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Quantity or Quality? Collaboration Strategies in Research and Development and Incentives to Patent

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Non-technical summary

Collaborative research and development (R&D) may be seen as a response to shifting knowledge environments enabling firms to cope with technological challenges. 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 may be specialization in expertise. However, narrowing expertise requires firms to seek complementary know-how elsewhere, for instance by collaborating in knowledge-intensive business areas like R&D.

While numerous previous studies found R&D alliances to be instruments 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), none of these studies paid attention to differences in the objective of the R&D collaboration and how these differences affect R&D productivity. Collaboration aiming at the joint generation of new knowledge, that is firms willing to undertake an R&D project jointly, may differ substantially from alliances aiming at the explicit exchange of already existing knowledge. This difference may translate into differences with respect to the alliances' effects on R&D productivity and eventually innovation output. Furthermore, while previous empirical studies found evidence for a positive effect of collaborations on innovation output, often measured in the number of patents, the effects on the technological value of these patents has not been studied to the same extent.

Using count data models controlling for unobserved heterogeneity for R&D-active manufacturing firms in Flanders in the period 2000 to 2009, this study aims to fill these gaps. We study the effects of R&D collaboration on patent activity in terms of quantity as well as quality differentiating between collaborative agreements by their declared objectives. The results suggest that being engaged in knowledge exchange alliances leads to more patent applications filed by the firms involved. However, once patent quality – as measured by the number forwards citations received in a five-year-window of the application date - is considered, we find knowledge creation alliances to lead to more valuable patents. In line with recent literature on strategic patenting, these results may indicate that patenting of collaborating firms is not only used to protect intellectual property, but also as a strategic tool. In other words, joint R&D may provide incentives to file patents that are indeed aimed at protecting valuable inventions from imitation by others, while exchange alliances drive "portfolio patenting" which has been shown to result in fewer citations for the individual patent.

Das Wichtigste in Kürze

Zusammenarbeit in Forschung und Entwicklung (F&E) stellt eine Reaktion auf sich zunehmend schnell verändernde Wissensumgebungen dar, die Unternehmen ermöglicht technologische Herausforderungen zu meistern. Wie Jones (2008) betont, erhöhen Innovationen den Wissenstock und somit die „Fort- und Weiterbildungslast" zukünftiger Innovatoren. Um dies zu kompensieren, können Unternehmen sich spezialisieren. Spezialisierung bedeutet aber auch, dass notwendiges komplementäres Wissen extern bezogen werden muss, beispielsweise durch Zusammenarbeit und Kooperationen in wissensintensiven Unternehmensbereichen wie der F&E.

Zahlreiche Studien unterstreichen daher die Bedeutung technologischer Zusammenarbeit für den Erwerb neuer Kompetenzen und für den Zugang zu spezialisiertem Wissen (e.g. Hamel, 1991; Hagedoorn, 1993; Hagedoorn and Schakenraad, 1994; Powell et al., 1996). Keine dieser Studien berücksichtigt allerdings Unterschiede in der Ausgestaltung von F&E-Zusammenarbeit im Hinblick auf den Inhalt und die Ziele solcher Allianzen. Zusammenarbeit mit dem Ziel gemeinsam neues Wissen zu schaffen, d.h. gemeinsame F&E Projekte durchzuführen, kann sich essentiell von solchen Allianzen unterscheiden, die den Austausch von bereits existierendem Wissen als wesentliches Ziel beinhalten. Diese Unterschiede können sich in der Wirkung der Zusammenarbeit auf die F&E-Produktivität und somit auf das Innovationsergebnis der beteiligten Unternehmen niederschlagen. Während bisherige Studien zwar Hinweise auf einen positiven Effekt von kooperativer F&E auf den Innovationserfolg - häufig gemessen an der Anzahl der Patentanmeldungen der beteiligten Unternehmen - fanden, blieb der Aspekt der Art der Kollaboration sowie des technologischen Wertes der resultierenden Patente weitgehend unbeachtet.

Mit dem Ziel diese Lücken in der Literatur zu schließen, untersucht die folgende Studie die Effekte von F&E-Kooperationen auf die Patentaktivitäten der beteiligten Unternehmen. Dabei unterscheiden wir zwischen Allianzen mit dem Ziel gemeinsam neues Wissen zu schaffen und solchen mit dem Ziel bestehendes Wissen auszutauschen. Die Datenbasis ist ein Panel F&E-aktiver Unternehmen in Flandern beobachtet über den Zeitraum 2000 bis 2009. Die Ergebnisse zeigen, dass Unternehmen in Austauschallianzen signifikant mehr Patente anmelden. Allerdings sind diese Patente nicht technologisch "wertvoller" als die nicht-kooperierender Unternehmen gemessen an der Zahl der Zitationen, die diese Patente im Durchschnitt in den fünf Jahren nach der Anmeldung erhalten. Wissenschaffende Allianzen, auf der anderen Seite, resultieren in wertvolleren Patenten. Im Einklang mit aktueller Forschung zu strategischem Patentieren deuten diese Ergebnisse darauf hin, dass kooperierende Unternehmen nicht ausschließlich zum Schutze ihres intellektuellen Eigentums patentieren, sondern auch aus strategischen Gründen. Mit anderen Worten, während gemeinsame F&E in der Tat Anreize schafft, resultierende Erfindungen Patentieren zu lassen, um diese wertvollen Erfindungen vor Imitation zu schützen, können Austauschallianzen zu Patentanmeldung mit dem Ziel ein Patentportfolio aufzubauen führen. Wie vorherige Forschung zeigt, ist diese Form des Patentierungsverhaltens dadurch gekennzeichnet, dass einzelne Patente innerhalb des Portfolios weniger Zitationen erhalten.

Quantity or Quality?
Collaboration Strategies in Research and Development and Incentives to Patent*

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Abstract

This study shows for a large sample of R&D-active manufacturing firms that collaborative R&D has a positive effect on firms' patenting in terms of both quantity and quality. When distinguishing between alliances that aim at joint creation of new knowledge and alliances that aim at exchange of existing knowledge, the results suggest that the positive effect on patent quantity is driven by knowledge exchange rather than joint R&D. Firms engaged in joint R&D, on the other hand, receive more forward citations per patent indicating that joint R&D enhances patent quality. In light of literature on strategic patenting, our results further suggest that knowledge creation alliances lead to patents that are filed to protect valuable intellectual property, while exchange alliances drive 'portfolio patenting', resulting in fewer forward citations.

Keywords: R&D Collaboration, Knowledge Exchange, Patents, Innovation, Count Data Models

JEL-Classification: O31, O32, O33, O34

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1. INTRODUCTION

Collaborative research and development (R&D) may be seen as a response to shifting knowledge environments enabling firms to cope with technological challenges. 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 may be specialization in expertise. However, narrowing expertise requires firms to seek complementary know-how elsewhere, for instance by collaborating in knowledge-intensive business areas like R&D.

Indeed, numerous previous studies found such R&D alliances to be instruments 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). Based on the presumption that R&D collaboration and knowledge alliances involve voluntary knowledge sharing and pooling of competencies, it has been argued that joint R&D not only reduces unintended spillovers to the partnering firm(s)[1], but also has the potential to increase R&D productivity (Brouwer and Kleinknecht, 1999; Van Ophem *et al.*, 2001; Branstetter and Sakakibara, 2002 among others).

R&D collaborations can take different forms from equity joint ventures to non-equity contractual arrangements.[2] Such alliances, however, may also differ in their design depending on their declared objective. Collaboration aiming at the joint generation of new knowledge, thus firms willing to undertake an R&D project jointly, may differ substantially from alliances aiming at the explicit exchange of knowledge. This difference may translate into differences with respect to the alliances' effects on R&D productivity and eventually innovation output.

However, while many studies analyze the effect of collaboration on innovation output, to the best of our knowledge, no study exists that distinguishes between *knowledge exchange alliances* (i.e. collaborations that aim at the exchange of already existing knowledge) and *knowledge creation alliances* (i.e. collaborations that aim at jointly developing new knowledge. The following study builds on the OECD R&D-survey that provides an explicit

[1] A large literature based on economic theory analyzed possible welfare benefits from R&D consortia stemming from the internalization of knowledge externalities and hence, improved incentives to invest in R&D which spur technological advances (see e.g. Katz 1986, D'Aspremont and Jaquemin 1988, or Leahy and Neary 1997). Empirical studies, therefore, focused on the effects on the technology performance of firms engaged in R&D alliances assuming that improved R&D output is welfare enhancing.

[2] See Hagedoorn *et al*. (2000) and Caloghirou *et al*. (2003) for comprehensive overviews.

question on the objective of a firm's R&D collaboration that allows us to differentiate between firms engaging in either one (or both) these types of collaboration.[3]

Moreover, the effect of collaborative R&D on the value of the generated knowledge has received little attention so far. While previous empirical studies found evidence for a positive effect on innovation output, often measured in the number of patents, the effects on the value or technological relevance of these patents has not been studied to the same extent. The following analysis aims to fill these gaps by studying the effects of R&D collaboration on patent activity in terms of quantity as well as quality, differentiating between collaborative agreements by the declared objectives of the alliance.

For the purpose of this study, we focus on R&D-active manufacturing firms in Flanders observed in the period 2000 to 2009. Estimating Poisson regression models that account for unobserved heterogeneity and feedback effects, our results suggest that R&D collaborations increase patent output. In particular, being engaged in knowledge exchange alliances leads to more patent applications filed by the firms involved. However, once patent quality – as measured by the number forwards citations received in a five-year-window of the application date - is considered, we find knowledge creation alliances to lead to more valuable patents. In line with recent studies on strategic patenting (e.g. Blind *et al*., 2009), these results point to the conclusion that exchange alliances may induce strategic patenting which increases the number of patent applications, but leading to a patent portfolio of strategic rather than technological value.

The reminder of this article is structured as follows. The following two sections review the related literature and set out our hypotheses. The subsequent sections describe the set-up of our econometric analysis and the data before we present the results and conclude.

2. RELATED LITERATURE

The impact of collaboration on innovation output has been of interest in economic literature for many years now. In line with this literature we analyze if and to what extent, innovation output in terms of patent quality and quantity differs depending on whether a firm engages in a (certain type of) collaboration for its R&D activities.

The empirical literature studying the relationship between R&D collaboration and innovation performance at the firm level so far can be roughly divided into three streams.

[3] More precisely, the survey asks the question of whether an existing R&D collaboration was set up to combine resources and abilities for the joint undertaking of an R&D project with the ambition to generate new knowledge or whether the collaboration aims at exchanging existing knowledge by one or several consortium partners in order to enable or facilitate its commercialization.

First, drawing from the argument that patents as tools to appropriate returns from R&D reflect successful R&D outcome, several studies investigated the effects of collaborative R&D on the patent productivity of the firms involved. Firms involved in R&D partnerships may benefit from a multitude of channels, like gaining access to complementary technological, marketing and manufacturing know-how and in some cases financial resources that reduce time and resource requirements which speeds up the R&D process (e.g. Mody, 1993, Mowery *et al*., 1996). Therefore a positive relationship is expected and indeed, these studies covering a variety of countries and industries generally find support for this hypothesis.

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. Czarnitzki and Fier (2003) show that collaborating firms in Germany are more likely to patent than non-collaborating firms. 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. Sampson (2005) finds a positive effect of recent collaboration experience on patent output of participating firms in the telecom equipment industry. Czarnitzki *et al.* (2006) find positive effects of collaboration on patent applications in Finland and conclude that innovation output could be improved by innovation policy that provides incentives to collaborate. Peeters and van Pottelsberghe (2006) find a positive relationship between an outward-oriented innovation strategy reflected in R&D partnerships and the size of firms' patent portfolios. Finally, Vanhaverbeke *et al*. (2007) find a positive relationship between technology alliances and patent citations. Thus, with the exception of the latter study, previous evidence reports evidence for a positive effect of collaboration on the quantity of patents rather than on their quality.

In the second stream of literature, studies do not use patents, but direct measures of innovation output. Deeds and Hill (1996) study 132 biotechnology firms and the effects of their alliance activity on the rate of new product development. They find an inverted U-shape relationship between the number of alliances and new product development, indicating that the beneficial effects diminish as the number of alliances increases and that at high levels the cost of entering an additional alliance outweigh the benefits. Schilling and Phelps (2007) argue that the design of alliance networks affects their potential for knowledge creation. When studying 1,106 firms in 11 industry-level alliance networks, they find firms in alliance networks that exhibit both high clustering and high reach measured in short average path lengths to a wide range of firms, have greater innovative output than firms in networks that do not exhibit these characteristics. Hoang and Rothaermel (2010) investigate 412 R&D projects of large pharmaceutical companies in the period 1980 and 2000 and show that exploitation alliances have a positive effect on R&D project performance as measured by the successful termination of the project, while exploration alliances have a negative effect. Most recent, Gnyawali and Park (2011) analyze in a case study setting collaboration between 'industry giants' and conclude that such R&D alliances foster technological advances.

The third stream uses - instead of patents – output measures derived from firm-level survey data. These output indicators include, for instance, firms' sales from product innovations and sales growth, but also more general performance measures like employment growth, and the firms labor productivity (e.g., 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). These studies generally find positive effects, but do not distinguish the type or objective of collaboration.[4]

Our present study follows the first stream of literature using patent data as key indicator of interest, because of mainly two reasons. First, patents are a widely used and recognized measure in the literature.[5] Indeed, they do not only constitute a measure of technological effectiveness of R&D which is comparable across firms and even industries (Katila, 2001; Penner-Hahn and Shaver, 2005; Somaya *et al*., 2007), they also confer property rights upon the assignee and therefore have a direct economic impact. Second, given that forward citations per patent are a recognized measure of the quality of the underlying technology or invention, using patents as our key indicator allows us to analyze the impact of the (type of) collaboration on both, patent quantity as well as quality, an aspect that so far received much less attention.

Furthermore, the incentives to patent a new invention also depend on firms' innovation strategy. We therefore argue that using patents as indicators allows us to study effects of collaboration also on patent strategy. Previous studies employing patent indicators as success

[4] Belderbos *et al*. (2004a) study differences between types of partners on sales of innovative products for a sample of Dutch firms and find positive effects from collaboration with universities and competitors.
[5] See Griliches (1990) for a survey.

indicator so far may underestimate the strategic role of patents and in particular the fact that collaborative R&D directly affect firms' patent strategy. Hence, by differentiating between collaboration agreements aimed at knowledge exchange and at joint knowledge creation, the current study intents to contribute to the existing literature in terms of taking into account heterogeneity in the declared purpose of R&D alliances and by considering the effects on patent quantity as well as quality.

3. HYPOTHESES

3.1 Collaboration and innovation performance

Previous well-known 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 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[6], we therefore expect a positive effect from R&D collaboration on patenting as a result of the broadening of the firms' knowledge and the acceleration of their innovation processes. Moreover, since the benefits from collaboration on a key corporate activity like R&D comes at the cost of secrecy, collaboration may likely 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 especially 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:

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 applied for, the inventor (and/or the patent examiner) notes all of the previous patents that the patent is based on. These citations, thus, identify the

[6] 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.

technological lineage of the invention. The number of forward citations received is therefore often used as a measure for patent quality as they can serve as an indicator for the technological importance of the patent. Traijtenberg (1990) and Harhoff *et al*. (1999, 2003) provide evidence of the correlation between patent value and citations received in subsequent patent applications. Also Hall *et al*. (2005) provide empirical evidence for a strong positive correlation between these citations and the estimated market value of the underlying invention. Patent citations are thus accepted as a reliable value indicator.[7] Because of the value creation potential of collaborations that pool firms' resources and exploit possible complementarities in expertise, we expect collaboration not only to lead to more patents, but also to more valuable patents.

Hypothesis 2: Patents filed by R&D collaborators receive on average more forward citations (in a five year window after the filing date) than patents filed by non-collaborative firms.

3.2 Creation Alliances, Exchange Alliances and innovation performance

Despite the substantial literature on R&D collaboration in both strategic management and industrial organization, surprisingly little attention is being paid to the different purposes of R&D alliances and how they translate into effects on output indicators like patents.

Firms engaged in *knowledge creation alliances* may 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. Indeed, rather than the firms seeking to absorb the knowledge of the partner, 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).[8] It can thus easily be argued that a joint R&D undertaking has a larger impact on R&D outcome as it involves a deeper dig into the partners' competencies and may allow exploitation of complementary assets in the knowledge production process. Moreover, joint R&D involves direct on-the-job exchange between R&D employees, allowing the transfer of tacit knowledge that goes beyond the current project (Mowery *et al*., 1996). Even in the case of co-specialization, firms learn from the partner's processes and may benefit from that for R&D outside the collaboration.

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[7] Numerous authors have concentrated on the analysis of indicators to determine the economic value of patents. See Lanjouw and Schankerman (2004) for an overview. However, one limitation to the use of patent citations is that citations can indicate further technological development and hence a depreciation of the invention over time. That is why it is resonable to limit the time window for forward citations when interpreting them as quality indicators.

[8] An example for a joint R&D undertaking is 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 effects from *knowledge exchange alliances* on firms' innovation output and their incentives to patent 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 of the biotechnology firm usually without actively contributing to the development of new knowledge. Given that knowledge exchange alliances do not involve joint research and development activities, they may trade explicit knowledge rather than tacit knowledge that would only be transmitted during a joint project. 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 competencies and transfer of tacit knowledge.

Moreover, as 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 patents filed, i.e. on the number of forward citations recieved. Indeed, 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. Indeed, in the case of joint R&D, the main purpose of a patent application would generally be the protection of the innovation rather than a strategic motive. As staged by Blind *et al*. (2009), firms using patents in non-strategic ways, but for their initially intended purpose of protecting innovations from imitation, receive on average a higher number of forward citations for their patents than companies that emphasize the strategic motives like blocking and exchange. 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 measured by the number of forward citations received than knowledge exchange alliances.

3.3 Collaboration and strategic motives to patent

As argued before, we also expect collaboration to affect firms' incentives to patent. Strategic patenting literature suggests that firms patent for many more reasons than the protection of their intellectual property through the exclusion of others.[9] According to Arundel and Patel (2003) all patents that are filed for motives other than the protection of the inventions in order to appropriate returns from the firms' R&D investments can be defined as strategic. Firms may strategically chose patent breadth and thus, for instance, may file more, but smaller patents or may refrain from patenting certain innovations. Thus, strategic motives to patent may have a substantial impact on the overall number of patent filings (Arundel, 2001; Arundel and Patel, 2003; Cohen *et al*., 2002; Blind *et al*., 2006; Thumm, 2004).

These strategic motives to patent comprise the possibility to block competitors in order to secure the firms' technological space against competitors which stresses the importance of patent portfolios compared to individual patents. Patents have also become tradable assets that play a crucial role for firm value in many technological fields. Additionally, advancements in the market for technology allow patent holders active in complex technologies to generate licensing revenues (Gulati, 1998; Eisenhardt and Schoonhoven, 1996; Arundel and Patel, 2003; Noel and Schankerman, 2006).

If the prevailing motive to patent is the protection of the firms' technological knowledge base compared to strategic motives, one can assume, as explained in the previous hypothesis, that the firms expect the protected invention to be rather valuable. If, however, blocking of competitors or other strategic reasons are the key motives of filing a patent, these objectives can be achieved by patents of rather mediocre quality (Blind at al. 2009). Moreover, blocking competitors can be related to a higher number of patents per se as blocking will be more successful if competitors are confronted with a higher number of patents claiming different aspects of a technology. Hence, the average quality of strategic patents is likely to be lower.

A similar argument can be made for firms intending to use their patent portfolio as bargaining chips in future R&D collaborations. Hall and Ziedonis (2001) for instance show that patents facilitate division of competencies in the semi-conductor industry since the increasing complexity of products requires the combination of several technologies. Firms can therefore signal their technological competencies by a large patent portfolio. Thus, if the collaboration induces strategic patents as opposed to collaboration resulting in relevant and valuable technology where the main purpose of the patent lies in IP protection, we expect that such

Hypothesis 5: Collaboration leads to a higher number of patent applications, but a lower number of forward citations for each of these patents.

[9] Several surveys provide evidence on the strategic value of patents (see e.g. Harabi 1995; Cohen *et al*. 2002; Blind *et al*. 2006).

4. RESEARCH DESIGN, METHODOLOGY AND DATA

4.1 Patent production function and econometric models

The aim of the following analysis is to investigate the role played by R&D collaboration on firms' patenting behavior. Indeed, when undertaking R&D activities, a firm can choose between (i) entering a collaborative agreement for the undertaking of its R&D activities and, if it does so, (ii) between whether this agreement should be based on joint knowledge creation or on the mere exchange of already existing knowledge.

Based on a panel of Flemish manufacturing firms with at least 5 employees (data to be described in the following section), we test the hypotheses derived in the previous section. In a first step, we are therefore interested in whether the different types of collaborative agreement 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 collaboration alliance impacts patent quality. In order to investigate this phenomenon, we count the number of times subsequent patent applications refer to filed patents of a firm in our sample as relevant prior art. Forward citations are typically interpreted as proxy for the importance, the quality or the significance of a patented invention. Previous studies have shown that forward citations are highly correlated with the social value (Trajtenberg, 1990) and the private value of the patented invention (Harhoff *et al*., 1999, Hall *et al*., 2005). Furthermore, forward citations reflect the economic and technological importance as perceived by the inventors themselves (Hall *et al*., 2005) and knowledgeable peers in the technology domain (Albert *et al*., 1991).

In order to explore our research questions empirically, we estimate a patent production function of the type first introduced by Pakes and Griliches (1980). The patent production function relates the number of patent applications made by a firm in a given year 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:

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

where $PAT_{i,t+1}$ 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.[10]

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. In line with the literature (see e.g. Hall and Ziedonis, 2001; Somaya *et al*., 2007), the remaining overdispersion, as reported 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 favour of a model where the variance is proportional to the mean (Wooldridge, 1999).[11] 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*.

Finally, the base line results will be contrasted to a series of extensions and robustness checks, taking potential endogeneity of collaboration into account, the fact that some firms do

[10]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.

[11] One solution could be 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 (Gourieux *et al*., 1984).

both types of collaboration simultaneously as well as potential correlation between past and future patenting activities. With regards to potential remaining serial correlation, we perform a robustness check estimating Generalized Estimation Equation (GEE) population-averaged models allowing for an autoregressive correlation of order one.

4.2 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. This 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 the end of 2011. 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 distribution of firms according to this classification in the sample is displayed in Table A.1 in the Appendix. The final sample contains a total number of 4,013 observations from 1,278 different firms, resulting in an unbalanced panel. On average, each firm is observed 3.1 times (min = 2, max = 9) in the period of interest.

Outcome variable

The outcome variable *PAT* is measured as the count of patents filed by firm *i* in period *t+1*. This allows us to see if collaboration in R&D activities in period *t*, as well as the type of the collaboration, has an impact on patenting activities in period *t+1*. Our second dependent variable (*AV_CITES*) is measured as the count of forward citations per patent received in a 5-year-window after the filing year. 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 (see Table 1).

R&D collaboration

The central variables in our analysis are related to the collaboration pattern of the firms. First, from the survey we derive a dummy variable equal to one if a firm collaborates in its R&D activities *(CO),* irrespective of the purpose of the alliance. Second, the survey distinguishes the type of collaboration which allows us to account for heterogeneity in the objectives of the collaborative engagement.

A collaboration may be set up to combine resources and abilities for a joint R&D project with the ambition to generate new knowledge. Such arrangements are covered by the dummy variable *CO_JOINT* that takes the value 1 if the firm reported that it was involved in such an agreement in the respective year. Another form of collaboration aims at the exchange of existing knowledge (*CO_XCHANGE*). Firms may be willing to reveal part of their technological know-how in exchange of access to that of the partner firm. Whereas the literature so far has focused on either R&D collaboration in general or on joint R&D, taking into account the knowledge exchange motive may add to the understanding of the effects on the firms' patenting activities.

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 collaboration agreements 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 labour-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 (*KAPINT*). 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(prePat)* and *d_prePAT (*as well as *ln(preCIT)* and *d_preCIT)* are included to control for the 'fixed effect' related to the firms' unobserved propensity to patent. The variable *ln(prePat)* is the logged average number of patents in the 5 years prior the beginning of our panel and *d_prePAT* is a dummy variable that takes the value one if the pre-sample patent mean is equal to zero. *Ln(preCIT)* 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_preCIT* 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.

Summary statistics of the main variables used in our models are displayed in Table 1.[12] 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 variable			
PAT	patent count	0.496	3.429	0	76
AV_CITES	citations per patent	0.113	0.998	0	27
		Control variables			
CO	dummy	0.265	0.441	0	1
CO_JOINT	dummy	0.235	0.424	0	1
CO_XCHANGE	dummy	0.211	0.408	0	1
ln(prePAT)	pre-sample patents$_{1995\text{-}1999}$	0.106	0.703	-1.609	6.002
d_prePAT	dummy (no pre sample patents)	0.847	0.360	0	1
ln(preCIT)	pre-sample citations$_{1995\text{-}1999}$	0.176	0.795	-1.856	6.444
d_preCIT	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(KAPINT)	fixed assets / employees	3.293	1.026	0	6.381
ln(R&D)	R&D empl/ employees	0.059	0.101	0	0.693

5. RESULTS

The main results from the PSM Poisson models are reported in Table 2. Column one shows the estimates of the base model, where we analyse the impact of any type of collaboration on patenting activity (Model 1). Conform to expectations, we find a positive effect of collaboration in general (*CO*) 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. When looking at the results of Model 2, distinguishing between firms involved in collaboration that aimed at joint knowledge creation and those aimed at knowledge exchange, it turns out that being engaged in exchange alliances has a positive effect on the number of

[12] Table A.2 in the Appendix shows cross correlations between the main variables used in the analysis. Table A.1 displays the variables for each industry group.

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 to find a larger effect of joint knowledge creation on patent applications. However, those findings confirm *Hypothesis 5*, implying that exchange collaborations may lead to patents filed for strategic reasons like for instance patent portfolio considerations rather than by motives to protect an individual invention. As expected, the effect of *ln(R&D)* as a measure for direct input in the patent production function is positive and significant. The 'fixed effect' is also highly significant, pointing to the importance of controlling for unobserved heterogeneity.

Table 2: Pre-Sample Mean (PSM) Poisson Models (4,013 obs., 1,278 firms)

Variables	PATENT APPLICAITONS$_{t+1}$ (*PAT*)		CITATIONS PER PATENT (*AV_CITES*)	
	Model 1	**Model 2**	**Model 3**	**Model 4**
CO	0.739 ***		0.762 ***	
	(0.218)		(0.249)	
CO_JOINT		0.166		0.961 ***
		(0.283)		(0.323)
CO_XCHANGE		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(KAPINT)	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).

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 collaboration get more often cited as prior relevant art than patents that get filed by firms that do not collaborate for their R&D activities. Model 4 distinguishes between creation and exchange alliances and finds opposite results from Model

2. In terms of patent quality, joint knowledge creation shows 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*, hypotethizing that creation alliances trigger quality, as opposed to exchnage alliances triggering quantity rather then quality as suggested in *Hypothesis 5*. Hence, this 'quantity-quality tradeoff' shown by Models 2 and 4, is in line with the excpetations from *Hypotheses 4 and 5.*

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.[13] 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.[14]

6. 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.

a) Controlling for recent patenting: the Exponential Feedback Model (EFM)

So far neglected in our analysis is the argument that patenting activity in the *recent* past is an important determinant of current outcomes and could as a consequence cause serial corelation. As a consequnece, the omission of this recent patenting activity may bias the results. In order to account for such 'feed forward effects' on future patenting, we estimate a

[13] 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.

[14] 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.

so-called exponential feedback model (EFM) using a pooled Poisson Maximum Likelihood Estimation method (see Blundell *et al*., 1995b). An alternative to the EFM would be the Linear Feedback Model (LFM, see Blundell *et al*., 2002). However, the LFM does better when the mean of Y is high and proportion of zeros small, whih is not the case with our data. Hence, given the large number of zeros in our dependent variable, especially in the number of forward citations, the EFM is more appropriate in our case (Cameron and Trivedi 2005, p. 806). The model can be written as

$$E\left(PAT_{i,t+1} \middle| X_{i,t}\right) = \exp\left(\rho PAT_{i,t-1} + \beta X_{i,t} + \gamma_i\right) \qquad (2)$$

where $PAT_{i,t-1}$ enters as additional regressor in the exponential term. The model for the number of citations per patent is defined analogously.

As shown in Table 3, our results hold if we allow for a one-year- lagged value of patent applications as additional regressor. Even though the significance of PAT_{t-1} and $\mathrm{AVCITES}_{t-1}$ illustrates the validity of this approach, the statistical significance of our main explanatory variables shows that our model does not lose its explanatory power due to the additional regressor. When comparing the results of the PSM model and the EFM (compare Tables 2 and 3), we see that the coefficient of the lagged patent variable is very small, and that the main explanatory variables' coefficient is close to the one of the main model. In terms of forward citations, the lagged variable's coefficient is higher, and the coefficients of (the types of) collaboration, slightly smaller than in the main model.

Table 3: Exponential Feedback Model (EFM) with pre-sample mean (4,013 obs., 1,278 firms)

Variables	PATENT APPLICAITONS$_{t+1}$ (*PAT*)		CITATIONS PER PATENT (*AV_CITES*)	
	Model 1	**Model 2**	**Model 3**	**Model 4**
CO	0.797 ***		0.593 **	
	(0.218)		(0.239)	
PAT$_{t-1}$	0.013 **	0.012 **		
	(0.005)	0.005		
AVCITES$_{t-1}$			0.128 ***	0.128 ***
			(0.013)	(0.013)
CO_JOINT		0.243		0.843 **
		(0.290)		(0.335)
CO_XCHANGE		0.516 **		-0.369
		(0.256)		(0.257)
ln(meanPAT)	0.609 ***	0.6 ***		
	(0.072)	(0.072)		
d_meanPAT	-0.933 ***	-0.975 ***		
	(0.337)	(0.334)		
ln(meanCIT)			0.076	0.086
			(0.100)	(0.100)
d_meanCIT			-1.623 ***	-1.584 ***
			(0.382)	(0.394)
ln(R&D)	3.285 ***	3.375 ***	1.795	1.886
	(0.816)	(0.833)	(1.503)	(1.488)
ln(AGE)	-0.155	-0.159	-0.378 **	-0.379 **
	(0.113)	(0.113)	(0.153)	(0.149)
ln(ASSETS)	0.321 ***	0.33 ***	0.487 ***	0.487 ***
	(0.085)	(0.086)	(0.091)	(0.089)
ln(KAPINT)	0.074	0.065	-0.17	-0.183
	(0.132)	(0.133)	(0.172)	(0.170)
GROUP	0.257	0.255	0.425	0.453
	(0.338)	(0.341)	(0.496)	(0.497)
Wald $chi^2(20)$	3,017.62 ***	3,175.07 ***	1,755.29 ***	1,683.83 ***
Joint sign. of industries $chi^2(3)$	5.70	6.63 *	10.28 **	9.54 ***
Joint sign. of years $chi^2(8)$	68.39 ***	63.59 ***	25.51 ***	23.47 **

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).

b) Controlling for joint adoption of collaboration strategies

Given that a considerable amount of firms in our sample undertake both types of collaboration simultaneously, we want to check whether our findings are confirmed if we i) drop the firms that are engaged in both types of collaboration 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 (*CO_JOINT, CO_XCHANGE*).[15]

[15] See Table A.2.

For that purpose of testing i) we drop all firms that were engaged in both types and perform the models on the remaining 3,283 observations. Dropping these firms naturally results in an insignificant correlation between the two variables *CO_JOINT* and *CO_XCHANGE*. As can be gathered from Table 4, the main findings remain unchanged. As expected, the coefficient of collaboration (Model 1) remains statistically significant. With regards to the type of collaboration a firm is involved in, we find, in line with our previous findings, that knowledge exchange alliances have a significant positive effect on the number of patent applications (Model 2). Compared to our previous results where we did not find a significant effect of knowledge creation alliances on patent application, when using only the sub-sample of firms that engage in either one type of collaboration, 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.

With regards to patent quality, we find, like for the full sample, that patents filed by firms engaged in any type of collaboration get significantly more forward citations per patent compared to firms that are not engaged in collaboration for their R&D activities (Model 3). Similarly, we find that patents filed by firms engaged in creation alliances receive significantly more forward citations than patents filed by firms that are engaged in exchange alliances (Model 4).

Table 4: Pre-Sample Mean (PSM) Poisson Models, excluding firms that do both types of cooperation (models 1-4) and excluding non-collaborators (models 5-6)

Variables	PATENT APPLICAITONS$_{t+1}$ (*PAT*)		CITATIONS PER PATENT$_{t+1}$ (*AV_CITES*)		PATENT APPLICAITONSt+1 (PAT)	CITATIONS PER PATENTt+1 (AV_CITES)
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
CO	0.628 **		1.027 ***			
	(0.246		(0.339)			
CO_JOINT		0.440 **		1.144 ***	0.059	0.591 *
		(0.223)		(0.387)	(0.271)	(0.349)
CO_XCHANGE		1.336 ***		0.504	0.456 **	-0.274
		(0.446)		(0.627)	(0.229)	(0.309)
ln(meanPAT)	0.616 ***	0.601 ***			0.609 ***	
	(0.100)	(0.104)			(0.076)	
d_meanPAT	-1.331 ***	-1.421 ***			-0.820 **	
	(0.332)	(0.325)			(0.386)	
ln(meanCIT)			0.099	0.099		0.170
			(0.095)	(0.098)		(0.158)
d_meanCIT			-1.594 ***	-1.548 ***		-1.748 ***
			(0.456)	(0.475)		(0.546)
ln(R&D)	3.836 ***	3.824 ***	0.644	0.479	2.081 ***	4.157 **
	(0.890)	(0.763)	(1.845)	(1.968)	(0.794)	(1.835)
ln(AGE)	-0.522 **	-0.538 **	-0.553 ***	-0.554 ***	-0.080	-0.542 ***
	(0.213)	(0.217)	(0.171)	(0.170)	(0.134)	(0.208)
ln(ASSETS)	0.431 ***	0.459 ***	0.594 ***	0.575 ***	0.261 ***	0.610 ***
	(0.098)	(0.101)	(0.106)	(0.115)	(0.079)	(0.165)
ln(KAPINT)	-0.308 **	-0.308 **	-0.222	-0.220	0.123	-0.299
	(0.133)	(0.124)	(0.191)	(0.194)	(0.172)	(0.291)
GROUP	-0.168	-0.202	0.077	0.115	0.418	0.482
	(0.392)	(0.393)	(0.588)	(0.607)	(0.475)	(0.575)
Wald $chi^2(20)$	3,697.91 ***	4,016.18 ***	386.41 ***	398.87 ***	2102.51 ***	230.31 ***
Joint sign. of industries $chi^2(3)$	5.32	5.86	10.85 **	9.81 **	16.47 ***	6.47 *
Joint sign. of years $chi^2(8)$	8.49	9.34	12.90	14.11 *	79.22 ***	13.77 *
# observations	3,283 of 1,184 firms	3,283 of 1,184 firms	3,283 of 1,184 firms	3,283 of 1,184 firms	1,599 of 357 firms	1,599 of 357 firms

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).

Next, we perform a robustness test as described in ii) and test on the full sample of 4,013 observations whether the joint adoption of both collaboration strategies has an added value compared to doing only one. For this purpose, we estimated the models as in equation (1), but additionally include a set of dummy variables for the different strategy combinations: *XCHANGE_only* (1 0), *JOINT_only*, (0 1) *NEITHER* (0 0), *and BOTH* (1 1). Table 5 presents the main results from these estimations.[16] The results show that for the number of patent applications in t+1, any collaboration strategy has a significant positive impact compared to not collaborating. In line with previous results, *CO_JOINT* alone (0 1) has a signficantly smaller effect than *CO_XCHANGE* alone (1 0). Being engaged in both types of collaboration (1 1), however, does not lead to more patent applications than *CO_XCHANGE* alone, i.e. the z-test of (1 1) - (1 0) > 0 is rejected. Hence, we can conclude that there is no complementarity between both types of collaboration.

For the number of forward citations per patent, we find in line with our previous results, that joint R&D alone (*CO_JOINT)* leads to more forawd citations than *CO_XCHANGE* alone. Firms engaged in both types of collaborations, again, do receive more citations per patent than non-collaborating firms, but not more than those solely engaged in *CO_JOINT.* Thus, the previous results are robust to the inclusion of the effect from joint adoption of both collaboration strategies and additionally reject the presumption that the two forms of collaboration are strategic complements.

Table 5: Pre-Sample Mean (PSM) Poisson Models (4,013 obs., 1,278 firms) with joint engagement in both alliance types

Variables *[CO_XCHANGE; CO-JOINT]*	PATENT APPLICAITONS (*PAT*)		CITATIONS PER PATENT (*AV_CITES*)	
0 1	0.564**	(0.236)	0.991***	(0.349)
1 0	1.307 **	(0.515)	0.518	(0.619)
1 1	0.851 ***	(0.229)	0.647**	(0.266)
0 0	reference category		reference category	
Wald chi2(21)	3,224.12***		498.65***	

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 2.

c) Effects of the type of collaboration conditional on involvement in an R&D alliance

So far, the sample contained firms engaged in a collaboration as well as firms that had never collaborated. Thus, we estimated average effects of collaborating firms compared to non

[16] The full estimation results from this exercise are available on request from the authors.

collaborating firms. Now, we test if our key insights hold if we consider only firms that were enaged at least once in an R&D alliance during the period under review and thus test whether conditional on collaborating, the two different types of collaboration differ in their effect on patent quantity and quality. Deleting non-collaborators from our sample reduced the number of observations to 1,599 units, corresponding to 357 different firms. Models 5 and 6 of Table 4 present the results. The results on the number of patent applications are in line with the ones on the full sample presented in Table 2. On the number of citations per patent the effect of *CO_JOINT* is less pronounced as before, but still positive and significant at the 10% level. Thus, the insights reagrding the types of collaboration are confirmed in the subsample of collaborating firms.

d) Controlling for potential endogeneity

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 in place to optimize a firm's patenting portfolio[17]. Similarly, one could argue that a firm chooses its collaborators ex-ante, based for instance on the patent stock of their potential R&D partner which signals the technological interest of the latter and hence provides firms with incentives to patent. In this case, the causality would go from patents to collaborations and not vice-versa. 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(PAT+1) and log(AV_CITES+1), respectively. We further performed IV Poisson regressions estimate by Generalized Methods of Moments (GMM).[18]

For the purpose of the IV regressions, we construct four instrumental variables that are correlated to the potentially endogenous variable of collaboration, but rather exogenous to patenting activity. The first instrument (*PC_COOP*), is defined as the share of collaborating firms belonging to the same region (based on a 2-digit zip code) and the same industry (based on a 2-digit NACE code). Hence, this instrument captures the collaboration potential of firms in the same region belonging to the same industry. The more potential collaboration partners

[17] Indeed, as shown by Hall and Ziedonis (2001), many firms set precise goals of the number of patents they want to apply for in a given year. In line with these goals, the number of patent applications filed by firms has risen considerably over the last 2 decades. However, this increased volume of patent applications appears to reflect a deeper reach into the existing pool of inventions rather than a shift in R&D activities per se.

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

available within geographic proximity and active in a technology directly related to a firm i's main activity (see e.g. Autant-Bernard *et al*., 2007 for an overview), the higher the probability that the given firm engages in a collaborative agreement. Our second instrument (*YEXP*), captures the number of years of experience a firm has in R&D collaboration (*YEXP* ∈ (0,9)). Indeed, a firm that has collaborated in the past is more likely to collaborate in the future.

The third instrument is a dummy variable equal to 1 if a firm qualifies as a small or medium-sized firm (*SME*). The first reason for the inclusion of this dummy relates to the nature of R&D activities. Since R&D often exhibits economies of scale, it might well be that only a consortium of firms has the necessary resources, both financially and physically, to undertake larger, more complex and more expensive research projects that are common nowadays. This is particularly true for SMEs. The second reason relates to the incentive to collaborate in light of receiving a potential subsidy form the Flemish Innovation Agency (the IWT). Indeed, while the IWT attributes subsidies to collaborators as well as to non-collaborators, the former get an additional 10% of the total cost of an R&D project covered, provided that at least one partner is an SME. Hence, given that for the same cost of applying for a grant an SME can receive an additional 10% covered if it collaborates in its R&D activities, this might encourage small and medium sized firms to enter R&D collaborations. Finally, given that we do not restrict our analysis to inter-firm collaboration but that we also have industry-science collaborators in our sample, we create a fourth instrument, being a dummy variable equal to one if a firm is located close to a university, based on a 2-digit zip code level (*UNICLOSE*). Being located close to a university may increase the propensity to collaborate, but has no direct effect on patenting.

Even though, admittedly, those instruments might not be the most powerful ones for our case, it has to be born in mind that it is a serious challenge to find instruments in the case of collaboration and patenting, because many variables affect both activities at least to some extent. Hence, although the instruments might not be ideal, the economic intuition behind the chosen instruments is valid and they are supported by the statistical test (the Hansen J test rejects over identification at the 1% level). As a consequence, the IV regressions provid a valid robustness check.[19] As shown by Table 6, the results from the IV models show that the

[19] 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,

positive effect of collaboration on patents and forwards citations do not alter when we control for potential endogeneity. 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).

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

	OLS IV		IV POISSON	
Variables	*ln(1+PAT)*	*ln(1+AV_CITES)*	*PAT*	*AV_CITES*
	Model 1	**Model 2**	**Model 3**	**Model 4**
CO	0.106 *	0.100 ***	0.771 **	1.632 **
	(0.054)	(0.035)	(0.393)	(0.767)
ln(meanPAT)	0.391 ***		0.663 ***	
	(0.038)		(0.070)	
d_meanPAT	-0.194 ***		-0.666 **	
	(0.040)		(0.308)	
ln(meanCIT)		0.041		0.156
		(0.045)		(0.111)
d_meanCIT		-0.114		-1.476 ***
		(0.078)		(0.436)
ln(R&D)	0.233 *	-0.102	3.410 ***	2.086
	(0.128)	(0.070)	(0.715)	(1.514)
ln(AGE)	-0.027	-0.007	-0.187	-0.449 ***
	(0.020)	(0.008)	(0.116)	(0.173)
ln(ASSETS)	-0.019 **	-0.006	0.380 ***	0.450 ***
	(0.009)	(0.006)	(0.074)	(0.088)
ln(KAPINT)	0.032 ***	0.014 ***	0.018	-0.148
	(0.007)	(0.004)	(0.123)	(0.183)
GROUP	-0.026 **	-0.010	0.326	0.418
	(0.013)	(0.009)	(0.337)	(0.470)
Test of excluded instruments (1st stage)	*F* = 317.57	*F* = 329.52		
Hansen J overid. test $chi^2(3)$	0.968	0.969	0.925	0.922

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).

e) 'Population-Averaged' Poisson Models with pre-sample mean

The Generalized Estimating Equation (GEE) approach adopts the exponential mean regression form given in equation (1) with assumed serial correlation structure. Pioneered by Liang and Zeger (1986), this 'population-averaged' approach and has been used in a broad range of count data models (see e.g. Ahuja and Katila, 2001; Somaya *et al*., 2007). The GEE method of modeling panel data is an extension of Nelder and Wedderburn's (1972) and

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.

McCullagh and Nelder's (1983) Generalized Linear Models (GLIM) approach to specification. Similar to Somaya at al. (2007), we check the robustness of our findings by re-estimating our model by the GEE technique, using a Poisson specification and a AR(1) correlation structure, i.e. $\mathrm{Corr}[\varepsilon_{it}, \varepsilon_{is}] = \rho^{|t-s|}$, $t \neq s$. As can be seen in the results reported in Table 7, our previous findings are confirmed.

Table 7: GEE Poisson models with pre-sample mean (4,013 obs., 1,278 firms)

Variables	PATENT APPLICAITONS$_{t+1}$ (*PAT*)		CITATIONS PER PATENT$_{t+1}$ (*AV_CITES*)	
	Model 1	**Model 2**	**Model 3**	**Model 4**
CO	0.311 **		0.746 ***	
	(0.157)		(0.243)	
CO_JOINT		-0.130		0.888 ***
		(0.182)		(0.342)
CO_XCHANGE		0.448 **		-0.243
		(0.187)		(0.302)
ln(meanPAT)	0.678 ***	0.671 ***		
	(0.067)	(0.067)		
d_meanPAT	-1.266 ***	-1.323 ***		
	(0.333)	(0.324)		
ln(meanCIT)			0.173	0.173
			(0.139)	(0.135)
d_meanCIT			-1.684 ***	-1.672 ***
			(0.441)	(0.444)
ln(R&D)	1.977 ***	1.945 ***	2.655	2.700
	(0.638)	(0.617)	(1.880)	(1.870)
ln(AGE)	-0.116	-0.124	-0.405 **	-0.398 **
	(0.114)	(0.111)	(0.165)	(0.160)
ln(ASSETS)	0.324 ***	0.331 ***	0.500 ***	0.502 ***
	(0.070)	(0.069)	(0.114)	(0.114)
ln(KAPINT)	0.024	0.032	-0.219	-0.225
	(0.127)	(0.125)	(0.194)	(0.193)
GROUP	0.062	0.036	0.434	0.458
	(0.324)	(0.329)	(0.522)	(0.522)
Wald $chi^2(20)$	2,984.98 ***	3,213.80 ***	406.17 ***	509.17 ***
Joint sign. of industries $chi^2(3)$	5.21	5.59	12.87 ***	11.72 ***
Joint sign. of years $chi^2(8)$	98.73 ***	101.58 ***	16.35 **	17.08 **

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Standard errors in parentheses are clustered and AR1 corrected. All models contain a constant, industry and year dummies (not presented).

7. DISCUSSION AND CONCLUSION

The intention of this paper was to study the effects of R&D collaboration on patent activity. Whereas our findings confirm previous works by suggesting a positive relationship between collaboration and patents, they add to that literature by distinguishing between the type of collaborations and by considering quantity as well as quality. In particular, the results shed light on the effects of knowledge exchange collaboration may have on patenting activity as opposed to joint R&D and how those effects differ when comparing patent quantity and patent quality.

Using a Poisson estimation accounting for unobserved heterogeneity in the propensity to patent, 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. Joint R&D, on the other, does have a positive significant impact on forward citations received, hence on patent quality. These findings are robust to a series of robustness checks. In line with recent literature on strategic patenting, these results may indicate that patenting of collaborating firms is not only used as a mere tool to protect intellectual property rights, but also as a strategic tool to construct firms' patenting portfolios. In other words, joint R&D may provide incentives to file patents that are indeed aimed at protecting valuable inventions from imitation by others, while exchange alliances drive 'portfolio patenting' which has been shown to result in fewer citations for the individual patent.

Indeed, as stated by Hall and Ziedonis (2001), in times of fast changing technology where firms advance quickly upon innovations made by others, strategic patenting in the aim of building a larger portfolio of the firm's 'right to exclude' may not only help reduce the holdup problem posed by external patent owners, but might also allow firms to negotiate access to external technology more favourably. As such, our study allows showing the multifaceted effects of and uses made by patent strategies at the firm level.

Whereas our study sheds light on the link between collaboration alliances and incentives to patent, it leaves open questions related to the social impacts of these results. As shown, R&D collaboration does lead to more patents, but whether these are also valuable depends on the purpose of the collaboration alliance. Strategic patenting resulting in patent portfolio races yielding more, but less valuable patents, could have detrimental effects on social welfare if it comes at the cost of socially valuable knowledge creation and diffusion.

On similar grounds, it would be intersting for future research to take into account the impact of exchange and creation alliances on product market output and firm performance. Indeed, while the current analysis allows us to draw 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 calls the second stage, namely, successful commercialisation. Furthermore, it would be worthwhile to compare the impact of these types of collaboration, differentiating between national and foreign partners. Indeed, while the knowledge pool accessible to a firm might be larger for firms that have foreign collaborating partners, transaction costs of such collaborations may be higher and ineffective protection for firms seeking to protect technology transferred across national borders might not only affect firms' incentives to engage in such types of collaboration but also influence the firms' patenting activities. Finally, it would be interesting to investigate if, and to which extent, R&D policies such as direct subsidies for R&D collaboration, for instance, play a role in driving either kind of collaborative activity as well as the effects on patenting both in terms of quality and quantity.

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APPENDIX:

Table A.1: Descriptive Statistics by industry classification (4,013 obs.)

Low-tech industries (1,682 obs.)

Variable	Unit	Mean	Std. Dev.	Min	Max
		Outcome variable			
PAT	patent count	0.304	2.853	0	67
AV_CITES	citations per patent	0.106	1.093	0	27
		Control variables			
CO	dummy	0.265	0.441	0	1
CO_JOINT	dummy	0.231	0.422	0	1
CO_XCHANGE	dummy	0.219	0.414	0	1
ln(prePAT)	pre-sample patents$_{1995-1999}$	0.068	0.468	-1.609	2.128
d_prePAT	dummy (no pre sample patents)	0.900	0.300	0	1
ln(preCIT)	pre-sample citations$_{1995-1999}$	0.111	0.653	-.8754	4.277
d_preCIT	dummy (no pre sample citations)	0.944	0.231	0	1
GROUP	dummy	0.598	0.491	0	1
AGE	years	29.205	18.800	1	108
ln(ASSETS)	tangible assets in million €	7.689	1.866	1.098	11.343
ln(KAPINT)	fixed assets / employees	3.474	1.031	0.066	6.305
ln(R&D)	R&D employees/ employees	0.034	0.061	0	0.693

Medium-tech industries (1,679 obs.)

Variable	Unit	Mean	Std. Dev.	Min	Max
		Outcome variable			
PAT	patent count	0.491	2.807	0	41
AV_CITES	citations per patent	0.090	0.525	0	6
		Control variables			
CO	dummy	0.256	0.437	0	1
CO_JOINT	dummy	0.225	0.418	0	1
CO_XCHANGE	dummy	0.194	0.395	0	1
ln(prePAT)	pre-sample patents$_{1995-1999}$	0.115	0.776	-1.609	5.276
d_prePAT	dummy (no pre sample patents)	0.794	0.405	0	1
ln(preCIT)	pre-sample citations$_{1995-1999}$	0.214	0.831	-1.238	5.207
d_preCIT	dummy (no pre sample citations)	0.886	0.318	0	1
GROUP	dummy	0.572	0.495	0	1
AGE	years	28.718	19.909	1	119
ln(ASSETS)	tangible assets in million €	7.420	1.831	0.693	13.004
ln(KAPINT)	fixed assets / employees	3.195	0.957	0	6.244
ln(R&D)	R&D employees/ employees	0.059	0.085	0	0.693

High-tech industries (322 obs.)

Variable	Unit	Mean	Std. Dev.	Min	Max
		Outcome variable			
PAT	patent count	1.991	7.770	0	76
AV_CITES	citations per patent	0.375	2.162	0	25
		Control variables			
CO	dummy	0.481	0.500	0	1
CO_JOINT	dummy	0.460	0.499	0	1
CO_XCHANGE	dummy	0.391	0.489	0	1
ln(prePAT)	pre-sample patents$_{1995-1999}$	0.381	1.302	-1.609	6.002
d_prePAT	dummy (no pre sample patents)	0.733	0.443	0	1
ln(preCIT)	pre-sample citations$_{1995-1999}$	0.488	1.374	-1.193	5.852
d_preCIT	dummy (no pre sample citations)	0.851	0.357	0	1
GROUP	dummy	0.720	0.449	0	1
AGE	years	25.497	24.906	1	126
ln(ASSETS)	tangible assets in million €	7.550	2.219	2.833	12.802
ln(KAPINT)	fixed assets / employees	3.013	1.015	0.142	4.465

ln(R&D)	R&D employees/ employees	0.159	0.163	0	0.693

'Other' manufacturing (330 obs.)

Variable	Unit	Mean	Std. Dev.	Min	Max
	Outcome variable				
PAT	patent count	0.033	0.285	0	4
AV_CITES	citations per patent	0.004	0.041	0	1
	Control variables				
CO	dummy	0.100	0.300	0	1
CO_JOINT	dummy	0.091	0.288	0	1
CO_XCHANGE	dummy	0.088	0.284	0	1
ln(prePAT)	pre-sample patents$_{1995\text{-}1999}$	-0.021	0.301	-1.690	2.610
d_prePAT	dummy (no pre sample patents)	0.955	0.209	0	1
ln(preCIT)	pre-sample citations$_{1995\text{-}1999}$	0.011	0.126	0	1.609
d_preCIT	dummy (no pre sample citations)	0.982	0.134	0	1
GROUP	dummy	0.442	0.497	0	1
AGE	years	25.818	16.114	1	85
ln(ASSETS)	tangible assets in million €	6.713	1.901	1	13.733
ln(KAPINT)	fixed assets / employees	3.136	1.191	0	6.381
ln(R&D)	R&D employees/ employees	0.022	0.078	0	0.693

Table A.2: Cross-correlations (4,013 obs.)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1 *PAT*	1												
2 *AV_CITES*	0.183	1											
3 *CO*	0.177	0.121	1										
4 *CO_JOINT*	0.185	0.130	0.925	1									
5 *CO_XCHAN*	0.185	0.112	0.862	0.763	1								
6 *ln(prePAT)*	0.644	0.266	0.228	0.237	0.221	1							
7 *d_prePAT*	-0.281	-0.225	-0.238	-0.255	-0.215	-0.353	1						
8 *ln(preCIT)*	0.390	0.311	0.222	0.244	0.209	0.515	-0.521	1					
9 *d_preCIT*	-0.355	-0.263	-0.244	-0.254	-0.219	-0.561	0.716	-0.727	1				
10 *GROUP*	0.107	0.083	0.167	0.159	0.172	0.153	-0.189	0.142	-0.161	1			
11 *AGE*	0.159	0.038	0.081	0.094	0.078	0.210	-0.124	0.232	-0.210	0.070	1		
12 *ln(ASSETS)*	0.226	0.161	0.234	0.240	0.218	0.268	-0.270	0.245	-0.280	0.448	0.247	1	
13 *ln(KAPINT)*	0.027	0.033	0.014	0.015	0.014	0.014	-0.061	0.000	-0.035	0.052	0.023	0.563	1
14 *ln(R&D)*	0.104	0.066	0.344	0.329	0.306	0.088	-0.131	0.118	-0.124	-0.015	-0.096	-0.118	-0.068