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When Can Firms Capture Value from Collaborating with Research Consortia?

Paul-Emmanuel Anckaert
KU Leuven
Department of Managerial Economics, Strategy and Innovation
paulemmanuel.anckaert@kuleuven.be

Bruno Cassiman
KU Leuven & IESE Business School
Department of Managerial Economics, Strategy and Innovation
bcassiman@iese.edu

Abstract
In this paper we examine how firms can benefit from linking to science through collaborating and co-patenting with research organizations. We compare patents developed solely by the firm with very similar co-patents developed by that firm in collaboration with the German research organization, the Fraunhofer-Gesellschaft. We find that firms develop higher quality technologies when they collaborate with a research organization while building upon technological prior art developed by that research organization. Additionally, when firms collaborate with a research organization while recombining their own technological prior art with the technological prior art of that research organization, we find the firm to be more likely to develop these technologies more intensely internally, resulting in higher quality technologies with higher quality follow-up technologies.

Jelcodes:O32,O31

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Paul-Emmanuel Anckaert[1] & Bruno Cassiman[1,2]

[1] Department of Managerial Economics, Strategy and Innovation, KU Leuven

[2] IESE Business School, Barcelona

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ABSTRACT

In this paper we examine how firms can benefit from linking to science through collaborating and co-patenting with research organizations. We compare patents developed solely by the firm with very similar co-patents developed by that firm in collaboration with the German research organization, the Fraunhofer-Gesellschaft. We find that firms develop higher quality technologies when they collaborate with a research organization while building upon technological prior art developed by that research organization. Additionally, when firms collaborate with a research organization while recombining their own technological prior art with the technological prior art of that research organization, we find the firm to be more likely to develop these technologies more intensely internally, resulting in higher quality technologies with higher quality follow-up technologies.

Keywords: Research collaboration, PRO, Industry-Science Linkages, Technology Trajectory

JEL Classification: O31, O32

1. Introduction

The empirical support for the importance of basic and scientific research as a driver for technology development, innovation and economic growth is, both at the macro as at the micro level, broad (e.g. Mansfield, 1991; Jaffe, 1989; Adams, 1990; Griliches, 1998; Rosenberg and Nelson, 1994; Stephan, 1996; Cohen et al., 2002). Nevertheless, still relatively little is known about how firms should exactly access the scientific and basic research developed at research organizations, and about how the insights stemming from this research should be transferred efficiently across the organizational boundaries. Before companies can translate research findings into new technologies and eventually into product and process innovation, they need to bridge the institutional gap existing between the scientific and technological communities (Cassiman et al., 2015). Mokyr (2002) argues that the diffusion of knowledge comes at a cost: individuals, researchers and firms need to be aware of extant knowledge and pay the associated cost of access. Thus, the ability of firms to build on and to integrate the knowledge developed by universities and research organizations will not only depend on the generated knowledge, but also on the quality of the mechanisms used for storing, transferring, accessing and absorbing that knowledge (Furman & Scott, 2011).

The most widely studied mechanisms to transfer knowledge across the organizational boundaries are research partnerships between firms and universities or public research organizations (PROs). These studies typically find a positive relationship between linking to science and the firm's innovative outcomes. However, we argue that these analyses pay little attention to the existing heterogeneity within the nature of collaborative agreements. With this paper we want to contribute to the existing evidence on this topic by explaining part of the heterogeneity within the innovative outcomes of collaborations between research organizations and firms. We examine to what extent both parties, the research organization as well as the firm, contribute to the collaborative agreement by the input of own technological prior art.

To conduct such an analysis the challenge is to find a setting in which (i) we can clearly observe collaboration between firms and research organizations, (ii) we can identify how both parties contribute to the collaboration, (iii) we can measure the innovative outcomes of these collaborations and (iv) we can distinguish between internal and external value. We claim that such a setting can be found in the development of co-patents between firms and the German research organization, the Fraunhofer-Gesellschaft. Co-patents allow us to exactly identify when a company collaborates with the German research organization. Using patent citation data we are also able to identify how firms and public research organizations recombine their own prior knowledge with external knowledge to generate new technologies. Moreover, patent networks allow us to investigate further internal development of a technology within the firm and to study to what extent these firm-research organization collaborations exploit the co-developed technology. As we are aware of the limitations related to the use of co-patents and the proposed patent measures, we will accurately motivate why this is a valid setting to address our research question.

Our findings suggest that collaborating with the German research organization leads to more original and more diverse patents with regard to technological and scientific prior art. On an aggregated level we do not find any proof that these co-patents are of a higher quality than very similar patents developed solely by the firm. However, we provide evidence that the collaborations have a positive and direct impact on the quality of the co-patents, if the co-patented technology builds on technological prior art developed by the research organization. Besides, we show that co-patenting with the Fraunhofer-Gesellschaft increases the likelihood of further internal development of that technology by the firm, when the collaborative patent recombines technological prior art from the research organization with prior art stemming from the firm. Additionally, we find these co-patents that recombine the firm's own prior technological art with technological prior art stemming from the research organization, to spur higher quality follow-up technologies.

The rest of this paper proceeds as follows: In the next section, we review the relevant prior literature on collaboration between research organizations and firms, and we discuss under which conditions firms can appropriate returns from these collaborations. In Section 3 we introduce our research setting. Section 4 describes the data and the methodology used in our empirical analysis. The results of our empirical analysis are presented in section 5. Section 6 discusses these results and concludes.

2. Theoretical Background

The Importance of Scientific Research & Efficient Industry-Science Linkages

A multitude of economic studies have indicated the importance of basic and scientific research to foster technology development, innovation and thus economic growth (e.g. Mansfield, 1991; Jaffe, 1989; Adams, 1990; Griliches, 1998; Rosenberg and Nelson, 1994). As a result collaborative agreements between industry and universities or public research organizations (PROs), where basic and scientific research typically are developed, are increasingly perceived as a mechanism to enhance innovation through knowledge exchange (Ankrah & Al-Tabbaa, 2015). However universities and public research organizations might conduct valuable research, the successful transfer from their findings to commercialization is not straightforward. The efficient and effective knowledge transfer and transformation is hindered by a range of factors, including: cultural differences between the business and science communities; lack of incentives; legal and technological barriers; and fragmented markets for knowledge and technology (EC, 2007). These factors lead to the appearance of a gap in the translation of scientific research into commercial inventions, the so-called translational gap (Graham et al., 2006; Cassiman et al., 2008; Comin et al., 2011).

Prior literature has focused on two key mechanisms to bridge this gap between the scientific community and industry: firm level connections on the one hand and individual researcher connections on the other hand. At the firm level, empirical studies have attempted to quantify technology and knowledge transfer through examining a number of different transfer mechanisms, such as networks, consultancy, collaborative and contract research, licensing, spin-out formation and teaching (e.g. Shane, 2002; Siegel et al., 2003; Di Gregorio & Shane, 2003; Finne et al., 2011). The most widely studied mechanisms to transfer knowledge across organizational boundaries are research partnerships between firms and universities or PROs. In general, prior literature investigated the impact of such cooperative agreements on firm performance using a knowledge production function approach (Audretsch and Stephan, 1996; Zucker et al., 1998; Cockburn and Henderson, 1998; Branstetter and Sakakibara, 1998). These studies found a positive effect from cooperation with universities and PROs on firms' innovative productivity and sales. Furthermore have surveys with the purpose to estimate the contribution of public research to industrial innovations found them to lead to higher sales and cost savings (Mansfield 1991, 1995, 1998). However, the degree of this positive impact is shown to depend on the firms' internal R&D level, as it supports the firm's ability to absorb the findings from public research and turn them into innovations (Beise & Stahl, 1999; Belderbos et al. 2004, 2006). A third stream of literature measures collaborations between firms and universities or PROs at the firm level by considering co-patenting as a reflection of firm-science institute collaboration. A recent study by Belderbos et al. (2014) shows that co-patenting with universities is associated with a higher market value, as the scientific collaboration may signal novel technological opportunities.

At the inventor level, there exists broad empirical evidence that inventor mobility across the institutional boundaries facilitates the effective transfer of knowledge and has a positive impact on innovative performance (e.g. Song et al., 2003; Singh, 2008; Singh & Agrawal, 2011). As our study focuses on the firm level, we do not go into detail about the prior literature on this topic, but we argue that it will be important to control for inventor specific characteristics and their mobility across the institutional boundaries in our empirical analysis.

The Cumulative Nature of Research, Recombinant Search & Absorptive Capacity

While the existing firm level analyses typically find an overall positive relationship between linking to science and the firm's innovation outcomes, these analyses usually pay little attention to the heterogeneity within the nature of these collaborative agreements. We suggest that in order to gain insight in the different mechanisms playing a role in these collaborative agreements it is essential to understand how both parties, the research organization as well as the firm, contribute to the collaboration. We do this by explicitly mapping (part of) the technology-road and by understanding how these firms and public research organizations recombine their prior internal R&D in order to generate new technologies.

This approach is in line with the proposition made by many scholars that the process of innovation critically relies on the recombination of existing ideas and artifacts (Scotchmer, 1991; Weitzman, 1996, 1998; Fleming, 2001). The importance of resource recombination as the source of new products and services was already stressed by Schumpeter in his seminal work in 1934. Prior studies distinguish between two types of knowledge recombination: the recombination of distant or diverse knowledge and the recombination of local or closer related knowledge. A firm that engages in local search, recombines a narrow set of knowledge elements which is most likely to lead to more incremental innovation (e.g. March, 1991; Fleming, 2001; Ethiraj & Levinthal, 2004; Kaplan et al., 2015). Weisberg (1999) stated that deep knowledge in one specific domain dampens the creativity by entrenching researchers into one way of thinking. At the other side, a firm that engages in more distant search, will be able to recombine their local knowledge with distant technological domains which might allow them to create more radical and valuable innovations (Stuart & Podolny, 1996; Fleming & Sorenson, 2004).

Nevertheless, to fully understand this process of recombination, one needs to find out how outside knowledge feeds and interacts with internal R&D (Cohen and Levinthal, 1989; Belenzon, 2012). Cohen and Levinthal (1990) suggest that the extent to which a firm is able to absorb external knowledge will depend on that firm's absorptive capacity. This is a result of the nature of knowledge, which is hard to codify and mostly tacit. Therefore it is difficult to transfer and embed it in the routines of the organization (Lim, 2009). In order to absorb knowledge, firms need to invest in resources to increase their absorptive capacity. While different mechanisms are studied to increase firms' absorptive capacity, the one most researchers have emphasized is the firm's prior related internal R&D (Jaffe, 1986; Gambardella, 1992; Henderson & Cockburn, 1996, Arora and Gambardella, 1994; Zucker and Darby, 1995).

Lim (2009) suggests that absorptive capacity exists in three different forms: disciplinary, domain specific and encoded. He argues that each of these types of absorptive capacity involves different ways of managing R&D and linking internal to external R&D for the transfer of the relevant knowledge. Disciplinary absorptive capacity is relevant in the case of very early stage, general and scientific knowledge. In this case linking internal to external R&D is found to be more successful when discipline-trained scientists are hired, ties with the academic community are developed and the act of scientific publications is encouraged. Domain specific absorptive capacity is important for intermediate and focused R&D, when solutions for specific technical problems are searched for. Therefore linking to the external R&D should be done by hiring people with domain-specific skills, funding of external R&D in specific areas while influencing the trajectory of the external R&D. The last form of absorptive capacity, encoded absorptive capacity, is relevant when very specific knowledge embedded in tools and processes needs to be transferred. Lim proposes that this should be done through collaboration with suppliers possessing the relevant embedded knowledge.

In summary, this study aims to contribute to the existing literature by analyzing how firms and public research organizations recombine their own prior knowledge with external knowledge to generate new technologies. Furthermore we examine how firm-research organization collaborations influence the firms' local and distant recombinant search.

Additionally we study to what extent the firm-research organization collaborations exploit scientific knowledge stemming from universities or research organizations.

3. Research Setting

In our empirical analysis we evaluate the impact of cooperative agreements between firms and research organizations by comparing the nature and impact of patents developed solely by the firm with very similar patents developed by the same firm in collaboration with the Fraunhofer-Gesellschaft.

The Fraunhofer-Gesellschaft is a German research organization with 67 institutes spread throughout Germany, each focusing on different fields of science. It employs around 23 000 people, mainly scientists and engineers, with an annual research budget of about € 1.7 billion, representing 2.5% of total R&D expenditures in Germany and making it one of the largest research organizations in Europe (Comin et al., 2011; Fraunhofer, 2012). The different Fraunhofer institutes work in close association with each other in order to pool their expertise in ad hoc interdisciplinary collaborative networks. Additionally, the Fraunhofer-Gesellschaft collaborates with other research organizations, institutions and universities in Germany and all over Europe (Fraunhofer, 2015). Of particular importance are Fraunhofer's ties with a number of selected partner universities: each of the Fraunhofer institutes collaborates closely with at least one of Germany's seventy research universities (Comin et al., 2011). The Fraunhofer institutes are often headed by university professors and located next to universities with the aim to complement academic research.

At the same time the Fraunhofer-Gesellschaft maintains close ties with the industry. A wide variety of companies contact the research organization when facing technological challenges. Expertise and knowledge from previous research projects as well as teams of high-educated scientists and engineers allow the Fraunhofer-Gesellschaft to provide technological solutions reasonably fast (Comin et al., 2011). When asked which PRO was of prime importance in 2300 questionnaires of companies in Germany, the Fraunhofer-Gesellschaft was mentioned most frequently (Beise & Stahl, 1999).

Linking this research setting back to the earlier discussed framework developed by Lim (2009), we could argue that the Fraunhofer-University collaborations embody the transfer of very early and exploratory knowledge, while the Fraunhofer-Industry collaborations embody the translation of early to intermediate focused R&D.

As mentioned before, we measure collaborative agreements through the development of co-patents. A co-patent is a patent owned by two or more assignees: in this case, both the firm and the research organization are assigned as applicant on the patent document. Therefore both parties have the right to exploit the invention on their own behalf. Previous research on the impact of co-patenting emphasized some concern about this practice. Due to these appropriation issues Hagedoorn (2003) defines co-patenting as a second-best strategy for firms, which they in general try to avoid. Belderbos et al. (2010) show a negative relationship between the proportion of co-patents in a firm's portfolio and the firms' financial performance. However, prior literature on the impact of co-patenting on innovative outcomes has largely ignored the type of partner involved in the co-patenting activities (Belderbos et al., 2014). Belderbos et al. (2014) find that the appropriation issues faced when two or more firms develop a co-patent are unlikely to play a role when firms team up with universities or research partners since they are less likely to compete with the firm in commercializing the invention. Consequently we claim that in our case the practice of co-patenting is a sound setting to evaluate the impact of cooperative agreements between firms and public research organizations.

Thanks to Fraunhofer's extensive collaborative agreements with all types of firms and its widely adopted practice of co-patenting with its industry partners, this research setting provides us with a substantial sample of patent data over time which allows us: to clearly observe the practice of collaboration between firm and research organization, to identify how both parties contribute to this collaboration, and to measure the value of the innovative outcomes of these collaborations, while we can distinguish between internal and external value at the same time.

4. Data & Methodology

Data and Sample

First, we collected all patent applications filed by the Fraunhofer-Gesellschaft (FhG) in collaboration with firms between 1991 – 2011, making use of the PATSTAT database (October 2011 edition). We found 2 579 co-patents in collaboration with 849 different companies. Next, we collected the complete single-applicant patent database for these 849 firms and matched both samples on application date, publication authority, technology class (FhG-ISI 35-classification) and applicant[1]. Our final matched sample contains 1 397 Fraunhofer-company co-patents and 1 383 single-company patents.

Additionally, in order to examine the impact of the Fraunhofer-company co-patents (period T) on their internal follow-up patents (period T + 1), we collected all self-citations by the firm to the focal patent sample developed in period T. Our final internal follow-up sample contains 544 follow-up patents, 276 single-company follow-up patents and 268 FhG-company follow-up patents.

Thanks to the use of patent data we can identify how these firms and the Fraunhofer-Gesellschaft recombine their prior internal R&D in order to generate new technologies. We analyze the patents' backward patent citations, reflecting the technical background of the patent. The collaborative patents can be split into four groups: (1) FhG-company patents that do not build on prior art stemming from one of both applicants, (2) FhG-company patents that build upon prior art developed by the German research organization, (3) FhG-company patents that build upon prior art developed by the company and (4) FhG-company patents that build upon technological prior art developed by the Fraunhofer-Gesellschaft as well as upon technological prior art developed by the company itself. We expect the collaborative partners to be more familiar with a certain component of prior art when it is developed within the

[1] We used coarsened exact matching to create a viable control group.

research organization or within the company (patent type 2, 3 and 4), than when it is developed by a third, external, party (patent type 1).

Table 1 below shows the classification of the different types of patents and the number of observations of each patent type in our sample.

Insert Table 1 about here

Measuring Knowledge Flows

In this paper we follow the method introduced by Belenzon (2012) to identify sequences of inventions using patent and citation data. We are able to identify how firms recombine their past inventions with external knowledge stemming from other firms, universities, research organizations, etc. and how these firms further develop their prior inventions internally.

Identifying knowledge flowing between different individuals and organizations is a highly complicated issue, and a controversial topic. However, since Jaffe, Trajtenberg and Henderson (1993) objected Krugman’s work and provided evidence that knowledge flows sometimes do leave a paper trail in the form of patent citations, patent citations have been used extensively to measure the diffusion of knowledge (Almeida & Kogut, 1999; Peri, 2005; Jaffe & Trajtenberg, 2002). The general assumption made in these works is that patent citations identify knowledge flows and further technological development of technologies: a citation from patent B to patent A indicates that the inventors listed on patent B knew about the existence of patent A and actively used its knowledge in developing patent B. Nevertheless, Alcacer & Gittelman (2006) show that one should be careful with the interpretation of citations as knowledge flows since citations made by inventors are usually not distinguished from citations made by the patent examiners. Citations added by the patent examiners are unlikely to reflect knowledge flows. Alcacer and Gittelman (2006) find that estimates using pooled citations would change in the case examiner added citations would be excluded.

As our data does not allow us to distinguish patent examiner given citations from inventor given citations, we focus on firm and research organization self-citations to identify when the firm or research organization further internally develops its past knowledge, potentially recombined with 'knowledge' from external sources. Self-citations are made by patents on which the firm itself builds upon in subsequent periods (Belenzon, 2012).

Dependent Variables

The main variables of interest in our study are the quality of the invention being developed in collaboration with the research organization and the likelihood of subsequent internal development of that invention by the firm.

The technological value, or quality, of an invention is typically measured by the degree to which a patent contributes to further developing advanced technology. The most used indicator to measure this is the number of forward citations received from subsequent inventions (Trajtenberg, 1990; Harhoff et al., 1999; Lanjouw & Schankerman, 2004; Gambardella et al., 2008). We analyze the total number of forward citations received by a patent since its application date, as well as we analyze a 3 year fixed citation window next to the date of application in order to control for truncation.

In order to measure the private-value of the invention, the value for the firm, we examine the number of self-citations (Belenzon, 2012). Self-citations are citations by a firm to its own technological prior art and reflect that firm's capacity to build further on its existing internal technologies (Hall et al., 2001, 2005; Jaffe & Trajtenberg, 2002).

Independent & Control Variables

Different patent indicators are of interest for our analysis. First, we include the number of backward citations. As mentioned before, the number of backward citations is a frequently used indicator reflecting the extent to which a patent relies on previous technological knowledge. We do not only use the patents' backward citations to examine the source of prior technological knowledge, but also to control for the amount of prior technological art cited by the patent and to measure the originality of the invention. Trajtenberg, Henderson and Jaffe (1997) made use of the diversity of technology fields presented in these backward citations to develop an invention originality-indicator. The originality score will be low if a patent cites prior art stemming from a narrow set of technology domains, whereas a patent will be more original if its backward citations are spread over a wide range of fields. It is calculated as 1 – the Herfindahl index reflecting the concentration of backward citations across technological classes (Trajtenberg et al., 1997). Additionally, we make use of the patents' backward citations to analyze the novelty in the technological knowledge origins on which the invention is building. An invention is identified as having novel technological knowledge origins if this invention draws technological knowledge from domains that were previously not used for serving the same purpose (Verhoeven et al., 2016). This novelty indicator, introduced by Verhoeven et al., identifies combinations between distinct IPC-codes from all patents cited by the focal patent and all distinct IPC-codes the focal patent belongs to. Next, each of the focal patent's 'citations pairs' can be compared to all citation pairs previously used to assess whether a certain pair is new (has never occurred before).

Furthermore do we include the count of citations to scientific work (non-patent references - NPRS). References to non-patent literature reflect closeness to scientific knowledge (Callaert et al., 2006). Patents with scientific references are found to contain more complex and fundamental knowledge (Cassiman et al., 2008) and to be of a significant higher quality (Branstetter, 2005).

Several patent, inventor and firm characteristics are controlled for in order to obtain consistent estimates. We include application year to control for changes in patent citation patterns over time and truncation. We control for technology class by including technology class dummies for the 35 technology classes as defined by Fraunhofer[2]. In addition we include technology scope, as the number of different IPC 3-digit classes listed on the patent, and the patents' publication authority.

As our study focuses on the level of firm connection, it is important to control for inventor specific characteristics. To control for these characteristics we include the total number of inventors, inventor experience, inventor citations and inventor link. Inventor experience is calculated as the average number of past patents filed by the inventors for each patent. Inventor citations controls for the average past quality of the inventors' patents and is measured as the average number of forward citations received within 5 years by the past patents of the inventors listed on the focal patent. Inventor link is a dummy variable which is one in case one of the inventors listed on the focal patent is listed on the technological prior art cited by that patent, and zero otherwise.

Controls at the firm level include firm size, firm scope and firm citations. Firm size is calculated as the total number of patents filed by the firm in the 5 years prior to the application year of the focal patent. Firm scope measures the number of distinct IPC-3 codes on the firm's patents over the last 5 years prior to the application year of the focal patent. Firm citations controls for the firm's average past patent quality and is measured as the average number of forward citations received within 5 years by the patents of the firm filed in the last 5 years prior to the application year of the focal patent (Cassiman et al., 2015).

[2] Fraunhofer developed a technology field classification of 35 different technology classes based on concordance with IPC codes.

Insert Table 2 about here

Methodology

Since our dependent variables are count variables with only non-negative integer values, nonlinear count data models are preferred to standard linear regression models. To estimate the number of forward (self) citations, we conduct Poisson quasi-maximum likelihood models (PQML). These models control for over-dispersion and a large number of zero's in the dependent variable (Silva and Tenreyro, 2006). Standard errors are robust and clustered by firm. As a robustness check we apply a Negative Binomial model, which allows for over-dispersion and heterogeneity across observations.

5. Analyses & Results

5.1 Focal Generation: Analysis of the original invention

In this section we discuss the differences in nature and technological impact between the patents developed solely by the company and the patents developed by the same company in collaboration with the Fraunhofer-Gesellschaft. We compare the FhG-company co-patents developed in period T (original invention) with their matched control set.

Insert Figure 1 about here

Descriptive Analysis

Table 3 provides the descriptive statistics and T-student tests on the difference of the means for the patent characteristics of the aggregated FhG-company co-patents and their matched controls, the single-company patents. In terms of technological value (forward citations), FhG-company patents do not seem to have a significant larger value than the single-company patents. Additionally, they do not appear to spur the process of internal development as measured by forward self-citations. The FhG-company patents are more likely to cite scientific literature (non-patent references binary), confirming their more science-driven nature. Analyzing the backward patent citations, we find the FhG-company patents to build upon a larger share of technological prior art than the single-company patents. More specific, we discover that FhG-company patents are more likely to cite prior technological art stemming from the German research organization itself, as well as prior art from other public research organizations or universities. Furthermore do the FhG-company patents seem to be more original, as measured by Trajtenberg's originality measure (on IPC-

3 level). Trajtenberg et al. (1997) argue that a higher score on this originality indicator reflects inventions characterized by more distant or diverse prior art recombinations. However, we do not find FhG-company patents to be more novel with respect to their technological knowledge origins than the single-company patents (novelty in technological knowledge origins).

Insert Table 3 about here

In Table 4 we present the descriptive statistics for the disaggregated Fraunhofer-company patents (cfr. Patent types - Table 1), taking the different sources of prior technical knowledge into account. These descriptive statistics suggest that the FhG-company patents with backward citations to prior technological art from one or both of the collaborative partners (patent type 2, 3 & 4) have a positive impact on the number of forward citations as well as they are of a more scientific (non-patent references), technological (backward citations) and original character. Furthermore do we find FhG-company patents building on prior art developed at the research organization itself or on prior art stemming from the company (patent type 2 & 3), to be more likely to draw technological knowledge from domains that were previously not used for the purpose of the invention (novelty in technological knowledge origins). Additionally do FhG-company co-patents with backward citations to both collaborative partners (patent type 4) lead to a strong increase in the number of forward self-citations by the firm.

Insert Table 4 about here

In summary, our descriptive statistics suggest the FhG-company co-patents to be of a more scientific and original nature than the single-company patents. However, these first descriptive results indicate that linking to science through a firm-research organization collaboration will only have a direct impact on patent quality when the collaborative co-patent builds on technological prior art of at least one of both collaborative partners. Additionally do the descriptive results propose that companies only seem to assimilate the knowledge captured by the co-developed invention when that invention recombines technological prior art of both collaborative parties.

<u>Quality and Subsequent Internal Development of the Focal Invention</u>

The results of the Poisson quasi-maximum likelihood estimations on the number of forward citations on the level of the original invention are displayed in Table 5[3]. The first estimation (1) suggests that collaboration with the Fraunhofer-Gesellschaft does not lead to an increase in the value of the developed patents, as measured by the number of forward citations. However, breaking down the aggregated FhG-company patents in the different patent categories in estimation 2, we find evidence that the FhG-company patents citing prior technological art developed by the research organization have a direct positive impact on the number of forward citations. Estimation 3 provides evidence that these findings are robust when we control for a 3-year citation window. Hence these results suggest that linking to science through a company-research organization collaboration only has a direct technological impact, as measured by forward citations, when the collaboration builds upon prior technological art developed by that research organization.

Running the same Poisson quasi-maximum likelihood estimation on the number of forward self-citations (by the firm) in model 4, we find that FhG-company patents recombining technological prior art from both collaborative parties, are significantly more

[3] As a robustness check we also estimated the estimations displayed in Table 5 making use of a negative binomial regression model. We obtain very similar results.

likely to be further internally developed by the firm. Building on the technology developed in collaboration with the research organization is an important way to capitalize and appropriate returns from this collaboration.

Insert Table 5 about here

5.2 Follow-Up Generation: Analysis of the Quality of Subsequent Internal Development

Next to analyzing the impact of the FhG-company collaboration on the level of the 'original invention', we examine the impact and technological influence of this collaboration on the follow-up technologies developed by the firm. In other words, we evaluate the impact of the FhG-company invention, and its recombination with other inventions, as input to follow-up discoveries. Internal follow-up patents are company patents developed in period T+1, citing their co-owned FhG-company patents developed in the previous period T. We compare the FhG-company internal follow-up patents with the internal follow-up patents of their matched control sample, the single company patents.

Insert Figure 2 about here

Quality of the Internal Follow-Up Inventions

Table 6 displays the results of our Poisson quasi-maximum likelihood count estimation on the number of forward citations to the internal follow-up inventions[4]. The results in model 1 reveal that the internal follow-up patents of the aggregated FhG-company patents do not get significant more forward citations than their matched controls. In estimation 2 we analyze the impact of the different types of FhG-company collaboration patents (in period T) on the quality of the internal follow-up patents (in period T+1). We find that the internal follow-up patents of FhG-company patents that recombined the technological prior art of the company itself with prior art developed at the Fraunhofer-Gesellschaft, benefit from a positive and significant increase in the number of forward citations. The internal follow-up patents of FhG-company patents that do not build on prior art developed at the company or research organization seem to be of a significant lower quality than those of their control group.

Insert Table 6 about here

5.3 Robustness

In this section we conduct a robustness check in order to test whether our results are actually driven by the collaboration with the research organization along with the recombination of the technological prior art developed at that research organization, rather than only by the recombination of the prior art stemming from the research organization, without collaboration. Therefore we generate a new control group and compare the technological value of the FhG-company co-patents that build on technological prior art developed at the research organization with very similar single-company patents that also

[4] As a robustness check we also estimated the estimations displayed in Table 5 making use of a negative binomial regression model. We obtain very similar results.

build on the research organization's prior art, but where the company does not collaborate with Fraunhofer while developing this new technology.

For the 186 FhG-company co-patents that build on technological prior art developed at the Fraunhofer-Gesellschaft, we create an alternative control group consisting of 1095 very similar[5] single-company patents that build on technological prior art stemming from the German research organization but that were not developed in collaboration with the research organization.

In order to compare the technological value of both patent samples we run additional Poisson Quasi Maximum Likelihood regressions. The results of our PQML estimations on the number of forward citations are presented in Table 7. We find Fraunhofer-Company co-patents that recombine prior art developed at the research organization to be of a higher technological value than their control group, the single-company patents that build on Fraunhofer's prior art but that were not developed in collaboration with the research organization. Thus, these results suggest that the positive effects of collaborating with the Fraunhofer-Gesellschaft are driven by the collaboration with the research organization along with the recombination of the technological prior art developed at that research organization, rather than only by the recombination of the prior art stemming from the research organization.

Insert Table 7 about here

This robustness check might even underestimate the effect of the collaboration between both partners: as we compare single-company patents with very similar patents developed by the

[5] We matched on application year, publication authority, technology class (FhG-ISI 35-classification) and applicant

same companies in collaboration with the Fraunhofer-Gesellschaft, we are not able to control for the potential internal knowledge spillovers resulting from this collaboration.

5.4 An Example: The Case of the Fraunhofer-Micronic Co-operation

An example to illustrate how a firm can benefit from this type of firm-research organization collaborations, and to clarify our quantitative findings, is presented by the case of the co-operation between the German research organization and the Swedish semiconductor pattern generator, Micronic Laser Systems AB. Micronic Laser Systems AB is a Swedish high-tech company engaged in the development, manufacturing and marketing of a series of extremely accurate laser writers for the production of photomasks, used for the manufacturing of semiconductors. The technology involved is known as microlithography.

Back in 1999 Micronic Laser Systems AB realized that to follow the International Technology Roadmap for Semiconductors (ITRS) a completely new writing technology was needed. Therefore Micronic decided to work together with the Fraunhofer Institute for Microelectronic Circuits and Systems (Fraunhofer IMS) for the development and commercialization of the new spatial light modulator (SLM) technology of pattern generators for the coming generations of semiconductor products. This new spatial light modulator (SLM) technology, building on developments made at the Fraunhofer IMS since the late 80's, provided a way to increase the current writing speed by exposing a million pixels or more in parallel (Micronic, 1999).

In the press release following to the announcement of the collaboration with the Fraunhofer IMS institute, Bert Jeppsson, president and CEO of Micronic Laser Systems AB at that time, stated: "This important development contract gives Micronic an ability to respond timely to our customers' demands for highly competitive Laser Pattern Generators." In the same press release Prof. Zimmer, head of Fraunhofer IMS, declared the industrialization of the SLM-technology in co-operation with Micronic to be an important milestone in the history of the Fraunhofer institute (Micronic, 1999). This short press release emphasizes how the Fraunhofer institute worked together with Micronic in order to devise them appropriate solutions to promote and safeguard their market leadership, while exploiting prior technologies developed at the German research institute (SLM-technology).

In our data sample we have 21 Fraunhofer-Micronic Laser Systems AB co-patents, matched with 21 very similar patents developed solely by Micronic[6]. Table 8 presents the different types of Fraunhofer-Micronic co-patents identified in our sample: 17 co-patents were developed without citing any prior art developed at Micronic or Fraunhofer, 3 co-patents cite prior technological art developed by the firm itself and only one co-patent cites prior art developed at the research institute before. The descriptive statistics for these different groups of patents are shown in Table 9. We find the Fraunhofer-Micronic co-patent that builds on prior technological art developed at the Fraunhofer-Gesellschaft to be of a high technological value (forward citations), to spur internal follow-up inventions (forward self-citations) and to be more science-based (non-patent references & backward citations to other public research organizations) compared to the other patent categories. An illustration of the citation tree of this patent can be found in Figure 3. This case clearly illustrates how companies that collaborate with the German research organization can benefit from the in-house knowledge and technological prior art developed at the Fraunhofer-Gesellschaft.

Insert Table 8 & 9 about here

Insert Figure 3 about here

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[6] We matched both samples on application date, publication authority, technology class and applicant.

6. Discussion & Conclusion

This study aims to analyze under which conditions firms can capture value from collaborating with research organizations. We do this by comparing the nature and impact of patents developed solely by the firm with very similar patents developed by the same firm in collaboration with the German research organization, the Fraunhofer-Gesellschaft. We add to the existing evidence by analyzing how different ways of technology recombination between the firms and the research organization have an impact on the innovative outcomes of their collaboration as well as on the further (internal) development of the co-developed technology.

The results of our study reveal a rather nuanced story. We find that firms only directly benefit from collaborating with a research organization, as measured by a forward citation premium, when the collaboration between both parties can build on technological prior art developed at the research organization. Analyzing the ability of the firm to exploit the technology developed in collaboration with the research organization, we show the collaboration to result in a significant higher likelihood of further internal development by the firm when this collaboration recombines technological prior art developed at the research organization with prior art stemming from the firm itself. Additionally we show these internal follow-up technologies to be of a higher quality than the internal follow-up technologies of their matched control group. Thus we provide evidence that in order to benefit from collaborating with a research organization it is essential for a firm that this collaboration exploits prior art developed at that research organization.

We argue that the recombination of own prior art should be interpreted broader than as just a signal of prior experience with respect to the developed technology. Both collaborative parties are familiar with a certain set of (different) technologies and have the potential to exploit this prior knowledge when developing new technologies. We claim that backward citations to one's own prior patents indicate the actual exploitation of own prior knowledge. Our study suggests that Fraunhofer-company collaborations that actually exploit prior art stemming from one or both of the collaborative partners, are also more likely to recombine their local knowledge with more distant technological domains, which results in the development of more valuable technologies.

Nevertheless, these findings should be interpreted carefully. As our analysis focuses on the short-term pay-offs of these collaborative agreements (focal and first follow-up generation), we want to stress that we do not claim the other types[7] of firm-research organization collaboration to have no added value at all. First of all, in the case of a more explorative collaboration between the firm and the research organization the pay-offs might only be visible in a later stage. Furthermore might a firm-research organization collaboration reflect the firm's strategic choice to outsource part of its R&D process to the research organization, and replace part of its own internal R&D by relying on the experience and knowledge of the research organization. Additionally does our research approach only allow us to compare the nature and impact of technologies developed solely by the firm with very similar technologies developed by the same firm in collaboration with the German research organization. As a result we do not observe the extent to which a collaboration with the research organization introduces the firm to new and disruptive technology trajectories.

These results, together with their limitations, suggest several avenues for further research. First, it would be interesting to go more into detail about each different firm-research organization collaboration observation and get a deeper understanding on how prior knowledge is actually exploited, without having to rely on, the sometimes doubtful patent measures to identify knowledge flows. Second, more information on the exact motives of the firm to collaborate with the research organization and on how the firm organizes itself

[7] Collaborative agreements that do not build on prior art developed at the research organization.

internally for this collaboration would increase our insights in the existing heterogeneity within the innovative outcomes of these collaborations. Third, replicating this study for different research centers could increase the generalizability of our findings and would help develop a deeper comprehension on the different types of industry – research organization collaborations and their impact on innovation.

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TABLE 1

Different co-patent types identified in our analysis, the number of internal follow-up patents by the firm is given between brackets

All Fraunhofer-Company patents (1 + 2 + 3 + 4):			
1,397 [268]			
FhG-Company patent (1):	FhG-Company patent with FhG backward citations (2):	FhG-Company patent with company backward citations (3):	FhG-Company patent with FhG and company backward citations (4):
1,078 [155]	**99** [27]	**133** [43]	**87** [43]
Controls:			
1,383 [276]			

TABLE 2
Description of Dependent and Independent Variables

Variable	Description
Forward citations	The number of times a patent is cited as technological prior art since its application
Forward citations (3y)	The number of times a patent is cited as technological prior art within 3 years since its application
Forward self-citations (by firm)	The number of times a patent is cited as technological prior art since its application by the firm itself
Backward citations	The number of different patents that are cited as technological prior art
Backward citations without self-citations	The number of different patents that are cited as technological prior art with exclusion of own prior art
Backward self-citations (by firm)	The number of different patents of the own firm that are cited as technological prior art
Backward FhG-citations	The number of different patents of the research organization that are cited as technological prior art
Non-patent references	The number of scientific publications that are cited as scientific prior art
Originality (IPC-3)	1 – the Herfindahl index reflecting the concentration of backward citations across technological classes (IPC 3-digit level)
Novelty in technological knowledge origins (IPC-3)	The number of new IPC-3 'citation pairs' divided by the total number of citation pairs made by the focal patent.
Technology Scope (IPC-3)	The number of different IPC-3 classes listed on a patent
Inventor Count	The total number of inventors on the patent
Inventor Experience	The average number of patents applied for by the inventorslisted on the patent before the application
Inventor Citations	The average number of forward citations (5 year citation window) to the patents applied for by the inventors listed on the patent before the application
Inventor Link	Dummy for inventor link between the focal patent and its technological prior art
Firm Size	The number of patents the applicant company applied for in the last 5 years before application
Firm Scope	The number of different IPC-3 classes appearing on the firm's patents applied for in the last 5 years before application
Firm Citations	The average number of forward citations received (5 year citation window) to the patents applied for by the firm in the last 5 years before application

Application Year	Dummy for application year
Publication Authority	Dummy for patent publication authority
Technology Class	Dummy for technology classes listed on the patent (FHG-35 classification)

TABLE 3

Descriptive Statistics: Aggregated Fraunhofer-Company co-patents versus Single-Company patents

	Fraunhofer-Company Patents			Single-Company Patents		
	Mean	Min	Max	Mean	Min	Max
Forward citations	3.303	0	108	2.948	0	133
Forward self-citations (by company)	0.191	0	9	0.199	0	26
Knowledge sources:						
Backward citations	3.273**	0	91	2.919	0	41
Backward citations without self-citations	2.777	0	80	2.606	0	41
Backward self-citations (by company)	0.291	0	14	0.291	0	12
Backward FhG-citations	0.205***	0	6	0.022	0	3
Backward PRO-citations (not FhG) - binary	0.125***	0	1	0.085	0	1
Non-patent references	0.744***	0	28	0.581	0	18
Non-patent references binary	0.349***	0	1	0.290	0	1
Originality (IPC-3)	0.530*	0	0.904	0.505	0	0.914
Novelty in technological knowledge origins - binary	0.081	0	1	0.081	0	1
Technology Scope (IPC-3)	1.745	1	5	1.782	1	10
N	1397			1383		

* p < 0.05, ** p < 0.01, *** p < 0.001

T-student tests in comparison with single-company patents

TABLE 4

Descriptive Statistics: Disaggregated Fraunhofer-Company co-patents versus Single-Company patents

	FhG-Comp patent (1)			FhG-Comp patent with FhG backward citations (2)			FhG-Comp patent with company backward citations (3)			FhG-Comp patent with FhG & company backward citations (4)			Single-Company patents		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Forward citations	2.436	0	108	6.192***	0	57	5.563***	0	83	7.299***	0	79	2.948	0	133
Forward self-citations	0.144	0	8	0.273	0	4	0.323	0	9	0.494***	0	9	0.199	0	26
Knowledge sources:															
Backward citations	1.952***	0	33	6.899***	1	40	6.774***	1	41	10.172***	1	91	2.919	0	41
Backward PRO-citations (not FhG) - binary	0.096	0	1	0.263***	0	1	0.150*	0	1	0.276***	0	1	0.085	0	1
Non-patent references	0.613	0	19	1.182***	0	7	0.910**	0	16	1.621***	0	28	0.581	0	18
Originality (IPC-3)	0.479	0	0.887	0.63***	0	0.904	0.571***	0	0.892	0.595***	0	0.887	0.505	0	0.914
Novelty in technological knowledge origins - binary	0.048**	0	1	0.212***	0	1	0.211***	0	1	0.138	0	1	0.081	0	1
Technology Scope (IPC-3)	1.721	1	5	2.010*	1	5	1.759	1	5	1.724	1	4	1.782	1	10
N	1078			99			133			87			1383		

$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

T-student tests in comparison with single-company patents

TABLE 5
PQML count estimation on the number of forward citations to the focal inventions

	(1) Forward Citations	(2) Forward Citations	(3) Forward Citations (3y)	(4) Self-Citations
FhG-Comp patents ALL (1+2+3+4)	0.007			
	(0.06)			
FhG-Comp patent (1)		-0.089	0.068	-0.172
		(-0.78)	(0.42)	(-0.71)
FhG-Comp patent with FhG backward citations (2)		0.502**	0.441*	0.084
		(2.99)	(2.44)	(0.34)
FhG-Comp patent with company backward citations (3)		0.271	0.182	0.376
		(1.16)	(0.70)	(1.02)
FhG-Comp patent with FhG & company backward citations (4)		0.010	-0.026	0.677*
		(0.03)	(-0.08)	(1.90)
Backward Citations	0.019*	0.016*	0.016	0.055***
	(2.02)	(2.06)	(1.63)	(3.48)
Non-patent References	0.012	0.024	0.014	-0.155*
	(0.65)	(1.46)	(0.52)	(-2.90)
Technology Scope (IPC-3)	0.126*	0.115*	0.066	0.106
	(2.56)	(2.37)	(1.26)	(0.78)
Inventor Link	-0.139	-0.156	0.006	0.049
	(-1.05)	(-1.14)	(0.04)	(0.19)
Inventor Count	0.006	0.006	-0.038	-0.017
	(0.25)	(0.24)	(-1.43)	(-0.33)
Inventor Experience	-0.001	-0.002	-0.002	0.000
	(-0.74)	(-0.80)	(-0.78)	(0.14)
Inventor Citations	0.027***	0.026***	0.030***	0.035***
	(5.75)	(5.38)	(7.41)	(6.16)
Firm Size	-0.000	-0.000	0.000	-0.000
	(-0.36)	(-0.37)	(1.01)	(-0.22)
Firm Scope	-0.000	-0.000	0.000	0.005*
	(-0.21)	(-0.22)	(0.11)	(2.21)
Firm Citations	0.004*	0.005*	0.004	0.002
	(2.52)	(2.49)	(1.84)	(0.74)
Application Year	Incl.	Incl.	Incl.	Incl.
Publication Authority	Incl.	Incl.	Incl.	Incl.
Technology Class	Incl.	Incl.	Incl.	Incl.
Pseudo log-likelihood	-10750.12	-10704.84	-2571.87	-1367.742
N	2780	2780	2780	2780

t statistics in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 6
PQML count estimation on the number of forward citations to the follow-up inventions

	(1) Forward Citations	(2) Forward Citations
FhG-Comp patents ALL (1+2+3+4)	-0.227	
	(-1.25)	
FhG-Comp patent (1)		-0.357*
		(-2.08)
FhG-Comp patent with FhG backward citations (2)		-0.132
		(-0.40)
FhG-Comp patent with company backward citations (3)		0.425
		(1.30)
FhG-Comp patent with FhG & company backward citations (4)		0.543**
		(2.62)
Backward Citations	-0.002	-0.006
	(-0.11)	(-0.38)
Non-patent References	0.028	0.031
	(0.58)	(0.67)
Technology Scope (IPC-3)	-0.197*	-0.216**
	(-2.43)	(-2.84)
Inventor Count	-0.005	-0.006
	(-0.10)	(-0.15)
Inventor Experience	-0.000	-0.000
	(-0.12)	(-0.00)
Inventor Citations	0.019	0.019
	(1.53)	(1.57)
Firm Size	0.000	0.000
	(0.42)	(0.79)
Firm Scope	-0.002	-0.003
	(-0.85)	(-1.34)
Firm Citations	0.011***	0.010***
	(3.97)	(3.31)
Application Year	Incl.	Incl.
Publication Authority	Incl.	Incl.
Technology Class	Incl.	Incl.
Pseudo log-likelihood	-3081.694	-3041.583
N	542	542

t statistics in parentheses
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

TABLE 7

Robustness Check: PQML count estimation on the number of forward citations to the focal inventions

	(1) Forward Citations	(2) Forward Citations (3y)	(3) Forward Citations without FhG citations
FhG-Comp patent	0.370*	0.448*	0.305*
	(2.22)	(2.13)	(1.84)
Backward Citation (external)	0.017**	0.010*	0.017**
	(3.20)	(2.24)	(3.06)
Backward Citation (Fraunhofer)	0.038	0.105	0.024
	(0.73)	(1.85)	(0.47)
Backward Citation (Company)	0.138*	0.120	0.131*
	(2.38)	(1.79)	(2.30)
Non-patent References	0.007	0.027	0.010
	(0.52)	(1.70)	(0.76)
Technology Scope (IPC-3)	0.110	-0.001	0.112
	(1.68)	(-0.01)	(1.78)
Inventor Link	-0.057	-0.014	-0.055
	(-1.37)	(-0.36)	(-1.28)
Inventor Count	-0.007	-0.037	-0.007
	(-0.27)	(-1.08)	(-0.29)
Inventor Experience	-0.001*	-0.001	-0.001*
	(-2.02)	(-1.54)	(-2.06)
Inventor Citations	0.007***	0.008***	0.007***
	(5.00)	(6.19)	(4.46)
Firm Size	-0.000	-0.000	-0.000
	(-1.41)	(-0.78)	(-1.37)
Firm Scope	-0.001	-0.000	-0.001
	(-0.30)	(-0.08)	(-0.34)
Firm Citations	0.001	0.000	0.001
	(1.05)	(0.08)	(0.96)
Application Year	Incl.	Incl.	Incl.
Publication Authority	Incl.	Incl.	Incl.
Technology Class	Incl.	Incl.	Incl.
Pseudo log-likelihood	-5651.11	-3362.63	-5197.74
N	1282	1282	1282

t statistics in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 8

Different co-patent types identified in our analysis of the Fraunhofer-Micronic Collaboration

All Fraunhofer-Micronic patents (1 + 2 + 3 + 4): **21**			
(1)	(2)	(3)	(4)
FhG-Micronic patent:	FhG-Micronic patent with FhG backward citations:	FhG-Micronic patent with Micronic backward citations:	FhG-Micronic patent with FhG and Micronic backward citations:
17	**1**	**3**	**0**
Matched Controls: **21**			

TABLE 9

Descriptive Statistics: Disaggregated Fraunhofer-Micronic co-patents versus patents developed solely by Micronic

	FhG-Micronic Patents (1)	FhG-Micronic patent with FhG backward cit. patents (2)	FhG-Micronic patent with Micronic backward citations (3)	Micronic patents (4)
Forward citations	1.59	40	0	4.19
Forward self-citations	0.47	3	0	0.52
Backward PRO-citations (not FhG)	0.058	1	0.33	0
Non-patent references	0.29	6	0.33	0.33
Originality (IPC-3)	0.70	0.80	0.71	0.73
N	17	1	3	21

FIGURE 1

An illustration of a 'citation tree' of the treatment group, the Fraunhofer-Company co-patents

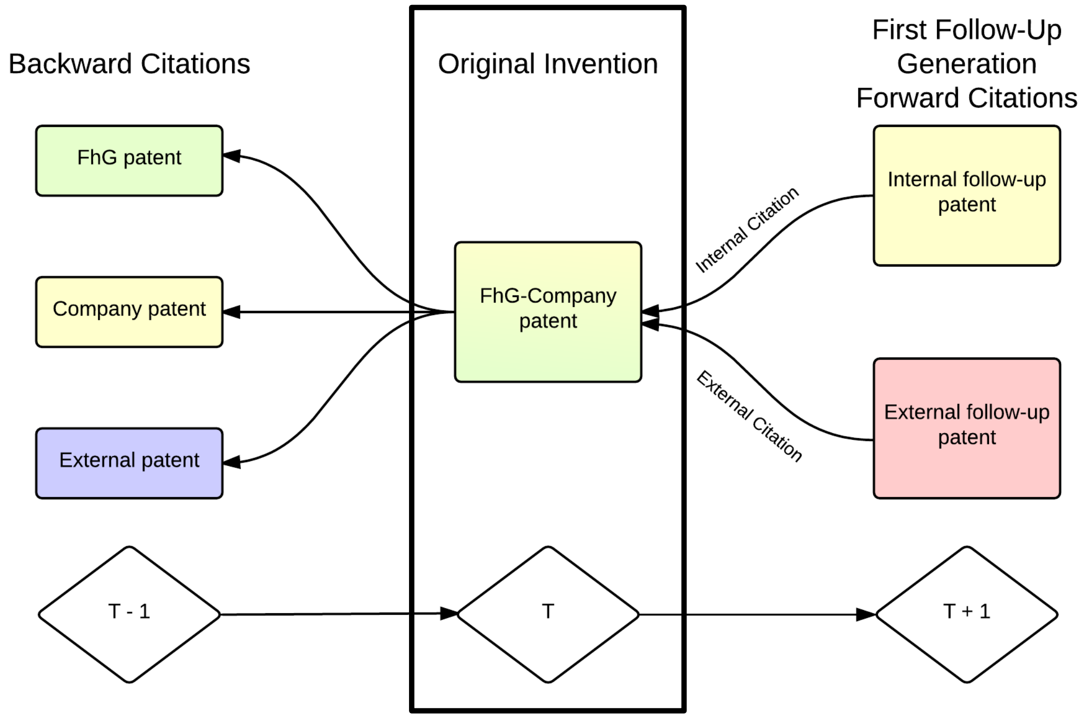

FIGURE 2

An illustration of a 'citation tree' of the treatment group, the Fraunhofer-Company co-patents

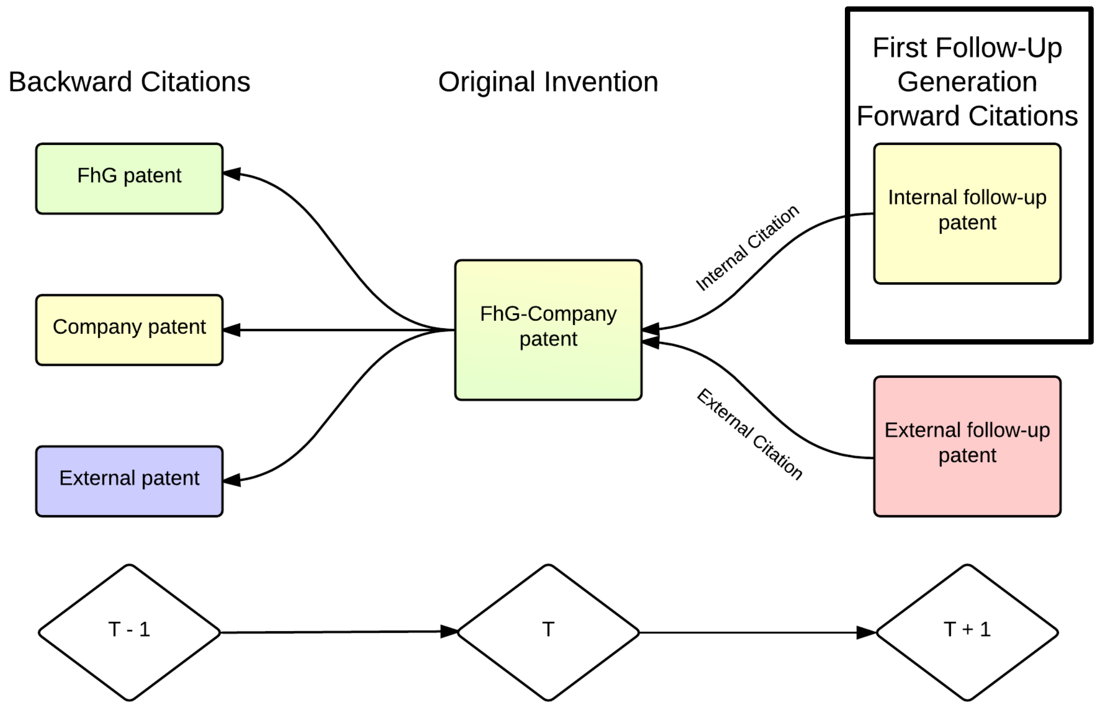

FIGURE 3

Illustration of a Fraunhofer-Micronic patent building on prior technological art developed at the Fraunhofer-Gesellschaft.