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TESIS DOCTORAL

The value of patent knowledge: Internal and external valuation

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Doctorado en Empresa y Finanzas

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To my parents

CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Abstract

This dissertation consists of three essays analyzing how patenting firms and external investors value the knowledge describe in the patent document. A patent is a document that bestows a temporary exclusivity right (20 years from the filing date) over the described invention. In the patent document, one can find information about assignees, inventors, application date, priority date, a list of prior art (backward citations), the invention technological classification, and the claims describing the invention. Therefore, a patent disclose a rich set of information, which might reveal a firm's valuable technological information and be used by competitors. Therefore, I study the patenting firm valuation of the information conveyed by the patent and how external investors value the patented knowledge.

In the first chapter, I study publicly firms' motivations to delay patent disclosure. The enactment of the American Inventors Protection Act (AIPA), in November 29, 2000, required U.S. patent applicants to have their patent application published 18 months after filing date but allowed them to opt for keeping it secret if they relinquished foreign patent protection. Using a sample of granted patents applied for by publicly traded companies, between 2000 and 2009, I investigate what drives large companies' decision to keep a patent secret up to grant. Particularly, in this chapter I investigate the effect of technological crowdedness, strategic use of in-house knowledge stock, and invention radicalness on the decision of opting out of pre-grant publication. Results show a negative association between technological crowdedness and pre-grant secrecy, while radicalness and the use of in-house knowledge stock are positively associated with the likelihood of a patent application being secret until grant.

In the second chapter, we use an event study methodology to investigate whether the stock market values innovation milestones. First, we investigate abnormal returns generated due to a patent grant event. Results point to investors, on average, not valuing the information disclosed in the patent document. We then test several explanations about why investors do not value patent grants on average: patent value is highly skewed, the number of patents granted is ever increasing and only some patents protect technology that results in successful products. By analyzing stock market reaction to the

approval of a drug by the U.S. Food and Drug Administration (FDA), we show that the stock market is able to value innovation that results in a product. This suggests that innovation that will clearly generate sales revenue in the short run are highly valued by investors. We point out some implications of these results.

Finally, in the third chapter, I look at the effect of firm's technological diversification on firm value (Tobin's q). Firm's technological knowledge base contributes to identifying technological opportunities and answering demand changes. Therefore, a firm with broader technology base might be better able to cope with technology uncertainties achieving higher future returns. Technological classes of the firm's patents were used to calculate an entropy index of technological diversification. Using a sample of 1,304 R&D intensive US firms over 16 years (1992-2007) I find that on average technological diversification has a positive and significant impact on firm value. Further, diving into industry level differences, results indicate that technological diversification matters to investors' assessment of firm's future cash flows in the electronic industry. On the other hand, in the chemical industry, technological diversification does not have a significant effect on Tobin's q.

Chapter 1

Why are they hiding? Patent secrecy and patenting strategies

1.1 INTRODUCTION

A patent provides a mechanism to protect inventors from competitors' imitation of their invention in exchange for a detailed disclosure of the patented invention so that any interested and skilled audience may be able to understand and replicate the knowledge conveyed by the patent document. The temporary exclusivity right bestowed by the patent rights urges inventors to strategically manage their patents to maximize the profits generated by the invention (Jell, 2011) and to sustain a competitive advantage that may be derived from the innovation (Teece, 1986).

The literature on patenting strategies focuses on the motivations driving the strategic uses, filing (Jell, 2011; Van Zeebroeck, 2009) and management of patents (Somaya, 2012). According to de Rassenfosse et al. (2008) and Jell (2011), in addition to the traditional motive to protect an invention against competitors' imitation, motives to patent include: blocking others, securing freedom to operate, and enhancing reputation. On the strategic management of patents, Somaya (2012) singles out some issues such as "signaling and information disclosure strategies, managing patents as real options, nonmarket strategies, and patent-related managerial capabilities" (Somaya, p. 1086, 2012). Filing strategies are related to procedural choices made by patentees in filing their patent applications. These choices may accelerate or delay the grant of a patent. Van Zeebroeck (2009) identifies patent filing strategies – the craft of a patent by making it longer and cumbersome to examiners to evaluate the patent, international filings, and the filing of divisional patents.

This study contributes to the patent filing strategies literature by analyzing patentees' decision, when filing a patent application, to delay the disclosure of the patent document. Enacted on November 29, 2000, the American Inventors Protection Act (AIPA) established the automatic publication of US patent applications 18 months after the earliest filing date[1]. Nonetheless, an inventor may choose to have the patent application secret up to grant[2]. However, this choice poses a trade-off: having the patent application secret up to grant requires relinquishing foreign patent protection. The AIPA law harmonized US patent law with international patent law. Although patentees faced

[1] Patent applications filed in a foreign jurisdiction were published by the foreign patent office before AIPA enactment; however, AIPA established the patent application publication by the US Patent and Trademark Office (USPTO) making patent applications available in the US at the same time they are published abroad.

[2] AIPA's opt out option requires applicants to certify that the invention disclosed in the application will not be subject of an application in another country or under an international multilateral agreement that requires publication 18 months after the filing date (35 U.S. Code § 122)

international publication before AIPA – when filing an international patent application, after AIPA this decision has to be taken together with the patent filing. In addition, in case the patentee wants to withdraw an intitial pre-grant publication choice, this is associated with nontrivial costs (Graham and Hedge, 2015[3]).

The option to keep the patent secret until grant was justified as a mechanism to protect small US inventors who may not have enough resources to protect themselves against competitors' imitation (Ragusa, 1992; Johnson and Popp, 2001; Graham and Hedge, 2012), because usually small inventors have limited resources to identify patent infringers and sue them. Graham and Hedge (2012) in their analysis of successful US patent applications filed between 1996 and 2005 find that 7.5% of the applications filed during 2001 and 2005 chose pre-grant secrecy. Interestingly, small inventors are not more likely to opt out than large ones (Graham and Hedge, 2012, 2015).

In this study, I investigate what drives large companies to opt out of pre-grant publication. In my sample of patents applied for by publicly traded firms, about 8.15% of the granted patents, during 2001 and 2010, were opted out of earlier patent application publication. Moreover, patents that were opted out of patent application publication had, on average, 20 months more secrecy time than those published pre-grant.

Choosing pre-grant application publication allows patentees to pursue foreign patent protection. Graham and Hedge (2012) report that 51% of US patent applications filed between January 1, 1995 and November 28, 2000, were also applied for in a foreign country. Unsurprisingly, inventors are more likely to seek foreign patent protection for their valuable inventions (Graham and Hedge, 2012). Moreover, earlier publication allows the patent owner, once the patent is granted, the right to seek reasonable royalties from the publication date to the grant (Hedge and Luo, 2016). Thus, inventors may be willing to have the application disclosed before the grant of the patent right in order to benefit from earlier royalty revenues and foreign patent protection.

In addition to foreign patent protection, patentees derive value from patent application publication as it signals firms' innovation capabilities (Hsu and Ziedonis, 2007; Ganglmair and Oh, 2014) and may preempt R&D rivals from introducing a substitute innovation and competing with the patenting firm (Ceccagnoli, 2008). Moreover, pre-grant publication of a patent application may assist managers, of

[3] Online Supplementary Materials.

competitor firms, in making more informed decisions about R&D investment and avoiding hold up (FTC, 2003). Additionally, as AIPA aims to harmonize US patent law with the patent system of other developed economies[4], pre-grant publication may be driven by (especially multinational) firms' willingness to conform to international standards. Furthermore, pre-grant publication fosters knowledge disclosure, increases business certainty and promotes rational planning (FTC, 2005).

Conversely, AIPA's opt out option provides an opportunity to, to some extent, combine secrecy and the exclusivity right allowing for strategic use of a combination of formal and informal intellectual property (IP) protection (Graham, 2004; Schneider and Veugelers, 2013). Foregoing earlier publication gives patentees more time to develop the invention without having the patent application disclosed. Pre-grant secrecy might give inventors a competitive advantage as competitors have access to the invention in a detailed[5] way only when the uncertainty regarding the patent award is solved favorably[6], hindering imitation and inventing around activities. Indeed, the major argument against patenting is that the knowledge disclosed in the patent document may give valuable information to competitors undermining innovators' profits (Scotchmer and Green, 1990) and stimulating competitors to design around the patent (FTC, 2003). According to Anton and Yao (2004), disclosing enabling knowledge, included in the patent description, increases the probability of imitation or inventing around the patented invention.

In evaluating publicly traded firms' choice to opt out of earlier patent application publication, the present study shows that not only invention characteristics but also strategic concerns are relevant to the decision to keep the patent application secret up to grant. Furthermore, I propose that companies' filing strategy of keeping the patent application secret up to grant, takes into account the competition the technology faces, the hazard of disclosing firm's internal valuable knowledge, and the invention specific characteristics. Results show that there is a negative association between technological crowdedness and pre-grant secrecy, whereas the more radical an invention the more

[4] Most of industrialized economies, like Japan and European countries, have adopted the 18 months publication rule long before it was implemented in U.S. (Ragusa, 1992)

[5] "The specification shall contain a written description of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to enable any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same, and shall set forth the best mode contemplated by the inventor of carrying out his invention" (35 U.S.C.112).

[6] Uncertainty is not totally mitigated by the patent grant as, after grant, U.S. patents can be challenged by litigation or by a patent re-examination requested to the USPTO (Graham et al., 2002; Lemley and Shapiro, 2005; Gans et al., 2008)

likely is the patent to be kept secret up to grant. Further, the more an invention builds on companies' in-house knowledge stock[7] the more likely it is to opt out of pre-grant patent application publication.

1.2 THEORY AND HYPOTHESES DEVELOPMENT

This section discusses the drivers of patentees' decision regarding earlier application publication and derives some hypotheses. In particular, I discuss large entities' incentives to disclose or not the inventions through earlier patent publication and how disclosing or not is linked to companies' overall patenting strategies.

When applying for a patent many factors may determine the earliest filing date[8] and, therefore, the publication date. However, this study investigates the motivations to opt out of patent application pre-grant publication, which has to be stated together with the filing of the patent application.

Assuming that firms maximize their profits (Arrow, 1962) then the choice of pre-grant secrecy is made always when it yields higher returns than publishing the patent. Besides motives to keep an invention secret as profit maximizing, minimizing competition, or further developing the invention (Anderson, 2011), delaying disclosure reveals inventor's believe that domestic (US) protection is enough.

In choosing pre-grant secrecy, patentees may evaluate this choice considering three main aspects of the invention protected by the patent: the competition faced by the invention (technological crowdedness), firm's technology strategy and how much internal knowledge the patent application publication discloses, and the invention specific characteristics (radicalness).

Technological crowdedness

Appropriating returns from an invention depends on the inventor's ability to exclude others from making, using or selling the invention (Arrow, 1962). In case the invention is bound to be incorporated in a firm's process or product, excluding competitors is an upmost requirement in order to achieve profits maximization. Therefore, the willingness

[7] In this chapter, I refer to in-house knowledge stock as the extent that a patent builds on a firm's previous patents, relying on the knowledge generated inside the company.

[8] John F. Martin (August 3, 2015) points out several reasons why patent application publication may occur in less than 18 months or even in more time. http://www.ipwatchdog.com/2015/08/03/the-myth-of-the-18-month-delay-in-publishing-patent-applications/id=60185/ - Access: September 11, 2016.

to patent depends on the effectiveness of the patent as an instrument to exclude and to appropriate returns from the innovation (Cohen et al., 2000).

Even though a patent exclusivity right enables innovation returns appropriation, it has been shown in the empirical literature that managers mostly rely on informal innovation appropriability mechanisms such as secrecy, instead of on formal mechanisms such as patents (Cohen et al., 2000; Levin et al., 1987; Arundel, 2001). Zaby (2010) and Heger and Zaby (2013) stress that the invention disclosure required by the patent implies heterogeneous costs for the patenting firms. The former argues that an inventor's propensity to patent depends on the extent of her technological lead, being more likely to rely on secrecy the more the inventor can appropriate monopoly rents without patent protection, i.e., the more difficult it is for a rival to imitate or reverse engineering the invention. The latter states that the propensity to patent depends on market barriers and on the relevance of the information disclosed.

Patents, by requiring the disclosure of the invention, represent a huge threat to innovating firms and may shrink innovators' competitive advantage and technological lead (Zaby, 2010). Opting-out of pre-grant patent application publication the patentee is delaying the disclosure of the invention, what in a higly competitive environment may give to the patentee similar benefits as secrecy. However, in case disclosure represent an important threat it is reasonable to expect that the inventor is going to opt for secrecy instead of delaying disclosure.

On the other hand, the literature has identified a set of motives to patent beyond the traditional motive of protecting an invention against competitors' imitation. These motives include: blocking competitors from using an invention (Cohen et al., 2000), securing freedom to operate (Henkel and Jell, 2009), gaining time to find a licensee or to evaluate an invention's potential (Henkel and Jell, 2010), signaling the firm's research capabilities (Hsu and Ziedonis, 2008; Ganglmair and Oh, 2014), and protecting a firm against infringing others' patents and incurring infringement suit costs (Hall and Ziedonis, 2001).

On patents as a tool to secure *freedom to operate*[9] (Henkel and Pangerl, 2008; Henkel and Jell, 2009; Jell, 2011), Henkel and Pangerl (2008) interviewed 56 IP experts from Germany's large companies asking about *defensive publication* strategies. The authors find that companies use publications such as peer-review journals, firm's

[9] Jell (2011) defines *freedom to operate* as freedom to make and use the invention in the first place.

reports, and patents in order to establish *prior art*[10] and secure *freedom to operate*, and then, hindering competitors from patenting similar technology (Jell, 2011).

Parchomovski (2000) and Litchman et al. (2000) point to strategical disclosure of research results, where in a patent race, firms may disclose intermediate results in order to raise the patentability bar for competitors. When such research outcomes become publicly available, they may hinder *novelty* and *nonobviusness*[11] of an otherwise patentable invention.

Gilbert and Newbery (1982) have highlighted a strategic use of patents – incumbents preempt innovators from entering the market through patenting. According to the authors, preemptive patenting is a strategy to assure monopolistic profits. Furthermore, Ganglmair and Oh (2014) claim that by announcing a pending application the innovator (leader) may derive a value of deterrence, i.e., deterring the competitor (follower) from innovating if the threat of infringement is sufficiently strong, giving the leader a competitive advantage.

On preemptive patenting, Gullec et al. (2012) use patent examination outcomes at the European Patent Office (EPO) to access patents applied for in order to preempt competitors. They find evidence of preemptive patent filing – patentees file patents that may not comply with patenting requirements (*novelty and nonobviousness*) but aim to block competitors, ensuring freedom to operate. Also empirically, Ceccagnoli (2008), using the Carnegie Mellon survey (CMS) (Cohen et al. 2000), shows that preemptive patenting improves R&D returns appropriability for incumbents, especially when they have greater market share, when there is a threat of market entry, or when the R&D competition is based on incremental innovations.

Considering the AIPA's option to opt out, patentees may be willing to have their patent published before grant, deriving value from preempting competitors from inventing a similar invention. Earlier publication does not mean that the patent will be granted. However, by publishing the patent application it signals, to rivals, patentee's research developments and may stop competitors from investing in the same

[10] *Prior art* refers to the knowledge publicly available at the time the patent is applied for. For an invention to be patented it has to be *novel* and *non-obvious*. *Nove*l means that the invention has not been patented before and under the *non-obviousness* bar, an invention cannot be patented if "the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which the subject matter pertains" (35 USC § 103a).

[11] 35 U.S.C. § 102 and 35 U.S.C. § 103, respectively.

technological area (Litchman et al., 2000). In addition, pre-grant patent application publication, besides disclosing private information, bears the uncertainty regarding the award of the property right and it may also add uncertainty to the marketplace regarding the rights entitled to the patent (Van Zeebroeck, 2011).

If the invention belongs to a technological area where the competition faced is high, publishing the patent application the patentee may derive a higher value by preempting rivals or securing freedom to operate than keeping the invention secret. Therefore, if the patentee is operating in a crowded technological area (in which there are many competitors inventing), she may be willing to publish the patent application before the patent is granted. Following the above argument, the first hypothesis states that:

> *Hypothesis 1: Firms are less likely to opt out of pre-grant publication of a patent application if the technology space is more crowded.*

Firm's internal knowledge

When designing patent filing strategies to maximize invention's returns, inventors might consider the trade-off imposed by AIPA. By forgoing pre-grant publication an assignee also forgoes foreign patenting, i.e., foreign patent protection and the revenues she can get from the exclusivity right or licensing it out in another country. Balancing this trade-off, a patented invention that relies on firms in-house knowledge stock might influence firms' disclosure choice in two opposite directions.

On the one hand, an invention that builds on firm's internal knowledge indicates that the firm has an advantage at follow-on innovations as the firm has already developed the underlying tacit knowledge. Then, having internal expertise that probably involves tacit knowledge, the published knowledge is protected in the sense that the tacit part is necessary in order to replicate the invention. Therefore, there is no danger on publishing the patent application because of this protection.

On the other hand, earlier patent application publication reveals a firm's technology direction without the assurance of exclusivity rights, giving to competitors the possibility to invent around or to imitate it. In this case, if the invention builds on external knowledge, there is a higher likelihood that others detect similar directions using this knowledge by their own means. However, if the patented invention relies more on a firm internal knowledge, by publishing the patent the firm might reveal interesting directions to use the firm's knowledge.

In this sense, a follow-on invention might be kept secret until the patent grant in order to protect a core invention or to mask firm's innovative and research direction. Moreover, publishing the patent without the exclusivity right might put at risk firm's competitive advantage, even more when the invention relies on internal knowledge. Tacitness also means that the invention can be kept secret more effectively, i.e., an inventor would probably prefer to keep it secret if the patent is finally not granted

Graham (2004) shows that firms inventing upon internal knowledge and valuing secrecy as an appropriability mechanism are more likely to delay the invention disclosure. Therefore, a firm building on its own knowledge may forgo earlier patent application publication, hiding internal knowledge and postponing spillovers from the application disclosure. By hiding its technology direction, choosing patent application pre-grant secrecy, a firm might secure or increase its competitive advantage as competitors get to knowing later in which direction the firm is innovating. This motivates hypothesis 2:

> *Hypothesis 2. Relying on internal knowledge has a positive effect on the likelihood of a patent application to be opted out of pre-grant publication.*

Radicalness and technology uncertainty

Besides firms' strategies and technology characteristics, invention specific characteristics also might influence firms' choice of opting out of earlier patent application publication. Moreover, the decision to keep the invention secret up to the patent grant comes once the decision to patent the invention is made. Keeping the patent application secret assures that the invention will be disclosed when the uncertainty regarding the patent grant is favorably solved.

In addition to the property right uncertainty, patentees bear the uncertainty associated with the patented technology, the patent value, and the market for the protected invention (Somaya, 2012). The further the invention departs from the knowledge and capabilities established inside the firm and in the industry, the greater the uncertainty and the risk, requiring the adoption of new technical skills and routines (Nelson and Winter, 1982; Schoenmakers and Duyster, 2010). Likewise, inventions are said to be radical, as opposed to incremental, when they significantly differ from the state-of-the-art technology. Hence, a radical invention means moving away from established techniques to a new combination of knowledge (Fleiming, 2001). Hurmelinna-

Laukkanen et al. (p.5, 2013) argue that “when the creation to be protected is notably different from earlier ones, lead time, secrecy, or tacitness, for instance, are effective forms of protection since it takes more time for others to overcome causal ambiguities related to the innovation”. Therefore, the uncertainty borne by radical inventions might prevent firms from pre-grant publication, opting to have more time to further develop the technology before it is disclosed. Accordingly, hypothesis 3a states:

Hypothesis 3a. Radicalness has a positive effect on the likelihood of a patent to be opted out of pre-grant publication.

On the other hand, market uncertainty might prompt inventors to publish a radical invention before grant. To accelerate the adoption and the development of complementary assets, companies with radical inventions may be willing to disclose the invention. Innovating firms may profit from free revealing the invention by accelerating innovation diffusion and user adoption (Harhoff et al., 2003b).

Furthermore, radical inventions are more complex and might be more difficult to imitate (Hurmelinna-Laukkanen et al., 2008); therefore, pre-grant publication may be less of a concern regarding returns appropriability. In addition, earlier publication allows foreign patenting, broadening invention geographical span. Based on this, the following hypothesis presents the opposite prediction to the former one:

Hypothesis 3b: Radicalness has a negative effect on the likelihood of a patent to be opted out of pre-grant publication.

1.3 DATA AND MEASURES

1.3.1 Data

The patent data comes from EPO’s Worldwide Patent Statistical Database April 2012 (“PATSTAT”) that contains patent information from all major patent offices, including the USPTO. From January 2, 2001, the USPTO adopted “kind codes” to differentiate between granted patents that were kept secret up to grant and patents that were published before grant, B1 and B2, respectively.

As the focus of this study is publicly traded companies and their choice of publishing or not the patent application, the sample contains patents applied for by publicly traded firms. Using Kogan et al. (2016)[12] database, I merged USPTO patents to CRSP *permnos* and then merged *permnos* to *gvkeys* (*Compustat*). These merging procedures yield a final sample[13] of 468,556 granted patents, applied for from November 29, 2000 to December 29, 2009 and granted up to November 02, 2010. The sample period is bounded by the AIPA enactment and database limitations (footnote 13). The merged patents were applied for by 2,645 different companies. In this sample, on average, 8.15% of the patents were opted-out. Figure 1.1 displays the proportion of opted-out patents along the analyzed period.

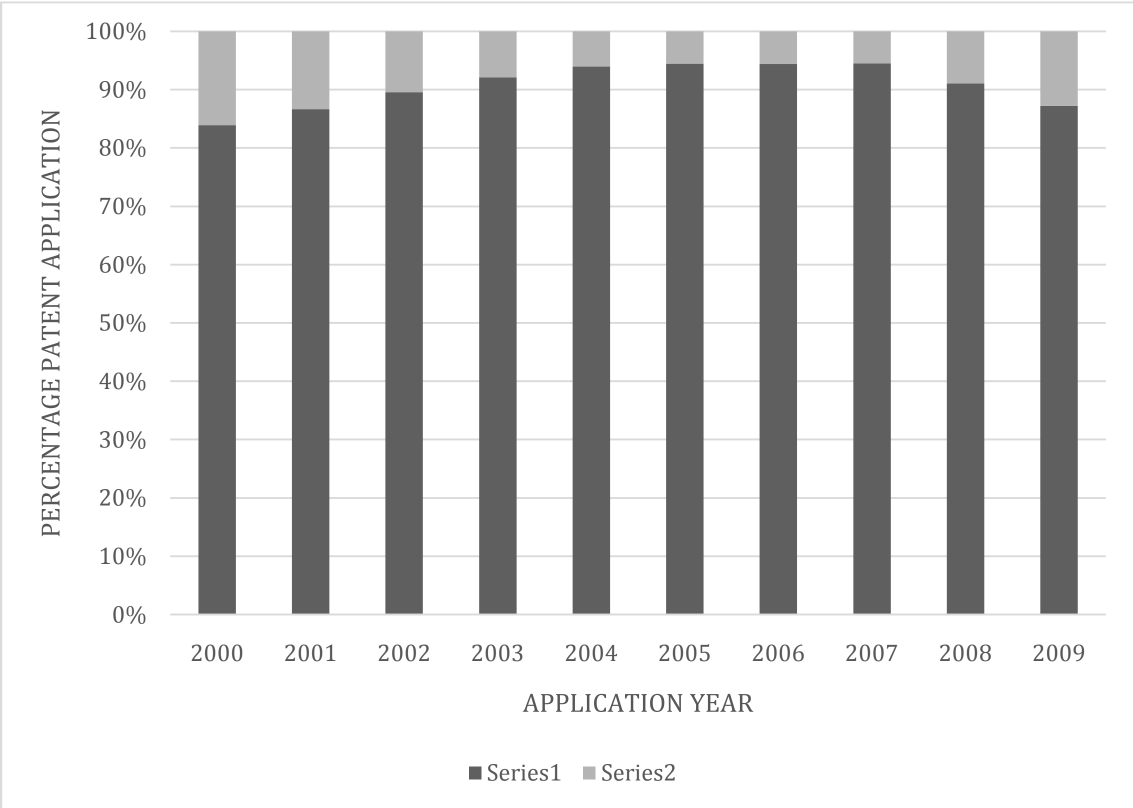

FIGURE 1.1 - Percentage of patent applications published and not published before grant– Granted patents up to 2010.

1.3.2 Dependent variable

To understand the drivers of opting out of pre-grant patent publication, patents were identified as published and not published before grant by the USPTO kind codes. The

[12] Kogan et al. (2016) provide a match for all USPTO granted patents up to 2010 and CRSP *permnos*.
[13] When merging with Compustat data I also dropped patents that had corresponding negative sales values.

dependent variable is equal to one if the patent's kind code is B1 (not published) and zero if it is B2 (published).

1.3.2 Independent variables

Technological crowdedness

To test *hypothesis 1* I follow Hedge et al. (2007) and measured technological crowdedness by counting the number of different assignees of the patents listed as reference (backward citations) and that are not the same as the assignee(s) of the focal patent. It indicates that the inventor is operating in a crowded technological area with a number of "nearby" patents and competitors (Hall et al., 2009). Cockburn and MacGarvie (2006) use the number of cited assignees to proxy for the number of potential licensors. Accordingly, as this number increases, the costs for a potential entrant increase.

Internal knowledge (Self-citation Ratio)

To test *hypothesis 2*, I use the ratio of self-citations to the backward citations to proxy for the degree to which each patent builds on in-house knowledge. Self-cited patents are patents assigned to the same assignee of the focal patent. Graham (2004) uses the backward self-citation ratio as a measure of the technology control a firm has over the technology trajectory in which the focal patent lies in and finds that the backward self-citation ratio combined with secrecy (measured by managers' response when secrecy is considered as an effective appropriability mechanism) is positively associated to patent filing strategies (filing continuation applications).

Radicalness

I use two variables to proxy for invention radicalness (*hypothesis 3*). First, I use the radicalness index provided by the OECD REGPAT Database[14]. Based on the patents cited by the focal patent, this index measures the number of different four-digits IPC (International Patent Classification) classes into which the focal patent is classified and to which the cited patents are not classified. It follows Shane (2001)'s definition but the OECD indicator (Squicciarini et al., 2013) is normalized by the total number of classes listed in the backward citations, considering the most disaggregated level available. Thus, the higher the index the more the focal patent builds on distinct knowledge and, therefore, represents a radical innovation. However, the radicalness index represents

[14] OECD, REGPAT database, February 2015

how radical is an invention to the firm, it does not imply that this technological novelty is on the invention level (Verhoeven et al., 2016).

Additionally, as a proxy for novelty in the invention level, I use the dispersion index proposed by Melero and Palomeras (2015) and create a variable *NEW COMBINATIONS.* This variable is a binary variable equal one when there was no previus IPC classes combination to calculate the index. The dispersion index measures the variance of the importance of past innovations in a given technological domain by the number of citations received (forward citations). The index is defined as follows

$$Dispersion\ index(DI) = \frac{\sigma^2}{\mu}$$

where σ^2 represents the variance and μ the mean of the standardized forward citations (Hall et al. 2001) received by previous patents assigned to the same combination of IPC 8-digits, the most disaggregated level. Following Melero and Palomeras, I assigned the index calculated using patents applied for during the previous five years before the focal patent was applied for.

1.3.4 Control variables

First, I control for patent characteristics – number of claims, patent scope (number of unique four-digit IPC subclasses) (Lerner, 1994), number of assignees, whether the patent is not part of a patent family, whether the assignee is from the US, and indicator variables for discrete and complex technologies[15].

Patent characteristics were found to be positively correlated with patent value (Harhoff et al., 1999, 2003a; Lanjow and Shankerman, 1999) and more valuable patents are internationally protected (Putnam, 1996). Hence, valuable patents might be published before grant as it also allows foreign patent protection. Controlling for patent characteristics, variables that might affect the likelihood of an application to be published before grant are held constant. Additionally, the model includes a dummy variable identifying patents that were not applied for outside the US and do not have any related international patent, i.e., singleton patents[16,17].

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[15] Von Graevenitz et al. (2011).

[16] Singletons patents are defined as "single patent applications that form patent families on their own because they are not related to any other application" (Martinez, p. 2, 2011)

[17] PATSTAT record data for DOCDB patent family and INPADOC patent family. DOCDB patent families referred to a set of patents that protect the same technical content, defined by European Patent Office's (EPO) examiners. Differently, INPADOC patent families, also called INPADOC extended

The claims define the invention to which protection is sought. The claims are the legally protected part of the patent document, over what the patentee can be sued or sue a possible infringer. Therefore, the number and content of claims can be seen as a measure of the breadth of a patent. With respect to patent scope, a patent allocated to more subclasses means that it has a greater technological potential and a greater market value (Lerner, 1994).

To identify the technological field of a patent I use the OECD classification, which is based on Schmoch (2008), and provides an IPC-technology concordance by main technology field.[18] First I identified four main technology groups, semiconductors, computers, biotechnology, and pharmaceutics. Also, I included a *dummy* variable when the patent is classified in more than one technology field, what may broaden the use of the given invenvion. Further, I classified patents by discrete or complex[19] technologies following Von Graevenitz et al. (2011). This classification does not include all technology fields; it means that there are some patents that are neither discrete nor complex.

Furthermore, I use some indicators based on patent characteristics, basic research and originality. Basic research is the ratio of non-patent literature (NPL) to backward citations, reflecting how much the patented invention relies on scientific knowledge. The originality index, first proposed by Trajtenberg et al. (1997), "refers to the breadth of technology fields on which a patent relies" (Squicciarini et al., p. 49, 2013). It is based on the different classes to which backward citations are allocated. Besides building on Hall et al. (2001), the OECD's originality index uses IPC 8-digits classification. The originality index reflects patents building on a wide array of technology classes.

On the firm level, I control for some firm characteristics. Firm size is proxied by the natural logarithm of sales. Firm size may also capture firms' financial constraints as smaller firms have bigger restrictions to access financial markets. I use the pre-tax foreign income (PIFO[20] in Compustat) and assign the value 1 if PIFO is greater than zero or 0 otherwise as a proxy for firms' foreign activities[21]. Having foreign operations

priority patent families, referred to a broader set of patents direct or indirectly linked by patent application priorities. In our main analysis, I used the DOCDB patent family definition.

[18] I use the technological field classification included in the OECD, REGPAT database, February 2016.

[19] According to Cohen et al. (2000), discrete technologies refer to products that are protected by few patents, whereas, complex technologies require many patents to protect a single product.

[20] Missing values were replaced by zero (Hanlon et al., 2015)

[21] As a robustness check I also include the continuous variable and results were similar.

makes foreign patenting more relevant and, therefore, can be related to the decision to have the patent application published 18 months after filing and protected in multiple countries. In addition, I control for the industry's competition intensity by the Herfindahl-Hirschman index (HHI)[22]. I also control for the total number of patents applied for by the company in the respective year.

1.4 EMPIRICAL RESULTS

Table 1.1 presents descriptive statistics and table 1.2 presents the correlation matrix. As already noted in the literature, patent characteristics – claims, patent scope, backward citations, have a very skewed distribution (Scherer and Harhoff, 2000; Harhoff et al., 2003a). In our sample, it can be seen from table 1.1 that, on average, patents that were opted out of pre-grant publication were secret for about 20 months more than patents that were published before grant[23].

In order to test the hypotheses I estimate a linear probability model (LPM) where the dependent variable is a binary variable equal to 0 if the patent application was published before grant and equal 1 if the patent application was not published before grant [24]. A LPM provides a simple and good approximation to the average partial effects (Wooldgridge, p. 563, 2010), moreover, the objective of this study is not to make forecasts but to identify the effect of the explanatory variables on the decision to publish or not a patent application. Table1. 3 reports the results, model 1 refers to the baseline model and model 2 presents the results including the control variables. The independent variables, crowdedness, internal knowledge (self-citation ratio), and radicalness are in logarithm. All estimations include company fixed effects, application year fixed effects and the standard errors are clustered by company.

Results show that hypothesis 1 cannot be rejected, as patents belonging to a crowded technological area are more likely to be published before grant. However, the size of the coefficient suggests that the effect of preemption is only marginally important in driving the choice of having the patent application published before grant. Regarding hypothesis 2, estimated results show that the more a patent builds on in-house knowledge stock the more likely it is to be kept secret up to grant. However, results

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[22] Calculated using Compustat by three-digit SIC codes.

[23] Grant lag (not-published) = 979 days (mean), 819 days (median); publication lag (published) = 365 days (mean), 281 days (median).

[24] I estimate all models using a random sample of 10% of the full sample, accounting for the proportions of the dependent variable, singleton patents, and technology fields, applying a logit specification, Results are robust and consistent with the ones presented here. Results available on request.

show a weakly support for hypothesis 2 as when adding the controls internal knowledge is not statistically significant anymore.

TABLE 1.1 – Descriptive statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) Mdn	(6) max
DV	468,556	0.0815	0.274	0	0	1
TOTAL	468,556	1,056	1,156	1	553	4,308
HHI	468,556	0.267	0.214	0.0427	0.226	1
SIZE	462,377	3.942	1.552	0	4.217	7.650
PATSCOPE	468,556	1.968	1.247	1	2	28
CLAIMS	468,550	18.48	13.17	1	17	418
ORIGINALITY	468,514	0.746	0.191	0	0.803	0.990
RADICALNESS	468,554	0.364	0.269	0	0.322	1
CROWDEDNESS	468,556	16.96	22.63	0	9	538
SINGLETON	468,556	0.462	0.499	0	0	1
INTERNAL KNOWLEDGE	468,554	0.0563	0.128	0	0	3
BASICR	468,554	0.284	1.847	0	0	144
NEW COMBINATION	468,556	0.000	0.03	0	0	1
DOM	468,556	0.610	0.488	0	1	1
NUMASSIGNEES	468,556	1.031	0.209	1	1	14
FOREIGN (PIFO)	468,556	0.310	0.462	0	0	1
COMPLEX	468,556	0.819	0.385	0	0	1
DISCRETE	468,556	0.147	0.355	0	0	1
RADICALNESS (DISCRETE)	468,554	0.0548	0.166	0	0	1
NEW COMBINATION (DISCRETE)	468,556	0.000	0.01	0	0	1
CROWD (DISCRETE)	468,556	2.678	11.69	0	0	538
INTERNAL KNOWLEDGE (DISCRETE)	468,554	0.00897	0.0586	0	0	3
RADICALNESS (COMPLEX)	468,554	0.293	0.279	0	0.209	1
NEW COMBINATION (COMPLEX)	468,556	0.000	0.02	0	0	1
CROW (COMPLEX)	468,556	13.47	20.72	0	2.079	461
INTERNAL KNOWLEDGE (COMPLEX)	468,554	0.0461	0.117	0	0	2
GRANT_LAG[a]	430,356	1131.22	497.12	130	1054	3596
GRANT_LAG[b]	38,200	978.62	588.35	97	819	3534
PUB_LAG[a]	404,339	364.65	212.51	2	281	2157

[a] Published patents (B2). Number of days.
[b] Not-published patents (B1). Number of days.

TABLE 1.2 – Correlation Matrix

	VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
(1)	DV	1																									
(2)	CROWD (COMPLEX)	-0.02	1																								
(3)	NC (COMPLEX)[a]	0.03	0	1																							
(4)	RADICALNESS (COMPLEX)	0.09	0.21	0.02	1																						
(5)	IK (COMPLEX)[b]	**0**	-0.05	**0**	0.02	1																					
(6)	IK (DISCRETE)[b]	-0.01	-0.1	0	-0.16	-0.06	1																				
(7)	CROWD (DISCRETE)	-0.04	-0.15	0	-0.24	-0.09	0.1	1																			
(8)	NC (DISCRETE)[a]	0.01	-0.01	**0**	-0.01	0	0.01	0.01	1																		
(9)	RADICALNESS (DISCRETE)	-0.04	-0.21	-0.01	-0.35	-0.13	0.24	0.5	0.03	1																	
(10)	COMPLEX	0.05	0.31	0.01	0.49	0.19	-0.33	-0.49	-0.02	-0.7	1																
(11)	DISCRETE	-0.06	-0.27	-0.01	-0.44	-0.16	0.37	0.55	0.03	0.79	-0.88	1															
(12)	RADICALNESS	0.07	0.05	0.02	0.76	-0.08	-0.03	0.05	0.01	0.24	-0.05	0.01	1														
(13)	NEW COMBINATION	0.03	-0.01	0.8	0.01	0	**0**	**0**	0.43	0.01	-0.01	**0**	0.02	1													
(14)	CROWD	-0.04	0.82	0	0.03	-0.1	-0.05	0.37	**0**	0.05	-0.05	0.02	0.08	0	1												
(15)	INTERNAL KNOWLEDGE	-0.01	-0.09	0	-0.06	0.88	0.4	-0.04	**0**	-0.01	**0**	0.01	-0.09	0	-0.12	1											
(16)	FOREIGN (PIFO)	0.01	-0.04	**0**	-0.03	0.01	0.03	**0**	**0**	**0**	-0.01	0.02	-0.04	0	-0.04	0.02	1										
(17)	NUMASSIGNEES	-0.03	0.08	**0**	-0.03	-0.02	-0.01	0.08	**0**	0.02	-0.03	0.04	-0.02	**0**	0.11	-0.03	0.03	1									
(18)	DOM	0.17	0.17	0.01	0.06	-0.07	-0.02	0.11	0.01	0.07	-0.08	0.06	0.12	0.01	0.24	-0.07	-0.22	-0.08	1								
(19)	SINGLETON	0.22	0.09	0.01	0.06	-0.01	-0.01	0.03	**0**	**0**	0	0	0.07	0.01	0.1	-0.01	-0.03	-0.04	0.38	1							
(20)	BASICR	0	-0.04	**0**	-0.06	-0.02	0.01	0.02	**0**	0.08	-0.11	0.13	-0.01	**0**	-0.03	-0.01	0.04	0.01	0.06	0.05	1						
(21)	ORIG	-0.05	0.14	0	0.32	-0.09	-0.01	0.13	**0**	0.18	-0.13	0.13	0.46	0	0.2	-0.09	0	0	0.08	0.01	**0**	1					
(22)	CLAIMS	0.07	0.14	0	0.04	-0.03	-0.02	0.06	**0**	-0.01	0.01	-0.01	0.04	**0**	0.17	-0.04	-0.01	-0.03	0.21	0.09	0	0.06	1				
(23)	PATSCOPE	-0.14	-0.01	-0.01	-0.14	-0.06	0.05	0.15	-0.01	0.11	-0.2	0.22	-0.09	-0.02	0.07	-0.03	0.05	0.04	-0.08	-0.1	0.1	0.29	-0.01	1			
(24)	SIZE	-0.17	-0.12	-0.01	0.01	0.1	-0.01	-0.11	0	-0.08	0.13	-0.11	-0.05	-0.01	-0.19	0.08	-0.17	0.06	-0.31	-0.19	-0.08	-0.05	-0.18	-0.02	1		
(25)	HHI	-0.07	-0.05	0	**0**	0.05	0.02	-0.04	**0**	-0.01	0.01	-0.04	0	0	-0.05	0.06	0.01	0.06	-0.19	-0.13	-0.06	0	-0.09	0.04	0.34	1	
(26)	TOTAL	-0.15	-0.06	-0.01	-0.01	0.14	-0.03	-0.14	-0.01	-0.14	0.21	-0.18	-0.12	-0.01	-0.15	0.11	-0.05	0.06	-0.28	-0.07	-0.05	-0.07	-0.13	-0.03	0.63	0.27	1

*Dependent variable (DV): 0 if patent published; 1 if patent not published. *Note:* All correlations are significant at 5% except the ones in bold. Obs.:498,556.

[a]NC= NEW COMBINATION

[b]IK= INTERNAL KNOWLEDGE

I test hypothesis 3a and 3b by using two variables, radicalness and the new combination *dummy*. This variable accounts for first time IPC 8-digits combinations, therefore, this patents bear the highest uncertainty. Considering both variables, hypothesis 3a cannot be rejected meaning that the more radical is the invention the more likely is the patent to be opted out of pre-grant publication.

In addition, I test differences among the two broad types of technologies, complex and discrete, reported in table 1.6. Model 1 shows results for the complex technology patents compared to others technologies, not classified in any of the two main categories. Model 3 displays results for discrete patents compared to other technologies. Results show that the effect of the independent variables on the likelihood of opting out of pre-grant patent application publication do not qualitatively differ between technology categories. The differences between the technology categories appear on the size of the coefficients. However, the effect of all variables have the same direction and are statisticaly significant.

TABLE 1.3 – Drivers of opting-out. Dependent variable: Published (0) or not-published (1)

VARIABLES	(1) LPM	(2) LPM
CROWDEDNESS	-0.019***	-0.018***
	(0.002)	(0.002)
RADICALNESS	0.054***	0.061***
	(0.009)	(0.009)
NEW COMBINATIONS	0.220***	0.194***
	(0.029)	(0.028)
INTERNAL KNOWLEDGE	0.038*	0.027
	(0.018)	(0.018)
Controls		Included
Company FE	Included	Included
Application Year FE	Included	Included
Constant	0.068***	0.030
	(0.013)	(0.040)
Observations	468,554	462,334
R-squared	0.329	0.343

Robust standard errors in parentheses. Standard errors are cluster by company in all models. *** p<0.001, ** p<0.01, * p<0.05.

1.5 ADDITIONAL ANALYSIS AND ROBUSTNESS TESTS

In this section, I present some additional analysis to further investigate the robustness of the results. In order to do that, I add an interaction term between internal knowledge and the industry competition, estimate the models using different samples, and investigate the motives to opt-out of earlier patent application publication by technology categories.

TABLE 1.4 – Drivers of opting-out. Dependent variable: Published (0) or not-published (1). Interaction

	(1)	(2)
VARIABLES	LPM	LPM
CROWDEDNESS	-0.017***	-0.019***
	(0.002)	(0.002)
RADICALNESS	0.061***	0.054***
	(0.009)	(0.009)
NEW COMBINATIONS	0.194***	0.220***
	(0.028)	(0.029)
HHI[†] X INTERNAL KNOWLEDGE	0.042[a]	0.053*
	(0.023)	(0.023)
CONTROLS	Included	
COMPANY FE	Included	Included
APPLICATION YEAR FE	Included	Included
Constant	0.030	0.067***
	(0.040)	(0.012)
Observations	462,334	468,554
R-squared	0.343	0.329

Robust standard errors in parentheses. Standard errors are cluster by company in all models. *** p<0.001, ** p<0.01, * p<0.05, [a] p<0.1.
[†]HHI=1-HHI

First, I estimate the previous models adding an interaction between the degree of competition (HHI) and the self-citation ratio (Table 1.4). This interaction is included to test the hypothesis that when an invention relies more one internal knowledge firms face the threat of losing competitive advantage. Thus, more competition would increase the likelihood of a patent application to be secret up to grant. The coefficient of the interaction term is positive and significant, even when adding the control variables. It suggests that the effect of building on internal knowledge on the likelihood of a patent being opted-out is more pronounced when the inventive firm is operating in a more competitive environment.

TABLE 1.5 – Drivers of opting-out. Singletons. Dependent variable: Published (0) or not-published (1)

VARIABLES	(1) LPM	(2) LPM	(3) LPM	(4) LPM
CROWDEDNESS	-0.024***	-0.019***	-0.019***	-0.024***
	(0.003)	(0.002)	(0.002)	(0.003)
RADICALNESS	0.079***	0.092***	0.092***	0.079***
	(0.012)	(0.013)	(0.013)	(0.012)
NEW COMBINATIONS	0.214***	0.193***	0.193***	0.214***
	(0.033)	(0.032)	(0.032)	(0.033)
INTERNAL KNOWLEDGE	0.010	0.007		
	(0.021)	(0.020)		
HHI† X INTERNAL KNOWLEDGE			0.014	0.017
			(0.024)	(0.024)
Controls		Included	Included	
Company FE	Included	Included	Included	Included
Application Year FE	Included	Included	Included	Included
Constant	0.076***	0.056	0.056	0.076***
	(0.014)	(0.070)	(0.070)	(0.014)
Observations	216,289	213,008	213,008	216,289
R-squared	0.417	0.427	0.427	0.417

Robust standard errors in parentheses. Standard errors are cluster by company in all models. *** p<0.001, ** p<0.01, * p<0.05, [a] p<0.1.
†HHI=1-HHI

Additionaly, as opting out of earlier publication requires the inventor to forgo foreign publication, I restrict the sample to singleton patents, i.e., patents that do not belong to a patent family, only applied for in the US. Although one can think that the main reason to publish the patent application is to seek foreign protection, when considering only patents applied in the US 84.5% of the patents were published before grant. Therefore, by restricting the sample to patents only filed in the US I am comparing patents that could have been secret, but were published instead, to pre-grant secret patents.

On average, patents that were not published before grant took less time to issue[25] and, therefore, pre-grant published patents may be underrepresented in my sample, as it includes patents granted up to 2010. In order to reduce this possible bias, all the regressions were re-estimated considering patents applied for between 2000 and 2007[26]. Results are consistent with the results presented above.

TABLE 1.6 – Drivers of opting-out. Dependent variable: Published (0) or not-published (1). Full sample and singleton subsample.

VARIABLES	(1) FULL	(2) SINGLE	(3) FULL	(4) SINGLE
CROWD (COMPLEX)	-0.018***	-0.025***		
	(0.002)	(0.003)		
NEW COMBINATION (COMPLEX)	0.250***	0.221***		
	(0.036)	(0.038)		
RADICALNESS (COMPLEX)	0.067***	0.093***		
	(0.010)	(0.013)		
INTERNAL KNOWLDGE (COMPLEX)	0.036+	0.007		
	(0.019)	(0.022)		
CROWD (DISCRETE)			-0.009***	-0.010***
			(0.001)	(0.002)
NEW COMBINATION (DISCRETE)			0.283***	0.288***
			(0.053)	(0.075)
RADICALNESS (DISCRETE)			0.029*	0.030
			(0.012)	(0.020)
INTERNAL KNOWLDGE (DISCRETE)			0.090**	0.070+
			(0.030)	(0.039)
COMPANY FE	Included	Included	Included	Included
APPLICATION YEAR FE	Included	Included	Included	Included
CONSTANT	0.055**	0.134***	0.071***	0.095***
	(0.018)	(0.022)	(0.012)	(0.019)
OBSERVATIONS	399,454	184,099	84,833	39,482
R-SQUARED	0.346	0.431	0.200	0.280

Robust standard errors in parentheses. Standard errors are cluster by company in all models. *** p<0.001, ** p<0.01, * p<0.05, [a] p<0.1.

I also test hypothesis 1 using two alternative measures of technological crowdedness. Calculating crowdedness index considering backward citations within a time lag difference of 10 and 20 years from the focal patent, respectively. One could

[25] In our sample, the grant lag of not published patents is 2.68 years (1.36 years standard deviation) whereas for published patents is 3.1 years (1.61 years standard deviation).

[26] Results available upon request.

expect that the effect of crowdedness is stronger if we consider the more recent cited patents. However, results do not show a substantial difference, they remain qualitatively and statistically similar[27].

Overall, the estimated results are qualitatively similar to the results for the full sample (table 1.5). However, the variable *internal knowledge* and the interaction term between HHI and internal knowledge, accounting for the use of internal knowledge in the patented invention becomes insignificant. This result suggests that, when there is no international competition for a given invention, internal knowledge is not a motive to opt-out of earlier patent application publication.

TABLE 1.7 – Drivers of opting-out. Dependent variable: Published (0) or not-published (1). Full Sample

VARIABLES	(1) LPM	(2) LPM	(3) LPM	(4) LPM
CROWDEDNESS	-0.019***	-0.018***	-0.019***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
RADICALNESS	0.055***	0.061***	0.055***	0.061***
	(0.009)	(0.009)	(0.009)	(0.009)
NEW COMBINATIONS	0.220***	0.194***	0.220***	0.194***
	(0.029)	(0.028)	(0.029)	(0.028)
INTERNAL KNOWLEDGE	0.038*	0.027	0.038*	0.027
	(0.018)	(0.018)	(0.018)	(0.018)
DISCRETE	-0.008*	-0.001		
	(0.003)	(0.003)		
COMPLEX			0.008**	0.003
			(0.003)	(0.003)
CONTROLS		Included		Included
COMPANY FE	Included	Included	Included	Included
APPLICATION YEAR FE	Included	Included	Included	Included
CONSTANT	0.072***	0.031	0.064***	0.029
	(0.013)	(0.039)	(0.012)	(0.040)
OBSERVATIONS	468,554	462,334	468,554	462,334
R-SQUARED	0.329	0.343	0.329	0.343

Robust standard errors in parentheses. Standard errors are cluster by company in all models. *** p<0.001, ** p<0.01, * p<0.05, [a] p<0.1.

As the effectiveness of patent protection differ by the characteristics of the technology that is protected, motives to opt-out might differ by technology categories.

[27] Results available upon request.

Results regarding technology moderation in the singleton subsample, complex or discrete, are displayed in table 1.6, model 2 and 4. Estimations resembled the ones described in the previous section for the full sample. In the case of the singleton patents subsample, however, two variables differ when considering the type of technology, while the other results are qualitatively and statistically similar. First, internal knowledge does not have a significant effect on the probability of keeping the patent secret before grant when the technology is complex. Second, when the technology is discrete, radicalness is not significant anymore.

TABLE 1.8 – Drivers of opting-out. Dependent variable: Published (0) or not-published (1). Singleton subsample.

VARIABLES	(1) LPM	(2) LPM	(3) LPM	(4) LPM
CROWDEDNESS	-0.024***	-0.019***	-0.024***	-0.019***
	(0.003)	(0.002)	(0.003)	(0.002)
RADICALNESS	0.080***	0.092***	0.080***	0.092***
	(0.012)	(0.013)	(0.012)	(0.013)
NEW COMBINATIONS	0.213***	0.193***	0.214***	0.194***
	(0.033)	(0.032)	(0.033)	(0.032)
INTERNAL KNOWLEDGE	0.011	0.007	0.010	0.007
	(0.021)	(0.020)	(0.021)	(0.020)
DISCRETE	-0.020***	-0.007		
	(0.006)	(0.005)		
COMPLEX			0.015**	0.006
			(0.005)	(0.005)
CONTROLS		Included		Included
COMPANY FE	Included	Included	Included	Included
APPLICATION YEAR FE	Included	Included	Included	Included
CONSTANT	0.096***	0.062	0.076***	0.056
	(0.016)	(0.070)	(0.014)	(0.070)
OBSERVATIONS	216,289	213,008	216,289	213,008
R-SQUARED	0.417	0.427	0.417	0.427

Robust standard errors in parentheses. Standard errors are cluster by company in all models. *** p<0.001, ** p<0.01, * p<0.05, [a] p<0.1.

Further, to understand the role of technology characteristics on the decision to opt out of earlier patent publication I estimate baseline and extended models (full sample and singleton patents subsample) including indicator variables for complex and discrete technologies (one at a time). Table 1.7 and 1.8 display the results. When considering the differences in the technology protected by a patent, discrete technologies are more likely to be published before grant whereas complex technologies are more likely to be kept secret until grant. Nevertheless, adding the control variables the technology effects become statistically insignificant.

1.6 DISCUSSION AND CONCLUSION

This chapter investigates three hypotheses on publicly traded companies' choice of delaying patent application publication – the effect of the competition faced by the invention or the effect of technological crowdedness, the effect of reliance on internal knowledge, and the effect of an important invention characteristic, radicalness.

Theoretical models illustrate the case where a leader and a laggard competing in a patent race may publish interim R&D results in order to raise the patentability bar by disclosing prior art and, therefore, preventing the rival firm from patenting (Baker and Mezzetti, 2005; Bar, 2006). However, these models usually focus on regular publication, e.g. scientific papers and company reports, as means of defensive publication. By analyzing firm's choice of publishing or not the patent application before grant I find, support for hypothesis 1 which states that if an invention belongs to a technological area where there are many others operating, i.e., in a crowded technological space, the patent is more likely to be published before grant. This result is aligned with Henkel and Pangerl (2008) and Jell (2011) where they show that the patent system is used for defensive publishing.

While publishing interim R&D results may prevent rivals from patenting, firms may strategically hide their internal knowledge, securing competitive advantage. Estimations for the baseline model (without the controls) support hypothesis 2, suggesting that firms are more likely to opt for pre-grant secrecy the more they rely on internal knowledge. However, estimates for the singleton subsample indicates that patents only filed nationally (in the US), published or not before grant, do not differ regarding the use of firms' own previous patents. Delaying the disclosure of a patent that builds on a firm's internal knowledge might help the firm to hide its technology direction, preserving strategic knowledge embodied in the patent. Moreover, by publishing the patent application before grant, inventors face the risk of revealing how to further use internal knowledge without being awarded the exclusivity right.

Patent preemption and internal knowledge strategies relate to the company strategies. Nevertheless, keeping the application secret up to grant also relates to the invention characteristics. For that reason, in addition to including patent characteristics, I investigate how being radical, as in Shane (2001), affects the firm's opting out decision. In addition, I include a variable which captures new combinations of IPC classes. In line with hypothesis 3a, I find that the more a patented invention differs from previous firms' inventions, the more radical it is, and being a new combination in the technological space, the more likely it is for the patent to be opted out of pre-grant application publication. Indeed, the variable accounting for new technologies combination, which means high technology uncertainty, turns out to have the biggest coefficient in all estimation models. Kim at al. (2016) state that firms may derive higher value by delaying patenting in a context of high uncertainty.

Johnson (2014) predicts that inventors are more likely to publish defensively their inventions for the less technically challenging inventions. Additionally, Ceccagnoli (p. 4, 2008) pointed out that "the more drastic the underlying innovation on which the R&D competition is based the lower the incentives for and the profits with preemptive patenting".

Regarding the technology domain of the invention, inventors report being more able to appropriate returns from the innovation in discrete technologies (Cohen et al., 2000), what in general makes patents from discrete technologies more likely to opt for pre-grant publication[28]. Furthermore, empirical evidence has shown that the propensity to patent and the value of patents differ by the nature of the technology, complex or discrete technologies (Mansfield, 1986). While patents more effectively protect discrete technologies, complex industries patent intensively in order to have a higher stake in cross-licensing deals (Cohen et al., 2000; Levin et al., 1987). Png (2015), analyzing the impact of the Uniform Trade Secrets Act (UTSA) implemented in the US, shows that complex industries patented significantly less as trade secret became stronger. Therefore, complex products may be more likely to opt for pre-grant secrecy taking advantage of the extra secrecy time earned by delaying disclosure.

Based on the stated results, this study makes two main contributions to the literature. First, it is the first study to evaluate public companies' motives to opt out of earlier patent application publication, using a large sample of patents. Although, the

[28] In this sample, 4.35% of the discrete patents were opted out of pre-grant patent application publication, while 8.83% of the complex patents were kept secret until grant.

publication of the majority of the patents occur before the patent is granted, still about 8.15% of publicly traded companies' patent applications are kept secret up to grant. Hence, this study contributes to increase our understanding of firms' filing strategies to capture value from their inventions and on how firms use the patent system. Second, this study unveils empirical evidence on preemptive and strategic behavior. On the one hand, pre-grant publication might be associated with preemption motives, as a crowded technological space increases the likelihood of earlier patent application publication. On the other hand, pre-grant secrecy might be associated with a firm hiding strategically its internal knowledge, specially in more competitive industries. Moreover, companies strategically have used patent pre-grant secrecy to guarantee exclusivity over radical and uncertain inventions by postponing invention disclosure.

Finally, our findings suggest some policy implications. First, AIPA's earlier publication rule has two main goals: to harmonize the US patent rules with the rest of the world (Allison et al., 2003) and to foster knowledge diffusion (Johnson and Popp, 2001). It has been shown that earlier publication fosters diffusion of R&D knowledge, preventing R&D duplication (Aoki and Spiegel, 2009; Baruffaldi and Simeth, 2015). Empirical findings show that inventions that are more radical are more likely to be secret up to grant; therefore, in the absence of this option radical inventions would be made available earlier. Second, pre-grant patent application secrecy is associated with internal knowledge protection, thus it might delay the development of new technologies and may hamper competition in a given technology domain. Consequently, revoking this option could accelerate the development of new technologies and boost competition.

Last but not least, we have to acknowledge that this analysis presents some limitations. First and more important, results are based on the analysis of only granted patents. This is because, by construction, it is not possible to observe opted out patent applications if they were not granted (the publication of a non-granted application is precisely one of the risks firms try to avoid when taking the opting-out decision). Note, less than 72% (Carley et al., 2015) of applications result in granted patents. Despite there is not much known regarding how the granted and not-granted applications (and their underlying innovations) differ, we can expect that there are differences between both groups. Results have thus to be interpreted carefully. Results would hold for the sample of applications if patent characteristics affecting the probability to get granted are the same across the two groups. Unfortunately, this evidence is not so far available. Moreover, controlling for many patent characteristics that might influence the probability of a patent being grant, results still hold. Second, the trade-off imposed by AIPA might be stronger to higher internationalized firms. Therefore, it might be important to control for other variables, in addition to PIFO, to capture firms' international operations – e.g., the number of foreign subsidiaries. Third, it might be that market uncertainty has a more important role in driving pre-grant secrecy decision, what would imply it to be explicitly controlled for. Finally, in analyzing publicly traded companies this result must be seen with cautions and might not be generalized to private, small firms.

Chapter 2

Patent value in financial markets: An event study

2.1 INTRODUCTION

Researchers have agreed that patents convey valuable information. Previous literature has shown that patent counts and patent quality, as measured by citations received by firm's patents (forward citations), are positively correlated with firm value – e.g., Tobin's *q*, future earnings (Griliches, 1981; Cockburn and Griliches, 1988; Hirschey et al., 2001; Hall et al, 2005; Gu, 2005). In addition to an aggregate measure of innovation, individual patents provide information about a particular innovation and a technology's future prospects as well as information that can reveal its value for the firm.

Assessing the value of a patent is relevant for several reasons: it provides information to policymakers about how the patent system rewards inventors; it helps account for the value of intangible assets and helps estimate more accurately firm value (Bessen, 2008); and finally, it aids in the measurement of R&D productivity and quality at the firm and economy level.

Previous research has looked at different types of patent value – private value and social value (Hirshleifer, 1971; Harhoff et al., 1999). Private value refers to the returns that a firm derives from a patent either by using it in its products, selling it on the market, or using it strategically to deter competitors from encroaching on its product space. The social value emanates from the disclosure of information and the knowledge spillovers that the patent generates for other firms.

Previous research has correlated various patent characteristics such as forward citations (Harhoff et al., 1999, 2003a; Trajtenberg, 1990; Lanjow and Shankerman, 1999; Hall et al., 2000, 2005), backward citations (Reitzig, 2004), and number of claims (Tong and Frame, 1994) to measures of patent value. Patent value has also been estimated through patent renewal rates (Lanjow et al., 1996; Pakes, 1984; Schankerman and Pakes, 1985; Bessen, 2008), litigations and relevant awards (Lanjow and Schankerman, 1997; Allison et al., 2003), and patent family size (the number of countries in which the patent is taken out) (Putnam, 1996).

The patent system exists to promote knowledge creation and innovation, and therefore, to circumvent the resource misallocation problem in knowledge production by transforming a public good[29] into a private good (Arrow, 1962). It does that

[29] According to Arrow (1962), knowledge has characteristics of public good: non-rivalrous and non-excludable. Non-rivalrous means that the use of a particular innovation by a producer does not preclude

through two mechanisms – 1) by letting those who create knowledge appropriate the returns to their creation and thus invest in knowledge production and 2) by diffusing knowledge to those who can further build on the knowledge created. The first is achieved through granting exclusivity right to the inventor for a certain period of time and the second through the public disclosure of the invention[30]. Researchers have argued that the disclosure of the invention has two strategic effects – 1) it lets competitors imitate and copy the invention after the patent expires and/or invent around the invention during the patent term and 2) the knowledge conveyed in the patent may signal to the firm investors or the general public the firm's research quality and capabilities (Long, 2002). This second function can in turn help generate investments by attracting external financing (Haussler, Harhoff, & Müller, 2012; Hsu and Ziedonis, 2008). It is not unreasonable then, to expect that a patent grant will generate positive value for the firm.

In this study, we use an event study methodology to investigate stock market valuation of individual patented inventions by measuring abnormal returns around a patent grant. Drawing on the market efficiency hypothesis, the company's stock price immediately incorporates a new, unanticipated, information release – in our study: the patent event. Therefore, an abnormal stock price movement on the event date reflects the value of the information described in the patent (Kothari and Werner, 2007). Stock market reaction to a patent event provides an ex-ante value measure, i.e., before the value of the innovation is realized. Thus, it helps managers to make better informed decisions regarding innovation investments.

We use a large sample of USPTO granted patents during 1995-2006 and evaluate stock market reaction to patent grants, calculating abnormal returns around the grant date. Further, we analyze different samples of patents that are deemed to be more valuable, highly cited patents and patents that are related to what eventually became successful products – pharmaceutical drugs. We do not find significant abnormal returns, on average, generated due to a patent grant in any of these samples.

Additionally, we investigate a possible anticipation reaction by estimating abnormal returns to events prior to the patent grant: patent application publication and

its use by others. Knowledge is a non-excludable good because the innovator is not always able to prevent others from using it without authorization once it has been disclosed and in the absence of patents.

[30] Throughout this chapter, we use invention and innovation interchangeably.

patent notice of allowance (NOA). We do not find evidence of anticipation through market reaction to patent events before grant, i.e., not significant abnormal returns.

The complexity and technicality of a patent document might preclude investors from assessing the value of the information conveyed by a patent. Moreover, innovation related information is hard to process causing investors to not pay attention and to underreact (Hirshleifer et al.,2013). In addition, a patent is highly uncertain as it usually happens at the beginning of the innovation project. To further test if the absence of abnormal returns is because of the inability of investors to value innovation we use a sample of US Food and Drug Administration (FDA) drug approvals. The approval of a drug means that this innovation is allowed to be commercialized, and therefore, is easier to investors to assess its value. In the case of FDA approvals, we find, on average, significant and positive abnormal returns around the event day, suggesting that investors react to an innovation related information with immediate impact on sales. A closer to market innovation also means less uncertainty regarding future cash flows.

There are few studies evaluating the value of an individual patent applying an event study (Austin, 1993; Liu, 2006; Plumlee at al., 2015) . This papers typically conduct analysis to restricted samples of particular sectors (i.e., biotechnology or other R&D intensive sectors), type of patents (those announced in the press)and type of firms (large firms). Our study aims to provide a more comprehensive analysis of this phenomena by examining the market reaction of a representative patent event. Our sample, thus, includes all patenting firms from all patenting sectors. We contribute to the patent valuation literature by analyzing the value, as represented by stock market abnormal returns, of several patent-related events and a product-related event (FDA approvals). After ruling out several alternative explanations, results indicate that the uncertainty and risky nature of innovation hamper investors in their ability to assess the value of information disclosed in the patent event. Therefore, following stock market reaction to patent events may not lead to optimal innovation investment decision, possibly leading to innovation myopia. Moreover, we study stock market reaction to a close-to-the-market innovation (FDA approvals) and highlight stock market's reaction differences.

2.2 THEORETICAL BACKGROUND

A patent is a document that bestows a temporary exclusivity right (20 years from the filing date) over an invention, product or process[31] that has to comply with novelty, nonobviousness, and usefulness criteria[32]. The patent results in the disclosing of technical information about the invention. Therefore, patent data have been used as a proxy for innovation even though they are imperfect measures of innovations – not all innovations are patented and the propensity to patent varies by industries, technologies, and countries (Griliches, 1990). Disclosing the invention through the patent works as a signal of the firm's knowledge and research quality (Anton and Yao, 2004).

Using patents as a measure of innovation, previous research has shown that innovation has a positive effect on measures of firm value and performance. Hirschey et al. (2001) find that the quality of the R&D output, measured by the citations received by the firm's patents, is positively correlated with the firm's book value of high-tech companies. Also investigating the effect of firm's patents' forward citations on firm value accounting based measures, Gu (2005) reports a positive association between patent citation impact and future realized earnings. However, the author finds stock market investors underreact when incorporating patent citation information on stock value and earnings forecast. As a result, even though changes in patent citations are significantly associated with firm's future returns, investors seem to partially ignore this information.

Previous studies report a positive relation between Tobin's *q*[33], as a measure of firm value, and different measures of patent quality and quality of firm's innovation output (Hall et al., 2005; Lanjow and Schankerman, 2004). In addition, Hirshleifer et al. (2013) find that the stock market recognizes the value of innovative efficiency, i.e., the ability of a firm to generate patents and patent citations per dollar invested in R&D, and accords higher valuations to firms that are more efficient. Therefore, stock price informativeness reduces the information asymmetry of the innovative activity thus spurring innovation (Blanco and Wehrheim, 2016).

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[31] http://www.wipo.int/patents/en/.

[32] Novelty refers to an invention being new compared to *prior art* (published inventions and previous patents). Moreover, to be patent an invention has to be non-obvious to a person having ordinary skills in the art and useful, meaning that it provides some benefits and is capable of use ([32] 35 U.S.C. § 102 and 35 U.S.C. § 103).

[33] Tobin's *q* measures the ratio of a firm's value to the replacement cost of its tangible assets (Villalonga, 2004).

Additionally, researchers have attempted to identify valuable individual patents. Determining patent value is a very difficult task as the value of an invention is unfolded over time and there are many worthless patents while just a few are highly valuable. Despite the limitations of the patent information, researchers have assessed patent value by renewal rates (Lanjow et al., 1996; Pakes, 1984; Schankerman and Pakes, 1985; Bessen, 2008), litigations (Lanjow and Schankerman, 1997; Allison et al., 2003), family size (Putnam, 1996), and forward citations (Harhoff et al., 1999, 2003a; Trajtenberg, 1990; Lanjow and Shankerman, 1999).

The rationale for these aforementioned measures is the following. In measuring patent value by the renewal rate, it is assumed that the firm (inventor) is going to pay renewal fees if the value of the invention is greater than the fee and costs associated with the renewal[34]. Not paying the renewal fee means abandoning the patent. Regarding litigations, the authors argue that a patent is going to be subject of a litigation suit if it is worth paying the legal costs, and litigated patents are identified as the most important patents by competitors (Allison et al., 2003). Family size refers to the number of countries where the patent is applied for. As it is costly to apply and to maintain a patent, the value of the patented invention increases with the family size. Finally, forward citations or the number of citations received by a patent capture not only the economic value but also the technological value of the invention. The more citations a patent received the more it has been important for future inventions and for further developments of a given technology. Other patent characteristics such as patent claims (Tong and Frame, 1994), backward citations (Reitzig, 2004), and the number of technology classes (Lerner, 1994) were also found to be correlated with patent value indicators.

Valuing patents is important because it gives us information about a different variable – the productivity of investments in innovation. Researchers are also interested in valuing patents such that they can proxy for the patents' quality and use them to understand economic indicators (e.g., innovation quality, R&D productivity, and the productivity of specific inventors or firms). According to Reitzig (2006), the value of a patent is determined by the value of its underlying technology, technical, legal and market uncertainty, and by the competition perceived by the patent holder.

[34] The USPTO require maintenance fees at 3.5, 7.5 and 11.5 years after the patent issuing date. https://www.uspto.gov/patents-maintaining-patent/maintain-your-patent,

Using a more direct measure of the value of an individual patent, Austin (1993) estimates patent value in the biotechnology industry through an event study. Using a sample of 258 solitary-event patents owned by the largest 20 biotechnology firms as of November 1991, Austin shows that the patent grant (official USPTO grant day) of patents that were subsequently announced in *The Wall Street Journal* generated significantly higher abnormal returns than the not announced patents group. In addition, product-linked patents, identified by the author, also generated higher abnormal returns than the patents not linked to products.

Liu (2006) investigates stock market reaction to 611 innovation announcements (FDA approvals, patent grants, scientific breakthrough, alliances or joint ventures, and other technological news) in the biotechnology industry, between 1983 and 1993. The author documents positive and significant abnormal returns for the innovations announcements. With respect to the innovations announcements considered, Liu's study includes 123 patent grant and 157 FDA approvals newswire announcements.

Considering the USPTO grant day as the event day, Plumlee et al. (2015) find significant and positive two days cumulative abnormal returns from the grant of a patent subsequent to a loan initiation. This is, the sample includes patents granted applied for firms for which the patent was granted within 6 months after a loan initiation, during 1993 to 2003. In this study, the authors do not claim that patents generate abnormal returns but that the specific sample of patents used as private information in order to get better loan conditions are indeed valuable.

Another study by Ramanathan et al. (2001) evaluates pharmaceutical patents and FDA approvals. In this study the authors conduct an event-study over a sample of 272 pharmaceutical patent grants, requiring the firm to have a drug previously approved by the FDA, and 537 drugs approved by the FDA, during 1974-1995. The authors find no significant abnormal returns due to the patent grant event and significant abnormal returns due to FDA approvals.

Assuming that variations in stock returns reflect shocks to the expected cash flow stream (Fama, 1990) a patent event, representing a successful R&D investment, will potentially increase a firm's revenue. As such, this event carries information that might be incorporated by the stock market and reflected in stock prices. Therefore, we test the following hypothesis:

Hypothesis 1: A patent grant event generates positive and significant abnormal returns.

A patent grants the patentee a right to exclude others, i.e., a negative right, which means it does not guarantee that the patented invention will be produced and commercialized. Conversely, a new product launch or the approval of a new product to be commercialized means that all the development costs were already incurred. Therefore, if the expected return from the commercialization of a product is positive, a new product-related information might be reflected in the abnormal returns of the firm stock price.

In this sense, we argue that an event conveying information of a closer to market innovation is going to generate abnormal returns, reflecting investors' expected returns from the innovation. Hence, hypothesis 2 states that:

Hypothesis 2: An announcement of a close-to-the-market generates positive and significant abnormal returns.

2.3 DATA AND METHODOLOGY

2.3.1 Event Study

The event study methodology, formalized by Fama et al. (1969), has a long tradition in finance and accounting. More recently, it has been implemented in marketing and management studies (Capron and Pistre, 2002; Sood and Tellis, 2009).

Standard event study methodology measures a stock's excess of return, abnormal returns (AR), generated due to the arrival of new information by using the residual of the return-generating model. Thus, ARs are the difference between the actual return during the event period and the returns that would have been expected if the event had not happened (Salinger, 1992). Following McWilliams and Siegel (1997)'s steps for an event study, we identified the event date of interest – the patent grant date, and defined the event window days surrounding the event date that may be affected by the event and may also generate abnormal returns. Then, we computed daily abnormal returns, cumulative abnormal returns, and tested the statistical significance of abnormal returns generated due to the patent event.

Daily abnormal returns are estimated by a two- step procedure. First, normal returns during the estimation window are estimated, i.e., the returns that would have been observed if the event had not taken place. Normal return-generating process is estimated through a window of 60 trading days preceding the event[35], from day 67 to day 7 prior the event (-67, -7)[36]. Kolari and Pynnönen (2010) argue that a factor model, such as the Fama and French (1993) three-factor model, extracts as much as possible of the common residual cross-sectional correlation, reducing cross-correlation in abnormal returns to a minimum. Therefore, we estimated the Fama and French three- factor model[37]:

$$(\mathrm{R_{it}} - \mathrm{R_{ft}}) = \alpha_i + \beta_{1i}(\mathrm{R_{mt}} - \mathrm{R_{ft}}) + \beta_{2i}\mathrm{SMB_t} + \beta_{3i}\mathrm{HML_t} + \varepsilon_{it} \quad (1)$$

where, $\mathrm{R_{it}}$ is the stock return of firm *i* over the time *t*, R_{ft} is the rate of return attributed to a risk-free investment at time *t*, usually the interest rate on a three-month U.S. Treasury Bill. R_{mt} accounts for the returns for all firms in NYSE, AMEX and NASDAQ at time *t*, SMB_t is the index of small versus big capitalization portfolios at time *t* and HML_t is the index of high versus low book/price ratio portfolios at time *t*.

Next, the abnormal returns ($\mathrm{AR_i}$) are computed by calculating the difference between the actual returns observed over the event window and the expected returns given by the above benchmark model. Thus,

$$AR_{it} = R_{it} - E[R_{it}] \quad (2)$$

where AR_{it} is the abnormal return, R_{it} is the observed return and $E[R_{it}]$ is the expected normal return over the event window *t* estimated by equation (1). To test the null hypothesis of zero abnormal returns we compute the cumulative abnormal returns ($\mathrm{CAR_i}$) aggregating through the event window for each security, assuming no confounding effects through the event window.

According to McWilliams and Siegel (1997) the longer the event window the more difficult it is to control for confounding events that may have an effect on

[35] There is no estimation window length standard as a variety of lengths has been used in prior studies (Campbell et al., 2003). In this study, we chose a 60 days period in order to retain a larger number of observations in our sample since we need to exclude those firms that have a patent event during the estimation window. The longer the estimation window, the more patent grants we need to exclude.

[36] Normal returns were also estimated using an event window of 30 days (-7,-37).

[37] In addition, we estimated normal returns using the market model where firm's returns are a function of the market returns, an intercept and, a random error (McWilliams and Siegel, 1997).

returns. As it is commonly used in the event study literature, we consider an event window of three days, one day before and one day after the event (-1,1)[38] (Sears and Hoetker, 2014; Alexy and George, 2013; Park and Mezias, 2005). One day before the event accounts for anticipation effects, whereas, including the day after the event captures announcement effects on price that may arise after stock market closing on the event day.

Hence, CARs are computed aggregating AR over the three days event window as follow:

$$CAR_i = \sum_{t=t_1}^{t=t_2} AR_{it} \tag{3}$$

where t_1 and t_2, respectively denote the beginning and the end of the event window. In additional analyses reported in appendix A.4, we employ a least square (OLS) regression where each event's CARs become the dependent variable explained by a set of variables accounting for patent and firm characteristics[39].

2.3.2 Patent grant data

The patent data comes from the NBER patent data project[40] (Hall et al., 2001), which contains USPTO granted patents from 1976 to 2006. Patent data was matched with the Center for Research in Security Price (CRSP) unique code (*permno*)[41] and patents that did not match were eliminated. To evaluate the patent grant event impact on stock market we selected patents applied for from June 8, 1995, when the patent term extension introduced by the TRIPS agreement was enacted in the U.S.[42] to the final grant day contained in the NBER database (December 26, 2006). The total number of patents matched to '*permnos*' is 567,009 applied for from June 8, 1995 onwards.

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[38] We also considered an event window of 5 days (-2,2).

[39] Appendix A.4.3 displays results for extended models estimations.

[40] https://sites.google.com/site/patentdataproject/Home. Revised as of August 2010. Accessed: June 18, 2013.

[41] Kogan, L., et al., 2016.

[42] Following the TRIPS agreement patent protection term was extended in U.S. from 17 years after grant to 20 years after filing date. http://www.uspto.gov/web/offices/com/doc/uruguay/20_year term.html.

Patenting intensive firms may have multiple patent events on the same day or during the normal return estimation window. To avoid confounding effects by the same type of event in estimating normal returns, multiple events in the same day by the same firm were eliminated and for each firm we dropped patents that were granted within an interval of 70 (40)[43] days from each other. This data screening lowered significantly the number of observations in our sample but it gives more confidence on the absence of confounding events over the estimation window. In addition to patent data screening, observations with missing stock returns during the event window and less than 30 days return information during the normal returns estimation window were dropped. Additionally, following standard practice in the literature we also excluded firms from the financial sector (SICs 6000-6999) and regulated utilities (SICs 4900-4999) (Hoberg and Phillips, 2010).

The final sample for the 60 (30) days normal return estimation window includes 17,193 (26,536) patents filed by 2,946 (2,950) different firms.

2.4 EMPIRICAL RESULTS

Equation 1 presents the model used to estimate normal returns and then we compute the abnormal returns as in equation 2. The data used to compute the three-factor model proposed by Fama and French (1993) come from CRSP and French's data library[44]. We winsorize the CAR variable at the 1% level to mitigate outlier problems. Descriptive statistics are displayed in appendix A.2 and A.3.

2.4.1 Patent grant event

Table 2.1 presents the results regarding the cumulative abnormal returns estimated for the patent grant event. Panel A of table 2.1 reports the CARs using the full sample of patents. While the first result is statistically significant (p-value<0.05), it is equal to zero, and not significant throughout all specifications. Therefore, first results indicate that, on average, we cannot accept our hypothesis that a patent grant causes the market to react positive and significantly.

As it is acknowledged by the literature, the value of a patent is very skewed, where few patents are valuable (Schankerman and Pakes, 1985; Harhoof et al., 2003).

[43] A normal return estimation window of 100 days (-7, -107) showed consistent results with the ones presented here (results available on request).
[44] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.htlm.

Moreover, scholars (e.g., Tratjenberg, 1990; Lanjow and Shakerman, 2001) have shown that the value of a patent is highly correlated with the number of citations received by the patent. The number of citations received is an indicator of the importance of a given patent to subsequent inventions, i.e., later patents built upon the knowledge describe in the cited patent. Although the number of forward citations is an ex-post value indicator, not observed by stock market investors at the moment of the patent grant announcement, Hall et al. (2005) argue that the market knows in advance about the value of particular innovations.

We examine if the absence of abnormal returns is due to the fact that the distribution is dominated by low quality patents. In order to check whether stock market investors assign value to more important patents we estimate the average CARs using a subsample of the top 10% and 1%[45] most cited patents[46]. Panel B in table 2.1 presents the results. No CARs generated in the two subsamples of patents were statistically significant at the conventional level, suggesting that investors do not react significantly to more important patents.

TABLE 2.1 - OLS Estimation. Dependent variable: Cumulative abnormal returns (CAR). Patent grant

PANEL A

	Estimation Window = 30 days	
Event window	CARs	Observations
(-1,1)	**0.000%****	26,536
(-2,2)	0.000%	26,536
	Estimation Window = 60 days	
Event window	CARs	Observations
(-1,1)	0.000%	17,193
(-2,2)	0.000%	17,193

PANEL B

Top 10% Forward Citations

[45] Top citations where calculated by technology areas (IPC classes), accounting for citations pattern differences.

[46] Appendix A.4.1 describe how we calculate forward citations accounting for censoring bias.

	Estimation Window = 30 days	
Event window	CARs	Observations
(-1,1)	0.00%	2,017
(-2,2)	0.00%	2,017
	Estimation Window = 60 days	
Event window	CARs	Observations
(-1,1)	0.002%	1,182
(-2,2)	0.002%	1,182
Top 1% Forward Citations		
	Estimation Window = 30 days	
Event window	CARs	Observations
(-1,1)	-0.002%	107
(-2,2)	0.005%	107
	Estimation Window = 60 days	
Event window	CARs	Observations
(-1,1)	0.004%	53
(-2,2)	0.017%	53

All regressions are estimated using robust standard errors clustered by event date.
Significance: * p<.1, ** p<.05, *** p<.01

We further estimate CARs generated due to a patent grant event using a sample of patents that eventually became products. We obtain a sample of patents related to drugs approved by the U.S. Food and Drug Administration (FDA), the Orange Book[47] where the patents associated with commercialized drugs are listed. This sample is expected to signify successful patents. According to Austin (1993), patents identified with products tend to be more valuable.

Considering a normal returns estimation window of 60 (30) days, the sample includes 203 (232) patents filed by 55 (55) different firms. Table 2.2 displays the CARs for the Orange Book patents. The absence of significant CARs suggests that the uncertainty borne by the patented invention prevents investors from assigning a value to the future profits that the invention can generate.

TABLE 2.2 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Orange Book patents

	Estimation Window = 30 days	
Event window	CARs	Observations
(-1,1)	-0.000%	232

[47] The authors received the Orange Book patent data by e-mail from the USPTO.

(-2,2)	-0.000%	232
Estimation Window = 60 days		
Event window	CARs	Observations
(-1,1)	0.000%	203
(-2,2)	0.000%	203

All regressions are estimated using robust standard errors clustered by event date.
Significance: * p<.1, ** p<.05, *** p<.01

To further corroborate these findings, we estimate abnormal returns around the grant date of patents listed in the Canadian Drug Bank[48]. We select patent of drugs patented for the first time, i.e., the parent patent of drugs approved by the FDA. We apply the same methodology described above. In order to retain a greater number of observations this sample includes patents granted from July 20, 1987 to February 08, 2010. Table 2.3 displays the results for 61 patent grants events, applied for by 19 different companies, for the 60 and 30 days estimation windows. Aligned with the previous results, the grants of patents protecting New Molecular Entities (NME) do not generate significant abnormal returns.

TABLE 2.3 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). NME patent grant (Canadian DrugBank)

Estimation Window = 30 days		
Event window	CARs	Observations
(-1,1)	0.005%	61
(-2,2)	0.004%	61
Estimation Window = 60 days		
Event window	CARs	Observations
(-1,1)	0.005%	61
(-2,2)	0.007%	61

All regressions are estimated using robust standard errors clustered by firm.

2.4.2 Market anticipation hypothesis

One explanation for the lack of significant abnormal returns may be that the value of the patented invention might be already reflected in the stock price; therefore, the stock market does not react, on average, to a patent grant event. In fact,

[48] Wishart DS, Knox C, Guo AC, Shrivastava S, Hassanali M, Stothard P, Chang Z, Woolsey J. DrugBank: a comprehensive resource for in silico drug discovery and exploration. Nucleic Acids Res. 2006 Jan 1;34(Database issue):D668-72.

the underlying hypothesis of an event study is that abnormal returns are generated when the information released was not anticipated (Brown and Warner, 1985). Although the grant day of a patent is a surprise (Austin, 1993), the value of the invention may be already incorporated in the firm's stock price as the firm may disclose the invention before the patent is granted. Moreover, during the examination process, after the enactment of the American Inventors Protection Act[49] (AIPA) the USPTO publishes the patent application 18 months after the earliest filing date.

In order to investigate whether the stock market accesses the value of the patented invention before the patent is actually granted, we considered two events: patent application publication and notice of allowance (NOA)[50]. Panel A, in table 2.4, presents the results regarding patent application publication[51], where it shows zero or virtually zero average abnormal returns. Zero abnormal returns indicate that investors, on average, do not assign a value to the information disclosed in a patent application.

Panel B displays the results for the NOA[52] event[53]. To estimate NOA abnormal returns we use three different event windows: 9 days (-1,7), 10 days (0,9), and 13 (-2, 10). The NOA is privately sent by the USPTO to the patentee; therefore, the patentee has the discretion to disclose the allowance of the patent. It means that the patent document *per se* is not published, instead what is announced is the allowance of the patent and what kind of technology it protects. Therefore, we expect the results to be nonsignificant as we are considering the USPTO date and patentees usually do not disclose having a NOA (Lansford, 2006). On average, we find zero CARs.

TABLE 2.4 **-** OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Patent Applications Publication (Panel A) and Notice of Allowance (Panel B)

[49] The American Inventors Protect Act (AIPA), enacted in November 29, 2000, established automatic publication of US patent applications, 18 months after the earliest filing date. However, AIPA gives to patentees an option to opt-out of pre-grant publication by certifying that the invention disclosed in the application will not be subject of an application in another country or under an international multilateral agreement that requires publication 18 months after the filing date (35 U.S. Code § 122).

[50] After examination, if the examiner has decided that the applicant is entitled to a patent under the law, a private notification is sent to the applicant by the USPTO – the notice of allowance – informing which claims will receive protection and specifying the required fees (37 CFR Section 1.311).

[51] When normal returns estimation window is 60 (30) days, the sample includes 6623 (9830) patents filed by 1664 (1668) different firms.

[52]Available at: http://www.uspto.gov/learning-and-resources/electronic-data-products/patent-examination-research-dataset-public-pair

[53] When normal returns estimation window is 60 (30) days, the sample includes 15639 (21332) patents filed by 3197 (3089) different firms.

PANEL A

Estimation Window = 30 days		
Event window	CARs	Observations
(-1,1)	0.000%*	9,830
(-2,2)	0.000%	9,830
Estimation Window = 60 days		
Event window	CARs	Observations
(-1,1)	0.000%***	6,623
(-2,2)	0.001%**	6,623

PANEL B

Estimation Window = 30 days		
Event window	CARs	Observations
(-1,7)	-0.002%**	21,332
(-2,10)	-0.002%**	21,332
(0,9)	-0.002%	21,332
Estimation Window = 60 days		
Event window	CARs	Observations
(-1,7)	-0.001%	15,639
(-2,10)	-0.003%**	15,639
(0,9)	-0.001%	15,639

All regressions are estimated using robust standard errors clustered by event date (Panel A) and firm(Panel B).
Significance: * p<.1, ** p<.05, *** p<.01

With respect to the NOA event, Lansford (2006) finds that a strategic disclosure of a NOA dampens negative stock market reactions to negative earnings announcement. On the other hand, Lansford stresses that the disclosure of patented information means the disclosure of private information that might have a negative impact on investors' reaction. However, the disclosure of non-financial information (NOA) has been found to have a positive effect on non-market financial measures (Plumlee et al., 2015).

In summary, patent disclosure events, on average, do not generate significant positive abnormal returns; therefore, we cannot accept hypothesis 1. These results indicate that not only the stock market does not anticipate the value of a protected invention but reinforce the hypothesis of investors not assigning value to patents given their technical knowledge and complex information (Liu, 2006; Gu, 2005). Further, appendix A.5 presents the results by pharmaceutical and electronic and computer industries, as patents are not as important in all industries. Results are consistent with the ones presented above.

2.4.3 *Product announcement*

Finally, we investigate whether the absence of abnormal returns is due to the uncertainty and highly technical information inherent to patents that make them difficult to be evaluated by the market. In order to test hypothesis 2, we conduct an event study on the event of approval of a drug itself by the FDA, rather than the patent for it to understand whether it is patents or innovation in general that the market has trouble evaluating. New molecular entities (NME) and new biological approvals data were collected from the FDA web page[54], from 1999 to 2014. Firms were hand merged to CRSP data and then we conducted an event study considering a 60 (30) days normal return estimation window with a sample of 189 (190) drug approvals for 87(87) different firms.

TABLE 2.5 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). FDA Announcements

	Estimation Window = 30 days	
Event window	CARs	Observations
(-1,1)	0.059%**	190
(-2,2)	0.055%**	190
	Estimation Window = 60 days	
Event window	CARs	Observations
(-1,1)	0.374%***	189
(-2,2)	0.537%***	189

All regressions are estimated using robust standard errors clustered by firm.
Significance: * p<.1, ** p<.05, *** p<.01

As it is shown in table 2.5, FDA approvals, on average, generated positive and significant CARs. An FDA drug approval generates, on average, between 0.06% and 0.5% abnormal returns during the considered event windows. This result suggest that although investors may not be sophisticated enough to understand the information conveyed by the patent or to evaluate the prospects of a newly patented invention, announcements related to closer to market innovations lead to positive stock market

[54] http://www.fda.gov/Drugs/DevelopmentApprovalProcess/HowDrugsareDevelopedandApproved/DrugandBiologicApprovalReports/NDAandBLAApprovalReports/ucm373420.htm. Accessed: February 2016.

reactions. In the case of a drug approval that may generate sales revenue in the short run, investors are able to recognize and assign a value to this event. Ergo, we cannot reject hypothesis 2.

2.5 DISCUSSION AND CONCLUSION

In this chapter, we investigate the stock market's reaction to innovation. Using patents as a proxy for innovation, we investigate the stock market's reaction to patent related events – application publication, allowance, and grant. We assume that the release of the information related to the patent event is a surprise. According to Austin (1993), even if the information regarding the invention and the firm's specific technology direction is known, the actual day of the patent event is not known. Moreover, we use a broad sample of patents, and conduct an event study where the event windows are set around the patent event day. On average, we cannot accept hypothesis 1 of positive and significant abnormal returns generated due to a patent event.

Therefore, we investigate different explanations for why patent events do not generate positive CARs. One explanation we consider is that the distribution of patent value is highly skewed and the positive valuation of the market may be lost in the averages we look at. To test this proposition we restrict our sample to only patents that are subsequently proven valuable through receiving citations in the top 10% or 1% of the citation distribution, or patents that resulted in products. For that we use a sample of patents related to drugs approved by the FDA – Orange Book listed patents and a sample of NME. Together with estimations for the top cited patents, these samples are considered to include valuable patents, i.e., valuable inventions. Even using samples of patents that are shown to be valuable later, we cannot accept the hypothesis of positive and significant abnormal returns.

Considering a possible leakage of information, i.e., the value of the invention is already incorporated in the firm's stock price, we investigate abnormal returns around the patent application publication event and the patent allowance (NOA) events. We do not find statistically significant CARs for the patent application publication event and even statistically significant, we document virtually zero abnormal returns to a NOA.

We interpret our results as suggesting that investors do not significantly react to patent-events either because it is a technical and complex document or because of the uncertainty regarding futures prospects of the invention.. The published patent document, apart from information regarding inventors, assignees, and dates, is a very technical document describing the invention in detail. This characteristic makes the patent a complex document, which prevents investors from fully understanding the information contained therein (Liu, 2006; Gu, 2005) and from assigning a value based on the future cash flows the patented invention might generate.

Finally, we calculate abnormal returns for the event of a drug approved by the FDA. When the event is related to a product that is associated with immediately pending sales, investors are able to value expected future cash flows generated by the invention. This is, a closer to market innovation bears significantly less uncertainty than a patent that usually comes out at the beginning of an innovation project.

Our results might seem to be at odds with the majority of previous results in the literature. However, we use a larger and broader sample, not restricted to a single industry, type of firms and events attracting media attention as Austin (1993) and Liu (2006) nor related to a specific firm event as Plumlee et al.(2015). Austin's paper, for example, used a limited and very specific sample of patents owned by large biotechnology firms, making results very specific as well. Liu (2006), in considering only the announced events, the sample is selected towards valuable patents, i.e., when a firm makes the innovation-related event announcement, it is more likely to be valuable.

Moreover, we contribute to the literature with a series of robustness tests in order to further explain why the stock market does not react significant and positively to a patent grant event. Results are aligned with Ramanathan et al. (2001), however, instead the authors do not provide any further explanation for the sample selection, methodology, and robustness of their results.

The absence of significant stock market reaction to a patent event may lead to innovation myopia and to resources misallocation. We propose that, investors and the society would benefit from the publication of an easier to access and interpret patent information.

Despite the advantages of an event study in capturing stock market reactions to an unexpected event our study has several limitations. Of specific importance is the fact that the screening process required to minimize confounding effects causes underrepresentation of patenting intensive industries. However, as shown in the literature, we would expect that the stock price of a more innovative firm already includes patents value. If the stock market assigns higher value to innovative efficient firms (Hirshleifer et al., 2013), a patent event of a firm that patent frequently might not be a surprise, therefore it would not generate abnormal returns. In addition, as we estimated longer event windows for NOA it may be that confounding effects happen to be included in the event window and drive our results. With these caveats, we think our study has a clear contribution to the patent valuation literature as it provides a direct measure of investors' ability to understand and value the information conveyed by the patent document.

Chapter 3

When diversification meets value:

Technological diversification, technology categories, and firm value

3.1 INTRODUCTION

Innovation generates economic growth (Grossman and Helpman, 1993) and improves the performance of the innovating firm (Klette and Kortum, 2004; Geroski et al., 1993). Moreover, investing in research and development (R&D) enable firms to build absorptive capacity, generate innovations, and to succeed in the market place (Cohen and Levinthal, 1990, Stock et al., 2001). Further, previous research shows that firms' technological diversification promotes innovation (Garcia-Vega, 2006; Leten et al., 2007). Thus, a firm investing in technological diversification becomes more innovative and better able to respond to market changes and, therefore, increasing its future viability. Then, technological diversification might affect firm's expected future performance, reflected on a positive market valuation.

This study investigates the effect of the degree of technological diversification on firms' market value[55] in R&D intensive industries, measuring technological diversification by firms' patents technology classification, during 1992-2007. In addition, I look at differences in investors' evaluation of technological diversification by technology categories. I find that the effect of technological diversification on firm value differs between technology categories.

Diversifying technologically means increasing the range of technology areas of a firm's technology base (Granstrand and Oskarsson, 1994). Then, it requires resources, physical and knowledge based, to develop and take advantage of technology cross-fertilization (Granstrand, 1998; Leten et al., 2007). Despite developing and acquiring internal ability to use a broad range of technologies, it also requires managers to coordinate and integrate multidisciplinary R&D (Granstrand and Oskarsson, 1994).

Granstrand (1998) argue that technology, as one kind of knowledge, is part of a firm's resources and, therefore, part of a firm's intangible capital. The relationship between firm value and intangible assets is well established in the literature. Considering the uncertain and risky nature of R&D and the innovative activity (Kline and Rosenberg, 1986), the financial markets' forward looking valuation of firm assets and investments is considered appropriate to value investment in R&D and intangible assets (Toivane et al. 2002). Previous evidence shows that, a positive and significant

[55] Throughout this chapter, market value and Tobin's *q* are used interchangeably, unless stated otherwise. Tobin's *q* is defined as the ratio of market value over replacement costs.

relationship exists between firm market value and R&D investments (e.g., Gleason and Klock, 2006; Chan et al., 2001; Blundell et al., 1999; Cockburn and Griliches, 1988; Griliches, 1981) and patents (e.g., Hall et al., 2005; Cockburn and Griliches, 1988; Blundell et al., 1999).

Regarding firm diversification strategies, product or business diversification might be motivated by the possibility of generating economies of scope, spreading and reducing risks and, sustaining firm growth (Cantweel et al., 2004). Moreover, firm diversification requires firms to coordinate and share new and existing assets (Zhou, 2011). On the one hand, business diversification may generate inefficiencies, having a negative effect on firm value (Wernefelt and Montgomery, 1988; Lang and Stulz, 1994; Berger and Ofek; 1995). On the other hand, it may generate economies of scope and, therefore, yield a market premium (Villalonga, 2004b).

However, firms might diversify technologically without business/product diversification (Gambardella and Torrisi, 2008; Brusoni et al., 2001), although, technological diversification also requires coordination and sharing of new and existing assets, tangible and intangible. Firms may also diversify technologically in order to better understand complex product systems, internally develop the different technologies embodied in a product, or to be able to identify and take advantage of new technology opportunities (Granstrand et al., 1997). Nevertheless, technological diversification might also create inefficiencies and resources misallocation, leading to losses. Ergo, is not obvious that the degree of technological diversification is positively associated with firm value as the future benefits generated by technological diversification and firm's ability to appropriate it might depend on the characteristics of the technology that is produced.

One way to classify a technology is by its returns appropriation mechanisms. The innovation literature describes technologies in two main categories: complex and discrete (Cohen et al, 2001). Complex technologies refer to products that are protected by many patents, generally held by different owners (e.g., electronics). On the other hand, discrete technologies refer to products protected by one or a few patents (e.g., drugs). This distinction is primarily used to identify firms' strategic patenting behavior and to evaluate the efficiency of patents as a tool to appropriate the returns to innovation, depending on the technology protected by the patent.

Still, the technological diversification effect on firm value might differ by technology characteristics because of two main reasons. First, as in complex technologies it is necessary to join different technologies to ensemble a product, a broader technological knowledge might be necessary to understand the different parts of a product and to appropriate returns from innovation. Whereas, discrete technologies, in general, do not need to join different technologies, making technology diversification less influential on firm value. A second reason is the technology innovation cycle. The innovation cycle, i.e., how long it takes from turning a promising technology into realized profits, differs by industry and technology, and might influence how the degree of technology diversification affects firm value. For example, Gu (2005) points out that the innovation cycle in the biotech and pharmaceutical industries (discrete technologies) is longer than in other innovation-intensive industries, around twelve to fifteen years. Conversely, in the electronic industry (complex technology) innovation cycle is considerably shorter. Hence, technological breadth might be more relevant for technologies with a shorter innovation cycle. In this sense, the average effect of technological diversification on firm value might be misleading, as shareholders might access technological diversification value differently depending on the technology category.

This study contributes to the literature on intangible assets valuation. Results show that technological diversification is associated with firm value beyond usual intangible indicators, R&D expenditure and patents. However, the value effect is mainly driven by the positive effect that technological diversification has on firm value for the electronic industry. Additionally, I show that the effect of the degree of technological diversification on firm value is asymmetrical, being positive for electronics and not significant for chemicals. To the best of my knowledge, this is the first study to investigate the effect of technological diversification on firm value considering different technology categories.

In the following section, I discuss the theoretical background and propose the hypotheses to be tested. Section 3 presents the data and variables descriptions and section 4 the empirical results. In section 5, I discuss the results and finally section 6 concludes with some implications, limitations, and future research.

3.2 THEORY AND HYPOTHESES

3.2.1 Technology diversification

Diversification has long been discussed in the strategic management literature (Ramanujam and Varadarajan, 1989). Earlier works focus primarily on product/business diversification, defining it as the variety of products, industries, or markets that a firm caters to (Gort, 1962; Berry 1975; Pitts and Hopkins, 1982). Moreover, Rumelt argues that “diversification takes place when the firm expands to make and sell products or a product line having no market interaction (technically, having zero cross price-elasticity) with each of the firm's other products” (Rumelt, p. 363, 1982). Thus, diversification is a strategic response to the risks and uncertainties of being dependent on a single market (Fai, 2001). It means that by diversifying the firm is spreading risk and securing income when the demand for one product is declining.

Together with the decision to diversify, managers also decide the direction of diversification. The literature identifies two main diversification strategies: vertical and horizontal (Ansoff, 1958; Fai, 2001). The former refers to upstream (input supply) or downstream (e.g., distribution channels) diversification, whereas the latter refers to output/product/market diversification. Likewise, some authors have differentiated between related and unrelated diversification (Chari et al., 2008). While related diversification presents opportunities to share resources and capabilities, unrelated diversification demands different resources and capabilities. Related diversification implies that the firm takes advantage of the synergies between the existing resources in order to diversify into new product markets, giving rise to economies of scope (Zhou, 2011). Moreover, product diversification frequently is justified as a response to market conditions, managers’ intent to enlarge the company, and strategic decisions to reduce business risks (Miller, 2004).

Although similar, technological diversification does not imply product diversification (Fai, 2001). Yet, generally technological diversification precedes product diversification as firms diversify following the technology capabilities already developed, i.e., a technology related diversification (Granstrand, 1998; Miller, 2004; Kim et al., 2016).

Technological diversification is often looked at from the point of view of the resource-based view (RBV) of the firm, as it involves the acquisition or the development of new knowledge, skills and routines. Further, the RBV theory stresses the importance of intangible resource endowments to achieve sustainable performance (Villalonga, 2004c). Accordingly, the existence of indivisible, difficult to imitate, and specific assets gives the firm a competitive advantage (Barney, 1991) and makes the firm better able to diversify technologically. The high transaction costs of firm’s specific assets motivate the firm to explore them internally, diversifying into new technologies (Leten et al., 2007). In addition, Granstrand (1998) argues that technology diversification fosters firm growth by generating economies of scale, scope, speed, and space[56].

3.2.2 Technology diversification and firm value

The evidence regarding the association between business (product/market) diversification and firm value is mixed, depending on the context, industry and firm specific characteristics (Park and Jang, 2012). Earlier work has found a negative association, i.e., a diversification discount. Diversification may lead to management and resource allocation inefficiency. Lang and Stulz (1994) using a sample of 1,449 US firms find a negative association between firm business diversification and Tobin's q throughout the 1980s, and this diversification discount is not explained by industry effects. Using a similar, but shorter, time span (from 1986 to 1991) and a sample of 3,659 US firms, Berg and Ofek (1995) also find a diversification (business) discount. However, the authors find that related diversification (in the same SIC two-digit code) mitigates the negative effect of diversification.

On the other hand, researchers claim that the diversification discount is a result of an estimation bias (Villalonga, 2004a). According to this view, diversification is an endogenous decision as it may be a result of managers' profit seeking choices when the firm is not realizing profits in the current industry (Miller 2004; Villalonga, 2004a). Villalonga (2004a), when using a propensity-score matching method to correct for this bias, finds that the diversification discount disappears and finds a diversification premium instead. Villalonga (2004b) using data from the Business Information Tracking Series (BITS) from 1989 to 1996 also reports a statistically significant diversification premium.

More recently, scholars have looked at a nonlinear relation between intra-industry product diversification and firm performance, using fine-grained product diversification data. Zahavi and Lavie (2013) find an U-shaped effect of product diversity on firm performance, measured by sales growth. Moreover, this effect is stronger as firms invest more on R&D, and attenuated by firms' intra-industry product

[56] Granstrand (1998) refers to economies of scale in the sense of diminishing average costs, economies of scope relate to technology cross-fertilization, economies of speed as the pace of a process and, economies of space regarding the location of the firm and externalities.

diversification experience. Hashai (2015) reports an S-shaped relationship between within-industry diversification and firm performance, measured as returns on sales. According to Hashai, the S-shaped relation is driven by "adjustment costs" at low levels of within-industry product diversification and "coordination costs" at high levels.

Miller (2004, 2006) investigates the moderation role of the firm's technological diversity into the relation between business diversification and firm performance. First, using a sample of 227 large US firms from 1980 to 1992, Miller (2004) argues that the observed diversification discount occurs because firms that diversified (product diversification) invest less in R&D and have broader technology (less specialized) assets than other firms in their industry prior to the diversification. Miller (2006) reports a positive association between firm performance and business diversification when the business diversification is based on technology diversity.

On the other hand, there is no dispute regarding the positive effect of intangible assets on firm value. To the extent that intangible resources generate value to the firm it has to be reflected in the firm's market value. Consistent with this argument, Griliches (1981) and Cockburn and Griliches (1988) show that patent stock and R&D stock have a positive effect on firm value (measured with Tobin's *q*). In addition, R&D investment shows a larger effect than patent stock. Megna and Klock (1993) investigate the effect of intangible assets on firms' value in the semiconductor industry. The authors find a positive effect of R&D and patent stock on firm value. Further, rivals' patents have a negative effect on the market value (Tobin's *q*) of the focal firm, while rivals' R&D stock has a positive effect. The authors argue that rivals' intangibles affect the focal firm's market value to the extent that the returns on intangibles cannot be fully appropriated, generating spillover effects. Hall et al. (2005) use three measures of firms' intangible assets: R&D to assets ratio, patents to R&D ratio and, citations to patents ratio, all stock variables. These ratios proxy for R&D intensity, R&D productivity, and the quality of the R&D outcome, respectively. Findings show that all ratios have a positive and significant effect on market value.

In the aforementioned studies, intangible assets are proxied by R&D and patents. However, following Granstrand (1998), I argue that firms' technological resources are also part of firms' intangible capital and contribute significantly and beyond the usual variables in explaining firm value. Technological diversification indicates firms' knowledge breadth which may enable them to exploit economies of scope in R&D,

enhance absorptive capacity by giving them access to a more diverse outside knowledge, reduce the risks of R&D by developing technological capacity in other areas, and enable the firm to extract more rents by creating more complex product and diverse systems (Kim et al., 2016). The literature provides evidence that technological diversification promotes firms' innovation performance (Garcia-Vega, 2006; Leten et al., 2007; Quintana-García and Benavides-Velasco, 2008). Garcia-Vega (2006) argues that technological diversification enable firms to absorb R&D spillovers from others technology fields and reduce innovation risk, creating incentives to increase R&D expenditure. However, Leten et al. (2007) report an inverted U-shaped relationship between technology diversification and firms' innovation performance given the high costs of coordination and integration that a highly technologically diversified firm may incur. Regarding the effect of technology diversification on financial performance, studies have found a positive effect on market value[57], moderating the relation between segment diversification and market value (Miller, 2006), and a positive direct effect on return on assets, profitability (Lin et al., 2006), and sales growth (Kim et al., 2016).

Then, as the degree of technological diversification is part of a firm's intangible capital, it has to be included on firm's market value. Therefore, in analyzing R&D intensive firms, hypothesis one states:

> *H1: On average, the degree of technological diversification has a positive effect on firm's Tobin's q.*

Technology diversity involves developing and/or acquiring new knowledge. As such it might also require a large amount of investment. Considering the risks and uncertainty inherent to the innovation activity, Kim et al. (2016) highlight the importance of technology diversity for a firm as a way to diversify risks and be able to quickly adapt to demand changes, especially in a fast-changing environment. Quintana-García and Benavides-Velasco (2008) investigate the effect of technology diversification on firm's innovation performance in the US biotechnology industry. The authors find that technological diversification has a stronger effect on exploratory

[57] In this paper, the author measures market value as the nominator of Tobin's q ratio, i.e., the price of outstanding common shares *times* the number of shares *plus* the book value of preferred stock *plus* the book value of debt.

inventions because a broader technological knowledge enables recombination of old knowledge and the solution of complex problems.

The literature has stressed the differences between technologies regarding the appropriability of the returns to innovation. Cohen et al. (2000) differentiate between discrete and complex technologies, where the former is characterized by one product protected by one or a few patents, and the latter is characterized by many complementary patents, typically held by different owners, protecting one product. A typical example of a discrete technology product is a chemical or a drug, where one or a few patents protect one molecule or structure, and these patents are generally held by a single owner. The consumer electronics industry is a typical example of complex technology, as many parts are protected by patents, forming a single device (Baron and Delcamp, 2010).

The difference in technology characteristics may influence the need for technological diversification and its impact on firm market value. For example, technological diversification may be more relevant in complex industries, where a product embodies many different technologies. On the other hand, a firm operating in a discrete industry, where products embody few and specific technologies, may require deeper rather than broader technological knowledge. Gambardela and Torrisi (1998) investigate the effect of technological diversification on firms' accounting performance measures in the electronics industry. The authors find that, for a sample of the 32 largest US and European firms in the electronic industry during 1984-1992, technological diversification had a positive effect on firm performance, sales and profits.

Besides differences regarding returns appropriation, complex and discrete technologies differ in the innovation cycle length. While discrete technology products take a long time between the idea materialization and profits realization, this time is shorter for complex technology products (Gu, 2005). It means that, in order to remain competitive firms need to be able to adapt and to quickly respond to market changes. Therefore, technological diversification might be more crucial in determining future viability for complex technologies.

Consequently, the impact of technological diversification on the market value of the firm is not homogeneous across industries. It depends on the technology characteristics and how relevant is the degree of technological diversification to generate future cash flow streams. Complex technologies might derive a greater benefit from technological diversification than discrete technologies. Indeed, in the discrete technology industries the degree of technological diversification may not provide additional information regarding a firm's intangible capital. Thus, the second hypothesis state that:

> *H2: The positive effect of technological diversification is stronger for complex technology industries than for discrete technology industries.*

3.3 METHODS

3.3.1 Data and sample selection

This chapter investigates the effects of technological diversification on the market value of R&D intensive firms. I use patent data from EPO's Worldwide Patent Statistical Database April 2012 ("PATSTAT") and firm level data from Compustat. My sample includes observations of firms that have a patent granted up to 2010[58]. I constructed a panel of patenting firms that patent at least in two consecutive years and have at least 5 years of available information in Compustat between 1992 and 2007. R&D intensive firms were defined as the ones whose primary two digit SIC code is 28 (chemicals and allied products), 35 (industrial and commercial machinery and computer equipment), 36 (electronic and other electrical equipment and components, except computer equipment), 37 (transportation equipment), and 38 (measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks) (Coad and Rao, 2008; Bernstein and Mamuneas, 2006). The final sample includes 1,304 firms in an unbalanced panel with 12,432 observations.

3.3.2 Measures

Dependent variable

The dependent variable is the logarithm of Tobin's q, defined as the ratio of market value to replacement value. Calculated as in Chung and Pruitt (1994), using Compustat data. I follow Villalonga and Amit (2006) and treat a Tobin's q greater than 10 as an outlier, dropping observations in this case. The relation between intangible assets and market value (Tobin's q) has been studied previously (e.g.,

[58] Using Kogan et al. (2011) data, US patents granted up to 2010 were matched to Compustat using CRSP *permnos* and *gvkeys* concordance table.

Griliches, 1981; Hall et al., 2005), where the natural logarithm of q is a linear and additive function of variables accounting for tangible and intangible assets. Moreover, according to Villalonga (2004c), using the natural logarithm of q avoid the pitfall of considering constant returns to scale in intangible assets investments.

Technological diversification

The main independent variable is the degree of technological diversification (TD). This index is calculated based on the International Patent Classification (IPC[59]). Examiners assign each patent to different IPC classes, according to the technology described in the patent document. Additionally, most of the patents are classified in many IPC classes what means that a given invention embraces many technologies. In order to capture the different technologies used to build a patented invention, an entropy index (Kim et al., 2016) was calculated using a firm's share of IPCs at the 6-digits (main group) level over all IPCs 6-digit classifications of a firm's patent applications in a given year[60]. As Aharonson and Schilling (2016) argue, a measure that considers patent subclasses provides a better picture of the firm's technology.

$$TD_{it} = \sum_{k=1}^{6668} IS_{ikt} \ln\left(\frac{1}{IS_{ikt}}\right)$$

where IS_{ikt} is firm i's IPC 6-digit share for group k at time t ($IS_{ikt} = I_{ikt}/I_{it}$ and I_{it} is equal to the total number of IPCs 6-digit level assigned to firm i's patents at time t). A moving average of three-years was used for each year observation to diminish concerns regarding noise and fluctuations of patent application and number of IPC classification assigned to patents (Kim et al., 2016). Moreover, using a three-year moving average lessens endogeneity concerns regarding simultaneity of technological diversification and firm performance.

[59] The IPC is a hierarchical classification of patents according to the technology categories they belong. For example, C01B 5/02 indicates a complete classification symbol, where C represents the section symbol, C01 the class symbol, C01B the subclass and, C01B 5/00 the main group. The last two digits narrow down the domain of the technology.

[60] In the sample of patents matched to Compustat there were 6668 different IPC 6-digits classes.

Control variables

The amount of R&D expenses indicates the firm's commitment to innovative activity. However, R&D outcomes may take time to be developed, commercialized, and then generate value to the firm (Hall et al., 2005). Nevertheless, it is established that R&D investment has a positive effect on firm market value (e.g., Griliches, 1981; Hall et al., 2005). Therefore, I include R&D intensity ($R\&D_t$), measured as the ratio of R&D expenses to total assets in a given year (Miller, 2006). Moreover, I include R&D intensity lagged one year ($R\&D_{t-1}$), accounting for the time lag between the investment in R&D and the R&D output[61].

As the key independent variable is calculated based on patent applications, I control for the number of patents applied by firm *i* (*TOTAL*) in a given year. Not controlling for the number of patent applications could bias our results, as a firm that patents more is more likely to have a higher TD index.

Additionally, following recent studies on diversification using market-based measures of performance (Miller, 2006), I include control variables common to this literature. *Capital intensity*, as the ratio of capital expenditure to total assets, gives an additional measure of tangible assets and is positively related to firm value. A firm's financial constraint is measured as an indicator variable equal to one if the firm did not pay dividends in a given year (*DIVID_NP*) (Lang and Stulz, 1994). The *leverage* variable is measured as the ratio of the book value of debt to market value, defined as the number of outstanding common shares times the price at the close of the year. Further, I control for other factors that can affect firm value as, *profitability* (the ratio of net income to sales), *size* (natural logarithm of a firm's number of employees) (Berger and Ofek, 1995), and *age*[62] (Kim et al., 2016). Finally, *market share (MKT SHARE)*, measured at the 2-digit SIC code level, proxy for a firm's efficiency in production and innovation (Smirlock et al., 1984). Blundell et al. (1999) reinforce the efficiency hypothesis and find that the impact of innovations on a firms' market value is larger for firms with a higher market share.

[61] It may be that further lags also affect firm's value as R&D outcomes are uncertain and may take longer than two years to generate a marketable innovation. However, it is out of the scope of this study to investigate the effect of R&D lags on *Tobin's q*.

[62] *Age* is a proxy variable calculated from when the firm appears in Compustat data to the focal year. My Compustat data runs from 1984 to 2013.

3.4 EMPIRICAL RESULTS

3.4.1 Descriptive statistics

Table 3.1 and 3.2 display the descriptive statistics and the correlations for all variables in the full sample of firms from 1992 to 2007. Technology diversification (TD) index ranges from 0 to 7.733, where the higher the index, the more technologically diversified a firm is. Regarding R&D intensity, past and current R&D have similar means, indicating the stickiness of R&D investment. Moreover, only 3.86% of the firm-year observations did not report R&D expenses (Dummy R&D=0).

From table 3.2, the correlation between R&D (log) and size and between sales (log) and size – 0.72 and 0.88, respectively – are high but do not represent any threat, as these variables do not enter simultaneously as explanatory variables in the regressions shown below. Although, most of the correlations are lower than 0.7, TD has a high correlation with size (0.66), market share (0.49), and with the total of yearly patent applications (0.45)[63].

TABLE 3.1 – Descriptive statistics

VARIABLES	(1) N	(2) MEAN	(3) SD DEVIATION	(4) MIN	(5) MEDIAN	(6) MAX
TD	12,432	2.360	1.387	0	2.197	7.733
TD (HHI)	12,432	0.745	0.252	0	0.829	0.996
TD4	12,432	1.593	1.003	0	1.482	5.325
TOBIN'S q	12,432	0.838	0.584	-5.583	0.796	2.294
TOBIN'S q_{t-1}	11,128	0.847	0.584	-5.583	0.804	2.294
BUSINESS DIVERSIFICATION	12,432	2.181	1.962	0	1	21
TOTAL	12,432	51.14	200.9	1	6	4,295
PROFITABILITY	12,290	-5.268	129.9	-11,909	0.0333	71.59
PROFITABILITY$_{t-1}$	11,002	-4.312	75.42	-4,940	0.0331	71.59
LEVERAGE	12,431	7.011	527.4	0	0.0725	41,910
R&D	12,432	0.126	0.185	0	0.0755	5.760
R&D$_{t-1}$	12,432	0.129	0.197	0	0.0755	5.893
SIZE	12,204	1.328	1.355	0	0.796	6.621
AGE	12,432	11.54	5.249	1	11	24
DUMMY (R&D=0)	12,432	0.0386	0.193	0	0	1
CAPITAL INTENSITY	12,272	0.0521	0.0477	0	0.0393	0.625
DIVIDENDS NOT PAID	12,432	0.643	0.479	0	1	1
R&D(log)	12,432	3.298	1.870	0	3.103	9.408
MKTSHARE	12,428	0.000	1.000	-0.321	-0.289	13.75
SALES (Log)	12,290	5.516	2.591	-6.908	5.553	12.48

[63] All variables included in the models have variance inflated factors (VIF) below the usual cut off value of 5.

3.4.2 Regression results

First, in line with Granstrand and Oskarsson (1994) and Gambradela and Torrisi (1998), I regressed sales (log) on the degree of technological diversification (TD index), R&D (log) expenses, size, age, with industry and year fixed effects. Results[64] (not tabulated) indicate a positive association between sales and the TD index, for the sample of R&D intensive industries. However, this result must be seen with caution as sales are measured at the aggregate level. More accurate measures of sales, embodying diversified technologies, require in depth surveys with more detailed information. Nonetheless, this preliminary result gives a flavor of the overall positive relation between technological diversification and sales.

Turning to the main analysis investigating the relationship between Tobin's q and TD, table 3.3 column 1 displays the results for the full sample of R&D intensive firms and column 2 and 3 the results for the chemical and electronic industries, respectively. Equations were estimated using the random effects model, accounting for the panel structure of the data. The random effects model is preferred to the fixed effects model because technology diversification, the main independent variable, changes slowly over time. Therefore, a fixed effects estimation would neglect important information (Miller, 2006). Moreover, Hall et al. (2005) argue that when considering market value as the dependent variable, to assume that differences between firms are fixed may not be a suitable assumption as firms change their strategies in response to market conditions.

The main variable of interest, the degree of TD index is positive for all samples, although statistically significant for the full sample and for the electronic industry subsample. Further, the coefficient of TD is larger[65] for the electronic industry than for the full sample.

Firm size is significant and negative, in line with Schwert (1983) and Lang and Stulz (1994) who report a negative effect of firm size on stock returns. A proxy for firm age is negative and significant in column 1. Loderer and Waelchli (2010) argue that older firms tend to develop organizational rigidities and, therefore, may be less profitable.

[64] Results available upon request.

[65] $\chi^2(1) = 8.31$, prob$>\chi^2 = 0.0039$.

TABLE 3.2 – Correlation matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	TOBIN'S *q*	1																			
2	TD	-0.13	1																		
3	TD (HHI)	-0.06	0.79	1																	
4	TD4	-0.19	0.93	0.74	1																
5	BUSINESS DIVERSIFICATION	-0.29	0.36	0.21	0.38	1															
6	TOBIN'S q_{t-1}	0.77	-0.13	-0.06	-0.18	-0.29	1														
7	PROFITABILITY$_{t-1}$	-0.05	0.02	**0.01**	0.03	0.04	-0.05	1													
8	SIZE	-0.37	0.66	0.38	0.65	0.52	-0.36	0.05	1												
9	AGE	-0.19	0.17	0.11	0.19	0.32	-0.19	0.02	0.33	1											
10	R&D(log)	-0.09	0.69	0.45	0.62	0.36	-0.06	**0.01**	0.72	0.25	1										
11	R&D	0.3	-0.09	-0.03	-0.13	-0.22	0.3	-0.17	-0.33	-0.19	**0**	1									
12	R&D$_{t-1}$	0.32	-0.1	-0.04	-0.14	-0.21	0.32	-0.13	-0.33	-0.21	-0.04	0.62	1								
13	DUMMY (R&D=0)	-0.09	-0.08	-0.06	-0.06	0.03	-0.09	**0.01**	**0**	0.03	-0.35	-0.14	-0.13	1							
14	LEVERAGE	-0.03	**-0.01**	**0**	**-0.01**	**-0.01**	**-0.01**	**0**	**0.01**	**0.01**	**0.01**	**0**	**0**	**0**	1						
15	PROFITABILITY	-0.03	**0.01**	**0**	**0.01**	0.02	-0.03	0.31	0.04	**0.01**	**0.01**	-0.08	-0.06	**0.01**	**0**	1					
16	DIVIDENDS NOT PAID	0.27	-0.36	-0.21	-0.39	-0.33	0.27	-0.03	-0.59	-0.29	-0.29	0.29	0.28	-0.06	**0**	-0.03	1				
17	CAPITAL INTENSITY	0.03	0.03	**0.01**	**0.01**	-0.06	0.07	0.03	0.08	-0.13	0.02	-0.02	-0.08	0.03	**0.01**	0.02	**-0.02**	1			
18	MKTSHARE	-0.21	0.49	0.23	0.49	0.33	-0.21	0.02	0.66	0.18	0.54	-0.13	-0.12	-0.02	0	**0.01**	-0.32	**0.02**	1		
19	TOTAL	-0.1	0.45	0.2	0.4	0.26	-0.1	**0.01**	0.46	0.14	0.45	-0.06	-0.06	-0.04	**0**	**0.01**	-0.2	0.07	0.6	1	
20	SALES (Log)	-0.39	0.57	0.35	0.57	0.47	-0.37	0.16	0.88	0.39	0.66	-0.48	-0.48	0.04	**0.01**	0.14	-0.54	0.08	0.51	0.36	1

Note: All correlations are significant at 5% except the ones in bold. Obs.: 12,432

Regarding the relationship between R&D investment and firm market value, a positive and significant association is well documented in the literature (Griliches, 1981; Cockburn and Griliches, 1988; Hall et al., 2005). Overall, R&D and R&D_{t-1} are positive and significantly associated with *Tobin's q*. The effect of R&D on firm market value reflects the discounted future cash flows that may be generated by the R&D expenditure. Considering the time needed to generate innovation outputs, past R&D expenditure is more relevant in generating current cash flows and, therefore, has a greater effect on current *q*.

Hall (1993) reports a decrease in the market valuation of R&D investment during the nineteen-eighties. However, I expect that any trend or shock that affects market valuation may affect all firms in the sample equally and then be included in the year fixed effects. Finding no relation between the number of patents applied and the value of a firm goes in line with previous literature, which establishes that simple patent counts are not (or weakly) correlated with firm value (Hall et. al., 2005)

Column 2 and 3 in table 3.3 displays the results by industry, chemical (SIC 28) and electronic (SIC 36). When investigating the effect of technology diversification by industry, we observe that technology diversification has a positive and significant impact on firm value in the electronics industry, whereas in the chemical industry technological diversification is not significantly related to firm value. As hypothesized, being more technologically diversified matters, especially in the case of complex technology industries. Firms with a larger technology breadth might be better able to quickly adapt to changes in the industry.

The electronic industry is characterized by a dynamic environment: both from the demand side requiring different devices and machineries and from the supply side, i.e., the competitive environment where firms have to compete meeting downstream requirements. In this context, being technologically diversified means that the firm has a broad technological knowledge and can respond quickly to market changes (Gambardela and Torrisi, 1998).

TABLE 3.3 – Random effects panel models for Tobin's *q*

VARIABLES	(1) Full sample	(2) SIC 28	(3) SIC36
TD	0.016**	0.001	0.033**
	(0.006)	(0.010)	(0.012)
SIZE	-0.134***	-0.126***	-0.165***
	(0.014)	(0.027)	(0.024)
AGE	-0.013***	-0.000	-0.011*
	(0.003)	(0.006)	(0.004)
R&D	0.084*	0.186***	-0.182
	(0.041)	(0.036)	(0.221)
$R\&D_{t-1}$	0.189***	0.161***	0.755***
	(0.047)	(0.031)	(0.159)
DUMMY(R&D=0)	-0.051	-0.130	-0.114
	(0.039)	(0.082)	(0.074)
LEVERAGE	-0.000	-0.412***	-0.009
	(0.013)	(0.077)	(0.096)
PROFITABILITY	-0.000	-0.000	0.005
	(0.000)	(0.000)	(0.006)
DIVIDENDS NOT PAID	-0.004	-0.029	-0.092**
	(0.022)	(0.072)	(0.033)
CAPITAL INTENSITY	0.801***	0.313	0.681***
	(0.146)	(0.246)	(0.205)
MKT SHARE[a]	0.030*	0.080	0.012
	(0.014)	(0.055)	(0.037)
TOTAL	0.000+	0.000	0.000*
	(0.000)	(0.000)	(0.000)
YEAR FE	Included	Included	Included
INDUSTRY FE	Included		
Constant	1.072***	1.202***	0.835***
	(0.041)	(0.093)	(0.078)
Observations	11,948	3,087	3,095
Number of comp	1,296	343	330
R-squared_overall	0.246	0.354	0.209
χ^2	1573	630.7	613.4
Prob > χ^2	0.00	0.00	0.00

Bootstrapped standard errors in parenthesis (500 repetitions). ***p<0.001, ** p<0.01, * p<0.05, [a] p<0.1
[a] Standardized variable.

The electronic products are classified as complex products, where many different agents might own the inventions embodied in a single product. Technological diversification is not only necessary to speed up demand response but also to be able to put together the different parts that make up a product. Indeed, if the technology is complex the firm needs to understand the different parts that compose a product to be able to produce products that comply with the specifications and that fit together.

Therefore, in a complex technology industry, a narrow technology base may hamper firms' ability to explore new technology opportunities (Hashai, 2015). Column 3 in table 3.3 shows that technological diversification has a positive and significant effect on market value.

On the other hand, results show that being technologically diversified has no effect on firms' market value for the chemical industry. Chemical industries are characterized by being more able to appropriate returns from innovation through patenting (Mansfield, 1986). Although, technology diversity as measured by patents' technological classes has a non-significant effect on firm value, current and past R&D expenditures do have a positive and significant effect. It suggests that, in the case of the chemical industry, characterized by discrete technologies, investors value the amount of resources allocated to research regardless of how diversified is the output.

3.4.3 Robustness

I conducted several robustness tests. First, I considered two possible sources of endogeneity, reverse causality and omitted variable bias. Managers learn from stock prices (Chen at al., 2007) and then take decisions based on previous stock market valuation. Then, to mitigate reverse causality concerns, I included the lag of the dependent variable, which also controls for heterogeneity assigned to the firm's past performance (Zahavi and Lavie, 2013). Table 3.4, columns 1 to 3 report the results. Overall results do not change, albeit the coefficient for the TD index is almost half for the electronic industry sample, still the relation between TD and Tobin's q is positive and significant for this industry. Another possible source of endogeneity comes from an omitted variable bias. In all estimations I included R&D intensity and capital intensity, which might also influence the ability of a firm to diversify technologically. However, in the absence of an instrument that affects technological diversification but not directly Tobin's q, this study is silent on causality claims.

TABLE 3.4 – Random effects panel models for Tobin's q (Additional controls)

VARIABLES	(1) Full sample	(2) SIC 28	(3) SIC36	(4) Full sample	(5) SIC 28	(6) SIC36
TD	0.014***	0.002	0.019**	0.015***	0.003	0.021**
	(0.004)	(0.009)	(0.007)	(0.004)	(0.009)	(0.007)
BUSINESS DIVERSIFICATION				-0.011***	-0.018**	-0.010**
				(0.002)	(0.006)	(0.004)
TOBIN'S q_{t-1}	0.722***	0.646***	0.700***	0.718***	0.632***	0.696***
	(0.014)	(0.032)	(0.025)	(0.014)	(0.032)	(0.027)
SIZE	-0.026***	-0.014	-0.032**	-0.020***	-0.008	-0.028*
	(0.006)	(0.014)	(0.010)	(0.005)	(0.016)	(0.011)
AGE	0.001	0.003	0.001	0.002+	0.003	0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
R&D	0.116**	0.193***	-0.203	0.115**	0.189***	-0.206
	(0.039)	(0.041)	(0.209)	(0.038)	(0.037)	(0.208)
R&D$_{t-1}$	0.059	0.020	0.582**	0.055	0.018	0.590**
	(0.050)	(0.039)	(0.195)	(0.052)	(0.037)	(0.200)
DUMMY(R&D=0)	-0.056**	-0.002	-0.094*	-0.053**	-0.000	-0.091+
	(0.017)	(0.047)	(0.046)	(0.018)	(0.046)	(0.053)
LEVERAGE	-0.000	-0.284***	-0.006	-0.000	-0.275***	-0.006
	(0.009)	(0.060)	(0.052)	(0.008)	(0.059)	(0.058)
PROFITABILITY	0.000	-0.000	0.001	0.000	0.000	0.002
	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.012)
PROFITABILITY$_{t-1}$	0.000	0.000	-0.004	0.000	0.000	-0.004
	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.010)
DIVIDENDS NOT PAID	0.008	0.038	-0.032	0.006	0.034	-0.033
	(0.010)	(0.038)	(0.020)	(0.010)	(0.040)	(0.021)
CAPITAL INTENSITY	-0.237*	-0.432*	-0.123	-0.261**	-0.419*	-0.143
	(0.094)	(0.174)	(0.147)	(0.098)	(0.187)	(0.142)
MKT SHARE[a]	-0.010*	0.028	-0.035+	-0.010+	0.038	-0.030+
	(0.005)	(0.027)	(0.018)	(0.005)	(0.026)	(0.018)
TOTAL	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
YEAR FE	Included	Included	Included	Included	Included	Included
INDUSTRY FE	Included			Included		
Constant	0.222***	0.299***	0.274***	0.234***	0.332***	0.280***
	(0.027)	(0.055)	(0.041)	(0.027)	(0.064)	(0.043)
Observations	10,674	2,733	2,784	10,674	2,733	2,784
Number of comp	1,293	340	330	1,293	340	330
R-squared_overall	0.638	0.661	0.605	0.639	0.663	0.606
χ^2	11490	3692	3063	12079	4419	2625
Prob > χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Bootstrapped standard errors in parenthesis (500 repetitions). ***p<0.001, ** p<0.01, * p<0.05, [a] p<0.1

[a] Standardized variable.

In addition, one may argue that firms diversify technologically because they are diversified business wise. Hence, I included the number of business segments of a firm, as recorded in the Compustat Segments File. As it has been already documented in the literature (Lang and Stulz, 1994; Berg and Ofek, 1995) business diversification is negatively associated with firm value. However, the relationship between TD and Tobin's *q*, remain significant for the full sample and the electronic industry sample (table 3.4, column 4 to 6). Further, I added the past profitability, resulting not significant in any specification. Including business diversification, lagged dependent variable, and lagged profitability changed the sign and significance level of lagged R&D, standardized market share, and capital intensity. Although it may require further investigation, it is out of the scope of this study to analyze the interrelationship of these variables. Moreover, the variable of interest (TD) stays robust.

I also used alternative measures of technological diversification. First, the same index was calculated using IPC classes at the four-digit level (TD4), while considering all classifications assigned to a given patent. Second, equations were estimated using a Herfindahl-Hirschman index type measuring the concentration of patents in a given technology (Quintana-García and Benavides-Velasco, 2008; Malerba and Orsenigo, 1997; Leten et al., 2007; Grandstrand and Oskarsson, 1994; Gambardella and Torrisi, 1998).

Table 3.5 presents the results using the two alternative measures. While the technological diversification coefficients were significant at lower levels (p<0.10), the sign of the coefficients remain the same. Moreover, while electronic firms have a premium by diversifying, results suggest technological diversification has a neutral or even a negative effect on firm value for firms in the chemical industry.

3.5 DISCUSSION

This chapter investigates the effect of technology diversification on firm's market value in R&D intensive industries. Using a sample of 1,304 US publicly traded firms, during 1992-2007, I constructed a technological diversification index (TD) based on patents technology classification (IPC). Moreover, the index is calculated using IPC 6-digits classification level (main group), which is a more disaggregated level aiming to capture not only technological area diversification but also diversification inside a given area. As expected, technological diversification has a positive effect on the value of firms in the sample of R&D intensive industries. However, when analyzing two subsamples of different technologies, electronics and chemicals, the effect of technological diversification on firms' market value differs.

TABLE 3.5 – Random effects panel models for Tobin's *q* (Alternative measures of technological diversification)

VARIABLES	(1) Full sample	(2) SIC 28	(3) SIC36	(4) Full sample	(5) SIC 28	(6) SIC36
TD (HHI)[a]	0.051**	0.013	0.061*			
	(0.016)	(0.041)	(0.030)			
TD4				0.008+	-0.015	0.021*
				(0.005)	(0.012)	(0.010)
BUSINESS DIVERSIFICATION	-0.011***	-0.018***	-0.010*	-0.011***	-0.017**	-0.010**
	(0.002)	(0.005)	(0.004)	(0.002)	(0.005)	(0.004)
TOBIN'S q_{t-1}	0.719***	0.632***	0.701***	0.720***	0.630***	0.699***
	(0.015)	(0.031)	(0.027)	(0.015)	(0.031)	(0.027)
SIZE	-0.014**	-0.007	-0.019*	-0.013*	-0.001	-0.023*
	(0.005)	(0.016)	(0.010)	(0.006)	(0.015)	(0.012)
AGE	0.001	0.003	0.002	0.001	0.003	0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
R&D	0.115**	0.189***	-0.188	0.118**	0.190***	-0.199
	(0.036)	(0.040)	(0.202)	(0.039)	(0.040)	(0.206)
$R\&D_{t-1}$	0.057	0.018	0.599**	0.057	0.019	0.594**
	(0.048)	(0.037)	(0.188)	(0.050)	(0.042)	(0.196)
DUMMY(R&D=0)	-0.056**	-0.001	-0.094+	-0.057***	-0.005	-0.092+
	(0.017)	(0.041)	(0.049)	(0.017)	(0.046)	(0.051)
LEVERAGE	-0.000	-0.275***	-0.006	-0.000	-0.276***	-0.006
	(0.008)	(0.055)	(0.058)	(0.006)	(0.056)	(0.060)
PROFITABILITY	0.000	0.000	0.002	0.000	0.000	0.002
	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.012)
$PROFITABILITY_{t-1}$	0.000	0.000	-0.004	0.000	0.000	-0.004
	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)	(0.010)
DIVIDENDS NOT PAID	0.006	0.034	-0.034+	0.006	0.033	-0.032
	(0.010)	(0.038)	(0.020)	(0.011)	(0.039)	(0.020)
CAPITAL INTENSITY	-0.263**	-0.420*	-0.139	-0.260**	-0.402*	-0.125
	(0.095)	(0.180)	(0.147)	(0.096)	(0.175)	(0.145)
MKT SHARE[b]	-0.009+	0.037	-0.031+	-0.010+	0.029	-0.033
	(0.005)	(0.027)	(0.019)	(0.005)	(0.026)	(0.021)
TOTAL	0.000	0.000	0.000+	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
YEAR FE	Included	Included	Included	Included	Included	Included
INDUSTRY FE	Included			Included		
Constant	0.226***	0.329***	0.267***	0.250***	0.361***	0.287***
	(0.030)	(0.066)	(0.047)	(0.030)	(0.058)	(0.043)
Observations	10,674	2,733	2,784	10,674	2,733	2,784
Number of comp	1,293	340	330	1,293	340	330
R-squared_overall	0.639	0.663	0.605	0.639	0.663	0.605
Chi2	14518	3863	2798	12380	3850	2813
Prob > chi2	0.00	0.00	0.00	0.00	0.00	0.00

Bootstrapped standard errors in parenthesis (500 repetitions). ***p<0.001, ** p<0.01, * p<0.05, [a] p<0.1.

[a] This index is the inverse of the HHI ($TD\_HHI=1-HHI_{TD}$)

[b] Standardized variable.

As noted before, technological diversification may or may not lead to business diversification (Granstrand and Oskarsson, 1994; Miller, 2006). Nevertheless, when diversifying technologically a firm has to acquire and/or develop new technological capabilities, i.e., the knowledge to use a new technology. This knowledge is not only embodied in new machinery but mainly tacit and requires hiring personnel and/or investing in training. Therefore, a firm that has a greater degree of technology diversification is better able to use this knowledge on existing products and to take advantage of technological opportunities (Granstrand et al., 1997).

Measuring firms' market value by Tobin's *q*, i.e., using a forward-looking performance measure, aims to capture how shareholders value firms' technological diversification (Bharadwaj et al., 1999). A positive effect on *q* reflects the belief that technological diversification has a positive impact on firms' future cash flows. Although, previous literature has shown a positive effect of intangible assets on *q,* diversifying technologically also demands high investment and does not necessarily generate high returns. However, by diversifying technologically firms create internal capabilities to understand complex product systems and to cope with ever changing consumer demands (Granstrand et al., 1997).

Indeed, empirical results show that the market values positively technological diversification. However, this valuation differs by technology characteristics of the industry. On the one hand, stock market investors do not significantly value technological diversification in the chemical industry (discrete technology), but R&D intensity has a positive effect. This result suggests that on discrete technology industries investors value the commitment to R&D activities but not patenting in multiple technological areas. On the other hand, the effect of technological diversification on firms' value for electronic industry (complex technology) is larger than the average effect on the firms' value of the full sample of R&D intensive industries. It suggests that, in complex technologies, the market values firms that are more able to understand a broad range of technologies and to comply with customer demands. Technological diversification might signals firms' technological competences and their broad spectrum of intangible assets (knowledge and diverse technology patents).

These results are robust to different specifications and alternative measures of technological diversification. Moreover, the degree of TD has an effect on firms' market value even after controlling for R&D intensity, capital intensity, and yearly patent applications that account for other types of firms' assets.

3.6 CONCLUSION

This study contributes to the literature on technological diversification. Despite a large number of studies on business and product diversification (e.g., Ramanujam and Varadarajan, 1989; Kuppuswamy and Villalonga, 2016), the focus on technological diversification is recent and scarce (e.g., Granstrand and Oskarsson, 1994; Kim et al., 2016). Using a large sample of US firms in R&D intensive industries over a period of 16 years, results show that there is a premium to technologically diversified firms. Further, the technological diversification premium differs by the technology characteristic of the industry, being significantly positive for complex technologies but not significant for discrete technologies.

Findings suggest that technological diversification matters when the innovation cycle is shorter, for example in the case of electronic industry. In this case, investors interpret a higher degree of technological diversification as increasing the future viability of the firm. In contrast, for the chemical industry, where the innovation cycle is longer, investors do not assess the degree of technological diversification as indicating a source of future cash inflows.

The main contribution of this study is to point out differences between technologies on how technological diversification is associated with firm value. If patenting in different technological classes is positively correlated with firm value, then not investing in technological diversification could hamper firms' ability to quickly adapt to market changes, especially in the complex technology industries. Moreover, managers when deciding how to allocate resources, in complex industries investing in technological diversification might generate value to the firm.

Still, this study has some limitations. First, by using Tobin's *q* as a measure of firms' value, the usual limitations of a market-based measure and the approximation used in this research applied (Bharadwaj et al., 1999). Further, by using a patent-based measure of technological diversification it assumes that the technological knowledge of a firm is reflected in its patents. However, as it is known, not all innovations and all firm knowledge is embodied in patents (Griliches, 1990), therefore, a patent-based measure in fact captures only the patented knowledge. Brusoni et al. (2001) show that even single-product firms are technologically diversified in order to coordinate with suppliers. Hence, patent indicators might capture different information depending on the technology protected by the patent. Thus, the difference in market valuation might be a result of strategic considerations regarding the patented technology.

The findings of this study calls for future research in many venues. First, even the literature has talked about short and long innovation cycles relating to the industry (Gu, 2005), as the industry level used in this study (SIC 2-digit) aggregates many different firms a more direct measure of innovation cycle could be adopted. Hirschey et al. (2001) propose a measure base on the time lag between citing and cited patents. Regarding the technological diversification, differentiating related and unrelated technological diversification (Kim et al., 2016) also might improve our understanding on the effect of technological diversification on firm value. Moreover, the firm innovating strategies, exploitative or explorative, might also influence market reaction. Finally, a question that remains to be answered is if the innovative activity of the firm, how innovative the firm is, plays a moderating role between technological diversification and firm value.

Appendix A

Appendix for "Patent value in financial markets: An Event Study"

A.1 DEFINITION OF VARIABLES

TABLE A.1 – Definition of variables

Dependent variable		
Cumulative abnormal returns (CARs)		
Independent variables		**Source**
BCITES	Number of cited patents (backward citations).	NBER
FCITES	Number of forward citations received received by a patent.	NBER
IPCNUM	Number of 4-digit IPC classes.	NBER
TPF	Categorical variable = 1 if the patent was filed at the European Patent Office (EPO), the Japanese Patent Office (JPO) and granted at the U.S. Patent Office (USPTO). Triadic patent families	OECD†
HHI	Herfindahl index calculated based on SIC 3 digits.	COMPUSTAT
q	Tobin's *q* (Chung, 1994).	COMPUSTAT
Controls		
PATSTOCK	Number of granted patents applied for by a given firm, from 1976, to the time of application publication/ patent grant event.	own calculations/NBER
ANALYST	Number of analysts covering the firm.	I/B/E/S
SIC 3	Categorical variable identifying 3-digits SIC	CRSP
Event day	Categorical variable identifying each event day.	Kogan et al. 2011/NBER
SIZE	The logarithim of the number of employees.	COMPUSTAT
GRANTLAG	Difference in days between filing day and grant day.	Kogan et al. 2011 / NBER
PUB LAG	Difference in days between filing day and publication day.	Kogan et al. 2011 /NBER
ALLOW LAG	Difference in days between filing day and mailing notice of allowance day	Kogan et al. 2011/ USPTO

† OECD Triadic Patent Families database, January 2013

A.2 DESCRIPTIVE STATISTICS

TABLE A.2.1a – Patent grant. 60 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (3 days)	17,193	0.000	0.000649	-0.00193	-0.0000231	0.00227
CAR(5 days)	17,193	0.000	0.000852	-0.00257	-0.0000271	0.00296
BCITES	16,764	17.10	26.07	1	10	541
NCLAIMS	17,193	21.51	17.45	1	18	374
GRANT LAG (DAYS)	17,193	879.7	418.5	151	790	3,658
TPF	17,193	0.354	0.478	0	0	1
FCITES	17,066	1.343	2.677	0	0.613	98.89
HHI	15,176	0.222	0.180	0.0150	0.173	1
SIZE	15,022	1.205	1.238	0	0.733	7.550
PATSTOCK	17,193	221.2	928.9	0	21	16,790
ANALYST	17,193	7.610	9.103	0	5	60
Tobin's q	14,983	2.981	3.373	0.0197	2.136	137.4
PHARMA	17,193	0.118	0.323	0	0	1
ELECOMP	17,193	0.155	0.361	0	0	1
NUMIPC	17,193	1.520	0.987	1	1	16
EVENT	17,193	301.6	149.8	1	298	567
COMPANY	17,193	1,339	825.8	1	1,272	2,946
SIC 3 digits	17,193	131.2	54.93	1	131	263

TABLE A.2.1b – Patent grant. 30 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (3 days)	26,536	0.000	0.000659	-0.00203	-0.0000228	0.00227
CAR(5 days)	26,536	0.000	0.000883	-0.00272	-0.0000215	0.00302
BCITES	25,925	17.70	27.55	1	10	548
NCLAIMS	26,536	21.42	16.90	1	18	374
GRANT LAG (DAYS)	26,536	881.2	419.8	145	791	3,809
TPF	26,536	0.357	0.479	0	0	1
FCITES	26,340	1.355	2.710	0	0.604	98.89
HHI	23,521	0.223	0.182	0.0150	0.172	1
SIZE	23,291	1.408	1.308	0	0.981	7.550
PATSTOCK	26,536	310.0	1,022	0	35	17,407
ANALYST	26,536	8.814	9.748	0	6	60

TABLE A.2.1b *Continued*						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	SD	Min	Median	Max
Tobin's q	23,233	2.924	3.105	0.00400	2.130	137.4
PHARMA	26,536	0.110	0.313	0	0	1
ELECOMP	26,536	0.170	0.376	0	0	1
NUMIPC	26,536	1.519	0.988	1	1	16
EVENT	26,536	309.2	148.4	1	308	568
COMPANY	26,536	1,288	833.3	1	1,186	2,950
SIC 3 digits	26,536	129.7	53.32	1	131	264

TABLE A.2.2a - Orange book patents’ grant. 60 days estimation window.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	SD	Min	Median	Max
CAR (3 days)	203	0.000	-0.000071	-0.000134	-0.000006	0.000187
CAR(5 days)	203	0.000	0.000106	-0.000221	-0.000002	0.000275
BCITES	198	19.95	33.63	1	9	232
NCLAIMS	203	22.69	19.35	1	18	132
GRANT LAG (DAYS)	203	881.9	499.5	200	757	2,841
TPF	203	0.872	0.335	0	1	1
FCITES	203	1.842	2.692	0	0.826	15.71
HHI	183	0.0921	0.0676	0.0527	0.0634	0.484
SIZE	182	2.022	1.788	0.0188	1.055	4.812
PATSTOCK	203	1,493	2,097	0	111	8,534
ANALYST	203	18.17	13.90	0	15	52
NUMIPC	203	1.956	1.073	1	2	5
Tobin's q	183	4.930	2.900	1.188	4.104	22.35
EVENT	203	74.10	44.09	1	72	154
COMPANY	203	24.59	15.23	1	21	55
SIC 3 digits	203	4.961	2.435	1	4	11

TABLE A.2.2b - Orange book patents’ grant. 30 days estimation window.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	SD	Min	Median	Max
CAR (3 days)	232	-0.0000315	0.000498	-0.00127	-0.00000648	0.00126
CAR(5 days)	232	-0.0000603	0.000736	-0.00208	-0.0000436	0.00217
BCITES	226	18.44	31.80	1	9	232
NCLAIMS	232	22.59	19.16	1	17	132
GRANT LAG (DAYS)	232	845.6	481.0	200	741	2,841
TPF	232	0.884	0.321	0	1	1

Table A2.2b - *Continued*						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	SD	Min	Median	Max
FCITES	231	1.915	2.766	0	0.781	15.71
HHI	212	0.0907	0.0655	0.0527	0.0634	0.484
SIZE	211	2.122	1.803	0.0188	1.131	4.812
PATSTOCK	232	1,601	2,129	0	307.5	8,534
ANALYST	232	19.13	14.15	0	17	52
NUMIPC	232	1.922	1.037	1	2	5
Tobin's q	212	4.901	2.801	1.188	4.104	22.35
COMPANY	232	24.08	15.05	1	21	55
EVENT	232	80.66	47.72	1	79.50	168
SIC 3 digits	232	5.026	2.497	1	4	11

TABLE A.2.3a - Patent grant. 60 days estimation window. Canadian DrugBank

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	SD	Min	Median	Max
CAR %(3 days)	61	0.00513	0.0430	-0.0680	0.000380	0.216
CAR %(5 days)	61	0.00689	0.0602	-0.118	0.00807	0.319
EVENT	61	30.34	17.36	1	30	60
COMPANY	61	9	5.31	1	9	19

TABLE A.2.3b - Patent grant. 30 days estimation window. Canadian DrugBank

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	SD	Min	Median	Max
CAR %(3 days)	61	0.00529	0.0437	-0.106	-0.000156	0.216
CAR %(5 days)	61	0.00449	0.0628	-0.194	0.0000534	0.304
EVENT	61	30.34	17.36	1	30	60
COMPANY	61	9	5.31	1	9	19

TABLE A.2.4a – Patent publication. 60 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (3 days)	6,623	0.00000448	0.0000752	-0.000202	-0.00000119	0.000248
CAR(5 days)	6,623	0.00000659	0.000108	-0.000269	-0.00000315	0.000344
ANALYST	5,219	11.69	9.889	1	9	55
BCITES	6,483	22.04	36.40	1	12	555
NCLAIMS	6,623	22.18	17.26	1	19	271
PUB LAG (DAYS)	6,623	371.2	221.4	92	297	1,967
TPF	6,623	0.365	0.481	0	0	1
FCITES	6,379	1.061	3.474	0	0	118.9
HHI	5,816	0.225	0.187	0.0135	0.169	1
SIZE	5,787	1.385	1.334	0.00300	0.932	7.496
PATSTOCK	6,623	480.6	1,992	0	49	45,616
Tobin's q	5,755	2.750	2.104	0.00400	2.150	29.41
NUMIPC	6,623	1.533	1.046	1	1	12
COMPANY	6,623	823.2	500.6	1	808	1,745
EVENT	6,623	185.1	72.15	1	197	282
SIC 3 digits	6,623	94.65	41.03	1	98	179

TABLE A.2.4b – Patent publication. 30 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (3 days)	9,830	0.00000206	0.00000711	-0.000208	-0.00000138	0.000238
CAR(5 days)	9,830	0.00000219	0.000101	-0.000284	-0.00000257	0.000327
ANALYST	7,951	12.77	10.33	1	10	58
BCITES	9,629	22.02	36.27	1	12	555
NCLAIMS	9,830	22.14	16.79	1	19	271
PUB LAG (DAYS)	9,830	375.8	216.4	92	309	1,967
TPF	9,830	0.373	0.484	0	0	1
FCITES	9,494	1.061	3.316	0	0	118.9
HHI	8,676	0.226	0.190	0.0135	0.163	1
SIZE	8,632	1.564	1.392	0.00300	1.160	7.496
PATSTOCK	9,830	619.5	2,036	0	73	45,616
Tobin's q	8,583	2.703	2.018	0.00400	2.144	29.41
NUMIPC	9,830	1.534	1.060	1	1	14
COMPANY	9,830	794.7	503.1	1	765	1,748
EVENT	9,830	187.3	70.52	1	198	283
SIC 3 digits	9,830	95.28	39.92	1	100	181

TABLE A.2.5a – Patent allowance. 60 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (9 days)	15,639	-0.0000133	0.00125	-0.00376	-0.0000433	0.00430
CAR (13 days)	15,639	-0.000028	0.00153	-0.00458	-0.000047	0.00499
CAR (10 days)	15,639	-0.0000101	0.00131	-0.00394	-0.0000399	0.00434
BCITES	15,296	17.24	25.72	1	10	545
NCLAIMS	15,639	21.61	18.08	1	18	596
TPF	15,639	0.342	0.474	0	0	1
FCITES	15,518	1.313	2.457	0	0.621	94.49
ALLOW LAG (DAYS)	15,639	697.7	411.5	18	609	3,697
COMPANY	15,639	1,515	890.8	1	1,486	3,197
EVENT	15,639	1,320	719.0	1	1,292	2,666
SIC 3 digits	15,639	141.5	63.26	1	135	288

TABLE A.2.5b – Patent allowance. 30 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (9 days)	21,332	-0.0000197	0.00137	-0.00429	-0.0000366	0.00443
CAR (13 days)	21,332	-0.0000237	0.00172	-0.00522	-0.0000436	0.00544
CAR (10 days)	21,332	-0.0000151	0.00146	-0.00448	-0.0000383	0.00478
BCITES	20,861	17.60	26.62	1	10	545
NCLAIMS	21,332	21.72	17.92	1	18	596
TPF	21,332	0.352	0.478	0	0	1
FCITES	21,169	1.335	2.502	0	0.614	94.49
ALLOW LAG (DAYS)	21,332	696.8	405.0	18	613	3,697
COMPANY	21,332	1,508	897.3	1	1,469	3,205
EVENT	21,332	1,373	722.4	1	1,354	2,713
SIC 3 digits	21,332	134.8	54.84	1	135	264

TABLE A.2.6a – FDA announcements. 60 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (3 days)	189	0.00374	0.0164	-0.00191	0.000148	0.114
CAR (5 days)	189	0.00537	0.0221	-0.00220	0.000196	0.132
COMPANY	189	33.21	25.04	1	25	87

TABLE A2.6b – FDA announcements. 30 days estimation window.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Median	(6) Max
CAR (3 days)	190	0.000590	0.00316	-0.00162	0.000127	0.0299
CAR (5 days)	190	0.000554	0.00312	-0.00226	0.000116	0.0287
COMPANY	190	33.21	24.97	1	25.50	87

A.3 CORRELATIONS

TABLE A.3.1a – Correlation matrix. Patent grant. 60 days estimation window.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	CAR (3 days)	1														
(2)	CAR(5 days)	0.74	1													
(3)	ANALYST	**0**	**-0**	1												
(4)	BCITES	-0.01	**-0**	-0	1											
(5)	TPF	0.02	0.02	-0	0.13	1										
(6)	NUMIPC	**0.01**	**0.01**	-0	**-0**	0.14	1									
(7)	*Tobin's q*	0.01	0.01	0.06	0.03	0.12	0.05	1								
(8)	PHARMA	**0.01**	**0**	-0	-0	0.27	0.27	0.15	1							
(9)	ELECOMP	**-0.01**	**-0**	0.04	-0	-0.1	-0.1	0.03	-0.2	1						
(10)	GRANT LAG (DAYS)	**0**	**0**	**0**	0.15	0.05	0.03	0.04	0.1	-0	1					
(11)	NCLAIMS	**0**	**0.01**	**-0**	0.13	0.06	**0.01**	0.03	**-0**	-0	0.11	1				
(12)	FCITES	0.02	0.01	0.02	0.06	0.07	**0.01**	0.05	-0	**0.01**	-0.2	0.08	1			
(13)	SIZE	**0**	**-0**	0.55	-0.1	-0.1	-0.1	-0.2	-0.2	-0.1	-0.1	-0.1	-0.1	1		
(14)	PATSTOCK	**0**	**-0**	0.28	-0	0.02	**0.01**	-0.1	**-0**	-0	-0.1	-0	**-0**	0.5	1	
(15)	HHI	**0**	**0.01**	-0.1	**0**	-0.1	-0.1	-0.1	-0.2	-0	-0	-0	-0	0.2	0	1

Note: Number of observations: 17,193. All correlations are significant at 10% level except the ones in bold.

TABLE A.3.1b – Correlation matrix. Patent grant. 30 days estimation window.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	CAR (3 days)	1														
(2)	CAR(5 days)	0.76	1													
(3)	ANALYST	**0.01**	**0**	1												
(4)	BCITES	**-0.01**	**0**	-0.03	1											
(5)	TPF	**0**	**0.01**	-0.05	0.13	1										
(6)	NUMIPC	**0**	**-0.01**	-0.02	-0.01	0.13	1									
(7)	*Tobin's q*	**0**	**0**	0.08	0.03	0.12	0.05	1								
(8)	PHARMA	**0**	**-0.01**	-0.01	-0.02	0.26	0.26	0.17	1							
(9)	ELECOMP	-0.02	**-0.01**	0.04	-0.02	-0.1	-0.08	0.04	-0.16	1						
(10)	GRANT LAG (DAYS)	**0**	**0**	0.01	0.14	0.05	0.03	0.03	0.09	-0.02	1					
(11)	NCLAIMS	**0**	**0.01**	-0.02	0.13	0.05	**0.01**	0.03	**-0.01**	-0.03	0.11	1				
(12)	FCITES	**0.01**	**0.01**	**0**	0.08	0.09	0.01	0.05	-0.01	**0.01**	-0.16	0.08	1			
(13)	SIZE	**0.01**	**0**	0.54	-0.06	-0.11	-0.06	-0.19	-0.18	-0.09	-0.12	-0.08	-0.06	1		
(14)	PATSTOCK	**0**	**-0.01**	0.29	-0.04	0.03	**0.01**	-0.06	**0**	-0.05	-0.06	-0.05	-0.02	0.49	1	
(15)	HHI	**0**	**0.01**	-0.06	**0**	-0.06	-0.05	-0.1	-0.19	-0.02	-0.03	-0.02	-0.03	0.18	0.04	1

Note: Number of observations: 26,536. All correlations are significant at 10% level except the ones in bold.

TABLE A.3.2a – Correlation matrix. Orange book patents' grant. 60 days estimation window.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	CAR (3 days)	1												
(2)	CAR(5 days)	0.86	1											
(3)	ANALYST	**0.01**	**0.06**	1										
(4)	BCITES	**-0.1**	**-0.1**	-0.23	1									
(5)	TPF	**-0.02**	**0**	**0.05**	**-0.19**	1								
(6)	NUMIPC	**0.1**	**0.07**	**0.03**	**-0.08**	**0.09**	1							
(7)	*Tobin's q*	**0.08**	**-0.01**	**-0.02**	**-0.11**	**-0.02**	**0.02**	1						
(8)	GRANT LAG (DAYS)	**0.04**	**0**	**-0.07**	0.37	-0.19	**-0.01**	**-0.05**	1					
(9)	NCLAIMS	**0.03**	**-0.03**	**-0.05**	**0.04**	**0.02**	**0.04**	**0.04**	**0.08**	1				
(10)	FCITES	**-0.1**	-0.12	**-0.06**	**0.02**	**0.02**	**0.05**	0.15	-0.27	**-0.04**	1			
(11)	SIZE	**0.03**	**0.07**	0.75	-0.21	**0.04**	**-0.03**	-0.18	**-0.11**	**-0.12**	**-0.1**	1		
(12)	PATSTOCK	**0.04**	**0.08**	0.49	-0.19	0.12	-0.14	-0.2	**-0.11**	**-0.11**	-0.14	0.81	1	
(13)	HHI	**0.02**	**0.02**	-0.24	**0**	-0.16	**-0.08**	-0.16	**0.07**	**-0.04**	**-0.07**	-0.17	**-0.1**	1

*Note:*Number of observations: 203. Correlations are significant at 10% level except the ones in bold.

TABLE A.3.2b – Correlation matrix. Orange book patents' grant. 30 days estimation window.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	CAR (3 days)	1												
(2)	CAR(5 days)	0.74	1											
(3)	ANALYST	**0.05**	**0.09**	1										
(4)	BCITES	**0**	**-0.02**	-0.23	1									
(5)	TPF	**-0.09**	**-0.04**	**0.06**	-0.19	1								
(6)	NUMIPC	**0.03**	**0.01**	**-0.02**	**-0.07**	**0.09**	1							
(7)	*Tobin's q*	0.17	**0.05**	**0.04**	**-0.1**	**-0.02**	**0.02**	1						
(8)	GRANT LAG (DAYS)	**0.08**	**0.02**	**-0.09**	0.38	-0.19	**0.01**	**-0.03**	1					
(9)	NCLAIMS	**-0.04**	-0.11	**-0.04**	**0.05**	**0.02**	**0.04**	**0.03**	**0.08**	1				
(10)	FCITES	**-0.1**	-0.12	**-0.07**	**0.01**	**0.02**	**0.08**	**0.11**	-0.26	**-0.01**	1			
(11)	SIZE	**0.06**	**0.03**	0.75	-0.21	**0.03**	**-0.07**	**-0.13**	**-0.11**	**-0.11**	**-0.11**	1		
(12)	PATSTOCK	**0**	**0**	0.52	-0.19	0.13	-0.16	-0.17	**-0.11**	**-0.1**	-0.16	0.81	1	
(13)	HHI	**0**	**0.07**	-0.26	**0**	-0.15	-0.09	-0.16	**0.06**	**-0.05**	**-0.1**	-0.22	-0.15	1

Note: Number of observations: 232. Correlations are significant at 10% level except the ones in bold.

TABLE A.3.3a - Correlation matrix. Patent publication. 60 days estimation window.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	CAR (3 days)	1												
(2)	CAR(5 days)	0.85	1											
(3)	ANALYST	**0.02**	**0.02**	1										
(4)	BCITES	**-0.01**	**0**	-0.06	1									
(5)	TPF	**0.01**	**0.01**	-0.08	0.13	1								
(6)	NUMIPC	0.03	0.02	**-0.01**	**-0.02**	0.14	1							
(7)	*Tobin's q*	**0**	**0.02**	0.07	0.04	0.14	0.07	1						
(8)	PUB LAG (DAYS)	-0.14	-0.17	**0.01**	-0.08	-0.08	**0.02**	**0.01**	1					
(9)	NCLAIMS	**-0.01**	**-0.02**	-0.02	0.06	0.05	**0.01**	0.07	0.08	1				
(10)	FCITES	0.05	0.06	**0**	0.1	0.07	-0.02	**0.02**	-0.1	0.04	1			
(11)	SIZE	**0.01**	**0.01**	0.5	-0.05	-0.15	-0.06	-0.25	**0.01**	-0.06	-0.04	1		
(12)	PATSTOCK	**0**	**0**	0.28	-0.04	-0.02	0.02	-0.08	0.03	-0.05	-0.03	0.43	1	
(13)	HHI	**-0.01**	**0**	-0.03	**-0.01**	-0.08	-0.07	-0.11	**-0.01**	-0.02	**-0.01**	0.2	0.02	1

Note: Number of observations: 6,623. Correlations are significant at 10% level except the ones in bold.

TABLE A.3.3b - Correlation matrix. Patent publication. 30 days estimation window.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	CAR (3 days)	1												
(2)	CAR(5 days)	0.84	1											
(3)	ANALYST	**0.01**	**0.01**	1										
(4)	BCITES	**-0.01**	**-0.01**	-0.07	1									
(5)	TPF	**0**	**0**	-0.07	0.12	1								
(6)	NUMIPC	0.02	0.02	**0**	**-0.01**	0.12	1							
(7)	*Tobin's q*	**0**	**0.02**	0.1	0.05	0.13	0.05	1						
(8)	PUB LAG (DAYS)	-0.07	-0.1	0.02	-0.09	-0.09	0.02	**0**	1					
(9)	NCLAIMS	**0**	**0**	-0.02	0.08	0.04	**0.02**	0.07	0.08	1				
(10)	FCITES	0.04	0.05	**-0.02**	0.09	0.06	**-0.01**	**0.01**	-0.11	0.03	1			
(11)	SIZE	**0**	**0.01**	0.5	-0.07	-0.14	-0.04	-0.26	0.02	-0.07	-0.05	1		
(12)	PATSTOCK	**-0.01**	**-0.01**	0.31	-0.04	-0.02	0.03	-0.09	0.03	-0.05	-0.03	0.46	1	
(13)	HHI	**0**	**0**	-0.04	**-0.01**	-0.09	-0.06	-0.13	**0.01**	-0.03	-0.01	0.21	0.04	1

Note: Number of observations: 9,830. Correlations are significant at 10% level except the ones in bold.

TABLE A.3.4a – Correlation matrix. Patent allowance. 60 days estimation window.

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	CAR (13 days)	1							
(2)	CAR (9 days)	0.83	1						
(3)	CAR (10 days)	0.88	0.84	1					
(4)	BCITES	**-0.01**	**-0.01**	**0**	1				
(5)	NCLAIMS	**0.01**	**0**	**0**	0.12	1			
(6)	FCITES	**0.01**	0.01	**0.01**	0.11	0.09	1		
(7)	ALLOW LAG (DAYS)	-0.02	**-0.01**	-0.02	0.14	0.1	-0.17	1	
(8)	TPF	**0.01**	**0.01**	0.02	0.12	0.06	0.08	0.02	1

Note: Number of observations: 15,639. Correlations are significant at 10% level except the ones in bold.

TABLE A.3.4b – Correlation matrix. Patent allowance. 30 days estimation window.

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	CAR (13 days)	1							
(2)	CAR (9 days)	0.85	1						
(3)	CAR (10 days)	0.89	0.86	1					
(4)	BCITES	-0.01	**-0.01**	**-0.01**	1				
(5)	NCLAIMS	**0.01**	**0**	**0**	0.13	1			
(6)	FCITES	**0**	**0**	**0**	0.09	0.09	1		
(7)	ALLOW LAG (DAYS)	**0**	**0**	**0**	0.12	0.1	-0.17	1	
(8)	TPF	**0.01**	0.01	0.01	0.12	0.06	0.08	0.03	1

Note: Number of observations: 21,332. Correlations are significant at 10% level except the ones in bold.

A.4 EXTENDED MODELS

In this section, we explain the independent and control variables used in the estimation of extended models and present the results.

A.4.1 Variables

Appendix A.1 describes the independent and control variables and data sources. Data on patent characteristics such as the number of patents cited (backward citations), the number of claims and the number of technological classes (international patent classification - IPC), in which the patent was classified by the USPTO, is readily available from the NBER dataset. The NBER dataset also includes the total number of citations received by a patent (forward citations). However, forward citations suffer a truncation problem, as all the future citations to a patent cannot be observed at any given date. One option to overcome this bias, the one we adopt in this study, is to scale the raw patent citation count by the average citation count of all patents applied in the same year and in the same technology class (Hall et al., 2001, 2005; Acharya and Xu, 2014). Another patent related variable is a categorical variable that takes value equal one, and zero otherwise, if it is a triadic[66] patent, which means that the patent is member of a triadic patent family[67] (Guellec and van Pottelsberghe de la Potterie, 2005).

In the extended models, besides patent characteristics we also included a set of variables that capture firm and industry characteristics. Widely used as a measure of intangible assets, Tobin's q measures the ratio of a firm's value to the replacement cost of its tangible assets (Villalonga, 2004c). Thus, Tobin's q was measured following the method proposed by Chung and Pruitt (1994), which does not require out-of-Compustat data.[68] Since patents bestow a legal monopoly over the patented invention, industry competition levels may affect whether investors see a patent as an asset able to generate future cash flows. As a measure of industry competition we calculated the Herfindahl-Hirschman index (HHI) using Compustat sales data aggregated by 3-digit SIC code (Standard Industrial Classification).

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[66] The patent was applied for in the European patent office (EPO), in the Japanese patent office (JPO) and granted by the USPTO.

[67] OECD Triadic Patent Families database, January 2013.

[68] Chung and Pruitt (1994) found that their approximate q explains at least 96.6 % of the variability of Tobin's q - calculated as in Lindenberg and Ross (1981).

Further, we include two binary variables. One if the firm belong to the pharmaceutical industry (*Pharma)* and a second dummy indicates whether the firm belong to the electrical components and computer and office equipment industry (*Elecomp)*.[69]

A.4.2 Control Variables

Event day dummies were included because calendar date clustering may generate contemporaneous correlations between residuals of different firms (Henderson Jr, 1990). Campbell, Lo, and Mackinlay (1997) suggests that one approach to solve the problem of covariance between individual sample CARs, due to event clustering, is to include dummy variables for the event date. Event clustering occurs for patent application publication and for patent grant. Patent grants are published every Tuesday in the *Official Gazette* for Patents in electronic form while application publications are published every Thursday, electronically, by the USPTO.

We control for patent stock as the stock[70] of patents hold by the firm may underpin the value bear by a single patent. Gambardella et al. (2012) found that increasing portfolio size is associated with higher returns. Moreover, Belenzon and Patacconi (2013) claim that large patent portfolio can signal firm's technological strength.

We also control for firm size (Gambardella et al., 2012; Bessen, 2008), as "the size of a firm is an important structural variable that affects the market returns on innovation" (Sood and Tellis, p. 445, 2009). Firm size is measured as the log of the number of people employed [71] (Hegde et al., 2009) and can affect returns to a patent event by two mechanisms. First, a larger firm may be more able to bear the innovation and patenting costs. On the other hand, small firms, concentrated in technology intensive sectors, tend to have innovative advantage over large firms, employing skilled labor and mainly acting as technology supplier to larger firms endowed with downstream capacity (Acs and Audretsch, 1987). Additionally, accounting for industries heterogeneities we include industry fixed effects, measure

[69] *Pharma* takes value one if SIC code - 3 digits is 283 and zero otherwise; *Elecomp* takes value one if SIC code - 3 digits is 367 or 357 and zero otherwise.

[70] In this study, we consider patent stock as the number of granted patents applied for by a given firm.

[71] In order to have only positive numbers we measure size=ln(1+number of employees).

by industry SIC code 3 digits aggregation level. The models also control for the time lag between filing a patent and the grant (*Grant lag)*, filing and patent publication (*Pub lag)*, and filing and allowance *(Allow lag)*.

A.4.3 Empirical results

We estimate extended models where the CAR is the dependent variable explained by patent and firm's characteristics. In our results, we fail to find covariates that are consistently related to the CARs generated due to a patent grant event. These results are in line with the argument that the technical nature of the patent document makes it difficult to be interpreted by non-knowledgeable investors (Gu, 2005).

TABLE A.4.1 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Patent grant

	60 Days				30 days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	(-1, 1)	(-1, 1)	(-2, 2)	(-2, 2)	(-1, 1)	(-1, 1)	(-2, 2)	(-2, 2)
NUMANALYST		-0.00000		-0.00000		0.00000		-0.00000
		(0.00000)		(0.00000)		(0.00000)		(0.00000)
BCITES	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
TPF	0.00001	0.00001	0.00004*	0.00004*	0.00001	0.00001	0.00002	0.00002
	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
NUMIPC	0.00001	0.00001	0.00000	0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Tobin's q	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
PHARMA	0.00029**	0.00029**	0.00004	0.00004	0.00010	0.00010	-0.00001	-0.00001
	(0.00011)	(0.00011)	(0.00013)	(0.00013)	(0.00010)	(0.00010)	(0.00008)	(0.00008)
ELECOMP	0.00030**	0.00030**	0.00008	0.00008	0.00008	0.00008	-0.00001	-0.00001
	(0.00011)	(0.00011)	(0.00013)	(0.00013)	(0.00010)	(0.00010)	(0.00008)	(0.00008)
GRANT LAG	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
NCLAIMS	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000+	0.00000+
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
FCITES	0.00000+	0.00000+	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
SIZE	-0.00001	-0.00000	-0.00001*	-0.00001+	0.00000	0.00000	0.00000	0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
PATSTOCK	-0.00000	0.00000	0.00000	0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
HHI	0.00002	0.00002	0.00007	0.00007	0.00001	0.00001	0.00004	0.00004
	(0.00003)	(0.00003)	(0.00005)	(0.00005)	(0.00003)	(0.00003)	(0.00004)	(0.00004)
EVENT DAY FE	Included	Included	Included	Included	Included	Included	Included	Included
SIC3 FE	Included	Included	Included	Included	Included	Included	Included	Included
Constant	-0.00047**	-0.00046**	-0.00054***	-0.00053**	-0.00031*	-0.00031*	-0.00058***	-0.00058***
	(0.00014)	(0.00015)	(0.00016)	(0.00017)	(0.00014)	(0.00014)	(0.00010)	(0.00010)
Observations	14,395	14,395	14,395	14,395	22,374	22,374	22,374	22,374
R-squared	0.05858	0.05858	0.06735	0.06735	0.04357	0.04357	0.04801	0.04801

Notes: Standard errors in parentheses. All regressions include robust standard errors clustered by firm. Significance: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE A.4.2 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Orange book patents

	60 Days				30 days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	(-1, 1)	(-1, 1)	(-2, 2)	(-2, 2)	(-1, 1)	(-1, 1)	(-2, 2)	(-2, 2)
NUMANALYST		0.00000		0.00000		0.00001		0.00001
		(0.00000)		(0.00000)		(0.00002)		(0.00003)
BCITES	-0.00000	-0.00000	-0.00000	-0.00000	0.00000	0.00000	0.00001	0.00001
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
TPF	-0.00001	-0.00001	-0.00010+	-0.00010+	0.00017	0.00019	-0.00028	-0.00027
	(0.00003)	(0.00003)	(0.00005)	(0.00005)	(0.00032)	(0.00033)	(0.00066)	(0.00067)
NUMIPC	0.00001+	0.00001+	0.00001	0.00001	0.00011	0.00011	0.00005	0.00004
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00009)	(0.00010)	(0.00015)	(0.00016)
Tobin's q	0.00000	0.00000	0.00000	0.00000	0.00004	0.00002	0.00003	0.00002
	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00005)	(0.00007)	(0.00010)	(0.00013)
GRANT LAG	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
NCLAIMS	0.00000	0.00000	0.00000	0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
FCITES	-0.00000	-0.00000	-0.00001**	-0.00001*	-0.00001	-0.00001	-0.00003	-0.00004
	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00004)	(0.00004)	(0.00005)	(0.00006)
SIZE	-0.00002*	-0.00003**	-0.00005*	-0.00005	-0.00006	-0.00010	-0.00016	-0.00021
	(0.00001)	(0.00001)	(0.00002)	(0.00003)	(0.00019)	(0.00024)	(0.00031)	(0.00031)
PATSTOCK	0.00000+	0.00000	0.00000+	0.00000*	0.00000	-0.00000	0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
HHI	0.00034	0.00031+	0.00080**	0.00079**	0.00319	0.00298	0.00554	0.00534
	(0.00022)	(0.00017)	(0.00027)	(0.00028)	(0.00245)	(0.00226)	(0.00496)	(0.00520)
EVENT DAY FE	Included	Included	Included	Included	Included	Included	Included	Included
SIC3 FE	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.00000	0.00003	0.00003	0.00003	-0.00153*	-0.00134	-0.00143	-0.00125
	(0.00007)	(0.00008)	(0.00012)	(0.00014)	(0.00074)	(0.00089)	(0.00187)	(0.00221)
Observations	179	179	179	179	206	206	206	206
R-squared	0.98452	0.98601	0.98042	0.98046	0.91573	0.91834	0.86523	0.86629

Notes: Standard errors in parentheses. All regressions include robust standard errors clustered by firm. Significance: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE A.4.3 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Patent application publication

	60 Days				30 days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	(-1, 1)	(-1, 1)	(-2, 2)	(-2, 2)	(-1, 1)	(-1, 1)	(-2, 2)	(-2, 2)
NUMANALYST		0.00000		0.00000		0.00000		0.00000
		(0.00000)		(0.00000)		(0.00000)		(0.00000)
BCITES	0.00000	0.00000	0.00000	0.00000**	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
TPF	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000+
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
NUMIPC	0.00000**	0.00000**	0.00000*	0.00000*	0.00000**	0.00000**	0.00000*	0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Tobin's q	0.00000	0.00000	0.00000	0.00000*	0.00000	0.00000	0.00000*	0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
PHARMA	0.00013***	0.00001	0.00011***	0.00003*	-0.00001	-0.00001	-0.00000	-0.00001
	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
ELECOMP	0.00013***	0.00001	0.00010***	0.00002+	-0.00000	-0.00001	-0.00001	-0.00001
	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
PUB LAG	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
NCLAIMS	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
FCITES	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
SIZE	-0.00000	-0.00000	0.00000	-0.00000	-0.00000	-0.00000	0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
PATSTOCK	0.00000	-0.00000	0.00000	0.00000	0.00000	-0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
HHI	-0.00001+	-0.00001	-0.00001	-0.00002	-0.00001	-0.00001	-0.00001	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
EVENT DAY FE	Included	Included	Included	Included	Included	Included	Included	Included
SIC3 FE	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.00004*	0.00015***	0.00012***	0.00021***	0.00006***	0.00006***	0.00007***	0.00008***
	(0.00002)	(0.00001)	(0.00002)	(0.00002)	(0.00001)	(0.00001)	(0.00002)	(0.00002)
Observations	5,411	4,858	5,411	4,858	8,096	7,433	8,096	7,433
R-squared	0.16953	0.17935	0.20225	0.21672	0.08889	0.09304	0.10318	0.10882

Notes: Standard errors in parentheses. All regressions include robust standard errors clustered by firm. Significance: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

TABLE A4.4 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Notice of allowance (NOA)

	60 Days			30 days		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	(-2, 10)	(-1, 7)	(0, 9)	(-2, 10)	(-1, 7)	(0, 9)
BCITES	-0.00000	-0.00000	0.00000	-0.00000	-0.00000*	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
NUMCLAIMS	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
FCITES	0.00000	0.00000	0.00000	0.00000	-0.00000	-0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)
ALLOW LAG	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
TPF	0.00006*	0.00006+	0.00008**	0.00004+	0.00004	0.00005*
	(0.00003)	(0.00003)	(0.00003)	(0.00002)	(0.00003)	(0.00003)
EVENT DAY FE	Included	Included	Included	Included	Included	Included
SIC3 FE	Included	Included	Included	Included	Included	Included
Constant	0.00071**	0.00087**	0.00053+	0.00082***	0.00102***	0.00083*
	(0.00025)	(0.00032)	(0.00029)	(0.00022)	(0.00030)	(0.00034)
Observations	15,178	15,178	15,178	20,703	20,703	20,703
R-squared	0.19936	0.20979	0.20784	0.15847	0.16115	0.15966

Notes: Standard errors in parentheses. All regressions include robust standard errors clustered by firm. Significance: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

A.5 CUMULATIVE ABNORMAL RETURNS BY INDUSTRY

The following tables display the average CARs generated due to a patent event – patent application publication, NOA, and patent grant, by industries: pharmaceutical and electronics and computer. Results are consistent with the results presented in the main analysis for all industries.

TABLE A.5.1 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Patent grant

PANEL A
Pharmaceutical

	Estimation Window = 30 days	
Event window	CARs	Observations
(-1,1)	-0.001%	2,921
(-2,2)	-0.002%	2,921
	Estimation Window = 60 days	
Event window	CARs	Observations
(-1,1)	0.001%	2,028
(-2,2)	-0.000%	2,028

PANEL B
Eletronics and computers

	Estimation Window = 30 days	
Event window	CARs	Observations
(-1,1)	-0.003%**	4,518
(-2,2)	-0.002%	4,518
	Estimation Window = 60 days	
Event window	CARs	Observations
(-1,1)	-0.001%	2,657
(-2,2)	-0.001%	2,657

All regressions are estimated using robust standard errors clustered by event day.
p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE A5.2 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Patent application publication

PANEL A

Pharmaceutical

Estimation Window = 30 days		
Event window	CARs	Observations
(-1,1)	0.000%	1,122
(-2,2)	0.000%	1,122
Estimation Window = 60 days		
Event window	CARs	Observations
(-1,1)	0.000%	775
(-2,2)	0.001%	775

PANEL B

Eletronics and computers

Estimation Window = 30 days		
Event window	CARs	Observations
(-1,1)	0.000%	1,898
(-2,2)	0.000%	1,898
Estimation Window = 60 days		
Event window	CARs	Observations
(-1,1)	0.000%	1,233
(-2,2)	0.000%	1,233

All regressions are estimated using robust standard errors clustered by event day.
p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE A5.3 - OLS Estimation. Dependent Variable: Cumulative Abnormal Returns (CAR). Notice of Allowance (NOA)

PANEL A

Pharmaceutical

Estimation Window = 30 days		
Event window	CARs	Observations
(-1,7)	-0.001%	2,361
(-2,10)	0.001%	2,361
(0,9)	0.001%	2,361

Estimation Window = 60 days		
Event window	CARs	Observations
(-1,7)	-0.004%	1,804
(-2,10)	-0.004%	1,804
(0,9)	0.000%	1,804

PANEL B

Eletronics and computers

Estimation Window = 30 days		
Event window	CARs	Observations
(-1,7)	-0.002%	3,365
(-2,10)	-0.002%	3,365
(0,9)	-0.002%	3,365

Estimation Window = 60 days		
Event window	CARs	Observations
(-1,7)	-0.004%	2,193
(-2,10)	-0.002%	2,193
(0,9)	-0.003%	2,193

All regressions are estimated using robust standard errors clustered by event day.
p<0.001, ** p<0.01, * p<0.05, + p<0.1

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