Quantity or Quality?
Knowledge Alliances and their Effects on Patenting*

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Abstract

This study shows for a large sample of R&D-active manufacturing firms over the period 2000-2009 that knowledge alliances have a positive effect on patenting in terms of both quantity and quality. However, when distinguishing between alliances that aim at joint creation of new knowledge and alliances that aim at the exchange of knowledge, results suggest that creation alliances lead to more valuable patents as they receive significantly more forward citations per patent. Knowledge exchange alliances, on the other hand, are associated with patent quantity, but not quality.

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1. INTRODUCTION

Enabling firms to cope with technological challenges, collaborative research and development (R&D) is often seen as a response to shifting knowledge environments. As stressed by Jones (2008), innovation increases the stock of knowledge and hence the "educational burden" of future cohorts of innovators. One way to compensate this development is specialization in expertise. However, narrowing expertise requires firms to invest in their knowledge development processes, for instance through seeking complementary know-how elsewhere (Zidorn and Wagner 2012). Collaborating with other organizations in knowledge-intensive business areas like R&D constitutes one form of accessing such external expertise.

Numerous previous studies found collaborative R&D to be an instrument used by firms to acquire new skills and to source specialized know-how (e.g. Hamel, 1991; Hagedoorn, 1993; Hagedoorn and Schakenraad, 1994; Powell et al., 1996; Eisenhardt and Schoonhoven, 1996; Gulati, 1998). Previous research further stressed that alliances have the potential to increase R&D productivity since voluntary knowledge sharing and pooling of competencies not only reduces unintended spillovers to the partnering firm(s), but also enhances innovation performance (Brouwer and Kleinknecht, 1999; Van Ophem et al., 2001; Branstetter and Sakakibara, 2002 among others)[i].

Although theory and previous empirical results illustrate the virtues of R&D alliances, our review of the related literature reveals that few empirical studies so far analyzed differences in the type of knowledge alliance. Even though previous research associated the search for knowledge to innovation, the primary focus of this literature was on organizational learning. The most famous of these concepts is the one of exploitation and exploration, as first introduced by March (1991)[ii]. Subsequent research repeatedly underlined the importance of balancing both these activities, since returns from exploitation have proximate, positive and predictable returns, whereas exploration is experimental, and hence more distant and uncertain. Another, associated concept distinguishes between scale and link alliances (Dussauge et al. 1998, 2000, 2004). By differentiating between firms that seek complementary know-how and skills (link alliances) and those alliances that are set up to facilitate larger projects and usually involve more similar partners (scale alliances), this typology separates between partnerships with the goal to increase the scale of existing activities or to develop new ones.

These findings contributed greatly to the literature by underlining that the type of knowledge sourcing matters in the search of new ideas. Building on these insights, the following analysis aims at further enhancing our understanding of how knowledge alliances might impact innovation performance. In other words, we explicitly zoom in on the type of knowledge alliances. In the terminology of March and Levinthal (1993), we focus on exploration activities. Indeed, in our setup, two types of knowledge alliances are introduced, both of which are an integral part of the R&D process, i.e. they take place *before* the exploitation or commercialization stage. The contribution of the following analysis is thus at least threefold: First, in line with previous literature, we study the effects of collaborative R&D on the firms' subsequent patenting activity. Second, we add to that literature by introducing the distinction between R&D creation and R&D exchange alliances to study how they affect firms' patenting activities. In particular, we differentiate between "*creation alliances*" that aim at the joint creation of new knowledge and "*exchange alliances*" that have the objective to exchange already existing knowledge which may then be used in independent research projects. Thus, compared to the typology of link and scale alliances (Dussauge et al. 1998, 2000, 2004), this study explicitly aims at identifying the impact of different types of knowledge alliances on innovation performance as measured by patenting activities. Finally, we shed new insights to previous studies by also taking into account the difference in impact on the value of the patented technology, as measured by the number of forward citations received, and not just the quantity.

Estimating Poisson regression models that account for unobserved heterogeneity and feedback effects on a large sample of R&D-active manufacturing firms in Belgium during the period 2000-2009, our findings support the idea that collaborative R&D promotes patenting. However, we find interesting differences between the different types of knowledge alliance. While exchange alliances increase the number of patents filed, knowledge creation alliances are associated with patent quality. These results are robust to a series of robustness tests. Finally, engaging in both forms of R&D alliance simultaneously does not seem to increase the returns to the individual collaboration strategy.

The reminder of this article is structured as follows. Section 2 reviews the related literature and sets out our hypotheses. Section 3 describes the set-up of our econometric analysis and the data. Section 4 presents the results and Section 5 concludes.

2. RELATED LITERATURE AND HYPOTHESES

Empirical literature studying the relationship between collaborative R&D and innovation has measured innovation performance in various ways. Deriving output measures from survey-data, many studies suggested a positive relation between being engaged in an R&D collaboration and innovation performance variables, such as for instance firms' sales from product innovations and sales growth, but also more general performance measures like employment growth, and the firms' labor productivity (see for instance, 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). Other studies employ direct measures of innovation success. Hoang and Rothaermel (2010) for instance investigate 412 R&D projects of large pharmaceutical companies in the period between 1980 and 2000 and show that experience in exploitation alliances had a positive effect on R&D project performance as measured by drug approval and the successful termination of the project. Experience in exploration alliances, on the other hand, had negative effects. Other studies using the exploitation/exploration dichotomy found that exploration alliances predict number of products in development while exploitation alliances increase the number of products on the market (Rothaermel and Deeds, 2004). Other studies using such direct measures and suggesting a positive effect are provided by Deeds and Hill (1996) who study the impact of alliances on 132 biotechnology firms and Schilling and Phelps (2007) who investigate the impact of 11 industry-level alliance networks. Shan et al. (1994) argue that alliances affect patenting activity in the bio-technology industry and that the causality goes exclusively from collaboration to innovation and not the other way around. Baum et al. (2000) find that variations in the configuration in alliance networks of start-up firms at the time of their founding results in significant differences in their early performance. More recently, Gnyawali and Park (2011) analyze in a case study setting collaboration between “industry giants” and conclude that such R&D alliances foster technological advances. Relatedly, Katila and Ahuja (2002), evaluating search depth (defined as the degree to which a firm revisits existing knowledge) and search scope (defined as the degree to which knew knowledge is explored), find an inverse U-shape relationship between a firm’s search behavior and the number of new products in the robotics industry.

Finally, a considerable number of studies use patent activity as a measure of innovation performance. For instance, Brouwer and Kleinknecht (1999) were among the first to find that a firm’s propensity to patent is significantly higher among R&D collaborators in a sample of companies in the Netherlands. Similarly, Van Ophem et al. (2001) find that firms participating in research partnerships file more patents than firms focusing on internal R&D only. Branstetter and Sakakibara (2002) study patenting activities of Japanese firms engaged in government-sponsored research consortia. They find that larger spillovers (measured by technological proximity between participating firms) improve research productivity and are therefore associated with more patent applications in subsequent years. Moreover, their results suggest that the benefits are stronger for consortia aiming at basic research. Czarnitzki and Fier (2003) show that collaborating firms in Germany are more likely to patent than non-collaborating firms and Sampson (2005) finds a positive effect of recent collaboration experience on patent output of participating firms in the telecom equipment industry. Peeters and van Pottelsberghe (2006) document a positive relationship between an outward-oriented innovation strategy reflected in R&D partnerships and the size of firms' patent portfolios. Czarnitzki et al. (2007) report positive effects of collaboration on having at least one patent application in subsequent periods for firms located in Finland and Germany. Finally, Vanhaverbeke et al. (2007) find a positive relationship between technology alliances and patent citations in a sample of ASIC[iii]-producers that were active in the period 1988-1996.

2.1 HYPOTHESES

2.1.1 R&D collaboration and innovation performance

Previous firm-level research suggests that a firm's innovativeness directly depends on its knowledge-base (e.g. Griliches 1984, 1990; Pakes and Grilliches 1984; Henderson and Cockburn 1996). Thus, as a firm's effective knowledge base increases through collaboration, a positive effect on innovation output can be expected. In line with evidence of firms' motives to engage in collaborative R&D[iv], we therefore expect a positive effect from R&D collaboration on patenting as a result of the broadening of the firms' knowledge base and the acceleration of their innovation processes. Firms involved in R&D partnerships may benefit from a multitude of channels, like gaining access to complementary technological and manufacturing know-how and in some cases financial resources that reduce time and resource requirements, speeding up the R&D process (e.g. Mody 1993; Mowery et al. 1996). Moreover, since the benefits from collaboration on a key corporate activity like R&D comes at the cost of secrecy, collaboration may be likely to increase the need for patent protection because it implies, at least to some extent, disclosing knowledge to the external partner. A legally enforceable protection mechanism such as a patent is therefore crucial for clarifying ownership not only for the firms' pre-existing knowledge-base, but also for co-developed inventions. Therefore, patents are likely to play a key role in the innovation process of collaborating firms as they seek to establish their property rights by patent protection. Both arguments stand in favor of a positive effect of R&D alliances on patenting activity. We thus hypothesize that:

Hypothesis 1: Firms engaged in collaborative R&D in period t file, on average, more patents than non-collaborating firms in subsequent periods.

Analogous to bibliographic analyses, the technological relevance or quality of patents can be approximated by the number of citations a patent receives in subsequent patent applications (forward citations). When a patent is filed, the inventor (and/or the patent examiner) notes all of the previous patents that the applied patent is based on. These citations, thus, identify the technological lineage of the invention. The number of forward citations received is therefore generally acknowledged as a measure for patent value or quality as they can serve as an indicator for the technological importance of the patent (Traijtenberg 1990; Harhoff et al. 1999, 2003; Hall et al. 2005). Because of the value creation potential of collaborations that pool firms' resources and exploit possible complementarities in expertise, we expect that R&D undertaken by such partnerships results in valuable and state-of-the art technologies. Based on this argumentation, we would expect collaboration not only to lead to more patents, but also to more valuable patents. We thus hypothesize that:

Hypothesis 2: Patents filed by R&D collaborators receive on average more forward citations than patents filed by non-collaborative firms.

2.1.2 Knowledge Creation, Knowledge Exchange and Innovation Performance

Given that the impact between creating and exchanging knowledge in the R&D process on innovation performance might differ substantially, the two following hypotheses will explicitly built on how these differences may be reflected in patenting activity.

Firms engaged in *knowledge creation alliances* benefit from the combination of resources in the R&D process, access to technological capabilities and the exploitation of complementary know-how which translates into higher R&D productivity. In line with parts of the notion of exploration and link alliances, rather than the firms seeking to absorb the knowledge of the partner, in this type of alliance each partner focuses on deepening and contributing its own knowledge in a way that complements the knowledge of the other partner (Gomes-Casseres et al. 2006). It can thus easily be argued that a joint R&D undertaking has a larger impact on R&D outcome as it involves the transfer and creation of tacit knowledge in addition to the exploitation of complementary assets in the knowledge production process. Moreover, given that joint R&D involves direct "on-the-job exchange" between R&D employees allowing the transfer of tacit knowledge, the benefits of such a knowledge alliance may have a positive effect on a firm's R&D competence, even beyond the scope of the mere project. Thus, creation alliances can be expected to impact innovative capabilities at the firm level and not just at the project level. An example of such a joint creation alliance aiming at developing a new technology is for instance the joint venture called S-LCD between Samsung Electronics and Sony Corporation, set up to develop and manufacture flat-screen LCD TV panels (see Gnyawali and Park (2011) for the case study). The aim of this alliance clearly consisted in developing a technology thus far unavailable on the market. Patent protection thus plays a vital role in this setting, as it is essential for the inventor to be able to protect his or her innovation.

The effects from *knowledge exchange alliances* on firms' innovation output are less clear. Knowledge exchange alliances may differ from creation alliances in the depth of the mutual involvement. Exchange of knowledge does not necessarily need to be mutual. For example, the case of R&D alliances between established pharmaceutical firms and small biotechnology firms described by Stuart (2000) can be labeled knowledge exchange collaboration. These are designed such that the pharmaceutical firm provides funding for a research project to its partner and in exchange acquires the right to observe the R&D process and results of the biotechnology firm, usually without actively contributing to the development of new knowledge. It is important to note however that exchange alliances differ from licensing agreements. Compared to a licensing agreement where there is a buyer and a seller with very limited interaction, in an exchange alliance, both partners are actively involved in the R&D process. Even if the knowledge that each partner contributes differs, all partners remain present beyond the exchange of the knowledge. Pure licensing agreements are thus not part of what qualifies in this study as exchange alliance. Given however, that knowledge exchange alliances do not involve joint development of new technologies, they may trade more explicit knowledge rather than tacit knowledge. This may therefore only be transmitted during a joint project, and not affect the firms' overall knowledge base to the same extent than a creation alliance. Likewise, the novelty involved of the developed products or technologies in this setting may concern a certain piece of technology rather than a genuine innovation. Thus, we expect that

Hypothesis 3: Knowledge creation alliances have a larger positive effect on the number of patent applications than exchange alliances as the former type involves more intense pooling of resources and competencies.

Moreover, given that creation alliances involve new R&D by definition (knowledge exchange alliances may or may not trigger additional internal R&D), we would not only expect an effect on the number of new patents filed but also on the quality of the filed patents, i.e. on the number of forward citations received per individual patent. As joint R&D is associated with transaction costs as well as the cost of spilling precious knowldege to the partner, firms may jointly undertake R&D projects only if they are expected to be sufficiently valuable to cover these costs. As valuable R&D would result in "prior art" technology, this would be reflected in a high number of citations received by resulting patents. We thus hypothesize that

Hypothesis 4: Knowledge creation alliances have a larger effect on patent quality as measured by the number of forward citations received than knowledge exchange alliances.

3. RESEARCH DESIGN, METHODOLOGY AND DATA

3.1 Patent production function and econometric models

Based on panel data of manufacturing firms in the Belgian Region of Flanders, we test the hypotheses derived in the previous section. In a first step, we are therefore interested in whether the different types of knowledge alliance have differing impacts on the number of patent applications filed. In a second step, we want to know if, and to what extent, the type of alliance impacts patent quality. In order to investigate this phenomenon, we count the number of times subsequent patent applications refer to patents of a firm in our sample as relevant prior art, averaged at the firm level.

In order to explore our research questions empirically, we estimate a patent production function of the type first introduced by Pakes and Griliches (1984). The patent production function relates the number of patent applications made by a firm in a given year to its collaboration status along with various firm specific characteristics. Because the number of filed patent applications is a non-negative integer value with many zeros and ones, we apply, as commonly done in the literature, count data models hypothesizing that the expected number of patent applications applied for during a given year is an exponential function of firm characteristics:

$$E(PAT_{i,t+1}|X_{i,t}) = \exp(X_{i,t} + \gamma_i) \tag{1}$$

where $patent_{i,t+1}$ denotes the number of patents applied for by firm i in period $t+1$ and $X_{i,t}$ is a vector of control variables, where i = 1, ..., N indexes the firm and t = 1, .. T indexes the time period. The number of patent applications is forwarded by one period in order to allow for a time lag between collaboration effects and patenting activity, hence avoiding direct simultaneity. γ_i is an overall time-invariant mean that measures the average patenting rates across firms, adjusting for the mix of the firms in the sample. The model for average citations per patent is defined analogously.[v]

Our baseline model is a Poisson model. Following Blundell et al. (1995, 2002), we relax the assumption of strict exogeneity and account for unobserved time-invariant firm heterogeneity by using the pre-sample patent stock as a proxy for the unobserved heterogeneity component γ_i. Indeed, as shown by Blundell et al. (1995, 2002), if the main source of unobserved heterogeneity is routed in the different values of the outcome variable Y_i with which the firms enter the sample (thus, patents in our case), the unobserved heterogeneity can be approximated by including the log of the Y_i from a pre-sample period average (Pre-sample Mean Approach, PSM). As suggested by Blundell et al., we define a dummy variable equal to one if a firm had never filed a patent within the pre-sample period. Given that the PSM Approach controls for time-invariant heterogeneity across firms, it helps reducing serial correlation and overdispersion. Rather than estimating a standard fixed-effects Poisson model, we opt for the PSM approach as, compared to the fixed-effects approach, it allows us – in line with our hypotheses - to take cross-sectional firm variation into account.[vi]

In line with the literature (see e.g. Hall and Ziedonis, 2001; Somaya et al., 2007), the remaining overdispersion, as reported by the Lagrange Multiplier (LM) test (Cameron and Trivedi, 1998), is interpreted as a diagnostic that we should report robust standard errors rather than as a rejection of the Poisson model in favor of a model where the variance is proportional to the mean (Wooldridge, 1999).[vii] It has been shown by Gourieroux et al. (1984) that because the Poisson model is in the linear exponential class, the Poisson coefficients estimates are consistent as long as the mean is correctly specified and that the robust standard errors are consistent even under misspecification of the distribution (Poisson Pseudo (or Quasi) Maximum Likelihood).

For the second step of our analysis, the aim is to investigate the impact of the R&D collaboration on patent quality and the econometric model is like the one outlined above. The only difference is the outcome variable, which is no longer the count of filed patent applications by firm i in period $t+1$, but the count of the number of forward citations received in a 5-year window after the filing year per patent filed in $t+1$.

3.2 Data description

Sample

The data for our analysis stem from the Flemish part of the OECD R&D survey. The survey is harmonized across OECD countries and is conducted every second year in order to compose the OECD Main Science and Technology Indicators with the collected data. The Flemish R&D survey is a permanent inventory of all R&D-active companies in Flanders. The survey data is complemented with patent information from a database issued by the European Patent Office (EPO). The “EPO/OECD patent citations database” covers all patents applied for at the EPO since its foundation in 1978 as well as all patents applied for under the Patent Cooperation Treaty (PCT) in which the EPO is designated, so-called “Euro-PCT applications”. Information from the Belgian patent office is used to draw information about patents filed in Belgium only. Patent data is available as a time series from 1978 until May 2012 and has been collected using text field search based on companies' names and adresses. All potential hits of the text field search engine have been checked manually before they were merged to the firm-level panel data based on a unique identifier (the VAT number of the firms). Further, we obtain financial details from the firms' balance sheets through the bel-first data base provided by Bureau van Dijk.

Our analysis covers the period from 2000 to 2009 and focuses only on manufacturing firms. The industries are classified between high-, medium, low tech and other manufacturing industries, following the OECD (2003) classification. The final sample contains a total number of 4,013 firm-year observations referring to 1,278 different firms, thus constituting an unbalanced panel. On average, each firm is observed 3.1 times (min = 2, max = 9) in the period of interest.

Outcome variables

The outcome variable *patent* is measured as the count of patents filed by firm *i* in period *t+1*. This allows us to test whether being engaged in a knowledge alliance in period *t*, as well as the type of the knowledge alliance, has an impact on patenting activities in period *t+1*. Based on the assumption that there might be spillover effects from collaborative activities in R&D that go beyond the joint R&D (and that these spillover effects might change according to the type of knowledge alliance), the output is measured at the firm level rather than at the project level. In other words, we are interested in the impact of an alliance on the overall number of patents filed by firm *i*, not just patents that stem from the jointly undertaken project.

Our second dependent variable (*average_citations*) is measured as the count of forward citations per patent received in a 5-year-window after the filing year at the firm level. Hall et al. (2005) stress that a patent's prime citation years are usually the ones early in a patent's life cycle, and more precisely in a three to ten-year window.[viii] Hence, we chose a five-year window in our case, given that this seems a reasonable choice, both in terms of what has been found in the literature as well as with respect to our 10-year-sample period.[ix]

As we are interested in measuring the average technological value produced at the firm level, we use the average number of forward citations *per patent* rather than the simple count of forward citations. That is, we divide the total number of citations by the total number of patents per firm. This has the advantage over citation counts that it does not confound the quality effect with a quantity effect (in the sense of more patents, more citations), a distinction that is crucial for our analysis.[x]

As shown in Table 1, on average, firms in our sample apply for 0.5 patents a year. In the subsample of patent-active firms, the average is higher with 5 patents per year on average. In terms of forward citations, each patent filed by a firm in our sample gets on average cited 0.11 times. For the subsample of patent-active firms, the average number of forward citations is of 1.3 times.

R&D alliances

The central variables in our analysis are related to the knowledge alliance patterns of the firms. First, from each wave of the survey we derive a dummy variable equal to one if a firm had been engaged in a knowledge alliance for the undertaking of its R&D activities *(collaboration)* during the two years preceding the survey year, irrespective of the purpose of the alliance. Second, the survey distinguishes the type of alliance which allows us to account for heterogeneity in the objectives of the partnership engagement. More precisely, the survey asks whether an existing R&D alliance had the objective to combine resources and abilities for the joint undertaking of an R&D project with the ambition to generate new knowledge or whether the alliance aims at exchanging existing knowledge between consortium partners in order to refine, implement, enable or facilitate their own R&D projects.

The former type of alliance is captured by a dummy variable (*creation_alliance)* that takes the value 1 if the firm reported that it was involved in such an agreement. For firms engaged in an alliance that aims at the exchange of knowledge, we create a separate dummy variable (*exchange_alliance).*[xi]

As can be gathered from Table 1, the majority of firms in the sample rely on in-house R&D exclusively for developing new products and processes. Roughly a third of the firms are more outward-oriented and engage in R&D alliances in order to access external knowledge as well as to share the risks and costs of innovation with other organizations. Organizations with which firms can collaborate to implement joint R&D projects or to exchange pre-existing knowledge are numerous. Potential partners include competitors, customers, suppliers, universities, research institutes, and consultants. The majority of these collaborations of the firms composing our sample aim at joint R&D (24%) whereas slightly fewer, but still a considerable number of firms, engage in knowledge transfer collaborations (21%).

Control variables

Several control variables are included in our analyses. R&D is usually considered as the most important determinant for patent productivity. Hence we control for R&D input at the firm level. To avoid confounding the effect of R&D spending with a mere size effect, the variable is measured as an intensity, namely the ratio of R&D employment to total employment (*R&D*).

In line with previous research, we control for firm size (see e.g. Ahuja and Katila, 2001; Hall and Ziedonis, 2001; Somaya et al., 2007). Size is measured by the book value of the firms' tangible assets *(assets*). Previous studies have shown that due to the fixed cost linked to having and maintaining a legal department, there may be economies of scale in applying for patents. Likewise, companies with capital-intensive production might rely more heavily on innovation activities than labor-intensive firms, and hence be more likely to file patents.

The capital intensity is measured as the ratio of fixed assets over the number of employees (*capital intensity*). Firm age is measured as the difference between the current year of observation and the founding year (*age*). In line with previous literature, age accounts for experience older firms might have in managing the patent application process, being therefore more efficient in their patenting activities for reasons that are not perfectly correlated to firm size (see e.g. Sorensen and Stuart 2000).

Given that the Poisson estimator has an exponential specification, we transform all our size-dependent independent variables as well as age into logarithms, ensuring that both dependent and independent variables are scaled in the same way. A group dummy (*group*) controls for whether or not a firm is part of a group such as a multinational company or a holding company for instance. Being part of a group may involve more professional innovation management, especially when compared to small, stand-alone companies, which might have an impact on the success of R&D projects and the efficiency of patenting activities. The variables *ln(meanPat)* and *d_meanPAT (*as well as *ln(meanCIT)* and *d_meanCIT)* are included to control for the "fixed effect" related to the firms' unobserved propensity to patent as described in section 3.1. The variable *ln(meanPat)* is the logged average number of patents in the 5 years prior the beginning of our panel and *d_meanPAT* is a dummy variable that takes the value one if the pre-sample patent mean is equal to zero. The variable *ln(meanCIT)* is measured as the average number of forward citations per patent in the 5 years prior the beginning of our panel received in a 5-year-window after the patent was filed. The variable *d_meanCIT* is a dummy variable that takes the value one if the pre-sample citation mean is equal to zero.

Four industry dummy variables are constructed at the two-digit NACE-level to break up manufacturing firms into groups that are characterized by the basic nature of their technology and innovative patterns, to control for heterogeneity across classifications stemming from differences in technological opportunities. The used classification groups industries into high, medium, low-tech and “other manufacturing” follows the OECD classification (OECD, 2003). Finally, year dummies are included to capture macroeconomic shocks.

Overall summary statistics of the main variables used in our models are displayed in Table 1. The average firm of our sample exists since 28.4 years (median is 23), has tangible assets of the amount of € 1,781 million, and employs 6.6 R&D employees for every 100 total employees. This number is higher in the subsample of patent-active firms with an average of 14 R&D employees for every 100 employees.

Table 1: Descriptive statistics (4,013 obs., 1,278 firms)

Variable	Unit	Mean	Std. Dev.	Min	Max
		Outcome variables			
patents	patent count	0.496	3.429	0	76
average_citations	citations per patent	0.113	0.998	0	27
		Control variables			
collaboration	dummy	0.265	0.441	0	1
creation_alliance	dummy	0.235	0.424	0	1
exchange_alliance	dummy	0.211	0.408	0	1
ln(meanPAT)	pre-sample patents$_{1995\text{-}1999}$	0.106	0.703	-1.609	6.002
d_meanPAT	dummy (no pre sample patents)	0.847	0.360	0	1
ln(meanCIT)	pre-sample citations$_{1995\text{-}1999}$	0.176	0.795	-1.856	6.444
d_meanCIT	dummy (no pre sample citations)	0.915	0.279	0	1
group	dummy	0.584	0.493	0	1
age	years	28.425	19.655	1	126
ln(assets)	tangible assets in million €	7.485	1.903	0.693	13.732
ln(capital_ intensity)	fixed assets / employees	3.293	1.026	0	6.381
ln(R&D)	R&D empl/ employees	0.059	0.101	0	0.693

Detailed summary statistics differentiating between firms’ alliance status are displayed in Table 2. More precisely, in Table 2 we distinguish between non-collaborating firms (I), firms that are engaged in any type of alliance (II), firms that are engaged in exchanges alliances (III) and firms that are engaged in creation alliances (IV). Those two types of collaboration are not mutually exclusive. We therefore add three additional categories, comprising firms that are exclusively engaged in either one type of the previous alliances (V and VI) and firms that are engaged in both these types of alliance simultaneously (VII). Table 3 presents t-tests on the mean difference between the various groups.

Table 2: Descriptive statistics by collaboration status

	I		II		III		IV		V		VI		VII	
	Non-collaborating firms, N=2950		**Firms engaged in any type of alliance, N=1063**		**Firms engaged in exchange alliances, N=848**		**Firms engaged in creation alliances, N=945**		**Exclusively exchange alliances, N=118**		**Exclusively creation alliances, N=215**		**Both types of alliances, N=730**	
Variables	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Outcome variables														
patents	0.130	1.973	1.509	5.675	1.720	6.261	1.640	5.963	0.458	2.024	0.674	1.944	1.925	6.677
average_citations	0.040	0.487	0.314	1.746	0.328	1.901	0.346	1.848	0.054	0.196	0.256	0.905	0.373	2.045
Control variables														
ln(prePAT)	0.009	0.358	0.372	1.190	0.405	1.253	0.406	1.245	0.105	0.048	0.242	0.061	0.454	1.328
d_prePAT	0.898	0.302	0.704	0.457	0.696	0.460	0.681	0.466	0.881	0.325	0.730	0.445	0.667	0.472
ln(preCIT)	0.070	0.009	0.470	1.266	0.498	1.325	0.526	1.324	0.021	0.417	0.360	0.996	0.575	1.404
d_preCIT	0.956	0.205	0.802	0.399	0.797	0.402	0.787	0.409	0.915	0.280	0.819	0.386	0.778	0.416
group	0.534	0.499	0.721	0.448	0.747	0.435	0.725	0.447	0.695	0.462	0.619	0.487	0.756	0.430
age	27.469	17.994	31.079	23.469	31.384	24.165	31.736	23.976	25.814	18.166	29.874	20.502	32.285	24.893
ln(assets)	7.217	1.775	8.228	2.045	8.285	2.067	8.307	2.079	7.594	1.620	8.001	1.944	8.397	2.110
ln(capital_intensity)	3.284	1.042	3.317	0.982	3.320	0.989	3.320	0.991	3.297	0.905	3.305	0.957	3.324	1.002
ln(R&D)	0.042	0.095	0.134	0.172	0.137	0.176	0.137	0.172	0.115	0.173	0.124	0.154	0.140	0.177

Table 3: P-values of the t-tests on mean differences of the groups of interest

Variables	I vs. II	I vs. III	I vs. IV	V vs. VI	V vs. VII	VI vs. VII
			Outcome variables			
patents	p<0.000	p<0.000	p<0.000	p=0.344	p<0.000	p<0.000
average_citations	p<0.000	p<0.000	p<0.000	p=0.002	p<0.000	p=0.231
			Control variables			
ln(prePAT)	p<0.000	p<0.000	p<0.000	p=0.077	p<0.000	p=0.007
d_prePAT	p<0.000	p<0.000	p<0.000	p<0.000	p<0.000	p=0.072
ln(preCIT)	p<0.000	p<0.000	p<0.000	p<0.000	p<0.000	p=0.126
d_preCIT	p<0.000	p<0.000	p<0.000	p=0.009	p<0.000	p=0.185
group	p<0.000	p<0.000	p<0.000	p=0.159	p=0.180	p<0.000
age	p<0.000	p<0.000	p<0.000	p=0.064	p<0.000	p=0.151
ln(assets)	p<0.000	p<0.000	p<0.000	p=0.042	p<0.000	p=0.107
ln(capital_ intensity)	p=0.350	p=0.349	p=0.340	p=0.944	p=0.771	p=0.799
ln(R&D)	p<0.000	p<0.000	p<0.000	p=0.640	p=0.137	p=0.175

While in the overall sample, a firm, on average, files 0.5 patents per year, within the group of firms engaged into an alliance, the average is 1.5 patents a year. As expected and as shown in Table 3, this is significantly more than the number of patents filed by non-collaborating firms, which file on avergae 0.13 patents a year. Likewise, firms engaged in exchange alliances as well as firms engaged in creation alliances file significantly more patents per year than non-collaborating firms (with an average of 1.7 and 1.6 patents a year, respectively). Interestingly, when comparing the average number of patents filed per year by firms that are engaged exclusively in either one type of collaboration, we do not find a statistically significant difference. Based on the descriptive statistics, we thus cannot draw a conclusion on the impact on the different type of collaboration on subsequent patenting activity. We do see though that firms engaged in both types of collaboration file significantly more patents per year than firms engaged in only one type of collaboration (see cases V vs. VII and VI vs. VII in Table 3). However, to see whether these results are robust to controlling for firm-level characteristics will be subject to the following econometric analysis. With respect to forward citations we find slightly different results. While similar to patent applications we observe that collaborating firms (regardless of the type) receive significantly more forward citations per patent on average than non-collaborating firms, we find that when comparing both types of collaboration, that patents filed by firms engaged in creation alliances receive significantly more forward citations than patents filed by firms engaged in exchange alliances. In line with these findings, patents filed by firms engaged in both types of collaboration receive on average significantly more forward citations than patents filed by firms engaged exclusively exchange alliances, while there is no significant difference between being engaged in both types of collaboration or only in creation alliances.

When considering the pre-sample patent and citation mean, the findings are similar to the findings on patent applications and forward citations. Collaborating firms have on average more patents and forward citations prior the start of the sample when compared to non-collaborating firms. Interesting to note is that firms engaged exclusively in creation alliances have significantly more patents as well as forward citations than firms engaged only in exchange alliances in the 5 years prior the sample start. While firms engaged in both types of collaboration agreements have significantly more patents in the pre-sample period than firms engaged in only one type of collaboration, this difference in not significant for firms engaged in creation alliances only in terms of forward citations.

As expected, we find that (either type of) collaborating firms are more often part of a group than non-collaborating firms. While there is no statistically significant difference between group-membership between firms engaged exclusively in either one type of collaboration, firms that are engaged in both types of alliances are more often part of a group than firms that are involved in only one type. With respect to age, we find that collaborating firms are on average older than non-collaborating firms. When comparing exchange and creation alliances, we see that firms engaged in exchange alliances are on average younger than firms engaged in creation alliances (as well as firms that are engaged in both types of alliances). While there is no significant difference in capital intensity between the groups, we see that collaborating firms have on average more tangible assets, i.e. are larger than non-collaborating firms. We further find that firms engaged in creation alliances (or both types of alliances) have more tangible assets than firms engaged in exchange alliances. Finally, we find that collaborating firms invest more in R&D than non-collaborating firms, without however finding a significant difference between the different types of collaboration. The descriptive statistics suggest that there is a difference between firms that chose to engage into (a specific type of) collaboration and firms that chose to rely in in-house R&D only. In the next section, we are thus going to present the results from a multivariate analysis that focuses on how these differences translate into patenting activity, ceteris paribus.

4. ECONOMETRIC RESULTS

The main results from the PSM Poisson models are reported in Table 4. Column one shows the estimates of the baseline model, where we analyze the impact of any type of knowledge alliance on patenting activity (Model 1). Conform to expectations, we find a positive effect of R&D alliances in general (*collaboration*) on patent output, which confirms *Hypothesis 1*. As shown by the coefficient of collaboration, a collaborative firm in period t is 73% more likely to file an additional patent in period t+1 than a firm that did not undertake a collaboration for it's R&D activities. As expected, the effect of *ln(R&D)* as a measure for direct input in the patent production function is positive and significant. The "pre-sample fixed effect" is also highly significant, pointing to the importance of controlling for unobserved heterogeneity.

With respect to patent quality, we find a statistically significant coefficient for overall collaboration (Model 3) confirming *Hypothesis 2*. In other words, patents filed by firms that undertake R&D activities in alliance with a partner get more often cited as prior relevant art than patents that get filed by firms that do not collaborate for their R&D activities.

When looking at the results of Model 2, distinguishing between firms involved in knowledge creation compared to firms involved in knowledge exchange alliances, it turns out that being engaged in exchange alliances has a positive effect on the number of patents filed. Interestingly, for creation alliances, we do not find a statistically significant effect on patenting, although the sign of the coefficient is positive. Thus, we find no empirical support for *Hypothesis 3* where we expected creation alliances to have a positive and significant effect on subsequent patent applications. Model 4, distinguishing between creation and exchange alliances on patent quality, finds opposite results compared to Model 2. In terms of patent quality, joint knowledge creation displays a positive and statistically significant coefficient. Thus, even though knowledge exchange in period *t* leads to *more* filed patents of the firms in period *t+1*, the patents filed by firms engaged in joint knowledge creation receive more forward citations. This confirms *Hypothesis 4*, hypothesizing that creation alliances trigger quality.

Table 4: Pre-Sample Mean (PSM) Poisson Models (4,013 obs., 1,278 firms)

Variables	PATENT APPLICAITONS$_{t+1}$		CITATIONS PER PATENT	
	Model 1	**Model 2**	**Model 3**	**Model 4**
collaboration	0.739 ***		0.762 ***	
	(0.218)		(0.249)	
creation_alliance		0.166		0.961 ***
		(0.283)		(0.323)
exchange_alliance		0.545 **		-0.304
		(0.250)		(0.308)
ln(meanPAT)	0.662 ***	0.649 ***		
	(0.073)	(0.073)		
d_meanPAT	-0.874 **	-0.923 ***		
	(0.346)	(0.342)		
ln(meanCIT)			0.185	0.185
			(0.147)	(0.143)
d_meanCIT			-1.621 ***	-1.598 ***
			(0.463)	(0.465)
ln(R&D)	3.466 ***	3.549 ***	2.582	2.636
	(0.752)	(0.767)	(2.213)	(2.195)
ln(age)	-0.146	-0.151	-0.409 **	-0.401 **
	(0.120)	(0.119)	(0.178)	(0.174)
ln(assets)	0.354 ***	0.362 ***	0.493 ***	0.497 ***
	(0.083)	(0.083)	(0.125)	(0.125)
ln(capital_intensity)	0.04	0.036	-0.194	-0.205
	(0.145)	(0.144)	(0.210)	(0.206)
group	0.196	0.196	0.437	0.461
	(0.339)	(0.340)	(0.537)	(0.535)
Wald $chi^2(20)$	2,770.86 ***	3123.18 ***	339.28 ***	439.78 ***
Joint sign. of	5.33	6.31 *	10.55 **	9.92 **
Joint sign. of years	66.86 ***	69.16 ***	19.68 **	20.60 ***

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Standard errors in parentheses are clustered, accounting for repeated observations at the firm level. All models contain a constant, industry and year dummies (not presented).

In Model 3 and 4, even though both, the coefficient of the pre-sample mean as well as the coefficient of *ln(R&D)* have the expected signs, neither one of them is statistically significant. This could be explained by the fact that contrary to patent history, forward citation history also largely depends on the importance attributed to a patented technology by other firms, and not solely be the patenting firm as is the case for patent history.[xii] Hence, the learning curve a firm goes through in terms of patent activities does not seem to follow a similar pattern in terms of forward citations. Similarly, while R&D is indispensible for patenting activity, forward citations also depend on the absorptive capacity of the citing firms, and hence on the R&D investment by the latter. Firm size is positive and significant in all models and age has no effect on the number of patents filed, but affects forward citations negatively. The latter result is in line with the idea that young firms drive the most radical technological advances.[xiii] Finally, while in the descriptive statistics we saw that collaborating firms are significantly more often part of a group than non-collaborating firms, group membership does not display a significant effect on patent applications or forward citations.

4.1 Extensions and robustness tests

Before concluding we test the sensitivity of the results to critical features of the econometric models and underlying variables by carrying out a number of robustness checks. Detailed results for these tests are available as supplemental material.

First, we control for the inclusion of a lagged dependent variable in an exponential Feedback Model (EFM) (see Blundell et al. 1995b). The previous results hold if we allow for a one-year- lagged value of patent applications as additional regressor.

Next, we control for joint adoption of both types of knowledge alliances given that a considerable amount of firms in our sample are engaged in both types simultaneously. Therefore we want to check whether our findings are confirmed if we i) drop the firms that are engaged in both types of alliances simultaneously from our sample and ii) explicitly test for the effect of joint adoption of both types of collaboration on patent productivity. More precisely, we want to see how robust our results are to the significant positive correlation between our key variables of interest (*creation_alliance*, *exchange_alliance*).

When doing i) we find with regards to the type of collaboration, in line with our previous findings, that knowledge exchange alliances have a significant positive effect on the number of patent applications. Compared to our previous results where we did not find a significant effect of knowledge creation alliances on patent application, we find that creation alliances have as well a positive impact on patent activity. The size of the coefficient of the latter, however, is substantially smaller, i.e. half the size of the coefficient of knowledge exchange alliances, confirming the previous results.

Next, we test ii) on the full sample to analyze whether the joint engagement in both alliance types has an added value compared to doing only one or the other. The descriptive statistics presented in Table 2 showed that firms engaged in both types of alliance had on average more patent applications than firms engaged in only one type. As a consequence, we are interested in knowing whether this finding is confirmed, all else equal. In order to do so, we re-estimated the models as in equation (1), but additionally include a set of dummy variables for the different strategy combinations: *exchange_only* (1 0), *creation_only*, (0 1) *neither* (0 0), and *both* (1 1). Table 5 presents the main results from these estimations. The results show that for the number of patent applications in t+1, any alliance has a significant positive impact compared to not collaborating at all. In line with previous results, the test of equality of coefficients for *creation_alliance* alone (0 1) and *exchange_alliance* alone (1 0) is rejected (Prob > chi^2 = 0.1231). In other words, this result confirms that exchange alliances have a significantly larger impact on patent applications in period t+1 than creation alliances. Being engaged in both types of alliance (1 1) has a significant positive effect, too. However, the effect of joint adoption is not significantly larger than the sum of the two exclusive collaboration strategies. Based on a one-sided test on the null that (1 0) + (0 1) - (1 1) < 0, we can conclude that the effect of joint adoption is not significantly larger than the effect of the sum both exclusive types of collaboration for the case of patent applications (Pr(T < t) = 0.9207). In other words, joint adoption does not lead to more patent applications than the sum of the effects of *exchange_alliances* and *creation_alliances*.

For the number of forward citations per patent, we find in line with our previous results, that joint R&D alone leads to more forward citations than *exchange_only* alone, which by itself does not have a significant impact on citations. Firms engaged in both types of alliances, again, do receive more citations per patent than non-collaborating firms, but not more than those solely engaged in creation alliances. Thus, the previous results are robust to the inclusion of these additional variables, accounting for the effect of joint adoption of both collaboration strategies.

Table 5: Pre-Sample Mean (PSM) Poisson Models (4,013 obs., 1,278 firms) with Joint Adoption

Variables *[exchange_only ; creation_only]*		PATENT APPLICAITONS		CITATIONS PER PATENT	
creation_only	(0 1)	0.564**	(0.236)	0.991***	(0.349)
exchange_only	(1 0)	1.307**	(0.515)	0.518	(0.619)
both	(1 1)	0.851***	(0.229)	0.647**	(0.266)
neither	(0 0)	reference category		reference category	
Log-Likelihood		-2,058.396***		-1,067.988***	

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Standard errors in parentheses are clustered, accounting for repeated observations at the firm level. All models contain a constant, industry, year dummies, and the set of control variables (not presented) as specified in the models presented in Table 4.

As a further test, we want to see the effects of the type of collaboration conditional on a firm's involvement in an R&D alliance at least once during the period under review. Deleting firms that never collaborated in the panel period from our sample reduced the number of observations to 1,599 corresponding to 357 different firms. The results on the number of patent applications are in line with the ones on the full sample presented in Table 4. On the number of citations per patent the effect of *creation_alliance* is less pronounced as before, but still positive and significant at the 10% level. Thus, the insights regarding the types of knowledge alliance are confirmed in the subsample of collaborating firms.

Finally, R&D collaboration is a potential source of endogeneity in our model, as firms' patenting activities and their collaboration strategies may depend on some common unobservable firm-specific factors, like for example innovation strategies to optimize a firm's patenting portfolio. Thus, although we used a lead of the dependent variable that rules out direct simultaneity, we want to test whether endogeneity is driving our positive results from collaboration on patenting. To do so, we conduct instrumental variable (IV) regressions. For reasons of comparison, we present the results from an OLS IV regression where the dependent variable is defined as log(*patents*+1) and log(*average_citationes*+1), respectively. We further performed IV Poisson regressions estimated by Generalized Methods of Moments (GMM).[xiv]

For the purpose of the IV regressions, we construct two instrumental variables that are correlated to the potentially endogenous variable of collaboration, but exogenous to the indivudual firm's patenting activity. The first instrument (*IV1*) is defined as the share of *collaborating* firms in the same industry (based on a 2-digit NACE code) and the same size class. Hence, this instrument captures the collaboration potential of firms active in similar technology areas. The more potential collaboration partners active in a technology directly related to a firm *i*'s main activity, the higher the probability that the given firm engages in a collaborative agreement (see e.g. Autant-Bernard et al. 2007 for an overview). Our second instrument (*IV2*), captures the number of years of experience a firm has in R&D collaboration

($IV2 \in [0,9]$). Indeed, a firm that has collaborated in the past is more likely to collaborate in the future. Given that past collaborations may have an impact on patenting activity, we control for such potential feedback effects in the IV Poisson models estimated by GMM by adding $patent\_applications_{t-1}$ and $average\_citations_{t-1}$ as additional regressors in the model.

We furthermore ran some statistical tests to verify the econometric validity of our instruments. As reported in Table 6, we find that our IVs are supported by statistical tests (the Hansen J test rejects over identification at the 1% level).[xv] As displayed in Table 6, the results from the IV models show that the positive effects of collaboration on patents and forwards citations do not alter when we control for potential endogeneity and feedback effects. Model 1 and 2 report the results from an ordinary IV OLS regression, and Model 3 and 4 from the IV Poisson regression estimated by Generalized Methods of Moments (GMM).[xvi]

Table 6: IV regressions controlling for potential endogeneity (2nd stage results; 4,013 obs., 1,278 firms)

	OLS IV		**IV POISSON**	
Variables	*ln(1+Patents)*	*ln(1+average citations)*	*Patents*	*average citations*
	Model 1	**Model 2**	**Model 3**	**Model 4**
collaboration	0.112 *	0.100 ***	0.623 *	1.443 **
	(0.058)	(0.037)	(0.368)	(0.721)
patent_applications$_{t-1}$			0.012 **	
			(0.005)	
average_citations$_{t-1}$				0.126 ***
				(0.015)
ln(meanPAT)	0.391 ***		0.594 ***	
	(0.038)		(0.070)	
d_meanPAT	-0.194 ***		-0.954 ***	
	(0.040)		(0.364)	
ln(meanCIT)		0.041		0.074
		(0.045)		(0.125)
d_meanCIT		-0.114		-1.578 ***
		(0.078)		(0.392)
ln(R&D)	0.224 *	-0.102	3.258 ***	0.596
	(0.129)	(0.071)	(0.814)	(1.970)
ln(age)	-0.027	-0.007	-0.173	-0.439 **
	(0.020)	(0.008)	(0.114)	(0.158)
ln(assets)	0.032 ** *	0.014 ***	0.350 ***	0.421 ***
	(0.007)	(0.004)	(0.076)	(0.096)
ln(capital_intensity)	-0.019 **	-0.006	0.002	-0.072
	(0.009)	(0.006)	(0.131)	(0.174)
group	-0.026 **	-0.010	0.308	0.367
	(0.013)	(0.009)	(0.350)	(0.508)
Test of excluded instruments (1st stage)	F = 501.96***	F = 552.28***		

Hansen J overid. test $chi^2(3)$	1.423	0.924	0.739	1.419

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Robust standard errors in parentheses are clustered by firm. The models contain a constant, industry and year dummies (not presented).

5. Conclusion and discussion

The intention of this article was to study the effects of knowledge alliances on patenting activity. Whereas our findings confirm previous work by suggesting a positive relationship between R&D alliances and patenting activity, they add to that literature by distinguishing between the type of knowledge alliance a firm is engaged in, and by differentiating how those different types of alliance impact both, patent quantity as well as patent quality.

Employing Poisson estimations that account for unobserved heterogeneity in the propensity to patent and testing the robustness of the estimation results in a series of checks, we find that knowledge exchange alliances have a significant positive impact on the number of patents filed, but not on the number of forward citations received per patent. Knowledge creation alliances, on the other hand, turned out to have a significant positive impact on forward citations received per patent, and hence on patent quality. These findings indicate that knowledge spillover effects beyond the joint project are weaker in exchange alliances than in creation alliances, pointing to the fact that the latter type of alliance seems to impact the overall technological value produced by the firm. This finding is in line with theoretical considerations that creation alliances promote the transfer of tacit knowledge which benefits the firms' overall technological performance. Inventions triggered via exchange alliances may build on more explicit know-how and thus are less likely to translate in firms' overall technological capabilities. On the other hand, given that codified knowledge is easier to copy, this type of alliance may increase the firms' incentives to seek patent protection and thus impacts the number of patents filed.

One could further hypothesize that, in line with recent findings on strategic patenting (Arundel 2001; Arundel and Patel 2003; Cohen et al. 2002; Blind et al. 2006; Thumm 2004), our results suggest that patenting of firms engaged in knowledge alliances may not only be used as a tool for protecting intellectual property rights, but also in a way aimed at building strategic patent portfolios. In other words, while creation alliances may provide incentives to file patents that are indeed aimed at protecting valuable inventions from imitation by others, exchange alliances may also drive "portfolio patenting", which has been shown to result in fewer citations for the individual patent in the portfolio (Blind et al. 2009).

Insights from this study complemented previous findings that stressed importance of taking alliance heterogeneity into account. By focusing on knowledge alliances, we were able to expand our understand on how the mode of knowledge interaction matters for technology advancement.

Despite all efforts, this study is not without limitations and future research will be needed to deepen the understanding of creation and exchange alliances and how they shape firms' technology management. In future research, it would be highly desirable to link collaborative R&D projects and their output more directly to the use of patents. It would moreover be insightful to take into account the impact of exchange and creation alliances on product market output and firm performance. Indeed, while the current analysis allows drawing conclusions with respect to firms' technological development, which, according to Mansfield (1986) indicates the first stage of successful innovation, we cannot draw conclusions of what he qualifies as the second stage, namely, successful commercialization. Moreover, especially for the case of exchange alliances, additional insights could be gained if the specific roles of the individual partners in an alliance would be known. Finally, the ideal empirical set up would have combined project-level as well as overall firm-level innovation performance. Such a setting would allow assessing the differences between direct and indirect knowledge spillovers and whether type of knowledge alliance plays a different role for both these performance levels.

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Endnotes:

[i] 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).

[ii] See Lavie et al. 2010 for a review of the literature on exploration-exploitation within and across organizations.

[iii] Application-specific integrated circuits.

[iv] See Hagedoorn et al. (2000) for a survey on firms' incentives to engage in R&D alliances. What they all have in common is that firms' expect the collaboration to be beneficial.

[v] It should be noted that while the patent counts are non-negative integers, the number of forward citations per patent are not strictly speaking count data, as the values are not necessarily integers. However, Wooldridge (2002, p. 676) points out that the Poisson estimator is correct and still has all desirable properties as long as the conditional mean is correctly specified even when the dependent variable is not an actual count. Robustness checks using the logged number of forward citations in a linear cross-sectional OLS regression as well as in a panel structure OLS regression have been estimated. The conclusions remained unchanged.

[vi] As a sensitivity test, we have estimated standard fixed- effect Poisson models, which did not yield different conclusions. These results are available from the authors as supplemental material upon request.

[vii] One solution could have been the use of a negative binomial (negbin) model since it allows for overdispersion. Even though the negative binomial addresses the limitations of the Poisson model by allowing the mean and the variance to be different and by adding a parameter that reflects unobserved heterogeneity among observations, the negative binomial model estimates would be inconsistent and inefficient if the true distribution is not negative binomial, while the poisson model is always consistent (Gourieux et al. 1984, Wooldridge 2002, p. 657). Based on the results obtained by a Hausman test on the similarity in the coefficients between a Poisson and a negbin estimation, we can conclude that negbin coefficients are not consistent in our case.

[viii] For the more recent patents in the sample, the window is truncated to citations in the years that were available. As stated however by Hall et al. (2005), the citation counts are inherently truncated, because at any point in time when collecting the citation count, we may miss out citations to that patent in the future.

[ix] It should be noted that we also tested using longer and shorter pre-sample periods as proxies for fixed effects in our model. However, given that the results were not very sensitive to this choice, we decided to use a 5-year-period which seems appropriate given the 10-year panel period.

[x] As a matter of illustration, the correlation between patents and citation counts is almost twice as high as the correlation between patents and average citations (0.3269*** for the former, against 0.1851*** for the latter). When the correlation is considered on the sample of patenting firms only, the correlation between patents and average citations is low and no longer statistically significant (with a correlation coefficient of 0.0455), while the correlation between patents and citation counts is still significant at a 1% level, and almost 5 times higher (0.2129***). Furthermore, in order to test the robustness of our findings, we weighted the forward citations by the average number of forward citation by technology class, based on a 4-digit IPC. The results were not affected by this weighting scheme.

[xi] The survey does not capture the exact start and end date of an alliance, but rather whether a firm had been engaged in an alliance during the two year period covered in each survey wave. Given that knowledge alliances are often formed for specific R&D projects running from several months to 2-3 years maximum (authors' calculation from IWT ICAROS database), this time structure seemed reasonable for our analysis. We further tested whether our findings were sensitive to experience in one specific type of alliance. No significant results were found for firms that were engaged in the same type of alliance in two consecutive waves.

[xii] The dummy for firms that did not receive any citations prior the sample start is negative and significant as one would expect, capturing the fact that firms that got citations are qualitatively different from those that either never patented or patented, but never received any citations for these patents.

[xiii] It should be noted that we experimented with non-linear specifications for firm size and firm age. The squared terms were, however, never statistically significant.

[xiv] See Windmijer and Santos Silva (1997) for technical details.

[xv] The criteria commonly used for evaluating the validity of instruments are not appropriate for IV Poisson estimation. As suggested by Staiger and Stock (1997) as rule of thumb, the partial F-statistic for the excluded instruments should be larger than 10 to ensure that instruments are not weak. The F-statistic exceeds 10 for both specifications of the OLS MODEL *(*see Table 6). However, it should be kept in mind that we should have estimated a binary response model at the first stage. For IV Poisson model no such rule of thumb exists, therefore we refrain from reporting Wald test statistics on the joint significance of the excluded instruments in the first stage, where the excluded variables were significant at the 1% level. Windmeijer and Santos Silva

(1997) remark that validity of the IVs can at least partially be settled by using the test of overidentifying restrictions.

[xvi] Details on the first stages of the OLS regressions can be obtained from the authors upon request.