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Patent Citations, University Inventor Patents, and Survival in the German Laser Source Industry (1960-2005)

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Abstract

The relationship between innovation and firm survival is analyzed for the population of German laser source producers from the beginning of the industry until 2005. Innovation effort is approximated by the generation of high quality patents in laser sources technology (IPC H01S) and by having patents with university inventors. Quality patents are defined as those in the upper quartile of the strongly right-skewed distribution of forward citations. Having quality patents is positive and statistically significantly associated with firm survival. New firms without relevant capabilities inherited at their birth may be capable of compensating for their lack of adequate pre-entry experience with corresponding innovative behavior. Having patents with university inventors is apparently not related to firm survival.

Keywords: firm survival, patent citations, quality patents, university-inventor patents, innovation

JEL classification: L25, M13, O30, O52

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1 Introduction[1]

A key element for understanding innovative processes and industrial evolution lies in considering the drivers of performance within firms and the impact of innovation on firm performance. In this context, firms need to be considered as not only optimizing agents within exogenous technologies, but rather as agents that continuously challenge such constraints and improve the given technologies (Lazonick, 2006). This is especially the case in knowledge intensive industries. Successful firms have to continuously engage in innovative behavior and invest relevant effort in improving their absorptive capacity (Cohen and Levinthal, 1989, 1990) and dynamic capabilities of knowledge creation (Zahra and George, 2002).

There are findings supporting that a firm's capabilities are indeed important for its survival and that these capabilities tend to be determined by the firm's pre-entry background (Helfat and Lieberman, 2002; Klepper, 2002) and time of entry (Klepper, 1996). However, there is less clear evidence on whether and to what extent innovative behavior contributes to compensate for lack of relevant capabilities at the time of market entry, especially in the case of new firm formation. In other words, to what extent does innovation contribute to overcoming the "doomed to fail" destiny of new inexperienced entrants?

Furthermore, although the literature contributions have made us aware that the processes of innovative firms are complex and holistic, they have also brought forward the concern of how to adequately operationalize measures for studying a firm's innovation efforts and capabilities for

[1] This paper is based on the project "Emergence and Evolution of a Spatial-Sectoral System of Innovation: Laser Technology in Germany, 1960 to Present" jointly conducted by the Friedrich Schiller University Jena, the University of Kassel, and the Technical University Bergakademie Freiberg. The author thanks Wolfgang Ziegler and Sebastian Schmidt for their support in processing the patent citation data, Guido Buenstorf for the access to his laser firms' data, and to Ljubica Nedelkoska, Michael Fritsch, and Sebastian Wilfling for helpful comments on an earlier version of this paper. Financial support from the Volkswagen Foundation is gratefully acknowledged.

creation. This is especially the case with regard to the analysis of groundbreaking technology industries over long periods of time. Such is definitely the case with the laser industry, with historical roots dating back more than forty years ago. At the same time, no firm acts in isolation, and its links with its environment are very important. Especially in the case of laser technology, it would be expected that interactions with the academic community would also be relevant for commercial success.

In this respect, the present paper aims to contribute to the empirical evidence between innovation and firm performance. This will be done by analyzing firm survival within an extended industry life cycle perspective. The extension consists of including measures concerning the quality of the innovation effort and the university-industry links. Such measures are absent in most of the current literature. Specifically, the paper analyzes first the influence of a firm's innovation behavior (considered as the generation of quality patents) in relation to its survival chances. Secondly, it considers whether relevant innovation effort can compensate for lack of adequate capabilities at the time of market entry. And finally, it explores to what extent firms having laser source patents with university-inventors tend to have better market performance.

The paper is organized as follows. It first presents the main theoretical framework and an overview of the evolution of the German laser industry (section two). Then it introduces the data (section three) and presents the laser patents, their citations, and the share of patent applications with the involvement of university-inventors (section four). In section five the empirical analysis is performed in the form of survival analysis, and section six concludes.

2 Theoretical framework

2.1 Firm survival and industry life cycle

In the framework of broadly defining industries according to official statistical industry classifications, the Industrial Organization perspective provides a rich literature on stylized facts regarding firm survival. One of the main regularities is that both age and size are key factors behind the chances of survival, with younger and smaller firms having lower survival perspectives (Geroski, 1995; Sutton, 1997; Caves, 1998). Nevertheless, the survival chances of new firms are likely to differ from industry to industry (Audretsch, 1995). Agarwal and Gort (2002) consider that both firm and industry characteristics are important for explaining firm survival. The firm's attributes include the stock of knowledge that the firm gets through learning-by-doing and about itself, and the firm's endowments. Both knowledge and endowments increase with age. Regarding the industry's attributes, what influences firm survival is the industry's technologically intensiveness and at which point of the industry life cycle the firm is currently in (i.e. infancy, growth or maturity) (Agarwal and Gort, 2002). A recent literature survey by Manjón-Antolín and Arauzo-Carod (2008) also presents evidence indicating that smaller and younger firms have higher hazard rates than larger and older ones. However, such effects are not uniform, but differ according to the firms' and industries' characteristics, e.g. the traditional relation between size, age, and survival holds only for single-establishment firms (Manjón-Antolín and Arauzo-Carod, 2008). Furthermore, other covariates such as R&D, industry life-cycle, scale, growth and entry rates also play a relevant role (Manjón-Antolín and Arauzo-Carod, 2008). With respect to R&D activities, while the likelihood of hazard is reduced for firms investing in R&D activities, such an effect may hold mainly for large firms and for firms investing in process rather than product innovation (Manjón-Antolín and Arauzo-Carod, 2008).

While most of these analyses relied on broad industry identification at the level of official classifications based on highly aggregated data, another strain of the literature has concentrated on a more detailed view. This is the Industry Life Cycle perspective, based on a narrow industry identification of a given product.[2] It is widely acknowledged that an industry cycle consists of three stages of evolution: the exploratory stage,

[2] Following Klepper (1997) the terms industry life cycle and product life cycle are used interchangeably.

the growth stage and the mature stage. In the first stage, many firms enter the market and there is intense product innovation. In the second stage, market growth is high but with declining rates of product innovation and competing product designs; entry reduces and a shakeout in the number of firms takes place. Finally in the mature stage, market entry becomes even rarer, market shares stabilize and process innovation is more important than that of the product (Klepper, 1996, 1997). In this framework, there are two key factors behind firm survival:

i) The pre-entry background of the firm or “heritage” (i.e. the background of the firm’s founder). The best performers tend to be those diversifying from a closely related industry. In the case of *de novo* firms, they become out-performers (or at least as good as the top performers) if their founders acquired relevant qualifications by having previously worked in incumbent firms that were already leading organizations in the industry (Klepper, 1997, 2002).

ii) The time of entry of the firm: early entrants tend to be the out-performers because they enjoy an incumbent advantage. This is because surviving incumbents grow and become larger and therefore can benefit more from process R&D. Eventually process R&D will reduce average cost, pushing down the industry price and making entry for new firms unprofitable. Such processes force the market exit of smaller and less capable innovators, and a shakeout in the number of active producers takes place (Klepper, 1996, 1997).

Although the Industry Life Cycle framework fits well to the formative stages of evolution in several industries, many industries present very different evolutionary processes (see Klepper, 1997, and Peltoniemi, 2011 for a review). For instance, the laser sources industry departs significantly from the shakeout prediction (Sleeper, 1998; Klepper and Thompson, 2006). Klepper (1997) and Klepper and Thompson (2006) suggest that the reason behind such a departure lies in the product’s characteristics, which allow the generation of market niches (i.e. submarkets) leading to a process of firm specialization. Sleeper (1998), and Klepper and Thompson (2006) describe that the market of laser sources can be considered as a composition of several submarkets in which firms specialize in a few laser sources applications. Their evidence for the years 1964 to 1994 shows continued entry and no first-mover advantages from early entrants.[3]

Klepper (1997) speculates that in the cases where submarkets are relevant, innovation played a central role for the industry evolution. This indicates that the continued presence of diverse specializing firms may promote innovation, especially if there are inter-submarket spillovers. In this respect it is necessary to study innovation during the formative stages of industries, for instance by relating the rate of innovation (measured by patent citation counts) with the firm survival (Klepper, 1997). Such suggestion appear promising given the evidence that forward patent citations tend to be an adequate measure of both the technological quality and the economic relevance of patents (Trajtenberg, 1990; Harhoff et al., 1999; Hall, Jaffe, and Trajtenberg, 2000, 2005).

2.2 Innovation effort, patenting and quality patents

Patent data has been found to be closely associated with firms' R&D expenditures (Griliches, 1990). Therefore, it is a relevant measure for grasping a firm's knowledge stock and innovative activity. In this respect a firm's patent portfolio can offer one approximation of the firm's effort for building capabilities and absorptive capacity. Its advantages against other relevant indicators (such as the amount of R&D or share of high skilled employees) lie in its broader availability over very long past time periods.

But patent counts alone are not informative enough about innovative behavior because patents vary enormously regarding their economic and

[3] However the newest evidence from the U.S. suggests that laser submarkets may become substitutes in the presence of technological advance that make one application highly competitive and flexible. The ongoing research by Bhaskarabhatla and Klepper (2011) has found that the development of the diode-pumped solid state laser may have generated a shakeout in the number of laser source producers. If this is the case, then it must be reconsidered whether the laser sources are the paradigmatically case of submarket evolution. Contrary to this development, the current data presents still a non-shakeout development in the laser industry in Germany (Buenstorf, 2007).

technological significance (Griliches, 1990; Trajtenberg, 1990). Studies of US Patent data (i.e. the NBER Patent Citation File) found that the distribution of the citations is very skewed, with a significant portion of patents receiving no citations at all (Hall, Jaffe, and Trajtenberg, 2000, 2002). In this respect, using forward citations is a more adequate way of identifying valuable patents (Trajtenberg, 1990; Hall, Jaffe, and Trajtenberg, 2000, 2005). Forward citations are the number of cites that a patent receives in its life time (or a certain defined period of time). They are mainly included by the patent examiners in order to delimit the reach of the new patent, determining to what extent the potential invention differs from the current state of knowledge and presents something different (Hall, Jaffe, and Trajtenberg, 2002). In this sense, citation counts can be considered as an “objective” measure of the relative importance of a patent (Griliches, 1990). Trajtenberg (1990) found a close association between citation-based patents and valuable innovations in computer tomography scanners. Harhoff et al. (1999) conducted a survey in Germany and in the United States which revealed that heavily cited patents were reported to be valuable by the firms which owned them. Also Hall, Jaffe, and Trajtenberg (2005) consider that patent citations contain significant information about the market value of firms and tackle intangible assets, in particular the “knowledge stock” of firms. They found that if a firm’s quality of patents increases so that on average these patents receive one additional citation, the firm’s market valued would increase by 3% (Hall, Jaffe, and Trajtenberg, 2005). Using data on British firms, Bloom and Van Reenen (2002) also found that patent citations are a valuable proxy of knowledge stocks and have a significant impact on firm market value.

However, patent citation data suffers from a major short-coming, namely citation truncation, and needs therefore to be properly handled (Hall, Jaffe, and Trajtenberg, 2000, 2002). Citation correction methods rely on the findings that patents tend to have a “citation life” cycle and that they tend to receive most of their forward citation within the first years after application (Hall, Jaffe, and Trajtenberg, 2000, 2002).

2.3 Quality patents and firm survival

There is little systematic evidence relating measures of patent quality, such as patent citations, with firm survival. Most of the research dealing with the economics of patenting has focused on the effects of patents on profitability and the stock market, mainly from a financial economics perspective rather than an industrial organizational one (Wagner and Cockburn, 2010).

There are two important exceptions. One is the Canter, Krueger, and von Rhein (2011) analysis of the effect of innovative behavior in the historical evolution of the German automobile industry. The other one is the Wagner and Cockburn (2010) study on the effect of quality patents on the survival of US internet-based and software firms, during the years 1998 to 2003.

Although Canter, Krueger, and von Rhein (2011) deal only with patent counts and do not consider a measure of patent quality, they employ a complex econometric setting that controls for endogenity and where patent counts are used as instruments for innovative behavior. Their findings suggest that innovative experience may compensate for the disadvantages of late entry and, to some extent, also the a pre-entry background.

Wagner and Cockburn (2010) construct firms’ patent portfolios considering patent counts and two measures of patent quality: forward citations and international filling patterns. After controlling for age, stock market and financial conditions, they find that patenting is significantly positively associated with firm survival. However, they did not find significant effects from quality patents on firm survival. Nevertheless, highly cited patents have a positive effect on the probability of exit via merger or acquisition, which suggests that quality patents may signal valuable intangible assets or technology knowledge.[4]

2.4 University-Industry linkages and firm performance

The positive impact and importance of academic research is widely recognized for a firm’s innovation activities (e.g. Mansfield, 1991, 1998; Cohen, Nelson and Walsh, 2002), for university to industry knowledge spillovers (e.g. Jaffe, 1989; Feldman, 1994), and for the emergence and commercial success of new industries relying on the tacit and embodied knowledge associated with star scientists (Zucker, Darby and Brewer 1998; Zucker and Darby, 2007). There is also evidence that such contributions from the academic community to the innovative activities of firms is carried out by different technology transfer mechanisms such as collaborations, patents, research contracts, etc. (e.g. Cohen, Nelson and Walsh, 2002; Geuna and Nesta, 2006). However, there is less systematic evidence regarding the effects of specific university-industry linkages on firm survival. There is especially no evidence concerning the possible impacts on performance, from having patent applications in which at least one inventor is affiliated with a university, i.e. university-inventor patents.

2.5 Evolution of the German laser industry

The laser is broadly acclaimed as being one of the most significant scientific inventions of the 20th century (e.g. Bertolotti, 2005). It generated an entirely new “science-based” industry (Bromberg, 1991; Grupp, 2000). According to Grupp (2000), the laser industry experienced two main stages of development. The experimentation phase was unusually long and slow, lasting more than 20 years. It started when the first operating laser was developed in 1960 by Theodore Maiman at the laboratories of

[4] Also another study considers the relation between patents and firm survival: Audretsch and Lehmann’s (2005) analysis of young and high-tech enterprises listed in the German *Neuer Markt*. However they do not consider finer measures of patent quality beyond simple patent counts.

the Hughes Aircraft Company in the United States. The early commercial lasers were primarily for scientific research and military defense contracts. However, such developments did not have high market success and most of the equipment was not suitable for commercial applications. Grupp (2000) suggests that it was only around 1982 that the market for commercial laser products took off and the expansion phase of this technology began. At this stage, laser technology diversified further and began to be integrated into several commercial applications.

The evolution of this science-based industry has attracted considerable attention in the literature[5] . Of special relevance for the present analysis are the findings by Buenstorf (2007) and Buenstorf and Geissler (2010). Similar to Sleeper (1998), Klepper and Sleeper (2005), and Klepper and Thompson (2006), Buenstorf (2007) found that the German laser sources industry deviates from the industry life cycle: neither first-mover advantages nor shakeout in the number of producers were detected. His analysis covered the complete population of 143 laser sources producers active between 1964 and 2003. Firms were classified according to their pre-entry background in: diversifiers (i.e. the pre-existing firms in related industries which diversified into laser manufacturing), corporate spin-offs (i.e. organized by employees of laser incumbents), academic startups (i.e. established by scientists from public research organizations), and other startups. Similar to the main findings by Sleeper (1998) for the U.S. case, the results show that indeed pre-entry background significantly affects firm survival. Specifically, diversifiers and corporate spin-offs were better performers. In contrast, academic startups had more than twice the exit hazard of all other entrants. This suggests that different capabilities (e.g. knowledge about market opportunities) and not only technological capabilities may have been very relevant for firm

[5] See for instance Sleeper (1998), Grupp (2000), Klepper and Sleeper (2005), Klepper and Thompson (2006), Buenstorf (2007), Buenstorf and Geissler (2010), Fritsch and Medrano (2010), Buenstorf, Fritsch, and Medrano (2010), Bhaskarabhatla and Klepper (2011).

survival (Buenstorf, 2007). Although the model proposed by Klepper and Thompson (2006) suggests that the hazard of exit should decrease with higher number of submarket specializations, the empirical results found that the number of submarkets in which each firm was active had no statistically significant relationship with survival (Buenstorf, 2007).

Furthermore, the German laser industry was characterized by sustained market entry and in general the industry did not concentrate strongly in space. Buenstorf and Geissler (2010) speculate that the forces behind this deconcentration may lie with the role of public research, particularly the decentralized and homogenous German university system. They suggest that public research had a de-agglomerating effect in two ways: universities generated potential entrants with academic roots and also knowledge spillovers in different regions from which potential entrants benefited (Buenstorf and Geissler, 2010).

These findings bring up the following considerations. Although the role of academic research was important for the dynamics of market entry, once entry took place, precisely those entrants with closer ties to the academic research community were the less likely to survive. This motivates the question of to what extent the firms' innovation efforts could overcome their lack of relevant capabilities, given their pre-entry backgrounds. More specifically, the question is to what extent innovation effort could also play a role in firm performance after controlling for the firm's pre-entry background and time of entry? It is very likely that such effort is important in a science-based and knowledge-intensive industry like the laser one, where the generation of commercially successful innovations required long development processes. Here "innovation effort" is understood in line with Cohen and Levinthal's (1989, 1990) conceptualization of "R&D effort" as the investment and activities that a firm performs for creating and/or increasing its absorptive capacity. This implies that it is not only a byproduct of the R&D from its current activities, but may also be constructed by the firm's effort to acquire new knowledge, often unrelated to its present activities. In this way, absorptive capacity could enable a firm not only to absorb external knowledge, but also to better evaluate, predict and exploit subsequent technological advances (Cohen and Levinthal, 1994).

In this context, the present paper focuses on whether innovation effort can also play a role behind firm performance, besides pre-entry experience. Given the lack of consistent and complete innovation measures for the whole population of firms, such as R&D expenditures or share of highly qualified employees, the focus is to consider the firms' patent portfolios related to laser sources development and to concentrate on the valuable laser patents as a proxy for relevant innovation effort. After identifying quality patents as those which are frequently cited, the paper speculates that obtaining quality patents should also increase a firm's survival chances.

Secondly, it considers that a firm may also be able to compensate for the lack of adequate capabilities from a non-experienced pre-entry background by engaging relevant effort in acquiring innovative experience. This implies the possibility of knowledge compensation between non-experienced backgrounds with relevant innovation experience.

Thirdly, it considers university-inventor patents as one of the possible channels of technology transfer contributing to the firm's innovative activities. Then it hypothesizes that firms having such patents profit from that interaction and in consequence have better market performance.

These considerations are synthesized in the following hypothesis:

H1: Firms with quality patents (i.e. highly cited patents) in laser technology tend to have better survival chances in the market of laser beam sources.

H2: Firms with relevant innovation effort (as measured by highly cited patents) may compensate for the lack of relevant capabilities inherited from their pre-entry background.

H3: Firms with laser patents with university-inventors tend to have better survival chances in the laser sources market.

3 Data

The dataset of patent applications and their forward citations obtained from the DOCDB database from the European Patent Office (www.epo.org), which has worldwide coverage. The patent codes were selected from those applications with priority in Germany assigned to the technological field "devices using stimulated emission" in the reclassified International Patent Classification (IPC) H01S, and all their sub-classes, either in the main or secondary class. Hence, patents that are related to applications of laser technology, such as printing and measurement, but not to the laser beam generation, were not considered. This search also considered the European Classification System (ECLA), which is an extension of the IPC used by the European Patent Office (EPO).

Once the patent application codes were identified, complete information about them was obtained from the DEPATISnet database (www.depatisnet.de) maintained by the German Patent and Trademark Office (DPMA). Because not all the bibliographic information about the early laser source patents are electronically coded, secondary sources such as the patent register of the Friedrich Schiller University Jena were consulted.[6] Information from the patent data was obtained about the inventors residing in Germany, their home address at the time of application and the applicant organizations. The time reference is the filing year for the period between 1961 to 2005.

Additionally, for considering the patent applications that may have taken the Patent Cooperation Treaty (PCT) route, further search was done in the STN database (www.stn-international.de) for finding the patent applications that applied directly to the EPO.

The total counts of forward citations are based on the INPADOC patent family information for each patent application. Considering the

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[6] These sources are *the Bibliographische Mitteilungen der Universitätsbibliothek Jena, 1960–1971*. This source was particularly used for collecting patents for the period 1961 to 1969, as these are not consistently documented in DEPATISnet.

patent family instead of the individual application document avoids double or under counting of the citations received. For each patent application it is assigned the total forward citations received from 1961 to 2010.

The names of the applying organizations have been manually and carefully standardized and then matched with information on the names of the laser source firms. The information about laser source producers is obtained from Buenstorf (2007), who identifies all German laser source manufacturers and includes detailed information about the time of market entry as well as the entrants' pre-entry experience. The dataset was assembled from a variety of sources, including trade publications, trade fair catalogs, listings in laser buyer guides, and firm registers (for a detailed description, see Buenstorf, 2007). Furthermore, this dataset distinguishes the type of exit, namely by cessation of producing activities or by mergers or acquisition (M&A). Based on this database, 154 firms are identified as producers of laser sources for the period between 1964 to 2005 in Germany.[7] Information regarding the age of the firm before market entry was also collected from business intelligence databases (e.g. Amadeus, LexisNexis, and Bundesanzeiger) and company web-sites (if available). However, given the long historical perspective of the study, there is such information for only 144 firms.

For identifying the university-inventor patents in laser sources technology, the *Vademecum* registers were consulted. These registers record all the university's departments, university's professors and heads of departments of German universities. [8] Because the important disciplines for laser sources technology are mainly physics and electric engineering, the information about all professors in those disciplines was collected from

[7] The total number of listed firms as source suppliers is 172 for this period, however the background information of 18 of these firms is unknown. Following Buenstorf (2007) these firms are excluded for the present analysis.

[8] Although the information provided from the *Vademecum* registers is one the most complete sources of universities inventors, it has the disadvantage that it does not systematically register scientists without the professor title (e.g. assistant professors and graduate students).

such registries for the period between 1961 to 2002.[9] The registers generally come in four-year intervals and the data was collected until the year 2002, when the new regulation that abolished the “professors' privilege” was introduced.[10]

The matching of inventors with university professors’ names followed the three steps process of parsing, matching and filtering proposed by Raffo and Lhuillery (2009). The matching algorithm was based on a qgram method and the filtering stage considered several additional comparisons (e.g. years and geographical information) for disambiguation.

For all of the above mentioned information, the data covers information for only West Germany from the years 1961 to 1989, and from 1990 on it includes both reunified West and East parts of Germany. For the former German Democratic Republic, patent data does not provide complete inventors’ information.

4 Laser patents and their citations in the German laser industry

4.1 Patent citations

There have been 3,272 patent applications in laser sources technology from German based organizations and applicants. The majority of these applications correspond to private firms (74 percent), followed by public research organizations (11 percent), private inventors (11 percent), universities (2 percent), and other types of organizations (e.g. foundations, private contract research) (1 percent). Regarding the patent counts

[9] For the purpose of this study “physics” includes the sub-classifications of general physics, theoretical physics, experimental physics, applied physics, technical physics, physical chemistry, and optics. “Electrical engineering” includes the areas of electrical engineering, high frequency technology, communication technology, and energy technology.

[10] Until 2002 university researchers in Germany were exempted from the legal obligation to disclose their inventions to their employers. Previously under the “professors’ privilege” *(Hochschullehrerprivileg)* university professors were allowed to keep the ownership of their inventions.

coming from the industry, about 67 percent have as assignee firms that are laser source producers.

A first look at the distribution of citations shows that it is highly skewed to the right, i.e. most of the applications receive few or no citations at all (see Figure 1). Specifically, about 61 received two or less citations, with zero cites (28 percent), just one (18 percent) or two (13 percent). Only 25 percent received 5 or more citations and only 10 percent had 11 or more cites. Very few patent applications received an extraordinary number of citations, with the highest number being 83. The skewness statistic (3,79) also supports the expectation of right skewed distribution.

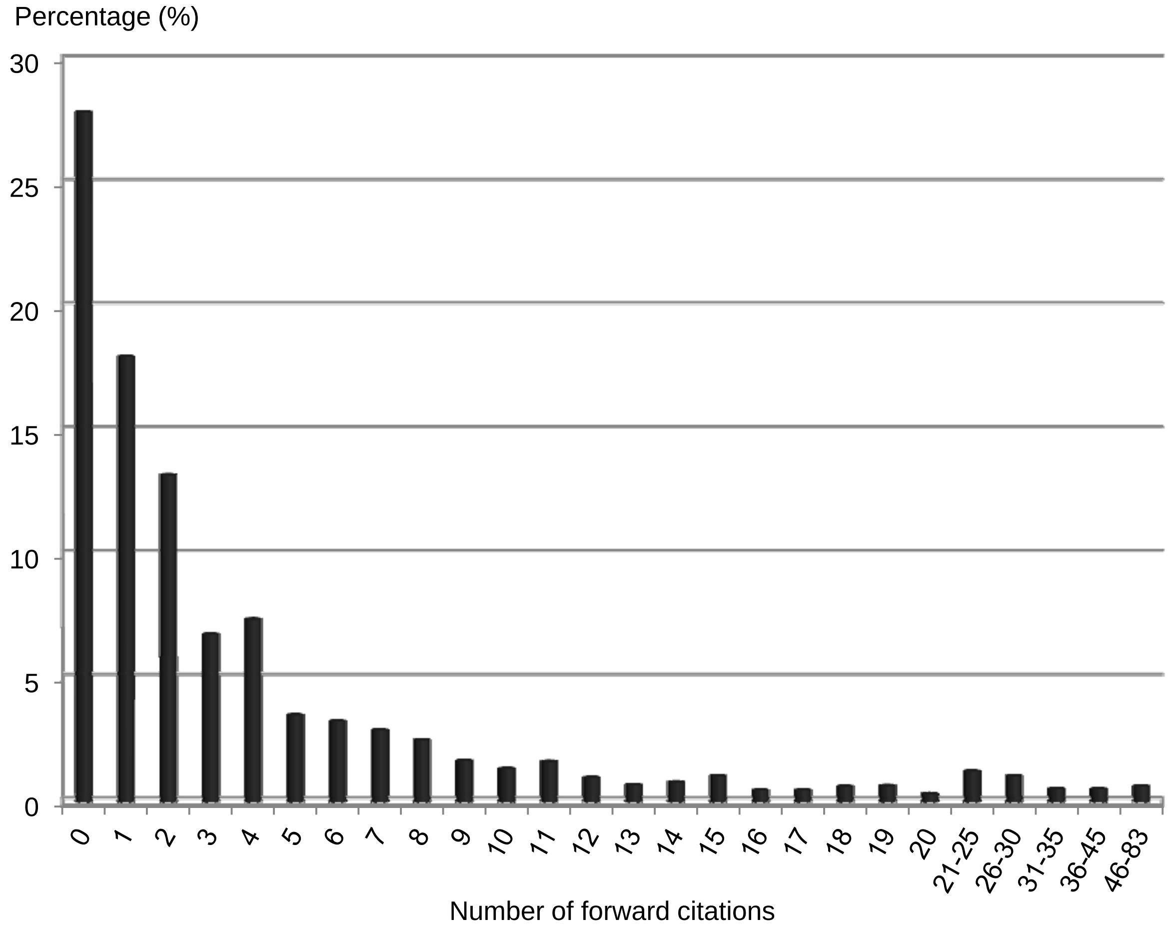

Figure 1: Distribution of citations counts to H01S patents (cited years: 1961-2005; citing years: 1961-2010)

However this picture is not complete given that the counts of forward citations are right truncated. As mentioned before, this problem exists because the citation process does not take place immediately, but it takes time. Although most of the citations tend to take place within the first ten years of the patent life span (Hall, Jaffe, and Trajtenberg, 2000), the right truncation problem remains due to the fact that it is not possible to observe all the citations received by patents closer to the present. For instance, while for a patent applied for in 1961 it is possible to observe all its received citations in its forty-nine year life span until 2010, for a patent applied for in 2005 there are only five years of observations. In order to solve this problem Hall, Jaffe, and Trajtenberg (2000, 2002) propose a methodology for “correcting” the citation counts by estimating a model of the citation frequency of each patent. This model assumes that patents have a “citation life” cycle determined by a combination of an exponential process of knowledge depreciation, an exponential process of knowledge diffusion, and by specific effects from the different technology fields, citing-years and cited-years patents (Jaffe and Trajtenberg, 1999; Hall, Jaffe, and Trajtenberg, 2000, 2002). The model estimates the lag-frequency between the patent application and the future cites it may receive, based on the available observable cites, and calculates coefficients for upward “correcting” such observed citation counts. This method is also employed in this paper and its estimation details are presented in Appendix B.

Under such upwardly “corrected” cites, the average number of citations increases, but still the new distribution of citations per patent remains strongly skewed to the right. About 54 percent of the patents either received no citation at all (28 percent), just one (13 percent) or two (13 percent). Only 25 percent received at least 6 citations, and about ten percent obtained 14 or more. The skewness statistics (3.80) indicates again a right skewed distribution. Therefore these findings support the claim that those H01S patents receiving a high number of citations are indeed different to the rest.

For defining a quality patent, the approach is similar to Wagner and Cockburn (2010) of considering citation thresholds from the upper percentiles of the citation distribution. Specifically three thresholds are defined for classifying high quality patents: i) the upper quartile (6 or more citations), ii) the upper quintile (8 or more citations) and iii) the upper decile (14 or more citations). These measures will be employed and compared for the econometric analysis in section five.

The information of the patent applications and their citations is used to construct firm patent portfolios. Given that the main purpose of the paper is to analyze the link between high quality patents and firm survival, only those patent applications are considering when the firm is active supplier to the laser market, i.e. the patent application year is smaller of equal to the year of market exit. An overview of the patenting behavior by firm background is provided in Table 1.

Table 1: Number of firms by pre-entry background and H01S patents' portfolios

Pre-entry background	Number of firms	Ever patented	At least one quality patent		
			>=6 cites	>=8 cites	>=14 cites
1=Diversifier	65 (42)	28 (43)	22 (55)	20 (56)	14 (54)
2=Corporate Spinoff	49 (32)	18 (28)	9 (22)	7 (19)	6 (23)
3=Academic startup/Other startup	40 (26)	19 (29)	9 (22)	9 (25)	6 (23)
Total	154	65	40	36	26
(The numbers in parenthesis are the percentage with respect to the total of each column)					

Table 1 classifies firstly the firms according to their pre-entry background and their patent portfolios in laser sources. The majority are experienced firms: diversifiers (42 percent) and corporate spinoffs (32 percent), while about 26 percent are inexperienced de novo firms, i.e. firms coming directly from academia or other startups. Only 65 from all laser firms (42 percent) had at least one laser source patent application. From those patenting and having at least one quality patent according to the first criteria, 55 percent corresponds to diversifiers, 22. 5 percent to corporate spinoffs, and 22.5 percent to other type of startups. These shares are fairly similar under the other citation thresholds, e.g. under the third one: 54 percent of the firms with quality patents are diversifiers, 23 percent are corporate spin-offs and 23 percent other type of startups.

As in Klepper (2002) and Canter, Krueger and von Rhein (2011), the group of “diversifiers” and “corporate spinoffs” can be considered as “experienced” firms. This is because they were established incumbents (or are their descendants) with already cumulated knowledge and developed capabilities in the production and/or the distribution of commercial products into the market. In contrast, the last group is considered as “inexperienced” firms because they are composed of de novo entrants without prior relevant experience in supplying to the market. They had to develop such capabilities from scratch.

4.2 University-inventor patents

With respect to the university-inventor patents, the matching and filtering between patent inventors and university professors identified 357 positive matches with higher certainty of correctly linking the same person. This implies a share of 11 percent of all the total applications, which is a much higher amount than the previous 2 percent share of university owned patents (i.e. patents where the assignee is a university). However the number of university-inventor patents linking universities with the active laser source producers is very low: only 89 patents (3 percent) of all the applications are between a source producer (as assignee) and a university-inventor.

Nevertheless, if one considers the yearly relative share of these patents, with respect to all patent applications, then the result is that this share has tended to increase in time. In the early years in the 1960s the share of university-inventor patents was at a low level of 5 percent from all patent applications. Then it started to increase at the end of the 1970s, peaking at the highest level of 23 percent in 1983 and then stabilizing around 20 percent in the 1990s. Even although the overall number of applications have tend to decrease around the year 2002, still the share of university-inventor patents in 2005 is at a level of 12 percent, being more than double from the initial shares prevailing forty-years ago (see Figure 2).

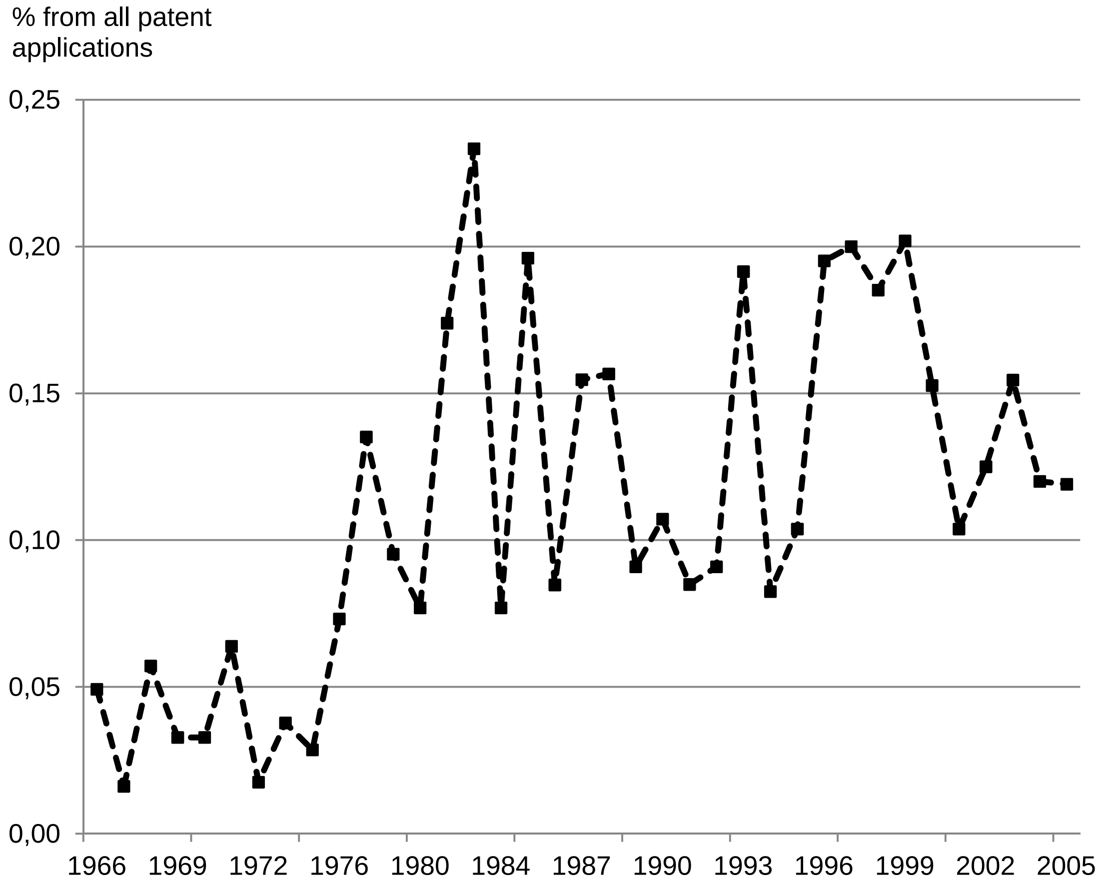

Figure 2: Share of patent applications with university-inventors involvement (percentage from total yearly applications), Germany, 1966–2005 [11]

5 Econometric Analysis

5.1 Patent citations and firm performance

For analyzing whether quality patents are related to firm performance, a survival analysis is performed. Following Buenstorf (2007), performance is measured by the number of years a firm was an active producer of laser sources to the market. In choosing the hazard model, the standard approach of the Cox proportional model is considered. This semi-parametric approach has the advantage of not making direct assumptions

[11] This information is available only for West Germany until the year 1989. From 1990 on the counts also include East Germany.

about the distribution of the time-to-event variable, but only with respect to the covariates of interest (Cleves, Gould, and Gutierrez, 2004).Specifically the model is:

$$h_i(t,X_i)=h_o(t)\ exp(\sum^{p}_{k=1} \beta_k X_{ik}]) \ , \qquad i=1,\dots,154 \qquad (1)$$

Where hi(t,X_i) represents the likelihood that firm *i* at time *t* experiences the event of market exit conditional on a vector of covariates. Time is measured in years, starting for each firm when they entered the market as a source producer and the failure event is market exit. Following Buenstorf (2007), survival only relates to the firm's activities in the laser source industry without implying whether the firm is defunct or still active. Two types of exits are distinguished: i) exit by end of commercial activities as laser source supplier, or ii) exit given merger or acquisition (M&A) from another firm. As in Buenstorf (2007), and in several other industry life cycle analysis of firm survival, the cases of M&A are not considered as failure, but rather treated as right-censored exits and excluded from the risk set. [12] This is because M&A may reflect different exit processes than exit due to bad performance such as the possible good performance of a promising firm. Additionally, the analysis will exclude the M&A cases and compare the results in comparison to the full sample. In the last part of section five, also more complex frameworks of competing risk estimations will be employed for considering whether quality patents have different effects for each type of exit.

The explanatory variables are:

- *Firm's patent portfolio of quality patents:* the number of patents in laser sources technology that received 6 or more corrected cites.

[12] In the cases where the firms were acquired by non-laser firms, they remain in the sample and are treated as if they remained independent. In the two cases where a firm enters and exits the market twice: Zeiss and Rofin Sinar, Buenstorf (2007) is followed and both entries are considered separately but for the last entry the patent portfolios are merged.

- *Pre-entry background:* firms are grouped in three main categories of “diversifiers” (i.e. firms that were incumbents in other areas and/or distributors of laser sources that entered production), “corporate spinoffs” (i.e. firms where one of the founders was previously employed by an incumbent producer of laser sources), and the joint category of “academic startups/other startups,” which includes both firms coming from universities or public research organizations and new firms whose background do not correspond to the previously identified categories. The reference group is the third one.

- *Time of entry into the industry*: following Buenstorf (2007) three cohort dummies are including for controlling the time of entry. The first one groups the historical entries during the experimental phase of the technology (1960-1984). The second (1985-1996) and third (1997-2005) consider the expansion and probable start of the consolidation phase, trying to balance the size given to the increasing number of entrants. The reference group is the first cohort.

- *Age*: it represents the age of the firm before market entry and it is estimated as the difference between its first active year and the date of incorporation/founding year.[13]

The survival analysis is made in stages successively adding variables. It begins with a simple model containing only one explanatory variable: the number of quality patents. Then it consequently controls for the firm’s pre-entry experience, time of entry and age. The estimates are presented in Table 2.

[13] Unluckily information on other control variables, such as size (e.g. number of employees prior to market entry) is not available for most of the laser firms.

Table 2: Quality patents and firm survival

	Pooled				Excluding exit by M&A
Variables	(I)	(II)	(III)	(IV)	(V)
Quality patents (>= 6 citations)	-0.014*	-0.012*	-0.012*	-0.012**	-0.016**
	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)
Diversifier		-0.554*	-0.576*	-0.746**	-0.461
		(0.310)	(0.316)	(0.377)	(0.324)
Spinoff		-0.673*	-0.669*	-0.876**	-0.479
		(0.354)	(0.388)	(0.425)	(0.385)
Cohort2 (1985-1996)			-0.061	-0.108	-0.306
			(0.476)	(0.490)	(0.481)
Cohort3 (1997-2005)			-0.390	-0.576	-0.559
			(0.599)	(0.626)	(0.597)
Age				0.003	
				(0.006)	
Observations	154	154	154	144	129
Log Likelihood	-175.4	-173.7	-173.5	-146.7	-163.6
pseudo-R2	0.007	0.017	0.018	0.025	0.021

Robust standard errors in parentheses. ***: statistically significant at the 1 percent level; **: statistically significant at the 5 percent level; *: statistically significant at the 10 percent level.

The first four columns from Table 2 (columns I to IV) present the results considering all the observations, while the last one (column V) excludes the exits due to merger or acquisition. As mentioned before, in the pooled regressions exit by M&A is not treated as a failure but as right censored. In all the models there is a statistically significant relationship at the ten or five percent level between having quality patents and a lower likelihood of exiting the market. Even when the background of the firm is controlled (column II), the time of entry (column III), and age (column IV), quality patents tend to decrease the likelihood of exit. Similar to Buenstorf (2007), pre-entry background affects firm survival: the “experienced” firms of diversifiers and corporate spinoffs have significantly lower chances of exiting the market than the inexperienced ones of “academic startups/other startups.” Time of entry does not affect firm performance and no first-mover advantage is detected. Although “age” has a counterintuitive positive sign, it is statistically insignificant and it is in line with the expectations regarding an industry defying shakeout and experiencing continuous entry.[14]

Given that exiting by M&A different process, in column V such observations are excluded from the sample. The effect of the coefficient becomes stronger and statistically significant at the five percent level. This suggests that when comparing only surviving firms against those which "truly" exited the market, the possession of quality patents tends to have a higher negative impact on the hazard of exit. Overall the estimates support hypothesis one (H1).

5.2 Innovative effort and knowledge compensation

In this section it is tested to what extent relevant innovative effort could compensate, at least partially, for the lack of adequate capabilities at firm birth for the inexperienced group of entrants. As in Canter, Krueger, and von Rhein (2011), the population of firms is classified into four groups according to both the background characteristics and innovative behavior:

- *Experienced innovator*: a diversifier or corporate spinoff with at least one quality patent.
- *Experienced non-innovator*: a diversifier or corporate spinoff without a quality patent.
- *Inexperienced innovator*: an academic startup or other startup with at least one quality patent.
- *Inexperienced non-innovator*: an academic startup or other startup with no quality patents.

The results of the survival analysis are presented in Table 3, considering as reference the last group of inexperienced non-innovators.

[14] Similar results of the non-statistically significance of "age" on survival are found in Sleeper (1998) for the U.S. laser source industry, and in Audretsch and Lehmann for high-tech firms in Germany (2005). Although differently measured, the results of "age" are also in line with Thompson's (2005) findings for the U.S. shipbuilding industry: controlling for the pre-entry experience of firms eliminates the dependence of survival on age.

Table 3: Quality patents and knowledge compensation

	Pooled			Excluding exit by M&A
Variables	(I)	(II)	(III)	(IV)
Experienced innovator	-1.089***	-1.120***	-1.157**	-0.939**
	(0.399)	(0.396)	(0.485)	(0.390)
Experienced non-innovator	-0.754**	-0.778**	-0.982**	-0.609*
	(0.320)	(0.357)	(0.382)	(0.366)
Inexperienced innovator	-1.500*	-1.529**	-1.540*	-1.189*
	(0.773)	(0.771)	(0.798)	(0.675)
Cohort2 (1985-1996)		0.034	0.034	-0.112
		(0.444)	(0.459)	(0.467)
Cohort3 (1997-2005)		-0.331	-0.466	-0.402
		(0.549)	(0.563)	(0.563)
Age			0.001	
			(0.006)	
Observations	154	154	144	129
Log Likelihood	-172.7	-172.4	-145.9	-164.1
Pseudo-R2	0.022	0.024	0.031	0.018

Robust standard errors in parentheses. ***: statistically significant at the 1 percent level; **: statistically significant at the 5 percent level; *: statistically significant at the 10 percent level.

As expected, the first column of Table 3 shows that all the other types of firms have statistically higher chances of surviving than the group of “inexperienced non-innovators.” “Experienced innovators” present a strong significantly negative relation on time to market exit, followed by the “experienced non-innovators”. Remarkably, the group of “inexperienced innovators” also has better survival chances than the reference group. Its hazard ratio of 0.223 (statistically significant at the ten percent level) implies that being an inexperienced firm with relevant innovative effort decreases the hazard of exit by 78 percent with respect to those inexperienced entries without such an innovative track record.[15]

Such a result remains robust when controlling for the time of entry (column II), the age of the firm (column III) and the exclusion of the exits

[15] This is computed 100 x [1-exp(-1.500)].

by M&A (column IV). Therefore the evidence supports the knowledge compensation hypothesis (H2).

5.3 University-inventor patents

The estimations regarding the impact of having patents with at least one inventor from a university are presented in Table 4. Contrary to the formulated expectations, having such types of patents in the firm's portfolio is not statistically related to having better survival odds in the market (columns I to III). As the estimations in Table 2, the inclusion of the background of the firm remains statistically significant (columns II and III).

Table 4: University- inventor patents and firm performance

	Pooled		
Variables	(I)	(II)	(III)
University-inventor patents	-0.037	-0.033	-0.031
	(0.026)	(0.025)	(0.027)
Diversifier		-0.591*	-0.740**
		(0.318)	(0.375)
Spinoff		-0.675*	-0.881**
		(0.388)	(0.425)
Cohort2 (1985-1996)		-0.047	-0.083
		(0.470)	(0.485)
Cohort3 (1997-2005)		-0.364	-0.535
		(0.594)	(0.619)
Age			0.002
			(0.006)
Observations	154	154	144
Log Likelihood	-175.9	-173.9	-147.2
pseudo-R2	0.004	0.016	0.022

Robust standard errors in parentheses. ***: statistically significant at the 1 percent level; **: statistically significant at the 5 percent level; *: statistically significant at the 10 percent level.

Although these estimates suggest that such linkage does not influence firm performance, the results must be interpreted with care given to the fact that only few firms ever engaged in such an arrangement. Moreover, this does not imply that the academic and industry interactions are not important, because there may be several other channels of technology transfer not considered in this study.[16]

5.4 Model diagnostics and robustness check

For all the previous models the proportional hazard assumption was tested by Schoenfeld residuals tests, and the results present no evidence against it.

Furthermore, the models are re-estimated by increasing upward the threshold for defining quality patents, firstly by considering at least 8 citations, and then by at least 14 cites instead of the previously defined criteria of 6 or more. The results regarding the relationship between quality patents and firm survival are presented in Table 5. With coefficients becoming of a higher magnitude when the threshold is of 14 cites, the negative relationship between quality patents and market exit still remains in every specification, being statistically significant at the ten or five percent level (see Table 5).

With respect to the knowledge compensation hypothesis, the results further support the possibility of compensating lack of adequate pre-entry experience with relevant innovative behavior. Under the 8 cites threshold, the coefficient estimates for the "inexperienced innovators" remain statistically and negatively significant at ten or five percent (see table 6).[17]

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[16] One limitation of the above-mentioned estimation is that it just considers the university-inventor patents in the firms' portfolios, but not the complete academic patents, namely those applications coming also from public research organizations such as the Max Planck Society and Fraunhofer-Gesellschaft.

[17] Regarding the knowledge compensation with a threshold of 14 or more citations, the estimation in this case is not adequate given that under "inexperienced innovators" the observations are all censored.

Table 5: Firm survival and alternative measures of quality patents (at least 8 citations vs. 14 citations)

Variables	Threshold: at least 8 citations				Threshold: at least 14 citations			
	Pooled		Excluding exit by M&A		Pooled		Excluding exit by M&A	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Quality patents	-0.016*	-0.016*	-0.016**	-0.022**	-0.035*	-0.036*	-0.035**	-0.045**
	(0.008)	(0.008)	(0.008)	(0.010)	(0.020)	(0.021)	(0.017)	(0.022)
Diversifier	-0.557*	-0.578*	-0.745**	-0.463	-0.551*	-0.572*	-0.750**	-0.459
	(0.309)	(0.315)	(0.376)	(0.323)	(0.310)	(0.316)	(0.377)	(0.324)
Spinoff	-0.675*	-0.672*	-0.880**	-0.483	-0.671*	-0.667*	-0.877**	-0.480
	(0.354)	(0.388)	(0.425)	(0.385)	(0.353)	(0.388)	(0.425)	(0.385)
Cohort2 (1985-1996)		-0.057	-0.104	-0.302		-0.058	-0.106	-0.305
		(0.476)	(0.490)	(0.480)		(0.477)	(0.490)	(0.481)
Cohort3 (1997-2005)		-0.387	-0.572	-0.555		-0.389	-0.578	-0.560
		(0.599)	(0.625)	(0.596)		(0.599)	(0.625)	(0.596)
Age			0.003				0.004	
			(0.006)				(0.006)	
Observations	154	154	144	129	154	154	144	129
Log Likelihood	-173.8	-173.5	-146.7	-163.7	-173.7	-173.4	-146.7	-163.6
pseudo-R2	0.016	0.018	0.025	0.021	0.017	0.019	0.026	0.021

Robust standard errors in parentheses. ***: statistically significant at the 1 percent level; **: statistically significant at the 5 percent level; *: statistically significant at the 10 percent level.

Table 6: Knowledge compensation and alternative measures of quality patents (8 citations)

Variables	Threshold: at least 8 citations		
	Pooled		Excluding exit by M&A
	(I)	(II)	(III)
Experienced_innovator	-1.186***	-1.157**	-0.993**
	(0.414)	(0.485)	(0.404)
Experienced_non-innovator	-0.759**	-0.982**	-0.595*
	(0.353)	(0.382)	(0.361)
Inexperienced_innovator	-1.527**	-1.540*	-1.185*
	(0.772)	(0.798)	(0.675)
Cohort2 (1985-1996)	0.015	0.034	-0.121
	(0.451)	(0.459)	(0.470)
Cohort3 (1997-2005)	-0.365	-0.466	-0.427
	(0.557)	(0.563)	(0.569)
Age		0.001	
		(0.006)	
Observations	154	144	129
Log Likelihood	-172.2	-145.9	-164.0
pseudo-R2	0.025	0.031	0.019

Robust standard errors in parentheses. ***: statistically significant at the 1 percent level; **: statistically significant at the 5 percent level; *: statistically significant at the 10 percent level.

5.5 Competing risks models: Stratified and non-stratified specifications

Finally, there is one important estimation issue left: to what extent do quality patents' effects differ by different types of failure events, namely on exit by market exit or by M&A? If such effects are different by type of exit, then an estimation explicitly considering them would be more adequate. In order to explore whether this is the case, Table 7 presents alternative specifications of the effect of quality patents by type of exit in a competing risks analysis' framework. This is done by Cox regressions in which the occurrence of one failure type excludes the other one. Following Lunn and McNeil (1995), the procedure is to first augment the data twice according to the two types of failures (exits). Then two alternative estimations are presented. In one procedure the type of failure “exit by M&A” enters directly as a covariate in a non-stratified regression. This approach is adequate under the assumption that the hazard functions of the types of exit have a constant ratio. In the second approach, the likelihood of exit is stratified by the type of failure (Lunn and McNeil, 1995).

The non-stratified Cox regressions are presented in columns I and II in Table 7. Here the dummy variable “exit by M&A” represents the relative risk of exit from a merger or acquisition in relation to market exit. The other main covariates are the firm’s portfolio of quality patents, and the interaction between exit by M&A with the “quality patents” variable. In the second column additional controls are included. This method has the advantage that by having a single underlying survival curve, all the coefficients are directly comparable in terms of risk. Column I presents that the risk of M&A exit is statistically significantly lower by a factor of exp (-0.584) than the risk of market exit. While “quality patents” is statistically significant, pointing out that quality patents may reduce the risk of market exit by a factor of exp(-0.013), the interaction term of “quality patents” and M&A is not. This may indicate that quality patents do not have a different effect for cases of M&A exit (columns I and II, Table 7).

In columns III and IV the regression is stratified by type of failure. The main covariates are the quality patents portfolio together with its interaction with exit by M&A. Now the interpretation of the estimates is not as straightforward as before because the relationship among the baseline hazard rates is not estimated (Lunn and McNeill, 1995). Nevertheless this specification allows to consider whether “quality patents” have a diverse effect by different types of exit. The results of the interaction term on columns III and IV present a non-significant statistically negative relation. This points out again, that all other things being equal, the risk of exit due to M&A exit is not differently affected by having “quality patents” (columns III and IV, Table 7).

Overall the evidence suggests that indeed “quality patents” do not have a different effect on the type of exit, and therefore the previous estimation framework of section 5.1 is appropriate.

Table 7: Alternative specifications: Competing risk models of quality patents and firm survival

	Unstratified Cox model		Stratified Cox model	
Variables	(I)	(II)	(III)	(IV)
Quality patents	-0.013*	-0.012**	-0.014*	-0.012**
(>= 6 citations)	(0.007)	(0.006)	(0.007)	(0.006)
Quality patents*M&A	-0.035	-0.025	-0.029	-0.020
	(0.042)	(0.042)	(0.043)	(0.041)
Diversifier		-0.499*		-0.502*
		(0.283)		(0.282)
Spinoff		-0.131		-0.132
		(0.305)		(0.304)
Cohort2 (1985-1996)		-0.650*		-0.651*
		(0.392)		(0.392)
Cohort3 (1997-2005)		-0.616		-0.618
		(0.477)		(0.477)
Exit due to M&A	-0.584**	-0.598**		
	(0.252)	(0.250)		
Observations	308	308	308	308
Log Likelihood	-317.7	-315.2	-271.2	-268.8
pseudo-R2	0.017	0.025	0.008	0.017

Robust standard errors in parentheses. ***: statistically significant at the 1 percent level; **: statistically significant at the 5 percent level; *: statistically significant at the 10 percent level.

6 Conclusions

This paper has presented evidence that firms that engage in innovative behavior and invest in high quality research will tend to have better market performance. Relevant innovation effort is proxied by quality patents, defined as those being frequently cited. Firms that have quality patents tend to have better survival chances. Firms lacking adequate capabilities, given their pre-entry backgrounds, may compensate for such disadvantages if they commit to generating quality research in the form of valuable patents. In this respect, the laser source industry in Germany presents a case where inexperienced entrants are not “doomed to fail” by birth given an inadequate background. Some of them can succeed by committing to relevant innovation effort and quality research.

With respect to linkages with the academic community, this study explored only one of such possible channels, namely having laser patents in which at least one inventor is a university professor. The results present that although the share of such patents is much higher than those appearing as university owned patents, only a small fraction of them actually link active source producers with university inventors. In this context, having university-inventor patents is apparently not related to having better survival chances in the laser sources market. However, this result does not mean that linkages with the academic community are not important for firm performance, but only suggests that other channels may be more relevant. Hence, more detailed analyses are needed on the other possible science-industry interactions and their impact on firm performance over time.

But do these results reflect only a specific industry development? Although they refer only to a science-based industry defeating the shakeout prediction, they can also be considered as one more contribution towards a broader industry evolution perspective. For instance, Malerba (2004) proposes to complement the industry life cycle approach with components from the sectoral innovation systems perspective, such as knowledge and networks. Grebel, Krafft, and Saviotti (2006) also suggest broadening the analysis, given that the industries emerging in the second half of the twentieth century present different evolution patterns than those that emerged in the first half. One of this divergence is the finding that early entrants may no longer benefit from the type of first-mover advantage that firms used to have in the past (Agarwal and Gort, 2001). Furthermore, Krafft (2004) suggests that specific knowledge dynamics at the local level also could influence the industry life cycle. In line with these insights, this contribution also argues for more interdisciplinary and empirical analyses of the evolution of innovative industries, considering also a firm’s innovation measures and linkages to the academic community.

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Appendix A

Table A1: Descriptive Statistics

Variable Name	Mean	Median	Minimum	Maximum	Standard Deviation	Number of observations
Survival years	9.883	9.000	1.000	44.000	6.791	154
Quality patents portfolio (>= 6 citations)	2.643	0.000	0.000	234.000	19.120	154
Quality patents portfolio (>= 8 citations)	1.948	0.000	0.000	173.000	14.136	154
Quality patents portfolio (>= 14 citations)	1.000	0.000	0.000	86.000	7.051	154
Diversifier (yes/no)	0.422	0.000	0.000	1.000	0.496	154
Corporate spinoff (yes/no)	0.318	0.000	0.000	1.000	0.467	154
Academic startup/ other startup (yes/no)	0.260	0.000	0.000	1.000	0.440	154
Cohort1 (1961-1984)	0.162	0.000	0.000	1.000	0.370	154
Cohort2 (1985-1996)	0.344	0.000	0.000	1.000	0.477	154
Cohort3 (1997-2005)	0.494	0.000	0.000	1.000	0.502	154
Experienced_innovator (yes/no)	0.201	0.000	0.000	1.000	0.402	154
Experienced_non-innovator (yes/no)	0.539	1.000	0.000	1.000	0.500	154
Inexperienced_innovator (yes/no)	0.058	0.000	0.000	1.000	0.235	154
Inexperienced_non-innovator (yes/no)	0.201	0.000	0.000	1.000	0.402	154
Age	14.507	5.000	1.000	140.000	27.472	144

Table A2: Correlation Table

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Survival years	1													
2	Quality patents portfolio (>= 6 citations)	0.437*	1												
3	Quality patents portfolio (>= 8 citations)	0.435*	0.999*	1											
4	Quality patents portfolio (>= 14 citations)	0.439*	0.998*	0.99*	1										
5	Diversifier (yes/no)	0.190*	0.134	0.13	0.131	1									
6	Corporate spinoff (yes/no)	-0.038	-0.074	-0.08	-0.075	-0.584*	1								
7	Academic startup/ other startup (yes/no)	-0.173*	-0.07	-0.07	-0.067	-0.506*	-0.405*	1							
8	Cohort1 (1961-1984)	0.270*	0.227*	0.22*	0.225*	0.194*	-0.187*	-0.020	1						
9	Cohort2 (1985-1996)	0.136	-0.050	-0.05	-0.047	-0.010	0.092	-0.086	-0.319*	1					
10	Cohort3 (1997-2005)	-0.328*	-0.112	-0.12	-0.122	-0.133	0.051	0.097	-0.434*	-0.715*	1				
11	Experienced_innovator (yes/no)	0.272*	0.265*	0.26*	0.265*	0.292*	-0.03	-0.297*	0.345*	-0.057	-0.204*	1			
12	Experienced_non-innovator (yes/no)	-0.066	-0.150	-0.15	-0.154	0.210*	0.380*	-0.640*	-0.264*	0.122	0.079	-0.543*	1		
13	Inexperienced_innovator (yes/no)	-0.037	-0.016	-0.01	-0.004	-0.213*	-0.170*	0.421*	-0.035	-0.064	0.086	-0.125	-0.269*	1	
14	Inexperienced_non-innovator (yes/no)	-0.168*	-0.070	-0.07	-0.071	-0.429*	-0.343*	0.847*	-0.001	-0.057	0.055	-0.252*	-0.543*	-0.125	1
15	Age	0.226*	0.417*	0.41*	0.420*	0.405*	-0.198*	-0.249*	0.311*	-0.071	-0.152	0.444*	-0.141	-0.112	-0.21*

* Statistically significant at the 5% level

Appendix B:

Hall, Jaffe, and Trajtenberg (2000, 2002) propose a method for solving the problem of truncation in patent citation data. Building on a former model of Caballero and Jaffe (1993) and Jaffe and Trajtenberg (1996), they model citation frequency as the likelihood that any patent applied for in year *t* (citing patents) will cite a patent applied for in year *s* (cited patents). They assume that citation is determined by the combination of an exponential process by which knowledge becomes obsolete, a second exponential process by which knowledge diffuses, and finally by the specific effects coming from different technology fields, citing years, and cited years (Jaffe and Trajtenberg, 1999; Hall, Jaffe, and Trajtenberg, 2000). Their citation frequency model is as follows:

$$C_{kst}/P_{ks} = \alpha'_o \alpha'_s \alpha'_t \alpha'_k exp\big(f_k(L)\big) \qquad (B-1)$$

Where C_{kst} is the total number of citations to patents in year *s* and technology *k* coming from patents applied for in year *t*. P_{ks} is the total of patents observed in technological field *k* in years *s*. Their ratio is the average number of citations received by each *s* patent from the total of patent counts in year *t*. This citation frequency is modeled as a multiplicative function of several cited year *(s)*, citing year *(t)*, technology field *(k)*, and citation lag *(L=t-s)* effects. The citation lag *L* is the years between the application year of the citing patent (*t* year) and the application year of the cited patent (*s* year). The function $f_k(L)$ represents the citation-lag distribution, which in Hall, Jaffe, and Trajtenberg (2000, 2002) is modeled as:

$$f_k(L) = \exp(-\beta_{1k}\, L)(1 - \exp(-\beta_{2k} L)) \qquad (B-2)$$

The parameter β_{1k} captures the obsolescence or depreciation of knowledge, while β_{2k} reflects the diffusion of knowledge. The summation of $f_k(L)$ over L is normalized to unity. Hall, Jaffe, and Trajtenberg (2000, 2002) estimate such model by nonlinear least squares, and group the cited years in five-year intervals, reflecting their assumption that “the true fertility of invention changes only slowly” (Hall, Jaffe, and Trajtenberg 2002, p. 443).

In this paper it is chosen a simpler version of their model given its focus on only one main technological field. Furthermore, the cited-year and citing-year effects are included in an additive way to make the estimation feasible. The model is:

$$C_{st}/P_s = \alpha_o * exp(-\beta_1 L)\big(1 - exp(\beta_2 L)\big) + \alpha_s + \alpha_t + \epsilon_{st} \qquad (B-3)$$

$$s = 1961, \ldots, 2005;\ t = 1964, \ldots, 2010$$

Year dummies are included to control for possible effects due to the increased number of citations made per patent and the increased number of citing patents. The cited years are also grouped into five-year intervals, while the citing years are included separately. Equation (B-3) is estimated with nonlinear least squares with cluster-robust standard errors grouping at the level of assignee. This is for considering that patent applications from the same assignee are not independent observations.

The choice of starting values is very important in nonlinear least square estimation and any good information about them should be used (Greene, 2008, p. 293). For the initial values of the parameters β_1 and β_2 the estimates from Hall, Jaffe, and Trajtenberg (2000, 2002) are taken. These studies provide the most reliable information in this respect, even though they use U.S. patent citation data (i.e., the NBER Patent Citations File). Their coefficients for the diffusion and obsolescence processes, when one is allowed to vary across different technological fields and the other remains constant, are smaller than 1 and their addition is also below unity.[18] From such estimates the following conditions for initial values are derived: i) a positive number between 0 and 1, and ii) numbers whose addition is below unity.[19]

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[18] Specifically, when obsolescence is the same across different fields and diffusion is allowed to vary, the estimated value of β_1 is 0.104. When the diffusion is taken as similar for different technological fields and depreciation is allowed to vary, their estimate of β_2 is of 0.436 (Hall, Jaffe, and Trajtenberg, 2002, p. 445).

[19] Such conditions are also present in a former study from Jaffe and Trajtenberg (1999) that uses a much larger of covariates including also the geographical information of both the potentially cited patent and the potentially citing patent.

The estimated from Equation (B-3) are used for constructing the expected distribution of the citation lags after controlling for the citing-year and cited-year effects. From such cumulative distribution upward correcting coefficients are estimated, which are presented in the first column in Table B1. As a comparison, the second column presents the results from Hall, Jaffe, and Trajtenberg (2002) for their technological field "Electrical & Electronic," which is the closest one to the laser source technology. The two estimates are fairly similar.

These coefficients can be used to adjust the total citation count for each patent. Take, for instance, two patents with five citations each, one applied for in 1961, the second in 2001. The first patent can be observed until its final 49th year lag of the citation-lag distribution (2010-1961=49); that is, its citation history up to 2010 equals its expected “life-time” citation count in Table B1. However, the second patent, applied for in 2001, can be observed only until its 9th lag from the complete 49 “life-time” citation lag distribution (2010-2001=9). The correcting coefficient estimates that a “typical” laser source patent is expected to obtain approximately 57 percent of its “life-time” citations nine years after its application. Therefore, in order to correct the total citation counts, these five citations are “deflated” by the coefficient 0.575, which gives an upward corrected total count of 8.7 citations.

Table B: Simulated cumulative lag distributions - comparison with the NBER Patent citations data's estimates

	Laser source patent citation data	**NBER Patent citation data, technological field "Electrical & Electronic"**
Lag (years)	Cumulated distribution lag	Cumulated distribution lag
1	0.043	0.048
2	0.109	0.115
3	0.183	0.187
4	0.259	0.259
5	0.332	0.327
6	0.401	0.390
7	0.465	0.448
8	0.522	0.502
9	0.575	0.550
10	0.622	0.594
11	0.664	0.635
12	0.701	0.671
13	0.735	0.705
14	0.765	0.735
15	0.791	0.763
16	0.815	0.788
17	0.836	0.811
18	0.855	0.832
19	0.871	0.851
20	0.886	0.868
21	0.899	0.884
22	0.911	0.898
23	0.921	0.911
24	0.930	0.923
25	0.938	0.934
26	0.946	0.943

27	0.952	0.952
28	0.958	0.960
29	0.963	0.968
30	0.968	0.975
31	0.972	0.981
32	0.975	0.986
33	0.978	0.991
34	0.981	0.996
35	0.984	1.000
36	0.986	
37	0.988	
38	0.990	
39	0.991	
40	0.993	
41	0.994	
42	0.995	
43	0.996	
44	0.997	
45	0.998	
46	0.998	
47	0.999	
48	1.000	
49	1.000	
	Cited years run from 1961 to 2005, and citing years from 1961 to 2010 Source: own estimation.	Cited years run from 1963 to 1999, and citing years from 1975 to 1999 Source: Hall, Jaffe, and Trajtenberg (2002), "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools. In: Patents, Citations, and Innovations. A Window on the Knowledge Economy", p. 450