*JOURNAL OF MANAGEMENT ACCOUNTING RESEARCH*
Vol. 30, No. 2
Summer 2018
pp. 163–185

American Accounting Association
DOI: 10.2308/jmar-52062

# Materializing Innovation Capability: A Management Control Perspective

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**ABSTRACT:** Recent research in strategic management claims that firms need appropriate structures for capabilities to materialize into performance. Following this argument, we posit that the design of management control systems influences a firm's ability to exploit innovation capability and translate it into innovation performance. While we argue for value communication and employee selection as suitable control practices in this context, we expect performance monitoring and behavior monitoring to obstruct the materialization of innovation capability in organizations. Moreover, we elucidate the role of perceived environmental uncertainty as a relevant contextual factor that influences the costs and benefits of management control practices and the extent to which they can support or hinder the innovation process. We empirically test our hypotheses by combining survey data with patent information of the firms in our sample. In sum, our study contributes to the innovation literature within and beyond the field of accounting by highlighting the crucial role of management control in translating a firm's innovation capability into actual innovation performance.

**Keywords:** innovation capability; value communication; employee selection; performance monitoring; behavior monitoring; innovation performance; resource based view.

## INTRODUCTION

Innovation is widely regarded as one of the key sources of competitive advantage in a constantly changing business environment (Davila, Foster, and Oyon 2009). Its relevance is underscored by the considerable amount of research on management control systems (MCS) in the context of innovation, which entails a long-standing debate and very different views on how innovation and MCS may be connected (Bisbe and Otley 2004; Chenhall and Moers 2015; Davila et al. 2009). In order to contribute to this discussion and create a more nuanced view on the role of management control for innovation, we rely on insights from management literature, which has long diverged from viewing innovation as a monolithic concept toward considering both innovation antecedents (e.g., capabilities) and innovation outcomes as separate variables (e.g., Atuahene-Gima 2005; Garcia and Calantone 2002). Most interestingly, management scholars posit that innovation capability *per se* does not necessarily directly translate into innovation outcomes and that apart from having the necessary capabilities for innovation, firms also need to pay attention to the successful exploitation of these capabilities (Menguc and Auh 2010).

In this study, we thus combine insights from the strategic management and management control literatures to investigate the role of management control practices in translating innovation capability into innovation performance. Recent studies on the Resource Based View of the firm suggest that differences in the productivity of resources and capabilities, rather than heterogeneity in resource and capability endowments *per se,* explain performance differentials (Newbert 2007). In other words,

We appreciate the comments and suggestions of Roland Speklé (editor) and the two anonymous reviewers. This study has also benefited from comments made by Josep Bisbe, Evelyn Braumann, Antonio Dávila, Angelo Ditillo, Otto Janschek, Frank Moers, and Gerhard Speckbacher. We further gratefully acknowledge the comments made by participants of the 2017 9th Conference on Performance Measurement and Management Control in Nice, the 2017 Academy of Management Annual Meeting in Atlanta, the 2017 European Accounting Association Annual Congress in Valencia, the 2017 Management Accounting Section Midyear Meeting in San Juan, the 2016 Nordic Accounting Conference at Copenhagen Business School, and the 2016 ERMAC Conference at WU Vienna.

Editor's note: Accepted by Roland Speklé.

*Submitted: December 2016*
*Accepted: February 2018*
*Published Online: February 2018*

to realize the value potential of these resources and capabilities, a firm must also be able to create a supportive organizational context (Barney 1997). Given that MCS constitute a major component of the internal organizational environment (Barney 1997; Bisbe and Otley 2004), we introduce the design of the management control system as an important determinant of why some firms are better at translating their innovation capability into innovation performance than other firms. More specifically, we rely on the well-known object-of-control framework by Merchant and Van der Stede (2012) to investigate the extent to which control practices help or hinder a firm in exploiting its innovation capability to drive innovation performance. We focus on four separate control practices, that is, value communication, employee selection, performance monitoring, and behavior monitoring.

Successful innovation outcomes are more likely to be accomplished if firms avoid scenarios in which employees lack direction in the innovation process due to its complex, multiple-function nature (Van de Ven 1986). We expect that value communication supports employees in this regard through shared values (Merchant and Van der Stede 2012) and by establishing an understanding of the overall direction of the firm through "a perception of goal congruence and by helping employees determine what is in the best interest of the collective" (Büschgens, Bausch, and Balkin 2013, 764). We thus hypothesize that the more firms rely on value communication, the better they are able to translate innovation capability into innovation performance. Similarly, we expect employee selection to positively interact with innovation capability on innovation performance since selecting employees with the proper skills and commitment toward the organization and its goals has been shown to be especially beneficial in complex decision contexts such as innovation processes (Abernethy, Dekker, and Schulz 2015).

Conversely, we expect that a stronger reliance on performance monitoring is less suitable in the context of innovation, as its pre-set performance standards introduce rigidities that reduce a firm's flexibility (Benner and Tushman 2003; Kleinschmidt, de Brentani, and Salomo 2007), as well as create negative behavioral effects among employees (Gardner 2012; Hoskisson and Hitt 1988). We hence argue that the higher the use of performance monitoring, the more firms are limited in materializing innovation capability into innovation performance. We predict a similar effect for behavior monitoring, since it relies on the *ex-ante* definition of procedures that have to be followed by employees. The variance-reducing nature of these practices, however, constrains employees in performing innovative activities and lowers their ability to adapt and learn during innovation processes (Goodale, Kuratko, Hornsby, and Covin 2011; Poskela and Martinsuo 2009).

In a supplementary analysis rooted in contingency-based research (Chenhall 2003), we investigate the sensitivity of these interaction effects between innovation capability and control practices in relation to the level of perceived environmental uncertainty a firm faces. In a situation of high perceived environmental uncertainty, employees not only have to cope with the complexities and immanent uncertainties of innovation processes *per se,* but also have to face uncertainty in the firm's external environment. While the stronger resulting lack-of-direction problem (i.e., employees lacking knowledge of how to individually contribute to innovation processes in light of external uncertainty) (Merchant and Van der Stede 2012) may increase the importance of control practices in guiding employees, it may be, at the same time, harder for controls to fulfill this role in a highly uncertain environment. In other words, the level of perceived environmental uncertainty may influence the costs and benefits of control choices for materializing innovation capability, potentially in different directions for different control practices.

To test our hypotheses, we rely on two separate data sources. We collected survey data of 238 manufacturing companies to measure the independent variables, and match it with patent data to capture innovation performance as a dependent variable. We find support for three out of our four hypotheses: As predicted, our findings indicate a positive and significant interaction effect with innovation capability for value communication, as well as negative and significant interaction effects for both performance monitoring and behavior monitoring. We do not find a statistically significant interaction effect for employee selection in our main sample. Additionally, in our supplementary analysis, we find evidence for the role of perceived environmental uncertainty as a key contingency factor for the effectiveness of control practices in translating innovation capability into innovation performance. While for employee selection and performance monitoring we find effects that are consistent with our initial expectations and stronger in a high-uncertainty setting than under low uncertainty, the results on value communication and behavior monitoring actually run counter to their respective effects in the main model. These findings indeed suggest that perceived environmental uncertainty may impact costs and benefits of control practices differently across control practices.

Our study makes several contributions to the innovation literature within and beyond the field of accounting. First, we pick up on the assumption made in the innovation literature and prior management studies that innovation capability and innovation performance are distinct constructs (Atuahene-Gima 2005). In explicitly considering variation in innovation capability across firms, we deviate from many prior management accounting studies that investigate the average effects of MCS in innovation contexts (e.g., Abernethy and Brownell 1997; Cardinal 2001). This enables us to take a different perspective and shed light on how different control practices influence a firm's ability to materialize innovation capability into innovation performance. Most importantly, we argue that neither innovation capability nor control practices *per se* affect innovation outcomes directly, but

rather drive innovation performance through their interaction. In doing so, our study also differs from the few prior studies that investigate performance implications of MCS, which mostly rely on path models based on the logic that MCS drive performance via intervening variables (e.g., Henri 2006; Widener 2007). Further, we highlight the performance consequences of a potential misalignment between the control system in place and a firm's innovation capability. By taking this different approach, we make a contribution to the literature on how control systems can influence outcomes at the organizational level (Bisbe and Otley 2004; Chenhall 2003; Grafton, Lillis, and Widener 2010).

We also contribute to the debate on whether MCS are beneficial or harmful in innovation-related contexts. While early work considered control practices to be detrimental to creativity and innovation (e.g., Amabile et al. 1996; Damanpour 1991), recent studies have painted a more positive picture indicating beneficial effects of MCS in innovation-related environments (e.g., Bisbe and Otley 2004; Davila 2005; Grabner 2014; Grabner and Speckbacher 2016). Our study provides a more nuanced view by showing that the extent to which individual control practices support or hinder firms in reaping the benefits of innovation capability is not uniform, but depends on the degree of external uncertainty a company faces. In doing so, we also add to prior research by extending contingency arguments to the level of interaction effects. Over and above the academic relevance of our study, the results of this study also inform corporate practice. To realize the benefits from innovation capability, firms have to make sure that they create a suitable organizational context by using appropriate control practices.

The remainder of this study is structured as follows. The second section contains a review on the theoretical background and derives hypotheses. The third section then outlines the research design, including sample, data collection, and main variables. The fourth section presents the empirical findings of our analyses. Finally, the study ends with a discussion of the findings and a conclusion.

## THEORY DEVELOPMENT AND HYPOTHESES

### Prior Literature on MCS and Innovation

Early work on the relationship between the design of MCS and innovation very often utilized the context of R&D departments as a central unit of analysis (e.g., Brownell 1985; Hayes 1977; Rockness and Shields 1984). Rockness and Shields (1984), for example, draw on the task characteristics in the R&D-context (Ouchi 1979) and highlight the importance of input controls such as social controls when there is little knowledge of the transformation process. Using a similar research setting, Abernethy and Brownell (1997) rely on two task characteristics (task analyzability, number of exceptions) to explain the performance implications of accounting, behavior, and personnel forms of control in R&D divisions of large firms. In the case of highest task uncertainty (low task analyzability, high number of exceptions) the authors find positive performance effects for personnel controls and negative performance effects for behavior controls. Interestingly, while Cardinal (2001) finds—consistent with these earlier studies—positive effects of input controls on innovation performance, she finds positive rather than negative effects of output and behavior controls on radical innovation. More recently, Ylinen and Gullkvist (2014) explore the effects of MCS on innovation and find a positive impact of organic controls on innovativeness in exploratory settings.

Overall, conclusions emerging from prior work revolve around the relevance of personnel control for innovation, but these studies provide mixed evidence on the effects of output and behavior controls in highly innovative contexts. Perhaps more interestingly, however, in contrast to management literature, prior management accounting studies on innovation mostly do not explicitly consider innovation capability in their conceptual models and consequently implicitly assume homogeneity of innovation capability across firms. This implicit assumption, however, disregards core tenets of the Resource Based View (i.e., heterogeneity in resource and capability endowments across firms and differences in the productivity of resources and capabilities across firms) (Barney 1991; Newbert 2007). Thus, the (average) effects of MCS on innovation as shown by prior literature might not be uniform, but rather conditional on their interplay with a firm's innovation capability.

Following up on prior management literature (e.g., Atuahene-Gima 2005; Menguc and Auh 2010), we thus bring innovation capability to the center of attention and investigate its interaction with management control practices. In doing so, we deviate from the broad literature looking at average effects between both MCS and innovation performance, and the characteristics of innovation contexts and MCS (e.g., Abernethy and Brownell 1997; Cardinal 2001). In the following section, we will define innovation capability and introduce the causal model that guides our hypothesis development.

### Innovation Capability and the Resource Based View

Following Adler and Shenhar (1990), we define innovation capability as a firm's ability to generate new solutions to address customers' current and future needs. Apart from the pure creation of novelty, innovation capability also encompasses both the ability to introduce new products and services and a firm's processes for carrying out innovation activities that cover, among others, areas such as product development, production processes, and marketing (Chenhall and Moers 2015; Ngo and O'Cass 2012).

The Resource Based View of the firm traditionally attributed performance differences across firms to heterogeneity with regard to resource and capability endowments (Barney 1991).[1] A newly emerging stream within the Resource Based View, which Newbert (2007) refers to as "organizing approach," however, acknowledges that performance differentials might not be caused by absolute differences in resource and capability stocks, but rather by differing levels of productivity of resources and capabilities across firms (Makadok and Barney 2001). Echoing this viewpoint, Gebhardt, Carpenter, and Sherry (2006) underscore the importance of understanding how firm-internal factors aid capability exploitation in order to advance our understanding of performance differentials across firms.

Scholars have incorporated these recent developments and argue that innovation capability only has potential value (Menguc and Auh 2010; Sok and O'Cass 2011), thus calling for the consideration of additional supporting factors responsible for different levels of exploitation of innovation capability (Atuahene-Gima 2005; De Luca, Verona, and Vicari 2010). In line with previous work (Barney 1997; Barney and Mackey 2005; Ketchen, Hult, and Slater 2007; Menguc and Auh 2010), we hence propose that exploiting the value potential of innovation capability depends on the alignment with other important organizational elements such as management control systems, compensation policies, and organizational structure.

Prior MCS research has, in fact, at least partially started to consider the role of management controls in this regard. Bisbe and Otley (2004), for instance, employ a similar causal model and empirically demonstrate a positive and significant interaction effect between innovation and interactive use of MCS on firm performance, suggesting that an interactive use of MCS aids firms in exploiting the value potential of innovation. Corroborating this claim that MCS play a role in the exploitation of capabilities, Grafton et al. (2010) demonstrate a positive relationship between the use of decision-facilitating measures by SBU-level managers for feedback control and the capacity to exploit existing capabilities. Consistent with this literature, we do not expect a direct relationship between control practices and (innovation) performance, but rather that innovation capability and MCS interact to influence innovation performance, thus suggesting an independent-variable interaction model as our causal-model form.[2] These interactions can be interpreted in the sense that MCS influence the degree to which firms are capable of exploiting innovation capability, as described below.

Innovation is a complex phenomenon that entails experimenting, risk-taking, taking advantage of exceptions, uncertainty, and volatility, as well as adapting to unpredictable opportunities (Davila et al. 2009). The management of innovation is further complicated by the fact that innovation usually depends on teamwork, cross-functional collaboration, and knowledge exchange (De Luca and Atuahene-Gima 2007). The involvement of multiple functions and disciplines as well as the necessity for cooperation among employees across different departments causes what Van de Ven (1986) describes as a problem of managing part-whole relationships. This means that employees involved in innovation lose sight of the "big picture" on the process of materializing innovation capability due to the "proliferation of ideas, people and transactions as an innovation develops over time" (Van de Ven 1986, 591), which is very closely related to the lack-of-direction problem outlined by Merchant and Van der Stede (2012). In this context, we expect that MCS serve as a reference point from which employees seek guidance and take their behavioral cues from (Covin and Slevin 2002; Davila and Ditillo 2017). However, applying control practices in this context is a difficult endeavor that requires finding an appropriate balance in guiding employees. While overemphasizing control or choosing inappropriate control practices can easily become detrimental to exploiting innovation capability (Davila et al. 2009), a certain degree of controls appears necessary to ensure that MCS bring guidance to the process without overly constraining it (Poskela and Martinsuo 2009).

Based on both the argument that MCS are major components of the firm-internal environment in the pursuit of innovation activities (Bisbe and Otley 2004) and the aforementioned control problem, we hence posit that properly aligned MCS may be instrumental in exploiting innovation capability and transforming it into innovation performance. Therefore, we state that depending on whether the behavioral cues triggered by the control practices fit the requirements of innovation processes or not, innovation capability can be exploited either more or less.

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[1] While resources serve as inputs into production processes (e.g., capital equipment, human resources, brand names, finance) (Grant 1991), capabilities (in prior literature often also labelled as skills, e.g., Day [1994] and Makadok [2001]) refer to "the capacity to perform a function or activity in a generally reliable manner when called upon to do so" (Amit and Schoemaker 1993; Helfat and Peteraf 2015, 835; Helfat and Winter 2011). Furthermore, capabilities are described as "information-based tangible or intangible processes" (Makadok 2001, 388) that deploy a firm's resources to achieve a desired goal. Capabilities can hence be understood as vehicles to make resources productive. In line with the organizing approach within the Resource Based View, we argue that MCS are part of the organizational support system that drives the productivity of capabilities (Barney 1997; Newbert 2007). This understanding of MCS is also consistent with early definitions of management control as a "process by which managers ensure that resources are obtained and used effectively and efficiently in the accomplishment of the organization's objectives" (Anthony 1965, 17).

[2] While, given our theoretical positions taken, the antecedents of innovation capability are out of the scope of our study, we do acknowledge that MCS might also have a role in building capabilities, as has been shown by Henri (2006). For completeness, we also tested for such an alternative causal model form, that is, an intervening-variable model (Luft and Shields 2003) with innovation capability as an intervening variable between management control practices and innovation performance. The results largely do not support this alternative causal model. First, only employee selection exhibits a positive and significant effect on innovation capability and second, there is no significant direct relationship between innovation capability and innovation performance.

To provide a comprehensive picture of the effectiveness of management control in an innovation setting (i.e., degree of exploitation of innovation capability), we build on the well-known object-of-control framework (Merchant and Van der Stede 2012).[3] In particular, we develop hypotheses on the implications of value communication (cultural control), employee selection (personnel control), performance monitoring (results control), and behavior monitoring (action control) for the exploitation of innovation capability or, more specifically, whether they may support or hinder firms in translating innovation capability into innovation performance.[4]

## Hypothesis Development

Value communication signals and enforces shared values and beliefs, and guides the actions of employees by giving them the ability to determine what is supposedly[5] in the best interest of the organization (Büschgens et al. 2013). Furthermore, it informs employees about the overall direction, decreases different interpretations of goals, and enhances the common understanding of goals (Poskela and Martinsuo 2009). These properties may be especially helpful to support the translation of innovation capability into innovation performance for the following reasons.

Innovation processes are typically characterized by difficulties to assess both market potential and technological feasibility, by a need for broad-scope market and technology search, as well as by long-term time horizons and uncertain returns (Danneels 2002). Attaining positive outcomes from innovation capability hence crucially hinges on firms efficiently screening, accessing, and assimilating knowledge (Nicholls-Nixon and Woo 2003). Since value communication provides a common ground for social action (Bartel and Garud 2009) and has been shown to facilitate the flow of information (Ayers, Dahlstrom, and Skinner 1997; Olson, Walker, and Ruekert 1995), it can be helpful in supporting these knowledge tasks. In a similar vein, Khazanchi, Lewis, and Boyer (2007, 872) suggest that "culture may provide an overarching frame of reference, helping align employee behavior with organizational objectives of innovation and meet paradoxical demands for control and flexibility."

Prior literature also underscores that the aforementioned complexities of innovation processes create innovation paradoxes (e.g., control-flexibility tensions) that may foster mixed messages and role ambiguity for employees (Khazanchi et al. 2007; Van de Ven 1986). Consequently, this leads to lack-of-direction problems for employees, which might inhibit employees' ability to deal with the extraordinary requirements of innovation processes. We posit that value communication is helpful in this regard since it helps guide employees' behavior by clarifying strategic domains while leaving enough leeway for employees to accommodate the dynamic requirements of innovation processes (e.g., coping with uncertainties as new market information emerges, reacting to unanticipated technological problems, probing and experimenting) and make interim improvements (Eisenhardt and Tabrizi 1995; Menguc and Auh 2010). Additionally, value communication aids the exploitation of innovation capability by fostering commitment, communication, and joint decision-making among employees (Koza and Dant 2007; Rijsdijk and van den Ende 2011). We hence reason that the more firms rely on value communication, the better they are able to translate innovation capability into innovation performance. We therefore state the following hypothesis:

**H1:** There is a positive interaction between innovation capability and the use of value communication on innovation performance.

Proper employee selection ensures that employees have the knowledge, skill, and ability to effectively perform their job demands (Patel, Messersmith, and Lepak 2013). The benefits of employee selection become especially salient the more complex and uncertain decision contexts are (Abernethy et al. 2015). As innovation processes are typically characterized by complexity and ambiguity (Van de Ven 1986), we argue that employee selection is helpful for materializing innovation capability. First of all, employee selection ensures that employees have the right competencies for their job, which increases the

[3] While the object-of-control framework is sufficiently comprehensive, there might still be a considerable variety of control practices within the four concepts introduced by Merchant and Van der Stede (2012). Malmi and Brown (2008), for instance, discuss the framework and argue that "[t]he strength of the typology lies in the broad scope of the controls in the MCS as a package, rather than the depth of its discussion of individual systems" (Malmi and Brown 2008, 291). In balancing this trade-off between comprehensiveness and specificity, we decided on using the object-of-control model as a frame and picked one core management control practice within each of the four categories, which we analyze in more detail. This allows us to reflect the broad set of control choices, while, at the same time, being able to formulate hypotheses that can be specific enough in regard to the mechanisms behind the four chosen control practices.

[4] It is important to note that we do acknowledge that control practices are *choices* made by firms. However, we do not assume that these choices are fully driven by capabilities nor that they influence them, and therefore these practices are exogenous in terms of our conceptual model. Our aim is to analyze the role of the control practices in place, which might have been installed by different decision makers for different purposes, and/or are even difficult to implement and/or change.

[5] In fact, just like suitable organizational cultures can contribute to success, flawed cultures often play a crucial role in important problems experienced by companies (e.g., Enron, Volkswagen emissions scandal). Notwithstanding its apparent importance, however, the *content* of a culture is not in the scope of our study. We rather point to the behavioral effects on employees arising from the mere communication of a set of shared values. In doing so, we abstract from the type of culture itself and thus specifically discuss the mechanisms behind value communication as a management control practice to guide employees by communicating values. We thank both reviewers for pointing out this issue.

likelihood that they will exploit the opportunities arising from a firm's innovation capability. Similarly, well-fitting employees perform their jobs more efficiently, which in turn makes them more flexible and frees up time to address the problems and exceptions typically occurring during innovation processes (Patel et al. 2013).

Second, prior literature posits that employee selection for goal alignment becomes more effective when managers are exposed to relatively high behavioral uncertainty (Grabner and Speckbacher 2016). Hiring practices can be used to sort employees according to their values and their commitment to organizational goals (e.g., Heskett, Sasser, and Schlesinger 2003; Snell 1992) in order to decrease the likelihood of dysfunctional behavior that might remain undetected by managers (Grabner and Speckbacher 2016).

Third, having highly skilled and committed employees also helps firms better integrate knowledge residing within a variety of different employees and consequently harness the strengths of innovation capability (Martinsons 1995; Scarbrough 2003). In addition to internal knowledge processes, proper employee selection also ensures that employees are capable of gathering and processing external information, which is especially important for innovation capability to thrive (Gupta, Raj, and Wilemon 1986). Thus, we state that employee selection increases the productivity of innovation capability.

**H2:** There is a positive interaction between innovation capability and the use of employee selection on innovation performance.

Performance monitoring involves the use of performance measures to monitor the achievement of pre-defined targets. Typically, the focus is set on the accomplishment of goals by correcting deviations from pre-set performance standards. Critical performance variables are monitored to coordinate the implementation of intended strategies (Henri 2006).

Returns from innovations, however, are not as easily captured *ex-ante* as they are uncertain, remote in time, and distant from the locus of action (Danneels 2002; Lavie, Stettner, and Tushman 2010). Moreover, innovation processes entail a multitude of uncertainties (Kleinschmidt et al. 2007) and very often follow an unpredictable commercialization process (Stringer 2000). Their outcome hinges on a firm's ability to take appropriate account of new knowledge, create variety, and flexibly exploit windows of opportunity (Danneels 2002; Soosay and Hyland 2008). As performance monitoring increases, however, it becomes more difficult to accommodate the multiple uncertainties and the need for information-processing capacity inherent in innovation processes. The resulting lack of flexibility might even lead to the exclusion or mismanagement of innovation processes (Kleinschmidt et al. 2007). As a consequence, the more firms rely on performance monitoring, the stronger the rigidities and variance-reducing mindset that prevent firms from reaping the benefits of an existing innovation capability become.

Apart from the misfit between the properties of performance monitoring and the features of innovation processes, there are also negative behavioral effects on employees that may hamper the exploitation of innovation capability. Performance monitoring affects employees' assessment of performance risk (Hoskisson and Hitt 1988) and introduces performance pressure (Gardner 2012). Previous research indicates that as the use of performance monitoring increases, employees are more likely to display risk-averse behaviors, rely on proven knowledge and routines, and take actions with predictable outcomes (Gardner 2012; Hoskisson and Hitt 1988). Additionally, the higher the use of performance monitoring, the more likely it limits employees' search span to strategically familiar areas (Poskela and Martinsuo 2009), thus potentially shifting their balance between divergent and convergent thinking toward the latter (Speckbacher 2017).

Based on both the misfit-argument as well as the behavioral implications outlined above, we conjecture that the more firms focus on performance monitoring, the less the value potential of innovation capability is exploited (Menguc and Auh 2010). We thus derive the following hypothesis:

**H3:** There is a negative interaction between innovation capability and the use of performance monitoring on innovation performance.

Behavior monitoring involves the standardization, monitoring, and approval of employees' tasks and activities. The effectiveness of behavior monitoring depends on managers' knowledge of the transformation process whereby ideas are turned into successful innovations. In light of the high failure rates of innovation projects observed in corporate practice, Bonner, Ruekert, and Walker (2002) argue that managers' knowledge of the transformation process is far from perfect. These knowledge deficits in turn render behavior monitoring ineffective or even detrimental to managing innovation processes.

Relatedly, behavior monitoring puts constraints on how innovative behaviors and initiatives are carried out (Cardinal 2001). These restrictions limit a firm's ability to learn during innovation processes, thereby diminishing the value of innovation capability (Goodale et al. 2011). Other factors associated with behavior monitoring that reduce the value-creating potential of innovation capability are reduced flexibility (Tatikonda and Rosenthal 2000), slower adaption capabilities (Poskela and Martinsuo 2009), and negative attitudes among employees (Ramaswami 1996). While successful innovation processes require variation-increasing activities, behavior monitoring introduces a variance-reducing mindset (Benner and Tushman 2003). We

therefore propose that the more firms rely on behavior monitoring, the less they are able to translate innovation capability into innovation performance. We formulate the following hypothesis:

**H4:** There is a negative interaction between innovation capability and the use of behavior monitoring on innovation performance.

## EMPIRICAL STUDY

### Sample and Data Collection

To test our hypotheses, we collected data on medium-sized firms in Germany and Austria using a survey method and subsequently added the firms' patent output retrieved from the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT).

The selection of firms contacted was based on data obtained from the Markus database (Bureau van Dijk Electronic Publishing). For the purpose of this study, we defined companies with 50 to 250 employees as medium-sized and excluded firms with more than one line of business. Both choices were intended to ensure that the firms in our study do not exhibit several distinct sets of control systems[6] or different levels of innovation capability across different parts of the organization. In addition, prior literature indicates that small- and medium-sized firms do not tend to structurally separate their innovation processes from the rest of the organization and hence very often do not have a separate R&D department (Lubatkin et al. 2006; Patel et al. 2013). Furthermore, Mitchell and Reid (2000) argue that the impact of MCS can be studied more directly in SMEs compared to larger firms. Overall, we thus argue that in the SME-context the whole firm constitutes a suitable unit of analysis for the purposes of this study. Finally, we also narrowed the sampling frame to manufacturing firms in the engineering industry (C280-C289), which can be considered an especially fitting environment for studying innovation through patent output, since it belongs to the few sectors where the majority of product and process innovations are actually patented (Arundel and Kabla 1998).

The specifications described above resulted in a target population of 2,465 firms, out of which a random sample of 1,400 firms was drawn. We then hand-collected the contact information of the general managers in these organizations, since it can be assumed that they are the most knowledgeable persons on organizational design choices in medium-sized companies (Grabner 2014). Given a lack of retrievable information on 43 managers, this process resulted in a total of 1,357 firms, which were contacted via email and asked to fill in a structured online questionnaire between winter 2008 and spring 2009. Over this period, we sent out four reminder emails and conducted follow-up calls, which generated a total of 238 completed questionnaires and a resulting response rate of 17.5 percent.

As a next step, we added patent information—more specifically, data on all granted patents filed in the six years after our survey took place (2009–2014)—to the individual firm observations. The six-year time frame allows us to capture a more robust measure of innovation performance, especially since prior research has argued for a potential multi-year time lag between innovation antecedents and actual patent applications (Kondo 1999). To retrieve the data, we made use of the 2015 Autumn Edition of the PATSTAT database, a consolidated dataset of patent activity in over 80 countries provided by the European Patent Office (2015). To obtain firm-level patent information, we queried the database by firm names, building on the name harmonization efforts by ECOOM, Eurostat, and SOGETI,[7] and considering abbreviations and other potential name variations. We then manually checked the matched patent data and excluded all patents that did not definitively correspond to the respective firm, thus following a rather conservative approach.

The average firm within this sample had 104 employees (s.d.: 52) and was 54 years old (s.d.: 42) in 2009. 84 percent of the respondents were general managers, while the remaining 16 percent were mostly high-ranking functional heads in their organization.

Given that we employed follow-up procedures to increase our response rate, we controlled for nonresponse bias. We used univariate ANOVAs in line with Armstrong and Overton (1977) and did not find significant differences between early and late respondents in regard to the items used in the survey.

[6] While we cannot fully rule out that control systems vary across departments and tasks in SMEs as well, we argue that there is less variety in this respect compared to larger firms. This conclusion is based on the idea that SMEs tend to lack the resources needed for supporting a variety of control mechanisms and tend to have, on average, less complex control systems in place (Garengo, Biazzo, and Bititci 2005).

[7] For further reference, see, Magerman, Grouwels, Song, and Van Looy (2009), Peeters, Song, Callaert, Grouwels, and Van Looy (2009), Du Plessis, Van Looy, Song, and Magerman (2009).

### Measurement of the Dependent Variable

*Innovation Performance* (*IP*) was measured using patent data from EPO's PATSTAT database. Building on key contributions of Jaffe and Trajtenberg (2002), empirical innovation research has frequently turned to the use of patent data for measuring innovation output. To do so, studies have both employed the count of granted patents (e.g., Berry 2014, Yanadori and Cui 2013) and the number of citations received by a firm's patents (e.g., Kehoe and Tzabbar 2015, Tian and Wang 2011), the latter of which is typically used to proxy for the technological impact or radicality of inventions (e.g., Kaplan and Vakili 2014). Given that our dependent variable intends to capture overall innovation performance (and thus both radical and incremental components), we follow the former approach in counting the number of granted patents for the firms in our sample. In fact, the legal requirements for a patent to be granted—i.e., making a novel, significant, and useful advance over existing knowledge (Somaya 2012)—coincide strongly with our conceptualization of innovation performance as the materialization of innovation capability.

More concretely, we use the number of granted patent families with a priority date from 2009 to 2014 to measure innovation performance. A patent family is a set of related patents across countries which protect the same invention. Controlling for families thus avoids double-counting the same invention multiple times. The priority date is the first date of filing a patent application and, as such, is the closest to the date of invention. By considering both patent families and priority dates, we are following the recommendations made in the OECD Patent Statistics Manual (OECD 2009).

The descriptive statistics for innovation performance show that, on average, a firm in our sample was granted 1.19 patents since 2009 with a standard deviation of 3.98 patents. This relation of standard deviation to mean corresponds with the typical distribution found in patent (count) data and is comparable to other studies using similar data (e.g., Penner-Hahn and Shaver 2005).

### Measurement of the Independent Variables and Control Variables

The independent and control variables employed in this study were collected through a structured survey with closed-ended questions in 2009. Where possible, existing multi-item constructs were adopted from prior literature[8] and slightly adapted to fit the specific empirical setting. This was realized by pretesting the survey instrument with four academics and five practitioners, whose remarks led to verbal refinements to clarify terminology and enhance the comprehensibility of the questions. All independent variables are multi-item constructs measured on a Likert scale with a range of 1 to 7. The respondents were asked to assess to what extent the statements applied in their organizations, with the end points anchored as 1 "does not apply" and 7 "fully applies."

Given the central role of construct validity in advancing survey-based MCS-research (Bedford and Speklé 2018), we performed several analyses to ensure the reliability and validity of our measures. We conducted factor analyses, tested Cronbach's alpha, and reviewed the response ranges of our variables. Table 1 shows a summary of the results, which overall support the unidimensionality of the constructs employed in this study. Based on this analysis, we then computed the final variables by averaging the items for each construct. As a next step, we analyzed the descriptive statistics and correlation matrix for all survey constructs. The results in Table 2 further support their discriminant validity, given that no inter-item correlation exceeds the Cronbach's alphas illustrated in the diagonals of the correlation matrix (Churchill 1979).

*Innovation Capability* (*IC*) was measured by adapting an existing scale called "competence exploration" used by Atuahene-Gima (2005).[9] The scale refers to the acquisition of competencies that focus on emerging markets and technologies, which corresponds to our conception of innovation capability as an antecedent for innovation outcomes. After our pretests with practitioners, we retained three items that referred to the firm's development of new product development skills and processes new to the industry, innovation skills in areas with no prior experience, and entirely new capabilities that are important for innovation. We established a three-year timeframe in our questions to measure the extent to which the firms had successfully acquired these competencies prior to our survey as an indicator for the presence of innovation capability.

The *Management Control Variables* we employed in this study were all based on pre-established items in empirical management control research which capture the same or similar concepts. We used the existing items as a starting point and refined them in qualitative pretests for our setting. As such, *Value Communication* (*VC*) was measured based on a scale from Widener (2007). Our final construct captures the firm's use of management controls that communicate its values, objectives, and corporate philosophy to employees. *Employee Selection* (*ES*) was adapted from Widener (2004) and refers to a firm's

[8] Given potential language barriers among our targeted respondents, the English constructs were translated into German. To ensure validity, all items were also translated back by an independent academic and checked against the initial wording.

[9] The term *innovation capability* is used extensively in the innovation literature (e.g., Ngo and O'Cass 2012; Romijn and Albaladejo 2002) and corresponds to the term *competence exploration,* which is more frequently employed in the marketing and management literatures (Atuahene-Gima 2005).

**TABLE 1**

**Construct Validity**

| | **Factor** |
|---|---|
| *Innovation Capability* (*IC*) | (0.71) |
| We have learned product development skills and processes (such as product design, prototyping, and customizing products for local markets) entirely new to the industry | **0.811** |
| We have strengthened innovation skills in areas with no prior experience | **0.831** |
| We have developed entirely new capabilities that are important for innovation (forecasting technological and customer trends, managing the product development process) | **0.892** |
| *Value Communication* (*VC*) | (0.75) |
| Our corporate objectives and the underlying corporate philosophy (mission statement) are deliberately communicated to employees | **0.908** |
| Our company consistently makes an effort to remind employees of our corporate philosophy (mission statement) | **0.917** |
| Our employees are aware of our company's core values | **0.899** |
| When recruiting new employees, we select applicants that fit especially well with our corporate philosophy (values, mode of operation) | **0.720** |
| *Employee Selection* (*ES*) | (0.63) |
| Our company invests an above-average amount of resources (time, money) in the recruiting process | **0.824** |
| We take pride in the fact that we hire the best employees available on the market | **0.743** |
| Candidates are required to undergo a multi-stage application process before being hired | **0.819** |
| *Performance Monitoring* (*PM*) | (0.81) |
| To what extent does your organization use performance measures (e.g., revenues, product quality) for the following purposes: | |
| Continuous tracking of progress towards goals | **0.884** |
| Monitoring results | **0.921** |
| Comparing outcomes to expectations | **0.891** |
| *Behavior Monitoring* (*BM*) | (0.56) |
| Even in matters of minor importance, the final decision has to be approved by a supervisor | **0.745** |
| There are standardized processes for a considerable share of the tasks performed by our employees | **0.688** |
| At our company, the employees' decisions and activities are monitored on an ongoing basis | **0.814** |
| *Perceived Environmental Uncertainty* (*PEU*) | (0.64) |
| The purchasing behavior of our company's customers can be predicted very well (R) | **0.782** |
| Technological advances in our company's main industry can be predicted very well (R) | **0.844** |
| The behavior and/or strategies of our suppliers can be predicted very well (R) | **0.791** |
| The behavior and/or strategies of our competitors can be predicted very well (R) | **0.781** |
| *Perceived Performance* (*PP*) | (0.82) |
| Compared to our main competitors the overall development of our company was very good | **0.924** |
| Compared to our main competitors the profitability of our company was very good | **0.886** |
| Compared to our main competitors the revenue trend of our company was very good | **0.909** |
| *Slack* (*SL*) | (0.72) |
| The firm has many resources available in the short run to fund initiatives | **0.894** |
| We consciously leave a lot of leeway in regards to resources to our employees so they can react flexibly to new circumstances and opportunities | **0.842** |
| In many areas, resources can be quickly made available so that our employees can flexibly realize projects | **0.807** |

This table provides an overview on the factor loadings per item (in bold), as well as the average variance extracted per construct (in parentheses in the top line of each construct). Reverse-coded items are marked with (R).

emphasis on recruiting as a form of management control, including resource allocations, scale, and quality of the recruiting process. *Performance Monitoring* (*PM*) was measured using three items related to the extent to which a firm exerts control through the use of performance measures to continuously track progress toward goals, monitor results, and compare outcomes to expectations. We based these items on a scale developed by Henri (2006). Finally, the items for *Behavior Monitoring* (*BM*) were also adapted from prior management control literature (e.g., Bonner et al. 2002) and closely correspond to the construct

**TABLE 2**

**Descriptive Statistics and Correlation Matrix of Variables**

**Panel A: Descriptive Statistics (n = 238)**

| | Number of Items | Mean | Std. | Min. | 1st Q. | Med. | 3rd Q. | Max. |
|---|---|---|---|---|---|---|---|---|
| *IP* | 1 | 1.19 | 3.98 | 0.00 | 0.00 | 0.00 | 1.00 | 41.00 |
| *IC* | 3 | 4.31 | 1.37 | 1.00 | 3.33 | 4.50 | 5.33 | 7.00 |
| *VC* | 4 | 5.12 | 1.22 | 1.00 | 4.50 | 5.25 | 6.00 | 7.00 |
| *ES* | 3 | 3.83 | 1.31 | 1.00 | 2.67 | 3.67 | 5.00 | 7.00 |
| *PM* | 3 | 5.45 | 1.22 | 1.00 | 5.00 | 5.67 | 6.33 | 7.00 |
| *BM* | 3 | 3.70 | 1.14 | 1.00 | 3.00 | 3.67 | 4.33 | 7.00 |
| *PEU* | 4 | 3.67 | 1.06 | 1.00 | 3.00 | 3.75 | 4.25 | 7.00 |
| *PP* | 3 | 5.26 | 1.15 | 1.00 | 4.67 | 5.33 | 6.00 | 7.00 |
| *SL* | 3 | 3.85 | 1.36 | 1.00 | 3.00 | 4.00 | 5.00 | 7.00 |
| *FS* | 1 | 4.53 | 0.48 | 3.30 | 4.13 | 4.45 | 4.94 | 5.52 |

*, **, *** Represent $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively, two-tailed test.

**Panel B: Correlation Matrix**

| | *IP* | *IC* | *VC* | *ES* | *PM* | *BM* | *PEU* | *PP* | *SL* | *FS* |
|---|---|---|---|---|---|---|---|---|---|---|
| *IP* | — | | | | | | | | | |
| *IC* | 0.067 | 0.795 | | | | | | | | |
| *VC* | 0.066 | 0.206*** | 0.884 | | | | | | | |
| *ES* | 0.010 | 0.378*** | 0.468*** | 0.707 | | | | | | |
| *PM* | 0.015 | 0.163** | 0.369*** | 0.220*** | 0.875 | | | | | |
| *BM* | 0.020 | 0.102 | 0.145** | 0.134** | 0.092 | 0.608 | | | | |
| *PEU* | −0.024 | −0.291*** | −0.145** | −0.235*** | −0.196*** | −0.181*** | 0.811 | | | |
| *PP* | 0.186*** | 0.170*** | 0.284*** | 0.135** | 0.223*** | 0.026 | −0.259*** | 0.891 | | |
| *SL* | −0.030 | 0.092 | 0.154** | 0.157** | −0.002 | 0.045 | −0.113* | 0.097 | 0.806 | |
| *FS* | 0.210*** | 0.179*** | 0.140** | 0.229*** | 0.092 | 0.019 | −0.202*** | 0.177*** | −0.187*** | — |

*, **, *** Represent $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively, two-tailed test.
The diagonal of the matrix shows the Cronbach's alpha for each variable (No value available for *IP and FS*, since they are not measured with a survey construct). The other cells of the table report bivariate correlation coefficients.

**Panel C: Cross-Tables**

| | Low VC | High VC | Total | Low ES | High ES | Total |
|---|---|---|---|---|---|---|
| *Low IC* | 71 | 48 | 119 | 83 | 36 | 119 |
| | (30%) | (20%) | | (35%) | (15%) | |
| *High IC* | 49 | 70 | 119 | 49 | 70 | 119 |
| | (21%) | (29%) | | (21%) | (29%) | |
| Total | 120 | 118 | 238 | 132 | 106 | 238 |

Observations were split at the median values of *IC*, *VC*, *ES*, *PM*, and *BM*. Relative amount of observations per quadrants to total observations are in parentheses.

*(continued on next page)*

used by Rijsdijk and van den Ende (2011) in measuring the standardization, monitoring, and approval of employees' tasks and activities.[10] As a final step, we added perceived environmental uncertainty, perceived performance, slack, and firm size as

[10] Given potentially different job goals and control systems for employees solely involved in administrative or supporting activities, we limited the scope of the questions on MCS to employees that take a direct part in the process of creating products and services (including all activities ranging from R&D to manufacturing).

**TABLE 2 (continued)**

**Panel D: Cross-Tables (Continued)**

| | Low PM | High PM | Total | Low BM | High BM | Total |
|---|---|---|---|---|---|---|
| *Low IC* | 65 | 54 | 119 | 75 | 44 | 119 |
| | (27%) | (23%) | | (32%) | (18%) | |
| *High IC* | 61 | 58 | 119 | 66 | 53 | 119 |
| | (26%) | (24%) | | (28%) | (22%) | |
| Total | 126 | 112 | 238 | 141 | 97 | 238 |

Observations were split at the median values of *IC*, *VC*, *ES*, *PM*, and *BM*. Relative amount of observations per quadrants to total observations are in parentheses.

*Control Variables. Perceived Environmental Uncertainty* (*PEU*), which prior research has identified as a key variable in innovation studies (e.g., Calantone and Rubera 2012), was measured based on an established scale adapted from Moers (2006). Its items measure the extent to which the firm can predict customer behavior, technological changes in the industry, as well as the behavior and strategies of suppliers and competitors. *Perceived Performance* (*PP*) was introduced, since better-performing firms may be assumed to have more funds available to invest in research and development and, more importantly, to finance the patenting process, which, according to literature from practice, typically comes with high financial costs (OECD 2009). We measured the construct based on a scale by Widener (2007) and asked firms to answer the questions retrospectively for the prior three years.[11] Prior innovation research has paid special attention to the relationship between slack resources and innovation performance (e.g., Damanpour 1991; Nohria and Gulaty 1996). Slack is argued to serve as a facilitator of innovation performance since it acts as encouragement to experiment, engage in risk-taking, and make proactive strategic choices (Chen and Huang 2010). Given its central position as an explanatory variable in innovation research (Nohria and Gulaty 1996), *Slack* (*SL*) was hence introduced as a further control variable. We based our items on the construct developed by Atuahene-Gima (2005) and slightly adjusted them to fit our setting. Finally, *Firm Size* (*FS*) was introduced as a fourth control variable to control for the effect the mere number of employees in an organization may have on the number of inventions made. It was measured using the natural logarithm of the number of employees, which we accessed from publicly available data on the firms that we surveyed.

## RESULTS

### Model Specification

Given that we measure innovation performance as a count variable which only takes nonnegative integer values and has a skewed distribution, a simple (multiple) linear regression model is not the most suitable choice. In fact, count-based models, such as the Poisson regression model, have been frequently used to match this type of data (Greene 2003). The basic Poisson regression, however, implicitly assumes that the variance of the dependent variable is equal to the mean, which can lead to an underestimation of standard errors and spuriously high levels of significance in the case of over-dispersed data (Cameron and Trivedi 1986). To counteract this issue, more generalized forms, such as negative binomial models, have been proposed in the past (Hausman, Hall, and Griliches 1984). Since our data shows the typical pattern of patent counts, including over-dispersion, we use a negative binomial regression model to test our hypotheses. This is in line with a large number of studies working with patenting figures (e.g., Miller, Fern, and Cardinal 2007; Penner-Hahn and Shaver 2005).

More specifically, given that our dependent variable exhibits a large amount of zero-observations, we employ a zero-inflated version of the negative binomial regression, which simultaneously generates an additional model predicting the occurrence of zero-observations in our data (Lambert 1992). In doing so, we separately model and control for the possibility of firms not being active in patenting at all (e.g., because they may follow other strategies, such as secrecy, to protect their inventions).[12] As a

[11] Due to the fact that objective data on performance of SMEs are very often not available (Lubatkin et al. 2006), we used a perceptual performance measure. While there has been quite some debate around the use of subjective versus objective measures of firm performance in prior management accounting research (e.g., Chenhall 2003; Selto, Renner, and Young 1995), Venkatraman and Ramanujam (1987) find a strong convergence between the two different methods. Nevertheless, we sought to test the appropriateness of our subjective measure. To do so, we were able to collect objective performance data (available for about half of our sample, i.e., 118 companies). In line with prior research in the SME-context (Dess and Robinson 1984), we also find a significant and positive correlation for those firms where objective performance data are available. Thus, we feel confident that our subjective assessment of performance accurately captures our construct of interest.

[12] In other words, we statistically separate the zero-observations of non-patenting firms from firms active in the patenting process that simply have not produced a patent in the years after our survey.

**TABLE 3**
**Main Analysis**

| Main Model | Model 1 | Model 2 |
|---|---|---|
| *IC* | −0.009 | 0.077 |
| | (0.146) | (0.139) |
| *VC* | −0.124 | −0.144 |
| | (0.124) | (0.114) |
| *ES* | −0.036 | −0.010 |
| | (0.138) | (0.138) |
| *PM* | −0.062 | 0.009 |
| | (0.119) | (0.100) |
| *BM* | 0.167 | 0.201* |
| | (0.116) | (0.118) |
| *PEU* | 0.246* | 0.480*** |
| | (0.145) | (0.132) |
| *PP* | 0.598*** | 0.572*** |
| | (0.139) | (0.129) |
| *SL* | −0.034 | −0.055 |
| | (0.095) | (0.081) |
| *FS* | 0.959*** | 1.076*** |
| | (0.314) | (0.301) |
| Intercept | −4.019*** | −4.738*** |
| | (1.496) | (1.447) |
| ***IC* × *VC*** | | 0.317** |
| | | (0.154) |
| ***IC* × *ES*** | | 0.059 |
| | | (0.120) |
| ***IC* × *PM*** | | −0.153* |
| | | (0.080) |
| ***IC* × *BM*** | | −0.205** |
| | | (0.082) |
| Inflate-Model | | |
| Prior Patents | −1.278*** | −1.145*** |
| | (0.347) | (0.299) |
| Intercept | 0.580 | 0.572* |
| | (0.353) | (0.340) |
| Log-pseudolikelihood | −276.30 | −268.29 |
| Wald Chi-square | 31.43 | 51.96 |
| Prob. > Chi-square | 0.000 | 0.000 |
| n | 238 | 238 |

*, **, *** Indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively, two-tailed test.
Robust standard errors are in parentheses. *IC*, *VC*, *ES*, *PM*, *BM*, *PEU*, *PP*, and *SL* are mean-centered.

predictor for this inflation-part of the model, we use the number of patents the firm produced in the six years prior to our survey (*Prior Patents*).

To control for possible heteroscedasticity, we also analyzed and report all models based on robust standard errors. In addition, to avoid potential effects from multicollinearity stemming from the interaction terms in Models 2 and 3, we mean-centered all survey constructs before entering them in our regression models (Aiken and West 1991).

As a basis for testing our hypotheses, we estimate a regression with the main effects of our independent variables, including controls, as a baseline model. Table 3 presents the results of this analysis (Model 1). Neither *IC* nor any of the MCS-variables appear to have a significant main effect on innovation performance, suggesting that on average—at least in our sample—innovation capability, value communication, employee selection, performance monitoring, and behavior monitoring by themselves do not significantly translate into innovation performance. This can, in fact, be seen as a first hint that the translation of innovation capability into innovation performance is contingent on its interplay with other variables. Overall, a

Wald test shows that our model significantly differs from the implied null hypothesis that the regression coefficients are equal to zero (Wald Chi-square = 31.43, p = 0.000).

### Hypotheses Tests

In order to test our hypotheses, we specify an interaction equation including four interaction terms for innovation capability with value communication, employee selection, performance monitoring, and behavior monitoring, respectively. The appropriate use of an interaction specification requires that the interacting variables are not strongly related, in the sense that certain values of one variable are only observed in combination with certain values of the other one (Hartmann and Moers 2003). The cross-tables in Table 2 (Panel C and Panel D) show that none of the distributions of firms across the four quadrants of high versus low *IC* and high versus low values of the four MCS-variables is heavily skewed, thus suggesting that capabilities and control practices are not aligned. This lends empirical support to our approach of estimating an interaction model (Table 3, Model 2).

Looking at the interaction coefficients we find support for three out of four hypotheses. As predicted, we encounter a positive, statistically significant coefficient for the interaction term of *IC* and *VC* (0.317; $p < 0.05$, two-tailed), as well as negative interaction coefficients for both *IC* and *PM* (–0.153; $p < 0.10$, two-tailed) and *IC* and *BM* (–0.205; $p < 0.05$, two-tailed). While these results thus represent empirical evidence for H1, H3, and H4, we do not find a statistically significant result for H2.

### Supplementary Analysis: The Role of Perceived Environmental Uncertainty

To deepen our understanding of these findings, and most importantly the lack of support for H2, we follow up on recent calls to shed light on boundary conditions of the Resource Based View (Ketchen, Hult, and Slater 2007; Schilke 2014). Contingency-based research has long acknowledged that the effectiveness of control choices differs depending on the context the firm operates in (Chenhall 2003). As discussed before, a fundamental characteristic of innovation is the uncertainty inherent to the innovation process in terms of technological uncertainty and project scope (O'Connor and Rice 2013; Shenhar and Dvir 1996). However, next to these uncertainties internal to the firm, at the same time such firms can also be exposed to varying degrees of uncertainty related to the external environment a firm faces (Davila 2000). Accordingly, the innovation literature describes perceived environmental uncertainty as one of the most important contingency factors since it exhibits influence on firms' information processing needs (Bisbe and Malagueño 2012; Calantone and Rubera 2012; O'Connor and Rice 2013).

Perceived environmental uncertainty typically implies that employees perceive themselves to be unable to comprehensively understand how the environment might change, the impact of those changes on means-ends relationships, and whether courses of action taken may still be successful (Bstieler 2005). Under such conditions, employees thus have to cope with an increased amount of complexity brought about by several factors, such as the need to make quick choices (Cannella, Park, and Lee 2008), to invest more time in information collection and interpretation (Bstieler 2005), and to be responsive to environmental changes (Moers 2006). Consequently, extant literature arrives at the conclusion that employees who are exposed to uncertain environmental conditions are in greater need for direction and guidance from top management (Agle, Nagarajan, Sonnenfeld, and Srinivasan 2006).

Internal and external forms of uncertainty are different from one another and need not move in the same direction (O'Connor and Rice 2013). However, if they do, firms need not only cope with the uncertainty stemming from innovation processes *per se,* but also need to face uncertainty coming from the external firm environment. Accordingly, we expect that the level of perceived environmental uncertainty influences the costs and benefits of the control choices made in an innovation context. Based on the increased complexity caused by high PEU, it is likely that employees have a higher need for guidance through the control system, rendering control practices that fulfill this function more important. At the same time, high PEU also increases the benefits of giving employees more freedom to react flexibly to unforeseen events and exploit their informational advantages. Consequently, high PEU makes it more difficult for control practices to satisfactorily fulfill their guidance role, which might make them less effective or even more counterproductive given that newly emerging market information during innovation processes requires flexible and swift decision-making (Bstieler 2005; Iansiti 1995). Thus, we investigate in a follow-up analysis, how far the proposed interaction effects are sensitive to the perceived level of uncertainty in a firm's external environment.

To do so, we split our sample into a subsample of firms at or below the median level of *PEU* (3.75) and a subsample of firms above this value. We then run our main-effect regression models (Table 4, Models 3a and 3b) and the regression model including the interaction effects on both subsamples separately (Table 4, Models 4a and 4b).

We find a positive, statistically significant interaction effect of *IC* and *VC* (0.552; $p < 0.01$, two-tailed) in the low-*PEU* subsample. However, the coefficient turns negative for high-*PEU* observations (–0.362; $p < 0.10$, two-tailed), suggesting that the use of value communication may actually become harmful for translating innovation capability into innovation performance

**TABLE 4**
**Supplementary Analysis**

| | Low PEU | | High PEU | |
|---|---|---|---|---|
| **Main Model** | **Model 3a** | **Model 4a** | **Model 3b** | **Model 4b** |
| *IC* | 0.015 | 0.114 | 0.079 | 0.084 |
| | (0.142) | (0.148) | (0.241) | (0.178) |
| *VC* | −0.238 | −0.443*** | 0.242 | 0.368** |
| | (0.157) | (0.147) | (0.187) | (0.168) |
| *ES* | 0.205 | 0.313* | −0.368 | −0.273* |
| | (0.141) | (0.186) | (0.232) | (0.156) |
| *PM* | −0.097 | 0.111 | −0.028 | −0.155 |
| | (0.153) | (0.129) | (0.167) | (0.157) |
| *BM* | −0.035 | 0.134 | 0.300 | 0.154 |
| | (0.145) | (0.141) | (0.216) | (0.175) |
| *PP* | 0.565*** | 0.463** | 0.509*** | 0.371* |
| | (0.171) | (0.186) | (0.144) | (0.190) |
| *SL* | 0.049 | −0.018 | 0.003 | 0.123 |
| | (0.116) | (0.118) | (0.192) | (0.153) |
| *FS* | 0.976 | 1.339*** | 1.145** | −0.098 |
| | (0.383)** | (0.412) | (0.547) | (0.476) |
| Intercept | −4.313** | −6.414*** | −4.648* | 0.946 |
| | (1.825) | (2.025) | (2.484) | (2.169) |
| ***IC* × *VC*** | | 0.552*** | | −0.362* |
| | | (0.159) | | (0.197) |
| ***IC* × *ES*** | | −0.201 | | 0.440*** |
| | | (0.150) | | (0.137) |
| ***IC* × *PM*** | | −0.094 | | −0.332** |
| | | (0.136) | | (0.168) |
| ***IC* × *BM*** | | −0.268*** | | −0.097 |
| | | (0.074) | | (0.245) |
| Inflate-Model | | | | |
| *Prior Patents* | −1.320*** | −1.310*** | −1.178* | −1.251** |
| | (0.410) | (0.440) | (0.684) | (0.541) |
| Intercept | 0.277 | −0.054 | 1.007* | 1.472*** |
| | (0.439) | (0.520) | (0.592) | (0.423) |
| Log-pseudolikelihood | −171.786 | −161.96 | −99.55 | −89.00 |
| Wald Chi-square | 33.15 | 80.93 | 18.97 | 855.56 |
| Prob. > Chi-square | 0.000 | 0.000 | 0.015 | 0.000 |
| n | 138 | 138 | 100 | 100 |

*, **, *** Indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively, two-tailed test.
Robust standard errors are in parentheses. *IC*, *VC*, *ES*, *PM*, *BM*, *PEU*, *PP*, and *SL* are mean-centered.

in settings of high perceived environmental uncertainty. This finding suggests that the benefits of value communication in the form of increased guidance (e.g., reduced role conflict and role ambiguity experienced by employees) are outweighed by the costs that go along with value communication under high perceived environmental uncertainty. A potential explanation for this cost argument may lie in literature on the groupthink-phenomenon, which sees conformity pressures as a potential cost to strong group cohesion that can ultimately obstruct innovation (Janis 1971; Van de Ven 1986). A lack of diversity among employees may thus ultimately reduce team effectiveness in an innovation context (Campion, Papper, and Medsker 1996). Given that the tendency to develop in-group conformity has been shown to increase with external ("out-group") pressure (Coser 1956), it is likely that in settings of high perceived environmental uncertainty the stronger susceptibility to groupthink may actually more than outweigh the otherwise positive effects of value communication in innovation processes. In fact, empirical research shows that firm performance in high-uncertainty settings is more vulnerable to a lack of intrapersonal

diversity (Cannella et al. 2008), suggesting that the dominance of either costs or benefits of value communication may change with the intensity of *PEU*.

With regard to employee selection our results indicate that the interaction term for *IC* and *ES* (0.440; $p < 0.01$, two-tailed) is highly statistically significant in the high-*PEU* subsample, whereas we do not encounter a statistically significant coefficient in the low-*PEU* subsample. Overall, this suggests that employee selection is indeed useful in translating innovation capability into innovation performance as we have hypothesized in H2, but only when firms face a high level of perceived environmental uncertainty. This finding is in line with the argument that employee selection should yield higher benefits in uncertain and complex settings because skilled and qualified employees, who are to a great extent the result of selection processes, are better equipped to deal with both the challenges they face and the resulting behavioral uncertainty. Our finding also ties to prior literature indicating that personnel controls such as employee selection are especially relied upon in uncertain and complex decision contexts (Abernethy et al. 2015; Peck 1994; Snell and Dean 1992). Widener (2004) follows a similar line of reasoning and states that employee selection is particularly beneficial when employees perform tasks characterized by behavioral uncertainty.

Furthermore, the results reveal that the interaction term for *IC* and *PM* (−0.332; $p < 0.05$, two-tailed) is stronger and statistically significant in our high-*PEU* subsample, whereas we do not encounter a statistically significant coefficient in the low-*PEU* subsample. This implies that the misfit between performance monitoring and innovation capability is especially high in a situation of high perceived environmental uncertainty. This finding is consistent with prior literature showing that under high-*PEU*, performance monitoring has negative performance consequences, given its focus on outputs and the difficulty to define meaningful targets (Govindarajan 1984). In this setting this may mean that the benefits of performance monitoring in the form of increased employee guidance are outweighed by its costs. Apart from the difficulty of defining appropriate performance measures and targets, the costs that go along with performance monitoring are inflexibility, which in turn makes it unsuitable to take appropriate account of the exception-based nature of innovation projects. Another drawback of performance monitoring is its negative behavioral consequences (e.g., risk-averse behaviors, reliance on actions with predictable outcome patterns, narrow search span), which seem to be exacerbated in a situation of high perceived environmental uncertainty. In line with this reasoning, a meta-analysis by Henard and Szymanski (2001) finds that less structured approaches are more important to the performance outcomes of innovations in more turbulent and uncertain environments.

Finally, we also find a negative, statistically significant coefficient for the interaction of *IC* and *BM* (−0.268; $p < 0.01$, two-tailed) in the low-*PEU* subsample, but no significant value for high-*PEU* observations. This finding is interesting yet counterintuitive, given that the effective use of behavior monitoring presupposes that the manager who designs and uses this control practice knows which employee actions are desirable and which are not (Grabner and Speckbacher 2016). Thus, one would expect that its use is ineffective or even counter-productive in settings of high PEU. However, our results suggest that in firms that are exposed to both internal and external uncertainty these negative effects are offset by the benefits of behavior monitoring in such settings. While, overall, the rigidities introduced by behavior monitoring as well as its tendency to impede information flows, participation, and cooperation within a firm (Song and Thieme 2006) appear to hamper the translation of innovation capability into innovation performance, its function as a boundary system that helps reduce (external) complexity for employees may become more salient in a setting of high perceived environmental uncertainty (Simons 1995), hence mitigating an otherwise negative impact on materializing innovation capability. Thus, under high perceived environmental uncertainty there appears to be a changing cost-benefit-relationship of behavior monitoring, since its guidance function for employees appears to at least offset its negative properties. Overall, this leads to an insignificant interaction effect in the high-*PEU* subsample. Conversely, a setting of low perceived environmental uncertainty may exhibit lower benefits stemming from the boundaries imposed by behavior monitoring, hence producing an overall negative interaction coefficient in the low-*PEU* subsample.

Taken together, the findings of our supplementary analysis provide exploratory support for considering perceived environmental uncertainty as a relevant contextual variable affecting the role of control practices in the innovation process, while, at the same time, suggesting that the size and direction of its impact may not be uniform across these practices. Thus, our findings are in line with Grabner and Moers (2013) suggesting that contingency-type assumptions do not only apply for individual variables but might also hold true for the interaction between different variables (i.e., innovation capability and management control variables in our case).

### Robustness Checks

In addition to our main analysis, we perform a series of robustness checks to further validate our empirical results. First, as an alternative to employing a zero-inflated estimation method, we reduce the number of zero-observations in our sample by excluding all firms that have not produced a patent in the six years prior to our survey and then run a standard negative binomial regression model. In doing so, we use our sampling method to exclude firms that may follow different protection mechanisms for their inventions altogether. In total, 117 firms belonged to this non-patenting group, leaving us with sample size of 121 firms for the robustness check. Within this sample, 32.2 percent of companies were granted no patents after 2009, 31.4 percent

**TABLE 5**
**Robustness Checks**

| Main Model | Model 5 | Model 6 | Model 7a (Low PEU) | Model 7b (High PEU) |
|---|---|---|---|---|
| *IC* | −0.049 | 0.006 | 0.051 | 0.084 |
| | (0.128) | (0.122) | (0.143) | (0.235) |
| *VC* | 0.028 | −0.039 | −0.399*** | 0.420* |
| | (0.124) | (0.127) | (0.147) | (0.162) |
| *ES* | −0.037 | −0.017 | 0.316** | −0.234 |
| | (0.132) | (0.135) | (0.153) | (0.174) |
| *PM* | −0.045 | −0.037 | 0.096 | −0.105 |
| | (0.117) | (0.106) | (0.123) | (0.157) |
| *BM* | 0.098 | 0.108 | 0.127 | 0.187 |
| | (0.111) | (0.119) | (0.132) | (0.154) |
| *PEU* | 0.192 | 0.305** | — | — |
| | (0.132) | (0.139) | | |
| *PP* | 0.519*** | 0.490*** | 0.454*** | 0.290* |
| | (0.127) | (0.115) | (0.154) | (0.149) |
| *SL* | −0.003 | −0.019 | 0.012 | 0.169 |
| | (0.090) | (0.077) | (0.121) | (0.140) |
| *FS* | 0.774*** | 0.797*** | 1.049*** | −0.070 |
| | (0.284) | (0.277) | (0.349) | (0.456) |
| Intercept | −3.043** | −3.288** | −4.785*** | 0.718 |
| | (1.309) | (1.295) | (1.673) | (2.035) |
| ***IC* × *VC*** | | 0.187† | 0.464*** | −0.434*** |
| | | (0.147) | (0.161) | (0.161) |
| ***IC* × *ES*** | | 0.055 | −0.231* | 0.456*** |
| | | (0.115) | (0.137) | (0.170) |
| ***IC* × *PM*** | | −0.125* | −0.072 | −0.339*** |
| | | (0.075) | (0.137) | (0.116) |
| ***IC* × *BM*** | | −0.146* | −0.236*** | 0.027 |
| | | (0.080) | (0.076) | (0.203) |
| Log-pseudolikelihood | −227.05 | −222.71 | −134.49 | −72.74 |
| Wald Chi-square | 24.96 | 30.13 | 53.47 | 122.79 |
| Prob. > Chi-square | 0.003 | 0.005 | 0.000 | 0.000 |
| n | 121 | 121 | 76 | 45 |

*, **, *** Indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively, two-tailed test.
† Indicates $p < 0.10$, one-tailed test.
Robust standard errors are in parentheses. *IC*, *VC*, *ES*, *PM*, *BM*, *PEU*, *PP*, and *SL* are mean-centered.

produced one patent, and the remainder generated two or more patents. The results of these regressions are presented in Table 5 and are largely consistent with the findings of our main analysis.

In a further robustness check, we take into consideration that some firms in our sample were acquired by another company in the years after our survey. During the manual checking of the match between firms and patenting output, we encountered 13 such cases. When excluding these firms from our analysis, the results remain robust. Next, we consider the skewed distribution of patent count data and assess to what extent our results may be affected by the observations with the highest values in our dependent variable. To do so, we winsorize our data at the 99th percentile and find that the results are largely consistent with the main analysis. Moreover, we also apply alternative sample splits for our supplementary analysis. The findings are robust to using the mean instead of the median of *PEU* as the cutoff value, to eliminating those sample firms that are exactly at the median of *PEU*, and to including firms with median-observations for *PEU* in the high-*PEU* subsample. Finally, all models are robust to controlling for a more fine-grained industry classification.

In summary, the empirical findings and subsequent robustness checks largely corroborate the hypothesized interaction effects between innovation capability and management control practices on a firm's innovation performance.

## CONCLUSION

This study contributes to the growing innovation-related stream of MCS research and follows up on the call for more thorough insights into the phenomenon of innovation (Chen 2017; Davila et al. 2009). In order to do so, we pick up on findings from innovation and management research and disentangle the concept of innovation into innovation capability and innovation performance. Building on this distinction and drawing on the Resource Based View, we theoretically argue and empirically demonstrate that management control practices and innovation capability interact to influence innovation performance, and thus control practices either help or prevent firms from materializing their capability. Our results suggest that, on average, value communication supports the translation of innovation capability into innovation performance, whereas performance monitoring and behavior monitoring appear to hinder the same process. This implies that the pure possession of innovation capability may not be enough, but that firms need to make sure that there is a fit between their capabilities and the control system in place to materialize them into innovation outcomes. In an additional step, our results indicate that perceived environmental uncertainty plays an important role as a contingency factor for the interaction effects between management control practices and innovation capability. Overall, our evidence suggests that high external uncertainty does not uniformly make the impact of management control practices in an innovation context more pronounced, but rather alters (and potentially even reverses) the cost-benefit relationship of MCS in the context of innovation. Taken together, these results underline both the importance of environmental uncertainty as a central element in contingency-based MCS research (Chenhall 2003) and the need for a more thorough investigation of its role in managing innovation, for instance by taking a more disaggregated view and considering how the type of uncertainty (e.g., Ditillo 2004; O'Connor and Rice 2013) may affect the effectiveness of control systems. Given that coping with uncertainty has, in fact, been suggested as the main role of MCS in an innovation context (Davila 2000), this area promises to be an especially relevant avenue for future research.

Our study contributes to innovation literature within and beyond accounting in several ways. First, we pick up on innovation and management literatures and distinguish innovation capability and innovation performance as separate constructs. To ensure a separate measurement of these constructs in our empirical study, we consciously collected them from different sources, with innovation capability as a self-reported measure and innovation performance as publicly available patent data. In doing so, we not only improve the validity of our study (Speklé and Widener 2018), but also disentangle innovation antecedents from innovation outcomes, and may hence contribute to understanding why MCS literature on innovation has so far produced partially contradictory findings (Bisbe and Otley 2004). Second, we deviate from intervening-variable models often employed in MCS research (e.g., Chenhall, Kallunki, and Silvola 2011; Henri 2006). Instead, we propose an independent-variable interaction model (Luft and Shields 2003), which adds to literature on how MCS interact with capabilities in organizations. Further, we add to prior research by highlighting the role of perceived environmental uncertainty as an important contextual factor that may affect the implications of MCS in an innovation setting (Chenhall 2003). In doing so, we follow Grabner and Moers (2013) in suggesting that a contingency-based argumentation can be fruitfully expanded to interaction relationships in a management control setting. Finally, we also contribute to the innovation literature outside the field of accounting by emphasizing that the control system is a crucial factor of the internal organizational environment whose design has important consequences for a successful management of the innovation process. Our findings thus contribute to the question of why some firms are better in materializing innovation capability than others (Menguc and Auh 2010). Relatedly, our findings also suggest that the return on investments in innovation capabilities can be significantly enhanced by a properly aligned and thus supporting management control system.

Nonetheless, it is important that the findings of this study be interpreted in the context of its limitations. First of all, in using four manifestations of controls within the object-of-control framework, we focus on a simplified set of established management control practices. At the same time, we are well aware that firms employ a wider variety of control mechanisms, which we do not specifically capture in this study. A fruitful avenue for future research may hence lie in investigating more specific, innovation-related types of controls, such as the choice of different types of (non-financial) performance measures, and the use of project milestone tracking, or stage-gate processes (Schultz, Salomo, de Brentani, and Kleinschmidt 2013). Furthermore, shedding more light on how controls are used in innovation management also offers interesting avenues for future research (Bisbe and Otley 2004; Cools, Stouthuysen, and Van den Abbeele 2017; Jørgensen and Messner 2009; Simons 1995). Another path could build on taking a more disaggregated look at the controls employed in this study, for instance by considering different types of culture being spread by the communication of values in organizations (e.g., Kruis, Speklé, and Widener 2016). Moreover, our study employs a rather broad concept when capturing overall innovation capability. Given that certain variations of innovation, such as explicitly incremental innovation processes, may follow different rules and produce different implications, it might be worthwhile for future studies to take a more fine-grained view on the concept when investigating its fit with management control practices. Finally, we also acknowledge that our sample is focused on a specific industry. For the sake

of generalizability, future research might take a look at different industries (e.g., service industry) in order to investigate the interplay of innovation capability and MCS in a different context.

Despite the aforementioned limitations, we believe that our study makes an important contribution to the broader innovation literature. By employing an interaction logic to capabilities and controls, we demonstrate how MCS can be a crucial tool for realizing the potential of innovation capability and translating it into innovation performance.

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