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Knowledge management capabilities and organizational risk-taking for business model innovation in SMEs

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ABSTRACT

In today's business environment with fast growing communication and information technologies, knowledge management (KM) capabilities are a valuable source for innovation. However, little is known about the particular KM capabilities that lead to business model innovation (BMI) and whether their effect is dependent upon the firm's orientation towards risk-taking. We examine the impact internal and external KM capabilities have on BMI and how these effects are moderated by its risk-taking tolerance. We empirically analyze a sample of 197 small and medium-sized enterprises (SMEs) applying structural equation modeling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA). The results from the SEM indicate that particularly external KM capabilities stimulate BMI. This relationship is strengthened for firms with a high risk-taking tolerance. Internal knowledge is only effective for firms with a low risk-taking tolerance. The fsQCA results substantiate these findings and refine the SEM by providing particular antecedent conditions for high levels of BMI.

1. Introduction

The fast rise of digital technologies has changed the business environment and has led to new ways in which firms can do business (Amit & Han, 2017; Massa, Tucci, & Afuah, 2017). New competitors are not necessarily established market players but can even be start-ups that compete against incumbents with different business models (Dushnitsky & Lenox, 2005; Zott & Amit, 2007). Some new business models have significantly changed the rules of the game in certain industries (e.g., Uber and the taxi industry, Netflix and the movie industry, and Airbnb in the accommodation industry) (Teece, 2018). In consequence, incumbent firms are forced to regularly change and innovate their business model (Amit & Zott, 2015). Business model innovation (BMI) is defined as "designed, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements" (Foss & Saebi, 2017, p. 201). BMI allows firms to create novel activities that go beyond product and process innovation (Osiyevskyy & Dewald, 2015) and was identified as a source of sustainable competitive advantages (Tallman, Luo, & Buckley, 2018).

Recently, studies started to investigate the antecedences that enable firms to react to environmental changes and to facilitate BMI proactively (e.g., Clauss, Abebe, Tangpong, & Hock, 2019a; Groskovs & Ulhøi, 2019; Ricciardi, Zardini, & Rossignoli, 2016). The process of BMI however might require firms to cannibalize existing revenue streams against uncertain streams of future revenues (Clauss et al., 2019a; Tellis, Prabhu, & Chandy, 2009). Thus, decisions to innovate the business model are often characterized by uncertainty concerning their costs, duration, and outcome (Teece & Leih, 2016). Large firms usually have the necessary resources to experiment with new business models (Sosna, Trevinyo-Rodriguez, & Velamuri, 2010). They can potentially create additional prototype business models as spin-offs without risking the survival of the firm (Karimi & Walter, 2016). This is not the case for small and medium-sized enterprises (SMEs), which have fewer resources available for business model experimentation. If a new business model fails, the challenge and risks associated with BMI are particularly high for SMEs (Laudien & Daxböck, 2016).

To minimize uncertainties and to improve the ability to make well-informed decisions, SMEs have to permanently identify innovative opportunities and threats arising from within and outside the boundaries of the firm (Sanchez & Ricart, 2010) and to sense and leverage the knowledge about these threats (Smith, Collins, & Clark, 2005). Following the theoretical arguments of dynamic capability theory (Teece,

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2007; Teece, 2018; Teece, Pisano, & Shuen, 1997) firms (e.g., SMEs in particular) require special knowledge management (KM) capabilities, which allow them to identify and process existing and new knowledge into innovative business opportunities (Swap, Leonard, & Mimi Shields, 2001; Teece, 2010). KM capabilities are those underlying organizational activities which facilitate the infrastructure and the processes for exploiting internal knowledge and acquiring, converting, and applying external knowledge sources (Gold, Segars, & Malhotra, 2001). For example, these KM capabilities could comprise the utilization of technologies to screen customer data, the distribution of new knowledge among the employees, or the organizational processes acquiring, storing, and using knowledge. The ability to gather internal and external knowledge and to apply it at the right time, is assumed to be essential for BMI (Teece & Leih, 2016). Thus, SMEs must develop an understanding of which KM capabilities to possess to be able to innovate the business model.

Although scholars propose that KM in general is an enabler of BMI (Malhotra, 2000; Martins, Rindova, & Greenbaum, 2015; Teece, 2018), studies have not yet empirically investigated how different types of KM capabilities influence BMI in SMEs. Drawing on previous research, which shows that different innovation types require different knowledge sources (Cohen & Levinthal, 1990; Snihur & Wiklund, 2019), we assume that the nature of KM capabilities required for BMI may differ from those required for product and process innovation and that particular KM capabilities (e.g., external and internal KM capabilities) are needed to effectively manage BMI in SMEs. Furthermore, we assume that the role of certain KM capabilities depends on the general strategic orientation of the firm. In particular the organizational risk-taking tolerance (i.e., the firḿs willingness to intentionally accept risk while exploiting innovative opportunities) will affect how knowledge is processed and utilized in the firm (Choo, 2013). Therefore, we further investigate the conditional effects of KM capabilities on BMI for varying degrees of organizational risk-taking tolerance in the SME context.

Our study provides three main contributions to research. First, we contribute to the emerging literature on the internal enablers of BMI (e.g., Clauss et al., 2019a; Groskovs & Ulhøi, 2019; Ricciardi et al., 2016) by providing a better understanding how particular KM capabilities affect BMI in SMEs. Theoretically, this also helps to specify the role of dynamic capabilities for BMI (e.g., Leih, Linden, & Teece, 2015; Teece, 2018). Second, we enrich the literature linking KM and innovation (e.g., Clauss & Kesting, 2016; Cohen & Levinthal, 1990; Trantopoulos, von Krogh, Wallin, & Woerter, 2017). So far, KM and KM capabilities have primarily been linked to product and process innovation. Thus, our findings provide new insights on how the nature of KM may vary according to the type of innovation and whether the innovation is pursued at a more holistic level. Third, we contribute to the literature on the particularities of BMI management for SMEs (e.g., Anwar, 2018; Clauss, Bouncken, Laudien, & Kraus, 2019b; Laudien & Daxböck, 2016).

2. Literature review

2.1. Business model innovation

Business models are conceptualized as an architecture of the three interrelated key elements: value proposition, value creation, and value capture (Clauss, 2017; Clauss et al., 2019a). These elements are configured as a mutually enforcing system that defines the organizational business logic (Martins et al., 2015; Teece, 2010). Throughout the last two decades, new technological developments have led to innovations in all elements of the business model. These include new market places where value can be offered (e.g., e-commerce), new ways of how value can be created (e.g., selling services instead of products) and new opportunities of how revenues can be captured (e.g., paying per use) (Massa et al., 2017). These developments show that BMI extends the scope of product and process innovation as key elements (e.g., revenue models) of a firms business model are being changed (Foss & Saebi, 2017). While product innovation refers to introducing new products and services and process innovation is defined as the implementation of new operations or manufacturing methods (Snihur & Wiklund, 2019), BMI is said to be a new and different type of innovation, which complements product and process innovation through a holistic perspective on innovation potentials in the elements of the organization (Massa et al., 2017). When analyzing the question of why some firms are superior and dominate markets (e.g., Apple), while others lose market share or fail entirely (e.g., Kodak), studies provide evidence that the successful firms reconfigured their business by innovating either specific components of the business model or the entire business model (Clauss et al., 2019b). The scope of BMI does not necessarily require radical changes in one or all business model elements but can also be the result of more incremental reconfigurations of these (Velu & Jacob, 2016).

Despite the increased interest in BMI among practitioners and in academia, previous research has been rather static and descriptive in nature. The main focus was set on defining a "blueprint for the coherence between the business model components" (Demil & Lecocq, 2010, p. 227), explaining case-based examples of BMI retrospectively (e.g., Amit & Zott, 2015; Sosna et al., 2010), or demonstrating the performance implications of BMI (e.g., Heij, Volberda, & Van den Bosch, 2014; Karimi & Walter, 2016). Only recently, researchers started to analyze internal capabilities that enable managers to proactively change their existing business model. Particularly the dynamic capability framework has provided a theoretical angle for analyzing this proactive BMI process (Foss & Saebi, 2017; Teece, 2018). Unlike ordinary capabilities which mainly sustain a firm's present operations, dynamic capabilities are responsible for sensing innovative opportunities, seizing new opportunities and transforming a firm's business model (Teece, 2018; Teece et al., 1997). In the search for internal enablers for BMI some scholars have directed their attention to exploring the particular microfoundations of dynamic capabilities. Achtenhagen, Melin, and Naldi (2013) for example, highlight the need for a balanced use of resources, the ability to experiment, and a balanced coherence of leadership capabilities, organizational culture, and employee commitment. Doz and Kosonen (2010) as well as Clauss et al. (2019a) identify micro capabilities of strategic sensitivity, leadership unity, and resource fluidity as enablers for BMI. Others have focused on the strategic decision making processes and the underlying cognitive behaviors that enable BMI (Martins et al., 2015; Osiyevskyy & Dewald, 2015).

This previous research has greatly advanced our understanding about the enabling factors that help firms to proactively carry out BMI. However, so far, studies have not analyzed the capabilities for identifying and utilizing knowledge as an enabler of BMI. We consider this an important omission, as KM can be considered to be a key microfoundation of sensing capabilities (Teece, 2007) and as new knowledge is traditionally considered to be a driver of the innovation process (Cohen & Levinthal, 1990; Smith et al., 2005). Although, Teece and Leih (2016) assume based on dynamic capability theory that the ability to gather new knowledge and to apply it at the right time is relevant for BMI, empirical analyses analyzing which KM capabilities firms should develop must still be done.

2.2. Knowledge management

In today's knowledge-based business environment, firms refer to themselves as organizations that continuously learn and leverage knowledge (Smith et al., 2005). The right knowledge and the ability to convert that knowledge for new value creation is said to lead to competitive advantage (Ozer & Vogel, 2015). Therefore, much attention has been placed on how to develop and maintain organizational knowledge (Mehta & Bharadwaj, 2015).

In general, two research streams on KM have been differentiated by literature: the static and dynamic KM (Hargadon & Fanelli, 2002). The static dimension refers to a firm's internal KM capabilities, which provide an inter-organizational basis for social interaction, knowledge storage, and knowledge availability. The focus lies on maintaining, replicating, and exploiting existing knowledge (Smith et al., 2005). The dynamic dimension captures a firm's external KM capabilities, emphasizing a firm's ability to acquire, convert, and apply knowledge arising from sources outside the boundaries of the firm (Smith et al., 2005). The focus lies on grasping external knowledge in order to analyze competitors and customers and to identify overall market developments and trends (Roberts, 2015). Both internal and external KM capabilities are interdependent and responsible for the firm's knowledge assets (Mehta & Bharadwaj, 2015). These knowledge assets comprehend know-how which is unique and difficult to imitate for competitors as they are mainly tacit and not accessible in public (He & Wang, 2009). Thus, KM capabilities provide the toolset for leveraging internal and external knowledge sources as such, that they can be captured and converted into productive outcomes (He & Wang, 2009).

2.3. Internal knowledge management capabilities

Internal KM capabilities are based on the socio-technological theory (Bostrom & Heinen, 1977), describing the social and technological perspective that form a firm's KM capabilities for maintaining and exploiting internal knowledge (Gold et al., 2001). The social perspective refers to the knowledge transfer relationships among the employees. They are embedded in a firm's organizational culture and structure and responsible for the transfer of informal and tacit knowledge (Swap et al., 2001). The technological perspective on the other hand, refers to the firm's information system used to maintain, store, and analyze knowledge (Lee & Choi, 2003). A firm's KM *culture, structure*, and *technology* constitute a firm's internal KM capabilities (Gold et al., 2001).

A firm's *KM culture* is considered to be a critical component (Blackler, 1995; Janz & Prasarnphanich, 2003), as it defines how and what knowledge is valued, shared, and stored inside the organization for potential innovative advantage (Alavi, Kayworth, & Leidner, 2005). Studies have shown that a firm's knowledge culture influences organizational effectiveness (Choo, 2013; Quinn & Rohrbaugh, 1983) and the firm's overall innovativeness (Nonaka & Takeuchi, 1995).

Closely linked to the organization's knowledge culture is its KM *structure*. It provides dictates on how and with whom knowledge is transferred and communicated throughout the firm. Centralized firm structures, characterized by hierarchical power in company decision making, mostly coincide with centralized KM structures (Anand, 2011). These hierarchical KM structures are said to inhibit communication and collaboration with colleagues from other business units and thus, promote the hoarding of information, causing asymmetric knowledge flows across the organization (Gold et al., 2001). Non-hierarchical and flexible knowledge structures on the other hand, have shown to improve the transfer of knowledge (Chen & Huang, 2007).

Explicit knowledge is mainly stored in the organization's information systems. Its *KM technology* provides data based systems in which organizational data and knowledge is stored and organizational processes mapped (Pan & Scarbrough, 1998). These technological systems comprehend intranets, internal search engines, knowledge tools, but also hard facts concerning warehouse and logistic data (Alavi & Leidner, 1999). Technological systems support KM by providing a pool of accessible knowledge and an analytic platform for analyzing and communicating data (Alavi & Leidner, 2001).

2.4. External knowledge management capabilities

Considering that organizations face environmental changes and competitive rivalry, firms need to be constantly aware of their dynamic environment and of new opportunities arising from new combinations of knowledge (Schumpeter, 1934). Studies have shown that a firm's innovativeness increases with the ability to exploit knowledge coming from sources outside of the firm (Valentim, Lisboa, & Franco, 2015). Thus, firms are in need of continuously updating their knowledge base, making sense of environmental changes and creating new knowledge out of external knowledge sources. External KM capabilities differ significantly from the internal ones (Hansen, 1999). A firm's capabilities to acquire new external knowledge, assimilate, and apply it for novel opportunities of value creation, are being called "absorptive capacity" (Cohen & Levinthal, 1990). Following Gold et al. (2001), a firm's KM capabilities are built up in three *processes*:

The *acquisition-oriented processes* mainly focuses on obtaining knowledge from various sources (Roberts, 2015), e.g., through social capital that is embedded in the relationships on an individual level and/or the organizational level between organizations and through network collaborations (Gold et al., 2001), or alternatively through the purchase of knowledge assets (Yew Wong & Aspinwall, 2004), or by simply scanning the environment (Velu, 2015). Referring to the latter, there have been several studies suggesting that companies require KM capabilities that scan the business environment and identify signals and clues concerning changes in customer demand, technological trends, and competitive actions (Day & Schoemaker, 2004; Teece et al., 1997).

To actually exploit external knowledge in order to seize innovative business model opportunities, firms have to further convert and apply the knowledge that has been acquired (Cohen & Levinthal, 1990). These operations incorporate the integration and filtration of new external knowledge and the replacement of outdated knowledge (Gold et al., 2001). The efficiency of these c*onversion-oriented processes* are dependent on a firm's internal KM capabilities and the ability of the firm to actually value new external knowledge (Lane & Lubatkin, 1998). Converting new external knowledge into the firm's organizational knowledge language and knowledge stock makes the external knowledge ready for use (Lane & Lubatkin, 1998). Finally, in the *application-oriented processes,* the newly generated knowledge needs to be effectively applied in the operative and the strategic activities of the firm (Gold et al., 2001).

3. Hypothesis development

3.1. Internal knowledge management capabilities and BMI

BMI arising from internal knowledge has lately been particularly dominant in the engineering industry, where companies try to reconfigure the way value is delivered to and captured form customers. Ever since Rolls Royce transformed their business logic from selling aero-engines to offering them on a service-based model called "power by the hour", many engineering firms are trying to restructure their business logic from within the firm by switching from a product-based to a service-based business, or a hybrid of both (Smith, 2013). Thereby, these firms refer to their core competencies and existing knowledge for innovating the value proposition by switching from a product to a service-oriented logic (Clauß, Laudien, & Daxböck, 2014). Similar examples can be found in the automobile industry, in which car manufacturers such as Daimler and BMW are not just selling cars, but provide convenient mobility by offering car sharing services such as ShareNow from Daimler and BMW, a joint venture of the previous Car2Go and DriveNow services built in 2019. Thus, BMI can arise from leveraging internal knowledge assets. Alavi et al. (2005) found that organizations that effectively manage their internal knowledge benefit from a pool of innovative knowledge assets which allow firm's to be aware of innovative opportunities. These innovative opportunities may arise from the R&D department in terms of new products and services, through innovative teams, or through other units that deal with value creation and value capture innovation. They can range from simple cost reduction opportunities to improving a firm's internal agility and its overall innovativeness (Alavi et al., 2005). Thus, strong internal KM capabilities may help firms to increase the awareness of potential business model opportunities arising from within the firm. Moreover, a profound understanding of the firm's underlying activities also enhances the awareness of the firm's internal strength and constraints that are relevant for strategic business model decision making. These decisions include, for example, the selection of the firm's business logic and the decision of which activities to perform internally and which to outsource (Quinn, 1999).

Once an innovative opportunity has been sensed and the strategic designing of the new business model has occurred, operational changes are necessary. Processes, resources, and core competencies must be transformed and reconfigured for new means of value creation (Zott & Amit, 2010). Considering that these changes are interdependent and cross-functional, BMI requires great collaboration and the transfer of knowledge throughout all levels and business units of the firm (Heij et al., 2014). The ability to transfer core capabilities and resources is underpinned by transferring knowledge captured in processes and routines that are tied to specific employees and are in most cases tacit (Nonaka & Takeuchi, 1995). Hence, BMI calls for a social setting with strong knowledge-sharing relations, which are embedded in the firm's organizational KM culture and structure (Swap et al., 2001) and supported through technological systems of knowledge storage (Gold et al., 2001). The firm's KM culture determines which knowledge is valued and through which means and frequency knowledge is shared (Chen & Huang, 2007). Studies have shown that a strong KM culture coupled with flexible and non-hierarchical KM structures positively influences knowledge-sharing across departments and business units, resulting in an optimized use of organizational knowledge (Cameron & Quinn, 2011; Chen & Huang, 2007; Choo, 2013). Moreover, a firm's KM technologies provide a pool of data storage and a database for accessing, analyzing, and sharing firm knowledge (Teece, 1998). When used appropriately, KM technologies have an enormous potential for leveraging internal knowledge, as they comprehend cross-functional data (Alavi & Leidner, 2001). Prior studies found that internal KM capabilities promote innovative ideas and foster a firm's overall innovativeness (Lee, Leong, Hew, & Ooi, 2013; Nesta & Saviotti, 2005). Following the reasoning above, we hypothesize that a firm's internal KM capabilities, consisting of a strong KM culture, a flexible and non-hierarchic KM structure, and KM technologies, enables BMI:

H1: Internal KM capabilities positively influence the firm's ability to innovate the business model.

3.2. External knowledge management capabilities and BMI

While external changes in the business environment may create new opportunities, they can also cause a threat to the current business model (Teece, 2007). Especially with digitalization and the "Internet of Things", ecosystems surrounding a firm's business model are constantly changing and influencing the way customers consume and businesses compete (Teece & Linden, 2017). Firms that are unable to grasp these changes may suffer from large losses and negative consequences. There are many case-in-point examples where firms focused too much on leveraging their current business model rather than focusing on changes occurring in their ecosystems (e.g., Blockbuster Video, Blackberry, Kodak, etc.).

Strong KM acquisition processes allow firms to constantly be aware of changes occurring in the business environment. They increase the overall alertness of potential threats and allow firms to continuously re-evaluate the competitive state of their business model. This ongoing evaluation process is critical for identifying innovative opportunities and for guiding the strategic positioning of the firm. Moreover, external knowledge acquisition can also be used for finding new partners, suppliers, distribution channels, and new customer relationships (Zott & Amit, 2010). Hence, the acquisition of external knowledge is critical for making strategic business model decisions. From an operational point, firms require conversion processes in order to integrate the acquired external knowledge into organizational knowledge and for developing new knowledge assets. Conversion processes enable firms to internally transform the external knowledge into firm language and to make it ready for experimentation (Gold et al., 2001). Finally, the application processes implements and adjusts operative and strategic activities of the current business model in order to solve problems and develop new technologies, products, revenue models, etc. (Valentim et al., 2015). Thus, strong external KM capabilities allow firms to acquire and recognize new external knowledge, convert it to firm knowledge, and apply it for commercializing novel BMI opportunities. Referring to the arguments above, we hypothesize:

H2: External KM capabilities positively influence the firm's ability to innovate the business model.

3.3. Organizational risk-taking tolerance, knowledge management capabilities and BMI

The organizational risk-taking tolerance reflects the firm's willingness to exploit uncertain business initiatives. It represents the extent to which organizations support risk-taking vs. control behaviors (Smith et al., 2005). These behaviors are embedded in the firm's climate (Ekvall, 1996) and have been found to affect many aspects of how organizations acquire, share, and leverage knowledge (Cameron & Quinn, 2011; Choo et al., 2006). Firms with a high risk-taking tolerance are said to foster KM behaviors that encourage an external focus on the environment and an internal focus on proactive knowledge-sharing (Choo, 2013). Thus, firms with a high risk-taking tolerance build external KM capabilities that enable them to identify new trends and technological developments, to evaluate opportunities, and to encourage entrepreneurial behaviors (Cameron & Quinn, 2011). Furthermore, they develop internal KM capabilities for leveraging internal opportunity recognition, creativity, and agility (Choo, 2013). Firms with a high risk-taking tolerance are said to emphasize KM behaviors that foster organizational experimentation and learning (Smith et al., 2005). They encourage trial and error and foster a climate that stresses internal knowledge testing and knowledge-sharing (Nahapiet & Ghoshal, 1998). Furthermore, they encourage employees to leverage knowledge sources and to seek ideas for new markets, trends, and products from both internal and external knowledge sources in order to promote creativity and innovation (Choo, 2013). Thereby, they move the organization towards disorder, leading to the discovery of new ideas (Smith et al., 2005). These characteristics support the "discovery-driven" approach to BMI, in which the innovation of a firm's business model is achieved through constant experimentation and learning (McGrath, 2010). Following the argumentation above, we expect varying preferences of organizational risk-taking to influence the way in which organizations manage and value knowledge. As firms with a high risk-taking tolerance foster KM behaviors that encourage organizational creativity and innovation, we hypothesize that the extent to which internal and external KM capabilities lead to BMI is strengthened when firms have a high risk-taking tolerance. The complete hypothesis model is visualized in Fig. 1.

Hypothesis 3: The effect of internal KM capabilities on BMI will be strengthened (weakened) when the firm's risk-taking tolerance is high (low).

Hypothesis 4: The effect of external KM capabilities on BMI will be strengthened (weakened) when the firm's risk-taking tolerance is high (low).

4. Methodology

4.1. Overview of the empirical design

We combined two different methods for testing and further exploring the relationships in our model based on a unique survey-based dataset of SMEs. First, we applied partial least squares (PLS) structural equation modeling (SEM) to test our model (Chin, 1998). It has been

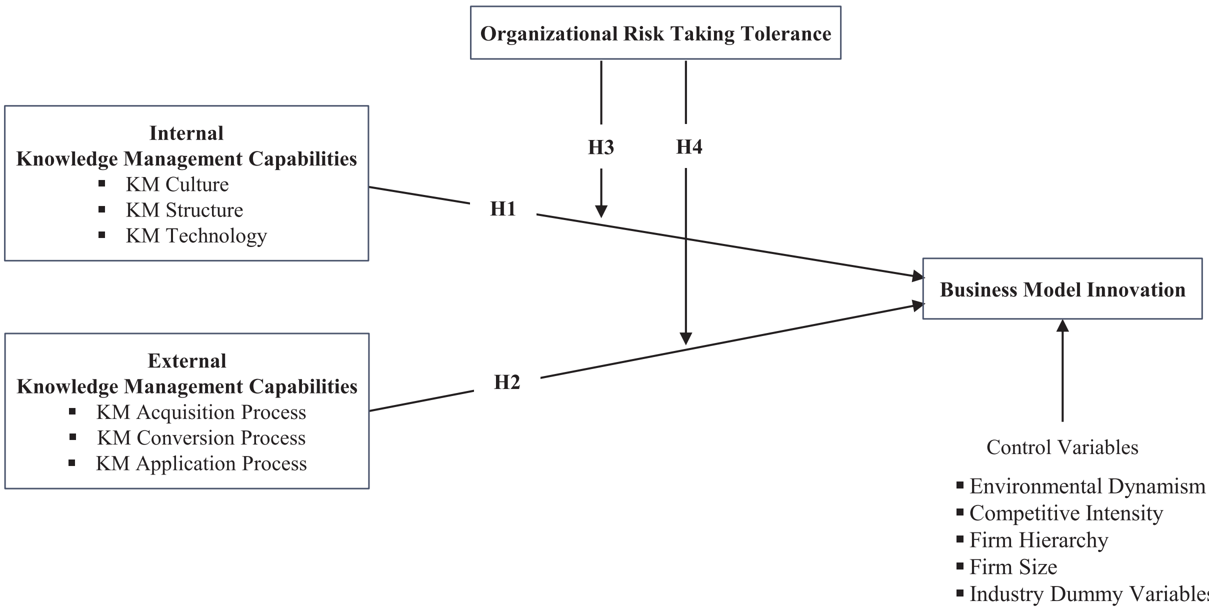

Fig. 1. Conceptual framework.

demonstrated that PLS is a robust method that has been continuously used in business research studies (Cepeda Carrión, Henseler, Ringle, & Roldán, 2016) and strategic management (Hair Jr., Sarstedt, Hopkins, & Kuppelwieser, 2014). In addition, PLS has some particularities that make the methodology suitable for our analysis in this study: First, it is the method of choice whenever models are based on either first order formative measures or higher order measures that use formative indicators at any level (Becker, Klein, & Wetzels, 2012; Lowry & Gaskin, 2014). Second, it is provides more accurate estimates than regression analyses if the moderation effect of latent variables should be tested (Chou & Yang, 2011; Titah & Barki, 2009). According to Chou and Yang (2011), the approach used to measure the latent variable in PLS allows for a subsequent assessment of the moderator's measurement error, which is not computed for regressions with moderators that comprehend latent variables with multi-item scales.

Second, we further run a fuzzy-set qualitative comparative analysis (fsQCA) for exploring how certain configurations of KM capabilities are linked to BMI in SMEs. Several problems of social science can be formulated in terms of sets and set relations, and then asymmetry can seem to be an important aspect of set-theoretic connections (Ragin et al., 2008). Traditional symmetric thinking in data analysis often suffer from disconnections between theory and empirical testing (Woodside, 2013). In general, if the relationships among variables are asymmetric, scholars have called for using a set-based approach to supplement a traditional symmetric approach such as regression analysis or SEM (Kraus, Ribeiro-Soriano, & Schüssler, 2018; Woodside, 2013). According to asymmetry thinking in data analysis, qualitative comparative analysis (QCA) is a technique that combines quantitative and qualitative methods that offers a middle path between quantitative and qualitative measurement (Ragin et al., 2008), and fsQCA is a set-theoretic approach for exploring sufficient conditions for a particular outcome based on Boolean logic (Ragin, 2009). Since a high degree of complexity can be captured by focusing on fsQCA rather than single effects of individual variables, fsQCA has recently received more attention in business studies (e.g., Kraus et al., 2018; Palmer, Niemand, Stöckmann, Kraus, & Kailer, 2019). Therefore, in addition to the test of the linear effects, this study combines five relevant antecedents (e.g., culture, structure, technology, acquisition process, conversion process, and application process of KM) to explore the configurations for achieving high BMI based on using fsQCA v. 2.5.

4.2. Data collection and sample

The sample data used for this study consists of survey data of 197 SMEs ($\leq$500 employees) in the technology sector that are represented in various industries (9.1% Automotive, 21.8% Biotechnology, 12.2% Engineering, 22.3% Electronics, and 34.5% others). These industries are subject to continuous technological developments and are thus, highly innovative. We collected the data at two international trade fairs that were held in Germany. The questionnaire was collected personally with a team of students who were knowledgeable of the topic. Exhibitors at the fair were personally addressed and asked for their knowledge about KM and BMI. The survey was then only handed out if a knowledgeable key respondent was available. The use of a key informant to obtain firm-level data is considered valid and reliable, particularly in the context of small to medium-sized firms, due to greater information transparency and limited organizational complexity (Homburg, Klarmann, Reimann, & Schilke, 2012). Hence, the formal positions of our respondents vary: 28.1% are top managers (e.g., CEO, COO etc.), 37.8% department or team leaders, and 34.1% are in other functional management areas.

The questionnaire was handed out in German and English. To ensure consistency of the translated German version to the original items, the back-translation method using two bilingual translators was applied (Brislin, 1970). Considering the importance of trade fairs in the technology sector, our sample can be considered as a good representation of the typical market in these industries (Rolf Seringhaus & Rosson, 1998). The use of trade fairs as the sampling frame also provided us the opportunity to assess the issue of nonresponse bias and sampling bias. We compared the available information about company size and product type between those firms who participated, those who decided not to participate, and those that were not selected. The results indicated no significant differences between them, suggesting that neither nonresponse bias nor sampling bias were serious concerns here. Table 1 summarizes the characteristics of our sample.

4.3. Measures

For measuring our model constructs, we used existing multi-item scales from published studies whenever available (Table 2). All items were quantified on a five-point Likert-type scale.

BMI: We have developed items that capture the various elements of

Table 1
Sample descriptions.

Descriptive characteristics	%
Country	
Germany	40.6
China	5.1
UK	5.1
Swiss	5.1
USA	3.1
Netherlands	3.6
France	3.1
Taiwan	2.0
Korea	2.0
Others	30.5
Industries	
Automotive	9.1
Biotechnology	21.8
Engineering	12.2
Electronics	22.3
Others	34.5
Firm size	
< 50	42.1
50–100	24.4
101–250	22.7
251–500	14.2

BMI: value proposition innovation, value creation innovation, and value capture innovation. In total we measure nine reflective items that mirror innovation in all dimensions of the business model canvas (Osterwalder & Pigneur, 2010) and match the second order constructs that were proposed by Clauss (2017).

Internal and External KM Capabilities: In order to measure internal and external knowledge capabilities, we used the two-stage hierarchical measurement model of Gold et al. (2001). The three first order constructs that measure *internal KM capabilities* are: *KM technology, KM structure,* and *KM culture*. *External KM capabilities* are measured by the three first order constructs*: KM acquisition process, KM conversion process,* and *KM application process*.

For measuring *Organizational Risk-taking Tolerance*, we adapted four items from Herzog and Leker (2010) and Tellis et al. (2009).

In addition to our focal constructs, we control for external and internal factors that might influence BMI. Considering that external changes are regarded as drivers of BMI (Amit & Zott, 2015; Heij et al., 2014), we include *competitive intensity* and *environmental dynamism* as external control variables. Both measures are based on the multi-item scales developed by Jaworski and Kohli (1993). The internal control factors are *firm size* and *firm hierarchy*. According to Schumpeter (1934), firm size matters for innovation, as only large firms have the resources required to invest in innovative projects. However, Hannan and Freeman (1984) argue that larger firms are more prone to organizational inertia, thereby hindering change processes. To account for these possible effects, we control for *firm size* by taking the logarithm of the number of firm employees. According to Damanpour (1991), firms with strong hierarchical structures and centralized decision making inhibit organizational innovativeness. Thus, we control for *firm hierarchy* by using five self-developed items. Finally, we control for the industry specific effects by including dummy variables for the four major industries in our study (*automotive, biotechnology, engineering,* and *electronic*).

4.4. Measurement model assessment

All psychometric properties of our reflective measured constructs were assessed according to common criteria in the literature (Hair, Ringle, & Sarstedt, 2011) (Table 2). In order to ensure an adequate indicator reliability, we kept only those items in our measurement model that showed standardized factor loadings above 0.6, which led to the exclusion of two items from the BMI scale. The standardized factor loadings of the remaining items ranged from 0.672 to 0.887. The composite reliability of all our constructs is very high and ranges from 0.870 to 0.944. Convergent validity was tested by computing the average variance explained per factor. All these values are above 0.5 and the squared average variance extracted values exceed the highest inter-construct correlations (Fornell & Larcker, 1981). Thus, discriminant validity according to the Fornell-Larcker criterion is given (Table 3). Moreover, the heterotrait-monotrait ratio of correlations (HTMT) was below the threshold of 0.85, which further substantiates discriminant validity (Henseler, Ringle, & Sarstedt, 2015).

For measuring the hierarchical second order constructs, a type II reflective-formative approach was applied, using the repeated indicator approach (Becker et al., 2012). The path weights of the first-order reflective constructs to the second order formative constructs were all significant (Diamantopoulos & Winklhofer, 2001). Furthermore, we tested for multicollinearity among the first-order constructs using the variance inflation factors. All variance inflation factors were below the threshold of 5 (Hair et al., 2011), indicating that multicollinearity is not an issue for the formative constructs (Table 4).

4.5. Analysis 1: Partial least squares

We calculate our model using the path weighting scheme. To obtain the standard errors for our structural model testing, we used nonparametric bootstrapping with 5,000 replications and mean replacement of missing values. The higher order constructs were specified using the repeated indicator method (Ringle, Sarstedt, & Straub, 2012). In order to calculate the latent interaction effects, we relied on the two-stage approach.

Attention was paid to the issue of common method bias (CMB), as the dependent and the independent variables were collected by the same respondent. Therefore, the issue was addressed ex-ante and ex-post to the data collection phase. To minimize CMB ex-ante, the development of the survey followed the guidelines by Podsakoff, MacKenzie, Lee, and Podsakoff (2003). We assured respondent anonymity, used established measurement scales and made sure that the structure of the questions was set in a counterbalancing order. Furthermore, our model includes significant latent interaction effects which can hardly be the result of CMB (Siemsen, Roth, & Oliveira, 2010). In addition, we conducted several ex post tests for CMB based on our dataset. First, we computed the Harman's one factor test by including all indicators of the dependent and independent variables into an exploratory factor analysis. The single factor only explains 24.71% of the variance, indicating that it does not account for a large percentage of the total variance (Podsakoff et al., 2003). Second, a correlational marker variable test was applied (Lindell & Whitney, 2001). We included *self-perception* as a marker variable as it is theoretically unrelated to our model constructs. We therefore asked the respondents to assess their firms' relative competitive advantage from 1 (no advantage) to 5 (very high advantage) related to the following dimensions: (1) cost/price, (2) quality, (3) technical performance, (4) reputation, (5) delays/responsiveness, (6) services, and (7) proximity. After controlling for this marker in a partial correlation analysis of our model constructs, no substantial changes of our zero-order correlations could be observed. Finally, as advised by Kock (2015), we examined whether multicollinearity indicates common method bias. However, as all variance inflation factors between the first order constructs are below 5, this potential issue could be ruled out as well. Thus, we found no indication that common method bias is a serious issue in our study.

4.6. Results of the PLS analysis and hypothesis test

We calculated and compared three models (I-III) (Table 5). Model I only includes the control variables with only two significant effects and a rather low R^2 of 0.132. Model II shows the main effects without interaction effects. As compared to Model 1, the R^2 of this model is

Table 2
Quality criteria of reflective first-order-constructs.

Construct	measurement item	Item loadings	AVE	CR
Business Model Innovation	**What were you able to accomplish in the last 1–5 years?**	–	0.521	0.884
Self-developed	Overall, dramatic cost advantages.*			
	Dramatic improvements of operative processes' effectiveness (e.g., R&D/production/ marketing).	0.684		
	Completely new sources of revenue.	0.736		
	A dramatic expansion of the product or services range.	0.737		
	Capture new consumer segments.*	–		
	Significant new sales and distribution channels.	0.772		
	Significantly improved satisfaction of customer desires and requirements.	0.799		
	Greatly improved efficiency in resources (HR, finance, technologies, etc.).	0.825		
	New forms of value or supply chains.	0.852		
Knowledge management technology	**My organization uses technology that allows…**		0.706	0.878
Gold et al. (2001)	It to search for new knowledge.	0.790		
	It to retrieve and use knowledge about its products and processes.	0.887		
	It to retrieve and use knowledge about its markets and competition.	0.842		
Knowledge management structure	**My organization('s)** …		0.633	0.873
Gold et al. (2001)	Structure facilitates the discovery of new knowledge.	0.798		
	Structure facilitates the creation of new knowledge.	0.775		
	Designs processes to facilitate knowledge exchange across functional boundaries.	0.847		
	Structure facilitates the transfer of new knowledge across structural boundaries.	0.758		
Knowledge management culture	**In my organization** …		0.649	0.880
Gold et al. (2001)	Employees are valued for their individual expertise.	0.672		
	Employees are encouraged to ask others for assistance when needed.	0.831		
	Employees are encouraged to interact with other groups.	0.864		
	Employees are encouraged to discuss their work with people in other workgroups.	0.840		
	My organization …			
Knowledge management acquisition process	Has processes for benchmarking performance.	0.751	0.617	0.889
Gold et al. (2001)	Has teams devoted to identifying best practices.	0.828		
	Has processes for exchanging knowledge with our business partners.	0.816		
	Has processes for acquiring knowledge about new products/services within our industry.	0.776		
	Has processes for acquiring knowledge about competitors within our industry.	0.752		
	My organization …			
Knowledge management conversion process	Has processes for filtering knowledge.	0.781	0.649	0.944
Gold et al. (2001)	Has processes for absorbing knowledge from individuals into the organization.	0.777		
	Has processes for absorbing knowledge from business partners into the organization.	0.866		
	Has processes for integrating different sources and types of knowledge.	0.841		
	Has processes for replacing outdated knowledge.	0.836		
	My organization …			
Knowledge management application process	Has processes for using knowledge to solve new problems.	0.729	0.660	0.921
Gold et al. (2001)	Matches sources of knowledge to problems and challenges.	0.811		
	Uses knowledge to improve efficiency.	0.796		
	Is able to locate and apply knowledge to changing competitive conditions.	0.852		
	Quickly applies knowledge to critical competitive needs.	0.820		
	Quickly links sources of knowledge in solving problems.	0.860		
Organizational risk-taking tolerance	Our company places high value on taking risks, even if there are occasional mistakes.	0.856	0.754	0.902
Tellis et al. (2009), Herzog and Leker (2010)	In our company, risky activities are commonplace.	0.866		
	Relative to other companies, we tend to favor higher-risk, higher return decisions.	0.884		
	Managers in our company rarely make risky decisions.*	–		
Environmental dynamism	Technological changes in our industry were rapid and unpredictable.	0.847	0.626	0.870
Jaworski and Kohli (1993)	The market competitive conditions were highly unpredictable.	0.808		
	Customers' product preferences changed quite rapidly.	0.719		
	Changes in customers' needs were quite unpredictable.	0.786		
Competitive intensity	Competition in our industry is cutthroat.	0.792	0.695	0.872
Jaworski and Kohli (1993)	There are many competitive rivalries in our industry.	0.832		
	Intensive competitor-related activities are a hallmark in our industry.	0.875		
Firm hierarchy**	In our organization the employees can directly communicate with the CEO.	0.783	0.604	0.884
Self-developed	In our organization it is easy to distribute new ideas to people responsible for decision making.	0.824		
	Our organizational reporting channels are unbureaucratic.	0.812		
	Our organization has lean organizational structures.	0.761		
	Our organization has a very flat hierarchical structure.	0.701		

Note:
* These items were excluded due to low factor loadings.
** As the items for firm hierarchy capture flat hierarchies, we reversed the answers.

Table 3
Descriptives and construct correlations.

Construct			Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12
Internal knowledge management capabilities	1	Knowledge management culture	3.855	0.738	0.805											
	2	Knowledge management structure	3.422	0.795	0.563	0.795										
	3	Knowledge management technology	3.600	0.914	0.346	0.317	0.840									
External knowledge management capabilities	4	Knowledge management acquisition process	3.238	0.814	0.359	0.418	0.395	0.785								
	5	Knowledge management conversion process	3.212	0.818	0.369	0.445	0.402	0.743	0.821							
	6	Knowledge management application process	3.510	0.792	0.464	0.541	0.390	0.596	0.731	0.812						
Moderator	7	Organizational risk-taking tolerance	2.782	0.912	0.052	0.123	0.041	0.225	0.202	0.205	0.869					
Control variables	8	Environmental dynamism	2.834	0.803	0.009	0.087	0.040	0.162	0.207	0.102	0.291	0.791				
	9	Competitive intensity	3.309	0.840	−0.032	0.029	0.018	0.231	0.314	0.114	0.257	0.439	0.834			
	10	Firm hierarchy	1.844	0.797	−0.340	−0.250	−0.171	−0.222	−0.259	−0.329	−0.148	0.106	−0.004	0.777		
	11	Firm size (employees)	4.144	1.130	−0.064	−0.030	0.031	0.002	0.002	−0.085	−0.002	0.227	0.140	0.239	1.000	
	12	BMI	3.300	0.677	0.234	0.188	−0.074	0.390	0.343	0.353	0.311	0.234	0.160	−0.184	−0.071	0.722

Note: Numbers on the main diagonal show the square-root of the AVE.

Table 4
Evaluation of the inner formative measurement model.

Construct/item	Path weight	t-value	VIF
Internal knowledge management capabilities			
Knowledge management culture	0.498***	14.073	1.535
Knowledge management structure	0.464***	15.252	1.502
Knowledge management technology	0.296***	8.488	1.165
External knowledge management capabilities			
Knowledge management acquisition processes	0.324***	20.760	2.263
Knowledge management conversion processes	0.373***	23.110	3.130
Knowledge management application processes	0.425***	25.162	2.175

Note:
*$p < 0.100$.
**$p < 0.050$.
*** $p < 0.010$.

Table 5
Hypothesis test and model fit.

Model **Dependent variable**: Business model innovation	I	II	III
Independent variables:			
Internal knowledge management capabilities		0.052 (0.091)	0.045 (0.082)
External knowledge management capabilities		0.276** (0.093)	0.282** (0.093)
Organizational risk-taking tolerance		0.192* (0.081)	0.187** (0.073)
Interaction terms:			
Organizational risk-taking tolerance * internal knowledge management capabilities			−0.202** (0.075)
Organizational risk-taking tolerance * external knowledge management capabilities			0.203** (0.067)
Control variables:			
Environmental dynamism	0.246** (0.087)	0.156 (0.092)	0.141 (0.088)
Competitive intensity	0.055 (0.093)	−0.019 (0.086)	−0.004 (0.086)
Firm hierarchy	−0.192* (0.075)	−0.044 (0.084)	−0.049 (0.079)
Firm size	−0.060 (0.079)	−0.063 (0.073)	−0.097 (0.067)
Industry = Automotive	−0.057 (0.086)	−0.069 (0.085)	−0.069 (0.083)
Industry = Biotechnology	0.044 (0.093)	−0.015 (0086)	−0.024 (0.086)
Industry = Engineering	−0.086 (0.085)	−0.091 (0.080)	−0.081 (0.079)
Industry = Electronics	−0.108 (0.102)	−0.081 (0.099)	−0.094 (0.098)
R^2	0.132	0.248	0.289
Adjusted R^2	0.095	0.203	0.239
SRMR	0.063	0.078	0.078
Q^2	0.054	0.104	0.123

Notes: *$p < 0.050$, **$p < 0.010$, ***$p < 0.001$, Values in parentheses show the standard error.

substantially higher with 0.248. Finally, Model III estimates our full hypothesized model including the interaction effects. This is used for the hypothesis test. This model explains a good share of 28.9% of the variance of BMI. Furthermore, this model shows a good overall model fit according to the standardized root mean square residual (SRMR) since the value of 0.078 is less than 0.080 (Hu & Bentler, 1999). The positive Q^2 value of 0.123 for BMI indicates good predictive relevance of this model.

The empirical findings support the hypothesized positive effect of

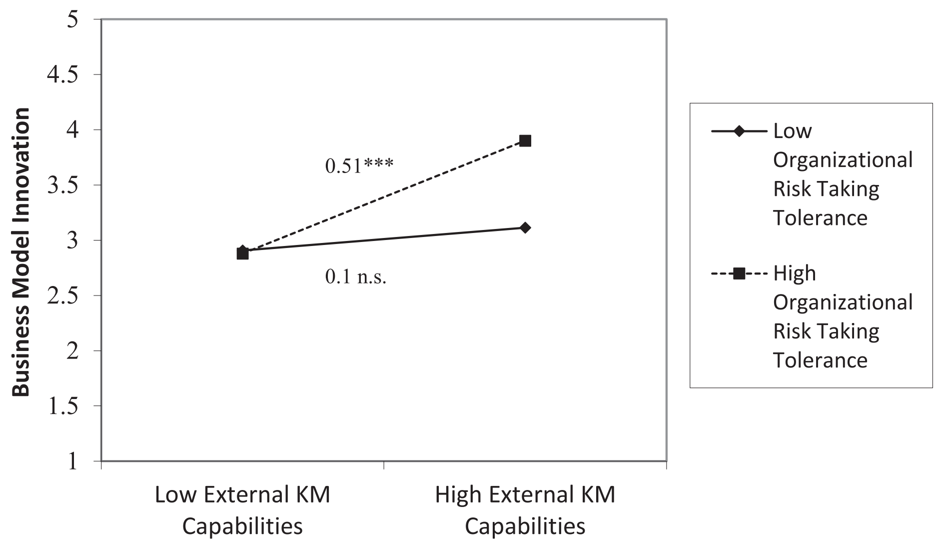

Fig. 2. Interaction between external knowledge management capabilities and organizational risk-taking tolerance. Note: n.s. not significant, *p < 0.100, **p < 0.050, ***p < 0.010.

external KM capabilities on BMI (β = 0.382, p < 0.01) (Hypothesis 2). However, internal KM capabilities show no significant effect on BMI (β = 0.045, p > 0.1), thus rejecting Hypothesis 1. We further postulated that the organizational risk-taking tolerance strengthens the extent to which internal and external KM capabilities enable BMI. Whereas our data support the effect of external KM capabilities on BMI (β = 0.203, p < 0.01) (Hypothesis 4), the moderation is negative and significant for the effect of internal KM capabilities on BMI (β = −0.202, p < 0.01). Therefore, Hypothesis 3 has to be rejected.

To better understand the moderating effects, we further plotted these in two different ways. We visualized the simple slopes and the marginal effects (Brambor, Clark, & Golder, 2006). Fig. 2 depicts the interaction between external KM capabilities and the organizational risk-taking tolerance. The regression lines show that high organizational risk-taking tolerance (+1 SD) strengthens the effect of external KM capabilities on BMI. However, for organizations with a low risk-taking tolerance (−1 SD), high levels of external KM capabilities seem to reduce BMI. Fig. 2 shows the marginal effects external KM capabilities have on BMI for different degrees of organizational risk-taking tolerance. It can be seen that this effect increases with an increase of organizational risk-taking tolerance and for low degrees of organizational risk-taking tolerance, this effect is insignificant (i.e., when the lower bound of the 95% confidence interval crosses the zero-effect line) (see Fig. 3).

Figure 4 visualizes the interaction between internal KM capabilities and organizational risk-taking tolerance. Here the effects are opposite to the ones found for internal KM capabilities. Under conditions in which firms have a high organizational risk-taking tolerance (+1 SD), there is no obvious difference between organizations with low or high internal KM capabilities. However, when firms have a low risk-taking tolerance (-1 SD), high internal KM capabilities lead to higher outcomes of BMI. Internal KM capabilities seem to gain importance for firms that are risk averse. This is further substantiated by looking at the marginal effects of internal KM capabilities in Fig. 5. We see that internal KM capabilities have a significant positive effect on BMI when the organizational risk-taking tolerance is low. This effect even shifts to a negative significant effect when the organizational risk-taking tolerance reaches a high degree.

4.7. Analysis 2: Fuzzy set qualitative comparative analysis

We follow standard procedures for running the fsQCA. First, data calibration focuses on transforming ordinary data into fuzzy-set membership with values ranging from 0 to 1. It is necessary to specify the values of an interval-scale variable that correspond to the threshold for full membership (e.g., fuzzy score equal to 0.95), the cross-over point (e.g., fuzzy score equal to 0.5), and the threshold for full non-membership (e.g., fuzzy score equal to 0.05) (Ragin, 2009). In line with

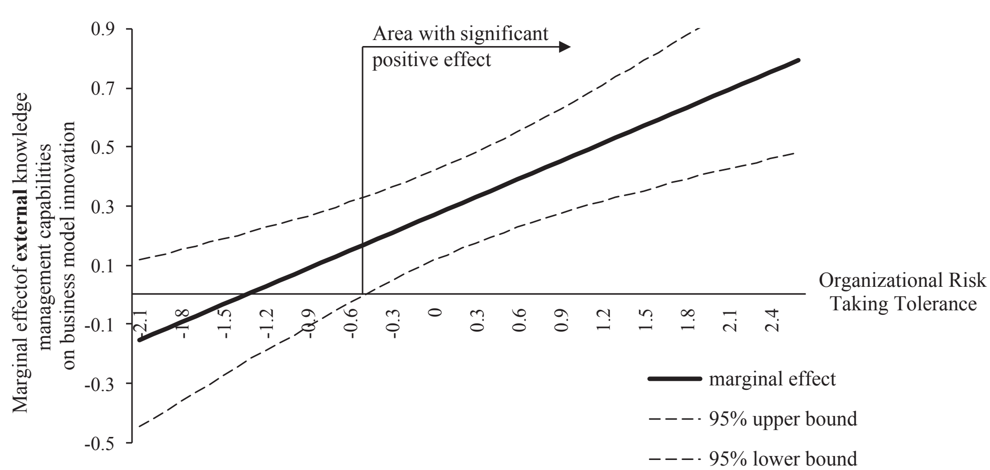

Fig. 3. Marginal effect of external knowledge management capabilities on BMI.

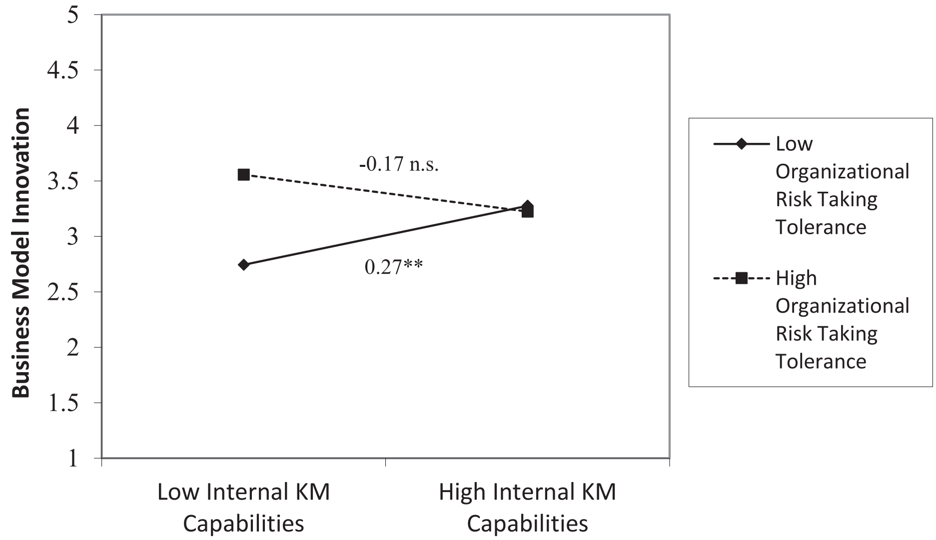

Fig. 4. Interaction between internal knowledge management capabilities and organizational risk-taking tolerance. Note: n.s. not significant, *p < 0.100, **p < 0.050, ***p < 0.010.

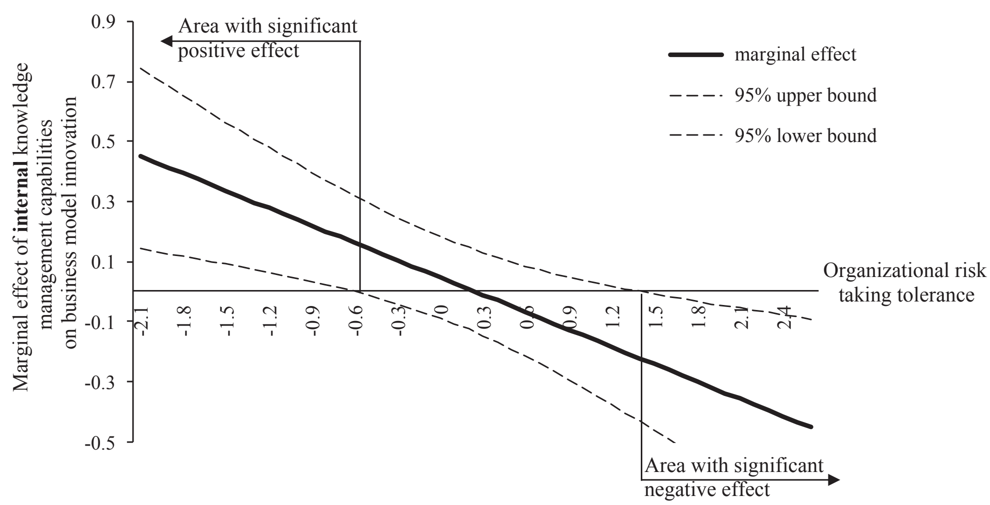

Fig. 5. Marginal effect of internal knowledge management capabilities on BMI.

previous studies (e.g., Kallmuenzer, Kraus, Peters, Steiner, & Cheng, 2019; Palmer et al., 2019), we set the original values of 5.0, 3.0, and 1.0 of relevant antecedents and BMI from five-point Likert scales to correspond to full membership (95%), cross-over anchors (50%), and full non-membership (5%). In the next step of the fsQCA, this study separates configurations that are fostering BMI from those that are not by specifying the consistent cutoff value as 0.85 and the number-of-cases threshold as 2 (Ragin, 2009) and uses the truth table algorithm to generate the different combinations of causal conditions that are sufficient for achieving high BMI. Following the recommendation of Ragin (2009), we then use standard analysis of fsQCA to generate the solutions. Finally, complex solution (no logical remainders used), intermediate solution (partial logical remainders are selected), and parsimonious solution (all logical remainders may be used) are three solutions produced for each fsQCA analysis. Because the intermediate solutions are generally superior to both the complex and parsimonious solutions (Ragin, 2009), this study relies on the intermediate solutions to combine relevant antecedents (e.g., KM culture, structure, technology, acquisition process, conversion process, and application process) into various causal recipes to explore how these contribute to BMI in two separate groups for low and high organizational risk-taking tolerance.

4.8. Results of the fsQCA

The fsQCA provides a more nuanced understanding of the configurations of internal and external KM capabilities that are beneficial for SMEs in changing their business model. In fsQCA, two indices are used to assess the quality and relevance of a solution (Ragin, 2009). The coverage index provides information on the relevance of conditions for the outcome, whereas a low degree of coverage indicates several paths (combinations of conditions) to the same outcome. The consistency index is analogous to a correlation that indicates how closely the subsets of conditions and the outcome are related to each other.

Table 6 shows intermediate solutions for achieving high BMI of two groups based on low (e.g., group 1) and high (e.g., group 2) organizational risk-taking tolerance with minimum solution coverage of 0.80 and solution consistency of 0.89. These configurations explain a large proportion of the outcome and show that a subset relation exists. This study further uses simple notations for causal configurations in which black circles "●" indicate the presence of causal conditions, white circles "○" indicate the absence or negation of causal conditions, and the blank cells represent "doesn't matter" conditions. Fig. 6 provides a more detailed illustration of the configurations for high BMI.

The results of the fsQCA analysis of the antecedent conditions for

Table 6
Intermediate solutions of high BMI.

Path	Antecedent						Coverage		Consistency	Solution	
	KMCU	KMST	KMTE	KMAC	KMCO	KMAP	Raw	Unique		Coverage	Consistency
1A	●	●	●	○		●	0.47	0.03	0.93	0.80	0.89
2A	●		●	●	●	●	0.70	0.03	0.93		
3A	●	●		●	●	●	0.70	0.03	0.93		
4A	●	●	○	○	○	○	0.30	0.02	0.94		

Notes:
1. KMCU = knowledge management culture, KMST = knowledge management structure, KMTE = knowledge management technology, KMAC = knowledge management acquisition process, KMCO = knowledge management conversion process, and KMAP = knowledge management application process.
2. Black circles indicate the presence of causal conditions (i.e., antecedents). White circles indicate the absence or negation of causal conditions. The blank cells represent "doesn't matter" conditions.

high levels of BMI reveal four pathway solutions. For all cases, KM culture presents a core condition for achieving BMI. Solution 1–3 provide pathways leading to high BMI independent of KM conversion processes as is the case in solution 1, independent of KM structure, as shown in solution 2, and independent of KM technology as provided by solution 3. These solutions indicate that high BMI can be achieved independent of KM conversion processes, KM structure, or KM technology, if all other KM capabilities are strongly developed. Finally, solution 4 indicates that even under the absence of external KM capabilities (KM acquisition, conversion, and application processes) and KM technology, BMI can be attained through high KM culture and structure.

5. Discussion and conclusion

While scholars acknowledge the necessity of KM capabilities for product and process innovation (Helfat et al., 2007; Velu, 2015), little is known about which particular KM capabilities SMEs rely on to innovate the business model. To address this research gap, this study was designed to advance our understanding of how particular KM capabilities affect the ability to innovate the business model in SMEs and to identify whether these effects are further moderated by a firm's risk-taking tolerance using two different methods of analysis, SEM and fsQCA, for increasing robustness and providing depth to the study.

The findings suggest that external KM capabilities of acquiring new external knowledge, converting it to be ready for use, and finally applying it for commercialization, are essential KM capabilities that enable SMEs to innovate their business model. Internal KM capabilities, emphasizing internal knowledge exploitation and replication, showed no significant effect on BMI. This finding might be related to the holistic and often disruptive nature of BMI that requires knowledge that is not available insight to the firm or might even be hindered by relying on traditional organizational knowledge. Snihur and Wiklund (2019) recently found that for BMI, firms mainly rely on various external knowledge sources, which include broad knowledge searches in distant industries and settings. Furthermore, our findings are in line with studies that have proposed that external knowledge sources may foster and generate ideas for BMI (Doz & Kosonen, 2010; Martins et al., 2015; Teece, 2018), and that BMI is triggered through changes occurring in the firm's extant ecosystem (Amit & Zott, 2015; Heij et al., 2014). Our results demonstrate that innovating a firm's business model in today's business environment requires firms to have an absorptive capacity – the ability to develop external KM capabilities. This then enables firms to become aware of large market trends and new opportunities arising from shifts in the firm's ecosystem (e.g., new technologies, changing customer demands, regulations, etc.) (Cohen & Levinthal, 1990). Furthermore, our findings showed the positive relationship external KM capabilities have on BMI is strengthened when firms have a high risk-

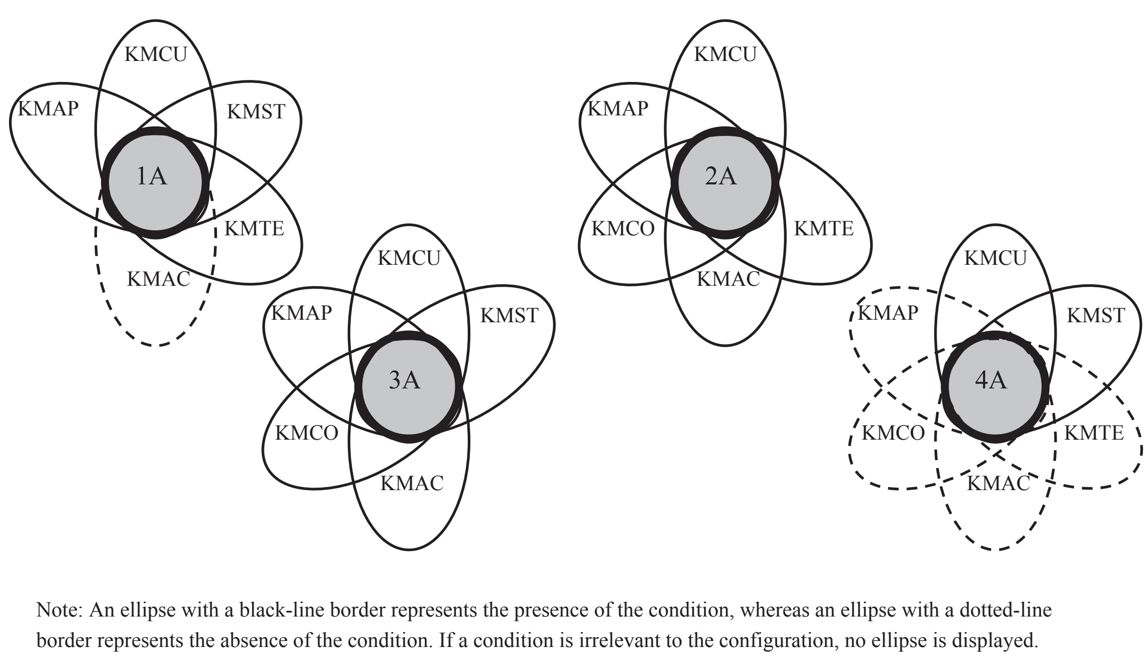

Fig. 6. Causal configurations for high BMI. Note: An ellipse with a black-line border represents the presence of the condition, whereas an ellipse with a dotted-line border represents the absence of the condition. If a condition is irrelevant to the configuration, no ellipse is displayed.

taking tolerance. However, this is not the case for firms with a low tolerance for risk-taking. Our findings depict that for firms with low organizational risk-taking tolerance, BMI is strengthened through internal KM capabilities. Thus, internal KM capabilities seem to gain importance for risk averse firms. These findings suggest that risk averse firms execute BMI opportunities that mainly arise from their internal knowledge assets (e.g., R&D department). A possible explanation may be that risk averse firms pursue less radical BMI or more efficiency oriented BMI (Clauss et al., 2019b). Risk averse firms are rather internally oriented and set on improving internal efficiency rather than engaging in risky projects (Cameron & Quinn, 2011). Organizations with a low risk-taking tolerance may focus on leveraging core competencies (Leonard-Barton, 1992) or replicating the business model without fundamentally changing its underlying logic (Heij et al., 2014).

The more nuanced findings of the fsQCA confirm that external KM capabilities represent core conditions in achieving high BMI. However, the results also demonstrate a conditional relationship between internal KM culture, structure and technology, and BMI in the presence of external KM capabilities. We reveal four pathways in which different combinations of internal and external KM capabilities provide conditions for high BMI. Whereas two configurations show that high external KM capabilities can be combined with most internal KM capabilities. Two pathways however suggest that internal KM capabilities can create high BMI in the absence of external knowledge acquisition. This speaks for a situation in which internal KM capabilities can only achieve their full potential if no new knowledge is acquired. For all pathways, KM culture presented a core condition for achieving BMI. These latter findings are in line with prior studies on product and process innovation which propose that successful innovation in incumbent firms is dependent on developing both internal and external KM skills (Helfat et al., 2007; Teece, 2007; Velu, 2015). However, while product innovation is mainly based on knowledge about customer preferences and specialized knowledge related to R&D, and process innovation is usually based on internal tacit knowledge of improving manufacturing efficiency paired with an external search of the latest technological improvements (Snihur & Wiklund, 2019), our findings indicate that BMI might be achieved through balanced mixtures of external and internal knowledge that captures knowledge related to all dimensions of the business model.

5.1. Contribution to research

Our study contributes to research in several ways. First, we contribute to the emerging literature on the internal enablers that drive BMI. Previous studies have highlighted leadership capabilities for identifying and experimenting with new business opportunities (Achtenhagen et al., 2013; Doz & Kosonen, 2010), resource capabilities for flexible use and re-use of resources (Clauss et al., 2019a; Doz & Kosonen, 2010; Teece, 2007), and cultural values and commitment to change (Hock, Clauss, & Schulz, 2016). We extend the knowledge in this discourse by shedding light on how organizational KM capabilities affect BMI for SMEs. So far, extant studies have mainly been conceptual without directly testing the proposed effect internal enablers have on BMI (Foss & Saebi, 2017). Our empirical findings substantiate prior conceptual and case study based studies by directly linking KM capabilities to BMI. In doing so, we follow the call for empirical research and causal-relationship testing and to advance theory building for BMI literature (Foss & Saebi, 2017). We specifically advance the literature that applies dynamic capability theory to BMI (Mezger, 2014; Teece, 2018). Our study substantiates the general assumption that dynamic capabilities facilitate a proactive BMI (Clauss et al., 2019a). As an important addition, we look into the microfoundations of organizational sensing and show that firms should develop the ability to acquire, convert, and apply knowledge for successful BMI. By including organizational risk-taking tolerance as a moderator, we take into account that enablers in general and required capabilities more specifically for BMI may vary according to individual firm-level variables (Foss & Saebi, 2017). Organizational risk-taking tolerance is a general orientation of the firm (Kreiser, Marino, Kuratko, & Weaver, 2013) and thus defines the overarching context in which KM capabilities operate. It determines the willingness of the organization to utilize new business opportunities in a situation of uncertainty and will therefore determine (Choo, 2013), how and to what extend new knowledge is been used. The analysis of the moderating role of an organization's risk-taking tolerance highlights that mirco-level dynamic capabilities are not necessarily universally beneficial for BMI. Dynamic capabilities that might be successful for BMI in one firm are not necessarily successful in another firm. As such, this empirical study represents a first step towards better understanding the underlying dynamics of micro-level capabilities.

Second, we contribute to the literature that links knowledge management and innovation (Cohen & Levinthal, 1990; Snihur & Wiklund, 2019; Trantopoulos et al., 2017). Prior studies in this field have primarily analyzed the role of different knowledge sources on product (Caloghirou, Kastelli, & Tsakanikas, 2004; Cohen & Levinthal, 1990) or process innovation (Trantopoulos et al., 2017). We support their general findings that knowledge is beneficial to innovation as it helps to identify new ideas such as customer demands, new technological opportunities, competitor moves, etc. More specifically, our findings show the importance of external KM capabilities that facilitate the identification of knowledge sources outside of the firm. BMI however is conceptually different from product and process innovation (Snihur & Wiklund, 2019; Wang, Voss, Zhao, & Wang, 2015). As such, this study provides a first starting point for better understanding how particular KM capabilities lead to BMI. This is in keeping with Snihur and Wiklund (2019) who believe that the more radical and holistic nature of BMI particularly requires a more distant knowledge search from outside of the firm. This is also in line with the argument that BMI ideas can be generated by adopting business model analogies from companies in other industries (Gassmann, Frankenberger, & Csik, 2014). The findings of our fsQCA, that configurations of external and internal KM capabilities might be complementary further supports initial findings from Trantopoulos et al. (2017) who show that additional external knowledge might even reduce process innovation if the firm lacks internal KM technology. Despite our initial findings, this clearly shows an avenue for future research on the dynamics of various KM capabilities in relation to different types of innovation and particularly BMI.

Third, although SMEs play an important role regarding economic growth in most economies, studies analyzing BMI processes in SMEs are relatively scarce (e.g., Anwar, 2018; Clauss et al., 2019b; Laudien & Daxböck, 2016). While BMI literature is mainly dominated by studies on large companies (Guo, Tang, Su, & Katz, 2017), this study contributes to the BMI literature by analyzing how internal enablers for BMI fit in the SME context. Our study paves the way for better understanding enablers that drive BMI in SMEs. This is particularly relevant as SMEs, because of their limited size and resources, are less able to experiment with new business models under high uncertainty but need to ensure that internal mechanisms for identifying and utilizing BMI exist. Our findings substantiate previous findings that SMEs' BMI benefits from a better recognition of opportunities (Guo et al., 2017), and that knowledge management is an important capability that SMEs need to establish in order to be successful on a long-term base (Bagnoli & Vedovato, 2014). Particularly, as KM is underrepresented in SMEs (Hutchinson & Quintas, 2008), our findings provide an important approach for SMEs to facilitate BMI. Additionally, our findings might be different to those in large firms. It is reasonable that the missing or even negative effect of internal KM capabilities of BMI comes from the limited size and thus also limited knowledge base and knowledge diversity within these firms. In contrast, large enterprises have more different business units and might therefore benefit to a larger extent from internal KM capabilities.

5.2. Managerial implications

This study provides useful implications for managers in SMEs. First, our findings depict that the effect specific KM capabilities have on BMI are dependent on the organizational risk-taking tolerance. For firms that are risk tolerant and willing to innovate the business model in a way that goes beyond the existing business model, managers are advised to develop external oriented KM capabilities that enable them to understand and interact with the ecosystem which surrounds the firm. These external KM capabilities should comprehend knowledge acquisition processes that particularly focus on increasing the sensitivity to changes in environmental trends. In order to develop these capabilities, managers are advised to implement processes that capture knowledge on the latest product and service developments, that exchange knowledge with business partners, and try to devote teams for identifying best practices, etc. Developing these processes sharpens the overall awareness of the firm and enables the organization to identify new business model opportunities and potential threats (Teece, 2010). Furthermore, external KM capabilities should comprehend processes for converting external knowledge to company knowledge and application processes for implementing new business models. In order to convert external knowledge, managers are advised to apply processes that absorb knowledge from individuals and business partners into the firm. These processes should further integrate different sources of knowledge and replace the firm's outdated knowledge. To finally apply the external knowledge for novel business model solutions, managers are advised to integrate processes that quickly link the newly converted knowledge for solving current problems, for experimenting with innovative ideas, and for increasing organizational efficiency. External KM capabilities are especially important if managers are not planning on innovating the BMI on their own, but rather through alliances with new suppliers, partners, etc.

However, if managers are in a firm with low risk-taking preferences, then we advise managers to leverage their internal KM capabilities. Especially when firms are not planning on entirely innovating the business model but want to improve and tweak the novelty or efficiency of certain business model components, strong internal KM capabilities have shown to be important. Thereby, managers should foster a socio-technological environment that strengthens the knowledge transfer relationships among employees within and across functional teams and integrate a knowledge information system that support these processes. Many examples of firms unable to adapt to changing market conditions (e.g., Blockbuster, Kodak, etc.) KM capabilities in order to sense economic developments and if necessary, to innovate the entire business model. Simply tweaking certain components of the business model or increasing the overall efficiency may not always be sufficient to remain competitive. Firms that are rather risk averse are therefore also advised to invest in external KM capabilities that help organizations to be aware of environmental developments. Therefore, we advise all managers to develop external KM capabilities in order to capture and make sense of technological trends and environmental developments. However, independent of the organizational risk-taking tolerance, managers are advised to develop a combination of both internal and external KM capabilities for BMI.

To finally apply new knowledge for novel business model solutions, the findings from the fsQCA propose the integration of different combinations of internal and external KM capabilities.

5.3. Limitations and future research

Our research has some limitations. When interpreting the data, it is important to consider the nature of the data basis for our empirical analysis. The data was collected at one point in time. The process of BMI is, however, a longitudinal process (Demil & Lecocq, 2010). Although the items for BMI were formulated to capture this process, by asking the firms about their changes within the last 1–5 years, we suggest future studies to collect data at several points in time. This would allow an in-depth analysis of processes and management behaviors that develop in the process of BMI. Furthermore, we rely on key informants in each organization. Although we did our best to ensure that these respondents were knowledgeable and in an adequate organizational position, in order to capture facets of BMI, multiple informants in each organization might be preferable. Although this issue is lower for SMEs, we encourage future studies to collect data with respondents at different levels in the firm.

From a theoretical perspective, our study only focused on external and internal KM capabilities. However, firms often engage in network collaborations, providing them access to relevant knowledge coming from outside the firm. In network collaborations, firms actively cooperate with key partners and customers to promote the exchange of knowledge (Dyer & Nobeoka, 2000). Thereby, they create "networks of learning" (Powell, Koput, & Smith-Doerr, 1996). Hence, network collaborations provide an additional stream of knowledge which can be used for identifying BMI opportunities. Therefore, we suggest future studies to analyze the knowledge stream arising from network collaborations and to study how they influence BMI.

Another source used to capture knowledge coming from outside the firm is the acquisition of knowledge through mergers and acquisitions (M&As) and joint ventures (JVs) (Dunlap, McDonough, Mudambi, & Swift, 2015). M&As are a fast way of gaining entirely new knowledge resources (Barney, 1991), while JVs are based on collaborative knowledge transfers with other firms. During joint projects, firms share knowledge and thereby increase their knowledge stock and improve core competencies (Rosenkopf & Almeida, 2003). Considering that M&A and JV are popular methods used to increase a firm's knowledge capabilities and their overall innovativeness (Dunlap et al., 2015), we encourage future research to analyze how the acquisition of knowledge through M&As and the knowledge transfer in JVs influences a firm's KM capabilities and the ability to innovate the business model.

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