Innovation, partner configuration and partner adaptation in R&D alliances

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Abstract: An important part in orchestrating innovation activities concerns the way in which firms configure and adapt their organizational boundaries with external collaboration partners to enhance their innovation performance. Past literature on strategic alliances has suggested that the type of partner a firm engages with to insource new knowledge may have an important impact on subsequent innovation success. Based on these insights, the current paper analyses what partner type configuration is appropriate for what type of innovation and firm size. It then goes on to analyzing how such partner configurations need to be adapted in order for the mix to always be beneficial for firms' innovation outcome. Using a large-scale sample, this paper finds that a complementary configuration of partner types and a dynamic adaptation thereof is important to ensure firm innovation success. It further elaborates that the adaptation differs depending on firm size and innovation type.

Keywords: Strategic alliances; partner configuration; partner adaptation; innovation performance; organizational boundaries; radical innovation; incremental innovation; firm size.

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1 Introduction

This paper explores the relationship between a firm's collaboration partner configuration, the dynamic adaptation thereof and its innovation performance. Extant literature has shown that collaboration is a desirable strategy to spread the risks and uncertainties linked to R&D activities. Furthermore, it allows access to additional competencies, know-how and other valuable resources. Accordingly, empirical studies have repeatedly indicated that pooling of complementary competencies, skill sourcing, and learning from the partner are all ways through which a firm may gain from R&D alliances (Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Hagedoorn, 1993; Powell, Koput, & Smith-Doerr, 1996; Shan, Walker, & Kogut, 1994; Zidorn & Wagner, 2013). A large number of studies have acknowledged positive impacts on innovation performance, showing that the gains of collaborative R&D can be substantial (Branstetter and Sakakibara, 2002; Brouwer et al., 2001; Brouwer and Kleinknecht, 1999; Faems et al., 2005 among others). Literature has also investigated the impact of various partner types on innovation performance, since each partner type has a different added-value on innovation outcome. Belderbos et al. (2006) for instance find that customer collaboration enhances market acceptance and product diffusion while competitor and supplier cooperation have the most direct positive impact on productivity growth. The lion's share of existing literature however investigates the impact of (different types of) collaboration on various innovation performance measures in a static way, often due to limited data availability (Belderbos, Carree, & Lokshin, 2006; Hottenrott, Lopes Bento, & Veugelers, 2015). While this enhances our knowledge on the impact of which type of partner leads to which type of firm performance improvement, it does not clarify whether – and to which extent – the dynamic adaptation of such partners matters.

A first contribution of this paper therefore lies in the analysis of the dynamic adaptation of collaboration partners. In a fast-changing environment, adaptation of partner scope may be key to guarantee ongoing success (Brown & Eisenhardt, 1997). As the economic environment changes, the innovation strategy of a firm has to change as well. Thereby, the needs of the partners it engages with may need adaptation. To this end, we introduce the concept of partner adaptation. To be able to control for the initial partner configuration, we further introduce the concept of partner configuration. Both of our introduced concepts will be analyzed in light of the degree of innovation novelty and of firm size.

Using a sample from the Swiss Innovation Survey for the years 1993-2013, we find that a configuration of complementary collaboration partners has a positive impact on innovation performance, for both radical and incremental innovation. This finding is mainly driven by SMEs, however. In terms of adapting the partner configuration, for radical innovation, closing down to a less open innovation strategy has no impact on innovation performance. Opening up to a higher diversity of partners has a positive impact for all partner types with the exception of science. This is true for both, SMEs and large-sized firms. For incremental innovation, we find that eliminating horizontal collaboration for large firms and science partners for SMEs has a positive impact on innovation performance.

While we are aware of the fact that we cannot claim causality with our analysis, we do believe that a thorough explorative empirical analysis such as ours can go a long way in filling the gap in the literature by overcoming the fragmentation of the literature. We go through great length to introduce two new conceptual measures allowing managers as well as policy-makers to enhance their understanding on how to optimize the collaboration partner blend and how to translate these concepts into careful empirical analysis.

2 Theoretical background and contextual framework

The theoretical contribution of this paper rests on an exploration of the mechanisms explaining how the initial configuration of a focal firm's collaboration partner mix and the subsequent dynamic adaptation thereof impacts innovation performance, taking the degree of innovation novelty into account. Since firms have many choices of external sources they can draw from in their quest for new ideas, we use a matrix allowing for any possible combination, resulting in a total of eight different configurations and seven different adaptations thereof.

Innovation performance and partner configuration

There is a wide consensus that firms benefit from research and development (R&D) collaborations (Caloghirou, Ioannides, & Vonortas, 2003). Through pooling of complementary skills and learning from the partner, collaborating firms can increase their innovation performance and thereby their competitiveness (Gomes-Casseres et al., 2006; Hagedoorn, 1993; Powell et al., 1996; Shan et al., 1994; Zidorn & Wagner, 2013). The image of the isolated innovator has faded away, and is replaced by a picture of increased collaboration among firms, between firms and customers, clients or suppliers and between firms and science, as joint effort has become a necessity for innovation in many instances to ensure that capabilities are in line with highly competitive markets and the fast-changing demands for new technologies. There is indeed no scarcity of examples of large-scaled firms that have shown, either through application or experimentation, that collaborating with external entities is advantageous to the focal firm. There are indeed ample empirical studies showing that firms engaged in R&D alliances typically outperform non-collaborating firms in terms of innovation (see e.g. Beck and Schenker–Wicki, 2014; Brouwer and Kleinknecht, 1999; Faems et al., 2005; Gulati et al., 2000; Hottenrott et al., 2015). Yet other studies, such as Belderbos, Carree and Lokshin (2004)for instance, investigate the impact of various partners in innovation performance. Their findings confirm a major heterogeneity in the goals pursued by the different collaborations. While competitors and suppliers concentrate more on incremental innovations (i.e. productivity growth, in the sense that they lead to higher sales of established products), university cooperations (and again competitors) are vital for creating market novelty sales. In a later study, Belderbos et al. (2006) take the partner configuration into account by analyzing the impact of having various types of partners simultaneously. The authors don’t focus on innovation output though, but rather on productivity growth and analyze pairwise complementarity thereof. While based on their analysis the authors cannot draw any direct conclusions on the impact of such partner mixes on innovation, they draw attention to the importance to further investigate these issues, as being able to directly link the partner configuration to innovation would help enhancing the impact of firms' collaboration strategies.

While the benefits of collaborative R&D on firm capabilities is undebated, literature also teaches us that collaboration comes at a cost, such as the risk of over searching (Beck & Schenker–Wicki, 2014; Deeds & Hill, 1996; Laursen & Salter, 2006), the pursuit of self-interest at the expense of the partner as well as the important costs of deterring such opportunistic behavior (Gulati, 1995; Williamson, 1985) or the risk of knowledge leakage beyond the joint project (Baumol, 1993; Hottenrott et al., 2015; Kesteloot & Veugelers, 1995; Shapiro & Willig, 1990).

Typically, these costs are explained by transaction cost economics (TCE). TCE relate firm boundaries to the fact that firms internalize what is either difficult to find in the market, costly to find in the market or vulnerable to opportunistic behavior in the market (Argyres & Zenger, 2012; Williamson, 1975, 1985, 1989). It is therefore important for firms to choose their partners – and the configuration thereof - wisely, as not doing so could result in high costs for the firm. While previous studies have shown that one type of partner may be more suitable for one type of innovation than another type of partner, we believe that differences in the configuration of partners may matter as well. Since the type of knowledge that is created and exchanged with one partner – say science – is fundamentally different from the type of knowledge that is created by another partner – say customers -, we reckon that there may be synergies between these knowledge types, leading to complementary as well as supplementary knowledge in the focal firm. Having a series of various partner types at the same time may therefore pay off by rendering the firm more attentive to outside knowledge. Likewise, Sampson (2005) shows that a broader configuration of alliance partners allows a firm to manage ambiguous and difficult situations more readily. By simultaneously drawing from knowledge of different angles, firms improve their management and reaction capacities as well. In this context, firms take the role as knowledge brokers, and bridge various knowledge domains enabling innovation (Hargadon, 1998). As such, having a complementary partner configuration at the same time may lead to multiplier effects in knowledge absorption and utilization in the focal firm, thereby widening the focal firm's capabilities beyond the individual collaboration partner, leading to a higher impact on innovation performance.

In order to fully account for the roles played by different partners and their simultaneous interaction, we don't conduct our analysis at the mere portfolio level. Rather, we account of all the possible partner configuration constellations by creating a vector of eight possible configuration types (see Figure 1). Because it is incredibly difficult to derive precise theories of how those different configurations impact (different degrees of) innovation performance, we analyze the vector of partner configurations empirically, without deriving a specific theory for each of the eight configurations.

Innovation performance and partner adaptation

With an increasing amount of knowledge and information available in the economy, the velocity of circulation of this knowledge is constantly increasing, shortening product life-cycles on the one hand and increasing the speed of changes in customer preferences on the other hand. The life-cycles of most products are getting increasingly shorter and new, cutting-edge technologies are rapidly being replaced through imitation. As a consequence, firms are increasingly confronted by what is commonly known as the commodity trap (Yun, Won, & Park, 2016). An inevitable consequence of this situation is that firms need to constantly adapt existing products and invest in the invention and creation of new products. This fast-changing environment pushes firm boundaries in the sense that firms' capabilities need to be constantly expanded and adapted. Indeed, in order to always have an appropriate partner for an optimal outcome, firms can no longer engage with one (or several) partners for life (Laursen, 2012). Since the expansion of internal firm boundaries is limited and very consuming in time and other resources, one way of enabling a faster adaptation to external knowledge and customer preference is through constantly adjusting external knowledge sourcing by assuring the appropriate configuration of collaboration partners. Some scholars indeed note that by ignoring timely adaptation of collaboration partners, not only may firms miss out in adjusting firm boundaries, they also may not fully benefit from potential complementarity effects between collaboration partners (Battisti, Colombo, & Rabbiosi, 2014; Jovanovic & Stolyarov, 2000).

In addition to increased learning opportunities and more adapted knowledge from partner adaptation, studies show that partner adaptation may have lower risks of collaboration-related costs. The pay-off of increased persistency of a long-term mutual collaboration commitment may come at the cost of relational myopia and inertia when the alliance partner no longer meets the needs of the focal firm or when another, better suited partner presents itself (Levinthal & March, 1993; Li & Rowley, 2002). As a matter of fact, Bakker and Knoben (2014) show that short-term alliances provide partners with more flexibility, which is essential to the learning curve in the focal firm (Lavie, Stettner, & Tushman, 2010). In terms of resource availabilities, there is more flexibility as well in the sense that the partnering firms only need to commit their resources for a specific time period (Sydow, Lindkvist, & Defillippi, 2004). Thereby partners are better able to provide the needed resources in terms of people, infrastructure or knowledge, as they know in advance when these resources will be freed up again and thereby utilizable for subsequent projects. This allows for a better management and planning of resource availability (Galunic & Rodan, 1998). In the same line of reasoning, alliances hold the inherent risk of conflicts. According to Zineldin and Dodourova (2005), between 60 to 70 percent of collaborative agreements are dissolved without achieving the desired results. Prompter partner adaptation may alleviate this risk of conflict. As there is more latitude with whom to work during the specific phase of the ongoing collaboration, literature shows that the risk of conflict is substantially reduced if collaboration agreements are for a determined period, thereby increasing the probability of successful project termination and reducing undesired costs (Schwab & Miner, 2008, 2011). Since R&D collaborations often times have poorly defined contracts because of the intangible nature of the activity itself, avoiding conflict through inertia in the collaboration may significantly improve the outcome (Caloghirou et al., 2003).

Yet other studies point out that firms see the switching of partners as an alternative to protect valuable intellectual property (Laursen & Salter, 2014; Levin, Cohen, & Mowery, 1987; Seo, Chung, & Yoon, 2017; Winter, 2006). The knowledge gained from previous experience with a partner helps partnering firms to learn about the focal firm's core technologies, on which its competitive advantage is based on. Therefore, too much familiarity with one partner may open the access to knowledge (technological, but also organizational and strategical) that was not destined to be shared with the R&D consortia. This leads to a situation in which, unless there is very strong trust in the relationship between the partners, such access to core knowledge may be abused. It may therefore be preferable to have a new partner to an "old acquaintances" (Li, Eden, Hitt, & Ireland, 2008). Previous research indeed shows that the knowledge between the partners spills over beyond the mere alliance objectives (Cassiman & Veugelers, 2002; Hottenrott & Lopes-Bento, 2016).

Finally, firms collaborate primarily to circumvent or lessen the effects of uncertainty in their environment (Wassmer, 2010). For their strategic alliances to fit this fast-changing environment, we would expect those alliances to be of a certain flexibility as well (Hoffmann, 2007). Failing to have this leeway in partner type configuration or adaptation may lead to a situation in which a static configuration of partners needs to reply and react to a fast-changing environment where needs and preferences change at a considerable pace. While staying with the same partner for a longer time may lead to a certain expertise between the partners, it may also lead to limitations, as shown by organisational psychology (see e.g. Dreyfus and Dreyfus, 2005; Hinds et al., 2001). Indeed, psychology research has shown that the more knowledge experts build in their field, the more inflexible they become (Kalish, Griffiths, & Lewandowsky, 2007; Lewandowsky & Thomas, 2009). In our setting, this behaviour would translate in a lack of responsiveness due to inertia in existing partnerships.

In line with our analysis on existing partner configurations, we also don't limit our analysis of dynamic partner adaptation to the portfolio level. As can be seen in Figure 1, we account for the fact that the adaptation of partners can go into seven different directions. Put differently, we illuminate for the fact that the direction of the adaptation and their effects can be different.

Degree of novelty and partner configuration

In line with Laursen and Salter (2006), we believe that it is vital to explore the differences in the innovation process to the degree of novelty (Dewar & Dutton, 1986; Freeman & Soete, 1997), since searching for new ideas means relying heavily on external sources. Indeed, one of the primary dimensions used to distinguish between degrees of innovation is the perpetuity between radical and incremental innovation (Garcia & Calantone, 2002; Tushman & Anderson, 1986). The former is typically defined as being new and different from prior solutions (Ritala & Sainio, 2014; Schilling, 2016: 48). Therefore, radical innovation is not only capable of significantly impacting firm performance, but it also has the potential to change the structure of the market, to create new markets or to render existing products obsolete. Furthermore, radical innovations have the potential to push the technological frontier of a firm or even sector and may allow a firm to enter new markets. It is however also often involved with higher costs and higher risks, since it is typically embodied in new, and thereby less familiar, knowledge (Schilling, 2016). Radical innovations are likely to present the greatest opportunity for performance differences (Marsili & Salter, 2005). Tushman and Anderson (1986) classify radical innovation in terms of 'competence enhancing' or 'competence-destroying'. This echoes that radical innovation may change competition patterns of firms active in the same industry (Anderson & Tushman, 1990). Realizing radical innovation requires therefore important R&D investments, and the risk of failure is considerable.

Incremental innovation on the other hand is more common, and even though the reward is often times smaller, it remains highly important for firms' profitability. It requires less effort as it is typically characterized as making minor changes from (or adjustments to) existing practices, products, and services (Ritala & Hurmelinna-Laukkanen, 2013; Schilling, 2016). Even though performance implications of incremental innovation may appear to be more modest (Marsili and Salter, 2005), they are considered "lifeblood of an organization" (p. 123), acting " as a competitive weapon in a technologically mature market" and "streamlining procedures based on existing technology [to] help alert a business in good times to threats and opportunities associated with the shift to a new technological plateau" (Johne & Snelson, 1988: 115). Hence, incremental innovations are crucial to ensure small improvements to existing products, helping to maintain or improve their competitive position over time.

To our knowledge though, little work has been carried out on the relationship between the degree of novelty of the innovation, the configuration of collaboration partner types and the adaptation thereof. In order to create comparative capabilities, it is vital however that firm boundaries are in line with their innovation strategies (Brusoni, Prencipe, & Pavitt, 2001). Indeed, searching for new ideas means that a firm has to rely heavily on its external knowledge sources. These in turn may differ with respect to whether a firm is looking for breakthrough ideas to innovate radically or rather for minor improvements to innovate incrementally. Indeed, for each potential source, firms have to build a certain pattern of interaction over time, constructing trust and a mutual way of working together. The adaptation of those sources will be equally impacted by the degree of novelty requested by the firm strategy, and assessing the partner mix and need for their adaptation provides a mechanism for understanding how firms search in the innovation ecosystem and how these sources are integrated with internal innovation efforts (Laursen & Salter, 2006).

3 Data and methods

3.1 Sample

The empirical analysis uses data derived from the Swiss Innovation Survey. This survey is conducted every three years by the Swiss Economic Institute (KOF) at ETH Zurich since 1990. The survey is part of the European Community Innovation Survey (CIS) of the European statistical office (Eurostat) and follows the guidelines described in the Oslo and Frascati manual developed by the Organisation for Economic Co-operation and Development (OECD, 1997, 2002). This dataset provides us with a representative sample of Swiss firms with at least five employees from both the manufacturing and service industries. The sample contains firm-level information on innovation activities, R&D expenditures, knowledge sourcing, intellectual property practices, and performance measures among many other firm characteristics. The CIS and the Swiss Innovation Survey constitute a reliable, valid and well-established source of information on firms' innovative activities and commercial success, thereby presenting the data requirements for the analysis at hand. Indeed, the CIS presents a series of advantages for our analysis when compared to other datasets such as for instance the SDC dataset, which is commonly used in this type of setting. A first advantage of the CIS is that it contains information on publicly as well as on non-publicly listed firms. This allows therefore a complete and representative picture of the Swiss economy. In existing administrative data, information is often times available only for publicly listed firms as the transactions for the other firms is not traceable. Since those are typically firms of larger size, knowledge about SMEs lags behind. A second advantage of the CIS is that since it is a survey and not mere observational data, our variables can be based on specific questions of interest to our research question, allowing for much more detailed information for the analysis at hand. Finally, and in line with Garriga et al. (2013), we believe that Switzerland is a particularly interesting setting to study because the national and industry context is different from that of many other European countries and characterized by high innovativeness and competitiveness. This difference in socio-economical background may play a vital role in shaping firms' external knowledge search strategies (Phene, Fladmoe-Lindquist, & Marsh, 2006) and will therefore add to our understanding of R&D collaboration impact. We further believe that given the different landscape of the Swiss economy, our findings will open directions for future research to undertake comparable studies. Last but not least, it should be noted that the datasets derived from these surveys have been used in a wide range of recent and prominent studies, allowing for comparability between findings (Arvanitis, 2012; Beck, 2016; Beck & Schenker–Wicki, 2014; Cassiman & Veugelers, 2002; Laursen & Salter, 2006; Leiponen & Helfat, 2010; Meuer, Rupietta, & Backes-Gellner, 2015). Indeed, the CIS has been specifically designed to inform European governments about the effects of policies on innovation performance. As such, these data are intended to provide valuable and comparable information on innovating firms in an EU context.

In our analysis, we use information from six consecutive waves covering a time period from 1999 to 2013. The postal survey received response rates of 33.8 % (1999), 39.6 % (2002), 38.7 % (2005), 36.1 % (2008), 35.9 % (2011), and 32.7 % (2013).[3] After eliminating the missing values, we restrict our sample to those firms that are observed at least in two consecutive waves. In total, our dataset comprises 3993 observations from 2087 different firms.

3.2 Empirical strategy

In our analysis, we focus on the role of the partner type configuration of the focal firm and the adaptation thereof in subsequent periods for innovation performance. Given the strong unbalanced nature of our panel dataset, we make use of the pooled cross-sectional structure of our data to estimate our models. For the equations that estimate firms' innovation performance, we apply pooled regression models with radical and incremental innovation performance as the dependent variables. These variables are measured as the ratio of the radical (incremental) innovative sales to the total turnover. Because these variables by definition range between 0 and 100, and because not all firms have innovative sales in each period, our data are characterized by corner solution outcomes around zero (Winkelmann & Boes, 2006; Wooldridge, 2010). For our analysis, we therefore use Tobit models to account for these censored dependent variables. With our approach, we are in line with previous empirical studies

[3] From 1999 until 2011, the survey was conducted every three years, but from the beginning of 2013 the Swiss Economic Institute changed the timing of the survey to every two years. The structure of the responses for different industry affiliations, regions, and sizes are largely consistent with the previous surveys. An overview on the innovation surveys from 1999 to 2013 and the corresponding innovation activities of Swiss firms from 1997 to 2012 can be found in Arvanitis et al. (2014).

that faced similar data characteristics (Bakker & Knoben, 2014). As argued in Greene (2003), standard Tobit models require the assumption of homoscedasticity. As likelihood ratio tests of the residuals indicate violations of the homoscedasticity assumption in our setting, we model the group-wise multiplicative heteroscedasticity by including firm size and industry dummies (Hathaway, 1985).[4] The Tobit models are estimated as follows:

$$InnoPerf_i^* = X'_{i,t-1}\beta + \epsilon_i, \qquad \epsilon_i \sim i.i.d.N(0,\sigma^2) \qquad (3.2)$$

$$InnoPerf_i = \begin{cases} InnoPerf_i^* \;\; if\; X'_{i,t-1}\beta + \epsilon_i > 0 \\ 0\; otherwise \end{cases} \qquad (3.3)$$

where $InnoPerf_i$ represents the non-negative observable innovation performance variable; this variable captures the radical innovation and incremental innovation performance respectively for the firm i.

$InnoPerf_i$ corresponds to the latent dependent variable $InnoPerf_i^*$ if this variable is above zero and to zero otherwise. Finally, to avoid direct simultaneity, we run our analysis by allowing for time lags between the main explanatory variables and the outcome measures as shown in Figure 1.

3.3 Measures

Dependent variables

In line with the previous literature (see, for instance, Laursen and Salter (2006)), we distinguish between radical and incremental innovation performance. Following Meuer et al. (2015), radical innovation performance (*RADICAL*) is measured as the firm's sales share of radical innovative products, i.e., products that are new to the firm, to the total turnover. Similarly, the incremental innovation performance (*INCREMENTAL*) is measured as the

[4] We therefore estimated the heteroscedasticity-robust model by a maximum likelihood function in which we replace the homoscedastic standard error term σ with $\sigma_i = \sigma\exp(Z'\alpha)$ in the likelihood function.

fraction of the firm's turnover with incremental innovative products, i.e., products that are significantly improved. In doing so, we follow the definition of radical and incremental innovation of previous studies using the same dataset (Beck et al., 2016; Garcia and Calantone, 2002; Meuer et al., 2015).

Main explanatory variables

With respect to our concepts of collaboration partner configuration and the adaptation thereof, we differentiate between eight simultaneous partner type configurations and seven possible adaptation mechanisms as demonstrated by Figure 1. The combinations of vertical, horizontal and scientific collaboration compose the eight possible configuration strategies. The subsequent adaptations of these configurations are characterized by either remaining persistent (i.e. not changing the partner configuration), opening up -or shunning down - towards vertical, horizontal or scientific partner types.

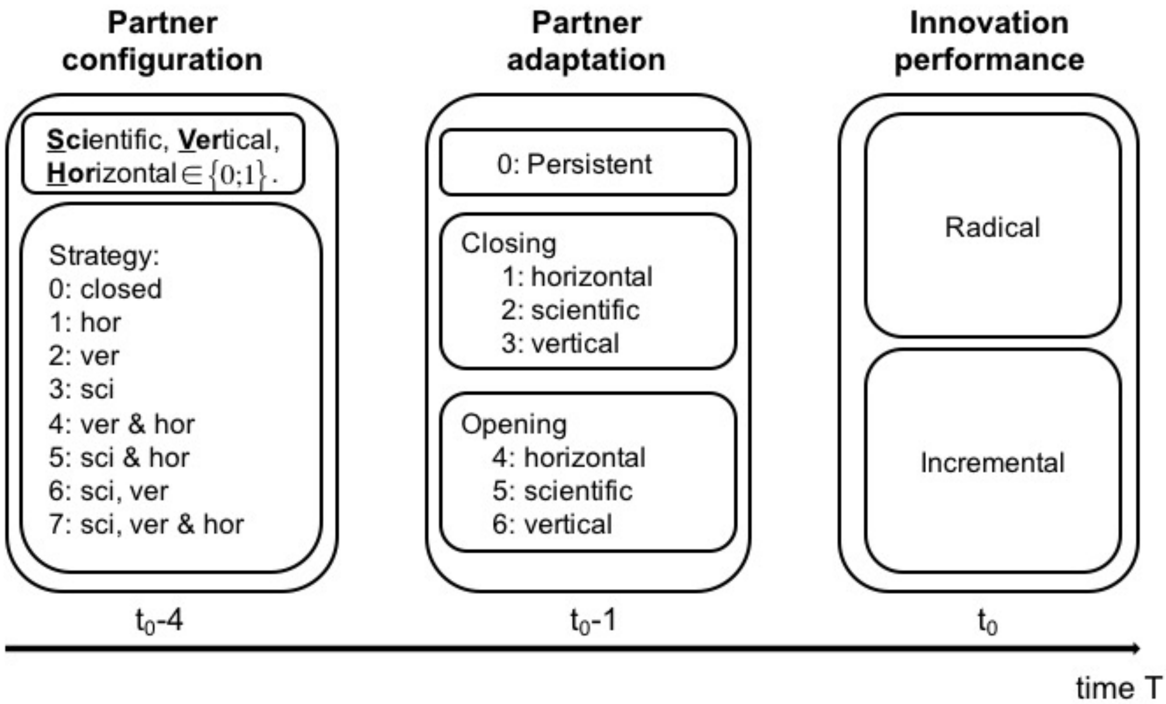

Figure 1: Conceptual framework

As a starting point, we introduce the measure *PARTNER CONFIGURATION* to capture the firm's simultaneous collaboration pattern. To construct this variable, we use information about firms' different R&D collaboration agreements with external collaboration partners such as suppliers, customers, clients, competitors, universities, and other research institutes.[5] Following Belderbos, Carree, Diederen, et al. (2004)), we aggregate this information and create three dummy variables that are each equal to 1 if a firm collaborates with a specific partner type. More precisely, we differentiate between vertical (*VER*, suppliers, clients or customers), horizontal (*HOR*, competitors), and institutional scientific partner types (*SCI*) (see Figure 1).

However, we do not stop at the simultaneous configuration pattern; we also take dynamic adaptation of the firms' search boundaries into account. With respect to this second concept, we introduce the measure *PARTNER ADAPTATION*, which analyzes what happens if a firm adapts its collaboration partner configuration between two points in time (t_0-4 and t_0-1). In line with the various partner configurations, a partner type adaptation in the firm's collaboration configuration can be described by seven different adaptation strategies: a firm can remain persistent within its pattern, it can open to either horizontal, scientific, and/or vertical partner types or it can shut down from those same partner types (see Figure 1).

Further controls

In our analysis, we further control for various factors that may influence firms' innovation outcomes. We include a measure for the firm's R&D investments: they are measured as the firm's R&D expenditures relative to its total turnover (*RDINT*). This measure accounts for the firm's R&D activities, thereby reflecting its general absorptive capacity and ability to conduct innovative activities. The receipt of public support is indicated by a dummy (*PUBSUB*). The receipt of a public grant may signal relevant competences and capabilities to successfully conduct R&D projects to other partner firms, and hence, may affect innovation success.

Furthermore, we include the firm age (*FIRMAGE*) and (the log of) the firm size (*LNFIRMSIZE*) to capture relevant firm characteristics. Moreover, we include the squared term

[5] We only use formal collaboration partners here, as defined in footnote 1.

of the two previously mentioned variables to take a non-linear relationship into account (*FIRMAGE2, LNFIRMSIZE2)*. In addition, we control for whether or not a firm belongs to a foreign group (*FOREIGN*), as foreign group members may show higher innovative performance due to spillovers from international group members. We also control for the foreign market activities of a firm. Highly export-oriented firms may be more innovative due to higher international competition than firms exclusively operating on a national market. We include a variable measuring the export share of the total turnover (*EXPORT*).

Moreover, seven industry-sector dummies account for the different propensities to innovate across sectors. Finally, we include six survey-year dummies in our set of control variables to control for time shocks.

3.4 Descriptive results

Table 1 reports descriptive statistics about the relevant variables for our analysis. The table shows that on average, firms generate approximately 7.0 % of their total turnover with radical innovative products, whereas 8.2 % of the turnover can be attributed to incremental innovative products. Moreover, 50.8 % of the firms in our sample innovate, 37.6 % conduct R&D activities, and 14.2 % collaborate in R&D alliances. Among the collaborating firms in our sample, 8.6 % collaborate with partners from scientific institutes, 13.0 % collaborate with vertical partners and 4.4 % collaborate with competitors. On average, the firms in our sample have 257 employees and 67 years. In addition, 85.1 % of the firms are SMEs. Further descriptive statistics of the industry, size-class distribution and cross-correlations are provided in Table A 1: and Table A 2: in the Appendix.

Table 1: Descriptive statistics of the relevant variables.

	Variable	Obs.	Mean	S.D.	Min.	Max.
1	RADICAL	3993	6.951	13.665	0	100
2	INCREMENTAL	3993	8.208	15.580	0	100
3	RELTECHPOT	3993	0.522	0.500	0	1
4	R&D	3993	0.376	0.485	0	1

5	COLLABORATION	3993	0.142	0.349	0	1
6	INNO	3993	0.508	0.500	0	1
7	SCIENCE	3993	0.086	0.280	0	1
8	VERTICAL	3993	0.130	0.337	0	1
9	HORIZONTAL	3993	0.044	0.205	0	1
10	RDINT	3993	1.118	4.748	0	178.79
11	FIRMSIZE	3993	256.821	1749.612	1	43038
12	FIRMAGE	3993	67.401	42.146	2	614
13	EXPORT	3993	22.451	33.522	0	100
14	FOREIGN	3993	0.148	0.355	0	1
15	SUBSIDY	3993	0.059	0.235	0	1

The initial collaboration partner-type configuration is reported in Table 2. The predominant initial configuration in our sample is non-collaborating firms, as is typically the case (see e.g. Hottenrott et al., 2015; Hottenrott and Lopes-Bento, 2016)). This is true for SMEs as well as for large-sized firms. For collaborating firms, we can see that, on average, large firms collaborate more than SMEs. Vertical collaborations or vertical collaborations jointly with science is the most frequently used configurations, for both large-sized firms and SMEs. Next to this configuration, the mix of vertical and horizontal collaboration is also well represented, especially among large-sized firms.

Table 2: Partner configuration according to firm size classes.

PARTNER CONFIGURATION:	Full sample		Small- and medium-sized firms		Large-sized firms	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
0: no collaboration	3,429	85.88	3014	88.65	415	69.98
1: horizontal	13	0.33	10	0.29	3	0.51
2: vertical	126	3.16	102	3.00	24	4.05
3: science	16	0.4	12	0.35	4	0.67
4: vertical & horizontal	74	1.85	56	1.65	18	3.04
5: science & horizontal	8	0.2	7	0.21	1	0.17
6: science & vertical	225	5.63	138	4.06	87	14.67
7: science & vertical & horizontal	102	2.55	61	1.79	41	6.91
Total	3,993	100	3,400	100	593	100

The dynamic changes of the firms' boundaries in terms of collaboration can be found in Table 3. The most frequent strategy is remaining persistent, clearly hinging towards a certain inertia in the firms composing our sample. This is especially true for SMEs, with 85.47% of the firms not changing collaboration strategy between two periods. Overall, closing down from partner types and opening up towards new partner types happens in an equilibrated manner. As illustrated by Tables 3, roughly 8,34% of the firms close down one partner type, while 8,47% open up towards a new partner type. When considering only SMEs, those proportions are slightly smaller, with 7,17% of firms closing down and 7,36% opening up. Large-sized firms show a higher activity, with 15,01% of closing adaption and 14,83 of opening adaptation. Overall, the highest adaptation activity for all firms of the sample concerns vertical collaboration partners, both in terms of opening up towards them or closing down from them. This is in line with the previous findings that vertical partners are predominant in the partner type composition. It does show though that firms do not stick to the partners they predominantly collaborate with but that they adapt according to their needs and to the circumstances.

Table 3: Partner adaptation according to firm size classes.

PARTNER ADAPTATION		Full sample		Small- and medium sized firms		Large-sized firms	
		Freq.	Percent	Freq.	Percent	Freq.	Percent
	0 persistent	3,322	83.20	2906	85.47	416	70.15
closing	1 horizontal	38	0.95	28	0.82	10	1.69
	2 scientific	38	0.95	29	0.85	9	1.52
	3 vertical	257	6.44	187	5.50	70	11.80
opening	4 horizontal	37	0.93	23	0.68	14	2.36
	5 scientific	44	1.10	33	0.97	11	1.85
	6 vertical	257	6.44	194	5.71	63	10.62
	Total	3,993	100	3,400	100	593	100

4 Empirical results

4.1 Configuration of collaboration partners

Table 4 presents the results of our first regression models, showing the link between partner configuration and innovation performance. When looking at single-type partners, we see that horizontal collaboration partners have a highly positive significant impact on radical innovations. This is not surprising. Radical innovations require new solutions and working jointly with partners from the same industry, thereby looking for similar solutions, may enhance the process of coming up with state-of-the art products. In this line of thinking, we see that the impact of collaborating horizontally has a negative effect on incremental innovations, albeit insignificant. This can be explained by the mere fact that if the changes to a product are minor, competitors compete in the same market and don't need input from within industry partners to adapt or improve already existing products. This is different when looking at vertical collaboration, displaying a positive and significant impact of similar magnitude for both radical as well as incremental innovation. Given that there is no direct competition with vertical collaborating partners, this result is not surprising. What is surprising though is the fact that science is insignificant of on both types of innovation outcome, albeit positive for radical. When considering the partner configuration, we see that especially for radical innovation, having a complementary mix of partners pays off. All types of partner configuration have a highly positive and significant impact on radical innovation performance, with the combination of science and horizontal being the largest one. Indeed, this configuration leads on average to an 18-percentage point increase in the estimated radical innovation sales ratio when compared to a situation of no collaboration partner. For the impact on incremental innovation, we find similar results, but generally lower in magnitude. The only non-significant configuration is the science/horizontal combination, which is not surprising since input that can be received from such partners is presumably not required to only incremental improvement of the product. In terms of control variables, all the variables go into the expected direction. These findings support that having a diversified configuration of collaboration partners is generally positively related to innovation performance.

Table 4: Tobit regressions on the impact for collaboration partner configuration on innovation performance.

PARTNER CONFIGURATION	RADICAL	INCREMENTAL
horizontal	11.464*	-12.892
	(6.063)	(8.373)
vertical	9.730***	9.306***
	(2.016)	(2.425)
science	3.203	-1.614
	(5.572)	(6.946)
vertical & horizontal	10.087***	15.476***
	(2.693)	(3.155)
science & horizontal	18.624**	9.609
	(8.276)	(11.099)
science & vertical	6.370***	4.638**
	(1.585)	(1.945)
science & vertical & horizontal	6.553***	7.817***
	(2.292)	(2.782)
R&DINT	0.760***	0.605***
	(0.077)	(0.106)
FIRMSIZE	9.708***	7.238***
	(1.551)	(1.859)
FIRMSIZE^2	-0.616***	-0.342*
	(0.153)	(0.186)
FOREIGN	0.292	0.428
	(1.136)	(1.391)
EXPORT	0.036**	0.096***
	(0.015)	(0.018)
SUBSIDY	4.104**	10.432***
	(1.594)	(1.922)
FURTHER CONTROLS	[YES]	[YES]
TIME DUMMIES	[YES]	[YES]
INDUSTRY DUMMIES	[YES]	[YES]
No. of observations	3,993	3,993

Note: Standard errors are clustered at the firm level, as firms appear more than once in the sample. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

4.2 Adaptation of collaboration partners

Next, we consider the impact of adapting the partner type configuration as opposed to collaboration inertia in Table 5. A first observation we can see is that horizontal collaboration – alone or in combination with another partner type – loses in significance when adaptation is taken into account. Looking at the adaptation, the results indicate that adapting the scope of collaboration configurations positively influences innovation performance when compared to collaboration persistency. The direction of the adaptation – i.e. closing down one partner type or opening up towards a partner type – depends on the innovation outcomes. In particular, our analysis shows that closing down horizontal or scientific collaboration has a positive impact on incremental innovation. This is in line with our previous findings which showed that those two types of collaboration had a negative impact on innovation outcome, even if insignificant. In the same line of thinking, opening up to vertical collaboration partners has a highly positive impact on incremental innovation. For radical innovation, the analysis doesn't reveal any positive effects from losing one partner type. We do find evidence though that opening up to either horizontal or vertical has a highly positive effect. While these findings partially support that partner type adaptation has a positive impact on innovation performance, they do not confirm that this adaptation is more important for incremental than radical innovation. While for incremental innovation the adaptation goes in both directions, i.e. opening up and closing down, it only goes in one direction for radical innovation.

Table 5: Tobit regressions on the impact of partner adaptation on innovation performance, accounting for initial partner configuration.

PARTNER CONFIGURATION & PARTNER ADAPTATION		RADICAL	INCREMENTAL
CONFIGURATION:			
	horizontal	9.653	-21.842***
		(6.288)	(8.458)
	vertical	10.296***	11.265***
		(2.499)	(2.968)
	science	-2.569	-10.411
		(5.772)	(7.300)
	vertical & horizontal	11.171***	16.148***
		(3.237)	(3.728)
	science & horizontal	13.822	2.766
		(8.689)	(11.441)
	science & vertical	7.189***	7.074***
		(1.985)	(2.415)
	science & vertical & horizontal	8.497***	7.828**
		(2.804)	(3.397)
ADAPTATION			
closing	horizontal	-1.792	12.616**
		(4.262)	(5.204)
	scientific	6.400	9.237*
		(4.066)	(4.857)
	vertical	0.953	0.397
		(2.128)	(2.536)
opening	horizontal	6.894*	4.721
		(3.521)	(4.425)
	scientific	2.055	1.711
		(3.642)	(4.246)
	vertical	11.237***	16.543***
		(1.515)	(1.817)
	CONTROLS	[YES]	[YES]
	TIME DUMMIES	[YES]	[YES]
	INDUSTRY DUMMIES	[YES]	[YES]
	No. of observations	3,993	3,993

Note: The standard errors are clustered at the firm level, as firms appear more than once in the sample. The time and industry dummies are jointly significant (not presented). ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

5 Additional empirical exercise

5.1 Firm size and partner configuration

In order to provide a completer picture of the research question at hand, we proceed by repeating the above exercise differentiating between SMEs and large-sized firms. Previous literature has indeed shown that R&D collaborations may have different impacts for SMEs when compared to larger firms (see e.g. Belderbos et al., 2006; Hottenrott and Lopes-Bento, 2016; Beck & Schenker-Wicki, 2014). Often times, a lack of in-house resources, the high entrepreneurial risk of uncertainty and the lack of reputation of the product or the firm in the market characterize the particularities and difficulties of innovation activities in SMEs and are used to explain SME failure (Baum, Calabrese, & Silverman, 2000; Bogers, 2011; Das & Teng, 1999; Uzzi, 1997). Specifically, SMEs often face an innovation paradox by having an innovative edge but failing to translate it into a marketable and profitable product. Even though SMEs are typically more flexible, less formalized, and quicker to make decisions, their financial resources for internal R&D are often times limited (Bessant, 1999; Lee, Park, Yoon, & Park, 2010; van de Vrande, de Jong, Vanhaverbeke, & de Rochemont, 2009).

Since the impact of R&D collaboration on SMEs remains ambiguous, the impact of different partner type configurations and the dynamic adaptation thereof is even more unknown.

In what follows, our analysis therefore investigates the impact of partner configuration and adaptation on innovation performance by differentiating the effects between SMEs and large firms. Table 6 demonstrates that partner configurations impact innovation performance differently according to firm size. While the signs on the coefficients are largely the same as for the overall sample, we see clear differences in the impact: for instance, while horizontal collaboration partners don’t have any impact on either type of innovation for SMEs, they have a very high positive impact on large-sized firms. Interestingly, the opposite is true for vertical collaboration partners.

In the same line, another interesting result is the fact that the vertical combined with horizontal collaboration has – in line with the previous results – a positive impact on all the outcome variables, expect for radical innovation of large-sized firms. This points to the fact that large-sized firms might have the required know-how in-house, respectively that they are wary to work with partners out of worry for disclosing critical information. While science collaborators by themselves didn't impact innovation performance, when combined with vertical collaboration, the impact turns positive, and mainly so for radical innovation in SMEs. This finding emphasizes that collaboration with science needs complementary types of partners in order to commercially exploit the knowledge gathered through science collaboration.

Finally, collaboration configurations consisting of partners composed by all three partner types are positively linked with increased radical and incremental innovation performance for SMEs and only radical innovation performance for large firms. Generally, large firms do not benefit to the same extent from the complementarity effects created from collaboration partners for innovation performance as SMEs, as their own assets and competencies are larger. This finding highlights the limitations and scarcity of resources in SMEs, and hence, it indicates that collaboration partner mix may be an appropriate means for SMEs to confront these problems. The controls have again the expected sizes and magnitude, irrespective of firm size.

Table 6: Tobit regressions on the impact for collaboration partner configuration on innovation performance, differentiating between SMEs and large-sized firms.

PARTNER CONFIGURATION	SMALL MEDIUM FIRMS		LARGE FIRMS	
	RADICAL	INCREMENTAL	RADICAL	INCREMENTAL
horizontal	5.084	-12.897	20.866**	-17.008
	(7.916)	(11.402)	(9.974)	(10.898)
vertical	11.937***	12.209***	1.982	-3.586
	(2.395)	(2.825)	(3.900)	(4.293)
science	1.130	-1.515	-1.110	-11.857
	(7.009)	(8.584)	(8.950)	(10.113)
vertical & horizontal	12.111***	14.027***	2.760	11.541**
	(3.232)	(3.843)	(4.559)	(4.775)
science & horizontal	11.813	-0.482	43.052	34.125
	(9.380)	(12.268)	(31.051)	(37.913)
science & vertical	7.955***	4.387*	4.256*	4.337
	(2.234)	(2.635)	(2.216)	(2.657)
science & vertical & horizontal	6.235*	10.405***	5.355*	-0.126
	(3.208)	(3.627)	(3.222)	(4.042)
Controls:				
R&DINT	1.405***	1.821***	0.624***	0.152
	(0.160)	(0.193)	(0.084)	(0.122)
FIRMSIZE	11.693***	16.541***	2.645	1.599
	(3.444)	(4.207)	(7.729)	1(1.279)
FIRMSIZE^2	-1.036**	-1.687***	-0.140	0.165
	(0.462)	(0.565)	(0.514)	(0.775)
FOREIGN	0.751	0.016	-2.065	-0.520
	(1.435)	(1.709)	(1.870)	(2.373)
EXPORT	0.037**	0.093***	0.011	0.108***
	(0.018)	(0.021)	(0.028)	(0.033)
SUBSIDY	4.716**	9.606***	2.090	10.353***
	(2.127)	(2.470)	(2.434)	(2.958)
FURTHER CONTROLS	[YES]	[YES]	[YES]	[YES]
TIME DUMMIES	[YES]	[YES]	[YES]	[YES]
INDUSTRY DUMMIES	[YES]	[YES]	[YES]	[YES]
No. of observations	3,400	3,400	593	593

5.2 Firm size and partner adaptation

Table 7 explores the impact of partner adaption on innovation performance taking firm size into consideration. In line with the result on the full sample, we see that reducing the number of collaboration partners is an efficient strategy for incremental innovation. For large-sized firms, this concerns horizontal collaborators. This is indeed in line with the findings from Table 6, where the impact of horizontal collaboration was negative. Even though it wasn't statistically significant, on average, the firms would benefit from dropping this type of collaboration partner for incremental innovations. The same holds true for science collaboration among SMEs. Table 6 showed a negative, albeit insignificant, coefficient for science collaboration. As can be seen in Table 7, if SMEs drop this partner type, they stand to benefit. In terms of adding additional partners to the collaboration configuration, we see a positive effect of adding horizontal partners for radical innovation in SMEs. This is in line with theoretical expectations, as compared to large-sized firms for which adding a horizontal partner does not enhance innovation performance, SMEs may lack crucial assets for the innovation process. Adding a science partner, on the other hand, benefits only large-sized firms, for both radical and incremental innovation. As mentioned before, in order to fully benefit from such a partner, some specific knowledge, competences and absorptive capacity may be needed, that is more present in large-sized firms than in SMEs. Finally, in line with the results on the full sample, adding a vertical partner benefits all types of firms and innovation outcome.

Table 7: Tobit regressions on the impact of partner adaptation on innovation performance, accounting for initial partner configuration and differentiating between SMEs and large-sized firms.

PARTNER CONFIGURATION & PARTNER ADAPTATION		SMALL MEDIUM FIRMS		LARGE FIRMS	
		RADICAL	INCREMENTAL	RADICAL	INCREMENTAL
CONFIGURATION					
	horizontal	7.171	-18.252	14.562	-27.061**
		(8.639)	(11.859)	(10.004)	(11.011)
	vertical	14.651***	13.994***	-1.899	-4.819
		(3.113)	(3.590)	(4.497)	(5.317)
	science	-5.676	-11.158	-1.126	-16.821
		(7.131)	(8.874)	(9.912)	(11.853)
	vertical & horizontal	15.747***	15.577***	-2.587	8.225
		(3.990)	(4.605)	(5.362)	(5.699)
	science & horizontal	5.232	-8.320	47.442	29.370
		(9.728)	(12.745)	(32.416)	(36.158)
	science & vertical	9.135***	4.854	4.268	8.290**
		(2.884)	(3.383)	(2.704)	(3.316)
	science & vertical & horizontal	8.999**	9.593**	5.015	0.649
		(3.924)	(4.503)	(3.942)	(4.910)
ADAPTATION					
closing	horizontal	-2.959	9.265	5.058	16.098**
		(5.760)	(6.889)	(6.396)	(7.569)
	scientific	7.831	10.441*	-2.335	4.720
		(5.027)	(5.822)	(7.175)	(9.104)
	vertical	-1.577	1.275	4.664	0.142
		(2.845)	(3.295)	(3.195)	(3.919)
opening	horizontal	9.830**	8.050	6.067	0.353
		(4.972)	(6.199)	(4.976)	(5.906)
	scientific	-3.752	-5.665	16.626***	20.200***
		(4.481)	(5.176)	(6.411)	(7.000)
	vertical	12.230***	15.494***	8.986***	15.089***
		(1.840)	(2.143)	(2.576)	(3.307)
	CONTROLS	[YES]	[YES]	[YES]	[YES]
	TIME DUMMIES	[YES]	[YES]	[YES]	[YES]
	INDUSTRY DUMMIES	[YES]	[YES]	[YES]	[YES]
	No. of observations	3,400	3,400	593	593

5 Robustness checks

Before concluding, we test our findings against some critical features of our sample. More precisely, since we are interested in firms' organisational boundaries with external collaboration strategies, the composition of their R&D activities is vital. Since firms that do all of their R&D externally may have different characteristics from firms that have internal as well as external R&D activities, we rerun our regressions on a sample where those firms that have no internal R&D – but rely exclusively on external R&D – are dropped. As can be seen by Tables A.4 and A.5 in the Appendix, the results of our regressions remain unchanged.

6 Discussions, implications and concluding remarks

6.1 Discussion

As a response to today's highly competitive and rapidly changing environment, which includes shorter product cycles and time to market, firms need to adapt their organizational boundaries and strategies effectively to meet these challenges (Bakker & Knoben, 2014; Brusoni et al., 2001; Carlile, 2004; Mohammed & Nadkarni, 2011). One of the response strategies for many firms is to form strategic inter-organizational R&D alliances with external collaborating partners in order to orchestrate the organizational boundaries in alignment with innovation objectives. While some aspects about the effects of knowledge searching on innovation performance are already known, this study contributes to our knowledge by shedding light on (i) the mix of partner type configuration, (ii) the adaptation of partner type configurations and (iii) the differences for SMEs and large firms for improving different types of innovation performance.

Using a sample from the Swiss Innovation Survey for the years 1993-2013, we find that a complementary configuration of collaboration partners has a positive impact on innovation performance, for both radical and incremental innovation. When disentangling SMEs from large-sized firms, we see that this effect is mainly driven by SMEs. This is in line with theoretical expectations that SMEs often lack crucial resources, not only of technological nature but also of market, managerial or financial nature, so that a partner diversity benefits their innovation performance more.

In terms of adapting the partner configuration, we find that for radical innovation, closing down to a less open innovation strategy has no impact on innovation performance. Put differently, firms do not benefit from in-sourcing knowledge from a less diversified partner configuration. This is contrary to our expectation that radical innovation benefits from a small pool of highly specialized partners. Indeed, we find that opening up to a higher diversity of partners has a positive impact on radical innovation, for all partner types with the exception of science. Adding a scientific partner in the collaboration configuration does not enhance performance. These findings hold for both, SMEs and large-sized firms. This finding points out to the necessity that firms need to build up necessary assets and resources to successfully manage and benefit from collaborations with science partners. For incremental innovation, we find that eliminating horizontal collaboration for large firms has a positive impact. This is not surprising since horizontal collaboration concerns partners that are active on the same market. Since incremental innovation often concerns minor changes, sharing those with direct competitors comes at a risk of disclosing knowledge which threatens the market share. For SMEs, adopting a less open innovate strategy by eliminating a science partner has, on average, a positive impact. Since SMEs often have a lesser developed absorptive capacity, the usefulness they can get from highly specialized partners doesn't seem to pay off when considering the high costs that it takes to build and maintain such a relationship.

6.2 Implications and concluding remarks

A series of managerial implications can be derived from our findings. A first interesting finding pertains to the fact that having a collaboration configuration consisting of partners of various types, i.e. being able to transfer, translate and transform diversified knowledge simultaneously across organizational boundaries – has a positive impact on innovation performance, irrespective of the type of innovation and of firm size. A second important finding concerns the fact that the adaptation of such partner type configurations differs according to innovation type and firm size. Managers should therefore be advised that a «one-size fits all strategy» does not work but that it is vital to adapt the configuration according to firm specific characteristics and strategic objectives. While these findings are based on firm-level analyses, it would be interesting to extend the analysis to the subsidiary level as similar conclusions may be true for smaller subsidiaries when compared to a larger group company too.

Our findings also allow drawing some policy conclusions. Policy makers increasingly stimulate collaboration with science, especially for SMEs (Beck, Lopes-Bento, & Schenker-Wicki, 2016). While their rationale behind this decision is clear and based on the fact that theoretically, SMEs can learn a lot from science providing them with a competitive advantage, based on our findings, this is not necessarily the case. Revising such conditions may thus be needed.

6.3 Future research and limitations

Given the nature of our data, we have to be careful about claims of causality. While establishing causality is crucial in order to verify theory, this was not the scope of our project. Our intent was to go beyond existing literature in an aim to enhance theories based on correlations, if the latter allow analyzing the dynamics that have thus far not received the needed attention in the literature (Arora, Belenzon, & Rios, 2014).

Moreover, this study focuses on the sequential adaptation of organizational boundaries in the context of innovative search behavior, but it cannot take the experience of the same partner into account. Indeed, it focuses on the *type* of partner, rather than the partner itself. While those are two different things, we believe that being able to account for both would provide a completer picture.

Finally, with the data at hand, we are not able to see whether the decision of adopting a closer collaboration configuration strategy by eliminating one partner type was based on a voluntary or involuntary termination of the partnership. Since the costs of both types of termination are different, being able to control for that would be a nice addition for future research.

Appendix

Table A 1: Descriptive statistics, industry distribution.

Industry	Number of firms	Percent
1 Construction, mining, energy	496	12.42
2 Consumer goods (food, beverages, tobacco, textiles, clothing)	261	6.54
3 Intermediate goods (paper, printing, chemicals, pharmaceuticals, rubber, plastics, minerals, basic metals)	607	15.20
4 Investment goods (fabricated metals, machinery & equipment, electrical equipment, electronics and optical products, medical instruments, watches, vehicles, and other manufacturing)	1,203	30.13
5 Traditional services (trade, transportation, telecommunications)	750	18.78
6 Knowledge-based services (banking, insurance, information technology & services, technical commercial services)	503	12.60
7 Other services	173	4.33
Total	3,993	100

Table A 2: Descriptive statistics, firm size distribution.

Size class	Size class distribution	Number of firms	Percent
1 Small-sized firms	1 – 49	1,918	48.03
2 Medium-sized	50 – 249	1,482	37.11
3 Large-sized	250 – max.	593	14.85
	Total	3,993	100

Table A 3: Cross-correlations

		1	2	3	4	5	6	7	8	9	10
1	collaboration	1.000									
2	vertical	0.950*	1.000								
3	horizontal	0.526*	0.481*	1.000							
4	science	0.753*	0.699*	0.380*	1.000						
5	RDInt	0.259*	0.254*	0.125*	0.272*	1.000					
6	Size	0.218*	0.216*	0.122*	0.237*	0.081*	1.000				
7	Age	0.020	0.008	0.011	0.025	-0.058*	0.226*	1.000			
8	foreign	0.081*	0.089*	-0.013	0.082*	0.110*	0.179*	-0.065*	1.000		
9	export	0.321*	0.307*	0.110*	0.322*	0.279*	0.243*	-0.019	0.297*	1.000	
10	subsidies	0.390*	0.353*	0.233*	0.487*	0.266*	0.178*	0.016	0.053*	0.251*	1.000

Table A 4: Robustness Tobit regression estimates for innovation outcomes accounting for partner type configurations.

PARTNER CONFIGURATION	RADICAL	INCREMENTAL
horizontal	12.230**	-12.383
	(5.963)	(8.430)
vertical	10.066***	9.351***
	(2.030)	(2.459)
science	3.621	-1.535
	(5.441)	(6.967)
vertical & horizontal	9.916***	15.613***
	(2.644)	(3.169)
science & horizontal	18.777**	10.042
	(7.643)	(11.196)
science & vertical	6.075***	4.938**
	(1.575)	(1.963)
science & vertical & horizontal	6.552***	7.916***
	(2.219)	(2.791)
R&DINT	0.747***	0.600***
	(0.074)	(0.106)
FIRMSIZE	9.367***	7.337***
	(1.524)	(1.876)
FIRMSIZE^2	-0.578***	-0.348*
	(0.149)	(0.187)
FOREIGN	0.59	0.297
	(1.132)	(1.402)
EXPORT	0.038**	0.096***
	(0.015)	(0.018)
SUBSIDY	4.016**	10.240***
	(1.577)	(1.936)
FURTHER CONTROLS	[YES]	[YES]
TIME DUMMIES	[YES]	[YES]
INDUSTRY DUMMIES	[YES]	[YES]
No. of observations	3,950	3,950

Note: Standard errors are clustered at the firm level, as firms appear more than once in the sample. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

Table A 5: Robustness Tobit regression estimates for innovation outcomes accounting for partner adaptation given an initial partner configuration.

PARTNER CONFIGURATION & ADAPTATION		RADICAL	INCREMENTAL
CONFIGURATION:			
	horizontal	10.083	-21.457**
		(6.192)	(8.494)
	vertical	10.493***	11.506***
		(2.508)	(3.000)
	science	-1.782	-10.805
		(5.663)	(7.329)
	vertical & horizontal	10.762***	16.478***
		(3.184)	(3.746)
	science & horizontal	14.519*	2.622
		(8.117)	(11.547)
	science & vertical	7.029***	7.663***
		(1.972)	(2.433)
	science & vertical & horizontal	8.572***	8.110**
		(2.715)	(3.410)
ADAPTATION			
closing	horizontal	-1.464	12.739**
		(4.193)	(5.215)
	scientific	5.092	10.216**
		(4.069)	(4.948)
	vertical	1.055	0.035
		(2.104)	(2.551)
opening	horizontal	6.704*	4.515
		(3.448)	(4.427)
	scientific	2.726	2.085
		(3.648)	(4.284)
	vertical	11.267***	16.873***
		(1.505)	(1.832)
CONTROLS		[YES]	[YES]
TIME DUMMIES		[YES]	[YES]
INDUSTRY DUMMIES		[YES]	[YES]
No. of observations		3,950	3,950

Note: the standard errors are clustered at the firm level, as firms appear more than once in the sample. the time and industry dummies are jointly significant (not presented). ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

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