MCS for innovation and disentangle its links to different innovation outcomes and contexts.

Our first objective aims to uncover the distinct manner in which MCS relate to product and process innovation. Looking at the distinct characteristics of the two innovation outcomes with respect to their knowledge content and management requirements, we confirm prior reports of a positive association between MCS and product innovation in general (Bedford, 2015; Bisbe & Malagueño, 2009, 2015; Bisbe & Otley, 2004; Cardinal, 2001; Davila et al., 2009a; Stouthuysen et al., 2017; Ylinen & Gullkvist, 2014). We complement and contribute to such a line of inquiry by theoretically postulating that MCS are also relevant for process innovation and that actually the positive influence of input and behavior controls might be even more pronounced for this type of innovation.

We then explore contextual characteristics and perform our empirical testing on how MCS relate to product and process innovation in distinct contexts and contribute to contingency research on the role of MCS. The different patterns we observe for high- and low-tech sectors (tables 4 and 5) can be further explained by the individual effects of each proxy on innovation outcomes (Table 7).

[Insert Table 7 near here]

With regards to input controls we only find a significant and positive association of such controls with process innovation in both contexts. Moreover, we confirm that input controls are statistically and economically more important for process innovation than for product innovation in low-tech firms. For high-tech firms, the positive association with process innovation comes from the importance of both personnel selection and training programs on process innovation. However, in low-tech sectors, training seems to improve the probability of carrying out product innovation and personnel selection is positively correlated with that of process innovation. A possible explanation is that high-tech firms that aim for product innovation are by structure better equipped, hence controlling such resources does not add to the possibilities of achieving their target. Such findings complement existing knowledge on MCS and innovation by uncovering and emphasizing their role for process innovation.

With regards to behavior controls, we find them to be similarly beneficial for product and process innovation in high-tech industries. For high-tech firms such a relationship is empirically driven by the significance of planning for product innovation, and that of planning, technological assimilation and external consulting for process innovation. This result contradicts the theoretical prediction that behavior controls would have no effect in high-tech firms. One possible explanation of the positive association is that firms operating in high-tech sectors do by definition have more knowledge on how to execute an innovation project and are hence able to design and implement appropriate behavior controls. Turning to low-tech industries, we find that behavior controls are more beneficial for process innovation, a result that is empirically related to the strong positive associations of standardization, planning, and technological assimilation with process innovation. Such a finding coincides with Abernethy and Brownell (1997) in that behavior controls function better in tasks that are not too variable. Accepting that high-tech sectors achieve more radical innovation and low-tech sectors achieve more incremental innovation, here we confirm the positive association of such controls for in both contexts. This finding complements Cardinal's (2001) results of a positive association of behavior controls with radical innovation and helps clarify the mixed results reported for incremental innovation.

For output controls, we find that they have similar positive associations with both product and process innovations in the two innovation contexts. As seen in Table 7, these results stem from the positive correlation of using indicators of innovative results with product innovation, and that of evaluating technological change with process innovation in the high-tech sectors. While these results contradict past research suggesting that high uncertainty makes the use of output controls less appropriate (Cardinal, 2001; Poskela & Martinsuo 2009), they possibly suggest that the improvements in measurability techniques for innovation management do allow for a better design and use of output controls in highly uncertain settings. In turn, the results for low-tech firms are empirically explained by the benefits of using indicators for both innovation outcomes and the fact that market research aids product innovation, and the evaluation of technological change assists process innovation. This confirms that the design of output controls needs to match the knowledge needs of the desired innovation outcome.

Chenhall (2007) argues that environmental uncertainty is associated with a more open, externally focused and non-financial style of MCS, yet little is known about the appropriate mix of controls. Our results point to the fact that in innovation contexts where product differentiation strategies are more common, competition is harsher and task complexity and uncertainty is higher (i.e. high-tech), both behavior and output controls are similarly beneficial for both product and process innovation. However, input controls are beneficial only for process innovation. In turn, in innovation contexts where task variety and uncertainty is lower, competition is milder and cost leadership strategies dominate (low-tech), input and behavior controls are more beneficial for process innovation whereas the positive significance of output controls is similar for the two innovation outcomes.

Overall, this study contributes to the literature in three ways. *Firstly*, it goes beyond the radical-incremental product innovation dichotomy that management accounting scholars have analyzed (Bedford, 2015; Dekker & van den Abbeele, 2010; Stouthuysen et al., 2017; Ylinen & Gullkvist, 2014) and highlights the importance of MCS for process innovation. *Secondly*, it joins management control and innovation literatures and explores in more detail the distinct role of MCS for different innovation outcomes and in distinct innovation contexts. *Thirdly*, it highlights the fact that MCS are important for innovation in both high- and low-tech settings but fulfil distinct managerial tasks. In high tech settings MCS help well equipped firms mitigate the high levels of uncertainty and task complexity whereas in low-tech sectors they serve as more general managerial mechanisms that critical assist less equipped firms to systematize and structure the whole innovation process. Furthermore, in such settings, effective MCS are those that are designed according to distinct characteristics of different innovation outcomes.

Our results carry along managerial implications that relate to the definition of organizational objectives that fit with the environment within which innovation unravels, the execution of such objectives and their possibilities of being fulfilled. More knowledge about the appropriateness of distinct control types in different environments would assist both the design and implementation of controls that match the innovation outcome and can allocate resources more efficiently.

The results of this study should be considered in light of its constraints. First, it is necessary to acknowledge the usual limitation of quantitative studies based on large secondary sources, namely that causation cannot be claimed. Second, as the data comes from a standardized survey, we design the proxies of different types of MCS based on the information available, which in some instances may not allow to fully capture all aspects of the construct. For instance, we lack information regarding the rewarding functions of the output controls as well as how MCS are used in each firm. Thirdly, we take a broad approach to our conceptualization and operationalization of both behavioral and output controls. For example, with respect to output controls, we do not follow existing literature that may narrowly measure output control only as reliance on financial measures. Instead, we broaden the conceptualization and take into account the use of various technological and market-related information sources that inform targets and results. As such, caution should be taken when generalizing our results to existing literature that has relied on a more narrow measurement of these controls. Finally, the study is contextualized in the Spanish institutional and business environment. However, such business environment bears many similarities with the majority of European countries hence we expect the results to be fairly generalizable. Notwithstanding such limitations, the results of this work have provided clear evidence in support or extension of prior research.

Future research could focus on several related avenues of enquiry. First, it could be possible to extend the level of depth with the use of complementary methods. We plan a more in-depth analysis of the variety of business models and innovation strategies used by the firms included in our dataset (e.g. open innovation, collaboration, in-house R&D, cost leadership vs. product differentiation) and their distinct links with control systems and innovation outcomes. Having established the general trend we are also eager to study in more detail (possibly through case studies) the design, use and implementation of these control mechanisms and the synergies or not that they present. Such an exercise would shed more light on the variety of information flows and knowledge management, a variety that is expected to be present both between and within sectors. Other interesting opportunities for research in this area lie in performing a more specific industry analysis (for instance, with a separation between services and manufacturing). The same applies to firm size. A detailed analysis of both large and small firms would make it possible to see whether significant differences exist between them regarding the use of MCS.

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