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R&D Partnerships and Innovation Performance: Can There be too Much of a Good Thing?

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R&D Partnerships and Innovation Performance: Can There be too Much of a Good Thing?

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Abstract

R&D collaboration facilitates the pooling of complementary skills, learning from the partner as well as the sharing of risks and costs. Research therefore repeatedly stresses the positive relationship between collaborative R&D and innovation performance. Fewer studies address the potential drawbacks of collaborative R&D. Collaborative R&D comes at the cost of coordination and monitoring, requires knowledge disclosure and involves the risk of opportunistic behavior by the partners. Thus, while for lower collaboration intensities the net gains can be high, costs may start to outweigh benefits if firms perform a higher share of their innovation projects collaboratively. For a sample of 2,735 firms located in Germany and active in a broad range of manufacturing and service sectors, this study finds that increasing the share of collaborative R&D projects in total R&D projects is associated with a higher probability of product innovation and with a higher market success of new products. While this confirms previous findings on the gains for innovation performance, we also observe that collaboration has decreasing and even negative returns on product innovation if its intensity increases above a certain threshold. Thus, the relationship between collaboration intensity and innovation follows an inverted-U shape and, on average, costs start to outweigh benefits if a firm pursues more than about two-thirds of its R&D projects in collaboration. This result is robust to conditioning market success to the introduction of new products and to accounting for the selection into collaborating. This threshold is, however, contingent on firm characteristics. Smaller and younger as well as resource constrained firms benefit from relatively higher collaboration intensities. For firms with higher collaboration complexities in terms of different partners and different stages of the R&D process at which collaboration takes place, returns start to decrease already at lower collaboration intensities.

Keywords: Innovation performance, product innovation, R&D partnerships, collaboration intensity, financing constraints, collaboration complexity, transaction costs, selection model, endogenous switching

JEL-Classification: O31, O32, O33, O34

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1. INTRODUCTION

Research on R&D partnerships repeatedly stresses the virtues of collaborative innovation. The pooling of complementary competencies, skill sourcing, and learning from the partner are all means through which partnering firms gain (Shan et al. 1994; Hagedoorn 1993; Powell et al. 1996; Gomes-Casseres et al. 2006; Zidorn and Wagner 2013). A large number of studies have identified positive effects on innovation performance, suggesting that the potential gains through collaborative innovation projects are high (Brouwer and Kleinknecht 1999; Van Ophem et al. 2001; Branstetter and Sakakibara 2002; Faems et al. 2005, among others).

Less research has addressed the potential drawbacks of collaborative R&D. In a broader context, studies have shown that searching for external knowledge from a variety of sources is only beneficial up to a certain point. Expanding the search beyond a threshold may result in "over-searching" (March 1991; Katila and Ahuja 2002; Laursen and Salter 2006, Grimpe and Kaiser 2010). Similar reasoning may hold for collaboration. R&D collaboration usually requires active commitment of the partners and the net returns from the partnership may depend on the firm's capacity to handle such commitments. As long as the benefits from collaborating outweigh the costs, a firm's innovation performance will increase with its collaboration intensity. After a certain threshold, however, this may no longer be the case. Thus, even though collaboration may positively influence innovation performance initially, engaging in additional collaborative projects may exhibit diminishing or even negative returns (Deeds and Hill 1996). The reasons are twofold: First, collaboration comes at the cost of coordination and monitoring (Rosenberg 1982; Mowery and Rosenberg 1989). Second, collaboration involves knowledge disclosure and the risk of opportunistic behavior by the partners (Foray and Steinmüller 2003; Bader 2008; Bogers 2011). Yet, the benefits and costs of collaboration may be highly firm-specific, depending on characteristics such as maturity or experience, availability of resources, and the alliance portfolio of the firm. For instance, gains from collaboration are potentially highest for firms with limited internal resources, such as small and medium-sized firms (SMEs), younger firms or firms that are overall financially constrained (Czarnitzki and Hottenrott 2011a; Lavie et al. 2010; Beckman et al. 2004). Moreover, SMEs or young firms may particularly benefit from collaboration through access to a broader and more diversified knowledge base (Hottenrott and Lopes-Bento 2014a). On the downside, SMEs and younger firms tend to be more resource constrained and may be required to budget managerial attention and available internal financial resources carefully. Therefore, the cost of coordination and monitoring may be especially high for such firms. Similarly, the competitive environment in which a firm operates may affect the benefits and costs of collaboration (Lavie et al. 2010). The cost of disclosure may be higher for firms in highly competitive markets in which information leakage quickly translates into a loss of market share. Finally, collaboration complexity in terms of diversification of partners and the variety of stages of R&D projects at which a firm collaborates may impact the gains and pains from collaboration. High complexity may increase management and coordination challenges, thereby reducing the net returns of collaboration (Leiponen and Helfat 2010; Beck and Schenker-Wicki 2014; van Beers and Zand 2014). Consequently, the relationship between collaboration intensity and innovation may not be linear, but may follow an inverted-U shape with the turning point depending on firm and market characteristics.

The present study addresses the gains and pains from collaborative R&D empirically. Our analysis puts forward the proposition that the effect of collaboration depends on its intensity, that is, on the number R&D partnerships in total R&D projects. For a sample of 2,735 firms located in Germany, we indeed find that increasing the share of collaborative projects in total projects is associated with a higher probability of product innovation and with a higher market success of new products. However, we find that, on average, this relationship turns negative for collaboration intensities higher than approximately 60% of all innovation projects. This threshold, however, varies according to firm characteristics, with the turning point ranging from 45% of collaboration intensity for financially well-endowed firms to circa 80% for young firms.

These results are robust to conditioning market success to the introduction of new products and to accounting for the selection into collaboration. Additionally, while many studies interested in external knowledge sourcing or the collaborative behavior of firms focus on particular industries, predominantly the pharmaceutical or semi-conductor sector, our study considers a sample that is more representative of the economy, comprising high-, medium and low-tech manufacturing and services.

The results of our study have implications for R&D management as well as for innovation policy. From a managerial perspective, it may seem rational to engage in collaborative R&D as opportunities for doing so open up. Overconfidence with regard to the expected returns from each of these relationships may lead to the engagement in more alliances than are actually beneficial. It thus seems advisable to balance collaborative and non-collaborative projects. When evaluating the potential benefits from additional collaborative projects, managers may want to consider the firm's overall project portfolio before deciding on future collaboration strategies. From a policy view, encouraging collaborative R&D may indeed foster innovation, which benefits not only the innovating firms but also the economy as a whole. Policy makers may nonetheless consider that the initial rationale of encouraging collaboration to enhance firms' competitiveness, and therefore customer surplus, may be undermined if used excessively. This seems particularly important in light of political encouragements to foster further R&D partnerships through R&D subsidies or other policy tools.

2. THE COLLABORATION – INNOVATION RELATIONSHIP

2.1 Gains from collaboration

There is a wide consensus in the economics and management literature that firms benefit from R&D collaborations. From a strategic management point of view, where collaboration and competition coexist, coordination, sharing of risks, resources and competencies, and the building of new knowledge are key channels through which firms gain from collaborating in

R&D (see, for instance, Caloghirou et al. 2003). In this context, the resource-based view suggests that in order to exploit existing resources (heterogeneous and immobile in nature) and in order to develop a long-term competitive advantage, firms need to also access external knowledge (Richardson 1972). For instance, the more basic or more radical the R&D activity, the higher the potential need for a diversified portfolio of collaboration partners. The knowledge-based view, which conceptualizes firms as mechanisms that enable knowledge creation, likewise asserts that R&D collaborations are a way to equip the firm with the knowledge it lacks internally to produce new or improved products (Un et al. 2010).

There is indeed a whole series of empirical studies showing that collaborating firms perform better than non-collaborating firms, especially in terms of innovation.[1] Brouwer and Kleinknecht (1999), for instance, were among the first to find that a firm's propensity to patent is significantly higher among R&D collaborators. Similarly, Van Ophem et al. (2001) find that firms participating in research partnerships file more patents than firms focusing on internal R&D. Branstetter and Sakakibara (2002) find similar results for firms in government-sponsored research consortia in Japan. Czarnitzki and Fier (2003) and Czarnitzki et al. (2007) show that collaborating firms in Germany are more likely to patent than non-collaborating firms and Peeters and van Pottelsberghe (2006) find a positive relationship between R&D partnerships and the size of firms' patent portfolios. Studying the technological relevance of the patented inventions, Vanhaverbeke et al. (2007) find a positive relationship between technology alliances and patent citations. Finally, Hottenrott and Lopes-Bento (2014b) argue that the type of alliance may affect the ability and the incentives to patent, i.e., patent quality and quantity, differently.

[1] Previous studies differentiate between contractual agreements between partners (see e.g., Hagedoorn et al. 2000 and Caloghirou et al. 2003 for comprehensive overviews) or collaboration partner (see, for instance, Belderbos et al. 2004a; Faems et al. 2005; Knudsen 2007).

While patenting activity may measure inventive activities, but not necessarily new products or the commercial success of new products, innovation measures typically derived from survey data further suggest a positive relationship between R&D collaboration and successful project terminations, the introduction of new products, sales from product innovations as well as sales growth (Klomp and van Leeuwen 2001; van Leeuwen 2002; Lööf and Heshmati 2002; Janz et al. 2004; Belderbos et al. 2004a,b; Faems et al. 2005; Hoang and Rothaermel 2010). In summary, these previous findings suggest that because of the inherent benefits of collaboration, it is positively associated with innovation performance.

2.2 Pains from collaboration

Besides expected gains, however, there are also certain risks and caveats linked to R&D collaboration. Deeds and Hill (1996) were among the first to suggest that the collaboration-innovation relationship may not be linear. Their results for a sample of biotechnology firms indeed suggest diminishing and even decreasing returns on new product development for very high numbers of collaborations. There could be several reasons for this observation.

First, transaction costs economics points to the cost of collaboration when contracts are incomplete. Incomplete contracts typically result from poor bargaining, which is directly related to the specificity of the assets at stake. The higher the intangibility of an asset, the more difficult it becomes to formulate a complete contract (see Caloghirou et al. 2003 for a review). Since knowledge is a highly intangible asset (irrespective of whether it is tacit or explicit), it is generally very difficult to formulate complete contracts in the context of R&D collaborations. Hence, there is an inherent risk that R&D collaborations can become very costly if each party's responsibility is not clearly specified in case of contingencies. Intuitively, this gets more important the higher the share of collaborative projects in a firm's R&D project portfolio. Moreover, the more collaboration projects a firm engages in, the higher the likelihood that partners or projects of lower marginal value are among them. Previous research has shown that the pursuit of self-interest at the expense of the partner as well as the important costs of deterring such opportunistic behavior can constitute a major cause of partnership instability (Williamson 1985; Gulati 1995; Deeds and Hill 1996).

In addition, firms may also find it difficult to assess the partner's value ex-ante due to information asymmetries and secrecy prior to the collaboration. Selecting ideal cooperation partners determines the degree to which complementarities in assets and know-how may eventually be realized. The quality of ex-ante screening and ex-post monitoring may decline as the number of alliances increases. Thus, every (additional) collaboration increases the burden on management, mainly through coordination effort including monitoring and transaction costs. Furthermore, coordination efforts for setting up a new collaborative project, especially when external parties are involved, constitute a drain on the resources available for other projects, which may affect the firms' overall innovation performance.

Further, collaborative R&D naturally comes at the cost of disclosure. At least part of the knowledge has to be revealed to the consortium partners. Collaborating firms may transmit not only codified but also tacit knowledge to the partner so that leakage risks go beyond the joint project (Hottenrott and Lopes-Bento 2014b). Indeed, partnerships bear the inherent risk of free-riding, where one associate tries to absorb the maximum knowledge from the other while concealing its own efforts (see e.g., Shapiro and Willig 1990; Baumol 1993; Kesteloot and Veugelers 1995). For example, partnerships with a substantial overlap in core businesses, geographic markets, and functional skills have a success rate of approximately only 30% as competitors are inclined to maximize their own individual objectives rather than the partnership's interests (Lokshin et al. 2011). In the survey used for the following analysis, indeed 60% of all firms declare perceiving leakage of information as a reason for not engaging in (additional) collaboration projects. Among already collaborating firms, this share is even higher at more than 70%.

Finally, the extent to which a firm can learn from additional partners may diminish with the number of partners, while the outflow of their internal knowledge goes to an increasing number of external agents. This implies that the higher a firm's collaboration intensity, the lower the marginal gain, whereas coordination costs increase.

2.3 Conceptual framework

Based on these arguments on the gains and pains from collaborating, we build our empirical model on the simple theory of a profit-maximizing firm that benefits from collaboration but also takes into account the transaction and disclosure costs when choosing the intensity of collaboration, that is, the ratio of collaborative over all innovation projects. When engaging in collaborative R&D, the firm realizes marginal benefits from collaboration *MB*. The function *MB*'s first derivate is positive ($MB' > 0$), but returns are decreasing as collaboration intensity increases ($MB'' < 0$). While the marginal benefit function is assumed to be strictly concave, the firm's collaboration cost function is expected to be linearly increasing or even convex. In other words, costs are increasing overproportionally when collaboration intensity increases ($C' > 0$ and $C'' > 0$). In equilibrium the firm engages in collaboration projects only if the expected benefits exceed expected cost. This yields a return function *R* that follows an inverse-U shape, that is $R' > 0$ and $R'' < 0$. This leads us to hypothesize that

H1: The relationship between the share of collaborative projects in total innovation projects and innovation performance follows an inverted-U shape.

Figure 1 graphically illustrates the marginal benefit, the marginal cost, and the net return curves. While abstracting from inherent uncertainty in both these aspects, the firm's optimal collaboration intensity is given by the share of joint projects in total innovation project JP^*. In a real-world context characterized by information asymmetries, uncertainty, and other managerial frictions, we expect that most firms may not choose the theoretically optimal collaboration intensity. In other words, we expect to see firms engaging in a whole range of collaboration intensities below and above the turning point in our data. Thus, the purpose of the following empirical exercise is to identify the turing point JP^* taking into account firms' heterogenity.

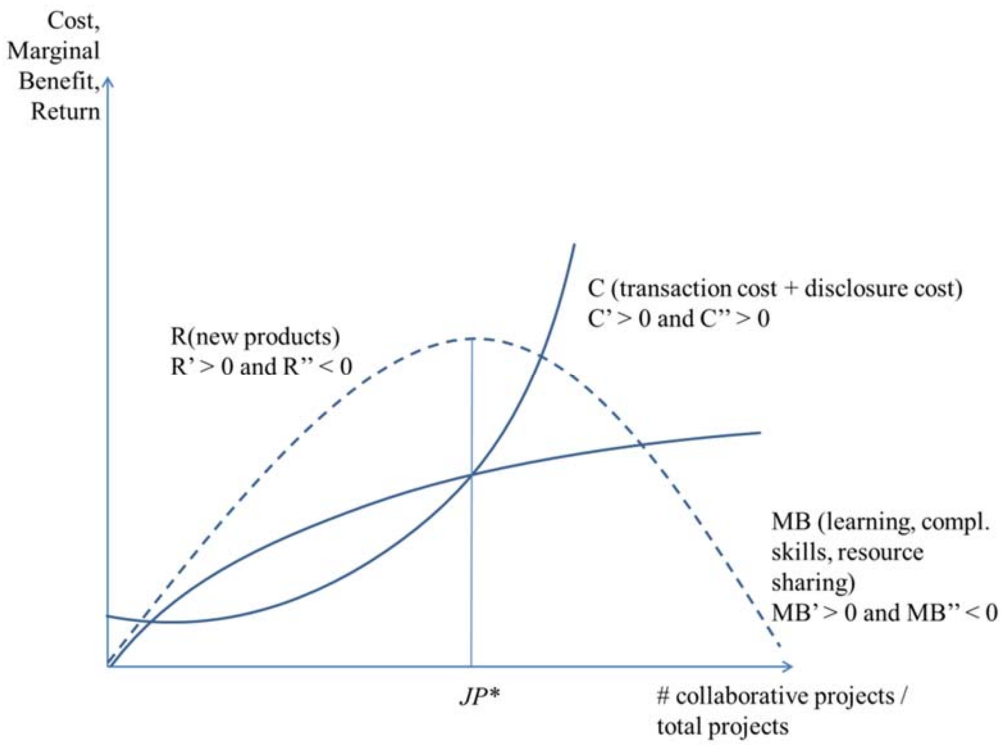

Figure 1: Optimal collaboration intensity

3. GAINS, PAINS, AND FIRM HETEROGENEITY

The extent to which firms benefit from increasing their collaboration intensity depends on the relative size of the marginal transaction and disclosure costs compared to the marginal benefits through learning, pooling complementary skills, and resource sharing. The optimal share of collaborative projects in all innovation projects may therefore be highly firm-specific. Smaller firms which may have limited resources, especially for R&D projects (Czarnitzki and Hottenrott 2011a), may gain relatively more from pooling resources with external partners by allowing them to expand their asset and knowledge base. At the same time, however, smaller firms' marginal costs of handling collaborative projects may be higher than in larger firms. Indeed, responses to the survey on which this study is based indicate that coordination costs are among the main factors that prevent firms from engaging in (new) collaborative projects. Interestingly, SMEs are significantly more likely to indicate that coordination costs are an important deterring factor than larger firms.[2]

Overall, the level of resource constraints within a firm may determine the relative costs or gains from engaging in additional joint projects (Lavie et al. 2010; Beckman et al. 2004). If a firm is not resource constrained, e.g., can hire additional R&D managers and project assistants, the benefits of collaborative projects may exceed marginal transaction costs. For instance, Park at al. (2002) stress the importance of available resources for realizing opportunities through strategic alliances. If resource expansion is impossible, for instance, because of financial constraints, current management may not be able to successfully handle collaborative R&D projects, thus reducing the returns to every additional project or even rendering the return negative.

A similar argument can be made for young firms with a high learning potential that gain through tapping the partner's experience. Indeed, it has been shown that younger firms are less established in their routines and skills, and are thereby more flexible to adapt to new environments (Hannan and Freeman 1984; Lavie et al. 2010). However, disclosure and transaction costs must be weighed against these gains, potentially reducing the number of collaborative projects a firm can handle and still benefit from it overall. Young firms may be particularly concerned with disclosing too much of their specific knowledge and consequently losing their competitive edge to more established competitors. Moreover, firms' own experience is an important predictor of innovation success through external innovation linkages (Love et al. 2014).

[2] Based on a dummy variable equal to one if a firm reported that coordination costs constitute a very important reason not to enter a (new) R&D collaboration, the test statistic from a one-sided t-test on the mean differences between SMEs and larger firms reports that coordination costs are significantly higher for SMEs than for large firms $\Pr(T < t) = 0.0384$. As is typically done in the literature, SMEs are defined as firms with less than 250 employees.

More generally speaking, for firms in more competitive environments, knowledge disclosure in R&D alliances to other firms may be relatively more costly, leading to a smaller optimal share of joint innovation projects. On the other hand, if firms are active in a more competitive environment, pooling competences and skills with one or several partners may be essential to ensure that they keep ahead of their competition (Lavie et al. 2010).

Based on these arguments, we hypothesize that

H2: The optimal share of collaborative projects in total projects varies with a firm's size, the level of resource constraints, maturity, and its competitive environment.

Finally, the diversity or complexity of a firm's collaboration portfolio may determine the extent to which a collaboration will translate into higher innovation performance (Leiponen and Helfat 2010; Beck and Schenker-Wicki 2014; van Beers and Zand 2014).

The complexity of the collaboration portfolio may increase along two main dimensions: the number of different types of partners (competitors, suppliers, customers, end-users, universities or public research institutions) and the number of stages within the R&D process in which collaboration takes place, ranging from idea generation and basic research to applied research, product development, and market introduction. With increasing complexity, managing collaborations may become increasingly costly. Furthermore, disclosure costs may increase with the number of different agents and with the variety of stages in the R&D process at which collaboration takes place. Collaboration complexity may limit the marginal returns to engaging in additional collaborative projects and may hence lower the optimal share in innovation projects, which maximizes the returns to collaboration. Therefore, we hypothesize that

H3: The optimal share of collaborative projects in total projects is lower for firms with a higher level of collaboration complexity.

4. IDENTIFICATION STRATEGY

We estimate innovation success models in which the share of collaborative projects is our main variable of interest. Testing our hypotheses thus requires detailed information on a firm's collaboration activities as well as on its innovation performance. We first consider the event of introducing a new product to the market as innovation success. In a second step, we examine the market success of product innovations measured by the firm's sales share from products that were new to the market. Third, we account for the conditionality of market success to the introduction of new products.

In a first step, we specify innovation performance as a discrete probability model which we estimate using probit models. The sales share due to new products, however, is a percentage and hence requires the estimation of a censored dependent variable model, as not every firm in our sample has product novelty sales in the period under review. For the second step, we therefore estimate Tobit models on new product sales that can be written as:

$$y_i^* = X'\beta + \varepsilon \tag{1}$$

where y^*_i is the unobserved latent variable. The observed dependent variable is equal to

$$y_i = \begin{cases} y^* & if\ X'\beta + \varepsilon > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

and X represents a matrix of regressors, β the parameters to be estimated and ε the random error term. However, the standard Tobit model requires the assumption of homoscedasticity in order for the estimates to be consistent (see Wooldridge 2002: 533–535). After conducting tests on heteroscedasticity (Wald tests and LR tests) using a heteroscedastic specification of the Tobit model, we estimated the model by a maximum likelihood function in which we replace the homoscedastic standard error term σ with $\sigma_i = \sigma \exp(Z'\alpha)$. In particular, we include five size-class dummies based on the number of employees and six technology classes (following the OECD 2003 classification) to model group-wise multiplicative heteroscedasticity.

Finally, we account for the conditionality of a positive sales share on having introduced a new product to the market. That is, the outcome variable y_i is only observed if a selection criterion is met, i.e., if $z_i > 0$, with z_i being the probability of the market introduction of a new product and y_i the relative market success of new product(s). We estimate the impact of collaboration intensity on market success, conditional on a firm having introduced at least one new product, as follows:

$$y_i = \begin{cases} \beta X_i' + u_{1i} & if\ z_i > 0 \\ - & if\ z_i \leq 0 \end{cases} \tag{3}$$

with $$z_i = \gamma w_i + u_{2i} \quad \text{and} \quad \begin{matrix} u_1 \sim N(0,\sigma) \\ u_2 \sim N(0,1) \end{matrix} \tag{4}$$

and $corr(u_1, u_2) = \rho$. This approach allows us to take the error term correlation into account (see Heckman 1976, 1979). Indeed, if $\rho \neq 0$, standard regression techniques applied to (3) would yield biased results; upwards biased in case of a positive error term correlation and downward biased in case of a negative error term correlation. The model proposed by Heckman accounts for such error term correlation by restoring the zero conditional mean through including an estimate of the selection bias. This procedure further allows us to take the censoring of our second stage outcome variable into account, that is, the truncated nature of the sales share from new products.

5. DATA AND VARIABLES

The following analysis makes use of the 2012 wave of the Mannheim Innovation Panel (MIP) covering the period 2009–2011. The MIP started in 1993 with the aim to provide representative innovation data for policy and research purposes. It is the German part of the European-wide Community Innovation Surveys (CIS) and thus provides internationally comparable data. The sample population is representative of all firms with at least five employees in the German business sector. The Centre for European Economic Research (ZEW), infas Institut für

Sozialforschung, and ISI Fraunhofer Institute conduct this survey on behalf of the German Federal Ministry of Education and Research. For a detailed description of the survey, see Peters (2008). We complemented this data with information on the firms' legal forms and the founding year as well as the firms' credit ratings from the Creditreform database. Creditreform is Germany's largest credit rating agency and provides firm-level information for nearly the entire population of firms in Germany. As a measure of firms' competitive environment, we obtained sales concentration indicators at the 4-digit NACE level from the German Monopolies Commission. The present study focuses on the information of 2,735 firms in manufacturing and business-related industries that had at least 10 employees in 2009[3] (see Table A.1 in the Appendix for the sample distribution across industries).

Innovation performance measures

The binary indicator (*new product*) takes the value one if a firm introduced at least one new product to the market (zero otherwise). This variable serves as an outcome variable in the probit model and in the first stage of our selection model. To measure market success, firms indicated the share in sales from these new products (*new product sales*). Since only firms with new products can have positive sales, this variable serves as an outcome variable in the Tobit model and in the second stage of the selection model.

Innovation projects and collaboration measure

Firms indicated the total number of innovation projects (*# all projects*) as well as the number of innovation projects in collaboration with external partners (*# joint projects*) during the period 2009–2011. From that information, we can calculate collaboration intensity as:

$$\textit{collaboration intensity} = \frac{\#\, \textit{joint projects}}{\#\ \textit{all projects}}$$

[3] We drop all firms that classify as micro firm according to the European Commission Recommendation 2003/361/EC of May 6, 2003, from the sample.

To capture non-linarities in the relationship between collaboration intensity and innovation, we include the squared values for collaboration intensity in addition to the original variable in all models.

Moderating factors

Both the likelihood of introducing a new product as well as its share of total sales may depend on firm size. We therefore include a firm size measure (*firm size*), i.e., the number of employees in all models. Since, the relationship may not be linear, we define size classes that distinguish small firms with less than 50 employees from medium-sized (> 50, but < 150 employees), and larger firms with more than 150 employees. We also define an SME dummy that takes the value one if the firms have 250 or fewer employees (*SME*). To account for the fact that financial constraints may play an important role in choosing the optimal number of collaborating partners, we include a measure for the level of financial flexibility. This measure is based on a firm's credit rating index (*credit rating*). The index issued by Creditreform, Germany's largest credit rating agency, ranges from 100 (best) to 600 (worst) and banks, customers, and suppliers frequently use it.[4] Firms' *age* is obtained from the Creditreform database and is measured as the count of years since the founding year. As previously mentioned, the maturity of a firm may determine the optimal collaboration intensity and young firms in particular may differ not only in their learning potential, but also in their capacity to handle alliances. Since the effect is likely to be non-linear over different stages of maturity, we construct four age classes with the youngest firms being less than seven years old (see Table 2). To take the impact of the competitive environment into account, we use a measure for sales concentration, i.e., the sales share of the 15 largest companies at the sector-level. The higher the value of this indicator, the more concentrated the sector in which firm *i* operates.

[4] See Czarnitzki and Hottenrott (2011b) for more details on the construction of the index.

As previously argued, the impact of an additional collaboration may depend on a firm's current collaboration complexity. Building on van Beers and Zand (2014), who stressed that collaboration diversity is multidimensional, we measure collaboration complexity based on the number of different partner types and the number of different stages of the innovation process at which firms collaborate (see Table 1). Previous studies have analyzed the former dimension in its impact on innovation performance (see e.g., Faems et al., 2010; Beck and Schenker-Wicki 2014) but have not paid attention to further complexity-shaping dimensions. Information on the collaboration partners and the stages at which firms collaborate is obtained directly from the innovation survey. Table 1 shows the 6 *x* 5 matrix on which firms indicated what type of partner they collaborate with and at which stage of the innovation process those projects take place.

Table 1: Collaboration complexity matrix (in percent of collaborators)

		Stage 1 idea generation	Stage 2 research/prototyping	Stage 3 applied research/design	Stage 4 development/testing	Stage 5 market introduction
Type 1	Universities/PROs	71.79	52.54	37.17	26.53	16.50
Type 2	Input suppliers (raw materials)	22.22	32.77	36.65	26.53	26.21
Type 3	Suppliers (machines /software/consulting)	5.13	9.04	16.23	18.37	21.36
Type 4	Customers	0.85	5.08	9.95	22.45	18.45
Type 5	End-users	0	0.56	0	4.76	12.62
Type 6	Competitors	0	0	0	1.36	4.85
	Total	100	100	100	100	100

The composite indicator *collaboration complexity* is then calculated as:

$$collaboration\ complexity = \sum_{s=1}^{5} stages \times \sum_{t=1}^{6} types\ .$$

For example, a firm that collaborates with universities at the idea generation stage and at the prototyping stage has a complexity value of *2 (stages) x 1(partner) = 2*. If it also collaborated with customers at the market introduction stage, the value would change to 3 *x* 2 = 6. Alternatively, a firm that collaborates with six different partners, but always in the market introduction phase, would also have a value *6 x 1 = 6*. The logic is that complexity increases over-proportionally with the number of different stages *and* different types of partners. The average value for collaborating firms in the sample is about seven, the median is six, and the maximum value is 30.

Control variables

We follow the literature and control for a series of firm characteristics that have been shown to impact innovation performance (see e.g., Peters 2009; Un at al. 2010). Since R&D is the most important input in the innovation production equation, we control for the firm's R&D intensity (*R&D intensity*), measured by R&D expenditures, divided by sales. To capture different exposure to international product markets, which affects both the pressure to innovate and the potential market size for the new product, we also include the firm's export intensity (*Export intensity*). We further account for the firm's ownership structure by including a dummy variable that is equal to one if the firm has a part of a national enterprise group (*national group*) and a dummy variable that captures multinational enterprises (*MNE*). We further distinguish firms according to their legal status as indicated in the credit reform database (*private*, *limited* liability and *public* companies). In addition, we control for structural regional differences between eastern and western Germany (*east*) and we include a set of 25 industry dummies that capture the differences in technological opportunities between sectors (see Table A.1 in the Appendix for details).

Finally, for identification reasons we need at least one independent variable that appears in the selection equation but does not appear in the outcome equation, that is, we need a variable that affects the probability of introducing a new product, but not the share of novelty sales in total sales (Sartori 2003). In our case, the firms' product portfolio diversification serves as an exclusion restriction that meets this condition. More precisely, firms indicate the share in sales that can be attributed to the single biggest product (*diversification*). The larger that value, the more concentrated a firm's product portfolio, and the smaller, the more diverse it is. The variable enters the first stage significantly, since a more concentrated product portfolio negatively affects the likelihood of new products. Once firms decide to launch market novelties, the market success of the latter is not driven by the diversification of the overall product portfolio. We test the validity of the exclusion restriction by performing a likelihood-ratio test (LR $chi^2(1) = 12.19$, Prob > $chi^2 = 0.0005$) which supports the choice of this variable.

Timing of variables

Our data structure is cross-sectional. That is, we observe both collaboration projects and innovation performance during the same period (2009–2011). The advantage of this measurement is that it accounts for the fact that collaborative projects usually last longer than a single year. The drawback is that we consider only the short-run effects of these projects on innovation performance. Likewise, most of the time-varying control variables refer to this period.

Sample characteristics

Table 2 shows the descriptive statistics for the main variables. About 14% of the firms in the sample have introduced a new product to the market and the average sales shares from these new products is 12%. On average, a firm in our sample had 5.8 innovation projects during the sample period 2009 to 2011 of which 1.8 were collaborative. This results in an average collaboration intensity of 0.16. Among collaborators, the collaboration intensity is naturally much higher with about 0.60. Approximately 74% of collaborating firms had more than one collaborative project and about 7% had more than 10. Roughly 12% of the firms undertake more than 60 percent of their projects in collaboration and about 8% even conduct all their innovation projects in collaboration. On average, a firm in our sample has 218 employees. This high average firm size in our sample does not reveal that approximately 80% of the firms have around 250 employees, i.e., are SMEs and the median firm has 41 employees. The average credit rating score is 228 and the average age 35 (median is 22). Firms have an R&D intensity of 3.2%, and an export intensity of 15%, on average. Finally, about 16% of the firms are part of a national enterprise group and around 15% are part of a multinational enterprise group.

Table A.2 in the Appendix presents the cross-correlations between variables. As expected, we see that there is a positive correlation between the introduction of a new product (or new product sales) and collaboration intensity as well as for several of the control variables, such as R&D intensity, export intensity, and the number of employees. Among the control variables, correlations are low to moderate.

Table 2: Descriptive statistics (2,735 obs.)

Variable	Unit	Mean	Std. Dev.	Median	Min.	Max.
Innovation indicators						
new product sales[§]	ratio	0.124	0.150	0	0	1
new product	count	0.139	0.346	0	0	1
Collaboration indicators						
# all projects	count	5.822	43.259	0	0	1,500
# joint projects	count	1.758	14.407	0	0	500
collaboration intensity	ratio	0.161	0.316	0	0	1
Moderating factors						
# Employees	count	217.735	1,028.106	41	10	32,400
< 50 employees	dummy	0.551	0.497	1	0	1
51–150 employees	dummy	0.247	0.431	0	0	1
> 150 employees	dummy	0.202	0.401	0	0	1
SME	dummy	0.865	0.342	1	0	1
Credit rating	index	228.254	50.683	222	100	600
< 200 points	dummy	0.252	0.434	0	0	1
201–330 points	dummy	0.725	0.447	1	0	1
> 330 points	dummy	0.023	0.150	0	0	1
Age	count	34.712	37.943	22	1	681
<7 years	dummy	0.067	0.251	0	0	1
8–15 years	dummy	0.166	0.372	0	0	1
16–35 years	dummy	0.486	0.500	0	0	1
> 35 years	dummy	0.280	0.449	0	0	1
Sales concentration ratio	ratio	0.748	0.169	0.773	0.520	1
Collaboration complexity[*]	index	7.394	6.255	6	0	30
Control variables						
R&D intensity	ratio	0.032	0.317	0	0	13
Export intensity	ratio	0.149	0.248	0	0	1
National group	dummy	0.156	0.363	0	0	1
MNE	dummy	0.149	0.357	0	0	1
Private	dummy	0.144	0.351	0	0	1
Limited	dummy	0.818	0.386	1	0	1
Public	dummy	0.038	0.191	0	0	1
East	dummy	0.361	0.480	0	0	1
Diversification	ratio	73.250	23.709	80	1	100

Notes: [§]*based on firms that introduced a new product. *based only on collaborating firms.*

6. RESULTS

We next proceed to the regression results of the impact of collaboration intensity on innovation performance. The left-hand side of Table 3 presents the results of the probit model.

Collaboration intensity and its squared value are both significant. First, collaboration intensity enters positively. The negative sign of the second-order term, though, suggests that the positive relationship between collaboration intensity and new products decreases or even turns negative for high collaboration intensities. Given the non-linearity of the probit model, the coefficient on the second-order term of collaboration intensity does not provide the change in the partial effect of the intensity variable (Greene 2010). Thus, we cannot derive the marginal effect of the second-order term from the estimated coefficient, but need to calculate the marginal effect of collaboration intensity on Pr(*new product*) at different values of the distribution of collaboration intensity. As suggested by Greene (2010), we perform a hypothesis testing based on the estimated coefficients and infer the magnitude of the effects by calculating the marginal predictions and average marginal effects. Figure 2 illustrates the results from these calculations graphically. The left-hand side shows the predictive margins and the right-hand side the average marginal effects over the range of possible collaboration intensities. We see that the probability of new products increases with collaboration intensity until it reaches a point where an increase in collaboration intensity has no effect on Pr(*new product*). Indeed, from about 20% total collaborative projects the innovation projects' returns start to decrease. At 60% of collaboration intensity, the marginal impact of innovation probability even turns negative for every higher value of collaboration intensity. The right-hand side shows the derivative, that is, the slope of the predictive margins curve and illustrates that the returns to increasing collaboration intensity start to decline at around 20% of collaborative project, but is still in the positive range until it reaches the 60% threshold. These results are confirmed in the Tobit models on new product sales on the right-hand side of Table 3 (Model 2). Indeed, when calculating the curve's turning point, we find the extreme value (maximum) to also be at around 60%, confirming the inverted-U shape in the relationship between collaboration intensity and innovation performance (Hypothesis 1). Finally, several of the control variables enter the innovation equation significantly. Being part of a national group is positively associated with new product introduction, but not with new product sales. Similarly, the group of largest firms is more likely to introduce a new product, but their new product sales share is not significantly higher than those of smaller firms. Private and limited liability companies tend to be less innovative compared to public ones. Young firms are more likely to have a product innovation and the competitive environment matters for both new products and new product sales.

Table 3: Probit and heteroscedastic-robust Tobit estimations (2,735 obs.)

	Model 1		Model 2	
	Coef.	s.e.	Coef.	s.e.
Collaboration intensity	4.271	(0.283) ***	0.697	(0.107) ***
(Collaboration intensity)^2	-3.495	(0.298) ***	-0.550	(0.123) ***
R&D intensity	-0.005	(0.050)	0.010	(0.036)
Export intensity	0.141	(0.164)	0.036	(0.023)
National group	0.021	(0.004) ***	0.009	(0.024)
MNE	0.213	(0.199)	0.034	(0.031)
# Employees				
51–150 employees	0.013	(0.059)	0.036	(0.057)
> 150 employees	0.199	(0.000) ***	0.043	(0.036)
Credit rating				
201–330 points	-0.059	(0.055)	-0.015	(0.007) **
> 330 points	0.221	(0.291)	0.063	(0.029) **
Private	-0.135	(0.047) ***	-0.050	(0.002) ***
Limited	-0.074	(0.034) **	-0.035	(0.001) ***
East	0.053	(0.110)	-0.004	(0.021)
Age				
8–15 years	0.102	(0.012) ***	0.002	(0.002)
16–35 years	0.123	(0.191)	-0.009	(0.021)
> 35 years	0.012	(0.225)	-0.020	(0.027)
Concentration	10.047	(2.751) ***	3.870	(1.796) **
(Concentration)^2	-6.367	(1.452) ***	-2.462	(1.123) **
Complexity	0.058	(0.003) ***	0.008	(0.001) ***
Industry dummies	yes		yes	
Turning point	0.611		0.634	
Log likelihood	-686.536		-301.890	
Lind/Mehlum test[5]	-		20.79**	

Notes: Both models contain a constant. Industry dummies included, not presented. *(**,***) indicate 10% (5%, 1%) significance.

[5] Lind and Mehlum (2010) argue that coefficient signs and significance (in addition to checking whether the extreme value is within the variable's range) is not sufficient to support (inverted) U relationships even in linear models. While very common in the literature, problems with this type of inference arise when the true relationship is concave (or convex) but monotone over relevant data values. Therefore, we perform the "appropriate U-test" that the authors suggest to test for the slope of the curve at several points in a linear OLS model. In our case, the estimated maximum is well within the data range. Accordingly, the t-test statistic clearly supports the hypothesis of an inverted-U relationship (see Lind and Mehlum 2010 for the technical details).

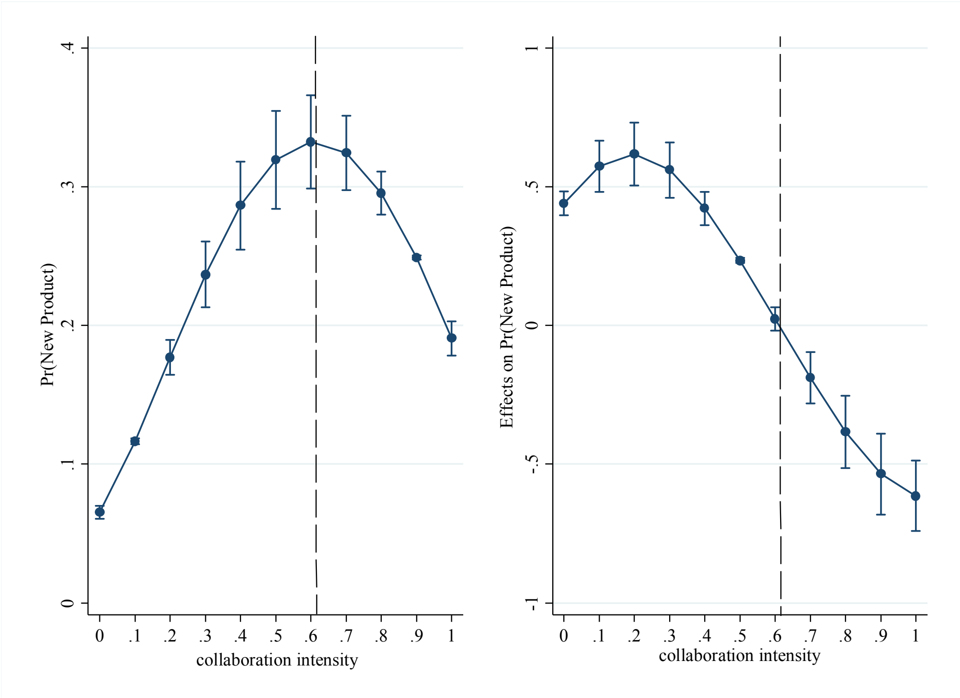

Figure 2: Predictive margins and average marginal effects of collaboration intensity on product innovation success (Model 1; 95% confidence intervals)

Table 4 presents the results from the selection models as outlined in Section 3. Column two shows the results from the first stage, that is, the probability of having a new product, and column three displays the second stage results. We see that the mills ratio is highly significant, underlining the appropriateness of the Heckman selection procedure. Compared to the results presented in Table 3, we see that the second stage effects are indeed slightly smaller for the full sample, but still show the same pattern and statistical significance. The maximum is still around 62% of collaborative projects in total innovation projects, thereby underlining the robustness of this result (see also Figure A.1 for a graphical illustration of the marginal effects on new product sales). Next, we explore how firm heterogeneity impacts this relationship. For that purpose, we re-estimate the baseline model (Model 1 of Table 3) and calculate the marginal effects of collaboration intensity on innovation success not only at different values of collaboration intensity, but also for different types of firms, varying the firm characteristic of interest while holding all other variables constant. The estimation results of the heterogeneity analyses are shown in Figure 3, where the predictive margin curves for the various cases are shown. The slope of the curves indicate the changes of increasing collaboration intensity on Pr(*new product*).

Table 4: Heckman section models (two-step estimation; 2,735 obs.)

	1st stage		2nd stage	
	Pr(new product = 1)		*new product sales %*	
Variable	Coef.	s.e.	Coef.	s.e.
collaboration intensity	3.662	0.480 ***	0.435	0.203 **
(collaboration intensity)^2	-3.083	0.445 ***	-0.354	0.171 **
R&D intensity	-0.008	0.088	0.202	0.032 ***
Export intensity	0.161	0.168	0.094	0.035 ***
National group	0.042	0.118	0.006	0.024
MNE	0.220	0.113 *	0.016	0.025
# Employees				
51–150 employees	-0.005	0.105	-0.065	0.022 ***
> 150 employees	0.155	0.123	-0.072	0.026 ***
Credit rating				
201–330 points	-0.052	0.097	-0.015	0.019
> 330 points	0.208	0.272	0.041	0.058
Private	-0.160	0.228	-0.019	0.047
Limited	-0.104	0.177	-0.025	0.032
East	0.058	0.088	-0.017	0.018
Age				
8–15 years	0.094	0.175	-0.055	0.034
16–35 years	0.106	0.161	-0.086	0.032 ***
> 35 years	-0.025	0.177	-0.073	0.035 **
Concentration	10.322	5.620 *	2.527	1.254 **
(Concentration)^2	-6.595	3.689 *	-1.661	0.826 **
Complexity	0.513	0.072 ***	0.067	0.027 **
exclusion restriction: diversification	-0.006	0.002 ***		
Industry dummies	yes			yes
Wald Chi^2(42)		159.62***		
Mills ratio (lambda)		0.154** (0.069)		

Notes: Both stages contain a constant. Industry dummies included, not presented. *(**,***) indicate 10% (5%, 1%) significance.

Firm heterogeneity results

For testing Hypothesis 2, we first estimate the impact of firm size on the relationship of collaboration intensity on innovation performance. To start, we estimate whether the collaboration threshold is different for SMEs compared to larger firms. As can be seen in the first panel of Figure 3, the threshold is slightly larger for SMEs than for larger firms. While large-size firms have a turning point at around 50% of collaborative projects in overall projects, for SMEs this point is at circa 65%. These results can be viewed in line with predictions by Rothaermel and Deeds (2004), who find that it may be advantageous for larger firms to integrate vertically rather than to engage in additional alliances. Given that in our sample we have predominantly SMEs, in the second panel we further test for a more fine-grained disaggregation of firm size, as displayed in the descriptive statistics in Table 2. We see that in this case, no significant differences exist between firms smaller than 50 employees, from 51 to 150 employees or larger than 150 employees. We can thus conclude that size only has a significant impact on the relationship between collaboration intensity and innovation performance when differentiating SMEs with larger firms.

The second test concerns differences in experience, which we proxy by firm age. For that purpose, we consider a firm as young if it has existed for less than seven years.[6] As we can see from the third panel in Figure 3, while the slope is overall flatter for younger firms, they benefit significantly longer from increasing their intensity of collaboration. Indeed, while the turning point for experienced firms is around 60% of collaborative projects in all projects, younger firms benefit up until around a collaboration intensity of 80%.

Furthermore, we explore whether different levels of financial constraints affect the returns to collaborating. We see in the 4th panel that firms with the best credit rating (credit rating from 201–330 points) experience negative returns from collaboration significantly earlier than other firms with a turning point of around 45%. Firms with worse credit ratings benefit from collaboration until an intensity of roughly 65%. This finding points to the conclusion that collaboration is important for firms with restricted access to loans and trade credit, which may therefore experience more constraints to funding innovation projects without a partner.

Fourth, we distinguish firms in highly competitive markets from those in less competitive industries. We use concentration indices to proxy the degree of competition in a particular sector. Competition is measured using a cut-off at the 25th and the 75th percentile of the sales

[6] We follow the definition of "young," as used by Schneider and Veugelers (2010). We further checked other cut-offs in terms of firm age: For higher cut-offs, the difference is less pronounced, and for smaller cut-offs the sample of young firms becomes unrepresentatively small.

ratio of the 15 largest firms in an industry. As can be seen from the 4th panel of Figure 3, we do not find significant differences in returns to collaboration for firms in different competitive environments. This result is not very sensitive to the choice of the concentration index and to variations in the cut-off criterion. However, we would like to stress that the competition measure used here might not reflect actual technological competition which can also be technology-based instead of sector-based.

Finally, we distinguish firms according to their collaboration complexity. As shown by the last panel of Figure 3, complexity impacts the effects of collaboration intensity on the introduction of new products significantly. Indeed, we see that the slope is steepest and the turning point largest (60%) for firms with lower innovation complexity (complexity ϵ [0, 2[). Firms within the highest complexity range (complexity ϵ]8, 30]) are overall more innovative. Nevertheless, we see that the inverse-U shape of the curve is flatter, indicting a lower marginal gain from increasing collaboration intensity. Firms belonging to the medium complexity range show continuously decreasing returns from an additional collaboration intensity. These firms perform, on average, better than the firms with lower complexity. However, they do not seem to have the necessary capacity to handle higher collaboration intensities with the same return as the high complexity collaborators, nor do they benefit as much as firms with very low complexity (Hypothesis 3). Finally, we explore heterogeneity in organizational and management structure (as stressed by Lavie et al. 2010), which we proxy by ownership structure (multinational enterprise, national group, and legal form). However, neither one of these characteristics turn out to capture differences in returns to collaboration.[7] More detailed information on the (R&D) management teams would be desirable to improve these tests. The detailed estimation results can be found in Table A.3 in the Appendix.

[7] Detailed estimation results available upon request.

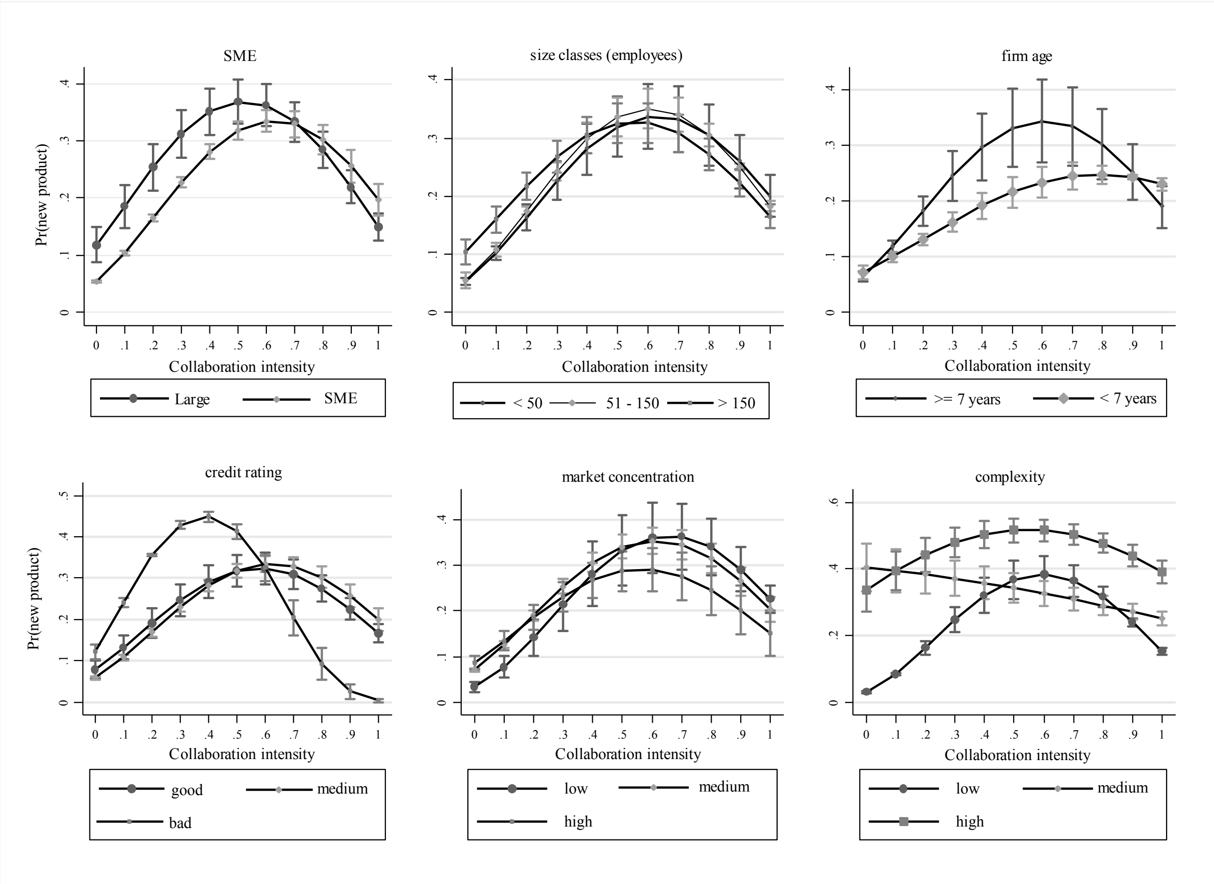

Figure 3: Predictive margins of collaboration intensity on product innovation success by moderating factors

7. ROBUSTNESS CHECK

Before concluding, we test the robustness of our results to the potential endogeneity problem arising from choosing to collaborate. Some unobserved characteristics that influence the probability to engage in collaboration could also influence the sales share in market novelties once the collaboration strategy is chosen. It could well be that more innovative firms are more likely to choose to engage in R&D collaboration. In this case, collaboration intensity would be endogenous in a regression of market novelty sales on R&D collaboration. In order to account for this, we estimate an endogenous switching model with a full information maximum likelihood method (FIML), by modeling the behavior of firms based on two regression equations and a criterion function I_i, that determines the collaboration status of a firm *i*:

$$I_i = 1 \quad if \quad \gamma Z_i + u_i > 0$$

$$I_i = 0 \quad if \quad \gamma Z_i + u_i \leq 0$$

$$y_{1i} = \beta_1 x_{1i} + \varepsilon_{1i} \quad if \quad I_i = 1 \tag{5}$$

$$y_{2i} = \beta_2 x_{2i} + \varepsilon_{2i} \quad if \quad I_i = 0 \tag{6}$$

with y_{ji} being the dependent variables in the continuous equations; x_{1i} *and* x_{2i} a vector of control variables (the same as in the previous equation) and β_1, β_2 and γ a vector of parameters. The correlation coefficient between ε_1 and u_i is $\rho_1 = \sigma_{21}^2 / \sigma_u \sigma_1$ and the one between ε_{2i} and u_i is $\rho_2 = \sigma_{31}^2 / \sigma_u \sigma_2$. In line with our Heckman equation, the selection equation includes an additional variable to improve identification. If $I_i = 1$, firm$_i$ chooses to collaborate and the sales in market novelties is determined by equation (5); otherwise, it is determined by equation (6). The first step of this model isolates the exogenous determinates of engaging in an R&D collaboration, like firm size, ownership structure, and R&D intensity, as well as an endogenous factor, namely the diversification of a firm's product portfolio likely to influence the choice of either collaboration strategy. We employ the share in sales that can be attributed to the single biggest product (*diversification*) as an exclusion restriction. Similar to the logic in the selection models, we argue here that the larger the value of diversification the more concentrated the product portfolio, which affects the collaboration likelihood negatively. A more diversified product portfolio, on the other hand, may provide more opportunities to engage in collaborative agreements. The market success of new products should, however, not be influenced. The second step, the outcome equation, then provides consistent estimates on market novelty sales while accounting for this endogenous selection. As can be gathered from Table 5, accounting for the selection into entering a collaboration does not fundamentally change our conclusions. We do, however, see that the correlation coefficients are significant. We further find that the estimated coefficients of collaboration intensity are smaller if the selection into collaboration is taken into account.

Table 5: Endogenous switching model (2,735 obs.)

	Stage 1		Stage 2			
	Pr(collaboration = 1)		*new product sales if*		*new product sales if*	
Variable	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
collaboration intensity					0.116	0.054 **
(collaboration intensity)^2					-0.092	0.047 **
R&D intensity	16.426	3.489 ***	0.609	0.320 *	-0.003	0.010
Export intensity	0.925	0.139 ***	0.004	0.003	0.007	0.024
national group	0.088	0.094	0.001	0.001	-0.004	0.011
MNE	0.178	0.092 *	0.001	0.002	-0.005	0.010
# Employees						
51–150 employees	0.137	0.080 *	-0.001	0.001	-0.028	0.010 ***
> 150 employees	0.548	0.096 ***	-0.001	0.002	-0.046	0.015 ***
Credit rating						
201–330 points	-0.225	0.077 ***	0.008	0.005	0.001	0.061
> 330 points	-0.620	0.258 **	0.008	0.005	0.020	0.037
Private	-0.535	0.202 ***	0.002	0.003	0.029	0.035
Limited	-0.071	0.170	0.003	0.003	-0.005	0.018
East	0.106	0.073	0.002	0.001	-0.016	0.011
Age						
8–15 years	-0.272	0.156 *	0.005	0.002 **	-0.047	0.035
16–35 years	0.223	0.146	0.002	0.001 *	-0.061	0.033 *
> 35 years	0.201	0.154	0.002	0.001	-0.054	0.034
Concentration	2.155	6.218	-0.072	0.106	0.996	0.657
(Concentration)^2	-1.344	3.951	0.042	0.064	-0.639	0.421
Complexity					0.020	0.006 ***
exclusion restriction:	-0.004	0.001 ***				
sigma0	-3.821	0.142 ***				
sigma1	-2.140	0.101 ***				
rho0	-0.017	0.019				
rho1	-0.569	0.226 **				
Industry dummies	yes		yes		yes	
Log likelihood			4,419.078			
Wald test of independent			$Chi^2(2) = 6.81$**			

Notes: Both stages contain a constant and standard errors are heteroscedasticity-robust. Industry dummies included, not presented. *(**,***) indicate 10% (5%, 1%) significance.

8. DISCUSSION AND CONCLUSIONS

This study provides an empirical analysis to test theoretical considerations suggesting that firms can benefit from collaborative innovation projects, but only up to a certain point. It has long been shown in the literature that a firm's innovation success depends not only on internal resources, but also on the knowledge it can gather from outside of the firm's boundaries. While the literature has provided ample evidence of the advantages of pooling knowledge and resources through R&D alliances, there is scarce literature pointing out that there may be too much of a good thing after a certain threshold. To deepen our understanding of the benefits and the costs of such alliances, the present study aims at filling this gap by providing evidence that the intensity with which a firm seeks external knowledge through partnerships matters. Using data of a sample of German firms from the Mannheim Innovation Panel, we show that higher collaboration intensities are not necessarily better. Indeed, we find that for high levels of collaboration intensity, the initially positive association between new product sales and collaboration intensity turns negative. In particular, we find that returns turn negative for collaboration intensities larger than 60% which corresponds to the mean collaboration intensity in the sample of collaborating firms. Depending on firm characteristics like size, age, level of resource constraints, and collaboration complexity, the optimal share of collaborative projects ranges from 45% for firms that are financially well-endowed to approximately 80% for young firms for which the returns outweigh costs up to relatively high collaboration intensities. Depending on the type of firm, the optimal collaboration intensity varies, with a considerable number of firms in our sample collaborating beyond their optimal threshold.

Thus, while collaboration may help firms to innovate, firm-specific transaction costs such as coordination efforts, monitoring, and the cost of disclosure, may countervail the benefits from engaging in R&D partnerships. The challenge that innovation managers and entrepreneurs face is to determine the right collaboration intensity for their firms. Our results challenge the maybe too optimistic view of openness through partnerships as a key component for creating inventions and innovative products, thereby provoking a re-think in those firms with high collaboration intensities. It seems worthwhile to continuously balance gains against costs and adjust collaboration strategies accordingly.

From a policy point of view, our findings point to the fact that R&D collaborations are not innovation-enhancing per se. Exempting R&D collaborations from anti-trust laws intends to raise EU firms' competitiveness. While our results do not undermine that collaboration may be a way to achieve this goal, they also depict that this goal may only be achieved if the strategy is used wisely and with certain moderation by participating firms.

This study has some limitations that call for future research. First, the collaboration measure used here is rather broad and does not take into account heterogeneity in alliances types and contractual arrangements. Different types of collaboration or the location of the partners may indeed have different levels of costs and gains attributed to them, which may lead to different calibration of the number of external partners that are beneficial to the firm (Giarratana and Mariani 2014). Equally important, the cross-sectional nature of our data does not allow us to take into account the dynamics between collaboration and innovation that occur as firms repeatedly engage in collaborative projects. Sampson (2005), for instance, stresses that alliance experience matters for returns from collaboration to materialize. It would therefore be interesting to see whether the costs and benefits to collaboration change as firms become more alliance experienced. Alliance experience could be valuable both in general and with a specific partner as trust has been found to predict the successful acquisition of tacit knowledge, which may be important for radical innovations (Sherwood and Covin 2008). Moreover, we may not capture all benefits and costs, especially when these only occur in the long run, and we suggest future research on longer-run alliance portfolio management.

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Appendix

Table A.1: Distribution of firms across industries

Industry	**Freq.**	**Percent**	**Cum.**
Mining	49	1.79	1.79
Food/tobacco	122	4.46	6.25
Textiles	94	3.44	9.69
Paper/wood/print	180	6.58	16.27
Chemical	91	3.33	19.60
Plastics/rubber	75	2.74	22.34
Glass/ceramics	61	2.23	24.57
Metal	214	7.82	32.39
Machinery	180	6.58	38.98
Electrical engineering	132	4.83	43.80
Medicine/optic/processing	110	4.02	47.82
Vehicles	74	2.71	50.53
Furniture	69	2.52	53.05
Energy/water/construction	176	6.44	59.49
Wholesale	103	3.77	63.25
Retail	36	1.32	64.57
Transport/post	201	7.35	71.92
Bank/insurance	57	2.08	74.00
IT/telecommunication	103	3.77	77.77
Technical services	174	6.36	84.13
Business-related services	117	4.28	88.41
Other services	251	9.18	97.79
Real estate	33	1.21	98.79
Media	33	1.21	100.00
Total	**2,735**	**100**	

Figure A.1: New product sales and collaboration intensity (selection model)

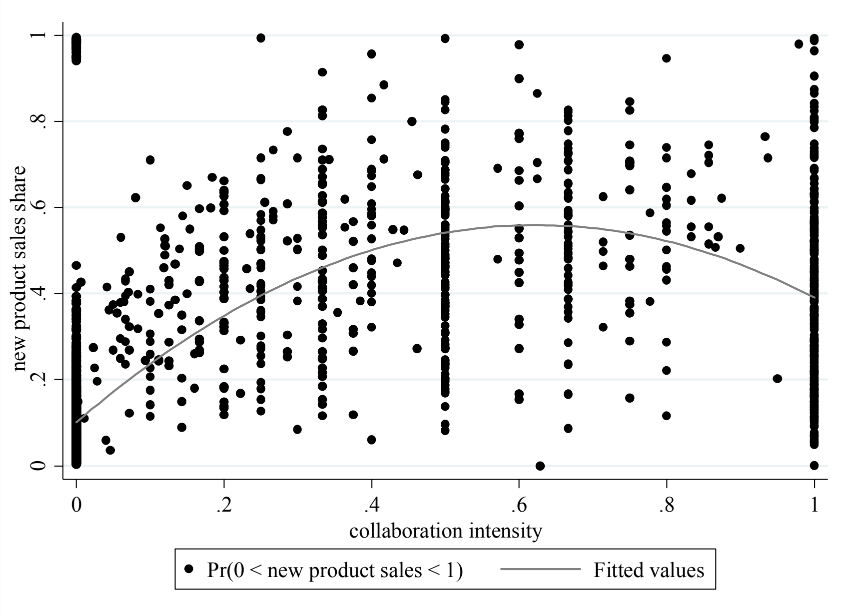

Table A.2: Cross-Correlations (2,735 obs.)

		1	2	3	4	5	6	7
1	*new product*	1.000						
2	*new product*	0.609*	1.000					
3	*collaboration*	0.403*	0.296*	1.000				
4	*(collaboration*	0.310*	0.242*	0.969*	1.000			
5	*R&D intensity*	0.085*	0.146*	0.168*	0.150*	1.000		
6	*export intensity*	0.271*	0.182*	0.248*	0.187*	0.032	1.000	
7	*national group*	-0.021	-0.027	0.013	0.022	-0.024	-0.068*	1.000
8	*MNE*	0.193*	0.081*	0.085*	0.031	-0.014	0.400*	-0.180*
9	*# employees*	0.163*	0.113*	0.034	0.009	-0.011	0.132*	0.040
10	*credit rating*	-0.048	0.018	-0.049*	-0.032	0.0523*	-0.090*	-0.064*
11	*private*	-0.108*	-0.069*	-0.151*	-0.131*	-0.035	-0.169*	-0.116*
12	*limited*	0.064*	0.032	0.120*	0.102*	0.025	0.127*	0.078*
13	*east*	0.002	0.012	0.049	0.056*	0.020	-0.147*	-0.011
14	*age*	0.009	-0.026	-0.038	-0.039	-0.046	0.083*	-0.052*
15	*concentration*	0.078*	0.047	0.074*	0.060*	0.024	0.102*	0.068*
16	*complexity*	0.515*	0.346*	0.553*	0.445*	0.094*	0.321*	-0.026

		8	9	10	11	12	13	14	15
8	*MNE*	1.000							
9	*# employees*	0.230*	1.000						
10	*credit rating*	-0.120*	-0.133*	1.000					
11	*private*	-0.143*	-0.032	-0.016	1.000				
12	*limited*	0.097*	-0.0340	0.085*	-0.870*	1.000			
13	*east*	-0.136*	-0.098*	0.064*	0.047	-0.005	1.000		
14	*age*	0.049*	0.074*	-0.187*	0.126*	-0.140*	-0.248*	1.000	
15	*concentration*	0.083*	0.050*	-0.047	-0.125*	0.069*	-0.064*	-0.025	1.000
16	*complexity*	0.233*	0.194*	-0.093*	-0.123*	0.074*	-0.011	0.023	0.076*

Note: *indicates significance at the 1% level.

Table A.3: Probit estimations with firm heterogeneity interactions (2,735 obs.)

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
collaboration	4.547 ***	3.818 ***	4.441 ***	3.989 ***	5.429 ***	5.650 ***
	(0.162)	(0.095)	(0.407)	(0.061)	(0.179)	(0.364)
(collaboration	-3.615 ***	-3.641 ***	-3.664 ***	-3.440 ***	-4.122 ***	-4.747 ***
	(0.109)	(0.062)	(0.377)	(0.028)	(0.194)	(0.370)
R&D intensity	-0.014	-0.008	-0.006	-0.008	0.024	-0.017
	(0.082)	(0.041)	(0.058)	(0.045)	(0.087)	(0.028)
Export intensity	0.123	0.118 ***	0.146	0.146	0.154 *	0.055
	(0.128)	(0.017)	(0.232)	(0.094)	(0.086)	(0.172)
National group	0.026	0.021 ***	0.030	0.043 ***	0.011	0.006
	(0.078)	(0.007)	(0.069)	(0.015)	(0.090)	(0.104)
MNE	0.214 ***	0.182	0.223	0.217 ***	0.186	0.194 ***
	(0.073)	(0.154)	(0.157)	(0.048)	(0.238)	(0.047)
# Employees						
51-150 empl.	0.022		-0.001	0.009	0.031	-0.014
	(0.083)		(0.066)	(0.091)	(0.037)	(0.026)
> 150 empl.	0.431 ***		0.183 ***	0.185 ***	0.214 ***	0.104
	(0.103)		(0.051)	(0.066)	(0.020)	(0.083)
Credit rating						
201-330 points	-0.051	-0.055 *	-0.045	-0.181	-0.051	-0.016
	(0.072)	(0.029)	(0.072)	(0.111)	(0.101)	(0.090)
> 330 points	0.239	0.229 ***	0.230	0.304 **	0.212	0.232
	(0.229)	(0.006)	(0.188)	(0.138)	(0.209)	(0.302)
Private	-0.140	-0.143	-0.160	-0.158	-0.163	-0.105
	(0.225)	(0.242)	(0.180)	(0.150)	(0.128)	(0.129)
Limited	-0.083	-0.074	-0.079	-0.090	-0.105	-0.084
	(0.324)	(0.440)	(0.131)	(0.253)	(0.208)	(0.166)
East	0.057	0.057	0.081	0.062	0.062 **	0.066
	(0.074)	(0.066)	(0.051)	(0.055)	(0.028)	(0.060)
Age						
8–15 years	0.083	0.092		0.120	0.088	0.067
	(0.094)	(0.095)		(0.098)	(0.265)	(0.074)
16–35 years	0.108	0.111		0.138 ***	0.106	0.097
	(0.213)	(0.286)		(0.046)	(0.077)	(0.149)
> 35 years	0.006	0.006		0.036	-0.017	-0.058
	(0.288)	(0.345)		(0.137)	(0.091)	(0.192)
Concentration	9.032 **	9.028 ***	9.772 ***	9.548 ***		10.332 **
	(3.797)	(1.983)	(2.527)	(1.038)		(5.231)
(Concentration)^2	-5.688 **	-5.715 ***	-6.156 ***	-6.051 ***		-6.570 *
	(2.671)	(1.099)	(1.496)	(0.760)		(3.370)
Complexity	0.057 ***	0.056 ***	0.058 ***	0.058 ***	0.059 ***	
	(0.004)	(0.003)	(0.008)	(0.004)	(0.005)	
Interaction effects:						
51–150 empl. #	0.238					
	(0.280)					
> 150 empl.#	-1.058 ***					
	(0.106)					
51–150 empl. #	-0.335					
	(0.285)					
> 150 empl. #	0.472***					
	(0.126)					
SME		-0.502***				
		(0.105)				

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SME # collab	0.658***				
	(0.088)				
SME # (collab	0.059				
	(0.104)				
Young		0.065*			
		(0.036)			
Young # collab		-2.031***			
		(0.356)			
Young # (collab		2.135***			
		(0.423)			
Credit rating 2 #			0.398***		
			(0.067)		
Credit rating 3 #			2.447***		
			(0.434)		
Credit rating 2 #			-0.065		
			(0.071)		
Credit rating 3 #			-4.911***		
			(0.619)		
concentration 2				0.443***	
				(0.087)	
concentration 3				0.571***	
				(0.137)	
concentration 2 #				-1.134***	
				(0.270)	
concentration 3 #				-1.997***	
				(0.215)	
concentration 2 #				0.599**	
				(0.248)	
concentration 3 #				1.095***	
				(0.152)	
Complexity 2					1.743***
					(0.100)
Complexity 3					1.546***
					(0.096)
Complexity 2 #					-5.893***
					(0.447)
Complexity 3 #					-3.807***
					(0.541)
Complexity 2 #					4.524***
					(0.399)
Complexity 3 #					3.063***
					(0.511)

Notes: All models contain a constant and industry dummies. Coefficients displayed. Clustered standard errors in parenthesis. *(**,***) indicate 10% (5%, 1%) significance level.