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Organizing for Open Innovation - Aligning Internal Structure and External Knowledge Sourcing

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Abstract

In the past decade, research on open innovation has brought renewed attention to ways how firms can gain from the interaction with external sources of knowledge and innovation. Complementary internal management practices, however, that explain why some firms benefit from open innovation more than others are still largely unexplored. This study adopts the notion of open innovation as external knowledge search and investigates its mutual interdependence with internal organizational structures of a firm?s innovation function. Drawing upon behavioral theories about organizational search and information processing, we hypothesize how structural dimensions such as specialization, formalization and decentralization affect gains from open innovation. Based on a sample of German manufacturing firms, we find higher performance gains from open innovation by aligning internal organizational structures in terms of lower specialization as well as higher formalization and decentralization. These organizational contingencies of open innovation further depend on firms? R&D intensity: (1) For firms with high internal R&D intensity, lower specialization is an effective means to turn a substitutional effect of open innovation into a complementary one. (2) For firms with low internal R&D intensity, higher formalization and decentralization are an effective means to enhance the substitutional effect of open innovation.

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Organizing for Open Innovation:

Aligning internal structure with external knowledge search

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Keywords: Open Innovation, innovative search, external knowledge, R&D intensity, organizational structure

1. Introduction

Innovation has traditionally been located solely in the realm of firms' internal activities, such as research & development. Yet, in light of recent advances in technology and significant changes in business conditions, Chesbrough has proposed that firms' need to make more systematic or "purposive" use of external knowledge in order to increase innovation performance (2006). In light of this observation, Chesbrough (2003) coined the term open innovation to describe a concept in which firms increasingly open up their boundaries in order to access external sources of knowledge and technology (outside-in perspective) and bring in-house inventions to markets via external paths (inside-out perspective).

The outside-in perspective of open innovation refers to firms' exchanges with a diversity of external knowledge sources (Laursen and Salter, 2006; Grimpe and Sofka, 2009). Extant research has shown that firms can benefit substantially from external knowledge integration and the utilization of a diverse set of external partners (e.g. Cassiman and Veugelers, 2006; Faems et al., 2010; Katila and Ahuja, 2002; Laursen and Salter, 2006). But previous research also suggests that this kind of openness has limitations (e.g. Deeds and Hill, 1996; Duysters and Lokshin, 2011; Rothaermel and Deeds, 2006). These limitations likely arise due to additional costs and new challenges that firms need to manage in order to appropriate and learn from external knowledge.

In this aspect, we focus on the challenge of learning. The extent to which firms can learn from external knowledge sources likely hinges on internal capabilities, processes, and skills. Recently, a number of scholars have called to investigate these organizational prerequisites in more detail (Dahlander and Gann, 2010; Van de

Vrande et al. 2010). One aspect already frequently studied in this context is absorptive capacity, i.e. firms' ability to recognize, assimilate and apply external knowledge for innovation (Cohen and Levinthal, 1990). Absorptive capacity has an obvious connection to open innovation and its performance effects (e.g. Laursen and Salter, 2006; West and Gallagher, 2006; Vanhaverbeke et al., 2007; Foss et al., 2011; Rothaermel and Alexandre, 2009; Spithoven et al., 2011). However, the concept of absorptive capacity bears considerable conceptual and empirical vagueness (Volberda et al., 2010). Therefore, it does not directly connect to open innovation and external knowledge search (Vanhaverbeke et al., 2007, p. 16). Most research approximates a firm's absorptive capacity by its internal R&D intensity (Lane and Lubatkin, 1998). But internal R&D intensity can also be viewed as an alternative knowledge search strategy that is in conflict and need of coordination with external search strategies (Laursen, 2012; Laursen and Salter, 2006).

Therefore, the objective of this study is to derive and investigate organizational dimensions of absorptive capacity (Jansen et al. 2005; Volberda et al., 2010; Foss et al. 2011) that are of relevance in managing open innovation. In particular, we aim to establish a more immediate and fine-grained theoretical connection between external knowledge sourcing on the one hand and organizational structures (Colombo and Delmastro, 2008; Burton and Obel, 2004; Miles and Snow, 1978; Mintzberg, 1979) on the other, based on behavioral theories about organizational search and information processing (Galbraith, 1973; Siggelkow and Levinthal, 2003).

Taking a contingency perspective, we investigate (1) how firms should align their internal organizational structure with their respective levels of external knowledge search, and (2) how this organizational alignment in turn differs with respect to the level of internal search and R&D. Analyzing data from a large-sale empirical study of

368 manufacturing firms, our investigation adopts the concept of “fit” from a moderation or interaction perspective (Venkatraman, 1989). Our study emphasizes three variables constituting an organization’s structure: specialization, formalization, and decentralization (Mintzberg, 1979; Pertusa-Ortega et al., 2010; Volberda, 1998). These have already been shown to be meaningful in a broader context of knowledge search, learning, and innovation (Pertusa-Ortega, et. al. 2010; Rivkin and Siggelkow, 2003). But the connection between these organizational practices and external knowledge sourcing in the understanding of open innovation has received only little attention in empirical research so far. Notable exceptions are mostly qualitative in nature (Bianchi et al., 2011; Chesbrough and Crowther, 2006; Dodgson et al., 2006; Sakkab, 2002). Foss et al. (2011) provide the only quantitative data we are aware of. However, their focus is on users as a single knowledge source and the mediating role of specific practices rather than on the moderating role of organizational structures.

The paper proceeds as follows. Section 2 presents open innovation in light of behavioral theories about firms’ organizational search and information processing. It derives hypotheses about how and when organizational structures of firms’ innovation activities should impact the extent to which firms can benefit from open innovation and external search processes. Section 3 describes our sample, measures and methods used in the analysis. The empirical results are presented in Section 4. Section 5 refers to the discussion and implications of our findings. The final Section 6 concludes with a summary of contributions, limitations and suggestions for further research.

2. Theory and hypotheses development

2.1. Open Innovation from an innovative search perspective

The exploitation and utilization of external knowledge and ideas in internal innovation processes can be regarded as the core of the open innovation model (Laursen and Salter, 2006). Firms' activities with regard to the connection with and exploitation of external knowledge sources can also be defined as firms' knowledge search strategies (Sofka and Grimpe, 2010). In other words, open innovation activities of firms find their expression in the specification of firms' search strategies.

Knowledge search is conceptualized as an activity by which organizations solve problems, and attempt to recombine knowledge for the objective of generating new products (Katila and Ahuja, 2002). By engaging in knowledge search, firms expand and renew their knowledge (base), which puts them in a position to be more innovative and successful (Levinthal and March, 1981; Rosenkopf and Nerkar; 2001). Knowledge search is one of the central aspects for the comprehension of firms' innovation success (Nelson and Winter, 1982; West, 2000).

Knowledge search processes require a lot of resources in terms of time, skills, and financial resources (Cohen and Levinthal, 1990; Levinthal and March, 1993). Therefore, search activities may be constrained in the alternatives considered, as organizations and management may suffer from cognitive limitations (Ocasio, 1997; Gavetti and Levinthal, 2000). Accordingly, search processes of firms are often very localized, which means firms search along trajectories, within fields, and with regard to knowledge they already are familiar with (Stuart and Podolny, 1996). In order to stay competitive and constantly renew their knowledge base, however, firms need to overcome these local search tendencies (Leonard-Barton, 1992; Rosenkopf and Nerkar, 2001; Stuart and Podolny, 1996).

Research has shown that it is beneficial for firms to differentiate their search efforts and to engage in more distant as opposed to local search (Laursen, 2012). This differentiation can relate to the distance of targeted technological fields (Katila and Ahuja, 2002), but also to organizational boundaries (Rosenkopf and Nerkar, 2001). External knowledge search beyond firms' organizational boundaries, as opposed to internal search within firms' R&D departments, has been shown to impact firms' innovation performance strongly (Laursen and Salter, 2006; Leiponen and Helfat, 2010; Rothaermel and Alexandre, 2009). Hence, research on external and internal knowledge search provides a theoretical and empirical foundation of open innovation.

However, also external knowledge search does not come free of limitations either. Considering these limitations and downsides, empirical research has found that external knowledge search and sourcing has an inverted U-shaped effect on innovation performance (e.g. Faems et al., 2010; Katila and Ahuja, 2002; Laursen and Salter, 2006; Rothaermel and Deeds, 2006; Rothaermel and Alexandre, 2009; Deeds and Hill, 1996; Duysters and Lokshin, 2011). Search activities and the relations to the respective external sources need to be managed, as well as the acquired knowledge inputs need to be processed by the organization in order to exert innovation impact. The constraints that firms face with regard to their processing capacities mainly derive from the restraints of attentive resources and the limitations of operational absorption capacities. Constraints may also result from a necessary coordination and balance with internal search in the form of R&D. Although there is evidence that external and internal knowledge search are complementary in some contexts (e.g. Katila and Ahuja, 2002; Cassiman and Veugelers, 2006; West, 2000), Laursen and Salter (2006) find that firms with high internal R&D intensity have difficulties in profiting from external knowledge search.

2.2. Organizational contingency of open innovation

To manage these constraints of open innovation, we argue that firms need to align their organizational structure according to the desired level of external knowledge search and internal R&D intensity. The notion of alignment can be described by the concept of "fit" which is largely based in the domain of contingency theory (Venkatraman, 1989). Contingency theory proposes that there is no one right way to design an organization, but certain organizational structures fit better given certain contexts or contingency factors (Galbraith, 1973). In the present study, we consider firms' mix of external knowledge search and internal R&D intensity as the contingency factor for the appropriateness of certain organizational structures, by which innovation performance then is jointly determined. As such, we follow the interaction approach, or the bivariate interpretation of fit, that assumes fit to be "an interaction effect of organizational context and structure on performance" (Drazin and Van de Ven, 1985: 515). We extend it to three variables in a regression-based analysis with moderator variables, interactions and sample splits (Venkatraman, 1989). While this conceptualization of alignment and fit has limitations compared to systems, multi-contingency or configurational approaches (Birkinshaw et al., 2002; Burton et al., 2002; Fiss, 2011), it can be seen as a first step towards more comprehensive organizational configurations (Venkatraman and Prescott, 1990).

Organizational structure has been shown to impact firms' effectiveness regarding the communication and processing of information (Galbraith and Nathanson, 1978; Mintzberg et al., 2003; Olson et al., 1995). It has also been connected to the ability of a firm to innovate (Argyres and Silverman, 2004; Damanpour, 1991; Tidd et al., 1997), to absorb, proceed upon, and learn from external knowledge (Jansen et al., 2005; Van den Bosch et al., 1999), and relate to external parties (Lane and Lubatkin, 1998). These aspects all represent ingredients for successful open innovation, yet the question remains as to how the organizational structure that a firm has implemented supports its open innovation activities directly.

Research has suggested that external knowledge can only be utilized successfully when firms manage to modify their organizational structure to facilitate open innovation (Bianchi et al., 2011; Dahlander and Gann, 2010). The potential to process information between internal units and these units and the external environment, respectively, is to a large extent determined by firms' organizational structure (Cohen and Levinthal, 1990; Van den Bosch et al., 1999). This highlights the importance of a firm's structural composition in the context of knowledge integration and innovation.

Organizational learning is largely dependent on a firm's contacts with external knowledge sources (Lane and Lubatkin, 1998). As a consequence, organizational search and a firm's openness towards external sources are seen as important mechanisms for organizational learning (Lane et al., 2006). In this concern, several studies have investigated the influence of organizational structure on a firm's search behavior (Cassiman and Valentini, 2009; Siggelkow and Levinthal, 2003; Zhang et al., 2007). De Boer et al. (1999) suggest that organizational structure embodied in basic organizational forms affects a firm's ability to integrate external knowledge.

Besides the ability to identify and source external knowledge, organizational learning is shaped by a firm's ability to link external and internal knowledge (Bessant and Venables, 2008). Cohen and Levinthal (1990) refer to this capability as the inwardlooking component of a firm's absorptive capacity, and highlight its importance for an effective organizational learning, as it facilitates efficient internal knowledge processing mechanisms (i.e. knowledge sharing). In this regard, previous studies have put forward the importance of organizational structure for inter-unit knowledge sharing (Tsai, 2002; Willem and Buelens, 2006), because it affects internal communication processes (Guetzkow, 1965), and also knowledge management (Lam, 2000; Pertusa-Ortega et al., 2010).

Following the argument of Cohen and Levinthal (1990), external search strategies remain ineffective without the ability of the firm to communicate and share internally what has been absorbed from the environment. In other words, even if a firm successfully manages to search for knowledge externally and to establish and maintain linkages to external knowledge sources, the firm will not be able to achieve high levels of innovation performance in the absence of internal knowledge-processing capabilities.

Organizational structures facilitate learning and innovation by balancing different static and dynamic elements. However, they overlap in the most fundamental and prevalent dimensions of specialization, formalization, and (de-) centralization (Burton et al., 2002; Burton and Obel, 2004; Miller and Dröge, 1986; Mintzberg, 1979; Olson et al., 2005; Volberda, 1996, 1998; Vorhies and Morgan, 2003; Walker and Ruekert, 1987). According to Walker and Ruekert (1987), using these dimensions one can resemble ideal-type organizational designs similar to those proposed by Burns and Stalker (1961) and their distinction of mechanistic and organic organizations, or the “organizational archetypes” identified by Mintzberg (1989). Hence, this study uses these three central structural dimensions to investigate the organizational contingencies of open innovation.

2.3. The moderating effect of specialization

The division of tasks and activities into subtasks and the assignment of these tasks to and only to specific members or units of the organization as their prime activity is referred to as “specialization” or “differentiation” (Mintzberg, 1979; Mintzberg et al., 2003). In firms that exhibit high degrees of specialization, increased division of labor creates groups of specialists, who direct their efforts to a well-defined but limited range of activities (Ruekert et al., 1985). In such an environment, tasks are "performed by someone with that function and no other" (Pugh et al., 1968: 73) Specialization and horizontal differentiation enhances firms’ knowledge performance due to accumulation and mastery of certain skills and abilities of specialists within their specific range of functions (Willem and Buelens, 2006; Pertusa-Ortega et al., 2010). However, Damanpour (1991) and Damanpour and Gopalakrishnan (1998) suggest that the positive effect of specialization refers to later stages of an innovation process.

Hence, specialization may be associated with certain drawbacks in the compatibility with firms’ efforts to organize a distributed external knowledge search. An increased generation of domain-specific knowledge due to high levels of specialization involves the development of different languages and views between the various subunits of a firm (Grant, 1996). Hence, specialization leads to decreasing differences within and increasing differences between subunits (Willem and Buelens, 2006). Although specific knowledge within multiple subunits indicates desirable knowledge heterogeneity at the firm-level, it is also associated with increasing structural and mental boundaries inside the firm (Olson et al., 2005; Pertusa-Ortega et al., 2010). An increase of inter-unit boundaries may increase the costs of communication and learning (Colombo and Delmastro, 2008), and thus inhibit knowledge transfer (Willem and Buelens, 2006). Since boundaries between subunits constitute the interfaces across which knowledge is transferred within the company, and each interface bears the risk of potential knowledge loss, a firm may not be able to fully leverage the potential of its external search strategy when specialization is pushed too far. Garud and Karaswamy (1995: 98) speak of the danger of units “hoarding knowledge”. This appears to be a major drawback, since it requires a firm-wide dissemination of knowledge, and thus learning processes between subunits, for the entire firm to benefit from external knowledge integration (Stieglitz and Billinger, 2007).

Van den Bosch et al. (2003) suggest that specialization, thus the division of tasks, equally leads to the division of knowledge. This may result in enormous efforts for re-integrating diverse knowledge-based activities if the respective specialized activities are part of a greater whole. And finally, Cohen and Levinthal (1990) argue that specialization undermines innovation performance by reducing diversity, which may be a prerequisite for accessing and absorbing new knowledge. Concerning external search and knowledge integration, low diversity might be indicated by external search being restricted only to specialists, thereby reducing the variety of external search. Though specialization may facilitate external search, it may likewise limit the variety in external knowledge sources, as specialists tend to pursue “narrow” search endeavours (Van den Bosch et al, 2003).

Summarizing, specialization may be conducive to the application of acquired knowledge, but leads to a narrow search focus and poses significant strains on the transfer and application of knowledge. Hence, the following hypothesis is stated:

Hypothesis 1*: Specialization negatively moderates the effect of external knowledge search on innovation performance.*

2.4. The moderating effect of formalization

Formalization is defined as the degree to which roles, authority relations, instructions, norms and sanctions, ways of communication, and procedures are defined by rules (Child, 1972; Khandwalla, 1977). Hence, the level of formalization reflects the individual firm member's degree of freedom in pursuing organizational tasks and in establishing intra- and inter-firm relationships (Argouslidis and Baltas, 2007; Ruekert et al., 1985). Formalization is often measured by the existence of job descriptions, manuals or control arrangements (Damanpour, 1991; Miller and Dröge, 1986).

The clear definition of rules and the assignment of distinct methods and procedures to functional roles in an organization yield the development of adeptness in a limited area of activities. This in turn results in lower error rates and higher process efficiency (Hage, 1965; Ruekert et al., 1985). Furthermore, formalization codifies best practices and provides organizational memory that facilitates the diffusion of organizational capabilities (for instance, capabilities of how and when to tap into external knowledge sources) as well as the application and the transfer of knowledge (Levitt and March, 1988; Lin and Germain, 2003; Pertusa-Ortega et al., 2010).

On the other hand, the strong emphasis on rules and procedures may lead to unchanging patterns of action and reduces process flexibility, as it hinders individuals from deviating from established behavior (Weick, 1979). This might constitute a substantial drawback, since flexibility has been found to facilitate innovation processes (Aiken and Hage, 1971; Damanpour, 1991). Scholars have argued that firms might risk to ignoring important innovation stimuli (Jansen et al., 2006), because formalization directs attention only towards restricted aspects of the firm's external environment, subsequently reducing the firm's scope of knowledge search (Jansen et al., 2005; Weick, 1979).

Yet, it has also been argued that the existence of norms and explicit procedures facilitates a firm's ability to identify and integrate external knowledge (Jansen et al., 2005; Vega-Jurado et al., 2008). Without formalization, external search and integration would suffer from being “disorganized, sporadic or ineffective” (Okhuysen and Eisenhardt, 2002: 383). Pertusa-Ortega et al. (2010) see formalization as a means to reduce ambiguity by “behavioral directives” rather than clear specifications. The reduced ambiguity enhances a firm’s ability to utilize external knowledge. Formalization offers the necessary procedures that facilitate communication with specific knowledge sources, and endows firms with the competence to access knowledge from these sources (Vega-Jurado et al., 2008).

Formalization may also improve a firm’s capacity to apply the knowledge. Through formalization, “guidelines” for communication and exchange can be established, thereby improving cooperation among employees and units (Cordón-Pozo et al., 2006). Cordón-Pozo et al. (2006) further argue that formalization also helps to transfer knowledge between units, as it lays out norms and procedures for engaging in such an exchange. Additionally, formalization was found to help by motivating employees to share explicit and tacit knowledge and by reducing costs associated with knowledge exchange (Dyer and Nobeoka, 2000; Jansen et al., 2005). Formalization is said to be similar to routinization (Feldman and Pentland, 2003), which is argued to enable flexibility (Becker et al., 2005) and reduce ambiguity (Pertusa-Ortega et al., 2010), which in turn may be beneficial for dealing with contingencies, engaging in experimentation, and creating new knowledge (Adler and Borys, 1996). Thus, the following hypothesis is proposed:

Hypothesis 2: *Formalization positively moderates the effect of external knowledge search on innovation performance.*

2.5. The moderating effect of decentralization

The degree of decentralization reflects the locus of decision-making power and refers to whether decision authority is concentrated or rather dispersed in an organization (Pfeffer, 1981). When decision-making authority is closely held by top managers (i.e. concentrated) the organizational structure is referred to as “centralized”. In contrast, “decentralized” structures exhibit a high degree of firm members' participation in decision-making, since decision rights are delegated to middle- and lower-management levels (Aiken and Hage, 1971). Accordingly, centralization and decentralization are opposite ends of the same scale (Olson et al., 2005).

Scholars have asserted that centralization can have a positive effect on innovation especially under dynamic environmental conditions (Adler and Borys, 1996; Gupta et al., 1986). Top-down directives, for example, offer clear lines of communication and involve unambiguous responsibilities. However, Colombo and Delmastro (2008) identified various sources of organizational failure due to concentrated decision authority, such as the occurrence of information transmission leaks and delays, the distortions of intra-firm communication, as well as information overload due to narrow communication channels. Due to increased levels of employee participation along all processes, decentralized organizations, on the other hand, tend to generate a higher variety of innovative ideas (Damanpour, 1991; Ullrich and Wieland, 1980). The dispersion of decision rights to middle- and lower-management levels enables the formation of sub coalitions and has a positive effect on the number of possible promoters of innovative projects (Thompson, 1965).

Accordingly, the literature proposes a rather negative relationship between centralization and firm innovativeness (Aiken and Hage, 1971). Scholars have suggested that decentralization facilitates knowledge integration and knowledge sharing. Foss et al. (2011), for example, investigate how established firms can adapt organizational structure and practices in order to more efficiently leverage user and customer knowledge. The authors argue that decision rights should be collocated with those employees who are best informed about what decision is appropriate in a given context.

Also Ruekert, Walker and Roering (1985) argue that decentralization is likely to be beneficial for innovating companies, since it empowers those employees who are close to the issue to make decisions and to implement them rapidly. Important for the external search activities of a firm, Cohen and Levinthal (1990) suggest that decentralization increases the number of potential recipients of external knowledge, thus increasing the number of a firm's interfaces with the external environment. Decentralization enhances the adoption of new attitudes and behaviors (Pertusa-Ortega et al. (2010), which is important for external knowledge use. With respect to knowledge sharing, previous research has suggested that decentralization increases the willingness to share knowledge (Gupta and Govindarajan, 2000). Additionally, decentralization broadens internal communication and improves the quality of knowledge sharing among subunits (Sheremata, 2000; Van Wijk et al., 2008).

Adding another perspective, broad external search comes along with great requirements for the attention allocation of management (Laursen et al., 2007). Yet, this managerial attention is a scarce good (Ocasio, 1997), and decentralization provides the opportunity for delegation to lower management levels. Here again, decentralization may be conducive, as investment needs may be best known on levels close to the external source. All in all, we propose:

Hypothesis 3: *Decentralization positively moderates the effect of external knowledge search on innovation performance.*

3. Data and methods

3.1. Sample description

The empirical analysis is based on cross-sectional survey data which was collected from February to April 2010. The target population of 3,709 German firms was selected from the Amadeus database (Bureau van Dijk) based being in the manufacturing sector and on availability of sufficient secondary data on firm size and financials. The selected firms were contacted via telephone in order to identify a contact person responsible for innovation-related activities and with a good overview of the respective firm's organization and strategy (e.g. head of R&D departments or leading innovation managers). Managers who were willing to participate received personalized emails containing a link leading to the online questionnaire. The questionnaire was pretested and based on the logic of the Eurostat Community Innovation Survey (CIS) to ensure interpretability of results in light of existing research (Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Leiponen and Helfat, 2010). To increase the response rate, a reminder e-mail was sent out three weeks after the initial mailing was initially sent. This was accompanied by follow-up phone calls to the firms which had initially indicated willingness to participate in the survey but had not responded up to that point. A final reminder e-mail was sent out a three weeks after that.

We received a total of 676 responses of which 382 responses were fully completed. 12 firms identified themselves as non-innovators. This proportion was considered as being too small to econometrically correct for a selection bias, so that we excluded these observations from the analysis. Additional 5 observations had to be excluded due missing data on secondary variables obtained from the Amadeus database. Thus, 365 firm observations are included in the analysis. The resulting response rate of around 10% has to be considered acceptable d 9.8%, given respondents from higher management levels to an online survey (Klassen and Jacobs, 2001).

To assess representativeness and non-response bias for our sample, we compared (1) the sampled firms with the non-respondents based on observable indicators from the Amadeus database, and (2) early and late respondents within the sample. While step (2) did not yield significant differences, step (1) revealed that our sampled firms are larger compared to the non-respondents.

All survey questions regarding external knowledge search and organizational practices refer to the average of a three-year period from 2007 to 2009. The innovation outcomes were asked to be evaluated only for the last year of that period. By doing so, we attempted to temporally separate the independent and the dependent variables in order to account for time lags between innovation activities and innovation outcomes. This also adds to overcoming potential common method bias concerns (Rothaermel and Alexandre, 2009).

3.2. Measures

The dependent variable of innovation performance was measured by the fraction of a firm's 2009 turnover stemming from products that had been (1) newly introduced to the market during the period 2007-2009, (2) new to the firm but not new to the market, and (3) significantly improved during the period 2007-2009. These three fractions were added to derive an overall measure of innovative sales.

The key independent variable of openness was measured by the number of external knowledge sources that firms used in its innovation activities during the period of 2007-2009. The list of external sources include: (1) other internal units, (2) suppliers, (3) customers, (4) competitors, (5) private research institutes and commercial laboratories, (6) universities and other higher education institutions, (7) public research institutes, (8) consultants and open innovation intermediaries, (9) public information (e.g. patens, industry-specific literature, scientific publications, company reports etc.), (10) official events (e.g. exhibitions and fairs, professional workshops and conferences, trade associations etc.). The internal reliability of these 10 indicators was sufficient (α=0.74).

The first structural measure of specialization was adapted from Gibson and Birkinshaw (2004) and Volberda (1996, 1998). It contained two items which were measured in 5-point Likert scales ranging from strongly disagree to strongly agree: (1) “Innovation activities in our company were separated into different functional areas (e.g. according to basic versus applied research; different products or regions)”; (2) “Innovation activities in our company were structurally separated from other functions (e.g. Marketing, Sales, Production)”. The internal reliability of these 2 items was sufficient (α=0.81), so that they were averaged and then standardized the results.

The structural measure of formalization was adapted from Desphandé and Zaltman, (1982) and Sommer et al. (2009). It contained two items which were measured in 5-point Likert scales ranging from strongly disagree to strongly agree: (1) “Innovation activities in our company were based on strict process steps and detailed task descriptions.”; (2) “Innovation activities in our company are based on detailed process planning and risk analysis”. A third item was constructed based on the usage of 16 different formalized tools that are relevant in the planning and controlling of innovation projects (e.g. patent analyses, NPV analysis, benchmarking, etc.). The internal reliability of these 3 items was sufficient (α=0.68), so that they were normalized, averaged and then standardized the result.

Finally, the measure for decentralization was adapted from Hitt and Brynjolfosson, (1997) and Mahr and Kretschmer (2010). On the one hand, it measures the extent to which decision-making power is delegated to lower hierarchical levels in the organization regarding the following issues: (1) The prioritization of innovation projects, (2) the coordination of innovation projects, (3) the allocation of specific innovation tasks, (4) the utilization of specific innovation methods, -procedures and –instruments. Respondents had to rate on a 4-point scale representing the follwoing hierarchical levels: 1 = team members, 2 = team leader, 3 = head of department, 4 = top management level. The internal reliability of these 4 items was sufficient (α=0.89), so that they were averaged and then standardized. On the other hand, decentralized structures may only be fruitful if employees not only have the decision rights, but are also motivated and empowered to execute them. Hence, an additional item was constructed based on the usage of 10 HRM practices to stimulate innovation within firms by setting incentives and providing sufficient training and experience (cf. Laursen and Foss, 2003). Following formative measurement logics, we averaged the two components of decentralization and then standardized the result.

We further added the following control variables: (1) R&D intensity, which was also used for the median split, was measured by the natural logarithm of R&D expenditures over sales per year on average during the period of 2007-2009. (2) Environmental uncertainty in terms of technological change and customer demands as well as equivocality in terms of technical complexity and uncertainty of innovation projects was measured by two items each, because these variables have been argued to influence organizational requirements with respect to information processing (cf. Daft and Lengel, 1986). (3) Slack resources were measured by the logarithm of cash resources averaged for the years 2006-2008. (4) Performance feedback was measured by the difference of a firms' return on assets minus their performance aspirations averaged over the three years from 2006-2008. Aspiration in turn was measured as a weighted average of own historical performance and the average performance of firms with the same two digit NACE code within our target population of 3709 firms. These financial measures have been shown to influence firms' search behavior (cf. Greve 2003) and were obtained from the Amadeus database. (5) Finally, firms size as the number of employees and firm age in years were obtained from the Amadeus database and included as natural logarithm. (6) Finally, industry dummies were created on the basis of grouping NACE codes from the Amadeus database.

3.3. Analysis

The dependent variable in our model is double censored (having an upper censoring point at the score 100 and a lower censoring point at scores that equal 0). The most appropriate method then to account for this censoring is a Tobit analysis (Greene, 2003). Our measure for innovation performance is skewed to the left, which compromises the underlying assumption of normally distributed residuals in the Tobit model. To account for this departure from the normality assumption, we employed a logarithmic transformation of the dependent variable. We employ interaction terms and / or median splits in the regression analysis both of which has been used before in similar studies (Laursen and Salter, 2006; Rothaermel and Deeds, 2006).

We do not solely rely on judging and comparing size and significance of coefficients which have been argued to be difficult in non-linear models and the presence of interaction terms or different scaling in subsamples (cf. Ai and Norton, 2003; Long, 2009). Hence, we conduct a number of post-estimation and test procedures: (1) we calculate Wald tests on the difference of coefficients from different equations; (2) we calculate Wald type tests on the difference of inflection points of inverted U-shape relationships. We interpret a significant shift to the right as an increase in a firm's capability to manage high number of external knowledge sources (Rothaermel and Deeds, 2006). This test is based on the comparison of the zero of two inverted U-shapes and involves the ratio of two coefficients which should resolve the scaling issue between different subsamples. (3) We compute predictions and marginal effects, which are not affected by scaling, for different levels of openness and the moderator variables and for each subsample. Instead of setting the other variables to their means, we compute these effects for each observation and then average the results. (4) Finally, these average predictions and marginal effects are then compared in terms of significant differences following the procedure suggested by Long (2009), in order to assess significant upward-shifts or in increase in slopes. The standard errors for the Wald test, predictions and marginal effects are obtained using the delta method (Greene, 2003).

4. Empirical results

Table 2 shows the first set of Tobit regression results. The base Model 1 confirms Laursen and Salter's (2006) hypothesis of an inverted U-shape relationship between openness and innovation performance, which is further qualified in the following analysis. Model 2 and 3 compare this relationship between firms with low and high degrees of **specialization**. A comparison of regression coefficients reveals that the effect of openness is only significant for firms with low specialization. While a likelihood-ratio comparison of all coefficients simultaneously is not significant ($\chi^2(15)=16.97$, $p=0.32$), a Wald test for single coefficients does reveal a significant difference for the linear term (diff=0.91, s.e.=0.44, p=0.02) and the squared term (diff=-0.07, s.e.=0.04, p=0.09) of openness. The Wald-type test for calculating the inflection points shows a significant inflection point at 7.20 knowledge sources (s.e.=0.45, p=0.00) for firms with low specialization. But it yields insignificant results for firms with high specialization (13.69 sources, s.e.=25.32, p=0.59), indicating that the relationship does not have a significant curvature.

----------------- Insert Table 2 about here --------------------

To further qualify these differences, we take a look at average predictions and marginal effects. Panel A in Figure 1 shows that firms with low specialization yield a higher innovation outcome than firms with high specialization for high level of openness, i.e. between 4 and 9 knowledge sources. Panel B shows that this difference is significant at least in the range of 5.5 to 8 knowledge sources. Panel C shows the average marginal effects of openness in innovation outcome, which is insignificant for firms with high levels of specialization over the entire range of openness. Hence, firms with high specialization do not seem to be able to benefit from open knowledge search. For firms with low specialization we find further evidence for an inverted U-shape indicated by marginal effects ranging from significant positive to significant negative.[1] Accordingly, Panel D shows the significant differences in marginal effects between low and high specialization firms. Finally, Model 10 in Table 3, where specialization is introduced via interaction terms, also provides evidence for a significant moderation such that specialization “flattens” the inverted U-shape relationship of openness on innovation outcome. All in all, we conceive this as support for Hypothesis 1 that specialization negatively moderates the effects of external knowledge search. On the basis of the empirical evidence up to now, we can say that high levels of internal specialization are detrimental for firms that want to benefit from high levels of external search.

------------------ Insert Figure 1 about here --------------------

Next, we compare firms with low and high levels of **formalization** in Models 4 and 5. This time, the coefficients referring to openness are significant for firms with both low and high degrees of formalization, albeit higher in magnitude for high formalization. A Wald test reveals that these differences are significant neither for the linear term (diff=-0.52, s.e.=0.59, p=0.38) nor for the squared term (diff=0.03, s.e.=0.04, p=0.46) of openness, while the entire coefficient vector is significantly different ($\chi^2(15)=47.75$, p=0.00). Wald type tests show significant inflection points of 6.91 knowledge sources (s.e.=0.77, p=0.00) for firms with low formalization and of 7.60 knowledge sources or firms with high formalization. This indication of a higher open innovation capability of firms with higher formalization, however, is not significant (diff=0.86, s.e.=0.86,

[1] For the sake of visual clarity, we do not include confidence intervals in graphs that show predictions and marginal effects of more than one group or subsample, but rather describe the ranges of significance verbally. These results are available upon request.

p=0.43).

------------------ Insert Figure 2 about here --------------------

Figure 2 displays average predictions and marginal effects for firms with low and high formalization. Panel A shows that firms with high formalization yield a higher innovation outcome than firms with low formalization already beginning with moderate levels of openness, i.e. from 3 up to the maximum of 10 knowledge sources. Panel B shows that this difference is significant from 5 knowledge sources onwards. Panel C shows the average marginal effects of openness in innovation outcome, which is positively significant for firms with low levels of formalization up to 5 knowledge sources and then turns insignificant. For firms with high levels of formalization we find evidence for an inverted U-shape indicated by marginal effects ranging from significant positive to significant negative. Panel D shows that the positive marginal effects of openness are significantly higher for firms with high formalization compared to firms with low formalization in the range of approximately 1 to 6 knowledge sources.

Model 13 in Table 4, where formalization is introduced via interaction terms, does not provide evidence for a significant moderation when judged on the basis of significant interaction terms. However, when Model 13 is used to calculate average predictions and marginal effects, the results show a significant upward shift due to formalization that is substantially identical to that obtained from Models 4 and 5. This result likely amounts to the ambiguity of testing moderating hypotheses via interaction terms in non-linear models as discussed above. All in all, we conceive this as support for Hypothesis 2 that formalization positively moderates the effects of external knowledge search. On the basis of the empirical evidence of an upward shift in the relationship between openness and innovation outcome, we can say that high levels of internal formalization are beneficial for firms such that they are able to gain more from a given (high) number of knowledge sources. There is no evidence that firms with high formalization are able to manage more knowledge sources, what might have been indicated by a higher inflection point.

Models 6 and 7 provide the basis for the comparison of firms with low and high levels of **decentralization**. The coefficients referring to openness are significant for firms with both low and high degrees of decentralization, albeit higher in magnitude for high decentralization. A Wald test reveals that these differences are significant neither for the linear term (diff=-0.31, s.e.=0.55, p=0.57) nor for the squared term (diff=0.01, s.e.=0.04, p=0.84) of openness, while the entire coefficient vector is significantly different ($\chi^2(15)=27.31$, p=0.03). Wald type tests show significant inflection points of 6.52 knowledge sources (s.e.=0.75, p=0.00) for firms with low decentralization and of 8.30 knowledge sources or firms with high decentralization. This difference in inflection points is marginally significant (diff=1.79, s.e.=0.98, p=0.07) and hence indicates a higher open innovation capability of firms with higher decentralization.

----------------- Insert Figure 3 about here -------------------

Figure 3 displays average predictions and marginal effects for firms with low and high decentralization. Panel A shows that firms with high decentralization yield a higher innovation outcome than firms with low decentralization beginning with approximately 4.5 up to the maximum of 10 knowledge sources. Panel B shows that this difference is significant from approximately 6 knowledge sources onwards. Panel C shows the average marginal effects of openness in innovation outcome, which is positively significant for firms with low levels of decentralization up to 6 knowledge sources and then turns negatively significant at about 8 knowledge sources, indicating an inverted U-shape with a significant curvature. For firms with high levels of decentralization we find significantly positive marginal effects of openness until up to 7.5 knowledge sources, but the negative downward slope after the inflection does not turn significant. Panel D shows that the positive marginal effect of openness is significantly higher for firms with high decentralization compared to firms with low decentralization in the range of approximately 2 to 8 knowledge sources.

Model 16 in Table 4, where decentralization is introduced via interaction terms, also provides evidence for a significant moderation effect of decentralization on the inverted U-shape relationship of openness on innovation outcome.

All in all, we conceive this as support for Hypothesis 3 that decentralization positively moderates the effects of external knowledge search. On the basis of the empirical evidence of an upward shift as well as an increase in the inflection point in the relationship between openness and innovation outcome, we can say that high levels of internal decentralization are beneficial for firms such that they are able to gain more from a given (high) number of knowledge sources and to manage more knowledge sources.

----------------- Insert Table 3 about here -------------------

We now turn to the investigation of differences between firms with low versus high R&D intensity. Models 8 and 9 in Table 3 provide the baseline comparison without organizational variables. The results basically confirm the substitution relationship between the use of external knowledge sources and internal R&D activities (Laursen and Salter, 2006). Only firms with low R&D intensity seem to benefit from open innovation, albeit with diminishing marginal returns. This is also confirmed by average prediction and marginal effects which are not shown due to limited space. For firms with high R&D intensity, the marginal effect of openness remains insignificant over the entire range of openness. For low R&D intensity firms we find significant positive and negative marginal effects indicating the inverted U-shape. However, the absolute prediction of innovation performance of firms with low R&D intensity never reaches the performance level of high R&D intensive firms, not even in the inflection point.

------------------ Insert Figure 4 about here --------------------

Models 11 and 12 now form the basis for investigating the effects of specialization in low and high R&D intensity firms. While the entire coefficient vector is significantly different ($\chi^2(18)=57.11$, $p=0.00$), the Wald test does show significant differences for neither the linear and squared terms of openness nor for the respective interaction terms. Except for the case of low R&D intensity and high specialization, Wald type tests find significant inflection points ranging from 6.5 to 7.6, but these are not significantly different. Panel A in Figure 4 displays the average prediction curves which are generated based on Model 11 and 12 for the two groups low versus high R&D intensity as well as low versus high specialization; i.e. -/+ 2 standard deviations of the moderator variable. It shows that in the case of low R&D intensity only firms with low specialization can benefit from open innovation up to a certain threshold of 6.5 knowledge sources, while firms with high specialization cannot judged on the basis of insignificant marginal effects.

In the case of high R&D intensity, again only firms with low specialization can benefit from open innovation. They can do so even more effectively than their counterparts with low R&D intensity, as evidenced by differences in absolute predictions in Panel B that start to turn significant from 5.5 knowledge source onwards. Furthermore, firms with high R&D intensity, but low specialization also do not experience a significant downward slope as their counterparts with low R&D intensity do. This qualifies the finding by Laursen and Salter (2006) in a sense that the absorptive capacity argument gains dominance over the “not-invented-here”-argument in firms that spread their R&D and innovation budget over the broader organization rather than financing specialist departments that might be more heavily affected by “not-invented-here” attitudes. As evidenced by significantly negative marginal effects, firms with high R&D intensity and high specialization experience a performance decline if they go open, albeit this effect is somewhat neutralized again for extreme levels of openness. All in all, the effect of specialization works in the same direction for low and high R&D intensity, albeit on a higher performance level for R&D intensive firms.

----------------- Insert Table 4 about here -------------------

Models 14 and 15 now form the basis for investigating the effects of formalization in low and high R&D intensity firms. The entire coefficient vector is significantly different

($\chi^2(18)=60.41$, p=0.00) in these two models. The Wald tests also show significant differences for the linear terms (diff=2.12, s.e.=0.78, p=0.01) and squared terms (diff=-0.15, s.e.=0.05, p=0.01) of openness, but not for the respective interaction terms. Wald type tests find significant inflection points only for low R&D intensity firms with low formalization (5.42 knowledge sources, s.e.=0.80, p=0.00) and with high formalization (8.30 knowledge sources, s.e.=0.75, p=0.00). This difference is significant (diff=2.88, s.e.=1.17, p=0.01) indicating an open innovation capability to manage more external knowledge sources for firms with high formalization, given low R&D intensity.

Panel C in Figure 4 displays the average prediction curves which are generated based on Model 14 and 15 for the two groups low versus high R&D intensity as well as low versus high formalization; i.e. -/+ 2 standard deviations of the moderator variable. It shows that in the case of high R&D intensity firms do not benefit from open innovation regardless of formalization, also revealed by insignificant marginal effects over the entire range of openness. In the case of low R&D intensity, more formalized firms can achieve higher performance by interacting with more knowledge sources. As Panel D shows, this difference is significant from about 7 knowledge sources onwards. All in all, we can conclude that the positive moderation effect of formalization that we found in the overall sample stems from the subsample of firms that try to substitute their low R&D intensity by the means of open innovation.

Models 17 and 18 now form the basis for investigating the effects of decentralization in low and high R&D intensity firms. The entire coefficient vector is significantly different ($\chi^2(18)=59.77$, p=0.00) in these two models. The Wald tests also show significant differences for the linear terms (diff=2.33, s.e.=0.99, p=0.02) and squared terms (diff=-0.16, s.e.=0.06, p=0.02) of openness, as well as for the respective interaction terms (diff=1.45, s.e.=0.72, p=0.05; diff=-0.09, s.e.=0.05, p=0.05). Wald type tests find significant inflection points for all four curves in Panel E of figure 4, but only for the case of low R&D intensity and high decentralization the inflection point of 7.71 knowledge sources (s.e.=0.39, p=0.00) goes along with significant marginal effects. The other three curves do not seem to have a significant curvature as evidenced by insignificant marginal effects. Panel F, however, shows that firms with low R&D intensity do more extensively benefit form open innovation if they are decentralized rather than centralized. All in all, we can conclude that the positive moderation effect of decentralization that we found in the overall sample is more pronounced in the sample of firms with low R&D intensity, but is also shared to small (albeit insignificant) extent with R&D intensive firms. That is why the positive moderation effect of decentralization in the overall sample is of larger effect size.

5. Discussion

Engaging in multiple knowledge exchanges with external sources for innovation has become a "must" for many firms. Multiple studies and articles have postulated a new paradigm of open innovation. However, in our research we find that a differentiated perspective is more appropriate. Using a sample of 368 German manufacturing firms, we confirm earlier studies that there can be too much of a good thing – in some situations broad external search never leads to higher performance. When differentiating between various levels of R&D intensity, we find that for the R&D intensive firms in our sample, engaging in open innovation has a significant under very dedicated organization structures. Still, these firms generally show a higher overall level of innovation performance than firms with low R&D expenditures (relative to their revenues). Also in the age of open innovation, being dedicated to

R&D seems to remain a good strategy. But in those firms where R&D resources are scare, we find that external knowledge sources can successfully complement and substitute internal R&D activities. Firms with low R&D intensity seem to benefit from open innovation, albeit with diminishing marginal returns. For those firms, the relationship between openness and innovation performance resembles an inverted U-shape (Faems et al., 2010; Katila and Ahuja, 2002; Laursen and Salter, 2006; Rothaermel and Deeds, 2006; Rothaermel and Alexandre, 2009; Deeds and Hill, 1996; Duysters and Lokshin, 2011).

To further explain the relationship between external search and innovation performance, we looked into inside the firm and studied the effect of different organizational structures on open innovation performance. Scholars have repeatedly suggested that a firm's organizational structure has a considerable impact on knowledge search and knowledge integration (Jansen et al., 2005; Li et al., 2008; Rivkin and Siggelkow, 2003; Siggelkow and Levinthal, 2003). Yet, explicit investigations of the effects of a firm's organizational structure on the generation of innovative knowledge via open innovation are scarce. Our study fills this gap by providing empirical evidence on the effect of a firm's organizational structure on the performance contribution of external search strategies. We specifically examined the effects of specialization, formalization, and decentralization as main structural constructs determining an organization's design (Olson et al,, 2005; Vorhies and Morgan, 2003; Walker and Ruekert, 1987).

With regard to **specialization**, we find that specialization negatively moderates the effect of a broad search for external knowledge. Utilizing a large number of external knowledge sources translates into superior innovation performance only for those firms with low levels of specialization regarding the organization of their innovation activities. On the contrary, firms who focus their innovation activities in a specialized organizational unit seem not to profit from open innovation. Similarly, we find that firms that have structured their innovation activities according to a product, technology, or region are much less likely to turning external search into performance than firms that have a broader, less structured organization. These findings are challenging current research that has associated specialization with positive effects due to higher propensities to search outside (Olson et al., 2005; Rothaermel and Hess, 2007). One could also have assumed that specialized organizations have a better capacity to utilize external knowledge and to exploit it in the later stages of innovation processes (Damanpour, 1991). But our results confirm an opposite view that specialization is generating self-focused silos of knowledge generation and exploitation. Specialists were found to engage in “narrow” search endeavors (Van den Bosch et al, 2003) and to create mental and structural boundaries (Olson et al., 2005; Pertusa-Ortega et al., 2010). With increasing inter-unit boundaries, the costs of communication and learning rise, and knowledge transfer is hampered (Colombo and Delmastro, 2008; Willem and Buelens, 2006). Profiting from open innovation demands "shared mental representations" (Knudsen and Srikanth, 2010) which intuitively are developed better in a non-specialized organization. This means, however, not that firms should never specialize their innovation activities. But our results suggest that these firms have to build a dedicated selection capability to identify the (very) few external sources which they then utilize to a high amount. In such a situation, firms could benefit from Rothaermel and Hess’ (2007) “star scientists” or “gate-keepers”, who manage the interface between a firm and its external environment (Tushman, 1977).

In general, our results suggest that the effects of organizational specialization have to be assessed before the background of firms' openness levels. This adds to theory as previous research has assumed a very general perspective on external knowledge integration for the investigation of specialization. Our analysis calls for a more differentiated view. Our results support the theoretical argument that organizational specialization brings costs and benefits for external search. It may facilitate the search activity itself up to a certain point, but then place a burden on the transfer and application of this knowledge within the organization. At low levels of openness, the knowledge acquired will be rather focused. Here, specialization may have a positive effect as search activities are more efficient. Should these firms consider increasing their openness levels, their structural arrangement would be detrimental to increasing innovation performance. So before engaging in open innovation, our research recommends that these firms need to restructure. There also may be a similar effect at very high levels of openness. For firms engaging in very broad search across all possible sources of external knowledge as considered in our study, specialization may become again preferable as now distributed search activities may not be able to manage the search anymore without incurring losses. Studying the latter aspect can become a starting point for future research. Also remember that specialization in our study relates to the organization of all innovation related activities of the firm. There may be a benefit of specializing the *open* innovation activities in one unit, i.e. creating dedicated units that support other units in their external research endeavors (Chiaroni et al., 2010; O'Connor and DeMartino, 2006), as also our findings with regard to formalization indicate.

Formalization positively moderates the effects of external knowledge search on innovation performance. Our research shows that the ability to benefit from open search and to integrate larger amounts of external knowledge is strongly supported by formalized procedures and dedicated planning tools. Firms with high levels of formalization benefit significantly more from a given number of external knowledge sources than firms with low formalization. This effect is even stronger for firms with low R&D intensity. We could however not confirm explicitly the intuitive assumption that firms with high formalization are also able to better manage more knowledge sources.

Our study confirms that open innovation is a new activity profiting from dedicated capabilities within the firm (Chiaroni et al., 2010). While for internal knowledge search, formalization has been shown to be a barrier as it restricts the scope of search (Jansen et al., 2005), we find that it is a strong facilitator for external search. Well documented procedures and organizational training programs building these routines may enhance the efficiency of knowledge search and prevent that members search in sources that provide no benefits for a given task (Benner and Tushman, 2003). Our results suggest that defining clear rules, mechanisms, and responsibilities for conducting the search and transfer may alleviate the information overload of hitherto unspecified knowledge search and transfer procedures. But when firms utilize rather few external sources, a positive variety-enhancing effects of lower formalization can contribute to higher innovation performance. This opens an interesting avenue for future research. We still do not know much about the exact content and focus of the formalized processes that truly enhance open innovation performance. How are these processes and methods defined, implemented, and executed by an organization? And when do strong formalized procedures and evaluation schemes become a hurdle for innovation, i.e. preventing the usage of a very new source of external knowledge or the application of an innovative method of open innovation?

Formalized processes also define procedures to evaluate external knowledge (Pertusa-Ortega et al., 2010). They may help to deal with risk from IP-related issues or to negotiate a price for formal knowledge acquisition, when required. In addition, formalization has been shown to facilitate knowledge integration (Weick, 1979). Open innovation profits from capabilities that enhance the absorptive capacity of firms to transform and exploit external knowledge stocks in a firm's internal innovation process (Jansen et al., 2005). These results call for more research on the organization of knowledge acquisition and exploitation activities in a firm. An especially interesting area of future research in this regard may be on the micro level of the individual (Foss et al., 2011). As formalization affects knowledge search, evaluation, and transfer behaviors on the individual level by substituting individual procedures by an organizational routine, future research should study in larger detail the effect of different kinds and designs of these planning tools. In our study, for example, we used an index value to capture the sheer extent of planning tools used. However, we expect that different organizations execute different planning tools differently. Further research may employ more fine-grained quantitative measures for formalization or disentangle the effects of formalization through the means of case studies. Looking into these aspects in larger detail will provide implications for the management of open innovation in practice.

Decentralization, i.e. the delegation of authority for innovation to lower levels in the hierarchy, has been shown to be a strong support for innovation performance in general (e.g. Thompson, 1965; Pierce & Delbecq, 1977; Pertusa-Ortega et al., 2010), especially when enhanced by dedicated training and HR tools. Decentralization also especially facilitates knowledge absorption and integration (Jansen et al., 2005). In our study, we find strong evidence that decentralization also positively moderates the effects of external (open) knowledge search. The organizational structures and supporting measures that correspond to a high degree of decentralization enable firms to gain more from a higher number of knowledge sources. Decentralization shifts the tipping point of the inverted U-shape of the openness-performance curve almost to its (right) extreme. Again, these results are more profound for firms with lower R&D intensity.

While these results confirm our hypothesis and are in line with previous research, they open a number of interesting new questions. For reasons of complexity, we did not engage in a further study of interaction effects between the three organizational factors. But there may be an interesting interaction between the need for formalized procedures and positive effect of dedicated regimes for conducting external search on the one hand side and the benefit of decentralized structures on the other. Decentralized organization may prevent the implementation of such procedures in an efficient way. Lin and Germain (2003), for example, found an interaction of formalization and decentralization with regard to the utilization of customer knowledge and concluded that decentralization follows formalization in the attempt to restructure organizations. Future research should study these interaction effects in larger detail. Secondly, decentralization may also be effected by specialization as understood in this research. Here, especially the interplay between a specialized support function for open innovation and decentralized innovation activities of empowered members of an organization would make an interesting subject of further investigation.

6. Conclusions

Building on a famous quote by Drucker (1985), today no one needs to be convinced any longer of the importance of open innovation – *how* to openly innovate is the key question. Our study contributes to this investigation, addressing recent calls to study the governance of open innovation initiatives and activities in larger detail. Taking a contingency perspective, we focus on the organizational structures that facilitate open innovation. The structure of a firm's organization has significant implications for the potential to generate and utilize knowledge (Pertusa-Ortega et al., 2010). Likewise, the search for external knowledge requires an appropriate organizational design (Cohen and Levinthal, 1990; Jansen et al., 2005).

We contribute to the state of this literature by a more immediate and fine-grained theoretical connection between the utilization of external sources of knowledge and organizational structure, as expressed by the level of specialization, formalization, and decentralization of the firms' innovation activities (Colombo and Delmastro, 2008; Burton and Obel, 2004; Miles and Snow, 1978; Mintzberg, 1979). We find that firms have to create an organizational fit between their internal organizational practices and their respective levels of external knowledge sourcing. To our awareness, our study is the first large scale empirical analysis of this connection, supplementing earlier qualitative research (Bianchi et al., 2011; Chesbrough and Crowther, 2006; Dodgson et al., 2006). Our results have relevance for managers who consider following recent calls for open innovation as the central organizational design variables or our study all represent variables that management can actively influence.

The actual implementations of both these three variables should be guided by the level of openness attained and the level of openness aimed at in a particular firm. We have seen that formalization and specialization not only differ in their effects for low and high degrees of openness but also in their marginal effects when increasing openness.

Of course this study is not without limitations. Of concern to this study, as to any other cross-sectional survey, is the issue of selection bias. It is hard to determine to what extent our results are affected. On the one hand this refers to the issue of response bias which cannot be entirely ruled out for our sample. We did not find differences between early and late responses, but based on observable indicators also available for non-respondents, larger and more established firms seem to have selected themselves for the study. It is likely that these firms also show higher innovation activity compared to a fully representative sample. On the other hand, this also refers to potential endogeneity bias which is probably of greater concern. Firms select themselves into the most promising strategic choices regarding the levels of R&D intensity and external search as well as organizational structures. These choices are very likely being made simultaneously in accordance with each other or some other variables, but very unlikely determined in a purely exogenous manner. It is hard to say which of these strategic variables can be considered as most stable or given in the long run, i.e. "quasi-exogenous". Given open innovation as the central phenomenon of interest which firms are supposed to pursue successfully, we adopted the notion of aligning organizational structure according to levels of external search (and R&D intensity). Based on our results or any other line of reasoning, however, we cannot determine whether this direction of alignment is preferable or more feasible. In short, our results should be interpreted as statistical association rather than causality.

Another issue of concern is measuring organizational structures which is inherently difficult due to its multidimensional nature. We tried to adopt an existing measure to our context of a firm's innovation function, but do not claim that these are perfect. Adopting a more complex multi-item measurement to tap into latent dimensions of organizational structure could be beneficial in future research. But we are sure that we have captured relevant facets of organizing firms' innovation function by relying upon a mix of subjective Likert scales and more objective organizational practices. Furthermore, we did not differentiate our results according to various measures of search (e.g. breadth and depth) or innovation success (e.g. sales from radically or incrementally new products) to keep analysis tractable and parsimonious. We leave this approach, popular in open innovation research, for future research.

Probably more relevant to our line of research would be the integration of other external moderator variables regarding firms' environmental context or innovation task. Furthermore, it would be interesting to see whether organizational search needs to be organized in different ways contingent on the kind of search, i.e. slack versus problemistic search. But analyzing more complex organizational configurations that are appropriate in the context of open innovation is likely to require other methods than regression-based techniques (Fiss, 2011). Nevertheless, with this study we hope to spark an interesting line of future research that overcomes some of the present limitations and investigates the complementary and situational effects of organizational practices for open innovation in more detail.

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Figures and tables

Figure 1: Average Predictions and Marginal Effects for Low and High Specialization

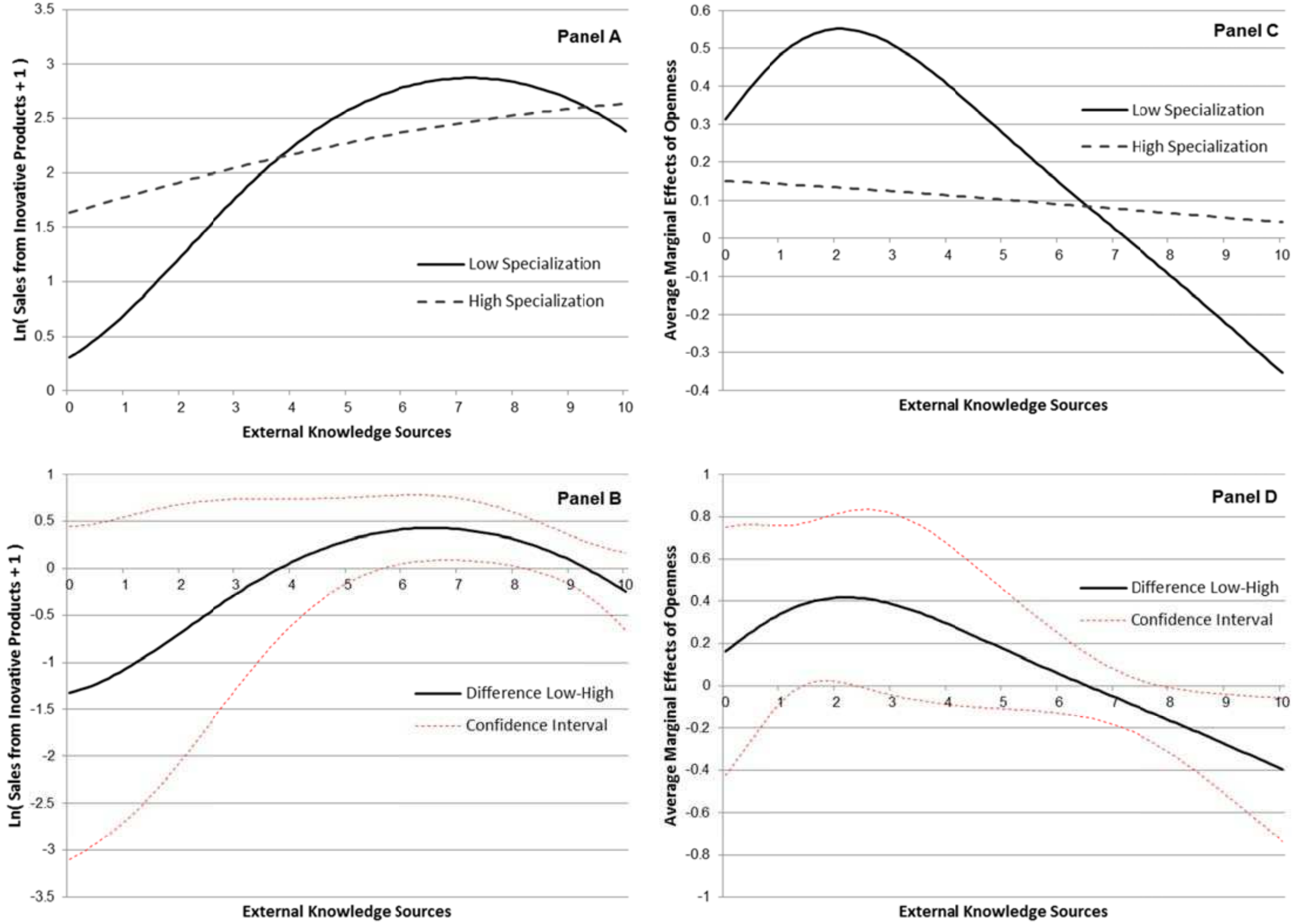

Figure 2: Average Predictions and Marginal Effects for Low and High Formalization

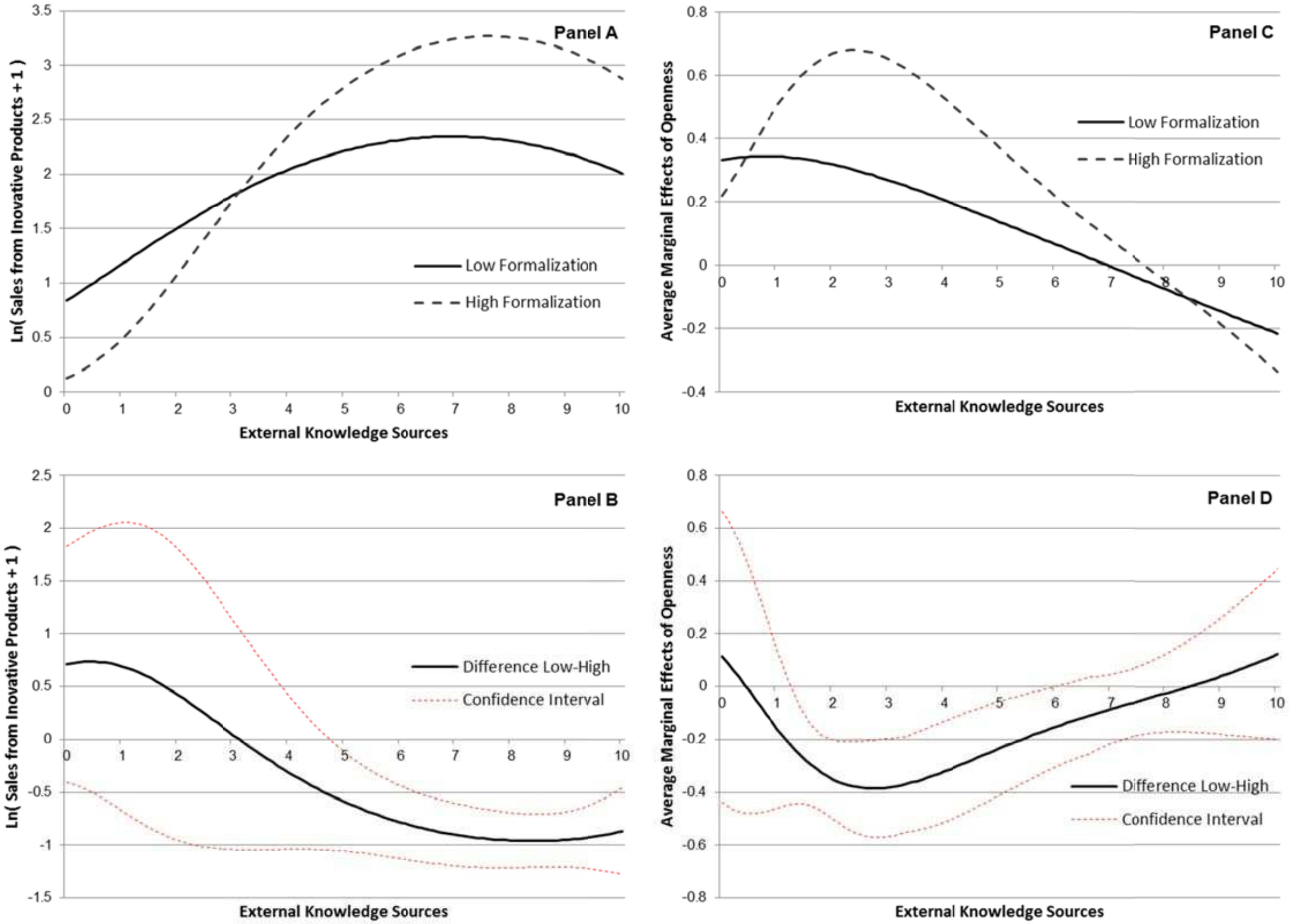

Figure 3: Average Predictions and Marginal Effects for Low and High Decentralization

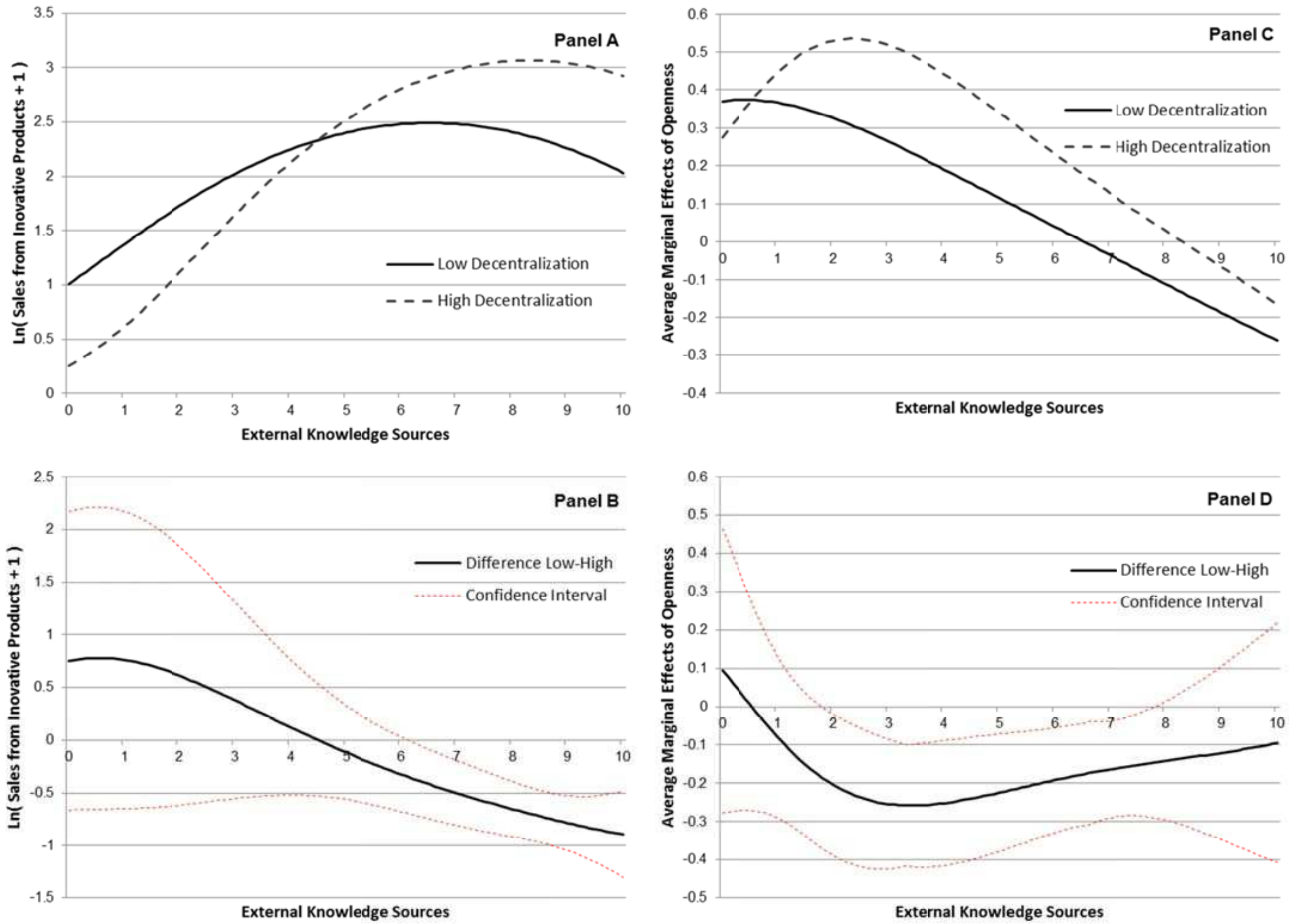

Figure 4: Average Predictions for Low and High Research Intensity

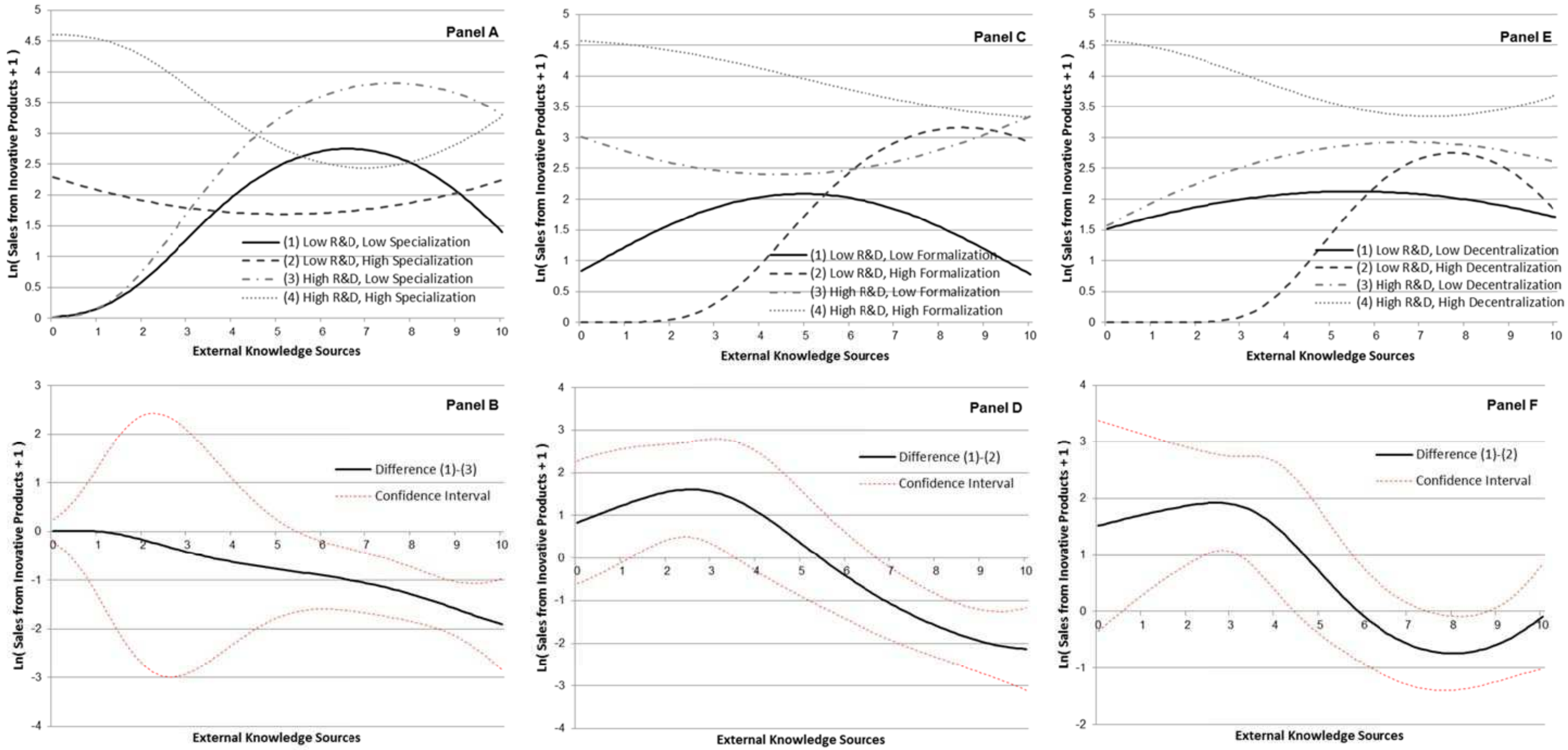

Table 1: Descriptive Statistics

Variable		Mean	Std.Dev.	Min	Max	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	Innovative Sales	2.78	1.48	0.00	4.62	0.18	-0.06	0.33	0.25	0.21	0.24	0.13	-0.05	0.40	0.24	-0.05	0.07	-0.26	0.18	-0.01	0.05	-0.03
(2)	Openness	6.88	1.91	0.00	10.00		0.02	0.38	0.35	0.03	0.22	0.17	-0.06	0.22	0.28	-0.05	0.01	-0.04	0.04	0.02	-0.08	0.03
(3)	Specialization	0.00	1.00	-1.18	2.84			0.05	0.07	0.08	0.14	0.02	-0.09	0.05	0.07	-0.02	0.06	0.04	-0.05	0.07	-0.08	-0.05
(4)	Formalization	0.00	1.00	-2.22	3.17				0.50	0.12	0.34	0.17	-0.01	0.32	0.40	0.01	0.03	-0.09	0.13	0.06	-0.11	-0.04
(5)	Decentralization	0.00	1.00	-2.00	3.24					0.02	0.32	0.17	-0.04	0.32	0.31	-0.06	0.00	-0.07	0.08	0.14	-0.07	-0.05
(6)	Uncertainty	0.00	1.00	-1.92	2.07						0.22	0.01	-0.05	0.16	0.00	0.00	-0.02	-0.07	0.08	0.00	-0.04	0.05
(7)	Equivocality	0.00	1.00	-2.46	2.08							0.16	-0.09	0.36	0.21	-0.08	0.11	-0.09	0.11	0.00	-0.10	-0.09
(8)	Slack resources	6.17	2.40	0.12	12.06								0.09	0.06	0.49	0.15	0.08	-0.07	0.06	0.05	-0.03	-0.10
(9)	Performance Feedback	-0.69	10.88	-64.48	52.95									-0.06	-0.06	0.07	-0.06	0.00	0.01	0.02	0.09	-0.02
(10)	R&D Intensity	1.23	0.83	0.00	4.39										0.08	-0.15	0.06	-0.23	0.33	0.01	-0.07	-0.11
(11)	Firm Size	5.04	1.47	1.61	9.11											0.21	0.01	-0.08	0.01	0.11	-0.05	0.03
(12)	Firm Age	3.17	0.89	1.39	5.26												-0.03	0.00	-0.04	0.06	0.08	-0.02
(13)	Machinery	0.32	0.47	0.00	1.00													-0.33	-0.31	-0.20	-0.22	-0.28
(14)	Metal Processing	0.19	0.39	0.00	1.00														-0.22	-0.14	-0.16	-0.20
(15)	Electronics	0.17	0.38	0.00	1.00															-0.13	-0.15	-0.19
(16)	Chemicals, Pharmaceutics	0.08	0.27	0.00	1.00																-0.09	-0.12
(17)	Other Finished Goods	0.09	0.29	0.00	1.00																	-0.13
(18)	Other Half-finished Goods	0.15	0.35	0.00	1.00																	

Table 2: Estimation Results – Part 1

Model	1		2		3		4		5		6		7	
Sample	**Full**		**Low Specialization**		**High Specialization**		**Low Formalization**		**High Formalization**		**Low Decentralization**		**High Decentralization**	
Independent variables	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)
Main Variables														
Openness	0.710 ***	(0.264)	1.107 **	(0.479)	0.199	(0.376)	0.677 *	(0.363)	1.199 **	(0.466)	0.6528 *	0.3793	0.962 **	(0.376)
Openness Squared	-0.048 ***	(0.018)	-0.077 **	(0.032)	-0.007	(0.027)	-0.049 *	(0.026)	-0.079 ***	(0.030)	-0.05 *	0.0289	-0.058 **	(0.025)
Controls														
Uncertainty	0.252 ***	(0.084)	0.352 ***	(0.105)	0.050	(0.140)	0.382 ***	(0.143)	0.126	(0.091)	0.3259 **	0.1378	0.193 **	(0.098)
Equivocality	0.052	(0.092)	0.061	(0.116)	0.107	(0.155)	-0.061	(0.145)	0.133	(0.114)	0.0445	0.1447	0.026	(0.120)
Slack resources	-0.013	(0.040)	-0.060	(0.053)	0.017	(0.059)	0.012	(0.074)	-0.036	(0.041)	-0.03	0.0656	0.013	(0.046)
Performance Feedback	-0.001	(0.008)	-0.008	(0.009)	0.012	(0.014)	0.002	(0.016)	-0.006	(0.007)	0.0007	0.0137	-0.003	(0.008)
R&D Intensity	0.587 ***	(0.115)	0.652 ***	(0.139)	0.525 ***	(0.202)	0.825 ***	(0.199)	0.306 **	(0.127)	0.5617 ***	0.1843	0.564 ***	(0.142)
Firm Size	0.274 ***	(0.068)	0.279 ***	(0.089)	0.295 ***	(0.105)	0.318 ***	(0.120)	0.179 **	(0.077)	0.4112 ***	0.1167	0.161 **	(0.079)
Firm Age	-0.096	(0.095)	-0.171	(0.116)	0.055	(0.163)	-0.156	(0.164)	0.020	(0.103)	-0.095	0.16	-0.076	(0.110)
Machinery	0.135	(0.261)	0.233	(0.315)	0.185	(0.453)	-0.340	(0.426)	0.686 **	(0.290)	-9E-04	0.4002	0.406	(0.326)
Metal Processing	-0.625 **	(0.286)	-0.334	(0.347)	-0.621	(0.501)	-1.243 ***	(0.473)	0.117	(0.320)	-0.535	0.428	-0.655 *	(0.369)
Electronics	0.248	(0.302)	0.412	(0.361)	0.425	(0.538)	-0.289	(0.533)	0.869 ***	(0.324)	0.1121	0.5065	0.396	(0.358)
Chemicals, Pharmaceutics	-0.188	(0.362)	-0.011	(0.454)	-0.163	(0.600)	-1.136 *	(0.636)	0.749 *	(0.390)	0.0255	0.6473	-0.110	(0.406)
Other Finished Goods	0.546	(0.343)	0.642	(0.396)	0.460	(0.640)	0.135	(0.523)	1.110 **	(0.437)	0.5738	0.5527	0.712 *	(0.421)
Other Half-finished Goods	*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*	
Constant	-1.539	(1.047)	-2.350	(1.843)	-1.062	(1.496)	-1.364	(1.472)	-3.045 *	(1.851)	-1.534	1.5607	-2.558 *	(1.528)
Error term standard deviation (σ)	1.513 ***	(0.066)	1.449 ***	(0.081)	1.524 ***	(0.106)	1.798 ***	(0.116)	1.143 ***	(0.067)	1.7526 ***	0.1103	1.211 ***	(0.073)
No of obs.	365		221		144		189		176		192		173	
Parameters (k)	16		16		16		16		16		16		16	
Log likelihood (2)	-676.93		-407.42		-268.84		-356.49		-293.40		-361.36		-303.37	
Log likelihood (k)	-619.57		-366.17		-244.92		-326.27		-269.44		-336.74		-269.18	
Chi-square	114.71 ***		82.50 ***		47.84 ***		60.45 ***		47.93 ***		49.25 ***		68.37 ***	
McFadden R^2	0.085		0.101		0.089		0.085		0.082		0.068		0.113	
LR test of equal coeffcient vector			$\chi^2(15)=16.97$ (n.s.)				$\chi^2(15)=47.75$ ***				$\chi^2(15)=27.31$ **			

Two-tailed t -tests; * < 0.1, ** p < 0.05, *** p < 0.01

Table 3: Estimation Results – Part 2

Model	**8**		**9**		**10**		**11**		**12**	
Sample	**Low R&D Intensity**		**High R&D Intensity**		**Full**		**Low R&D Intensity**		**High R&D Intensity**	
Independent variables	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)
Main Variables										
Openness	0.929 **	(0.426)	-0.097	(0.391)	0.755 **	(0.313)	0.889 **	(0.433)	0.178	(0.422)
Openness Squared	-0.066 **	(0.030)	0.009	(0.027)	-0.050 **	(0.021)	-0.064 **	(0.032)	-0.008	(0.028)
Moderator					*Specialization*		*Specialization*		*Specialization*	
Moderator (M)					2.228 **	(1.086)	1.573	(2.328)	2.441 **	(1.025)
Openness * M					-0.743 **	(0.316)	-0.608	(0.647)	-0.781 **	(0.312)
Openness Squared * M					0.053 **	(0.022)	0.048	(0.044)	0.054 **	(0.022)
Controls										
Uncertainty	0.467 ***	(0.157)	0.177 **	(0.088)	0.249 ***	(0.083)	0.448 ***	(0.157)	0.198 **	(0.087)
Equivocality	-0.016	(0.150)	0.100	(0.106)	0.055	(0.092)	-0.002	(0.150)	0.097	(0.104)
Slack resources	-0.042	(0.070)	0.038	(0.042)	-0.006	(0.039)	-0.028	(0.069)	0.036	(0.041)
Performance Feedback	-0.013	(0.017)	0.000	(0.007)	-0.002	(0.008)	-0.012	(0.016)	-0.001	(0.007)
R&D Intensity	0.659	(0.404)	0.122	(0.178)	0.580 ***	(0.114)	0.596	(0.402)	0.136	(0.173)
Firm Size	0.463 ***	(0.120)	0.075	(0.075)	0.264 ***	(0.068)	0.454 ***	(0.120)	0.078	(0.073)
Firm Age	-0.188	(0.167)	-0.060	(0.105)	-0.102	(0.094)	-0.183	(0.165)	-0.081	(0.102)
Machinery	-0.159	(0.419)	0.590 *	(0.315)	0.235	(0.260)	-0.125	(0.415)	0.811 ***	(0.314)
Metal Processing	-0.820 *	(0.436)	-0.080	(0.371)	-0.508 *	(0.285)	-0.791 *	(0.433)	0.174	(0.370)
Electronics	-0.149	(0.591)	0.861 ***	(0.330)	0.343	(0.302)	-0.127	(0.587)	1.034 ***	(0.330)
Chemicals, Pharmaceutics	-0.147	(0.583)	0.189	(0.426)	-0.095	(0.359)	-0.177	(0.583)	0.394	(0.418)
Other Finished Goods	0.097	(0.549)	1.325 ***	(0.419)	0.516	(0.341)	-0.059	(0.553)	1.460 ***	(0.409)
Other Half-finished Goods	*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*	
Constant	-2.517	(1.702)	2.186	(1.569)	-1.786	(1.213)	-2.383	(1.845)	0.951	(1.691)
Error term standard deviation (σ)	1.835 ***	(0.121)	1.124 ***	(0.065)	1.492 ***	(0.065)	1.815 ***	(0.120)	1.090 ***	(0.063)
No of obs.	188		177		365		188		177	
Parameters (k)	16		16		19		19		19	
Log likelihood (2)	-347.52		-288.57		-676.93		-347.52		-288.57	
Log likelihood (k)	-322.84		-270.26		-614.60		-321.15		-264.89	
Chi-square	49.36 ***		36.64 ***		124.65 ***		52.73 ***		47.36 ***	
McFadden R^2	0.071		0.063		0.092		0.076		0.082	
LR test of equal coeffcient vector	$\chi^2(15)=52.95$ ***						$\chi^2(18)=57.11$ ***			

Two-tailed t -tests; * < 0.1, ** p < 0.05, *** p < 0.01

Table 4: Estimation Results – Part 3

Model	13		14		15		16		17		18	
Sample	**Full**		**Low R&D Intensity**		**High R&D Intensity**		**Full**		**Low R&D Intensity**		**High R&D Intensity**	
Independent variables	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)	Parameter	(S.E.)
Main Variables												
Openness	0.838 **	(0.343)	1.710 ***	(0.657)	-0.412	(0.414)	1.057 ***	(0.338)	2.132 **	(0.889)	-0.202	(0.426)
Openness Squared	-0.058 **	(0.023)	-0.117 ***	(0.043)	0.029	(0.028)	-0.070 ***	(0.023)	-0.142 **	(0.058)	0.013	(0.029)
Moderator	*Formalization*		*Formalization*		*Formalization*		*Decentralization*		*Decentralization*		*Decentralization*	
Moderator (M)	-0.398	(0.887)	-1.974	(1.456)	0.812	(1.462)	-1.708 *	(0.965)	-3.968 **	(1.928)	1.466	(1.921)
Openness * M	0.169	(0.243)	0.470	(0.393)	-0.057	(0.406)	0.473 *	(0.262)	1.069 **	(0.510)	-0.376	(0.511)
Openness Squared * M	-0.010	(0.017)	-0.019	(0.027)	-0.003	(0.027)	-0.029 *	(0.016)	-0.067 **	(0.034)	0.027	(0.033)
Controls												
Uncertainty	0.242 ***	(0.083)	0.446 ***	(0.153)	0.169 *	(0.087)	0.262 ***	(0.083)	0.480 ***	(0.155)	0.193 **	(0.087)
Equivocality	0.016	(0.093)	-0.010	(0.150)	0.076	(0.107)	0.033	(0.093)	-0.020	(0.152)	0.060	(0.105)
Slack resources	-0.005	(0.039)	-0.025	(0.068)	0.037	(0.042)	-0.014	(0.039)	-0.049	(0.069)	0.046	(0.042)
Performance Feedback	-0.003	(0.008)	-0.015	(0.016)	0.001	(0.007)	-0.002	(0.008)	-0.013	(0.016)	0.001	(0.007)
R&D Intensity	0.526 ***	(0.116)	0.486	(0.401)	0.088	(0.175)	0.552 ***	(0.116)	0.640	(0.408)	0.094	(0.175)
Firm Size	0.216 ***	(0.071)	0.363 ***	(0.123)	0.044	(0.077)	0.271 ***	(0.070)	0.475 ***	(0.124)	0.033	(0.076)
Firm Age	-0.102	(0.094)	-0.181	(0.163)	-0.054	(0.105)	-0.092	(0.095)	-0.175	(0.165)	-0.038	(0.104)
Machinery	0.101	(0.258)	-0.202	(0.408)	0.619 **	(0.310)	0.139	(0.259)	-0.082	(0.417)	0.673 **	(0.310)
Metal Processing	-0.649 **	(0.283)	-0.788 *	(0.427)	-0.091	(0.366)	-0.663 **	(0.285)	-0.808 *	(0.437)	0.024	(0.367)
Electronics	0.181	(0.301)	-0.235	(0.586)	0.846 ***	(0.327)	0.229	(0.300)	-0.031	(0.589)	0.913 ***	(0.325)
Chemicals, Pharmaceutics	-0.233	(0.358)	-0.353	(0.575)	0.218	(0.420)	-0.245	(0.362)	-0.060	(0.585)	0.118	(0.424)
Other Finished Goods	0.562 *	(0.339)	0.048	(0.534)	1.352 ***	(0.413)	0.526	(0.340)	0.048	(0.551)	1.470 ***	(0.414)
Other Half-finished Goods	*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*		*(Ref.)*	
Constant	-1.526	(1.371)	-4.839 *	(2.610)	3.636 **	(1.682)	-2.766 **	(1.371)	-7.137 **	(3.538)	2.831	(1.738)
Error term standard deviation (σ)	1.493 ***	(0.065)	1.782 ***	(0.117)	1.103 ***	(0.063)	1.499 ***	(0.065)	1.805 ***	(0.119)	1.101 ***	(0.063)
No of obs.	365		188		177		365		188		177	
Parameters (k)	19		19		19		19		19		19	
Log likelihood (2)	-676.93		-347.52		-288.57		-676.93		-347.52		-288.57	
Log likelihood (k)	-614.97		-317.73		-267.03		-616.26		-319.82		-266.56	
Chi-square	123.92 ***		59.57 ***		43.08 ***		121.34 ***		55.41 ***		44.03 ***	
McFadden R^2	0.092		0.086		0.075		0.090		0.080		0.076	
LR test of equal coeffcient vector			$\chi^2(18)$=60.41 ***						$\chi^2(18)$=59.77 ***			

Two-tailed t -tests; * < 0.1, ** p < 0.05, *** p < 0.01