

Discussion Paper No. 14-108

**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 pooling of complementary skills, learning from the partner as well as sharing risks and costs. Research therefore repeatedly stressed the positive relationship between collaborative R&D and innovation performance. Fewer studies addressed potential drawbacks of collaborative R&D. Collaborative R&D comes at the costs of coordination and monitoring, requires knowledge disclosure and involves the risk of opportunistic behaviour by the partners. Thus, while the net gains from collaboration can be high initially, cost may start to outweigh those benefits if firms engage in multiple collaborative projects simultaneously. This study explicitly considers a firm's collaboration intensity, that is, the share of collaborative R&D projects in the firms' total R&D project portfolio. For a sample of 2,891 firms located in Germany, active in a broad range of manufacturing and service sectors and of which 86% are SMEs, we indeed find 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 we can confirm previous findings in terms of gains for innovation performance, we also find that collaboration has decreasing and even negative returns on product innovation if its intensity increases above a certain threshold. Consequently, the relationship between collaboration intensity and innovation has an inverted-U shape. In particular, costs start outweighing 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.

**Keywords:** Innovation performance, product innovation, R&D partnerships, collaboration intensity, SMEs, transaction costs, selection model, endogenous switching

**JEL-Classification:** O31, O32, O33, O34

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## 1. INTRODUCTION

Research on R&D partnerships repeatedly stressed the virtues of collaborative innovation. 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 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 addressed 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 attractive up to a certain point. Further expanding the search 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. Even though collaboration may positively influence innovation performance initially, engaging in additional collaborative projects is likely to exhibit diminishing or even negative returns (Deeds and Hill 1996). As long as the benefits from collaborating outweigh the costs, a firm’s innovation performance will increase with the number of collaborative projects. After a certain threshold, however, this may no longer be the case. The reason for this may be twofold: First, collaboration comes at the costs of coordination and monitoring (Rosenberg 1982; Mowery and Rosenberg 1989). Second, collaboration comes at the cost of disclosure and the risk of opportunistic behaviour by the partners (Foray and Steinmüller 2003; Bader 2008; Bogers 2011). Just as gains from collaboration are potentially highest for firms with limited internal resources, such as small and medium-sized firms (SMEs), pains may be particularly high for those firms as well. Indeed, SMEs may predominantly benefit from collaboration through access to a broader and more diversified knowledge base because of their relative small size (Hottenrott and Lopes-

Bento, 2014a). On the downside, SMEs tend also to be more resource constrained and required to budget managerial attention and available internal financial resources more carefully. Therefore, cost of coordination and transaction may be especially important for SMEs. Similarly, cost of disclosure may be higher for smaller than for larger firms in highly competitive markets in which information leakage quickly translates into a loss of market share. Consequently, the relationship between collaboration intensity and innovation may not be linear, but follow an inverted-U shape.

The present study addresses the gains and pains from collaborative R&D empirically. Our analysis puts forward the preposition 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 2,891 firms located in Germany, 86% of which are SMEs, 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 this relationship turns negative for collaboration intensity higher than about 60% of all innovation projects. This result is 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 collaborative behaviour 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 at the management as well as the policy level. 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 beneficially. It thus seems advisable to balance the collaborative and non-collaborative

projects. When evaluating potential benefits from additional collaborative projects, managers should consider the firm's overall project portfolio before deciding on future collaboration strategies. From a policy view, encouraging collaborative R&D seems beneficial for innovation performance, which not only benefits 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 further fostering R&D partnerships through R&D subsidies or other policy tools.

The article proceeds as follows. Section 2 sets out or hypotheses. Section 3 describes the identification strategy and section 4 presents the data. Section 5 elaborates on the results and Section 6 concludes.

## **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 results than non-collaborating firms, especially in terms of innovation.<sup>1</sup> 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. Vanhaverbeke et al. (2007) find a positive relationship between technology alliances and patent citations. Hottenrott and Lopes-Bento (2014b) argue that the type of alliance may affect the ability and the incentives to patent, that is, patent quality and quantity, differently.

While patenting activity may measure inventive activities, but not necessarily new products or 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

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<sup>1</sup> 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).

2010). In line with previous findings, we hypothesize that because of the inherent benefits of collaboration

*H1: Collaborative R&D projects are positively associated with innovation performance.*

We expect this to hold in general, although we would assume that for SMEs the potential gains may be higher as their internal resource base is usually smaller and less diversified.

## *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 and their results for a sample of biotechnology firms indeed suggests diminishing and even decreasing returns on new product development for very high numbers of collaborations. The reasons for this observation may be several.

First, transaction costs economics point to the costs of collaboration when contracts are incomplete. Incomplete contracts typically result from poor bargaining, directly related to the specificity of the assets at stake. The higher the degree of 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 number of collaborative projects. 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 pursuit of self-interest at the expense of the partner as well as the important costs of

detering 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 resources available for other projects which may affect the firms' overall innovation performance. This may be even particularly severe when firms have a relatively high collaboration intensity and face resource constraints.

In light of limited resources in SMEs, especially for R&D projects (Czarnitzki and Hottenrott 2011), we would expect these costs to matter even more for the latter than for larger firms. Indeed, data from a survey asking firms to indicate the main factors that prevent them from engaging into (new) collaborative projects supports this view. SMEs are significantly more likely to indicate that coordination cost are an important deterring factor than larger firms.<sup>2</sup>

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 this leakage risks to go beyond the joint project (Hottenrott and Lopes-Bento 2014b). Indeed, partnerships bear the

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<sup>2</sup> 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 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 typically done in the literature, SMEs are defined as firms with less than 250 employees.

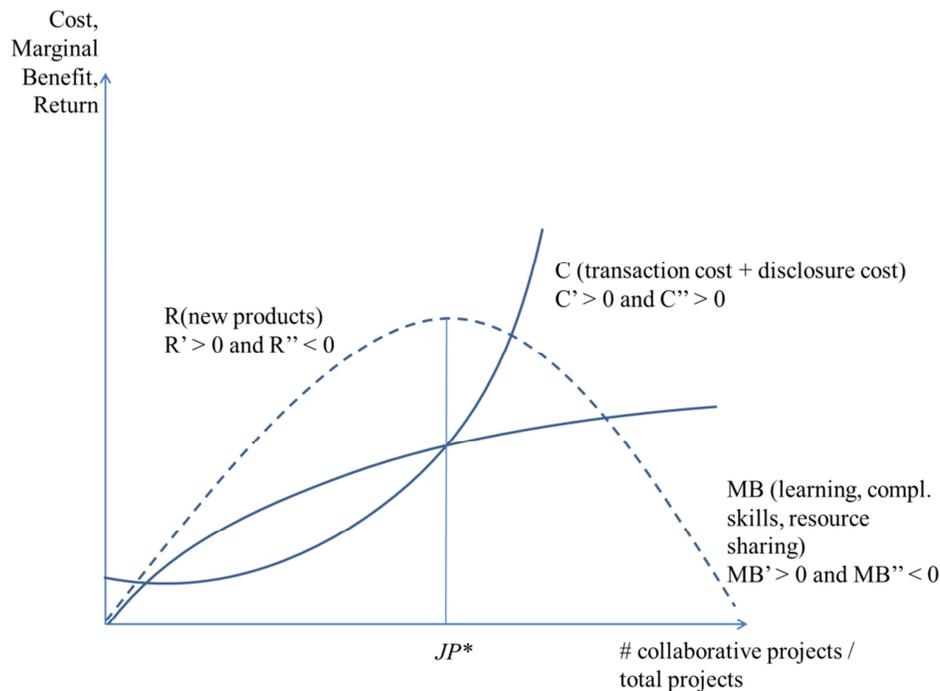
inherent risk of free-riding, where one associate tries to absorb a maximum of knowledge from the other while concealing its own efforts (see e.g. Shapiro and Willig 1990; Baumol 1993; Kesteloot and Veugelers 1995). For example, partnerships with substantial overlap in core businesses, geographic markets, and functional skills have a success rate of about 30% as competitors are inclined to maximize their own individual objectives rather than the partnership's interests (Lokshin et al., 2011). In the same survey as mentioned earlier, indeed 60% of all firms declare to perceive leakage of information as a reason for not engaging in (additional) collaboration projects. Among already collaborating firms, this share is even higher with 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 more collaborative projects a firm pursues, the lower the marginal gain, while coordination costs increase.

Based on these arguments on the gains and pains from collaborating, we build our empirical model on the simple theory of a profit maximising firm that benefits from collaboration, but also takes into account transaction and disclosure costs when choosing the level of collaborative R&D projects. When engaging into collaborative R&D, the firm realizes marginal benefits from collaboration  $MB$ . The function  $MB$ 's first derivative 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 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

*H2: The relationship between the share of collaborative projects in total innovation projects and innovation performance follows an inverted U-shape.*

Figure 1 illustrates the marginal benefit, the marginal cost and the net return curves graphically. While abstracting from inherent uncertainty in both these aspects, the firm's optimal collaboration intensity will be 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 engage 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 turning point  $JP^*$ .



*Figure 1: Optimal collaboration intensity*

### 3. IDENTIFICATION STRATEGY

Testing our hypotheses requires detailed information about a firm's R&D activities as well as about 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.

For our first step, we specify innovation performance as discrete probability model which we estimate using a simple probit model. The sales share due to new products, however, is a percentage and hence requires estimation of a censored dependent variable model. For the second step, we therefore estimate Tobit models on new product sales written as:

$$y_i^* = X' \beta + \varepsilon \quad (1)$$

where  $y_i$  is the unobserved latent variable. The observed dependent variable is equal to

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

and  $X$  represents a matrix of regressors,  $\beta$  the parameters to be estimated and  $\varepsilon$  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  $\sigma$  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:

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

with

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

and  $\text{corr}(u_1, u_2) = \rho$ . This approach allows taking 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 positive error term correlation and downward biased in case of 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 taking the censoring of our second stage outcome variable into account, that is, the truncated nature of the sales share from new products.

#### 4. 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 for 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). The present study focuses on information of 2,891 firms in manufacturing and business related industries that had at least ten employees in 2009<sup>3</sup> (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 indicated to have introduced at least one new product to the market (zero otherwise). This variable serves as 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 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:

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

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

To capture non-linearities 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.

### *Controls*

Both the likelihood to introduce a new product as well as its share of total sales may depend on firm size. We therefore include the firm's size measured by the number of employees (*firm size*) in both stages of the model. Moreover, the relationship may not be linear so that we include also the squared value of *firm size*. Due to the skewness of the firm size distribution, these variables enter in logarithms. 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 market pressure, which affects both pressure to innovate as well as 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 an enterprise group. Finally, we include a set of 25 industry dummies that capture differences in technological opportunities between sectors (see Table A1 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 i.e. 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, 112). In our case, the firm's product portfolio diversification serves as exclusion restriction that meets this condition. More precisely, firms indicated 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 affects the likelihood for new products negatively. Once firm decided to launch market novelties, the market success of the latter should not be impacted by the diversification of the overall product portfolio.

#### *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 short-run effects of these projects on innovation performance. Likewise, our control variables refer to this period.

#### *Descriptive statistics*

Table 1 shows the descriptive statistics for the main variables, displaying the means, medians, maximums and minimums of the variables that we use in the subsequent regression models. About 15% of the firms in the sample have introduced a new product to the market and the average sales shares from these new products is 13%. On average, a firm in our sample had 6.3 innovation projects during the sample period 2009 to 2011 of which 1.8 were collaborative. This results in an average collaboration intensity of 0.17. Among collaborators, the collaboration intensity is naturally much higher with about 0.53. About 20% of the firms had more than one collaborative project and about 3% had more than ten. Collaboration intensity thus ranges from zero to one. Roughly eleven percent of the firms undertake more than 60 percent of their projects in collaboration and close to 9% even conduct all their innovation projects in collaboration. On average, a firm in our sample has 240 employees. This high average firm size in our sample does not reveal that more than 86% of the firms

have 250 or less employees, i.e. are SMEs. The median firm size with 42 employees provides a more accurate picture. Firms have an R&D intensity of 3.5%, and an export intensity of 15%, on average. Finally, about 31% of the firms are part of an enterprise group.

**Table 1: Descriptive statistics**

<b>Full Sample, N=2891</b>						
Variables	Unit	Mean	Std. dev.	Median	Min	Max
<i>new product</i>	dummy	0.148	0.355	0	0	1
<i>% new product sales<sup>§</sup></i>	ratio	0.127	0.159	0.800	0	1
<i># all projects</i>	count	6.251	43.023	0	0	1500
<i># joint projects</i>	count	1.778	12.892	0	0	500
<i>collaboration intensity</i>	ratio	0.167	0.32	0	0	1
<i># employees</i>	count	239.77	1266.38	42	10	38.384
<i>R&amp;D intensity</i>	ratio	0.035	0.331	0	0	12.757
<i>export intensity</i>	ratio	0.154	0.251	0.001	0	1
<i>group</i>	dummy	0.314	0.464	0	0	1
<i>SMEs</i>	dummy	0.861	0.346	1.000	0	1

<sup>§</sup>The percentage of products new to the market is conditional on having at least one product innovation that is new to the market.

## 5. RESULTS

Table 2 presents the results of the probit and tobit estimations for both, the full sample and for SMEs only. The main variables of interest, namely collaboration intensity and its squared value, allow drawing conclusions with regard to our hypotheses. First, collaboration intensity enters positive and significant in both first and second stage confirming H1. Second, the squared value enters negative and significant suggesting an inverted U-shape relationship between collaboration intensity and both the likelihood to introduce a new product to the market (Model 1) as well as for the sales share from new products, i.e. market success of new products (Model 2). When we calculate the curve's turning point, we find the extreme value (maximum) to be at around 0.61-0.62 for both outcome variables. Thus, a share of

collaborative projects in all innovation projects larger than 62% may be detrimental for innovation performance, while lower collaboration intensities are beneficial.

Lind and Mehlum (2010) argue, however, 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. 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, as the commonly reported criteria may be misleading if the estimated extremum is too close to the end point of the data range. In our case, the estimated maximum at about 62% is well within the data range (see Figure 2). Accordingly, the t-test statistics derived from the probit and heteroscedastic tobit models clearly support our second hypotheses of an inverted U-relationship (see Lind and Mehlum 2010 for the technical details).

As we can see from Models 3 and 4 in Table 2, the results for the full sample are not biased by the inclusion of large firms as similar conclusions can be drawn in the subsample of small and medium sized firms. The similarity of the results thus indicate the results are mainly driven by the SMEs in our sample. Performing the analysis on (the limited number of) large firms only, does not yield significant coefficient estimates. Finally, all control variables have the expected signs and industry dummies are jointly significant.

Table 3 presents the results from the selection models as outlined in section 3. Columns one and three show the results from the first stage, that is, the probability to have a new product and columns two to four display the second stage results. We see that the mills ratio is highly significant underlining the appropriateness of the Heckman selection procedure. In addition to the full sample results, we again show results for the sub-sample of small and medium-sized firms (SMEs). Compared to the results presented in Table 2, 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% collaborative projects underlining the robustness of this result.

**Table 2: Probit and heteroscedastic-robust tobit estimations**

Variable	Full sample (2,891 obs.)						SMEs (2,489 obs.)					
	Model 1			Model 2			Model 3			Model 4		
	<i>Pr(new product = 1)</i>			<i>new product sales %</i>			<i>Pr(new product = 1)</i>			<i>new product sales %</i>		
	$\hat{\partial}y/\hat{\partial}x$	s.e.		Coef.	s.e.		$\hat{\partial}y/\hat{\partial}x$	s.e.		Coef.	s.e.	
<i>collaboration intensity</i>	0.703	0.039	***	0.910	0.093	***	0.549	0.027	***	1.008	0.121	***
<i>collaboration intensity</i> <sup>2</sup>	-0.578	0.040	***	-0.736	0.074	***	-0.443	0.031	***	-0.811	0.095	***
<i>ln(size)</i>	-0.048	0.021	**	0.016	0.040		-0.017	0.048		0.150	0.166	
<i>ln(size)</i> <sup>2</sup>	0.007	0.002	***	0.002	0.003		0.003	0.006		-0.015	0.020	
<i>R&amp;D intensity</i>	0.012	0.015		0.054	0.043		0.007	0.011		0.052	0.043	
<i>export intensity</i>	0.038	0.019	*	0.047	0.039		0.026	0.017		0.053	0.048	
<i>group</i>	0.005	0.010		0.009	0.014		0.001	0.008		0.009	0.016	
<i>Extremum point</i>	0.608			0.618			0.620			0.621		
<i>Log likelihood</i>	-790.416			-400.293			-614.13			-338.798		
<i>Lind-Mehlum Appropriate U t-test</i>	9.54***			7.38***			8.50***			6.76***		
<i>Joint significance of industries</i>	7028.01***			8828.73***			2957.74***			7.0e+08***		

Notes: Industry dummies included, not presented. (\*\*, \*\*\*) indicate 10% (5%, 1%) significance.

**Table 3: Heckman section models (two step estimation)**

Variable	Full sample (2,891 obs.)						SMEs (2,489 obs.)					
	Model 1			Model 2			Model 1			Model 2		
	1st stage <i>Pr(new product = 1)</i>			2nd stage <i>new product sales %</i>			1st stage <i>Pr(new product = 1)</i>			2nd stage <i>new product sales %</i>		
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
<i>collaboration intensity</i>	5.275	0.366 ***		0.605	0.297 **		5.361	0.411 ***		1.064	0.500 **	
<i>(collaboration intensity)<sup>2</sup></i>	-4.337	0.370 ***		-0.493	0.245 **		-4.322	0.412 ***		-0.854	-0.854 **	
<i>ln(size)</i>	-0.362	0.139 ***		-0.087	0.029 ***		-0.166	0.427		-0.219	0.126 *	
<i>ln(size)<sup>2</sup></i>	0.052	0.014 ***		0.008	0.003 ***		0.027	0.055		0.025	0.016	
<i>R&amp;D intensity</i>	0.089	0.069		0.141	0.020 ***		0.071	0.070		0.137	0.025 ***	
<i>Export intensity</i>	0.282	0.149 *		0.103	0.036 ***		0.251	0.172		0.138	0.053 ***	
<i>group</i>	0.041	0.088		0.006	0.020		0.010	0.098		0.003	0.028	
<i>exclusion restriction: diversification</i>	-0.005	0.001 ***					-0.01	0.002 ***				
<i>constant</i>	-0.823	0.577		-0.109	0.221		-1.150	0.940		-0.078	0.379	
<i>Extremum point</i>		0.608			0.614			0.620			0.623	
<i>Lind-Mehlum Appropriate U</i>												
<i>t-test<sup>§</sup></i>				2.92***						2.77***		
<i>Joint significance of industries</i>		94.62***			29.55			170.31***			15.17	
<i>Mills ratio (lambda)</i>				0.165**						0.270**		
<i>Number of censored observations</i>				2,463						2,181		

Notes: Industry dummies included, not presented. \* (\*\*, \*\*\*) indicate 10% (5%, 1%) significance. §based on linear regression model on new product sales (2nd stage).

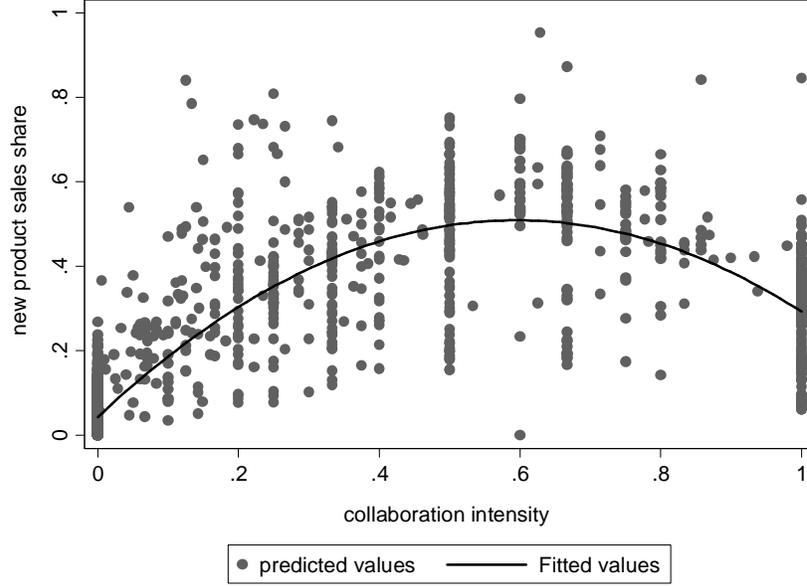


Figure 2: new product sales and collaboration intensity

## 6. ROBUSTNESS CHECK

A concern that could be raised is the potential endogeneity of choosing to collaborate. Some unobserved characteristics that influence the probability to engage into 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 chose to engage into 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 by 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  $i$ :

$$\begin{aligned}
 I_i &= 1 & \text{if} & & \gamma Z_i + u_i > 0 \\
 I_i &= 0 & \text{if} & & \gamma Z_i + u_i \leq 0
 \end{aligned}$$

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

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

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  $\beta_1, \beta_2$  and  $\gamma$  a vector of parameters. The correlation coefficient between  $\varepsilon_1$  and  $u_i$  is  $\rho_1 = \sigma_{21}^2 / \sigma_u \sigma_1$  and the one between  $\varepsilon_{2i}$  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<sub>*i*</sub> 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 into 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 one collaboration strategy.. We employ the share in sales that can be attributed to the single biggest product (*diversification*) as exclusion restriction. Similar to the logic in the selection models, we argue here that the larger the value of diversification the more concentrated 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 4, 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 and that the

extremum point has slightly moved to the left. In particular, we find it at 54% for the full sample and at 58% for SMEs.

**Table 4: Endogenous switching model**

Variable	Full sample (2,891 obs.)									SMEs (2,489 obs.)								
	Model 1									Model 2								
	Stage 1			Stage 2						Stage 1			Stage 2					
	<i>Pr(collaboration = 1)</i>			<i>new product sales if collaboration = 0</i>			<i>new product sales if collaboration == 1</i>			<i>Pr(collaboration = 1)</i>			<i>new product sales if collaboration = 0</i>			<i>new product sales if collaboration == 1</i>		
Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		
<i>collaboration intensity</i>						0.113	0.057	**							0.190	0.065	***	
<i>(collaboration intensity)2</i>						-0.103	0.049	**							-0.162	0.057	***	
<i>ln(size)</i>	-0.082	0.146		-0.003	0.003		-0.054	0.015	***	-0.328	0.348		-0.002	0.004		-0.093	0.060	
<i>ln(size)2</i>	0.027	0.014	**	0.000	0.000		0.004	0.001	***	0.061	0.043		0.000	0.001		0.008	0.007	
<i>R&amp;D intensity</i>	3.778	1.864	**	0.518	0.017	***	0.010	0.016		3.075	1.252	**	0.388	0.106	***	0.008	0.016	
<i>Export intensity</i>	0.999	0.183	***	-0.004	0.006		0.016	0.026		0.775	0.260	***	-0.011	0.005	**	0.014	0.034	
<i>group</i>	0.149	0.065	**	0.002	0.002		-0.006	0.010		0.044	0.066		0.000	0.002		0.002	0.009	
<i>Exclusion restriction: diversification</i>	-0.005	0.001	***							-0.004	0.003							
<i>constant</i>	-1.529	0.377	***	0.007	0.007		0.283	0.086	**	-0.788	0.642		0.007	0.008		0.348	0.165	**
<i>sigma0</i>	0.031	0.007	***							0.028	0.005	***						
<i>sigma1</i>	0.120	0.014	***							0.134	0.016	***						
<i>rho0</i>	0.004	0.007								-0.697	0.251	***						
<i>rho1</i>	-0.491	0.139	***							-0.548	0.127	***						
<i>Extremum point</i>							0.549									0.585		
<i>Joint significance of industries</i>	6.3e+10***			4.8e+10***			7.4e+9***			3.1e+06***			1.8e+08***			1.2e+08***		
<i>Wald test of independence of equations</i>				Chi <sup>2</sup> (2) = 10.30***									Chi <sup>2</sup> (2)=14.41***					

## 7. 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 not only depends on internal resources, but also on 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, the literature pointing out that there may be too much of a good thing after a certain threshold is still scarce. 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 for external knowledge through partnership matters. In particular, using data of a sample of German firms from the Mannheim Innovation Panel, we show that more is 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 the curve to turn for collaboration intensities larger than about 0.6. The mean collaboration intensity in the sample of collaborating firms is about 0.6 and the median is 0.5. That is, about half of the firms of our sample may have collaboration intensities that are beyond what is actually beneficial in terms of innovation performance. Thus, while collaboration may help firms to innovate, transaction cost such as coordination efforts and monitoring as well as the cost of disclosure, may countervail the benefits a firm can get from engaging into R&D partnerships. The challenge that innovation managers and entrepreneurs face is to determine the right collaboration intensity of their firms. Our results certainly do not suggest that a share of collaborative projects larger than 60 percent is too high for every firm. They do however challenge the maybe too optimistic view of openness as a key component for creating inventions and innovative products, thereby provoking thoughts in those firms with high

collaboration intensities. It seems worthwhile to continuously balance gains against costs and adjusting collaboration strategies accordingly. The results presented here were derived from a sample of mostly SMEs. It may well be that the conclusions are SME-specific, pointing to the trade-off that these firms face when balancing gains and pains from collaboration and which are likely to differ for larger firms.

From a policy point of view, our findings point to the fact that R&D collaborations are not necessarily welfare enhancing through more innovation 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 achieving this goal, they also depict that this goal may only be achieved if the strategy is used wisely and with a certain moderation by participating firms. If collaboration costs start outweighing their benefits, the competitiveness of the firms, and, as a consequence the welfare of consumers, will be impacted negatively.

The present study has some obvious limitations that call for future research that can address these. First, the collaboration measure used here is rather broad and does not take into account heterogeneity in alliances types and partners. Different types of collaboration or 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 taking 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 thus be interesting to see if 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).

We further suggest future research to study much closer how firms manage their alliance portfolios and how certain types of collaboration (intensities) benefit at the research and/or development stage of an R&D project. Moreover, we may not capture all benefits and costs, especially when these only occur in the long run. Finally, it would be interesting to see if the turning points identified in our paper would change significantly in a sample dominated by larger firms.

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## Appendices

**Table A1: Distribution of firms across industries**

<b>Industry</b>	<b>Freq.</b>	<b>Percent</b>	<b>Cum.</b>
<i>Mining</i>	49	1.69	1.69
<i>Food/tobacco</i>	127	4.39	6.09
<i>Textiles</i>	96	3.32	9.41
<i>Paper/wood/print</i>	189	6.54	15.95
<i>Chemical</i>	105	3.63	19.58
<i>Plastics/rubber</i>	80	2.77	22.35
<i>Glass/ceramics</i>	67	2.32	24.66
<i>Metal</i>	224	7.75	32.41
<i>Machinery</i>	195	6.75	39.16
<i>Electrical engineering</i>	145	5.02	44.17
<i>Medicine/optic/processing</i>	123	4.25	48.43
<i>Vehicles</i>	80	2.77	51.19
<i>Furniture</i>	72	2.49	53.68
<i>Energy/water/construction</i>	179	4.39	58.08
<i>Wholesale</i>	105	3.63	63.51
<i>Retail</i>	33	1.14	64.65
<i>Transport/post</i>	212	7.33	71.98
<i>Bank/insurance</i>	66	2.28	74.26
<i>IT/telecommunication</i>	112	3.87	78.14
<i>Technical services</i>	187	6.47	84.61
<i>Business related services</i>	124	4.29	88.9
<i>Other services</i>	259	8.96	97.86
<i>Real estate</i>	27	0.93	98.79
<i>Media</i>	35	1.21	100
<b>Total</b>	<b>2,891</b>	<b>100</b>	

**Table A2: Cross-Correlations (2,891 obs.)**

	1	2	3	4	5	6	7	8	9	10
<b>1</b> <i># all projects</i>	1									
<b>2</b> <i># joint projects</i>	0.6386*	1								
<b>3</b> <i>collaboration intensity</i>	0.0532*	0.1832*	1							
<b>4</b> <i>collaboration (dummy)</i>	0.2166*	0.2211*	0.8360*	1						
<b>5</b> <i># employees</i>	0.5091*	0.2695*	0.0155	0.1273*	1					
<b>6</b> <i>R&amp;D intensity</i>	0.0328	0.0619*	0.1516*	0.1523*	-0.0089	1				
<b>7</b> <i>export intensity</i>	0.1780*	0.1182*	0.2435*	0.3844*	0.1426*	0.0293	1			
<b>8</b> <i>group</i>	0.1236*	0.0699*	0.0807*	0.1907*	0.1920*	-0.0168	0.2665*	1		
<b>9</b> <i>diversification</i>	-0.0498*	-0.0142	-0.1048*	-0.1591*	-0.0799*	0.0126	-0.0951*	-0.0549*	1	
<b>10</b> <i>% new product sales</i>	0.1107*	0.2110*	0.2562*	0.3105*	0.0826*	0.1892*	0.1710*	0.0458	-0.0353	1
<b>11</b> <i>new product</i>	0.2048*	0.1936*	0.3743*	0.5337*	0.1601*	0.1008*	0.2848*	0.1422*	-0.1336*	0.5941*

Note: \* indicates a 1% significance level.