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Essays on Finance and Innovation

by

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Abstract

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In this dissertation I examine the topic of the economics of innovation, focusing on the impact of a firm's innovative activity on its financial decisions and performance outcomes and on other market participants including its competitors, suppliers and customers.

In the first chapter, "The Dark Side of Patents: Effects of Strategic Patenting of Firms and Their Peers", I provides evidence that firms can benefit from patents of low productive value by focusing on the main purpose of patents: capturing market share and defending the monopolistic profits of the firm by deterring entry in the same product market. I introduce the new way of defining such "strategic" patents, of high private value to the firm but low technological contribution, by combining data on stock market-based measure of economic value of patents and a citation-based measure of patent technological knowledge spillover. Using data on patent applications, I find that strategic patenting by firms indeed leads to an increase in market concentration. Additionally, strategic patents have a smaller but still positive effect on the total factor productivity of firms, while having a significant positive effect on profit growth. For the closest competitors, I observe a reduction in total factor productivity and innovative output as well in both profit and sales growth following strategic patenting, signaling an absence of the positive technological spillover to the other firms operating within the same product market that would be characteristic for technological patents. Finally, I find that strategic patents force competitors change their innovative strategy to be able to continue to compete in the product market by shifting from exploration to exploitation of firm's existing patent technological knowledge and redirecting it into the new market area.

While the first chapter focuses on the impact that a firm's patent application has on the competitive environment, the second chapter, "Patent-Induced Shock Propagation Through the Supply Chain", examines the spillover effect of a firm's innovative activity through its production network. This paper sheds light on how innovation by the focal firm affects the firms it is related to via the firm's customers, and what it in turn tells us about the type and purpose of this innovative activity, its effectiveness, and the overall market structure. By identifying firm idiosyncratic shocks with a firm's patent application, I find that affected

suppliers impose positive output and profitability spillovers on their consumers, which in turn translates into significant revenue increase of other firm's customers' suppliers. The observed effects are especially pronounced for patents exhibiting high economic value.

In the third chapter, "R&D Tax Credits, Innovation Search Strategy, and Unintended Outcomes" (with Lee Fleming, Benjamin Balsmeier, and Joel Stiebale), we observe that while R&D tax credits appear to increase R&D expenditures and total patenting, it remains less clear how they change innovative search strategies, influence the types of inventions that result, and ultimately shape industrial and competitive dynamics. We develop a simple model that predicts a stronger focus on the exploitation of previously known technologies, due to the need to generate short-term profit in order to take advantage of the credit. Matched estimations from the Californian tax credit of 1988 support these predictions. We then explore the competitive impact of such credits on treated firms and find increased valuation, blocking and strategic patenting, and markups, as well as decreased new market entry. Using stock market reactions, we also illustrate positive externalities for distant competitors in the technology space and negative externalities for proximal competitors. Subsequent introductions of R&D tax credits in other states illustrate qualitatively similar, though quantitatively smaller, effects. While tax credits appear to benefit recipients, they may also contribute to declining economic dynamism.

To my mother Elena,
without whom none of this would have been possible.

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Chapter 1

The Dark Side of Patents: Effects of Strategic Patenting on Firms and Their Peers

1.1 Introduction

In the recent years, the answer to the question about the benefits of patenting to the firm and the market as a whole has no longer become obvious. The earlier literature focused heavily on emphasizing the positive aspects of patents as an embodiment of the innovative activity of the firm, leading to sales growth, job creation, and an increase in the firm's total factor productivity. But this "bright side" of patents is just one side of the coin, as firms can benefit through issuing the patent not from the straightforward productivity gains a patented innovation can bring to the company, but from the harm a new patent can do to the firm's competitors in the same product market.

The phenomenon of the so-called "strategic" patents is still largely theoretical, and its existence has yet to be demonstrated empirically in a general market setting. In this paper, I will shed some light on what strategic patents are, how they shape the industry environment, and which firms tend to engage in this type of patenting.

I introduce a definition of a strategic patent that combines the observation of Abrams, Akcigit, and Grennan (2013) on the non linear nature of the relationship between the economic value of the patent and its scientific value (measured by the number of forward citations) and Kogan, Papanikolaou, Seru, and Stoffman (2017) stock market-based measure of private value of innovation. Strategic patents exhibit negative relationship between forward citations and the economic value of the patent as opposed to the positive relationship conventionally attributed to productive (technological) patenting activity; more technologically valuable patents bring higher value to the innovating firm as well as high positive spillovers to the market (reflected in higher forward citations). Another name that can be given to the strategic patent type is "defensive", as the main purpose of the patent is to protect the exclusive rights granted by the previously issued technological patents, thus defending the firm against possible entrants into the product market, who could deprive the firm of its monopolistic profit.

This paper introduces a new measure for defining strategic patents, consistent with previously published observations on characteristics attributed to this type of patent and its effect on innovative market activity. Using this definition, I will test the following hypotheses regarding the nature of strategic patents. First, for a patent aimed at defending the firm's market position, I expect a decrease in market competition following strategic patent issuance. Second, compared to regular technological patents, that exhibit a positive relationship between the patent economic value and forward citations, strategic patents should lead to smaller increase in a firm's total factor productivity. Highly cited, high-valued patents are such due to their radical nature as innovations, increasing the firm's labor productivity and creating positive spillovers for potential market entrants and existing competitors. In contrast, a strategic patent derives its high value not from the patent's contribution to a firm's technological improvement – be that through new product line introduction or development of a more cost-effective production process, – but rather from protection it offers to the previously granted technological patents, thus not increasing total factor productivity. Third, I observe negative effect on the outcomes for the patenting firm's peers following a strategic patent including but not limited to reduction in growth of profit, output, and total factor productivity. At the same time, this mechanism behind strategic patenting leads to the boost of profits of a patenting firm generated by the breakthroughs in the field compared to the effect of similar technological patents not supported by the follow-up strategic one. The results are robust to controlling for industry and strategic patent definitions.

This paper contributes to the following strands of research. First and foremost, this paper extends the analysis of the effect of patent issue on firm performance outcomes from the patenting firm itself to its peers using the whole universe of market industries. The standard literature on the impact of innovation represented by patenting activity, focuses mostly on how it affects the firm's own performance, stock market price, and market value (Pakes, 1986; Hall, Jaffe, and Trajtenberg, 2001; Kline, Petkova, Williams, and Zidar, 2019; Farre-Mensa, Hegde, and Ljungqvist, 2016; Balasubramanian and Sivadasan, 2011; Kogan, Papanikolaou, Seru, and Stoffman, 2017). Of the papers examining the effect of firm's patenting on rival firms, it is worth noting the work of Austin (1993), whose analysis is limited to a small sample of the biotechnology industry in the early 1990s, and papers by Megna and Klock (1993), Jaffe, Trajtenberg, and Henderson (1993), and Cockburn and MacGarvie (2011) examining the R&D spillover effect, again only on a subsample of industries. These studies conclude that firms benefit from the patents of rival firms, though there is still some evidence that patent rights can impose costs on rival firms – this idea is further developed as the main focus of this paper.

Second, this is the first paper to empirically illustrate the difference in effect of strategic patents on the patenting firm market structure, the performance of the patentee, and its closest product market peers. Previous literature on the strategic use of patents (Abrams, Akcigit, and Grennan, 2013; Farrell and Shapiro, 2008; Noel and Schankerman, 2013; Hall and

Ziedonis, 2001; Ziedonis, 2004; Hegde, Mowery, and Graham, 2009; Galasso and Schankerman, 2010; Cockburn and MacGarvie, 2011; Von Graevenitz, Wagner, and Harhoff, 2011) examines either the theoretical implication of strategic patenting or, on the empirical side, its effect on the subsequent patenting activity by the firm and within the patent technology class, mostly with a focus on a specific technological industry. This paper introduces the novel approach of identifying the strategic patent based on both the data on patent forward citations and the market stock return-based measure of patent value introduced in Kogan et al. (2017). This method allows me to test the implications of the issuance of strategic patents by the firm for the whole sample of patenting public firms.

The rest of the paper is organized as follows. Section 1.2 describes the data and empirical setting, including the methodology of constructing the economic value of innovation used in classifying patents as strategic or technological. Section 1.3 outlines the empirical strategy, while Section 1.4 presents the main results of the strategic patent effect on market concentration, firms' total factor productivity and profit growth, and peers' outcomes. Section 1.5 discusses alternative interpretations of results, Section 1.6 presents robustness checks, followed by conclusion in Section 1.7.

1.2 Empirical Setting and Data

The approach of identifying strategic patents among a firm's patent portfolio relies on finding an appropriate measure of a patent's economic value. In this section, I discuss the methodology of estimating return-based patent value introduced in Kogan, Papanikolaou, Seru, and Stoffman (2017). After describing the data used in this paper, I illustrate that by using this measure of patent value one can consistently distinguish strategic patents from technological ones by testing the observations already established in the literature about strategic patent behavior (i.e., strategic patents are more likely continuation and divisional patents, they are more prevalent in recent years, and lead to stifling of innovative activity within the product market in the follow-up years). Finally, using the new definition of the strategic patents, I introduce some additional stylized facts on the type of innovations that strategic patents tend to cover, and in what industries this type of patenting activity has become most prevalent over the years using the aggregated patent technological classification introduced by Hall et al. (2001), in which the existing 400+ USPTO classes are aggregated into 6 main categories: Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, Mechanical, and Others[1].

[1]For details on which patent technological classes belong to each of the six categories see Hall, Jaffe, and Trajtenberg (2001).

1.2.1 Motivation for Patenting: Strategic vs. Technological Patents

Patents play an important role in a firm's value creation process. Owning a U.S. patent gives a firm the exclusive right to make and sell its innovation within the country. Patent ownership can be used by a firm to enter a profitable new market and attract extra revenue, thus positively affecting its balance sheet, increasing its profit margin, and leading to an overall increase of the firm's share prices and valuation. The direct source of income derived from patent ownership ranges from patent licensing and ownership transfer to entering the litigation process with the purpose of obtaining damages for patent infringement (Miele, 2000).

In addition to the direct profit that a firm accrues from its patent ownership, it can also derive an indirect benefit, namely from the defensive nature of patents that leads to the increase in the patenting firm's market share. Thus, patents can be used to deter competitors from operating or entering a patentee's product market. Just the threat of a patent infringement suit can lead to the delay of competitor's entry into a new market, which can negatively affect that firm's growth and overall presence within the industry as well as the number of patents filed within the same product market that follows the strategic patent.

While most valuable (technological) patents generate both direct (revenue increasing – *productive* value) and indirect (entrance deterring – *strategic* value) benefits to their owners, recent studies have shown a resurgence of patents of predominantly strategic value: patents whose sole purpose is to prevent subsequent entry into a given product market and thus protect the profits generated by related technological patents issued to these firms – mostly continuation applications, focused on a different aspect of the same technology, or divisional applications, focused on a particular invention mentioned in the original patent.

An example of a continuation strategic patent is the "slide-to-unlock" patent by Apple issued on October 2012, the third in the series of "slide-to-unlock" patents issued to the firm[2]. The initial patents specified the "predefined path" of the movement on a screen to unlock the device, which was an easy obstacle for competitors to overcome while avoiding patent infringement suits. This newly issued patent, on the other hand, covers any uninterrupted movement on a touch-sensitive display which leads to unlocking the device. Hence, one can classify this patent as strategic because: 1) it was extremely effective in preventing other firms in the industry from using this design without licensing their devices, thus making Apple products superior and more desirable in the eyes of customers, in turn protecting the monopolistic profit that the firm was deriving from its prior technological patents; 2) it was not contributing to further technological advancement since it is not a breakthrough invention – the novelty of this particular invention, the slide-to-unlock mechanism, had already been included in two previous patents, which is reflected in the low number of forward citations this patent received compared to its predecessors.

[2]Examples from IP Asset Maximizer blog from January 24, 2014 "Strategic Patenting Part: Why So Few Patents Create Real Value" by Jackie Hutter, see http://ipassetmaximizerblog.com/strategic-patenting-part-1-why-so-few-patents-create-business-value/.

Strategic patents do not necessarily need to be continuation patents (although they more frequently fall into this category compared to other types of patents as shown in Abrams et al. (2013) and further supported by the results in this paper in Table 1.6). An example of a strategic stand-alone patent is the "Method and System for Placing a Purchase Order Via a Communications Network" patent number 5,960,411 granted to Amazon.com in September 1999, a.k.a. the "one-click" patent (Jaffe and Lerner, 2004). As the name suggests, this technology patented a method allowing customers to execute purchases with "one-click" using systematically pre-stored information of a customer's payment method and shipping address. This patent was extremely successful in preventing competitors such as Barnes and Noble and Apple from offering a similar feature (e.g. "Express Lane" by B&N) to their consumers without licensing it from Amazon, thus making "one-click" one of the most valuable of the company's patents. At the same time, the technological contribution of this patent has been a topic of heated debate on whether such broad and trivial software concepts should even be eligible for a patent grant. In addition to non-obviousness concern, the novelty of the technology has been put to the test due to the existence of prior art in an electronic cash e-commerce setting, forcing Amazon to limit the applicability of the patent claim only within a shopping cart e-commerce environment.

Both examples illustrate the distinctive characteristic of strategic patents, which is their high economic value despite low technological knowledge contribution. These observations further imply that the previously established positive relationship between patent value and forward citations (i.e., such papers as Harhoff, Narin, Scherer, and Vopel (1999), Hall, Jaffe, and Trajtenberg (2005), Nicholas (2008) find a statistically significant positive effect of patent citations on excess return) is no longer valid for high-value patents.

1.2.2 Data and Sample Selection

To estimate the effect the strategic patents have on industry and on individual firms operating within the market, I construct the dataset combining information on individual patent applications, firm stock market return, balance sheet information and total factor productivity, and product market participants list.

The data on patent application number, U.S. invention classification, filing date, publication date, issue date, and patent number come from the public-use administrative data provided by the United States Patent and Trademark Office (USPTO). I use the sample of patent applications filed after November 29, 2000 and published by December 31, 2013, as this is the starting point for when the USPTO began providing information on rejected patent applications in addition to patented ones. The information on rejected applications is used as a control group to compare the impact of granting the strategic vs. the scientific patent on a firm's and its peers performance. I merge this dataset with administrative data from the USPTO Patent Application Information Retrieval (PAIR) to get information on patent examiner identification as well as examiner art unit (similar to Kline et al. (2019)). The information on application assignee name and patent citations for granted patents is extracted from Google Patents and is provided by the Coleman Fung Institute for Engineering Leadership.

Each patent application is matched to the respective corporations that filed for the patent based on the probabilistic record linkage as described in Wasi and Flaaen (2015) and Hall et al. (2001) using the name of the patent assignee and the name of the firm in the CRSP/Compustat Merged database. Additionally, I use the patent technology categories classification of Hall, Jaffe, and Trajtenberg (2001), which divides all patent applications into six broad technology groups based on patent U.S. technology class and subclass. The technology classes which were not previously attributed to one of the categories by Hall et al. (2001) I manually added to one of the categories.

To identify strategic patents from scientific ones, the patent application data are merged with the information on daily stock return from the CRSP dataset. A firm and its competitors' profitability and performance data come from the CRSP/Compustat Merged database. Product market competitors are defined using Text-based Industry Classification TNIC3 as described in Hoberg and Phillips (2010, 2016). For the analysis, I use only the top 50th percentile of closest product market competitors based on the product description proximity score accompanying every firm pair in TNIC3. An average patentee in any given year has 40.48 closest competitors.

All continuous variables are winsorized at the 5th and 95th percentiles of their distributions. The financial accounting variables are adjusted for inflation using the CPI from the Bureau of Economic Analysis using 2014 as the base year.

Table 1.1 describes the construction of final sample of patent applications linked to the patenting firms' balance sheet information. I make the following restrictions for my sample. First, I drop all patent applications that are not matched based on assignee name, leaving me with a sample of public firms. Second, I limit the analysis to utility patents. Third, I focus solely on applications filed by a single assignee to avoid the possible complications related to the joint ownership of the patent. Finally, I only include companies that have at least five years of pre- and post- filing outcomes to ensure I have enough observations covering the post-filing and post-granting period for the subsample of eventually granted patents (patent approval takes on average 22 months). These sample restrictions result in a final dataset consisting of 102,807 patent applications filed by 1,423 firms, out of which 57.11 percent were granted.

Figure 1.1 shows the total number of patent applications grouped by technological category and year of patent filing. The largest patent filing fields are Computers & Communications, followed by Electrical & Electronic and Drugs & Medical, comparable to the Chemical category. This graph also illustrates changes in the patenting activity from year to year. One can observe a significant increase between 2001 and 2005 (32 percent) with an even more dramatic drop (54 percent) over the following four years in the absolute number of patent applications filed within the Computers & Communications field, paralleled closely by the patent filing trend in Electric & Electronic (43 and 62 percent respectively), and the rest technological categories though to a lesser extent.

Next I introduce a way of classifying patents into strategic and technological based on the observable characteristics such as the patentee's firm's stock market reaction to patent filing news (economic value of patent) and patent forward citations (technological value of the patent).

1.2.3 Measures of Economic and Technological Value of the Patent

For computing the empirical measure of the *economic value* of patent, I follow the approach introduced by Kogan, Papanikolaou, Seru, and Stoffman (2017) based on the firm's stock market movement as a response to the patent application announcement. Economic value of the patent j (or, as the authors call it, *private* value ξ_j) is constructed as the product of market capitalization M_j of the firm at $t = -1$, where t is the date of filing the patent by the firm and an estimate of stock return related to the patent application filing $\mathbb{E}[\upsilon_j|r_j]$. This product is weighted by the number of patents applied for by this firm during the same day N_j, and adjusted by unconditional probability of a patent application being successful $\bar{\pi}$ (Carley, Hegde, and Marco (2015) estimate it being 56 percent):

$$\xi_j = (1 - \bar{\pi})^{-1} \frac{1}{N_j} \mathbb{E}[\upsilon_j|r_j] M_j \tag{1.1}$$

I construct the economic value of innovation for each patent of each firm in my sample using this approach. I use the filing date of the patent as opposed to the granting date as in Kogan et al. (2017) in order to control for the value of the patent applications that were eventually rejected by the patent examiner office. To ensure that stock fluctuations only reflect patent announcement-related events, following Kogan et al. (2017), I decompose the stock return into patent-specific (value of the patent) and patent-unrelated components and assume that the private value of the patent follows a normal distribution truncated at zero (thus suggesting that a patent has necessarily a positive value to the patenting firm).

As for the *technological value* of the patent,its estimated total knowledge contribution, I use the number of the patent's forward citations (available for granted patents only). This variable suffers from a truncation problem. That is, more recent patents tend to have fewer forward citations by construction due to an increasing number of missing observations of pending patent applications citing this particular innovation (Hall, Jaffe, and Trajtenberg, 2001). To alleviate this issue in my analysis, I will control for the time period over which the forward citations were measured. The availability of data on citations up to the year 2014 allows me to compute forward citations over the three-year period following the filing date of the patent. Figure 1.2 illustrates the distribution of patent forward citations over the years of patent filing using both raw and truncated (over the next three years only) measures. As evident from the graph, the distribution of raw citations is heavily skewed to the right, an issue which is alleviated by the truncated measure of technological value.

Figure 1.3 shows the total share of granted patents as well as the proportion of strategic vs. technological patents among granted applications sorted by technological category. Electrical

& Electronic has the highest share of applications being granted (70 percent), while the lowest proportion of granted applications falls into Drugs and Medical (30 percent). Besides the Others field, Computers & Communications and Drugs & Medical are the two categories with highest share of strategic patents granted to the firms. The evolution of strategic patenting over time is presented in Figure 1.4, illustrating a steady increase in the percentage of granted strategic patents among all technological categories beginning in 2004 with the peak at 2008, with Drugs & Medical field exhibiting the smallest change when compared to other categories.

Using the new economic value of a patent based on a firm's stock market movement in response to a patent application, I confirm that by using this measure, one can replicate the inverted U-shape relationship between the private measure of a patent and its scientific value as shown in Abrams, Akcigit, and Grennan (2013), by regressing the number of patent-forward citations on economic value of the patent and patent value squared using the subsample of granted patents. Results are presented in Table 1.2. All specifications control for year of filing, examiner art unit, and firm fixed effect. Standard errors are clustered at examiner art unit by filing year level. Measure of patent economic value is normalized to unit standard deviation for ease of result interpretation. Using the new measure for patent value, I still find the positive relationship between the value of patent and forward citations at all sample winsorization levels, while inclusion of the quadratic term, which is highly significant, does not lead to the deterioration of the overall fit.

Hence, based on the observation of a nonlinear relationship between economic value and forward citations for high-value patents, the following analysis will focus on the differences in the effect strategic patents have on the patentee and its competitors in comparison to technological patents. The patent is defined as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its technological value (Balsmeier, Kurakina, Stiebale, and Fleming, 2019).

1.3 Research Design

In order to analyze the effect that strategic patenting has on the patentee's performance and productivity outcomes and the product market environment for both patenting firm and its peers, I run the following regression relating the post-patent filing outcomes to patent strategic status:

$$y_{it} = \beta_0+\beta_1\cdot X_{i,t-1}+\beta_2\cdot X_{-i,t-1}+\gamma\cdot I(PatentGranted_{ij})+\delta\cdot I(StrategicPatent_{ij})+\alpha_i+\theta_{jt}+\epsilon_{ijt} \tag{1.2}$$

where i denotes the patenting firm, $\{$-$i\}$ is the portfolio of patenting firm peers, j is the examiner art unit, t is the year of patent filing, γ is the effect of patent being granted, δ is the effect of strategic patent being granted as opposed to other granted patents, $X_{i,t-1}$ is the vector of firm controls including the previous year's return on assets, cash flow, firm's

Q, sales volatility and growth, and leverage. α_i is the firm fixed effect, θ_{jt} is the examiner art unit by year of the filing fixed effect, ϵ_{ijt} is the noise.

This equation suffers from the potential endogeneity problem, where both the estimates of γ and δ end up being biased if the status of the patent (rejected or accepted) and its strategic characteristic are correlated with unobservable characteristics of later firm outcomes: $\mathbb{E}[\epsilon_{ijt}|I(PatentGranted_{ij})] \neq 0$ and $\mathbb{E}[\epsilon_{ijt}|I(StrategicPatent_{ij})] \neq 0$. For example, at the time of filing, the firm might be of the higher intrinsic quality, thus being able to both file for a more valuable patent and have it granted as a novel innovation, and at the same time improve its future performance (Farre-Mensa, Hegde, and Ljungqvist, 2016). Thus, it is possible that post-filing outcomes are determined simultaneously with the type of the patent the firm files. To solve this issue, I will employ the matching technique defined in Blackwell, Iacus, King, and Porro (2009), Angrist (1998), Card and Sullivan (1988), and Sarsons (2017).

The use of matching as an empirical tool helps to control for the confounding effect of pre-treatment variables in the data, thus improving the balance between the control and treated groups by making them more similar in terms of distribution of covariates. I implement the coarsened-exact match for granted and non-granted patents as well as for strategic and other patents within the matched granted subsample. Using my starting sample of filed applications described in Section 2.3 consisting of 102,807 distinct observations, I first perform an exact match between granted and non-granted patents on the year of patent application filing and its technological category, and I match coarsely on the size of the patentee and economic value of the application using an average of 25 bins for each variable. I then repeat this procedure on a subsample of granted patents only, matching between the strategic and nonstrategic granted patents. For both matches, I match with replacement of individual patents but only let each patent pair be matched once.

Table 1.3 Panel A shows the comparison between the economic values of the patent of the control and treatment groups (granted vs non-granted patents and strategic vs. all other granted patents). By construction there is no difference in the economic value of the patent among the three groups (non-granted, strategic, and other granted patents) at the percent significance level. At the same time, strategic patents exhibit a significantly lower number of forward citations than other patents within the matched sample by construction as evidenced in Panel B. This table illustrates the main goal of this matching procedure: controlling for the economic value of the patent. This avoids the case where the effect of strategic patenting on the performance of the patentee is driven purely by the higher economic value of strategic as opposed to scientific and non-granted applications (i.e. in general higher performing patents).

Table 1.4 and Table 1.5 present summary statistics for the final samples grouped by type of issued patent, comprised of 8,858 granted – non-granted pairs, and 4,430 strategic – non-strategic granted patents. All variables are calculated as firm averages over the five-year period preceding patent issuance. Firms issuing strategic patents tend to have lower baseline profit, return on assets, and growth opportunities as measured by Tobin's Q, as well as being more financially constrained by lower cash flows and higher leverage. At the same time, there is no significant difference between the two samples in terms of sales and total assets (by matching sample construction – controlling on firm size), and R&D costs.

1.4 Results

1.4.1 Strategic Patent Characteristics

Before I move to the main results of the paper, the evaluation of the causal effect of strategic patenting, this section presents some descriptive analysis of the characteristics of strategic and technological patents. Following the previous studies (Abrams et al., 2013), Table 1.6 shows the prevalence of continuing applications, that is continuation or divisional patents, among those issued for purely strategic reasons, the main purpose of which is extending the patent protection covering the previously patented technology. The results present the estimates of the simplified baseline model (1.2) using the full sample of high-performing granted patents in Panel A and the matched sample of granted patens in Panel B, where the dependent variable is the indicator whether this particular patent is classified in the USPTO PAIR dataset as continuation (PAIR: CON) – column (1), continuation in part (PAIR: CIP) – column (2), divisional patent (PAIR: DIV) – column (3), or any one of the three mentioned before – column (4).The estimated coefficient on $I(StrategicPatent_{ij})$, δ, is significant and positive; thus, strategic patents are more likely to fall into continuing applications category as opposed to their technological counterparts (2.94-4.25 percentage points higher, depending on the sample). This can be explained by noting that the strategy of filing a continuation or divisional patent is less beneficial for technological patents, as the marginal benefit of extending the patent prosecution is lower in this case compared to strategic patents that lack intrinsic technological value.

In addition to commonly being applications supporting earlier existing patented technologies, the strategic nature of the patents and their low level of technological knowledge spillover is reflected by the type of innovative search strategy underlying the strategic patent filing, as presented in Table 1.7, using a similar model to that in Table 1.6. Column (1) shows that strategic patents, on average, have a higher number of backward citations, indicating that the larger share of innovative search was being performed in more well-developed and mature fields with rapid innovative growth (Abrams et al., 2013; Balsmeier, Fleming, and Manso, 2017a), while results of columns (2) and (3) signal the patentee's tendency towards engaging in exploitation of technologies within previously known areas of expertise, reflected in the increased number of self-citations (citations of other patents owned by the same patentee) and the increase in the probability that the patent was filed within the technological class previously known to the firm (i.e. firm has at least one patent granted in this technological class since 1976).

The results discussed above – namely the prevalence of continuation/divisional patents and patents both within more developed mature fields and derived from previously known areas of firm's expertise – confirm that the newly introduced measure of strategic innovation based on stock market response to the patent application and number of forward citations is consistent with the purpose of strategic patenting and characteristics of such patents previously described in the existing literature (Abrams et al., 2013).

1.4.2 Effect of Strategic Patenting on Market Concentration

In the previous sections, I discussed industry trends as well as established the prevalent types of innovation activity that patenting firms engage in when filing for strategic vs. technological patents. In this section, I present the main results of this paper, which forms on the effect of strategic patenting on product market concentration.

Table 1.8 shows the results of the estimation of equation (1.2) on a matched sample of top-performing patent applications using the baseline measure of product market concentration, the Herfindahl-Hirschman Index, based on Compustat data on firm's net sales and Hoberg and Phillips (2010) TNIC3 industry classification, defined as:

$$HHI_{jt} = \sum_{i=1}^{F_j} s_{ijt}^2 \tag{1.3}$$

where s_{ijt}^2 is the squared market share of year t firm i in industry j. Market share is computed as a ratio of a firm's sales to total industry j sales, and F_j is the number of firms within the product market. TNIC3 based HHI is firm specific as each firm has a unique set of competitors in each year. For the main analysis, I chose the industry classification based on TNIC3 as it enables me to determine the closest firm peers that are likely to be affected by the patent issue based on the proximity of the products offered by the firms within the market. The industry definition based on firms' product description is important in this case since the main hypothesis regarding the nature of strategic patenting tested in this paper is that strategic patents prevent other firms from continuing to operate or entering into the same product market as the patentee. Alternative industry classifications are described in this paper's section on external validity (subsection 1.6.1). The coefficients of interest are γ, which shows the effect of granting of the technological patent on the outcome, while $\gamma + \delta$ shows the impact of the strategic patent issuance. The dependent variable is the outcome (i.e. HHI in this case) averaged over five post-filing years. All specifications control for the filing year, examiner art unit, and firm fixed effects. Standard errors are clustered at examiner art unit by filing year.

Column (1) presents the results of the estimation of the baseline model, with the only indicators being whether the patent application was granted, $I(PatentGranted_{ij})$, whether the granted patent was of strategic nature, $I(StrategicPatent_{ij})$, and a series of fixed effects. The coefficient on $I(StrategicPatent_{ij})$, δ, is positive and significant and equal to 0.00261, while the effect of granting of technological patent on market concentration, γ, is negative and equal to -0.00202, thus leaving the overall effect of strategic patenting, $\gamma + \delta$, positive and significant. Column (2) adds controls for baseline patenting firm level characteristics $X_{i,t-1}$ described in Section 3, while column (3) additionally incorporates the respective peer firm controls into the regression, $X_{-i,t-1}$. The estimated coefficient δ is positive and significant for all three specifications, suggesting on significant increase in market concentration following strategic patent issuance by the patentee. Columns (3) through (5) repeat the analysis using an alternative measure of market concentration, namely the total number of product market peers. The results remain the same, showing a decrease in the number of firm's competitors over the next five years after the application. Thus, these estimates are consistent with the definition of the purpose of strategic patenting: protection of the market share held by the patenting firm and prevention of competitors' entry into the product market, thereby leading to an increase in average post-strategic patent filing HHI.

1.4.3 Effect of Strategic Patenting Total Factor Productivity

The second hypothesis tested in this paper focuses on the contribution of strategic patenting to firms' and their competitors' total factor productivity. While technologically "novel" innovation leads to higher mark-ups and improvement of firms' productivity, thus positively contributing to aggregate economic growth (Kline et al., 2019), patenting for strategic purposes does not have technological advancement as a main goal. On the contrary, these patents are aimed at supporting and preserving the monopolistic profit generated by the previously technological patents issued to the firm and are intrinsically of low scientific value. This gap between the effect of technological and strategic patents on firms' total factor productivity is illustrated in Table 1.10. For the dependent variable, I use revenue-based total factor productivity as in İmrohoroğlu, Ayşe and Tüzel, Şelale (2014), which is the measure of the capital and labor effectiveness free of the effect of measured firm costs.

The coefficient estimates in Table 1.10 are consistent with the hypothesis. Column (1) only controls for firm and examiner art unit by filing year fixed effects, while column (2) adds firm level controls. Coefficients on $I(PatentGranted_{ij})$ are all positive and significant in all specifications, which is consistent with the beneficial effect of innovative activity on a firm's total factor productivity (e.g. Kogan et al., 2017). Additionally, a strategic patent grant, $\gamma + \delta$, leads to a 20.63 to 24.78 percent lower but still positive effect on total factor productivity compared to a technological patent, depending on the regression specification, thus confirming the low contribution of strategic patents to the post-filing total factor productivity.

A similar but fundamentally different picture is unveiled for the portfolio of the patenting firm's closest competitors (Table 1.10 columns (3) and (4)). Both coefficients γ (effect of technological patent issue) and δ (effect of strategic patent grant relative to technological patent) have the same signs as for the patentee: γ is positive and significant, while δ is negative. However, the overall effect of strategic patent, $\delta + \gamma$ is negative, and constitutes on average 2.6 (column (3)) to 2.26 (column (4)) percent drop in the total factor productivity of the competitors, while technological patenting leads to a quantitatively similar increase in peers' total factor productivity (2.3 and 2.92 percent respectively).

Thus, the competitors' results suggest that the presence of positive spillover effect of technological patents on the productivity of closest market competitors: competing firms are benefiting from the new productive technology and knowledge created by the patenting firm in the long run despite the inability to directly use that patented invention without infringing on the patent or paying licensing fees. On the other hand, strategic patent issuance has a negative spillover effect on the patentee's peers, which comes predominantly from: a) low total factor productivity effect of strategic patents on the patenting firm itself, b) low technological knowledge spillover of strategic patents (reflected in low forward citations), and c) high defensive nature of such patents aimed at pushing the competitors out of the product market.

Hence, as far as total factor productivity is concerned, technological patents lead to the increase of TFPR of all firms within the product market, while strategic patents have only a negligibly small positive impact on the patentee's own productivity and a significant detrimental effect on the productivity of its peers.

1.4.4 Effect of Strategic Patenting on Firm's and Its Peers' Performance

Now I turn to the question of the effect of strategic vs. technological patenting on a firm's and its peers' performances. Previous studies have shown a general positive effect of firm's innovative activity on its performance outcomes, such as future growth in terms of profit, output, capital, employment and total factor productivity (Kogan et al., 2017), firm productivity and worker compensation (Kline et al., 2019), employment and sales growth (Farre-Mensa et al., 2016), and firm size, factor intensity, productivity and scope (Balasubramanian and Sivadasan, 2011). Table 1.12 presents the results of estimating equation (1.4) following Kogan et al. (2017), where the dependent variable, $Y_{i,t+\tau}$, is the growth of the firm's profit, sales, and cost of goods sold (COGS) over the horizon τ of one to five years in future post-patent filing, illustrating the significant difference in the effect of patenting activity on the firm's performance depending on the purpose of the patent: technological or strategic.

$$\begin{aligned} logY_{i,t+\tau} - logY_{it} =& \beta_0 + \beta_1 \cdot X_{i,t-1} + \beta_2 \cdot X_{-i,t-1} + \gamma \cdot I(PatentGranted_{ij}) + \\ & \delta \cdot I(StrategicPatent_{ij}) + \alpha_i + \theta_{jt} + \epsilon_{ijt} \end{aligned} \tag{1.4}$$

Results of Table 1.12 show that a technological patent grant has a immediate negative effect on a firm's profit growth for up to four years following the patent announcement. Relative to technological patents, strategic patents exhibit a long-run positive increase in profit growth for four years onwards after the patent issuance, while there is no significant effect on profits of technological patents in the long run (5 years). Hence, implementation of novel innovative technologies puts a strain on the profitability of a company generating the positive product market spillovers, thus leading to the dilution of the monopolistic profits of the patentee. Panel B shows that the effect on profit growth does not come from sales increase, as there is no effect of either strategic or technological patent grant on firm sales growth. Instead, the main mechanism behind this change in the patentee's profit growth lies in the effect of innovation on the cost of goods sold, as illustrated in Panel C of Table 1.12.

Technological patent issuance, γ, has a significant positive effect on firm's COGS growth one through five years after the patent application, while the effect of granting of strategic patent, $\gamma + \delta$, is negative and significant in the long run (four and five years after the patent filing). Thus, all patent issuance-related fluctuation in the firm's profit growth come through the cost channel. Implementation of novel innovative technology puts a strain on the profitability of a company, increasing the cost of the production of goods. Strategic patents have a very small effect on a firm's costs due to these patents' lack of intrinsic scientific value, while the gradual decrease in the COGS growth over the years after the strategic patent application can be attributed to the increased monopolistic power of the patentee within the product market.

Hence, while Table 1.12 illustrates the positive incentive of a patentee to pursue strategic patents instead of technological ones, Table 1.13 shows the negative spillover effect that strategic patents have on firm's closest competitors. All competitors' outcome measures and controls are computed as the equally weighted average over all patentees' peers within the industry as defined by the TNIC3. The analysis in Table 1.13 shows a significant but short-lived (two years after the patent application) negative effect on the average growth rate of competitors' profit following strategic patenting, which is followed by the negative long-run effect of novel (technological) patents, that manifests within three to four years after the patent filing. A similar trend is observed for competitors' sales growth, providing support to the idea of market share capture by the patentee through strategic patent issuance. Panel C of Table 1.13 examines the relationship between the type of innovative activity by the firm and the closest competitors' cost of goods sold. The effect is similar to the one observed for the patentee itself: an increase in the cost of goods sold following the issue of technological patent, and a drop of costs following a strategic patent application grant. Despite the same direction of the sign of the effect on COGS growth for competitors and for the firm, the underlying mechanisms could be different, in particular that of the strategic patent. Technological patents provide positive knowledge spillovers through which the firm may get access to new technologies, thus increasing the COGS growth. At the same time strategic patents lead to the drop in COGS growth that is a direct consequence of the decrease in sales growth as the result of the patentee pushing its peers out of their product market.

1.4.5 Effect of Strategic Patenting on Peers' Innovative Activity

In subsection 1.4.1, I established that strategic patents are more likely to fall into the categories of continuation patents and patents derived within the previously well-developed and mature fields. In this section I focus on how strategic patenting by the firm affects its competitors' innovative search and activity.

For this analysis, I will use the following innovation measures as the dependent variables in the regression (1.2) following Manso, Lin, and Liu (2018): R&D expenditure to total assets as a measure of competitors' innovative input; number of filed and granted applications as a measure of competitors' innovative output; and the number of explorative patents as well as number of patents issued within the technological classes previously known to the competitors' as indicators of the type of innovative search conducted by the patentee's peers. I define a patent as explorative if at least 70[3] percent of its citations are not derived from the firm's previously existing knowledge pool, which is comprised of the firm's previous patents, or patents cited before by the firm's earlier patents filed within last five years (Manso et al., 2018). As in the previous analysis, all of the competitors' outcome measures and controls are computed as the equally weighted averages over all of the patentees' peers within the industry defined by TNIC3, and the dependent variable is the outcome averaged over five post-filing years.

The results are shown in Table 1.15. Since one of the main goals of a strategic patent is to stifle further innovative activity in the field, we indeed observe a negative effect of strategic patent issuance on the number of patents filed within the following five year period by peers (3.11 percent decrease). At the same time, there is no significant effect on the average number of patents granted to competitors, which can be explained by: a) absence of quality deterioration of the competitor's patent issuance, or b) independence of the examination procedure of the competitors' patents from the focal firm's patent. Though we observe a decrease in innovative output by the patentee's peers, there is nevertheless a significant increase in the competitors' expenditures in research and development. Combined with the observations that competitors file for patents within the previously known technological classes and the filed patents are less explorative, one can conclude that strategic patent issuance makes it harder for competitors to generate new patent ideas. The competing firms are pushed out of the product market, thus forcing them to try to generate patents in different technological classes that do not clash with the patentee's strategic patent area of market dominance. The drop in the explorative nature of patents could be an attempt to redirect the firm's existing patent technological knowledge and expertise into new areas of the market.

Hence, strategic patenting by a firm forces its competitors to shift the method by which they implement an innovative search strategy by increasing the effort and resources from exploration of new technological areas within the known patent classes to exploitation of a previously existing knowledge pool to adapt it for the new previously unexplored patent categories.

1.5 Heterogeneous Effects

1.5.1 The Role of Technological and Product Proximity Within Peer Groups

If a strategic patent's main goal is to protect the firm's monopolistic position by preventing other competitors from continuing to innovate and operate in the same area as now covered by the issued patent, we would expect strategic patenting to affect peers differently depending

[3] The results are robust to using 80 or 90 percent cut-offs.

on their closeness to the patentee in terms of technological exposure and their product market proximity.

Following Bloom, Schankerman, and Van Reenen (2013) and Jaffe (1986), I construct two measures of technological and product proximity. Technological proximity, TP_{ij}, between firms i and j is defined as:

$$TP_{ij} = \frac{(K_i K_j')}{(K_i K_i')^{1/2}(K_j K_j')^{1/2}} \tag{1.5}$$

where K_i is the vector of average shares over the last five years of a firm's i patents within each technological class. Similarly, following (1.5), I calculate product proximity using the vector of average shares over the last five years of a firm's i sales within the four digit SIC industry.

To test the roles of technological and product proximity on the effect strategic patent issue, I allocate all patentee's competitors into two groups, *Low* and *High*, depending on whether the proximity score (technological or product) of the firm with this competitor is below or above the year's sample median. I then rerun the baseline regression (1.2) and (1.4) on competitors' outcomes.

These results are presented in Table 1.16 for competitors' total factor productivity and R&D expenditures, Table 1.17 for competitors' performance growth (for the sake of conciseness I present the results of the growth over the two years following the patent application filing, since this is the time period over which the original results in Table 1.13 were most pronounced; this is likely due to the timing of the patent application's publication, which happens 18 months after the filing, thus making the pending patent's existence public knowledge), and Table 1.18 for the effect of competitors' innovative activity. One can observe that the results of the effect of strategic patenting on market competitors' productivity and performance are stronger within more technological and product-diverse industries (the coefficient estimate on $I(StrategicPatent_{ij})$ is negative and significant for the *Low*-group only on TFPR (columns (1) through (4) in Table 1.16) and two year profit and sales growth (panels A and B in Table 1.17), while it is positive and significant for the effect on the R&D expenditures (columns (5) through (8) in Table 1.16). One possible interpretation of this result is that strategic patenting prevents distant competitors – in terms of technological and product similarity within the product market – from extending their business operations into the patentee's specific technology and product niche now protected by the strategic patent, thus limiting their options for growth while staying within their own product market.

As for the type of innovative search and the effect of strategic patent issue on innovative output, a similar trend is present for product proximity – the results are stronger on competitors that are more distant in products space as illustrated in the second panel of Table 1.18. There is no heterogeneity in terms of the effect of technological proximity on the number of granted patents, nor on the number of explorative patents (negative and significant for both *Low* and *High* samples). Meanwhile, the more technologically close firms to the patentee suffer most in terms of the drop in the number of filed patents as well as the decrease in the number of patents filed within the previously known technological classes – a result consistent with the main idea behind strategic patents: preventing follow-on innovation within the technological class of the patentee.

1.5.2 The Role of Patentee's Level of Technological Advancement

While the previous section examines the role of technological and product proximity between the patentee and its peers in the strength of the negative spillover effect of strategic patent grant, in this section I will focus on an additional dimension of the heterogeneity, the level of technological advancement of the patentee, which helps to answer the question: What types of firms – industry leaders or laggards as defined by Aghion, Bloom, Blundell, Griffith, and Howitt (2005) – tend to benefit the most from strategic patents? A firm is classified as a technological "leader" if its technological gap is lower than the year's median value, signaling that the firm is closer to the technological frontier firm. If the gap is larger than the year's median value, such a firm is classified as a "laggard". The technological gap for each firm is calculated as:

$$Gap_i = (TFP_{F,t} - TFP_{i,t})/TFP_{F,t} \tag{1.6}$$

where F (for "frontier") is the firm with the highest total factor productivity within the industry defined by TNIC3 in year t.

Table 1.19 shows the results of the regression (2) separately estimated for the subsamples of technological leaders and laggards market concentration, number of competitors, and effect on peers' total factor productivity and research and development expenditures. The effect of strategic patenting on market concentration and number of firms within the same product market is statistically significant for the sample of laggard firms as opposed to that of leaders (for which there is no observable impact of strategic patenting on market concentration). This striking point shows that it is the laggard firms that benefit the most from issuance of defensive patents, as they otherwise are not being able to "keep up" and compete successfully with their product market peers in the race of novel innovative ideas, thus resorting to drastic measures such as having a strategic patent to protect their market share and profits.

Last but not least, there is no difference in the effect of strategic patent issued by the leader or a laggard on competitors' total factor productivity: in both cases, there is a significant negative effect on peers' productivity following the patent grant. As for the innovation input produced by the competitors, there is a significant increase in R&D expenditures if the strategic patent is granted to the industry technological leader. Competitors take a more severe hit in sales and productivity when trying to compete with the already dominant market leader, which forces them to spend more effort and resources on innovative activity to regain their footing in the competitive environment.

1.6 External Validity

This section is devoted to robustness checks to ensure the validity of the presented results. I will focus on two potential concerns related to the analysis: the definition of firm's competitors and the economic and scientific measures' thresholds for classifying patents into either the strategic and technological type.

1.6.1 Alternative Definition of Firm's Peers

The main analysis of this paper uses the Text-based Industry Classification introduced by Hoberg and Phillips (2010). The firm's closest peers are defined based on the product similarity score using product descriptions available from SEC 10-K filings. The authors show that TNIC3 classification is superior to standard classification based on three-digit SIC codes in providing the list of closest firm's competitors. The concern is whether TNIC3 is indeed a reasonable classification to be used in the context of capturing the areas of technological competition among firms. Thus, in this section I will check how robust the results of the paper are to the use of alternative industry classifications (similar to Ozoguz, Rebello, and Wardlaw, 2018), by repeating the analysis as in Table 1.8, Table 1.10 and Table 1.13 using SIC3 code and random industry classifications.

I will first present the results of the effect of filing the strategic patent on market concentration using the standard three-digit SIC codes for industry definition. Column (1) to (3) of Table 1.9 shows that when using all three regression specification (fixed effects only, firm level controls, and peer level controls), the findings on the positive effect of strategic patenting on market concentration as measured by HHI remain independent on the approach used in identifying the firm's peers. Columns (4) to (6) provide the falsification test, in which for each patentee, I identify "pseudo-competitors" by generating a random sample of firms from other industries and assign them as the focal firm's peers (Ozoguz et al., 2018). As expected, there is no significant effect of having a strategic patent granted to the firm on the composition and concentration of such a pseudo-industry.

The same analysis is repeated in Table 1.11 and Table 1.14, examining the effect of strategic patenting on peer total factor productivity and performance. As with the market concentration the results stay unaffected by the change in the industry classification from TNIC3 to a standard three-digit SIC code in terms of their significance and direction of the sign, while falsification results show no significant effect of firm's own patenting activity on random market participants.

1.6.2 Strategic vs. Technological Patents Definition Thresholds

The main body of the analysis presented in this paper relies on the definition of a strategic patent as a patent that falls into the top 50th percentile distribution of the economic value of the innovation measured by equation (1.1) and bottom 50th percentile of the scientific value estimated by forward citation. Table 1.20 presents the results of the baseline regression

(1.2) for the effect of strategic patenting on market concentration using alternative cut-offs to classify patents into strategic vs. technological (top 40 (30/20/10) percent and bottom 40 (30/20/10) percent, or top 40 (30/20/10) percent and *not* top 40 (30/20/10) percent). One can see that a positive and significant effect of strategic patent issuance on market concentration is consistently present across the spectrum of cut-offs, with the only exceptions being the most restrictive ones (10 percent in columns (4) and (8)) where the share of strategic patents in the sample is extremely small – 3.74 and 2.70 percent respectively.

1.7 Conclusion

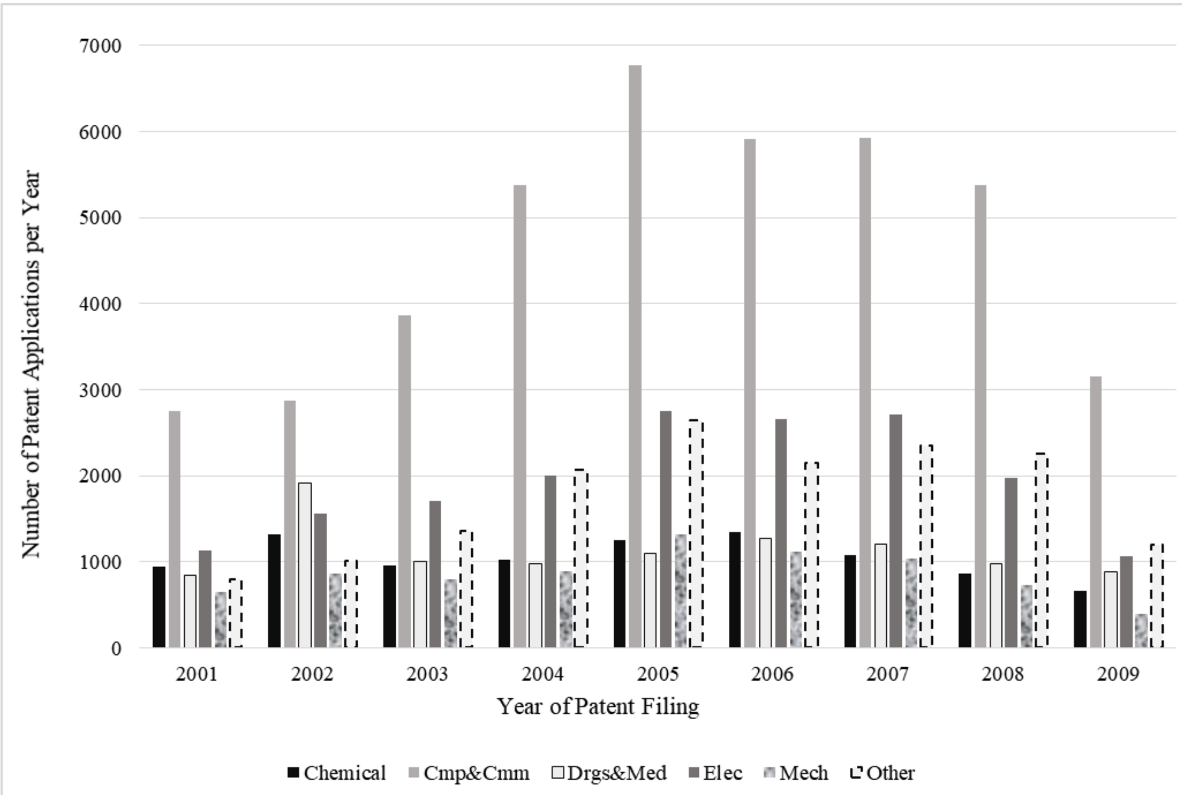
In this paper, I introduce a new way of classifying patents as strategic (purely defensive) and technological (productive). I show that, consistent with previous research, strategic patents are more likely to fall into continuation and divisional categories, and are usually patents generated within well-established and previously known technological areas to a firm. Using a new-market based measure of patent classification, I estimate the impact of strategic patenting by a firm on market concentration, firm's and competitors' productivity and performance, and competitors' following innovative activity. I find that, compared to truly novel technological patents, strategic patents lead to an increase in the firm's product market concentration, shown by the significant positive effect on firm-specific Herfindahl-Hirschman Index computed based on TNIC3 industry classification. This observation is further confirmed by a corresponding decrease in the number of competitors in the market following the strategic patent grant. In addition, a strategic patent grant leads to an increase in the firm's long-term profit growth while having a much lower, though still positive impact on the revenue-based total factor productivity of the firm when compared to scientific patents. I find evidence of the harmful impact that strategic patents have on their closest competitors, leading to a significant decrease in average sales and profit growth, as well as a decrease in peers' productivity, along with a drop in innovative activity and a shift in peers' innovative search strategy to exploit a previously existing knowledge pool to adapt it for the new previously unexplored by the firms' patent technological classes. Industry technological laggards benefit the most from the issuance of strategic patents, while the negative spillover effect is especially strong for competitors that are more distant from the patentee in terms of technological and product proximity.

These results confirm the existence and main purpose of strategic patents in protecting a firm's market niche and preventing competitors from entry. This paper provides new evidence on the detrimental effect of a specific type of patent activity on innovation, and thus potentially on aggregate economic growth. The estimates presented in this paper suggest that patentees have a higher incentive to file such defensive patents than technological ones, thus compromising the product market structure and leading to an increase in monopolization at the expense of technological progress.

The implications of these results are especially important and should considered during the patent examination process. The patent examination office should enforce stricter rules on patent selection to allow only truly "innovative" patents to be granted, thus preventing firms from exploiting the patent system by undertaking aggressive campaigns to get strategic patents. The main limitation of this paper's analysis is that it is yet impossible to establish ex-ante the type of patent that a firm has filed for. Thus, this paper should be viewed as the first step towards identifying the impact of strategic patenting on the market and its participants.

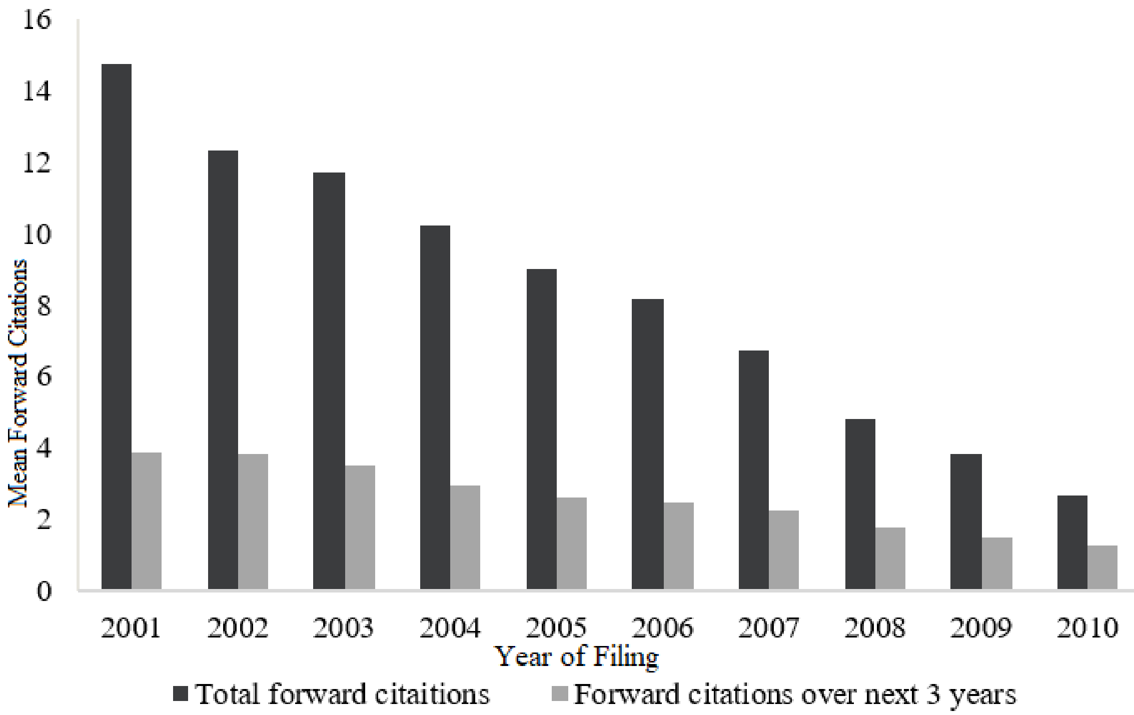
1.8 Figures and Tables

Figure 1.1: Distribution of Patent Applications by Technological Categories



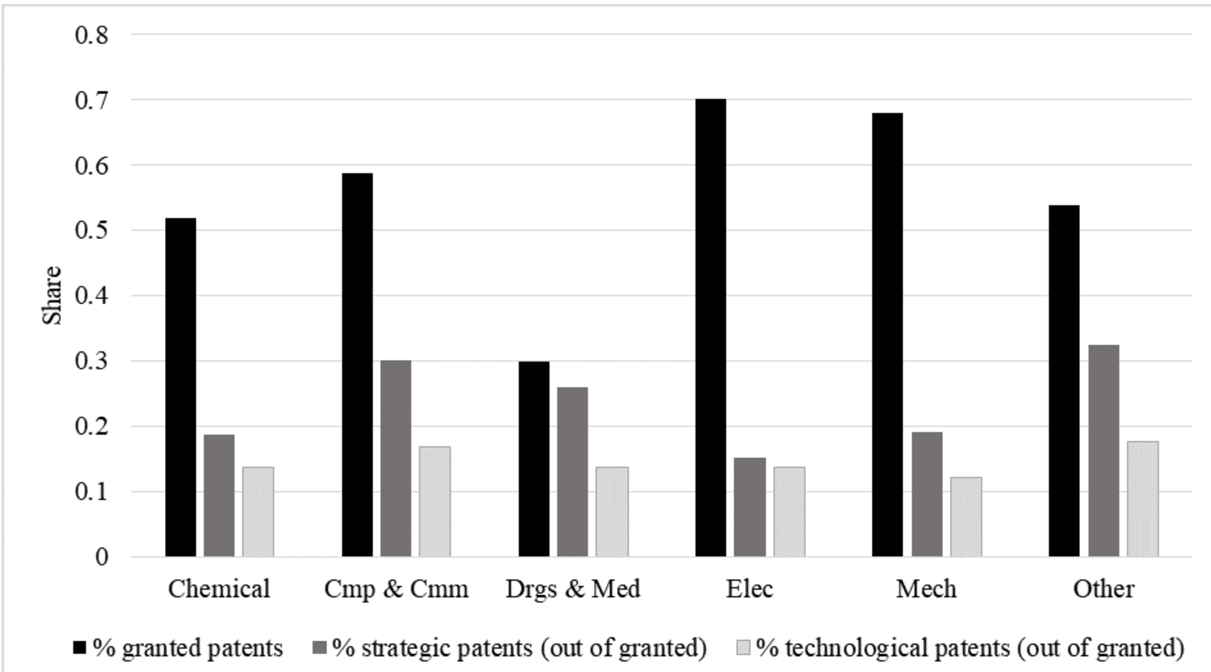
Notes: This graph plots the total number of patent applications by year of filing for each of the six technological categories as in Hall et al. (2001): Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, Mechanical, and Others.

Figure 1.2: Average Forward Citations by Year of Filing



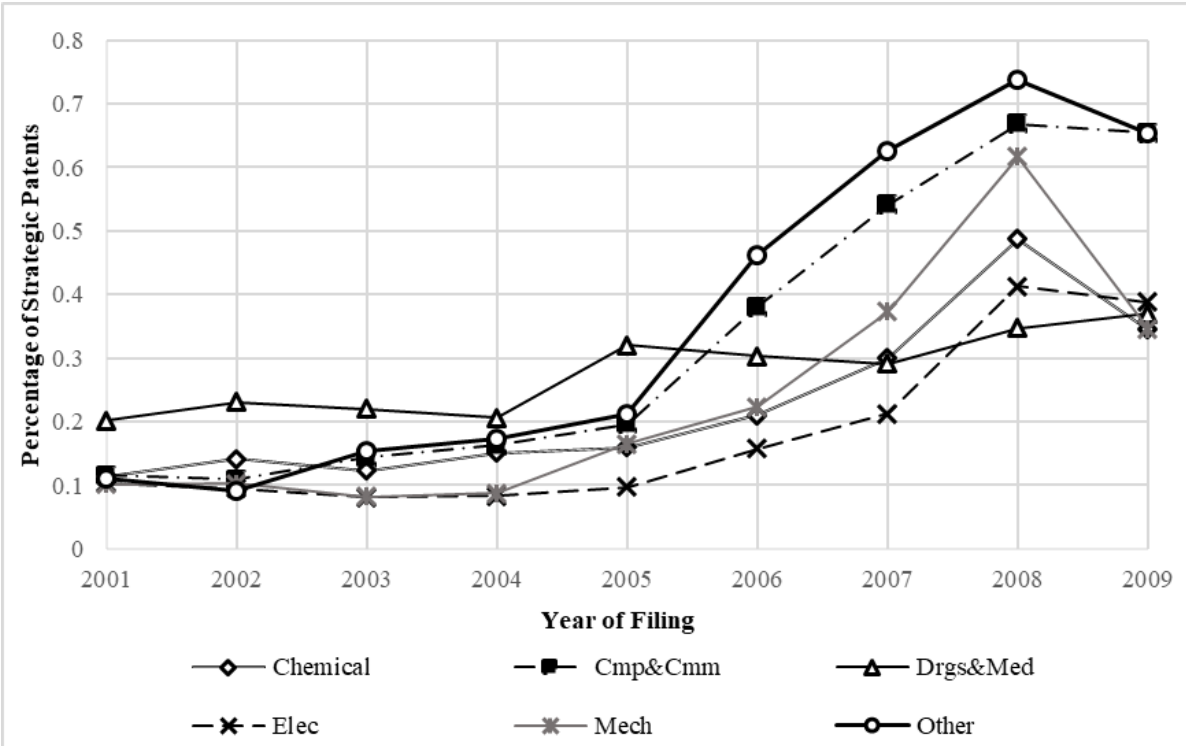
Notes: This graph plots the mean patent forward citations by year of patent application filing using the total number of forward citations received by the patent calculated as of December 2014 (total forward citations) vs. the number forward citations over the three years following the filing of the patent.

Figure 1.3: Share of Granted, Strategic and Technological Patents by Technological Categories



Notes: This graph plots the percentage of granted patents (out of the total number of applications filed across all sample years) vs. the shares of strategic vs. technological patents among the granted applications only for each of the six technological categories as in Hall et al. (2001): Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, Mechanical, and Others. The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value measured by forward citations.

Figure 1.4: Share of Strategic Patents Granted by Technological Categories



Notes: This graph plots the share of strategic patents (out of the total number of granted applications) by year of the filing for each of the six technological categories as in Hall et al. (2001): Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, Mechanical, and Others. The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value measured by forward citations.

Table 1.1: Sample Construction

	Application-assignee pairs	Applications	Assignees
Panel A: USPTO Sample			
Full sample (applications filed btw 1910 and 2014)	9,231,170		
Published between 2001 and 2013	3,622,547		
Utility application	3,618,310		
Non-missing assignee	2,020,837	1,938,922	287,632
Panel B: USPTO-Compustat merge			
Assignee is a public firm (matched to permno)	651,112	478274	4530
Filled by single assignee	387,380	387,380	4432
Non-missing TNIC3 industry classification	210,004	210,004	2127
At least 5 years of pre- and post- filing outcomes	102,807	102,807	1423
Panel C: Final sample composition	Frequency	Percent	
% non-granted patents	44,120	42.90%	
% granted patents	58,717	57.10%	
% strategic patents	16,074	27.38%	
% nonstrategic patents	42,643	72.62%	

Notes: This table shows the construction of the final sample used in the analysis. I start with selecting the patent applications for which the publication date is available (applications filed after November, 29 2000 and published before December, 31 2013). Secondly, I limit the analysis to utility patents only. Each patent application is then matched to the respective public firm that owns the patent based on probabilistic record linkage as in Wasi and Flaaen (2015), Hall et al. (2001) using the name of the patent assignee and the name of the firm in CRSP/Compustat Merged database. I focus only on applications filed by a single assignee to avoid the possible complications related to the joint ownership of the patent. Finally, I only keep companies that have at least five years of pre- and post-filing outcomes to make sure there is enough observations covering the post-filing and post-granting period for the subsample of eventually granted patents.

Table 1.2: Effect of Private Value of Innovation on Forward Citations

Forward citations vs Patent value						
	Level of patent value winsorization					
	1%		5%		10%	
Patent value	0.125***	0.30259***	0.123***	0.33715***	0.126***	0.37004***
	(0.031)	(0.09913)	(0.028)	(0.10471)	(0.029)	(0.10986)
Patent value^2		-0.18385**		-0.20145**		-0.22504***
		(0.07976)		(0.07888)		(0.08146)
Observations	58402	58402	58402	58402	58402	58402
Adjusted R^2	0.356	0.356	0.356	0.356	0.356	0.356

Notes: This table shows the results of regression of number of forward citations on the economic value of the patent and the value of the patent squared. The economic value of the patent is constructed using equation (1.1); the number of forward citations is measured over the period of five years after the patent grant. The table uses the data on the full sample of granted patents, taking into account the sample restriction criteria described in Section 2.3. The economic value of the patent is normalized to unit standard deviation and winsorized at the top and bottom 1, 5 or 10% level for columns (1) and (2), columns (3) and (4), and columns (5) and (6) respectively. The patent value is scaled to unit standard deviation. All specifications control for filing year, examiner art unit, and firm fixed effect. Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.3: Matched Sample for Granted vs. Non-Granted, and Strategic vs. Productive Patents

Matched patent characteristics				
Panel A: Economic value of patent				
	Productive patent	Strategic patent	Diff	P-value
mean	0.60624	0.6246	-0.01835	0.0526
sd	(.4514598)	(.4396055)		
N	4,430	4,428		
	Granted	Not Granted	Diff	P-value
mean	.6113345	.615423	-.0040885	0.7282
sd	(.4501657)	(.4456427)		
N	8,858	8,858		
Panel B: Forward citations				
	Productive patent	Strategic patent	Diff	P-value
mean	7.55237	.5392954	7.013075	0.000
sd	(7.298607)	(.7646118)		
N	4,430	4,428		

Notes: This table shows summary statistics for the economic value of the patent (equation (1.1)) and its scientific value (forward citations) for the matched sample of granted and non-granted patent applications, and strategic vs. scientific within the subsample of granted patents only. The samples are matched exactly on year of patent filing and patent category, and they are matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). Patents are classified as strategic and technological, based on what part of the private economic value and forward citations distribution the patent falls: top 50th percentile of economic and bottom 50th percentile of forward citation distribution for strategic (top 50th and top50th percentiles for technological). The economic value of the patent and forward citations are normalized to unit standard deviation and winsorized at 5% using annual breakpoints.

Table 1.4: Summary Statistics: Matched Sample

Baseline outcomes 5 years before filing	Full sample (matched)		Not granted		Granted	
	Mean	SD	Mean	SD	Mean	SD
Sales	5791.304	1240.726	5802.071	1244.701	5780.402	1236.668
COGS	3429.973	1053.839	3561.139	1047.446	3297.173	1043.671
Profit	3.106529	.8794184	2.937869	.6741455	3.27729	1.019009
CAPX	.038391	.0111492	.0386769	.0112487	.0381015	.0110407
R&D	.0215395	.0253409	.02097	.0235977	.0221165	.0269819
Assets	10317.13	2426.412	10377.41	2401.52	10256.1	2449.99
ROA	.0986064	.033165	.097073	.0323551	.1001531	.0338941
Q	1032.73	1118.44	1028.601	1025.847	1036.915	1205.078
Cash flows	.0876981	.045632	.0858527	.0432705	.0895681	.0478364
Leverage	.1435946	.1182835	.1725376	.1107704	.1142663	.1184368
HHI	.2349692	.1943404	.3085566	.2186578	.1604651	.1287238
N	16802		8453		8349	

Notes: The table reports the summary statistics for the full matched sample. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and firm's baseline sales outcome (averaged over five pre-filing years). Profit is sales minus cogs, divided by lagged total assets. R&D is the ratio of the firm's research and development expenditures to lagged total assets. Assets are the firm's total assets. ROA is the ratio of income before extraordinary items to assets. Tobin's Q is the ratio of the sum of total assets and the difference between market and book value of total common equity, to total assets. Leverage is the sum of long-term debt and debt in current liabilities divided by total assets. HHI is the Herfindahl-Hirschman Index of industry defined by the TNIC3 classification (Hoberg and Phillips, 2010). Sales, cogs, CAPX, and cash flows are defined as ratios to the firm's total assets. Each baseline variable is measured as an average over five pre-filing years. All monetary values are expressed in real 2014 dollars. All variables are winsorized at 5% using annual breakpoints.

Table 1.5: Summary Statistics: Matched Sample – Strategic vs. Productive Patents

	Technological patent		Strategic patent	
Baseline outcomes 5 years before filing	Mean	SD	Mean	SD
Sales	5852.046	1148.209	5829.199	1153.648
COGS	3281.264	1013.571	3343.279	1012.953
Profit	3.417481	1.07072	3.27681	.9548148
CAPX	.0389919	.0101751	.0374794	.0109295
R&D	.0214943	.0259183	.0210923	.0239833
Assets	10377.73	2293.066	10384.34	2254.226
ROA	.1003565	.0327222	.0983189	.0321474
Q	1078.862	1179.356	979.1003	1162.159
Cash flows	.0899955	.0474111	.086565	.0421492
Leverage	.0992661	.113484	.1159596	.1139457
HHI	.1472519	.121739	.1614995	.1284747
N	3337		4165	

Notes: The table reports the summary statistics for the subsample of strategic and technological patent subsamples. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). Profit is sales minus cogs, divided by lagged total assets. R&D is the ratio of the firm's research and development expenditures to lagged total assets. Assets are the firm's total assets. ROA is the ratio of income before extraordinary items to assets. Tobin's Q is the ratio of the sum of total assets and the difference between market and book value of total common equity, to total assets. Leverage is the sum of long-term debt and debt in current liabilities divided by total assets. HHI is the Herfindahl-Hirschman Index of industry defined by the TNIC3 classification (Hoberg and Phillips, 2010). Sales, cogs, CAPX, and cash flows are defined as ratios to the firm's total assets. Each baseline variable is measured as an average over five pre-filing years. All monetary values are expressed in real 2014 dollars. All variables are winsorized at 5% using annual breakpoints.

Table 1.6: Strategic Patent Characteristics – Continuation Patents

Dependent variable:	Continuation (CON)	Cont. in part (CIP)	Divisional (DIV)	CON+CIP+DIV
	(1)	(2)	(3)	(4)
Panel A: Full sample				
I(strategic patent)	0.02584***	0.00265	0.01940***	0.04246***
	(0.00405)	(0.00247)	(0.00320)	(0.00492)
N	51242	51242	51242	51242
Adjusted R-square	0.073	0.043	0.065	0.087
Panel B: Matched sample				
I(strategic patent)	0.02044***	-0.00458	0.01418**	0.02939***
	(0.00706)	(0.00467)	(0.00588)	(0.00873)
N	14283	14283	14283	14283
Adjusted R-square	0.076	0.047	0.057	0.074

Notes: The table reports the results of regression of the probability of the patent being a continuation (USPTO PAIR: CON – continuation, CIP – continuation in part) or divisional patent (USPTO PAIR: DIV) on an indicator variable of patent strategic status. The results are estimated on the sample of top-performing patents in the full (non-matched sample) and matched sample. Patent applications are classified as top-performing if at the date of patent filing the economic value of the patent is higher than the year's median. The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). All specifications control for filing year, examiner art unit, and firm fixed effect. Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.7: Strategic Patent Characteristics – Self- and Backward Citations

Dependent variable:	Backward citations	Self-citation	Known class patent
	(1)	(2)	(3)
Panel A: Full sample			
I(strategic patent)	4.77512***	1.37945***	0.68126***
	(0.27133)	(0.06269)	(0.00576)
N	51242	51242	51242
Adjusted R-square	0.058	0.051	0.529
Panel B: Matched sample			
I(strategic patent)	3.41059***	1.06031***	0.59480***
	(0.47763)	(0.10877)	(0.00855)
N	14283	14283	14283
Adjusted R-square	0.032	0.056	0.381

Notes: The table reports the results of regression of measures of innovation search strategies on an indicator of patent strategic status. The results are estimated on the sample of top-performing patents in the full (non-matched sample) and matched sample. Patent applications are classified as top-performing if at the date of patent filing the economic value of the patent is higher than the year's median. The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). Column (1) dependent variable is the total number of patent backward citations. Column (2) regresses the total number of patent self-citations: number of citations of other patents issued to the same patentee. In column (3) the dependent variable is an indicator if the firm already has a patent granted within the same technology class (back to 1976). All specifications control for filing year, examiner art unit, and firm fixed effect. Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.8: Strategic Patent Effect on Market Concentration

Dependent variable:	HHI (TNIC3)			Number of competitors		
	(1)	(2)	(3)	(4)	(5)	(6)
I(granted patent)	-0.00202**	-0.00176*	0.00037	-0.08635	-0.00400	-0.00165
	(0.00097)	(0.00094)	(0.00081)	(0.15790)	(0.13998)	(0.13429)
I(strategic patent)	0.00261***	0.00264***	0.00207***	-0.29888**	-0.27339**	-0.27208**
	(0.00075)	(0.00074)	(0.00065)	(0.14714)	(0.13600)	(0.13246)
Firm level controls	N	Y	Y	N	Y	Y
Peer firm averages controls	N	N	Y	N	N	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y
Mean of outcome variable	0.19	0.19	0.19	40.48	40.48	40.48
N.	15166	15166	15111	15049	15049	14994
Adj. R-square	0.931	0.934	0.943	0.972	0.976	0.977

Notes: This table shows the results from equation (1.2) of the impact of the strategic patent issue on the patentee using the matched sample. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). Columns (1), (2) and (3) report the effect of technological and strategic patent grant on post-filing HHI based on TNIC3 industry classification and measured in equation (1.3). Compared to column (1), column (2) adds firm level controls from Table 1.4. Columns (3) adds the respective peer firms controls to the regression. Peer firms are defined as the top 50th percentile of closest competitors using the TNIC3 industry classification. The controls for competitors are calculated as equal-weighted averages. Columns (4), (5) and (6) repeat the analysis using the number of competitors within the firm's product market as a dependent variable. All specifications control for filing year, examiner art unit, and firm fixed effect, as well as the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.9: Strategic Patent Effect on Market Concentration: Robustness

	SIC3			Random		
Dependent variable:	Herfindahl-Hirschman Index (HHI)					
	(1)	(2)	(3)	(4)	(5)	(6)
I(strategic patent)	0.00041**	0.00040**	0.00033*	0.00153	0.00150	0.00192
	(0.00019)	(0.00019)	(0.00019)	(0.00181)	(0.00181)	(0.00145)
Firm level controls	N	Y	Y	N	Y	Y
Peer firm averages controls	N	N	Y	N	N	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y
Mean of Outcome Variable	0.06	0.06	0.06	0.24	0.24	0.24
N.	15171	15171	15171	14987	14987	14790
Adj. R-square	0.993	0.993	0.993	0.920	0.921	0.943

Notes: This table shows the results from equation (1.2) of the impact of the strategic patent issue on market concentration using the matched sample. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). Columns (1), (2) and (3) report the effect of technological and strategic patent grant on post-filing HHI measured in equation (1.3) based on industry classification using three-digit SIC codes. Column (2) adds firm level controls from Table 1.4, while columns (3) adds the respective peer firms controls to the regression. The controls for competitors are calculated as equal-weighted averages. Columns (4), (5) and (6) repeat the analysis using the set of "pseudo-competitors", created by generating a random sample of firms from other industries and assign them as the focal firm's peers (Ozoguz et al., 2018). All specifications control for filing year, examiner art unit, and firm fixed effect, as well as the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.10: Strategic Patent Effect on Firm's and Competitors' Productivity

Dependent variable:	Total factor productivity (TFPR)			
	Patenting firm		Competitors	
	(1)	(2)	(3)	(4)
I(granted patent)	0.00441**	0.00468***	0.00460*	0.00584**
	(0.00173)	(0.00167)	(0.00270)	(0.00248)
I(strategic patent)	-0.00350**	-0.00352**	-0.00980***	-0.01035***
	(0.00161)	(0.00155)	(0.00236)	(0.00220)
Firm level controls	N	Y	N	N
Peer firm averages controls	N	N	N	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y
Mean of outcome variable	0.40	0.40	-0.20	-0.20
N.	14491	14423	14383	14333
Adj. R-square	0.820	0.989	0.548	0.594

Notes: This table shows the results from equation (1.2) of the impact of the strategic patent issue on patentee's and competitors' total factor productivity using the matched sample. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). This table reports the effect of technological and strategic patent grant on post-filing revenue-based total factor productivity as in İmrohoroğlu, Ayşe and Tüzel, Şelale (2014). Columns (1) and (2) show the effect on patenting firm TFPR. Compared to column (1), column (2) adds firm level controls from Table 1.4. Columns (3) and (4) repeat the analysis for the firm's closest peers. Peer firms are defined as the top 50th percentile of closest competitors using the TNIC3 industry classification. Both the dependent variable and controls for competitors are calculated as equal-weighted averages. All specifications control for filing year, examiner art unit, and firm fixed effect, as well as the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.11: Strategic Patent Effect on Competitors' Productivity: Robustness

	SIC3		Random	
Dependent variable:	Total factor productivity (TFPR)			
	(1)	(2)	(3)	(4)
I(strategic patent)	-0.00357***	-0.00237**	-0.00040	0.00059
	(0.00098)	(0.00094)	(0.00386)	(0.00384)
Peer firm averages controls	N	Y	N	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y
Mean of Outcome Variable	-0.3329	-0.3329	-0.3268	-0.3268
N.	15086	15086	14256	14193
Adj. R-square	0.407	0.485	0.382	0.404

Notes: This table shows the results from equation (1.2) of the impact of the strategic patent issue on the peers' productivity using the matched sample. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). Columns (1) and (2) report the effect of technological and strategic patent grant on post-filing peers' TFPR measured as in İmrohoroğlu, Ayşe and Tüzel, Şelale (2014) based on industry classification using three-digit SIC codes. Column (2) adds peer level controls from Table 1.4. The controls for competitors are calculated as equal-weighted averages. Columns (3) and (4) repeat the analysis using the set of "pseudo-competitors", created by generating a random sample of firms from other industries and assign them as the focal firm's peers (Ozoguz et al., 2018). All specifications control for filing year, examiner art unit, and firm fixed effect, as well as the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.12: Effect of Strategic Patenting on Future Performance: Patenting Firm

	Patenting Firm Horizon				
Growth over *t* years	1y	2y	3y	4y	5y
Panel A: Profit growth					
I(granted patent)	-0.00616***	-0.00440**	-0.00418**	-0.00446*	0.00009
	(0.00173)	(0.00214)	(0.00203)	(0.00252)	(0.00199)
I(strategic patent)	0.00399**	-0.00047	0.00256	0.00652***	0.00523***
	(0.00186)	(0.00212)	(0.00196)	(0.00237)	(0.00194)
Panel B: Sales growth					
I(granted patent)	-0.00032	0.00050	-0.00042	-0.00174	-0.00005
	(0.00154)	(0.00169)	(0.00158)	(0.00172)	(0.00148)
I(strategic patent)	0.00106	-0.00206	-0.00046	0.00065	0.00089
	(0.00139)	(0.00143)	(0.00130)	(0.00153)	(0.00122)
Panel C: COGS growth					
I(granted patent)	0.00697***	0.01101***	0.00710***	0.00439*	0.00713***
	(0.00253)	(0.00256)	(0.00220)	(0.00251)	(0.00236)
I(strategic patent)	-0.00297	-0.00822***	-0.00703***	-0.00589**	-0.00734***
	(0.00263)	(0.00260)	(0.00240)	(0.00263)	(0.00254)
Mean of outcome var					
Profit growth	-.0116212	-.0186785	-.0184162	-.0227024	-.0323135
COGS growth	.0100984	.0137407	.0243124	.0303634	.0344101
Sales growth	-.0020482	-.0019204	.00208	.0055556	.0013411
Firm level controls	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y
N.	14482	14433	14289	14069	13909

Notes: This table reports the estimates of equation (1.4) for firm profit, sales, and COGS growth over the horizon of one to five years (all variables are scaled by firm's total assets). Profit is measured as sales minus COGS. All specifications control for filing year, examiner art unit, and firm fixed effect, as well as firm controls as in Table 1.4 and the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.13: Effect of Strategic Patenting on Future Performance: Competitors

	Competitors' Horizon				
Growth over *t* years	1y	2y	3y	4y	5y
Panel A: Profit growth					
I(granted patent)	0.00070	0.00119	-0.00681*	-0.00801**	-0.00705**
	(0.00258)	(0.00303)	(0.00353)	(0.00334)	(0.00323)
I(strategic patent)	-0.00296	-0.00794***	-0.00376	0.00133	-0.00044
	(0.00241)	(0.00276)	(0.00334)	(0.00285)	(0.00298)
Panel B: Sales growth					
I(granted patent)	0.00191	0.00277	-0.00107	-0.00463*	-0.00430*
	(0.00182)	(0.00226)	(0.00284)	(0.00275)	(0.00259)
I(strategic patent)	-0.00352**	-0.00710***	-0.00595**	-0.00293	-0.00163
	(0.00171)	(0.00209)	(0.00275)	(0.00253)	(0.00243)
Panel C: COGS growth					
I(granted patent)	0.00246	0.00503**	0.00506*	-0.00050	-0.00131
	(0.00182)	(0.00222)	(0.00274)	(0.00260)	(0.00285)
I(strategic patent)	-0.00308*	-0.00609***	-0.00415*	0.00046	-0.00018
	(0.00164)	(0.00196)	(0.00241)	(0.00224)	(0.00255)
Mean of outcome var					
Profit growth	-.0129493	-.0176281	-.013407	-.0228812	-.0173855
COGS growth	-.0073255	-.0049462	-.0044343	-.0140857	-.0131229
Sales growth	-.0086251	-.0062763	-.0118789	-.0185781	-.0134813
Peer firm averages controls	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y
N.	14414	14414	14405	14395	14395

Notes: This table reports the estimates of equation (1.4) for firm profit (sales minus COGS), sales, and COGS growth over the horizon of one to five years for competitors (all variables are scaled by firm's total assets). Competing firms are defined as the top 50th percentile of closest peers using TNIC3 industry classification from Hoberg and Phillips (2010). The dependent variables and controls are calculated as equal-weighted averages for specified competing firms. All specifications control for filing year, examiner art unit, and firm fixed effect, as well as competitors' portfolio controls as in Table 1.4 and baseline level measures of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.14: Effect of Strategic Patenting on Future Performance: Competitors: Robustness

	Competitors' Horizon									
	SIC3					Random				
Growth over *t* years	1y	2y	3y	4y	5y	1y	2y	3y	4y	5y
Panel A: Profit growth										
I(strategic patent)	-0.00155	-0.00658***	-0.00186	0.00078	0.00006	-0.00044	0.00266	0.00172	0.00291	-0.00059
	(0.00165)	(0.00245)	(0.00248)	(0.00236)	(0.00260)	(0.00201)	(0.00253)	(0.00278)	(0.00315)	(0.00396)
Panel B: Sales growth										
I(strategic patent)	-0.00266*	-0.00615***	-0.00285	0.00042	0.00066	-0.00030	0.00283	0.00336	0.00284	0.00146
	(0.00137)	(0.00198)	(0.00207)	(0.00216)	(0.00223)	(0.00197)	(0.00232)	(0.00245)	(0.00266)	(0.00264)
Panel C: COGS growth										
I(strategic patent)	-0.00237**	-0.00454***	-0.00211	0.00088	0.00235	-0.00110	0.00043	0.00355	0.00336	0.00193
	(0.00118)	(0.00172)	(0.00192)	(0.00198)	(0.00192)	(0.00192)	(0.00274)	(0.00304)	(0.00328)	(0.00340)
Mean of outcome var										
Profit growth	-.004075	-.0045239	.0023908	.0006938	.0010699	-.0251715	-.0525175	-.0955685	-.1109429	-.0808922
COGS growth	-.0068544	-.0127797	-.0098859	-.0159901	-.0263093	-.004534	-.0015688	-.0204236	-.0215566	-.0659981
Sales growth	-.0036926	-.0061924	.001569	.0025009	-.0023276	-.0269559	-.0229385	-.054869	-.0727935	-.0458429
Peer firm averages controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N.	15116	15116	15116	15116	15116	14486	14429	14429	14415	14396

Notes: This table reports the estimates of equation (1.4) for firm profit (sales minus COGS), sales, and COGS growth over the horizon of one to five years for competitors (all variables are scaled by firm's total assets). The dependent variables and controls are calculated as equal-weighted averages for specified competing firms. Columns (1) through (5) report the effect of technological and strategic patent grant on post-filing peers' profit, sales and COGS growth, where peers are defined based on industry classification using three-digit SIC codes. Columns (6) through (10) repeat the analysis using the set of "pseudo-competitors", created by generating a random sample of firms from other industries and assign them as the focal firm's peers (Ozoguz et al., 2018). All specifications control for filing year, examiner art unit, and firm fixed effect, as well as competitors' portfolio controls as in Table 1.4 and baseline level measures of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.15: Strategic Patent Effect on Innovation by Competitors

Dependent variable:	*R&D/Assets*	Explorative Patent, 70%	Explorative Patent, 80%	Explorative Patent, 90%	Filed patents	Granted patents	Known class patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(strategic patent)	0.00181***	-0.13678**	-0.11493**	-0.10020**	-1.35857*	-0.52967	-3.34109***
	(0.00044)	(0.06430)	(0.05380)	(0.04851)	(0.73994)	(0.43745)	(1.01809)
Peer firm averages controls	Y	Y	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y	Y
Mean of outcome variable	0.09	3.56	2.96	2.67	43.71	24.44	42.61
N.	14450	14234	14234	14234	14234	14234	14234
Adj. R-square	0.941	0.521	0.512	0.525	0.660	0.596	0.660

Notes: The table reports the results of regression (1.2) of an indicator of patent strategic status on the competitors' innovative activity and search following Manso et al. (2018). Competing firms are defined as the top 50th percentile of closest peers using TNIC3 industry classification from Hoberg and Phillips (2010). Column (1) shows the effect of strategic patenting by the focal firm on competitors' R&D expenditures scaled by total assets. Column (2) through (4) shows the effect on the number of explorative patents issued by competitors. A patent is defined as explorative if at least 70 (80/90) percent of its citations are not derived from firm's previously existing knowledge pool, which is comprised of this firm's previous patents, or patents cited before by the firm's earlier patents filed within last five years. Column (5) shows the impact on total number of filed patents by the peers, while column (6) – number of patents granted. Results of column (7) examine the effect of strategic patent issue of the number of patents filed by competitors within the previously known to them technological classes (firm has at least one patent granted in this technological class since 1976). The dependent variables and controls are calculated as equal-weighted averages for specified competing firms. All specifications control for filing year, examiner art unit, and firm fixed effect as well as competitors' portfolio controls. Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.16: Effect of Strategic Patenting on Competitors: Role of Technological and Product Proximity Within Peer Groups

Dependent variable:	Competitors' total factor productivity (TFPR)				Competitors' R&D/Assets			
	Technological proximity		Product proximity		Technological proximity		Product proximity	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(strategic patent)	-0.01086***	-0.00505	-0.01236***	0.00057	0.00306***	-0.00004	0.00127**	-0.00089*
	(0.00368)	(0.00351)	(0.00372)	(0.00270)	(0.00080)	(0.00052)	(0.00062)	(0.00052)
Peer firm averages controls	Y	Y	Y	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Mean of outcome variable	-0.18	-0.11	-0.12	-0.17	0.10	0.08	0.09	0.08
N.	13763	13393	13885	13107	14287	13556	14287	13163
Adj. R-square	0.610	0.603	0.567	0.571	0.820	0.862	0.845	0.889

Notes: This table shows the results from equation (1.2) of the impact of the strategic patent issue on the peers' productivity and R&D expenditures (scaled by total assets) by technological and product proximity. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). Competing firms are defined as the top 50th percentile of closest peers using TNIC3 industry classification from Hoberg and Phillips (2010). Following Bloom et al. (2013) and Jaffe (1986) technological and product proximity are defined using (1.5). All patentee's competitors are allocated into two group, *Low* and *High*, depending on whether the proximity score (technological or product) of the firm with this competitor is below or above the year's sample median. Columns (1) through (4) report the effect of technological and strategic patent grant on post-filing peers' TFPR measured as in İmrohoroğlu, Ayşe and Tüzel, Şelale (2014). Columns (5) through (6) show the effect on competitors' R&D/Assets. All specifications control for filing year, examiner art unit, and firm fixed effect, as well as competitors' portfolio controls and the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.17: Effect of Strategic Patenting on Future Profitability of Competitors: Role of Technological and Product Proximity Within Peer Groups

Dependent variable:	Competitors' Horizon (2y)			
	Technological proximity		Product proximity	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Panel A: Profit growth				
I(strategic patent)	-0.01171***	-0.00228	-0.00646**	-0.00034
	(0.00435)	(0.00231)	(0.00328)	(0.00294)
Panel B: Sales growth				
I(strategic patent)	-0.01244***	-0.00233	-0.00683***	-0.00276
	(0.00350)	(0.00289)	(0.00259)	(0.00226)
Panel C: COGS growth				
I(strategic patent)	-0.00489	-0.00009	-0.00251	0.00155
	(0.00383)	(0.00330)	(0.00327)	(0.00324)
Mean of outcome var				
Profit growth	.0308789	.008932	.0256976	.0142365
COGS growth	.032305	.0157822	.0240983	.0234099
Sales growth	.027146	.0040606	.0114064	.0183562
Peer firm averages controls	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y
N.	14204	13528	14194	13135

Notes: This table reports the estimates of equation (1.4) for firm profit (sales minus COGS), sales, and COGS growth over the horizon of two years for competitors (all variables are scaled by firm's total assets) by technological and product proximity. The sample is matched exactly on year of patent filing and patent category, and it is matched coarsely on the economic value of the patent and the firm's baseline sales outcome (averaged over five pre-filing years). The patent is classified as strategic (technological) if it falls into the top 50th percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but bottom (top) 50th percentile of distribution of its scientific value (measured by forward citations). Competing firms are defined as the top 50th percentile of closest peers using TNIC3 industry classification from Hoberg and Phillips (2010). Following Bloom et al. (2013) and Jaffe (1986) technological and product proximity are defined using (1.5). All patentee's competitors are allocated into two group, *Low* and *High*, depending on whether the proximity score (technological or product) of the firm with this competitor is below or above the year's sample median. Columns (1) and (2) report the effect of technological and strategic patent grant on competitors performance by technological proximity. Columns (3) and (4) repeat the analysis by product proximity. All specifications control for filing year, examiner art unit, and firm fixed effect, as well as competitors' portfolio controls and the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.18: Strategic Patent Effect on Innovation by Competitors: Role of Technological and Product Proximity Within Peer Groups

Dependent variable:	Explorative Patent, 90%		Filed patents		Granted patents		Known class patents	
	Technological proximity							
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(strategic patent)	-0.38088***	-0.49037***	-1.78946	-10.66122***	-1.60589**	-4.72812***	-1.81411	-10.55613***
	(0.10696)	(0.18073)	(1.71019)	(2.68025)	(0.62921)	(1.55710)	(1.68784)	(2.66123)
Peer firm averages controls	Y	Y	Y	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Mean of outcome variable	4.96	10.02	57.34	188.04	35.39	99.04	54.75	185.471
N.	13349	13493	13349	13493	13349	13493	13349	13493
Adj. R-square	0.740	0.721	0.617	0.810	0.732	0.773	0.622	0.811
	Product proximity							
	Low	High	Low	High	Low	High	Low	High
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
I(strategic patent)	-0.69267***	0.03910	-9.75301***	1.30532	-5.43489***	0.46474	-9.75533***	1.30461
	(0.15988)	(0.10531)	(2.78096)	(1.85387)	(1.59193)	(0.98638)	(2.77231)	(1.84881)
Peer firm averages controls	Y	Y	Y	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Mean of outcome variable	9.90	6.07	193.39	55.907	105.70	34.81	190.63	53.684
N.	13891	12961	13891	12961	13891	12961	13891	12961
Adj. R-square	0.755	0.560	0.837	0.505	0.804	0.461	0.838	0.500

Notes: The table reports the results of regression (1.2) of an indicator of patent strategic status on the competitors' innovative activity and search following Manso et al. (2018) by technological and product proximity. Competing firms are defined as the top 50th percentile of closest peers using TNIC3 industry classification from Hoberg and Phillips (2010). Following Bloom et al. (2013) and Jaffe (1986) technological and product proximity are defined using (1.5). All patentee's competitors are allocated into two group, *Low* and *High*, depending on whether the proximity score (technological or product) of the firm with this competitor is below or above the year's sample median. A patent is defined as explorative if at least 70 (80/90) percent of its citations are not derived from firm's previously existing knowledge pool, which is comprised of this firm's previous patents, or patents cited before by the firm's earlier patents filed within last five years. A patent is a "known class patents" if a firm has at least one patent granted in this technological class since 1976). All specifications control for filing year, examiner art unit, and firm fixed effect, as well as peer level controls as in Table 1.4 and the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.19: Strategic Patent Effect on Market Concentration and Competitors by Patenting Firm's Proximity to Technological Frontier

Dependent variable:	HHI		Number of Firms		Competitors' TFPR		Competitors' R&D/Assets	
	Laggard	Leader	Laggard	Leader	Laggard	Leader	Laggard	Leader
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(strategic patent)	0.00331***	0.00028	-0.62998***	0.07806	-0.00897**	-0.00704***	0.00036	0.00137***
	(0.00118)	(0.00045)	(0.17337)	(0.11112)	(0.00420)	(0.00229)	(0.00065)	(0.00046)
Firm level controls	Y	Y	Y	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Mean of outcome variable	0.23	0.17	29.49	42.56	-0.19	-0.20	0.07	0.11
N.	5404	8912	5394	8850	5321	8920	5434	8921
Adj. R-square	0.969	0.985	0.987	0.979	0.598	0.692	0.955	0.937

Notes: This table shows the results from equation (1.2) of the impact of strategic patent issue on the patentee using the matched sample separately by group using the proximity of the patentee to the technological frontier firm. The firm is defined as a leader if its technological gap measured as in equation (1.6) is lower than the year's median value, signaling that the firm is closer to the frontier firm. If the gap is larger than the year's median value, then the firm is classified as a laggard. Columns (1) and (2) report the effect of technological and strategic patent grants on post-filing HHI based on TNIC3 industry classification and measured in eq.(1.3). Columns (3) and (4) repeat the analysis using the number of competitors within the firm's product market as a dependent variable. Columns (5) and (6) examine the effect on the competitors' TFPR defined as in İmrohoroğlu, Ayşe and Tüzel, Şelale (2014), and columns(7) and (8) – on peers' R&D expenditures. Competing firms are defined as the top 50th percentile of closest peers using TNIC3 industry classification from Hoberg and Phillips (2010). All specifications control for filing year, examiner art unit, and firm fixed effect, as well as firm (or peers) controls as in Table 1.4 and the baseline measure of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Table 1.20: Robustness Check: Alternative Definitions of Strategic and Technological Patents

Dependent variable:	Herfindahl-Hirschman Index (TNIC3)							
Definition of strategic patent: top % economics value, bottom % scientific value	top 40%, bottom 40%	top 30%, bottom 30%	top 20%, bottom 20%	top 10%, bottom 10%	top 40%, bottom 60%	top 30%, bottom 70%	top 20%, bottom 80%	top 10%, bottom 90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(granted patent)	-0.00022	0.00005	0.00037	0.00454***	0.00021	0.00098*	0.00071	0.00341***
	(0.00070)	(0.00074)	(0.00100)	(0.00176)	(0.00062)	(0.00059)	(0.00067)	(0.00093)
I(strategic patent)	0.00218***	0.00216***	0.00178*	-0.00139	0.00191***	0.00147***	0.00201***	-0.00027
	(0.00060)	(0.00067)	(0.00091)	(0.00167)	(0.00053)	(0.00055)	(0.00061)	(0.00085)
Firm level controls	Y	Y	Y	Y	Y	Y	Y	Y
Peer firm averages controls	Y	Y	Y	Y	Y	Y	Y	Y
Year, Art Unit, Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
% strategic patents in the sample	.1238243	.1007908	.069898	.037478	.1011604	.065229	.0464073	.0270118
N.	40765	30541	20321	10099	40765	30541	20321	10099
Adj. R-square	0.958	0.969	0.981	0.988	0.958	0.969	0.981	0.988

Notes: This table shows the results from equation (1.2) of the impact of the strategic patent issue on the patentee's HHI measured in equation (1.3) using the matched sample using alternative cut-offs for defining strategic patents. The patent is classified as strategic if it falls into the top 40th (30/20/10) percentile of the distribution of the private economic value of the patent as measured by equation (1.1), but (not) bottom 40th (30/20/10) percentile of distribution of its scientific value (measured by forward citations). All specifications control for filing year, examiner art unit, and firm fixed effect, as well as firm level controls as in Table 1.4 and baseline level measures of the dependent variable (calculated over the five pre-filing years). Standard errors are clustered at examiner art unit by year of filing. Standard errors are reported in parentheses. Levels of significance: *10%, **5%, and ***1%.

Chapter 2

Patent-Induced Shock Propagation Through the Supply Chain

2.1 Introduction

A firm's relationship with its upstream supplier is of key importance to the company's profitability. Empirical evidence shows that there is a close connection between the performances of economically linked firms, ranging from the return predictability (Cohen and Frazzini, 2008) to natural disaster shock propagation from supplier to customer (Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2016; Barrot and Sauvagnat, 2016). While these relationships have been empirically documented, little is still known about the effect of true firm-level idiosyncratic shock on the supply chain. Motivated by this discrepancy between the data used in the existing literature and the conclusions the previous research in this area tries to draw, in this paper I will examine the effect of idiosyncratic productivity shock to the supplier on its customers using patent application as the source of variation in the supplier's performance.

The effect of the supplier's patent on the customers is of interest to us for several reasons. Firstly, a patent-based measure of innovation is a good proxy for the firm's total factor productivity shock as it has been shown to be positively related to revenue-based firm productivity and firm growth (Kogan et al., 2017). Secondly, patent application constitutes a truly firm-specific shock, which makes its use as the shock to the supplier a superior setting than that used in other papers examining the effect of firm-level idiosyncratic shock propagation through the supply chain using natural disasters. Lastly, patent application is a publicly available measure that can be easily observed by the market participants (customers in our case) and can thus have an effect on related firms' outcomes.

This paper contributes to several strands of literature. First, it relates to the considerable empirical and theoretical research that documents the importance of the output-input linkages in propagation and amplification of these shocks. Such empirical papers as Carvalho et al. (2016), and Barrot and Sauvagnat (2016) focus on how the effect of natural disasters propagates through the downstream supply chain. These papers find evidence of both upstream and downstream propagation of the shock, documenting the significant sales underperformance of customers of those suppliers, who were hit by the disaster, as well as an indirect propagation to the customers' customers and suppliers' suppliers, though the intensity of the shock decreases as it travels the supply chain. In addition, Barrot and Sauvagnat (2016) show that input specificity is the key driver of the propagation of firm-level shocks as well as the horizontal propagation of the shock from one supplier to other suppliers of the same firm.

Other related papers are based on multi-industry real business cycle models. Using this framework, they show that idiosyncratic shocks to industries' productivities can generate aggregate fluctuations. These are works by Long and Plosser (1983), Horvath (1998, 2000), Dupor (1999), Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), and Atalay (2017).

This paper contributes to the literature above by using patent allowance data as a firm-level idiosyncratic shock to the supplier, which is a better measure of the total factor productivity shock (in the sense that it is truly firm-specific, occurs more frequently than the shocks used previously (i.e. Barrot and Sauvagnat (2016) has 41 natural disaster shocks, while in this paper I use 208 first patent applications) and does not solely present a negative shock to the company but also a potentially positive one).

Secondly, this paper relates to the literature on the effect of patents on firm performance (Pakes, 1986; Hall et al., 2001; Kline et al., 2019; Farre-Mensa et al., 2016; Balasubramanian and Sivadasan, 2011; Kogan et al., 2017). These studies find positive effects of patenting on firm outcomes, such as firm productivity and worker compensation in Kline et al. (2019), employment and sales growth in Farre-Mensa et al. (2016), and firm's size, factor intensity, productivity and scope in Balasubramanian and Sivadasan (2011).

Of papers examining the topic of innovation and the supplier-customer relationship, it is worth noting Chu, Tian, and Wang (2019) documenting the effect of customer-supplier geographic proximity on the innovation of the supplier. Wang and Shin (2012) model the impact of downstream competition on upstream innovation and show that only if manufacturers set the wholesale prices does the downstream competition induce more innovation in a supply chain. Krolikowski and Yuan (2017) empirically illustrate the effect of the customers' concentration and bargaining power on suppliers' innovation.

My paper contributes to the existing literature on the effect of innovation by combining these two strands of literature into one, examining the effect of patent application on the supply chain by looking at the performance outcomes of the customers of the patent filing firms using the news on patent initial allowance as a firm-level idiosyncratic shock to the supplier.

The paper proceeds as follows: Section 2.2 describes the data and summary statistics, Section 2.3 describes the empirical strategy, Section 2.4 discusses results, and Section 2.5 concludes.

2.2 Data and Summary Statistics

To conduct the empirical analysis, I construct the dataset combining the information from the following sources.

The data on patent applications, group art unit, invention U.S. classification, filing date, publication date, issue date, patent number as well as patent allowance decision comes from the universe of patent applications submitted to the US Patent and Trademark Office (USPTO) since late 2000. The sample consists of patent applications filed after November 29, 2000 that were published by December 31, 2013. I remove all of the applications that are missing the assignee names and cannot be matched to Compustat. Kogan et al. (2017) provide their final estimates of patent value for their sample of granted patent. For the applications that were never granted, I replicate the economic value of the patent application around the publication date, which according to Kogan et al. (2017) produces similar results as using patent issue date.

The data on supplier-customer relations comes from Compustat Segment files, which exist because firms are required to disclose certain financial information for any industry segment that makes up more than 10% of consolidated yearly sales, assets, or profits as well as the identity of any customer representing more than 10% of the total reported sales. Each supplier in the sample has at least one and at most 16 customers, with an average of 4.4 customers per supplier. Similar to Barrot and Sauvagnat (2016), I include each firm in the sample starting five years before and ending five years after it was listed as either a supplier or a customer in the Compustat Segment dataset.

Firms' financial data is retrieved from Compustat North America Fundamentals Annually database. All continuous variables are winsorized at the 5th and 95th percentiles of their distributions. I adjust my computation of sales and cost of goods sold for inflation using the CPI from Bureau of Economic Analysis with 2014 as the base year.

Patent application data is merged to Compustat data based on the name of the assignee, which is matched using the name standardization routine used by the NBER Patent Data Project (Hall et al., 2001). Based on the previous literature examining the effect of patenting on firms' outcomes (Balasubramanian and Sivadasan, 2011; Farre-Mensa et al., 2016; Kline et al., 2019), I will be limiting the sample to first time patent applicants only, excluding the applications by firms that had the patent grants before the start of the published application sample. The final sample consists of 208 first time applications (suppliers) and 210 customers that together result in 392 unique supplier-customer pairs (or 2013 supplier-customer-year observations) for the analysis of the propagation effect.

Table 2.1 shows the descriptive statistics of the sample of suppliers that filed for patent for the first time and their respective customers, as well as some characteristics of the suppliers' patents. All summary statistics are as of the year of the patent application was filed. Consistent with the previous studies of supplier-customer relationships (Williams and Xiao, 2017), customers are significantly larger than suppliers: average supplier assets are \$983.9 million dollars, compared to \$3.78 billion dollars in average assets of customers. As for the patent characteristics, on average 8.9% of first time patent applications are initially allowed.

Eventually 63.4% of first patents are granted.

2.3 Empirical Design

Following Kline et al. (2019), I use difference-in-difference strategy to evaluate the effect of supplier patenting activity on customers' performance outcomes such as revenues, costs, and employment. The concern so far is that patenting as a shock to firm's productivity can contain market-wide components; thus, the increase in all firms' productivity in the market can lead to an increase in the revenue of both supplier and customer. To alleviate this concern, I will use initial decision on the suppliers' first patent, which, as Kline et al. (2019) has shown, is independent on the firm's baseline performance and cannot be predicted by the characteristics of the firm during the year of the filing, making it a great candidate for a true firm-specific shock.

Table 2.2 replicates the analysis in Kline et al. (2019) by using the linear probability model for predicting the patent application initial allowance status using first time innovating supplier's firm performance outcomes in the year of the patent application. The results show that the majority of the baseline covariates are individually and jointly insignificant for the whole analysis sample (columns (1) and (2)) and for the top valued patent applications (columns (3) and (4)). Based on the findings from Table 2.2, I will proceed treating initial patent allowance as a truly firm-specific shock.

In addition, I specifically focus on the effect of high-value patent applications, which according to Pakes (1986) and Kline et al. (2019) are more likely to generate a significant response in a firm's own outcomes and thus would have a higher impact on other firms as the effect of innovation shock propagates throughout the supply-chain network. I define high-value patent applications as those whose economic value, estimated following Kogan et al. (2017), falls into the top quintile of the distribution of the measure. The economic value of a patent, ξ_j, is calculated as the product of estimate of patent news-related stock return, $\mathbb{E}[\upsilon_j|r_j]$, times the market capitalization, M_j, of the firm on the day prior to patent granting date (or publication date for non-granted applications), adjusted for the number of patents, N_j, issued that day and the unconditional probability of success of the patent application, $\bar{\pi}$, equal to 56% following Carley et al. (2015): $\xi_j = (1-\bar{\pi})^{-1}\frac{1}{N_j}\mathbb{E}[\upsilon_j|r_j]M_j$.

I run the following difference-in-difference regression at the firm year level for the suppliers sample and at the customer-supplier year level for the customers of affected suppliers sample:

$$\begin{aligned} Y_{it} =& \beta_0 + \beta_1 \cdot Q5_i \cdot Post_{it} + \beta_2 \cdot (1-Q5_i) \cdot Post_{it} + \beta_3 \cdot Q5_i \cdot Post_{it} \cdot I(IA_i) + \\ & \beta_4 \cdot (1-Q5_i) \cdot Post_{it} \cdot I(IA_i) + \alpha_i + \mu_i + \tau_t + \epsilon_{it} \end{aligned} \tag{2.1}$$

where $Q5_i$ is a dummy variable equal to one if the patent application lies in the top quintile of the economic value distribution, $Post_{it}$ is a dummy variable equal to one if the decision on the application was has already been made, $I(IA_i)$ is a dummy variable equal to one if the patent examiner issued an initial allowance of the patent application, α_i is firm level fixed effects, μ_i is examiner art unit fixed effect, and τ_t is year fixed effects. Standard errors are clustered at firm and filing year by decision year level. The main dependent variables of interest are customers' yearly sales growth, costs of goods sold growth (Barrot and Sauvagnat, 2016), and logarithm of employment (Kline et al., 2019).

2.4 Results

2.4.1 Effect on Innovating Suppliers

First before moving to the main focus of this research, namely the propagation of the effect of the patent application through the supply chain (both vertically and horizontally), I examine the effect of patenting on the suppliers' firm performance outcomes. As a patent grant could allow the firm to raise its product price by creating a barrier to competition for rival firms as well as increasing firm's total factor productivity, thus making it profitable for the firm to implement the patented technology, we expect an increase in the firms' revenues and employment following the patent application allowance, especially for economically valuable patents.

The results of the regression 2.1 are presented in Table 2.3. The main coefficients of interest are β_3 and β_4, which represent the impact of the initial patent application allowance on the for patents in the top-quintile of the economic values compared to initially rejected patent applications and the effect on low-valued patents respectively. Consistent with previous literature, there is a significant and positive effect of the initial allowance of high-valued patent applications on suppliers' total sales, while showing no significant sales response after the initial allowance the low-valued applications. Further I observe no significant effect of initial allowance on either sales or cost of goods sold growth rates (columns (2) and (3)). Column (4) exhibits a negative response of employment level when the high-valued patent application receives an initial allowance. While contradictory to the results in Kline et al. (2019), that shows a positive impact of initial allowance on employment, this observation can be interpreted as innovative activity leading to more cost efficient use of firm's labor. This discrepancy can also be potentially driven by the difference in the response of large public firms examined in this paper's sample and that of private firms, which are the main focus of Kline et al. (2019). All specifications control for firm, examiner art unit, and year fixed effect. Standard errors are clustered at examiner art unit by filing by decision year.

2.4.2 Downstream Propagation: Effect on Customers

In this section I estimate the impact of the supplier's innovative activity on the customers' sales, cost of goods sold, and employment. The results of the regression (2.1) on the sample of the customers of affected suppliers are presented in Table 2.4. Once again, I focus on the effect of the top-performing patent applications on the firm's outcomes. The main variables of interest is the dummy $Q5 \cdot Post_{it} \cdot I(IA_i)$, which is equal to one if the supplier has a high-value patent application initially allowed by the examiner in year t and zero otherwise, which we compare to the effect of the low-value patent application initial allowance, $(1-Q5) \cdot Post_{it} \cdot I(IA_i)$. Same fixed effects are present as in the suppliers' regression, and standard errors are clustered at supplier-customer pair and filing year by decision year level.

Column (1) shows a significant increase in customer's total sales following the initial allowance of high-value patent application to the supplier. Similarly, one can observe that the initial allowance is associated with significant increases in both sales and COGS growth (columns (2) and (3)), while the estimates in column (4) show the negative impact on customers' employment. Thus, one can observe that an allowance of high-value patent application propagates to the customers' sales, cost of goods sold, and employment, and is similar qualitatively to that of suppliers, though quantitatively is much smaller. Therefore, one can conclude that the positive effect of suppliers' innovative activity is propagating vertically through the supply chain.

This suggests that consumers benefit from the valuable patents of their suppliers through the introduction of new/better product by the supplier, which in turn can help the customers improve their production costs (if used as intermediate input) or which they can then sell for higher prices to their own customers.

To ensure the causal relationship and the absence of prior trends, I examine the timing of the customers' sales growth, cost of goods sold growth, and employment response to the suppliers' patent application initial allowance following Williams and Xiao (2017) by running the regression 2.1 for the aforementioned dependent variables separately for each year from $t-1$ to $t+3$ relative to the year of the initial decision. The results are presented in Table 2.5. One can observe that the effect of supplier innovation shock is present in customer's sales and COGS growth starting only from year t and peaks for the sales growth one year after the supplier's patent application was initially allowed, while the effect on COGS growth is the strongest in the year of the initial allowance. For both growth rates the impact of innovation shock is short lived, not lasting beyond the two year mark after the initial decision. In contrast, the effect on customer's employment is persistently negative and significant from t until $t+3$ for the presented sample. These results confirm that the absence of prior trends in the customers' performance outcomes and reject the possibility of the potential reserve causality between the supplier's patent application's initial allowance and customers' sales and cost of goods sold growth and employment decline.

2.4.3 Horizontal Propagation: Effect on Customers' Other Suppliers

Last but not least, I explore whether the effects documented above spill over to other related suppliers that are not directly affected by the patent shock, only indirectly though their common relationship with the same customer. As observed by Barrot and Sauvagnat (2016), the direction of the effect is unclear and depends on the degree of complementarity across intermediate input suppliers: if they are substitutes, negative, as improvement of the production of their competing supplier can reduce the sales of other suppliers servicing the same customer, while the opposite for complements as related suppliers can partake in the boost of sales from the patenting supplier. The sample consists of 172 customers and 1781 other suppliers, which together form 153,457 customer-supplier by application pairs.

Using the similar identification strategy as for the customer analysis, the results of the regression (2.1) for the sample of other suppliers of the patenting firm's customers are presented in Table 2.6. Column (1) shows that the coefficient of $Q5 * Post_{it} * I(IA_i)$ for total sales is positive and significant, suggesting the complementarity across the suppliers. The effect is present for the subsample of the high-value as well as low-value patents, although for the low-value patent applications this effect is quantitatively much smaller and is only significant at 10 percent level. Columns (2) and (3), on the other hand, illustrate a significant slow down in the sales and COGS growth of the related suppliers following the initial allowance of the high-value patent to the customer's innovating supplier, while results on employment in column (4) suggest an increase in employment – opposite to the effect of the initial high-value patent application allowance on the patentee itself. Nevertheless, the results are still consistent with the intermediate input complementarity hypothesis despite the slow down in the sales increase of the other suppliers. The increase in employment can be interpreted as the firm's attempt to increase the firm's productivity to sustain the increased demand and thus the increase in sales. Thus, the results of Table 2.6 are consistent with the presence of the significant horizontal spillover effect to the other suppliers working with the same customer.

2.5 Conclusion

In conclusion, in this research I have presented evidence that patent-induced shock to the supplier propagates to its customers and translates in both long-run revenue increases and employment growth. The effect is especially strong for patent applications of high economic value. The increase in the customer's revenues spill over to other suppliers, suggesting complementarity across intermediate input suppliers. This empirical analysis on the effect of patent issue on the innovating firms themselves and their related firms presented in this paper sheds light on a broader question of whose interests the firm has in mind while applying for patent, what types of innovation benefit the firm the most, what are the externalities of patenting activity (social value of the patent), and what are the driving forces of innovation in aggregate economy.

This paper shows that innovative activity by the firm can be beneficial not only to the firm's own performance but also has a positive spillover effect on the firms connected through the supply chain, both vertically and horizontally.

While this study has been performed on the sample of public firms only, quite significantly limiting the sample of first-ever patenting firms, this research will benefit from the access to the private firms database, extending the sample and thus making the presented analysis more comprehensive.

Table 2.1: Summary Statistics

	Analysis sample					Top-quintile sample				
Panel A: Supplier Characteristics	Mean	SD	25th	Median	75th	Mean	SD	25th	Median	75th
Supplier R&D	0.091	0.141	0.000	0.035	0.136	0.083	0.081	0.019	0.070	0.113
Assets	983.897	2279.108	83.703	197.800	535.788	121.581	230.647	29.185	48.119	102.280
Leverage	0.154	0.203	0.000	0.069	0.244	0.123	0.142	0.000	0.096	0.202
ROA	0.043	0.164	-0.053	0.072	0.142	-0.062	0.205	-0.195	0.005	0.082
Supplier Q	1807.916	1688.999	738.436	1162.311	2362.326	1326.575	1301.206	485.468	901.787	1549.009
Cash Flows	0.068	0.173	0.029	0.086	0.150	-0.044	0.208	-0.123	0.015	0.107
Employment	0.799	0.843	0.191	0.438	1.095	0.371	0.623	0.088	0.157	0.266
Sales Growth	0.128	0.380	-0.072	0.055	0.274	0.120	0.466	-0.110	0.017	0.260
Sales Volatility	0.165	0.186	0.048	0.111	0.209	0.201	0.176	0.097	0.156	0.267
Herfindahl (TNIC3)	0.248	0.227	0.098	0.170	0.311	0.315	0.271	0.135	0.230	0.347
Predicted Patent Value	3.539	6.059	0.567	1.703	3.581	0.247	0.119	0.146	0.254	0.345
% Patents Initially Allowed	8.9					14.3				
% Granted Patents	63.4					54.3				
Firm Observations			207					44		
Panel B: Customers Characteristics	Mean	SD	25th	Median	75th	Mean	SD	25th	Median	75th
Customer R&D	0.013	0.023	0.000	0.013	0.015	0.014	0.028	0.000	0.007	0.015
Assets	9052.351	3787.100	6295.232	11463.000	11463.000	7957.094	4256.280	3989.413	11463.000	11463.000
Leverage	0.216	0.108	0.155	0.254	0.259	0.185	0.116	0.083	0.210	0.259
ROA	0.103	0.050	0.093	0.093	0.093	0.113	0.068	0.093	0.093	0.131
Customer Q	825.033	624.385	476.983	732.067	1008.645	827.554	648.018	366.640	767.361	1008.645
Cash Flows	0.077	0.048	0.060	0.073	0.075	0.095	0.075	0.060	0.075	0.101
Employment	2.694	0.520	2.839	2.904	2.904	2.700	0.620	2.896	2.904	2.904
Sales Growth	-0.003	0.096	-0.031	-0.026	-0.016	0.011	0.109	-0.032	-0.024	0.006
Sales Volatility	0.056	0.111	0.000	0.000	0.068	0.078	0.120	0.000	0.023	0.115
Herfindahl (TNIC3)	0.218	0.193	0.086	0.167	0.284	0.216	0.232	0.088	0.145	0.230
Firm Observations			392					82		

Notes: This table shows the summary statistics for the affected supplier (Panel A) and its customers (Panel B) using both the whole sample of firm-first patent application pairs, and a subsample of top valued patents (top-quintile sample), where the value of the patent defined as in Kogan et al. (2017). All variables summary statistics is measured in the year of supplier patent application filing. All variables are winsorized at the 5th and 95th percentiles. Definition of the variables can be found in the Appendix A.1.

Table 2.2: Covariate Balance Test for Patent Initial Allowance

Dependent Variable:	Initially allowed			
	Analysis sample		Top-quintile sample	
	(1)	(2)	(3)	(4)
log(employees)	-0.01397	-0.01851	-0.05019	-0.02065
	(0.01920)	(0.07663)	(0.05370)	(0.04104)
Sales	-0.00790	0.18848	-0.15081	-0.22490
	(0.04772)	(0.19811)	(0.10520)	(0.17463)
COGS	-0.02229	-0.26392	0.20590	0.33561
	(0.05657)	(0.22841)	(0.13828)	(0.21183)
Sales Growth	0.01019	0.33107	-0.07753	-0.25284
	(0.05263)	(0.27386)	(0.10834)	(0.29525)
Sales Volatility	0.00292	0.03472	-0.12703	0.04379
	(0.07291)	(0.18089)	(0.10601)	(0.15678)
Supplier R&D	-0.07564	-0.56573	-0.72918	-1.01700
	(0.09874)	(0.83881)	(0.56260)	(0.79702)
ROA	0.26002*	-0.24457	0.08513	-0.25025
	(0.15486)	(0.75884)	(0.21910)	(0.31102)
Leverage	0.03500	-0.23522	-0.01330	0.00897
	(0.07169)	(0.43564)	(0.17742)	(0.17431)
Cash Flows	-0.27496	0.06293	0.06384	0.35487
	(0.19607)	(0.84887)	(0.23273)	(0.34103)
EAU x FY FE	No	Yes	No	Yes
N.	221	91	49	46
p-value	0.1852	0.4994	0.9645	0.9278

Notes: This table shows the results of the linear probability model estimates, where the dependent variable is the probability of supplier's first time patent application being initially allowed by the examiner (similar to Kline et al. (2019)). Definitions of the dependent variables can be found in Appendix A.1. All variables are measured at the year of patent application. Columns (1) and (2) show the results for the full sample of applications, columns (3) and (4) – only for the sample of top 20 percent of performing patents defined using the economic value of the patent following Kogan et al. (2017). Columns (2) and (4) control for application year by examiner art unit fixed effects. P-values indicate the results of the coefficients' joint significance test. Standard errors are Standard errors are presented in parentheses and clustered by examiner art unit and filing year by initial decision year. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively..

Table 2.3: Idiosyncratic Shock – Supplier Outcomes

Dependent Variable:	Sales	Sales Growth (t-1,t)	COGS Growth (t-1, t)	Log(Empl)
	(1)	(2)	(3)	(4)
Q5 * I(Initially Allowed)	0.24245**	0.01853	0.28671	-0.31061**
	(0.09571)	(0.12458)	(0.22006)	(0.13120)
(1-Q5)* I(Initially Allowed)	-0.09924	-0.04828	-0.01979	0.01649
	(0.13820)	(0.08002)	(0.11140)	(0.07085)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Examiner Art Unit FE	Yes	Yes	Yes	Yes
N.	3508	3261	3261	3698
Adjusted R^2	0.337	0.010	0.020	0.938

Notes: This table shows the results estimation of equation (2.1) for the sample of first time innovating suppliers. Estimates reflect the interaction of the dummy of patent value category ($Q5$ vs. $(1-Q5)$ estimated following Kogan et al. (2017)) and indicator of post-decision and indicator of the patent application initial allowance. All specification control for firm, examiner art unit and year fixed effects. Column (1) outcome variable is firm's total sales, measured as ratio of firm's total sales at t to assets at $(t-1)$; column (2) and (3) outcome variables are sales and COGS growth relative to the previous year, respectively; column (4) outcome variable is logarithm of employment. Standard errors are presented in parentheses and clustered by examiner art unit and filing year by initial decision year. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 2.4: Downstream Propagation – Baseline

Dependent Variable:	Sales	Sales Growth (t-1,t)	COGS Growth (t-1, t)	Log(Empl)
	(1)	(2)	(3)	(4)
Q5 * I(Initially Allowed)	0.04950**	0.02351***	0.02212***	-0.03977***
	(0.02449)	(0.00882)	(0.00839)	(0.01506)
(1-Q5)* I(Initially Allowed)	0.00378	0.01581	-0.00411	0.00431
	(0.02323)	(0.01531)	(0.01658)	(0.00621)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Examiner Art Unit FE	Yes	Yes	Yes	Yes
N.	1942	1942	1942	1962
Adjusted R^2	0.904	0.278	0.213	0.979

Notes: This table shows the results estimation of equation (2.1) for the sample of the customers of first time innovating suppliers. Estimates reflect the interaction of the dummy of patent value category ($Q5$ vs. $(1-Q5)$ estimated following Kogan et al. (2017)) and indicator of post-decision and indicator of the patent application initial allowance. All specification control for firm, examiner art unit and year fixed effects. Column (1) outcome variable is firm's total sales, measured as ratio of firm's total sales at t to assets at $(t-1)$; column (2) and (3) outcome variables are sales and COGS growth relative to the previous year, respectively; column (4) outcome variable is logarithm of employment. Standard errors are presented in parentheses and clustered by examiner art unit and filing year by initial decision year. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 2.5: Customer Sales and COGS Growth Dynamics

Panel A:	Customer Sales Growth in				
	t-1	t	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)
Q5 * I(Initially Allowed)	0.00820	0.01666**	0.02351***	0.01077	0.00943
	(0.01863)	(0.00818)	(0.00882)	(0.01137)	(0.00719)
(1-Q5)* I(Initially Allowed)	0.00644	0.01581	0.00099	-0.00348	-0.00744
	(0.00801)	(0.01531)	(0.00479)	(0.00570)	(0.00496)
N.	1914	1942	1916	1867	1826
Adjusted R^2	0.234	0.278	0.238	0.223	0.190
Panel B:	Customer COGS Growth in				
	t-1	t	t+1	t+2	t+3
	(6)	(7)	(8)	(9)	(10)
Q5 * I(Initially Allowed)	0.01460	0.02212***	0.00952	0.01248*	0.00403
	(0.01389)	(0.00839)	(0.00912)	(0.00729)	(0.00642)
(1-Q5)* I(Initially Allowed)	-0.00344	-0.00411	0.00803	-0.00688	-0.00499
	(0.01756)	(0.01658)	(0.00754)	(0.00707)	(0.00984)
N	1914	1942	1916	1867	1826
Adjusted R^2	0.164	0.213	0.243	0.185	0.198
Panel C:	Customer Log(Employment)				
	t-1	t	t+1	t+2	t+3
	(6)	(7)	(8)	(9)	(10)
Q5 * I(Initially Allowed)	-0.05271	-0.05313**	-0.03977***	-0.04765***	-0.04735**
	(0.03442)	(0.02634)	(0.01506)	(0.01743)	(0.01877)
(1-Q5)* I(Initially Allowed)	-0.00781	0.00008	0.00431	0.00026	-0.00256
	(0.00917)	(0.00751)	(0.00621)	(0.00736)	(0.00712)
N	1930	1962	1926	1879	1842
Adjusted R^2	0.978	0.979	0.975	0.968	0.967

Notes: This table shows the results estimation of equation (2.1) for the sample of the customers of first time innovating suppliers for each year from $t-1$ to $t+3$ relative to the initial decision year. Estimates reflect the interaction of the dummy of patent value category ($Q5$ vs. $(1-Q5)$ estimated following Kogan et al. (2017)) and indicator of post-decision and indicator of the patent application initial allowance. All specification control for firm, examiner art unit and year fixed effects. Panel A outcome variable is firm's total sales growth, measured as growth relative to the previous year of firm's total sales to previous year assets ratio; Panel B outcome variables is COGS growth relative to the previous year; Panel C outcome variable is logarithm of employment. Standard errors are presented in parentheses and clustered by examiner art unit and filing year by initial decision year. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 2.6: Horizontal Propagation – Relates Suppliers' Outcomes

Dependent Variable:	Sales	Sales Growth (t-1,t)	COGS Growth (t-1, t)	Log(Empl)
	(1)	(2)	(3)	(4)
Q5 * I(Initially Allowed)	0.06239***	-0.68237***	-0.51719***	0.03497***
	(0.00957)	(0.18117)	(0.16906)	(0.00609)
(1-Q5)* I(Initially Allowed)	0.01900*	-0.26625	-0.10164	0.00528
	(0.00993)	(0.18551)	(0.08559)	(0.00544)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Examiner Art Unit FE	Yes	Yes	Yes	Yes
N.	141154	141144	141140	145638
Adjusted R^2	0.627	0.061	0.058	0.970

Notes: This table shows the results estimation of equation (2.1) for the sample of other suppliers of customers of first time innovating suppliers. Estimates reflect the interaction of the dummy of patent value category ($Q5$ vs. $(1-Q5)$ estimated following Kogan et al. (2017)) and indicator of post-decision and indicator of the patent application initial allowance. All specification control for firm, examiner art unit and year fixed effects. Column (1) outcome variable is firm's total sales, measured as ratio of firm's total sales at t to assets at $(t-1)$; column (2) and (3) outcome variables are sales and COGS growth relative to the previous year, respectively; column (4) outcome variable is logarithm of employment. Standard errors are presented in parentheses and clustered by examiner art unit and filing year by initial decision year. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Chapter 3

R&D Tax Credits, Innovation Search Strategy, and Unintended Outcomes

3.1 Introduction

Because unwanted knowledge spillovers make it difficult for firms to appropriate the full value of investment in innovation, several policy measures, most notably research and development (R&D) tax credits, aim to increase corporate R&D spending (Arrow, 1962; OECD, 2014; Becker, 2015; Bloom, Van Reenen, and Williams, 2019). Much work has established that this intent usually succeeds. While early empirical studies provided relatively pessimistic estimations of the impact of tax credits on spending (Altshuler, 1988), more recent research has fairly reliably returned elasticities around unity or higher (Hall, 1993; Hall and van Reenen, 2000; Bloom, Griffith, and Van Reenen, 2002; Dechezleprêtre, Einiö, Martin, Nguyen, and van Reenen, 2016). Hence, there is a consensus that a dollar in lost tax revenue results in approximately a dollar of increased R&D spending.

The question raised by Hall (1993) remains pertinent, however, "...of whether this R&D spending truly reflects increased spending of the sort envisioned by Congress (research and experimentation in the laboratory or technological sense), or merely a relabeling of related expenses as research, and an increase in such expenses as new-product-related market research, etc." Policy makers assumedly prefer research and experimentation as such efforts generate greater positive externalities, typically in the form of knowledge spillovers from new technologies and breakthroughs. Despite this intent, however, it remains unclear precisely how tax credits influence search and how any such changes in search affect positive and negative externalities. Incompletely answered questions include 1) do firms use tax credits to research and experiment with new and novel technologies or simply refine extant approaches, 2) how much private value is created by the treated firms, 3) whether tax credits encourage new market entry or mainly fund development of extant product lines, and 4) how these credits impact competitors' value creation and the possibility of negative externalities such as those due to strategic patenting and blocking of competitors' innovation streams.

To better understand the mechanisms by which R&D tax credits influence innovation strategies and outcomes as well as the impact of credits on industry peers, this study first develops a simple two-period model of R&D investment based on Manso (2011) in which firms choose between exploring a new area of technology vs. exploiting a known area. Exploration is more likely to fail in period one; however, firms gain a better estimate of the likelihood of success in period two. When firms choose in the presence of a tax credit, they are more likely to choose exploitation, because tax credits become less attractive in the absence of success and profits (Hall, 2019). We find consistent supporting evidence for these predictions from matched estimates from the case of California as a quasi-natural experiment as well as subsequent policy changes in other states.

We then elaborate empirically on the strategic and industrial implications of this shift in search strategy. Firms appear to generate large private returns as measured by stock market reactions (Kogan et al., 2017) and rising markups (De Loecker, Eeckhout, and Unger, 2020). This increase in private value comes mainly from an increased focus on the exploitation of the firm's existing technological trajectories; most of the increase in patenting is concentrated in technological areas known to the firm, and firms appear less likely to enter new markets. We further observe increased blockings of patent applications at the European Patent Office (Lück, Balsmeier, Seliger, and Fleming, 2019), caused by patents filed from California firms following the introduction of tax credits. Consistent with this increase in blockings of others' applications, we find that after the tax change, stock prices react negatively to patents filed by other firms in the same industry – if those patents are similar or "close" in the technology space. The total value of competitors is still positively affected by the change in tax credits, but this is largely driven by industry peers that operate far away in technology space, presumably because those firms can incorporate the innovation into technology streams (Hegde, Herkenhoff, and Zhu, 2019) which do not directly compete with the generating stream. These findings suggest that much of the private value generation comes from getting further ahead of competitors that were technologically close and imply that there exist unintended side effects of R&D tax credits on close technological competitors. R&D tax credits outside of California did not fall on similarly fertile ground. Consistent with the argument that California's tax credit provided a one-time advantage to its firms, we find consistent but weaker and not always significant effects in states that introduced tax credits later.

3.2 Literature Review

Accurate assessment of the impact and foregone opportunities of tax credits presents many challenges (Hall, 1993); as a result, most empirical work has compared incremental investment to lost taxes. The Hall and van Reenen (2000) literature survey reports that tax credits typically demonstrate an elasticity around or greater than one, with some time lag presumably due to firms' adjustment costs (e.g. employment). More recent work has estimated similar long-run elasticities in a sample of OECD economies (Bloom et al., 2002). Bronzini and Iachini (2014) use a regression discontinuity design, finding that an Italian program had a significant impact on small firms. Dechezleprêtre et al. (2016) estimate a much larger elasticity of 2.6. Pless (2019) confirms this result, additionally showing that tax credits and subsidies are complements for smaller firms and substitutes for larger firms and that small firms are more likely to invest in product, rather than process, innovations.

Recent work has begun to estimate the impact of R&D tax credits on other innovation outcomes. David, Hall, and Toole (2000) literature survey finds mixed results and subsequent work has not converged. Czarnitzki, Hanel, and Rosa (2011a) use a matched survey of Canadian manufacturers and report increased product innovation, however, Cappelen, Raknerud, and Rybalka (2012) find that Norwegian tax credits are associated with new processes but not with new products or patents. Bérubé and Mohnen (2009) report positive effects of R&D tax credits on R&D spending outside the U.S. but somewhat weaker evidence in terms of patenting. Closest to our work, Dechezleprêtre et al. (2016) use a change in the eligibility criteria for R&D tax subsidies in the UK in 2009 to demonstrate a relatively large increase in R&D spending, moderate increases in patenting, and modest increases in future prior art cites to those patents. They identify private value creation (as measured by patents) and positive externalities (as measured by future prior citations) by exploiting an asset-based size threshold and a regression discontinuity design. Additional work has argued that tax credits may allocate spending inefficiently, due to redistributions of R&D spending from affected to unaffected regions (Wilson, 2009).

3.3 Why and How R&D Tax Credits Might Impact Value Creation and Capture

The theoretical motivation for R&D tax credits emerged from Arrow (1962); firms cannot bear the entire risk of invention and are unlikely to succeed in appropriating all the benefits, and this remains especially true for basic research and knowledge production, which are arguably the most valuable investments to society. The emphasis on basic research rests on the argument that it generates the most valuable positive externalities to other inventors, mainly through knowledge spillovers and diffusion (Nelson, 1959; Griliches, 1992; Hall, 1996; Mohnen, 1996; Hall and Wosinska, 1999). Policy makers hope that lower R&D costs induce firms to conduct basic research, search for novel technologies, and discover breakthroughs – some of which will be taken up by other firms, including competitors. The expected spillovers justify the subsidies.

Several scholars have pointed out, however, that we should expect firms to use tax credits to maximize the private returns to their R&D investment (Hall, 1993; Hall and van Reenen, 2000; Bloom, Van Reenen, and Williams, 2019). This might not necessarily imply investments in or outputs of fundamental knowledge, novelty, and spillovers. This exploration of new technologies has been referred to in other research as “external effort” (Akcigit and Kerr, 2018) or “horizontal innovation” (Pless, 2019) and shown to provide approximately

80% of economic growth (Akcigit and Kerr, 2018).

Realistically, we would only expect fundamental research in new technologies if firms cannot generate higher returns per R&D dollar by exploiting extant technologies. In contrast to other mechanisms intended to generate positive externalities such as scientific funding schemes, R&D tax credits are explicitly intended to avoid discriminating between types of inventions in order to keep costs of administration low[1]. Firms also need to generate a profit to take advantage of the tax credit; for small and young firms – often thought to be the most innovative, often explicitly founded to develop a specific breakthrough – this may be particularly difficult. Finally, there is no rule that requires firms to share the new knowledge generated through tax credit money with other firms. Instead, firms are incentivized to limit spillovers and exclude others from using their inventions – for example, by patenting defensively and strategically, with the intent to block others from following in their technological wake. To inform these intuitions, we incorporate tax credits into a classic model of innovative search (March, 1991; Manso, 2011).

3.4 The Base Model

We assume a two-period model (Manso (2011) shows that the fundamental logic and results hold for longer periods and team production). In each period, a firm decides to invest in either a exploitation (well-known) or a exploration (novel) research strategy. Investing in exploitation has a known probability p of success (S) and $1-p$ of failure (F), with $S > F$. Exploration has an unknown probability q of success (S) and $1-q$ of failure (F). The only way to learn about q is by exploring. The expected probability of success when exploring is $\mathbb{E}[q]$ when the investment is made for the first time, $\mathbb{E}[q|S]$ after experiencing a success with exploration, and $\mathbb{E}[q|F]$ after experiencing a failure with exploring. From Bayes' rule follows: $\mathbb{E}[q|F] < \mathbb{E}[q] < \mathbb{E}[q|S]$.

Exploration requires that the firm experiments. Hence, it is initially not likely to succeed when it explores. Exploration may still be perceived as more beneficial than exploitation because after the first period, the firm updates its beliefs about the probability q of success with exploration, meaning that if the firm succeeds in finding something interesting in the first period, exploration is then perceived as better than exploitation. This is captured as follows:

$$\mathbb{E}[q] < p < \mathbb{E}[q|S]$$

Following Manso (2011), we assume risk-neutrality and a discount factor of δ and compare the expected payoffs of two action plans. The first relevant action plan requires exploitation in both periods, as there is no chance to learn about something new if a firm sticks to its

[1]Some R&D tax credit designs were meant to avoid funding of incremental inventions by limiting the tax credit to R&D increases beyond prior threshold levels, i.e. only big increases of R&D would be subsidized. However, there was no rule saying that increases of R&D expenditures actually needed to be directed towards radical inventions.

own knitting. This gives the payoff $\pi(exploit)$:

$$pS + (1-p)F + \delta(pS + (1-p)F)$$

The other relevant action plan, exploration, is to experiment in the first period and continue exploring only if success occurs. This action plan gives the payoff $\pi(explore)$:

$$\mathbb{E}[q]S + (1-\mathbb{E}[q])F + \delta(\mathbb{E}[q](\mathbb{E}[q|S]S + (1-\mathbb{E}[q|S])F) + (1-\mathbb{E}[q])(pS + (1-p)F))$$

It follows that the total payoff from exploration is higher than the total payoff from exploitation if:

$$\mathbb{E}[q] \geq \frac{p}{(1+\delta(\mathbb{E}[q|S]-p)}$$

3.4.1 Adding R&D Tax Credits

We now introduce R&D tax credits into the model. Tax credits allow firms to deduct a fraction tr of their R&D expenses from their taxable income. Given tr, firm profit in each period is given by $(1+f(tr, R\&D))S$ in case of success and zero in case of failure because the firm makes no profits, i.e. no taxable income from which R&D expenses could be deducted. Implications of the model remain the same if we allow firms to achieve a positive result after failure as long as there is a risk of generating a lower amount of taxable income than the total amount spend on R&D. If firms know for certain that they will generate taxable income larger than their R&D expenses in all periods, the model reduces to the baseline result, so it would predict no change in the direction of research. Reflecting that the monetary payback from R&D tax credits increases in the nominal tax credit rate but not necessarily at a proportional rate, we assume f is monotonically increasing in tr. The payoff $\pi(exploit)$ becomes:

$$p(1+f(tr, R\&D))S + (1-p)F + \delta(p(1+f(tr, R\&D))S + (1-p)F)$$

The payoff $\pi(explore)$ becomes:

$$\begin{aligned}\mathbb{E}[q](1+f(tr, R\&D))S + (1-\mathbb{E}[q])F + \delta(\mathbb{E}[q](\mathbb{E}[q|S](1+f(tr, R\&D))S + (1-\mathbb{E}[q|S])F) \\ + (1-\mathbb{E}[q])(p(1+f(tr, R\&D))S + (1-p)F)\end{aligned}$$

It follows that the total payoff from exploration is higher than the total payoff from exploitation if:

$$\mathbb{E}[q] \geq \frac{1+f(tr, R\&D)}{1+f(tr, R\&D) + \delta(\mathbb{E}[q|S] - p(1+f(tr, R\&D)))}p \tag{3.1}$$

Proposition 1: *Firms that can claim R&D tax credits are more likely to pursue exploitation search strategies.*

Motivation: The coefficient multiplying p on the right-hand side of equation (3.1) is increasing in $f(tr, R\&D)$. Since $(tr, R\&D)$ is monotonically increasing in tr, the firm is more prone to exploit when R&D tax credits are offered. ■

The intuition is that R&D tax credits make experimenting and exploration more costly relative to exploitation because it increases the likelihood that R&D costs can either not be expensed or expensed only later at a discounted rate. That exploration may yield higher returns than exploitation does not matter since the size of the monetary returns from governmental tax credits are determined by R&D inputs only.

While we cannot directly observe R&D managers' investment choices between exploration and exploitation, we can observe R&D outcomes through the types of inventions that a firm patents. After confirming prior findings of an increase in R&D spending and patenting following the introduction of credits, we test the model's predictions with patent-based measures of exploitation and exploration (Balsmeier, Fleming, and Manso, 2017a).

3.5 Data

3.5.1 Patents and Firm-Level Data

The empirical analysis is based on all public US based firms that field at least one patent in a given year between 1977 through 2006. Using this sample as a baseline we supplement it with patent (Balsmeier, Li, Chesebro, Zang, Fierro, Johnson, Kaulagi, Lück, O'Reagan, Yeh, and Fleming, 2017b), PATSTAT (de Rassenfosse, Dernis, and Boedt, 2014), market (Kogan et al., 2017), and Compustat data. Measures are aggregated to the firm level of analysis based on the application year of a patent. Due to the need for patent-based measures, the sample comprises only firms that applied for at least one patent over the whole sample period (as such, the results may not generalize to firms without patentable innovations; in unreported regressions, however, we find qualitatively comparable results if we include all non-patenting firms as well, often with larger marginal effects). Models that rely on changes in state tax law further limit the sample to firms with U.S. state level headquarter location information. In order to limit selection in and out of the sample, we require firms to be observed at least 2 times (results remain robust to keeping only firms that can be observed more than 10 years, implying that the effect is not driven by firm entry). Table 3.1 provides summary statistics; see section B.1 for variable definitions.

3.5.2 R&D Tax Credits

Between 1980 and 2006, 32 U.S. states introduced R&D tax credits. Following arguments from Lerner and Seru (2017), we focus on the case of California before broadening the analysis to other states. First, California firms constitute the largest part of the patenting activity within the country with private R&D playing a crucial role in their widely acknowledged extraordinary growth, and tax credits have been under-appreciated as a potentially important fuel for that growth. Second, treated firms in different states and times are often not comparable in terms of how the credit interacts with other tax laws, which expenses actually qualify for the credit, which firms fulfill the eligibility criteria, the firms' pre-treatment technological portfolio, and the potential for knowledge spillovers to other firms and states. Due to these interactions, estimating an average treatment using R&D tax credits across all states and time periods remains problematic (see Lerner and Seru (2017) for examples of unrevealed heterogeneous impacts of state law changes on innovation in the recent literature)[2]. Third, the composition of the treated as well as the untreated firms changes greatly over time such that it is difficult to define a common control group that suits each state's R&D tax credit introduction. Fourth, the California R&D tax credit was one of the first significant provisions and not of temporary nature, while especially in later years, firms outside California may have anticipated further changes in R&D tax credit provisions such that the estimated effects might be confounded (Rao, 2016). These arguments notwithstanding, we illustrate qualitatively similar though quantitatively weaker effects in Appendix B.1 for the effects of subsequent tax credits in states other than California.

The nominal R&D tax credit introduced by California on 1987 was initially 8% before it was raised to 11% in 1998. To identify the impact of California's policy change, we restrict the sample to 10 years before and 10 years after the tax credit introduction and take all firms situated in states that had not introduced any R&D tax credit in the sampling period as the control group. Thus, we also avoid the confounder of California's introduction of an alternative incremental R&D tax credit in 1998. Further, we remove firms that were only active before or only after the tax credit introduction to limit potential influences from self-selection into or out of the sample. All models are estimated and consistent for full and coarsened exact matching (CEM) matched samples.

The effective R&D tax credit rate differs sometimes from the nominal rate because of the interplay of R&D tax credits with other investment and federal taxes[3]. In the main part of our study, we focus on the effective rate because it is the source of exogenous variation that drives the actual R&D costs of the affected firms. We deviate slightly in this respect from the past literature, which took the user costs of R&D as their main explanatory variable. This variable takes alternative investment opportunities and interest rates into account, as introduced by Hall and Jorgenson (1969). While this should reflect actual R&D user costs more accurately, it could incorporate calculations that are predictable by firms, such as interest rates, thereby creating endogeneity concerns (Bloom et al., 2002). However, by focusing on the effective rates and effect of the exact timing of the R&D tax credit introduction, we base our identification only on variation that is actually caused by policy change (not interest rates or other extant corporate taxes)[4]. This reduces potential endogeneity biases and al-

[2]We also observe heterogeneous impacts of R&D tax credit introductions across states and time, as further discussed below.

[3]The details are explained in Wilson (2009), or specifically for California in Hall and Wosinska (1999). The results are qualitatively the same if we take the nominal rate instead of the effective rate as shown in the Appendix B.2.

[4]Alternatively, we estimated all models using just the nominal rate and found qualitatively similar results, see Appendix B.2.

lows us to more accurately relate our findings to the actual introduction of R&D tax credits. For easier comparisons with the literature, we provide estimations based on the user costs of R&D calculated according to Hall and Jorgenson (1969) in the Appendix B.3. We also show results based on alternative R&D tax credit rate calculations that exploit the distribution of inventors across states within the same firm (Bloom, Schankerman, and Van Reenen, 2013). This approach is arguably the least likely to be confounded by endogeneity (Babina and Howell, 2018) and reveals similar results (see Appendix B.3 for details).

3.5.3 Empirical Methodology

Following the literature, we estimate variations of the following specification using OLS:

$$Y_{it} = \alpha_0 + \beta \cdot R\&D\,Tax\,Rate_{it-3} + \delta_t + f_i + \epsilon_{it} \tag{3.2}$$

where Y stands for our various patent-based measures introduced above, $R\&D\,Tax\,Rate$ is the effective R&D tax credit rate three years before Y is observed, δ denotes a full set of year fixed effects to control for varying macroeconomic conditions, f controls for time-invariant unobserved firm and state characteristics that may confound our identification of β, and ϵ_{it} is the error term. Results remain consistent with alternative specifications with further firm level controls.

To explore potential adjustments of firms to R&D tax credit provision over time (Hall, 1993), we alternatively estimate a more flexible version where we allow the marginal effects of the R&D tax credit introduction to vary over time. Instead of the R&D tax credit rate in (3.2), we include dummy variables for each of the 5 years before and 10 years after the policy change and leave the rest of the specification unchanged. The coefficients of $\beta_{-5,\ldots,-1}$ serve as a placebo test for whether firms may have expected changes in R&D tax credits or systemically differ from firms situated in non-affected states before the treatment.

$$Y_{it} = \alpha_0 + \sum_{\tau=-5}^{10} \beta_\tau \cdot t_{i\tau} + \delta_t + f_i + \epsilon_{it} \tag{3.3}$$

While much of the empirical literature on tax credits (and innovation in general) relies on patent data, it is worth acknowledging the data's shortcomings. In this particular context, for example, we assume that the outcomes of all firm R&D investments can be observed, i.e., all R&D results in a patent or are not kept as trade secrets. Lessening these concerns, results strengthen when all firms, and not just patenting firms, are included.

3.5.4 Evidence for Model Predictions

Our basic model proposes that firms that can claim R&D tax credits will shift their innovation strategies towards exploitation. Before testing this prediction, we confirm prior results in the tax credit literature. Since increases in R&D may need some time to be reflected in patent applications, we regress these measures on the effective R&D tax credit rate in $t-3$ (see corresponding graphs of a more flexible model in Appendix B.1). Dependent variables are all taken as $log(Y+1)$. Table 3.2 shows the results for the effective tax credit rate and a) R&D expenditure and b) total number of patents applied for in year t, before and after matching.

The results in Table 3.2 model (a) show that a one percentage point increase in R&D tax credits leads, on average, to an increase of R&D expenditures of about 4.5 percent three years after its introduction. The effect size is almost twice as large as estimated in other studies, which reflects the difference in the main explanatory variable which is here the effective tax rate while in most prior studies it is the user costs; alternatively it may reflect a particularly effective policy change in California. Estimates for the full sample, as used in previous studies, reveal estimates of around 2 percent, closer to prior studies. The number of patents increases by about 3.6 percent.

Figure 3.1 illustrates the yearly trends of the full model (3.3), revealing how the impact changed over time. Consistent with prior studies, we find an increasing impact over time. Given that we seek evidence of a shift in search strategy, and because firms increase their overall rate of patenting following the credit, we estimate proportional measures in Table 3.3. In other words, tax credits appear to increase the amount of patenting by firms; however, given that increase, does the firm shift towards exploitation? Model (a) regresses the proportion of a firm's patents in a given year that are classified in a technology class that is new to the firm, as observed from a lack of prior patenting by the firm in that technology class. It estimates a shift towards known technologies. Model (b) regresses the proportion of patents without at least one self-citation to the firm's prior patents (self-citation indicates that the firm is building directly upon previously patented technology). It also indicates a shift towards exploitation. Model (c) considers the distribution of the firm's patents in a given year, compared to the firm's extant patent portfolio, which is measured as the technology class-based overlap held by the same firm up to $t-1$ and the patents applied in t (Fitzgerald, Balsmeier, Fleming, and Manso, 2019). Again, it indicates a consistent shift toward known technologies.

These proportional measure results support the argument that tax credits precede a shift in patent outcomes from new to the firm technologies towards known technologies. Because tax credits increase the absolute amount of patenting, the absolute numbers of new technology patents in some cases does increase – however, we consistently observed a decrease in the proportion of exploration patents. Consistent with a model that requires profits in order to take a tax credit, it appears that credits cause innovation search strategies to shift in favor of known technologies.

3.6 Empirical Implications of a Change in Search Strategy

Having established a baseline model of how tax credits influence search strategy, we now investigate the product and competitive implications of a shift in innovation search strategy in favor of previously known technologies. Here we show a suite of consistent outcomes, including an increased valuation, markups, defensive and strategic patenting, and decreased entry into new markets. Overall, the tax credits appear to increase the valuation of firms in the same industry. However, we also demonstrate negative externalities by illustrating a decrease in valuation of technologically close competitors.

3.6.1 An Increase in Firm Valuation

Firms which took advantage of the tax credit experienced increased stock market valuation in subsequent years. Table 3.4 estimates a variety of models based on stock market reaction to patent issuance (Kogan et al., 2017). The panels in Figure 3.2 illustrate similar outcomes over time. Most of the value increase correlates with patenting in known technologies. We offer approximations of the value of these credits to California firms without making restrictive assumptions. Given the average portfolio value of $165.55 million US dollars (in dollar values of 1982), this implies an absolute return of $7.97 million current US dollar per one percentage point increase in R&D tax credit per firm, which implies $109.2 million per California firm and $37.7 billion in total for all California firms in the sample. The amount may be underestimated as we only take publicly listed patenting firms into account that were active before and after the tax introduction. Potential further positive impacts from additional firms that joined California because of the R&D tax credit or positive spillovers to other firms might lead to higher estimations. At the same time, credits may also have caused negative externalities through strategic patenting business stealing, which will be analyzed in further detail below.

3.6.2 An Increase in Blocking, Strategic Patents, and Mark-ups

Here we investigate mechanisms that may have contributed to the increase in firm valuation, for firms that took the tax credit. First, we modeled the number of future inventions that are "blocked" by treated firms' patents (for a detailed exposition of the data and measure, please see Lück et al. (2019)). The idea is loosely opposite that of a prior art citation – rather than indicating a positive knowledge spillover, a blocking citation prevents a future patent from issuing because it invalidates the novelty claim of the future patent.

We define a blocked patent as a denied EPO patent application that refers to a given US patent as a X or Y-type of prior art (X applies when the a single document invalidates the novelty of the application, Y applies when the document in combination with another document invalidates the application). Results are robust to counting all X and Y citations (Czarnitzki, Hussinger, and Leten, 2011b). Table 3.4 model illustrates a positive and significant correlation between tax credits and future blockings.

Table 3.5 shows consistently positive and significant results for the number of strategic patents and treated firms' markups (De Loecker and Warzynski, 2012; De Loecker, Eeckhout, and Unger, 2020). We define a strategic patent as falling into the top 50% of the stock market value reaction in a given year but receiving no future prior art citation (Kurakina, 2020). We estimate the treated firms' markups, defined as prices over marginal costs (please see Appendix B.4 for details). Figure 3.3 illustrates blocked and strategic patents over time.

Tax credits appear to discourage subsequent innovation in an area and to precede higher margins. The results of Table 3.5 and Figure 3.3 suggest that firms used R&D tax credits at least partly to gain advantage over competitors in known technological trajectories rather than to search for novel technologies or invent breakthroughs. (Please note that models with proportional variables have not been estimated yet for these outcomes).

3.6.3 An Decrease in New Market Entry

Perhaps surprisingly, firms which took advantage of tax credits were less likely to subsequently enter new markets. To establish this empirically, we use the Compustat Historical Segment files, which offer information on each firm's sales generated across industries at the SIC 3-digit level. Based on these data, we calculated the amount of sales generated in industries where the same firm had not generated any sales beforehand, and the number of industries entered, measured as the number of distinct industries, where the focal firm had not generated any sales beforehand. We use information in $t + 3$, or 6 years after tax credit introduction, to allow for a sufficient time lag between investment into new product development, patenting of new technologies and the actual introduction of new products to the market. Table 3.6 illustrates how R&D tax credits do not appear to encourage firms to enter new markets, as indicated by the number of new industries entered and sales generated in those industries. Table 3.7 illustrates similar results for the proportional measures (the results hold, even if the increased number of patents is taken into account).

This analysis also partly addresses concerns that our results are only valid for patenting firms while others may have actually invested in explorative research to enter new markets but did not patent their inventions. Even if they had not patented their inventions, we would expect to see increases in markets new to the firm if firms invested in novel products.

3.6.4 Spillovers and Competitive Effects

One of the central arguments to justify R&D tax credits are knowledge spillovers to other firms, yet spillovers are notoriously hard to measure. One common approach is to count future cites from other firm's patents. The main downside of this approach is that future cites are not only capturing positive knowledge spillovers but also potential business stealing effects, especially when they come from competing firms' patents (Bloom et al., 2013). Further, potentially competing firms that do not enter technological areas of the focal firm or leave that area in response to the tax credit remain undetected. Those firms would typically enter the group of non-citing firms and are thus implicitly assumed unaffected. Negative externalities are therefore hard to detect and easy to miss with future cites, creating potential upward bias in assessing the externalities of tax credits.

To overcome this issue, we extend the approach of Kogan et al. (2017). Instead of measuring the private value of a patent via stock market reactions of the focal firm, we measure – with a very similar technique – the reactions of competing firms' stock prices. In contrast to Kogan et al. (2017), we allow stock market reactions to be negative in order to capture positive as well as negative externalities of patents. These negative externalities could, for instance, arise from business stealing or from blocking competitors from entering technological areas of the focal firm.

We estimate the economic value of the focal firm's patent to its competitors within the same 3-digit SIC industry as the patenting firm. For each firm within the same industry as the focal firm, we follow Kogan et al. (2017) and compute the value of innovations based on the information on the firms' stock price reaction around the date of the patent grant obtained from CRSP dataset. The estimate of economic value of the patent of firm j to the competing firm i (ξ_{ij}), is constructed as the product of the market capitalization of firm i (M_i), measured at $t = -1$, where $t = 0$ is the date of the announcement of firm j's patent grant, and an estimate of the stock return of firm i (the competitor) related to j's patent issue ($\mathbb{E}[v_{ij}|R_i]$). We further adjust this measure by the number of patents granted to firm j (N_j) on day t and the unconditional probability of success of a patent application $\bar{\pi}$ (56% according to Carley, Hegde, and Marco (2015)).

$$\xi_{ij} = (1-\bar{\pi})^{-1}\frac{1}{N_j}\mathbb{E}[v_{ij}|R_i]M_i \tag{3.4}$$

The patent related cumulative expected stock return of the competing firm $\mathbb{E}[v_{ij}|R_i]$ is calculated using the three day event window $(0, +2)$ around the date of firm j patent announcement assuming the normal distribution of the value of the patent v_{ij}. We deviate from Kogan et al. (2017) by not truncating at zero to allow negative reactions. Due to potential blockings and business stealing effects, it is less plausible that the value of a focal firm's patent for competitors is a strictly positive random variable. The final sample consists of 189,383 firm-event dates (event defined as the issue of the patent by the focal firm) from 1977 to 1997 with an average of 73 industry peers per firm per date.

As expected and illustrated in Figure 3.4, most firms' stock prices do not react or react very little when the market learns about competing firms' granted patents. On average, positive and negative reactions cancel out, including some impressive outliers. Part of those reactions may reflect noise, which works against us in finding significant results in our regression analysis. To analyze the value externalities of California's tax credit introduction, we calculate the average reaction of all competing firms' stocks to every granted patent that the focal firm applied for in a given year. We then calculate the average reaction per year and focal firm. In the case of the competing firm got a patent granted at the same day as the focal firm, we treat those cases as missing values as it is impossible to decompose the stock market movement into reaction due to the focal or competing firm patent issue.

The average potentially masks significant heterogeneity though. Positive knowledge spillovers might be more likely to occur when competing firms are active in the same technology space as the focal firm and less likely to occur the further away competing firms are in technology space. On the other hand, if patents are mainly used to exploit extant technologies and to shield the focal firm from additional competition, it might be the firms that are close in technology space that are negatively affected. To test which conjecture holds, we follow Bloom et al. (2013) and Jaffe (1989) in calculating for each competing and focal firm the pair-wise technological proximity based on the distribution of patents across technology classes per firm. In particular, we employ the following variant of the Jaffe (1989) technological proximity measure to estimate similarity in technological space of firm i's patents and its competing firm j's patents using patent counts per USPTO three-digit technology classes k:

$$Technological\ Proximity_{\ i,j} = \frac{\sum_{k=1}^{K} f_{i,k} f_{j,k}}{(\sum_{k=1}^{K} f_{i,k}^2)^{1/2} (\sum_{k=1}^{K} f_{j,k}^2)^{1/2}} \tag{3.5}$$

where $f_{i,k}$ is the fraction of patents granted to firm i that are in technology class k such that the vector $f_{i,k}$ locates the firm's patenting activity in K-dimensional technology space[5]. $Technological\ Proximity_{\ i,j}$ is basically the cosine angle between both vectors and will be zero for a given firm year when there is no overlap of patents' technology classes compared to competing firm's technology classes, and $Technological\ Proximity_{\ i,j}$ will equal one when the distribution of firm i's patents is identical to patents accumulated by firm j. Bloom et al. (2013) study and discuss alternative measures of technological similarity in detail but find little differences in their results.

We then calculate the total and average stock market reactions separately only for competing firms (same 3-digit SIC) that have a technological proximity score above 0.9 (0.8,. . . ,0.5) and below 0.5 (0.4,. . . , 0.1). All variables are windsorized at the 1% and 99% level to restrict the influence of outliers on the estimates.

The results of Table 3.8 show that the overall impact on competitor value is positive (column a). The aggregation masks differences across the technological proximity with the focal firm. Competitors that are close in technology space experience negative externalities on their stock prices, pointing to business stealing effects or effective strategic patenting of the focal firm. The overall positive impact is driven by competing firms that are in the middle of the technological proximity distribution. Those firms are presumably not too directly competing to be negatively affected but still close enough to have the absorptive capacity to profit from the knowledge production of the focal firm.

[5]Results are robust to taking all prior patents applied by given firm into account, changing the threshold value from 5 to 10 years, and applying a 15% depreciation rate to a firm's past patent stock per technology class when calculating the innovative search measure.

3.7 Matching and Robustness

In order to address concerns that differences between California firms and firms in the control group might confound our estimations, we re-estimate all models presented above based on a sample of California and other firms that are comparable in observable firm characteristics and industry composition.

Before matching, California firms are on average significantly more R&D intensive, being younger and smaller compared to the average firm outside of California. California firms are also overrepresented in the manufacturing sector and underrepresented in the transportation and construction sector. If R&D tax credits are more (or less) effective for firms with those characteristics or in certain sectors, our previous estimates might not be representative for the average effects of R&D tax credits on those outcomes.

To balance the sample with regard to the aforementioned characteristics, we use Coarsened Exact Matching (CEM). CEM has the advantage over classic matching procedures, such as propensity score matching, to balance across the entire distribution of observables, which improves causal inference (for details and comparison see Iacus, King, and Porro (2012, 2019) and King and Nielsen (2019)). The matching procedure identifies for each California firm the most similar firm in in the control group. To maximize similarity at time of treatment, we match on firms' average R&D intensity, age, and size in 1987 and 1986 plus firms' industry affiliation. The CEM algorithm identified matches for 405 out of 419 California firms. We re-estimate all models presented above based on the matched sample. For brevity, we only present the estimated coefficients for the effective R&D tax credit rate (see Tables 3.9 through 3.12). The results provide basically the same picture as estimated previously but often with slightly lower marginal effects (not statistically different) and a higher fraction of explained within firm variance, which supports the usefulness of the matching procedure.

Over the last few decades, many states have followed California by introducing their own R&D tax credit schemes with varying effective rates. Despite the methodological problems discussed above, we re-estimated all models including all states that introduced R&D tax credits over the period of 1980 to 2006. The results are shown in the Appendix B.1. In the full sample, we still find large private returns as measured by increased patenting and private value creation. The marginal effects are most often significantly lower, though, and there is only weak evidence for positive knowledge spillovers as measured by future cites while the increased focus on known technologies and increased blockings and markups remain[6].

[6]The reasons for the differences in effects are not easy to disentangle. Time seems to play a role as we find lower effects in terms of significance and economic magnitude the more we move to the later years of the sample, which can be explained by a lower relative advantage of havening R&D tax credits when many technology intensive firms were already situated in states that had tax credits in place. Another explanation, as we discuss above, is measurement error due to interaction with other reforms which would bias our results in the full sample towards zero.

3.8 Discussion

Negative externalities of tax credits including blocking, strategic patenting, and negative impacts on competitors have been largely neglected in the broader literature on the impact of different kinds of R&D subsidies (see for example: Howell (2017); Bøler, Moxnes, and Ulltveit-Moe (2015); Moretti and Reenen (2015); Le and Jaffe (2017); Azoulay, Zivin, Li, and Sampat (2019); Lach (2002); Branstetter and Sakakibara (2002)). This might have occurred due to missing data or because classic theory (Arrow, 1962) did not consider the interplay between the unconditional provision of R&D subsidies and the patent system[7]. Hall (1993), Hall and van Reenen (2000), and Hall (2019) emphasize that when firms face lower costs of R&D, they will maximize their private returns rather than the social benefits to their innovative efforts. Our evidence confirms that expectation. It further highlights that R&D tax credits can encourage strategic (miss-)use of the patent system. Increased blockings and increased markups point to unintended consequences of R&D tax credit provision. The introduction of R&D tax credits in 28 U.S. states over the 1980s and 1990s may have contributed to the exceptionally large increase of markups over the same period (De Loecker, Eeckhout, and Unger, 2020). This finding is crucial because revenue-based productivity gains due to R&D subsidies found earlier (Einiö, 2014) have to be viewed in a different light if they are driven by increased market power and markups rather than innovation that enables new products or increased efficiency of the production process.

This finding could warrant a reconsideration of Arrow's original theory. Classically it is argued that firms underinvest in R&D because they are afraid of knowledge leakage to competitors, which reduces the appropriability of the returns to innovation. If R&D tax credits would – as intended – solve that problem, this implies larger knowledge spillovers. The missing evidence on significant direct knowledge spillovers as measured by patent citations – although R&D spending increases – suggests that firms either did not patent useful knowledge in the first place, or that patents are quite effective in limiting follow-on innovation (Galasso and Schankerman, 2015). We provide evidence for the former explanation but cannot rule out that the latter might play an important role as well. Regardless of which explanation actually holds, it calls for a reconsideration of the idea to combine unconditional R&D tax credit provision with a patent system that intends to solve (and may in some cases have already solved) the same appropriability problem.

Others who explicitly incorporate costs or negative externalities of R&D subsidy schemes in their analyses consider costs stemming from the time and effort spent on the application processes, the shadow costs of public funds (Takalo, Tanayama, and Toivanen, 2013a,b, 2017), windfall gains (González, Jaumandreu, and Pazó, 2005), or negative externalities on entry (Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018). These studies do not consider, however, the interplay of tax credits with the patent system, which allows firms to use tax credits for strategic purposes, potentially raising rivals' costs (Salop and Scheffman, 1983; Shleifer

[7]That patents can inhibit competition has been shown by Cockburn and MacGarvie (2011).

and Vishny, 1989) or stealing business from competitors (Bloom et al., 2013)[8]. Neglecting this interplay between tax credits and the patent system leads to potential overestimations of social benefits, at least in industries where patents are effective in solving the appropriability problem and are often used to harm competitors. Relatedly, Acemoglu, Robinson, and Verdier (2017) show that subsidizing incumbents can be harmful for economic growth. Consistent with their model, the negative side effects (blockings, strategic patents, and markups) that we find are entirely driven by large firms.

Though we have not investigated whether new to the firm technologies are more likely to spill over, these results and other recent work suggest that is probably the case. While our theory and measures are different, our results are consistent with recent work (Akcigit and Kerr, 2018) and (Pless, 2019) that finds evidence that large firms are more likely to invest in refinement and process innovation, particularly in the presence of tax credits. Future work should investigate the knowledge diffusion of different types of inventions.

This research remains too immature to support strong policy prescriptions. Hall and van Reenen (2000) show that many countries provide R&D support for small and medium-sized companies. Future work should investigate whether the blocking and markup effects are solely driven by relatively large incumbent firms or whether they are a concern for small and medium-sized firms as well. Given the large values found here, it also may be that tax credits by themselves can generate enough private value to justify themselves – spillovers may be less important.

3.9 Conclusion

R&D tax credits are intended to raise private investment in innovation because firms are thought to be unlikely to fully appropriate the returns to their investment and because investment in fundamental research and knowledge production is thought to generate desirable externalities for the larger economy. While prior work has established that tax credits indeed increase R&D investment, the mechanisms by which the increased R&D spending affect the firm and the larger economy remain less clear. Focusing on California's 1987 tax change as the cleanest experiment, this paper finds that patenting increased valuation for treated firms, through seemingly not through research and experimentation but through their refinement of known technologies. Treated firms also patented more defensively and strategically, with the effect of blocking further development of promising areas. These results held up to Coarsened Exact Matching (CEM).

Methodologically, this research exploited new measures that enabled a more detailed and nuanced understanding of how tax credits influence the nature of innovation and knowledge spillovers. The work applies recent results from an event study of patent grant and stock prices in order to quantify the private value of particular patents, at least on publicly traded

[8]If the patent system or intellectual property rights (IPR) are very effective, it can be shown that IPRs can be too strong from social planner's view (Acemoglu and Akcigit, 2012), and R&D tax incentives will rarely be helpful in such cases.

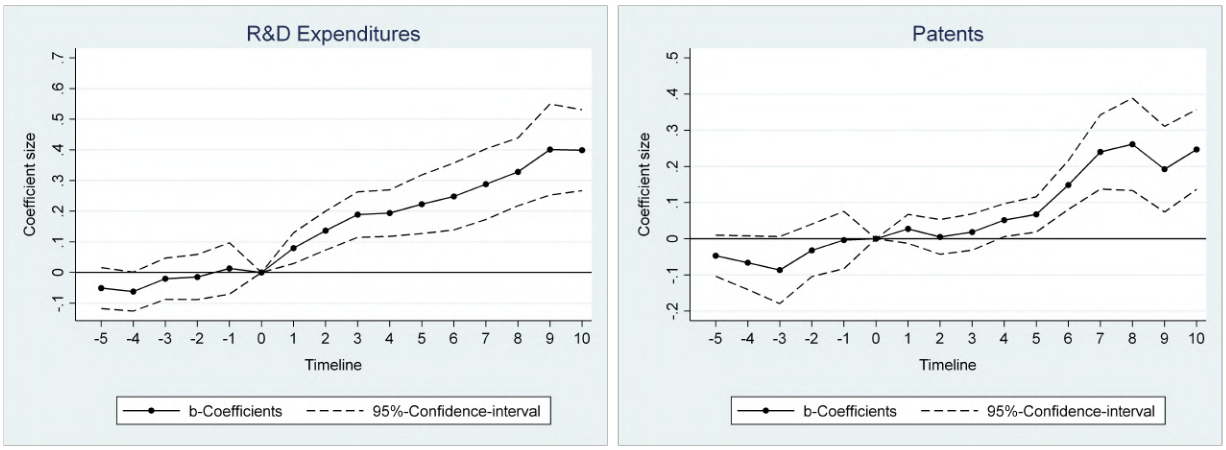
firms (Kogan et al., 2017). It integrates European patent data that enables us to estimate whether a particular patent blocks future patenting in an area and offers a new measure that highlights financially valuable but poorly cited patents.

The research also offered a simple model to motivate the empirics, based on the need to generate profits in order to take the credit. This model could be extended, for example, is it really the case that higher losses do not reduce taxes? Losses can be carried forward up to 20 years and 1 year backward, i.e., does the result still hold when discounted future tax savings are taken into account? One can also build an argument based on uncertainty/variance of profits. Uncertainty is arguably higher for exploration, and tax credits are not applicable when losses occur. They don't generate higher payoffs for unexpectedly high returns as well since they are based on R&D inputs, not profits generated from innovation.

Following Lerner and Seru (2017), this work sought to understand the impact and mechanisms of one tax credit in detail (Hall and Wosinska, 1999) before broadening the analysis and considering a number of later tax credit changes. It found that the benefits of tax credits for other states were qualitatively similar to California, although the effects were quantitatively smaller. It appears that California firms exploited a huge benefit in getting ahead of their out-of-state competitors. If that is correct, then Silicon Valley's success becomes easier to understand and more difficult to replicate.

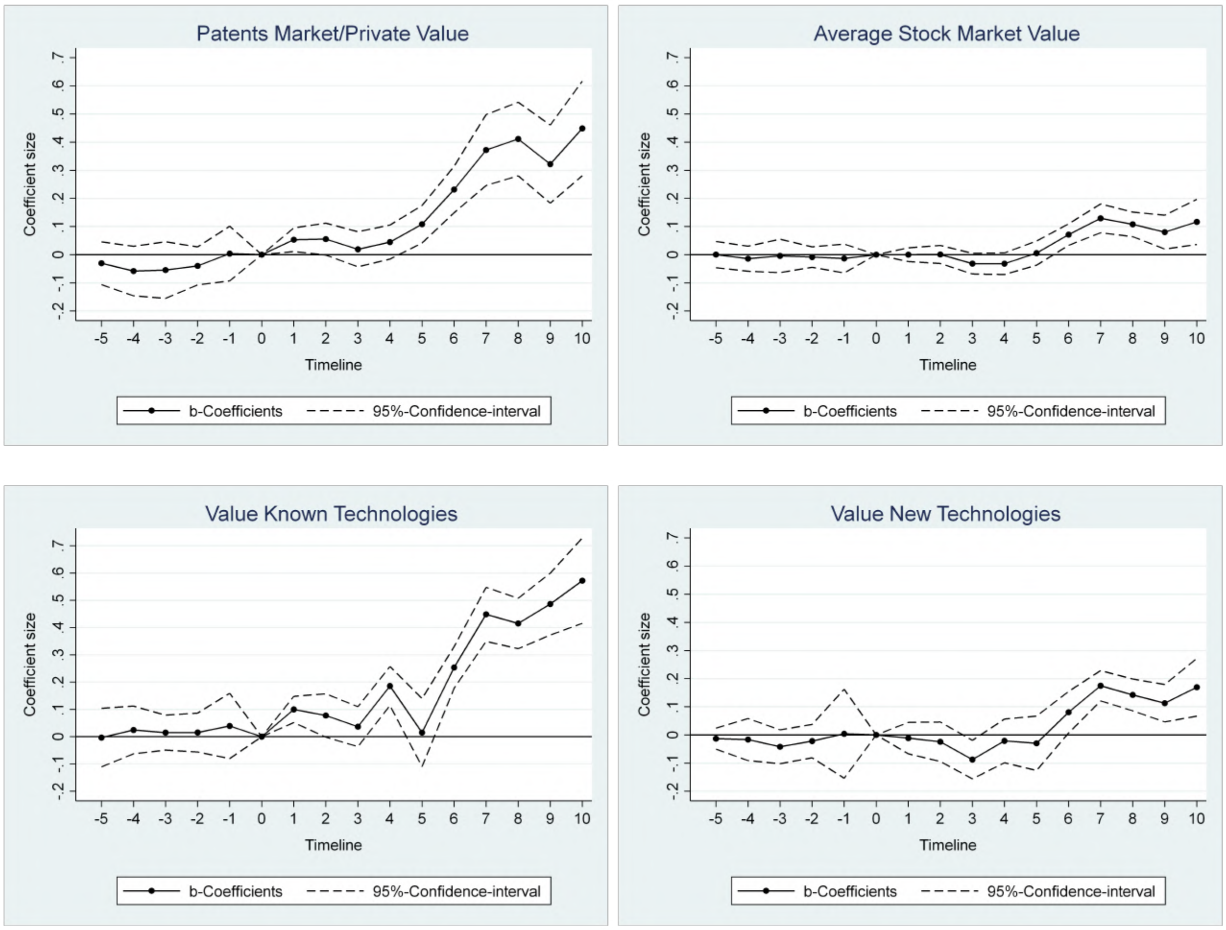
3.10 Figures and Tables

Figure 3.1: Yearly Impact of the California Tax Credit of 1987



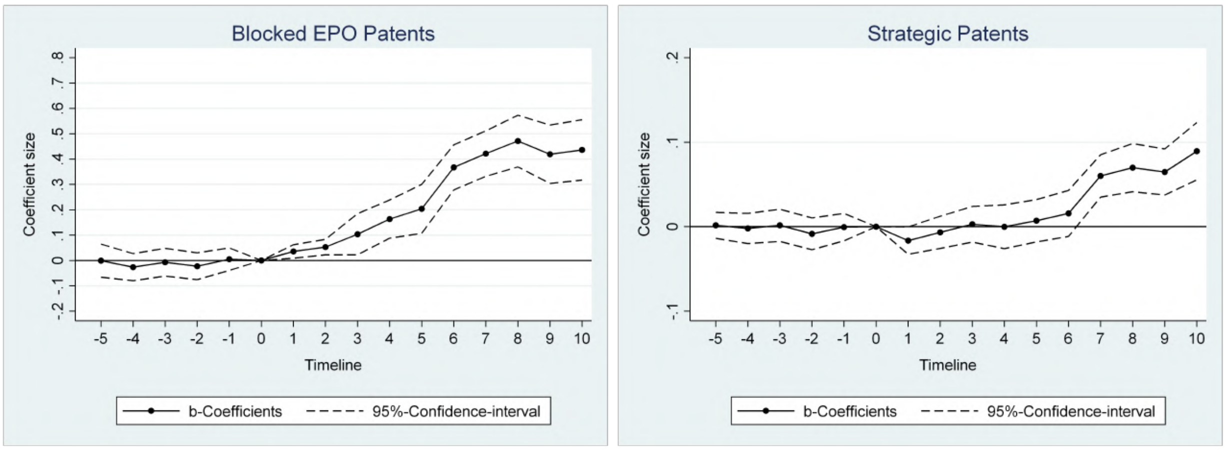
Notes: The figures plot the coefficients β_τ from regression (3.3), where the dependent variables are R&D expenditures and total number of patents applied for in year t, respectively. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Figure 3.2: The Impact of R&D Tax Credits on Stock Market Value over Time



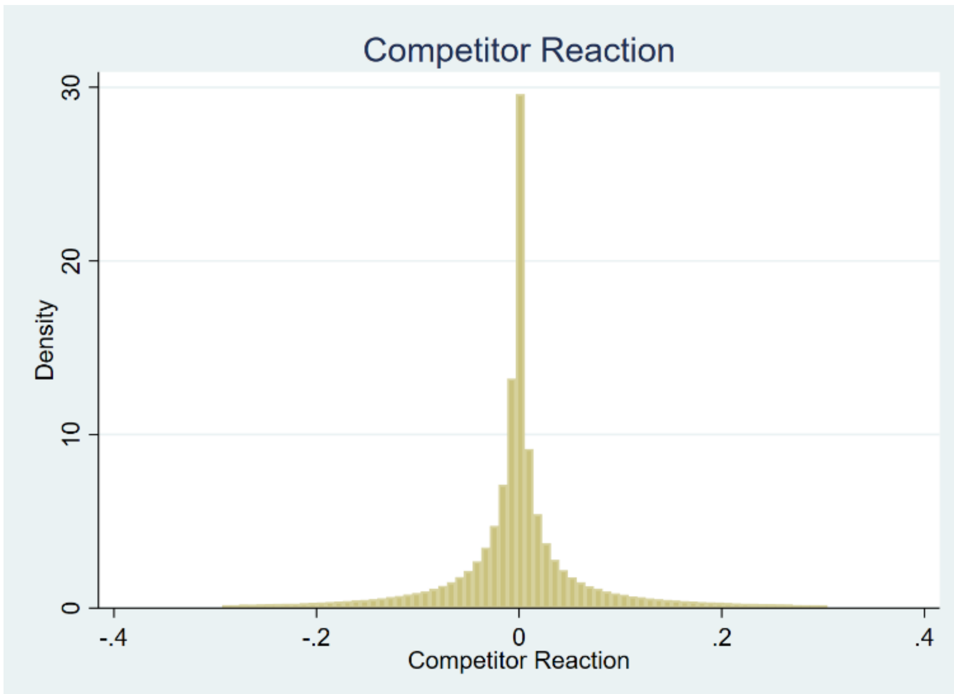
Notes: The figures plot the coefficients β_τ from regression (3.3), where the dependent variables are as in Table 3.4: (a) total private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents; (b) private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents; (c) total stock market response to patents filed within the previously known 3-digit technological class (i.e. the firm has filed beforehand in that class); (d) total stock market response to patents filed within the new 3-digit technological class (the firm has never filed beforehand in that class). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Figure 3.3: Changes in the Number of Blocked European Patents and of Strategic Patents for California Firms Following the 1987 Tax Credit



Notes: The figures plot the coefficients β_τ from regression (**??**), where the dependent variables are as in Table 3.5: (a) Blocked EPO Patents is the total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report); (b) Strategic Patents is the total number of patents that fall into the top 10% of the stock market value reactions in a given year but not into the top 10% of future citations. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Figure 3.4: Histogram of Stock Market Reactions to Industry Peers (3-digit SIC Industry) Patent Grants



Notes: The figure plots the histogram of stock market reaction of firm's competitors to the news of the patent grant as measured by equation (3.4) following Kogan et al. (2017). In contrast to Kogan et al. (2017), to account for both positive and potentially negative effect competitors' reaction to patent news, we do not impose the positive truncation assumption on the value of the stock market response related patent news, ν. Competitors are defined as firms operating within the same SIC 3-digit industry as the focal firm. Reactions of lowest and highest 5% of distribution are not included.

Table 3.1: Summary Statistics (1977 – 1997, California Plus Control States)

Variable	N	Mean	Median	SD	Min	Max
Eff. R&D Tax Credit %	22257	0.73	0	2.20	0	10.03
R&D	22257	0.25	0	1.86	0	56.72
Patents	22257	10.28	0	62.74	0	3630
Future Cites	22257	201.08	0	1514.92	0	95373
Average Future Cites	22257	9.01	0	80.52	0	11247
Patents Known Tech	22257	9.20	0	61.42	0	3611
Patents New Tech	22257	1.08	0	2.64	0	61
Backward Cites	22257	2830.56	0	47324.71	0	4807832
Backward Self-Cites	22257	310.81	0	3465.56	0	174906
Stock Market Value	22257	174.71	0	1883.02	0	126274.2
SM Value New Tech	22257	7.20	0	72.49	0	3469.29
SM Value Known Tech	22257	148.78	0	1775.47	0	124154.3
% Value New Tech	6210	50.10	40.92	40.54	0	100
Blocked EPO Patents	22257	4.61	0	43.07	0	2762
Strategic Patents	22257	1.36	0	12.13	0	515
Sales New to the Firm	20225	40.79	0	572.68	0	46226
New Industries Entered	20225	0.11	0	0.39	0	6

Notes: The table reports summary statistics of the variables used in the study. Eff. R&D Tax Credit is the effective R&D tax credit that firms could maximally receive as calculated by Wilson (2009). The nominal rate was 8% since 1987. Patents is the total number of eventually granted patents applied for in a given year. Future Cites is the total number of future cites collected by patents applied in year t. Average Future Cites is the average number of future cites collected by patents applied in year t. Stock Market Value is the total private value of patents applied in year t, measured as the sum of all market reactions to publications of these patents (data from Kogan et al. (2017)). Patents New Tech is the number of patents that are filed in a 3-digit technology classes where the given firm has never filed beforehand in that class (note that this measures new to the firm technologies and not necessarily new to the world technologies). Patents Known Tech is the number of patents that are filed in a 3-digit technology classes where the given firm has filed beforehand in that class. SM Value Known Tech is the total private value of patents filed in a 3-digit technology class where the given firm has filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. SM Value New Tech is the total private value of patents filed in a 3-digit technology classes where the given firm has not filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. % Value New Tech is the proportion of the latter two variables in percent. Backward Cites is the total number of backward cites made by patents applied in year t. Backward Self-Cites is the total number of self-backward cites made by patents applied in year t. Blocked EPO Patents is the total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report). Strategic patents is the total number of patents that fall into the top 10% of the stock market value reactions in a given year but not into the top 10% of future citations. Sales New to the Firm are sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand in that industry, measured in $t+3$. New Industries Entered is the total number of SIC 3-digit industries where the given firm has never generated sales beforehand in that industry, measured in $t+3$.

Table 3.2: The Impact of R&D Tax Credits on R&D and Patenting

	a	b	c	d
	R&D	Patents	R&D	Patents
	Original sample		After matching	
R&D tax credit rate$_{t\text{-}3}$	3.817***	3.943***	2.968***	3.817***
	(0.477)	(0.335)	(0.581)	(0.480)
N	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.306	0.091	0.066	0.029

Notes: The table reports the effect of R&D tax credits on firm's R&D expenditures and total number of patents applied for in year t using original and matched samples. R&D tax credit is measured as effective R&D tax credit rate at $t-3$ following Wilson (2009). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.3: The Impact of R&D Tax Credits on Novel Technologies

	a	b	c
	New class	No self-citations	Internal search proximity
R&D tax credit rate$_{t\text{-}3}$	-1.226***	-0.1000***	-1.184***
	(0.164)	(0.028)	(0.159)
N	9411	9376	7061
Firm fixed effects	Yes	Yes	Yes
R^2	0.412	0.446	0.498

Notes: The table reports the effect of R&D tax credits on firm's innovation search strategy, measured using: (a) proportion of firm's patens in year t in a new to the firm technological class; (b) proportion of patents without self-citations (citations to firm's prior patents); (c) technology class-based overlap in the firm's patent portfolio held up to $t-1$ and patents applied in t following Fitzgerald et al. (2019). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.4: Impact of the California Tax Credit of 1987 on Financial Value as Measured by Stock Market Impact – Exploitative vs. Explorative Patents

	a	b	c	d	e
	Stock market reaction (KPSS total)	Stock market reaction (KPSS average)	Stock market reaction only patents in known classes	Stock market reaction only patents in new classes	Fraction of value coming from new to firm patents
R&D tax credit rate$_{t\text{-}3}$	5.662***	1.979***	5.490***	2.577***	-1.635***
	(0.553)	(0.344)	(0.607)	(0.272)	(0.195)
N	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.100	0.029	0.030	0.064	0.045

Notes: The table reports the effect of R&D tax credits on the economic value of firm's innovation measured by the stock market reaction to the patent publication news following Kogan et al. (2017). R&D tax credit is measured as effective R&D tax credit rate at $t-3$ following Wilson (2009). The dependent variable is: (a) total private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents; (b) private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents; (c) total stock market response to patents filed within the previously known 3-digit technological class (i.e. the firm has filed beforehand in that class); (d) total stock market response to patents filed within the new 3-digit technological class (the firm has never filed beforehand in that class); (e) fraction of value coming from new to firm patents measured as the ratio of the dependent variable in (d) to (a). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.5: The Impact of R&D Tax Credits on Blockings, Strategic Patents and Markups

	a	b	c
	Blocked EPO patents	Strategic patents	Markup
R&D	0.058***	0.022***	-0.019
	(0.018)	(0.005)	(0.057)
log(age)	-0.854***	-0.031	-0.026
	(0.059)	(0.024)	(0.026)
log(total assets)	0.226***	0.074***	0.066**
	(0.030)	(0.016)	(0.024)
R&D tax credit rate $_{t\text{-}3}$	5.651***	0.920***	0.552**
	(0.497)	(0.148)	(0.213)
N	22257	22257	22033
Firm fixed effects	Yes	Yes	Yes
R^2	0.314	0.028	0.009

Notes: The table reports the effect of R&D tax credits on patent blocking, strategic patenting and firm's markups. R&D tax credit is measured as effective R&D tax credit rate at $t-3$ following Wilson (2009). Blocked EPO Patents is the total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report). Strategic patents is the total number of patents that fall into the top 10% of the stock market value reactions in a given year but not into the top 10% of future citations. Markups are defined as prices over marginal costs following De Loecker et al. (2020). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.6: The Impact of R&D Tax Credits on Sales in New to the Firm Markets

	a	b
	Sales in new to the firm industries in t+3	New industries entered in t+3
R&D	0.007	-0.006*
	(0.009)	(0.003)
log(age)	0.063	0.002
	(0.053)	(0.009)
log(total assets)	0.043**	-0.001
	(0.016)	(0.004)
R&D tax credit rate $_{t\text{-}3}$	-1.021**	-0.143**
	(0.408)	(0.064)
N	20225	20225
Firm fixed effects	Yes	Yes
R^2	0.033	0.035

Notes: The table reports the effect of R&D tax credits on firm's entry into the new market as measured using numbers of new industries entered and sales generated in those industries. Sales New to the Firm are sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t + 3$. New Industries Entered is the total number of SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t + 3$. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.7: The Impact of R&D Tax Credits on Sales in New to the Firm Markets, with Proportion of New to the Firm Patents as a Predictor

	(a)	(b)	(c)	(d)
	Sales in new to the firm industries in *t*+3 (share)	New industries entered in *t*+3 (share)	Sales in new to the firm industries in *t*+3 (share)	New industries entered in *t*+3 (share)
R&D tax credit rate$_{t-3}$	-0.789*	-0.143**	-1.118**	-0.212***
	(0.438)	(0.063)	(0.527)	(0.074)
N	20215	20215	11343	11343
Increase in # patents control	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.148	0.134	0.149	0.142

Notes: The table reports the effect of R&D tax credits on firm's entry into the new market as measured using proportional measures of new industries entered and sales generated in those industries (expressed as shares to the total sales at $t+3$ and total number of industries the firm operates in at $t+3$, respectively). Sales New to the Firm are sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t+3$. New Industries Entered is the total number of SIC 3-digit industries where the given firm has never generated sales beforehand, measured in t+3. Compared to (a) and (b), columns (c) and (d) additionally control for the number of new patents issued by the firm. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.8: The Impact of R&D Tax Credits on Competitors' Stock Value Within the Same 3-digit SIC Industry

	a	b	c	d	e	f	g	h	j	k	l
	All competitors	tech prox > 0.9	0.9≥tech prox>0.8	0.8≥tech prox > 0.7	0.7≥tech prox > 0.6	0.6≥tech prox > 0.5	0.5≥tech prox>0.4	0.4≥tech prox > 0.4	0.3≥tech prox > 0.2	0.2≥tech prox > 0.1	tech prox≤ 0.1
R&D	0.196	0.012	-0.018	-0.010	0.002	0.008	0.239	0.197	0.188	0.210	0.139
	(0.162)	(0.007)	(0.049)	(0.059)	(0.059)	-0.07	(0.154)	(0.160)	(0.168)	(0.130)	(0.124)
log(age)	-0.453	-0.008	-0.055	-0.022	-0.274	-0.214	-0.053	-0.097	-0.030	-0.002	0.006
	(0.962)	(0.022)	(0.107)	(0.239)	(0.270)	-0.309	(0.754)	(0.736)	(0.647)	(0.538)	(0.371)
log(total assets)	0.373	0.011*	0.018	0.034	0.083	0.123*	0.368*	0.358*	0.296*	0.202	0.109
	(0.275)	(0.006)	(0.015)	(0.045)	(0.057)	-0.06	(0.204)	(0.179)	(0.162)	(0.138)	(0.100)
R&D tax credit rate$_{t-3}$	18.861***	-0.531***	-0.809**	0.238	4.873***	7.429***	10.871***	8.650**	8.157***	3.626	-2.538
	(4.910)	(0.145)	(0.362)	(0.800)	(0.956)	-0.992	(3.549)	(3.520)	(2.794)	(2.347)	(2.223)
N	22257	22257	22257	22257	22257	22257	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.063	0.094	0.077	0.062	0.074	0.076	0.055	0.054	0.057	0.054	0.057

Notes: The table reports the effect of R&D tax credits on the sum of all competitors (3-digit SIC) stock market reactions to a focal firm's patents applied for in a given year. Columns (a) to (f) is only competitors that have a technological proximity measure with the focal firm that is larger than $0.9, \ldots, 0.5$. Columns (g) to (l) is only competitors that have a technological proximity measure with the focal firm that is smaller than $0.5, \ldots, 0.1$. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.9: The Impact of R&D Tax Credits on Patents, Cites, and Stock Market Value (Matched Sample)

	a	b	c	d	e	f
	R&D	Patents	Future cites	Av. future cites	Value	Average value
R&D tax credit rate$_{t\text{-}3}$	2.808***	3.158***	4.762***	1.474*	4.637***	1.351**
	(0.611)	(0.379)	(0.832)	(0.761)	(0.702)	(0.492)
N	12590	12590	12590	12590	12590	12590
Firm fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.425	0.126	0.087	0.039	0.192	0.138

Notes: The table reports the effect of R&D tax credits on firm's R&D expenditures, total number of patents applied for in year t, citations and economic value of innovation using matched samples. R&D tax credit is measured as effective R&D tax credit rate at $t-3$ following Wilson (2009). (Average) Future Cites is the (average) total number of future cites collected by patents applied for in year t. Value is the total private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents following Kogan et al. (2017). Average value is the average market reaction to publications of firm's patents applied in year t following Kogan et al. (2017). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.10: The Impact of R&D Tax Credits on Patents in New vs. Known to the Firm Technologies (Matched Sample)

	a	b	c	d	e	f
	Patents known	Patents new	New classes	Value known	Value new	Fraction value new
R&D tax credit rate$_{t-3}$	3.440***	1.002***	0.931***	4.938***	1.862***	-4.632***
	(0.355)	(0.223)	(0.203)	(0.565)	(0.425)	(0.892)
N	12590	12590	12590	12590	12590	3662
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.141	0.035	0.037	0.097	0.067	0.230

Notes: The table reports the effect of R&D tax credits on firm's patenting activity within the known and new to the firm technological classes using matched sample. Patents Known is the number of patents that are filed in a 3-digit technology classes where the given firm has filed beforehand in that class. Patents New is the number of patents that are filed in a 3-digit technology classes where the given firm has never filed beforehand in that class (note that this measures new to the firm technologies and not necessarily new to the world technologies). New classes is the number of 3-digit technology classes where the given firm has never filed beforehand in that class. Value Known is the total private value of patents filed in a 3-digit technology class where the given firm has filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Value New is the total private value of patents filed in a 3-digit technology classes where the given firm has not filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Fraction Value New is the proportion of the latter two variables in percent. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.11: The Impact of R&D Tax Credits on Backward Citations (Matched Sample)

	a	b
	Back cites	Back self-cites
R&D tax credit rate $_{t\text{-}3}$	6.053***	6.220***
	(1.379)	(1.065)
N	12590	12590
Firm fixed effects	Yes	Yes
R^2	0.112	0.153

Notes: The table reports the effect of R&D tax credits on firm's total number of backward cites and total number of backward self-cites made by patents applied for in year t using matched sample. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table 3.12: The Impact of R&D Tax Credits on Sales in New to the Firm Markets (Matched Sample)

	a	b
	Sales in new to the firm industries in *t*+3	New industries entered in *t*+3
R&D tax credit rate $_{t\text{-}3}$	-1.157**	-0.205**
	(0.408)	(0.064)
N	11351	11351
Firm fixed effects	Yes	Yes
R^2	0.041	0.044

Notes: The table reports the effect of R&D tax credits on firm's entry into the new market as measured using numbers of new industries entered and sales generated in those industries using matched sample. Sales New to the Firm are sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t+3$. New Industries Entered is the total number of SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t+3$. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Bibliography

Abrams, David S., Ufuk Akcigit, and Jillian Grennan, 2013, Patent Value and Citations: Creative Destruction or Strategic Disruption?, NBER Working Papers 19647, National Bureau of Economic Research, Inc.

Acemoglu, Daron, and Ufuk Akcigit, 2012, Intellectual property rights policy, competition and innovation, *Journal of the European Economic Association* 10, 1–42.

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr, 2018, Innovation, Reallocation, and Growth, *American Economic Review* 108, 3450–91.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2012, The Network Origins of Aggregate Fluctuations, *Econometrica* 80, 1977–2016.

Acemoglu, Daron, James A. Robinson, and Thierry Verdier, 2017, Asymmetric Growth and Institutions in an Interdependent World, *Journal of Political Economy* 125, 1245–1305.

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, 2015, Identification Properties of Recent Production Function Estimators, *Econometrica* 83, 2411–2451.

Aghion, Philippe, Ufuk Akcigit, and Peter Howitt, 2014, What Do We Learn From Schumpeterian Growth Theory?, in *Handbook of Economic Growth*, volume 2 of *Handbook of Economic Growth*, chapter 0, 515–563 (Elsevier).

Aghion, Philippe, Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005, Competition and Innovation: an Inverted-U Relationship, *The Quarterly Journal of Economics* 120, 701–728.

Akcigit, Ufuk, and William R. Kerr, 2018, Growth through Heterogeneous Innovations, *Journal of Political Economy* 126, 1374–1443.

Altshuler, Rosanne, 1988, A Dynamic Analysis of the Research and Experimentation Credit, *National Tax Journal* 41, 453–466.

Angrist, Joshua D., 1998, Estimating the Labor Market Impact of Voluntary Military Service Using Social Security Data on Military Applicants, *Econometrica* 66, 249–288.

Arrow, Kenneth, 1962, Economic Welfare and the Allocation of Resources for Invention, in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, NBER Chapters, 609–626 (National Bureau of Economic Research, Inc).

Atalay, Enghin, 2017, How Important Are Sectoral Shocks?, *American Economic Journal: Macroeconomics* 9, 254–80.

Austin, David H., 1993, An Event-Study Approach to Measuring Innovative Output: The Case of Biotechnology, *The American Economic Review* 83, 253–258.

Austin, David H., 2000, Patents, Spillovers, and Competition in Biotechnology, Technical report.

Azoulay, Pierre, Joshua S Graff Zivin, Danielle Li, and Bhaven N Sampat, 2019, Public R&D Investments and Private-sector Patenting: Evidence from NIH Funding Rules, *Review of Economic Studies* 86, 117–152.

Babina, Tania, and Sabrina T. Howell, 2018, Entrepreneurial Spillovers from Corporate R&D, Working Paper, National Bureau of Economic Research.

Balasubramanian, Natarajan, and Jagadeesh Sivadasan, 2011, What Happens When Firms Patent? New Evidence from U.S. Economic Census Data, *The Review of Economics and Statistics* 93.

Balsmeier, Benjamin, Mohamad Assaf, Tyler Chesebro, Gabe Fierro, Kevin Johnson, Scott Johnson, Guan-Cheng Li, Sonja Lück, Doug O'Reagan, Bill Yeh, Guangzheng Zang, and Lee Fleming, 2018, Machine Learning and Natural Language Processing on the Patent Corpus: Data, Tools, and New Measures, *Journal of Economics & Management Strategy* 27, 535–553.

Balsmeier, Benjamin, Lee Fleming, and Gustavo Manso, 2017a, Independent Boards and Innovation, *Journal of Financial Economics* 123, 536–557.

Balsmeier, Benjamin, Maria Kurakina, Joel Stiebale, and Lee Fleming, 2019, R&D Tax Credits, Innovation Search Stratetgy, and Unintended Outcomes, Working paper.

Balsmeier, Benjamin, Guan-Cheng Li, Tyler Chesebro, Guangzheng Zang, Gabe Fierro, Kevin Johnson, Aditya Kaulagi, Sonja Lück, Doug O'Reagan, Bill Yeh, and Lee Fleming, 2017b, Machine Learning and Natural Language Processing Applied to the Patent Corpus, *Journal of Economics and Management Strategy*, forthcoming.

Barrot, Jean-Noël, and Julien Sauvagnat, 2016, Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks, *The Quarterly Journal of Economics* 131, 1543–1592.

Becker, Bettina, 2015, Public R&D Policies and Pprivate R&D Investment: A Survey of the Empirical Evidence, *Journal of Economic Surveys* 29, 917–942.

Bérubé, Charles, and Pierre Mohnen, 2009, Are firms that receive R&D subsidies more innovative?, *Canadian Journal of Economics* 42, 206–225.

Blackwell, Matthew, Stefano Iacus, Gary King, and Giuseppe Porro, 2009, CEM: Coarsened Exact Matching in Stata, *Stata Journal* 9, 524–546.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2013, Identifying Technology Spillovers and Product Market Rivalry, *Econometrica* 81, 1347–1393.

Bloom, Nicholas, John Van Reenen, and Heidi Williams, 2019, A Toolkit of Policies to Promote Innovation, *Journal of Economic Perspectives* 33, 163–84.

Bloom, Nick, Rachel Griffith, and John Van Reenen, 2002, Do R&D Tax Credits Work? Evidence from a Panel of Countries 1979-1997, *Journal of Public Economics* 85, 1–31.

Blundell, Richard, Rachel Griffith, and John van Reenen, 1999, Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms, *Review of Economic Studies* 66, 529–554.

Bøler, Esther Ann, Andreas Moxnes, and Karen Helene Ulltveit-Moe, 2015, RD, International Sourcing, and the Joint Impact on Firm Performance, *American Economic Review* 105, 3704–39.

Branstetter, Lee G., and Mariko Sakakibara, 2002, When Do Research Consortia Work Well and Why? Evidence from Japanese Panel Data, *American Economic Review* 92, 143–159.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, 2016, How Does Hedge Fund Activism Reshape Corporate Innovation?, Working Paper 22273, National Bureau of Economic Research.

Bronzini, Raffaello, and Eleonora Iachini, 2014, Are Incentives for RD Effective? Evidence from a Regression Discontinuity Approach, *American Economic Journal: Economic Policy* 6, 100–134.

Cappelen, Ådne, Arvid Raknerud, and Marina Rybalka, 2012, The Effects of R&D Tax Credits on Patenting and Innovations, *Research Policy* 41, 334–345.

Card, David, and Daniel Sullivan, 1988, Measuring the Effect of Subsidized Training Programs on Movements in and out of Employment, *Econometrica* 56, 497–530.

Carley, Michael, Deepak Hegde, and Alan Marco, 2015, What is the Probability of Receiving a U.S. Patent? *17 Yale J.L. & Tech.*

Carvalho, Vasco, Makoto Nirei, Yukiko Saito, and Alireza Tahbaz-Salehi, 2016, Supply Chain Disruptions: Evidence from the Great East Japan Earthquake, Discussion papers, Policy Research Institute, Ministry of Finance Japan.

Chu, Yongqiang, Xuan Tian, and Wenyu Wang, 2019, Corporate Innovation Along the Supply Chain, *Management Science* 65, 2445–2466.

Cockburn, Iain, and Megan MacGarvie, 2011, Entry and Patenting in the Software Industry, *Management Science* 57, 915–933.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic Links and Predictable Returns, *The Journal of Finance* 63, 1977–2011.

Criscuolo, Paola, and Bart Verspagen, 2008, Does it Matter Where Patent Citations Come from? Inventor vs. Examiner Citations in European Patents, *Research Policy* 37, 1892–1908.

Czarnitzki, Dirk, Petr Hanel, and Julio Miguel Rosa, 2011a, Evaluating the Impact of R&D Tax Credits on Innovation: A Microeconometric Study on Canadian Firms, *Research Policy* 40, 217–229.

Czarnitzki, Dirk, Katrin Hussinger, and Bart Leten, 2011b, The Market Value of Blocking Patent Citations, Available at SSRN: https://ssrn.com/abstract=1803315.

David, Paul A., Bronwyn H. Hall, and Andrew A. Toole, 2000, Is Public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence, *Research Policy* 29, 497–529.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger, 2020, The Rise of Market Power and the Macroeconomic Implications, *The Quarterly Journal of Economics*.

De Loecker, Jan, and Paul T Scott, 2016, Estimating market power Evidence from the US Brewing Industry, Working Paper, National Bureau of Economic Research.

De Loecker, Jan, and Frederic Warzynski, 2012, Markups and Firm-Level Export Status, *American Economic Review* 102, 2437–71.

de Rassenfosse, Gaétan, Hélène Dernis, and Geert Boedt, 2014, An Introduction to the Patstat Database with Example Queries, *Australian Economic Review* 47, 395–408.

Dechezleprêtre, Antoine, Elias Einiö, Ralf Martin, Kieu-Trang Nguyen, and John van Reenen, 2016, Do Tax Incentives for Research Increase Firm Innovation? An RD Design for R&D, Cep discussion papers, Centre for Economic Performance, LSE.

Dobbie, Will, and Jae Song, 2015, Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection, *American Economic Review* 105, 1272–1311.

Doraszelski, Ulrich, and Jordi Jaumandreu, 2013, R&D and Productivity: Estimating Endogenous Productivity, *The Review of Economic Studies* 80, 1338–1383.

Dupor, Bill, 1999, Aggregation and Irrelevance in Multi-Sector Models, *Journal of Monetary Economics* 43, 391–409.

Einiö, Elias, 2014, R&D Subsidies and Company Performance: Evidence from Geographic Variation in Government Funding Based on the ERDF Population-Density Rule, *The Review of Economics and Statistics* 96, 710–728.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist, 2016, The Bright Side of Patents, Working Paper 21959, National Bureau of Economic Research.

Farrell, Joseph, and Carl Shapiro, 2008, How Strong Are Weak Patents?, *American Economic Review* 98, 1347–69.

Fitzgerald, Tristan, Benjamin Balsmeier, Lee Fleming, and Gustavo Manso, 2019, Innovation Search Strategy and Predictable Returns, Working Paper, Haas School of Business.

Forlani, Emanuele, Ralf Martin, Giordano Mion, and Mirabelle Muûls, 2016, Unraveling Firms: Demand,Productivity and Markups Heterogeneity, Working Paper Research 293, National Bank of Belgium.

Frakes, Michael D., and Melissa F. Wasserman, 2016, Procrastination in the Workplace: Evidence from the U.S. Patent Office, NBER Working Papers 22987, National Bureau of Economic Research, Inc.

Frakes, Michael D., and Melissa F. Wasserman, 2017, Is the Time Allocated to Review Patent Applications Inducing Examiners to Grant Invalid Patents? Evidence from Microlevel Application Data, *The Review of Economics and Statistics* 99, 550–563.

Galasso, Alberto, and Mark Schankerman, 2010, Patent Thickets, Courts, and the Market for Innovation, *The RAND Journal of Economics* 41, 472–503.

Galasso, Alberto, and Mark Schankerman, 2015, Patents and Cumulative Innovation: Causal Evidence from the Courts, *The Quarterly Journal of Economics* 130, 317–369.

Gallini, Nancy T., 1984, Deterrence by Market Sharing: A Strategic Incentive for Licensing, *The American Economic Review* 74, 931–941.

González, Xulia, Jordi Jaumandreu, and Consuelo Pazó, 2005, Barriers to Innovation and Subsidy Effectiveness, *The RAND Journal of Economics* 36, 930–950.

Griliches, Zvi, 1992, The Search for RD Spillovers, *The Scandinavian Journal of Economics* 94, S29–S47.

Guellec, Dominique, and Bruno van Pottelsberghe de la Potterie, 2007, *The Economics of the European Patent System* (Oxford University Press).

Hall, Bronwyn, and John van Reenen, 2000, How effective are fiscal incentives for R&D? A review of the evidence, *Research Policy* 29, 449–469.

Hall, Bronwyn H., 1993, R&D Tax Policy During the Eighties: Success or Failure?, *Tax Policy and the Economy* 7, 1–36.

Hall, Bronwyn H., 1996, The Private and Social Returns to Research and Development: What Have We Learned?, in Bruce L.R. Smith, and Claude E. Barfield, eds., *Technology, R&D, and the Economy*, 140–183 (The Brookings Institution, Washington, DC).

Hall, Bronwyn H., 2019, Tax Credits for Innovation, Working Paper, UC Berkeley.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools., NBER Working Papers 8498, National Bureau of Economic Research, Inc.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2005, Market Value and Patent Citations, *RAND Journal of Economics* 36, 16–38.

Hall, Bronwyn H., and Marta Wosinska, 1999, The California R&D Tax Credit: Description, History, and Economic Analysis, Technical report, A Report to the California Council on Science and Technology.

Hall, Bronwyn H., and Rosemarie Ham Ziedonis, 2001, The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995, *The RAND Journal of Economics* 32, 101–128.

Hall, Robert E., and Dale W. Jorgenson, 1969, Tax Policy and Investment Behavior: Reply and Further Results, *The American Economic Review* 59, 388–401.

Harhoff, Dietmar, Karin Hoisl, and Colin Webb, 2005, European Patent Citations: How to Count and how to Interpret Them, LMU Discussion Papers, Munich.

Harhoff, Dietmar, Francis Narin, F. M. Scherer, and Katrin Vopel, 1999, Citation Frequency And The Value Of Patented Inventions, *The Review of Economics and Statistics* 81, 511–515.

Harhoff, Dietmar, and Markus Reitzig, 2004, Determinants of Opposition Against EPO Patent Grants–the Case of Biotechnology and Pharmaceuticals, *International Journal of Industrial Organization* 22, 443–480.

Hegde, Deepak, Kyle Herkenhoff, and Chenqi Zhu, 2019, Patent Disclosure and Innovation, Technical report, Available at SSRN: https://ssrn.com/abstract=3158031.

Hegde, Deepak, David C. Mowery, and Stuart Graham, 2009, Pioneering Inventors or Thicket Builders: Which U.S. Firms Use Continuations in Patenting?, *Management Science* 55, 1214–1226.

Henderson, Rebecca, and Iain Cockburn, 1994, Measuring Competence? Exploring Firm Effects in Pharmaceutical Research, *Strategic Management Journal* 15, 63–84.

Hoberg, Gerard, and Gordon Phillips, 2010, Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis, *Review of Financial Studies* 23, 3773–3811.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy* 124, 1423–1465.

Horvath, Michael, 1998, Cyclicality and Sectoral Linkages: Aggregate Fluctuations from Independent Sectoral Shocks, *Review of Economic Dynamics* 1, 781–808.

Horvath, Michael, 2000, Sectoral Shocks and Aggregate Fluctuations, *Journal of Monetary Economics* 45, 69–106.

Howell, Sabrina T., 2017, Financing Innovation: Evidence from R&D Grants, *American Economic Review* 107, 1136–64.

Iacus, Stefano M., Gary King, and Giuseppe Porro, 2012, Causal Inference Without Balance Checking: Coarsened Exact Matching, *Political Analysis* 20, 1–24.

Iacus, Stefano M., Gary King, and Giuseppe Porro, 2019, A Theory of Statistical Inference for Matching Methods in Causal Research, *Political Analysis* 27, 46–68.

Im, Hyun Joong, Young Joon Park, and Janghoon Shon, 2015, Product Market Competition and the Value of Innovation: Evidence from US Patent Data, *Economics Letters* 137, 78–82.

İmrohoroğlu, Ayşe and Tüzel, Şelale, 2014, Firm-Level Productivity, Risk, and Return, *Management Science* 60, 2073–2090.

Jaffe, A. B., 1989, Characterizing the "Technological Position" of Firms, with Application to Quantifying Technological Opportunity and Research Spillovers, *Research Policy* 18, 87–97.

Jaffe, Adam B., 1986, Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value, *American Economic Review* 76, 984–1001.

Jaffe, Adam B., and Josh Lerner, 2004, *Innovation and Its Discontents: How Our Broken Patent System is Endangering Innovation and Progress, and What to do About it* (Princeton University Press).

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson, 1993, Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, *The Quarterly Journal of Economics* 108, 577–598.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, 2018, Measuring Technological Innovation over the Long Run, NBER Working Papers 25266, National Bureau of Economic Research, Inc.

King, Gary, and Richard Nielsen, 2019, Why Propensity Scores Should Not Be Used for Matching, *Political Analysis* 27.

Kline, Patrick, Neviana Petkova, Heidi Williams, and Owen Zidar, 2019, Who Profits from Patents? Rent-Sharing at Innovative Firms, *The Quarterly Journal of Economics* 134, 1343–1404.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological Innovation, Resource Allocation, and Growth, *The Quarterly Journal of Economics* 132, 665–712.

Krolikowski, Marcin, and Xiaojing Yuan, 2017, Friend or foe: Customer-supplier relationships and innovatio, *Journal of Business Research* 78, 53–68.

Kurakina, Maria, 2020, The Dark Side of Patents: Effects of Strategic Patenting on Firms and Their Peers, Working Paper, Haas School of Business.

Lach, Saul, 2002, Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel, *The Journal of Industrial Economics* 50, 369–390.

Le, Trinh, and Adam B. Jaffe, 2017, The Impact of R&D Subsidy on Innovation: Evidence from New Zealand Firms, *Economics of Innovation and New Technology* 26, 429–452.

Lerner, Josh, and Amit Seru, 2017, The Use and Misuse of Patent Data: Issues for Corporate Finance and Beyond, NBER Working Papers 24053, National Bureau of Economic Research, Inc.

Lerner, Josh, and Jean Tirole, 2002, Some Simple Economics of Open Source, *The Journal of Industrial Economics* 50, 197–234.

Lerner, Josh, and Jean Tirole, 2005, The Scope of Open Source Licensing, *Journal of Law, Economics, Organization* 21, 20–56.

Long, John B., and Charles I. Plosser, 1983, Real Business Cycles, *Journal of Political Economy* 91, 39–69.

Lück, Sonja, Benjamin Balsmeier, Florian Seliger, and Lee Fleming, 2019, Early Disclosure of Invention and Reduced Duplication; an Empirical Test. *Management Science*, forthcoming.

Malmendier, Ulrike, Enrico Moretti, and Florian Peters, 2011, Winning by Losing: Evidence on Overbidding in Mergers, Tinbergen Institute Discussion Papers 11-101/2/DSF25, Tinbergen Institute.

Manso, Gustavo, 2011, Motivating Innovation, *The Journal of Finance* 66, 1823–1860.

Manso, Gustavo, Chen Lin, and Sibo Liu, 2018, Shareholder Litigation and Corporate Innovation.

March, James G., 1991, Exploration and exploitation in organizational learning, *Organization Science* 2, 71–87.

Megna, Pamela, and Mark Klock, 1993, The Impact on Intangible Capital on Tobin's q in the Semiconductor Industry, *American Economic Review* 83, 265–69.

Miele, Anthony L., 2000, *Patent Strategy: The Manager's Guide to Profiting from Patent Portfolios* (John Wiley & Sons, Inc.).

Mohnen, P., 1996, RD Externalities and Productivity Growth, Technical report, Science-Technology Industry Review, Paris, OECD.

Moretti, Claudia Steinwender, Enrico, and John Van Reenen, 2015, The Intellectual Spoils of War? Defense R&D, Productivity and International Technology Spillovers, Working Paper.

Nelson, Richard, 1959, The Simple Economics of Basic Scientific Research, *Journal of Political Economy* 67.

Nicholas, Tom, 2008, Does Innovation Cause Stock Market Runups? Evidence from the Great Crash, *American Economic Review* 98, 1370–96.

Nicholas, Tom, 2014, Are Patents Creative or Destructive?, *Antitrust Law Journal* 79, 405–421.

Noel, Michael, and Mark Schankerman, 2013, Strategic Patenting and Software Innovation, *The Journal of Industrial Economics* 61, 481–520.

OECD, 2014, Trends in R&D Tax Generosity and Potential Loss of Predictability in Tax Regimes, 2001-11, Working Paper, OECD Science, Technology and Industry Outlook, Paris.

Ozoguz, Arzu, Michael J. Rebello, and Malcolm Wardlaw, 2018, Information, Competition, and Investment Sensitivity to Peer Stock Prices, *SMU Cox School of Business Research Paper* 18-24.

Pakes, Ariel, 1985, On Patents, R&D, and the Stock Market Rate of Return, *Journal of Political Economy* 93, 390–409.

Pakes, Ariel, 1986, Patents as Options: Some Estimates of the Value of Holding European Patent Stocks, *Econometrica* 54, 755–784.

Pless, J., 2019, Are 'Complementary Policies' Substitutes? Evidence from R&D Subsidies in the U.K., Working Paper, University of Oxford.

Rao, Nirupama, 2016, Do Tax Credits Stimulate R&D Spending? The Effect of the R&D Tax Credit in its First Decade, *Journal of Public Economics* 140, 1–12.

Rockett, Katharine E., 1990, Choosing the Competition and Patent Licensing, *The RAND Journal of Economics* 21, 161–171.

Salop, Steven C, and David T Scheffman, 1983, Raising Rivals' Costs, *American Economic Review* 73, 267–71.

Sarsons, Heather, 2017, Interpreting Signals in the Labor Market: Evidence from Medical Referrals [Job Market Paper], Working Paper.

Serrano, Carlos J., 2010, The Dynamics of the Transfer and Renewal of Patents, *The RAND Journal of Economics* 41, 686–708.

Shapiro, Carl, 2011, Competition and Innovation: Did Arrow Hit the Bull's Eye?, in *The Rate and Direction of Inventive Activity Revisited*, 361–404 (National Bureau of Economic Research, Inc).

Shleifer, Andrei, and Robert W. Vishny, 1989, Managerial Entrenchment: The Case of Manager-Specific Investments, *Journal of Financial Economics* 25, 123–139.

Takalo, Tuomas, Tanja Tanayama, and Otto Toivanen, 2013a, Estimating the Benefits of Targeted RD Subsidies, *The Review of Economics and Statistics* 95, 255–272.

Takalo, Tuomas, Tanja Tanayama, and Otto Toivanen, 2013b, Market Failures and the Additionality Effects of Public Support to Private R&D: Theory and Empirical Implications, *International Journal of Industrial Organization* 31, 634 – 642.

Takalo, Tuomas, Tanja Tanayama, and Otto Toivanen, 2017, Welfare Effects of R&D Support Policies, Cepr discussion papers, C.E.P.R. Discussion Papers.

Toivanen, Otto, and Lotta Väänänen, 2016, Education and Invention, *The Review of Economics and Statistics* 98, 382–396.

Von Graevenitz, Georg, Stefan Wagner, and Dietmar Harhoff, 2011, How to Measure Patent Thickets–A Novel Approach, *Economics Letters* 111, 6–9.

Wang, Jingqi, and Hyoduk Shin, 2012, Impact of Downstream Competition on Innovation in a Supply Chain, Available at SSRN: https://ssrn.com/abstract=2078743.

Wasi, Nada, and Aaron Flaaen, 2015, Record Linkage using Stata: Preprocessing, Linking, and Reviewing Utilities, *Stata Journal* 15, 672–697.

Williams, Ryan, and Steven Chong Xiao, 2017, The Real Effect of Stock Prices on the Supply Chain, Available at SSRN: https://ssrn.com/abstract=2528021.

Wilson, D., 2009, Beggar Thy Neighbor? The In-State, Out-of-State and Aggregate Effects of R&D Tax Credits, *The Review of Economics and Statistics* 91, 431–436.

Ziedonis, Rosemarie Ham, 2004, Don't Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms, *Management Science* 50, 804–820.

Appendix A

Chapter 2 Appendix

A.1 Variables Description

All variables are winsorized at the 5th and 95th percentiles of their distribution and presented in millions of dollars. Monetary values are expressed in 2014 dollars. Variables definitions follow Williams and Xiao (2017):

1. **R&D** – ratio of firm's R&D expenditures at t to assets at $(t-1)$.
2. **Assets** – natural logarithm of total assets.
3. **Leverage** – ratio of the sum of long term debt and debt in current liabilities to total assets.
4. **ROA** – earnings before extraordinary items at t to assets at $(t-1)$.
5. **Q** – ratio of the sum of total assets and the difference between market value and book value of total common equity to total assets.
6. **Cash Flows** – ratio of the sum of income before extraordinary items, depreciation and amortization and R&D Expenses to assets at $(t-1)$.
7. **Employment** – logarithm of firm's total employment.
8. **Sales** – ratio of firm's total sales at t to assets at $(t-1)$.
9. **COGS** – ratio of firm's costs of goods sold at t to assets at $(t-1)$.
10. **Sales Growth** – the growth in sales between t and $(t-1)$ divided by sales at $(t-1)$.
11. **Sales Volatility** – the standard deviation of the ratio of sales to totals assets over $(t-3)$ throughout $(t-1)$.
12. **COGS Growth** – the growth in COGS between t and $(t-1)$ divided by COGS at $(t-1)$.
13. **Herfindahl** – Herfindahl index of industry defined by the three digit TNIC3 code (Hoberg and Phillips, 2010, 2016).
14. **Predicted Patent Value** – economic value of the patent measured as in Kogan et al. (2017).
15. **% Patent Initially Allowed** – share of firm's patent applications that received initial allowance by the examiner (in percentages).
16. **% Granted Patents** – share of firm's patent applications that were eventually granted (in percentages).

Appendix B

Chapter 3 Appendix

B.1 Full Sample (1978-2006) Estimations

The following tables show descriptive statistics and estimations of the main specification introduced in section 1.2.2 based on the full sample, i.e. all states that introduced R&D tax credits between 1980 and 2006.

Variables Description

1. **Patents** – number of eventually granted US patents applied for in year t.
2. **Future Cites** – total number of future cites collected by patents applied for in year t.
3. **Average Future Cites** – average number of future cites collected by patents applied for in year t.
4. **(Stock Market) Value** – total private value of patents applied in year t, measured as the sum of all market reactions to publications of these patents (data from Kogan et al. (2017)).
5. **Average Value** – average private value of patents applied in year t, measured as the average market reaction to publications of these patents (data from Kogan et al. (2017)).
6. **All Competitors** – total private value (negative or positive) of patents applied in year t for a firm's competitors, measured as the sum of all competitor's market reactions to publications of these patents (data from Kogan et al. (2017)).
7. **Patents New** – number of patents that are filed in a 3-digit technology classes where the given firm has never filed beforehand in that class (note this measures new to the firm technologies and not necessarily new to the world technologies).
8. **Patents Known** – number of patents that are filed in a 3-digit technology classes where the given firm has filed beforehand in that class.
9. **New Class** – number of new technology classes entered where the given firm has never filed beforehand in that class.
10. **Stock Market Reaction only Patents in Known Classes** – total private value of patents filed in a 3-digit technology class where the given firm has filed beforehand in that class, measured as the sum of all market reactions to publications of these patents.
11. **Stock Market Reaction only Patents in New Classes** – total private value of patents filed in a 3-digit technology classes where the given firm has not filed beforehand in that class, measured as the sum of all market reactions to publications of these patents.

12. **Back Cites** – total number of backward cites made by patents applied for in year t.

13. **Back Self-Cites** – total number of backward self-cites made by patents applied for in year t.

14. **Blocked EPO Patents** – total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report)

15. **Strategic Patents** – total number of strategic patents, i.e. patents that fall into the top 50% of the stock market value reactions in a given year but receive no future citation.

16. **Sales in New to the Firm Industries in** $t + 3$ – sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand in that industry, measured in $t + 3$.

17. **New Industries Entered in** $t + 3$ – total number of SIC 3-digit industries where the given firm has never generated sales beforehand in that industry, measured in $t + 3$.

Table A1: Summary Statistics

Variable	N	Mean	Median	SD	Min	Max
R&D Tax Credit %	70839	0.03	0	0.05	0	0.2
R&D	70839	0.26	0.01	1.68	0	66.21
Patents	70839	10.93	0	77.35	0	4365
Future Cites	70839	136.81	0	1042.39	0	82639
Average Future Cites	70839	8.59	0	51.36	0	11247
Patents Known Tech	70839	9.87	0	76.27	0	4356
Patents New Tech	70839	1.06	0	2.62	0	108
Stock Market Value	70839	186.68	0	1941.98	0	126274.2
SM Value New Tech	70839	8.61	0	135.60	0	23748.81
SM Value Known Tech	70839	159.87	0	1831.94	0	124154.3
% Value New Tech	21932	48.74	37.98	40.59	0	100
Blocked EPO Patents	70839	4.27	0	37.59	0	2762
Strategic Patents	70839	0.39	0	5.52	0	528
R&D Tax Credit %	70839	0.03	0	0.05	0	0.2

Notes: The table reports summary statistics of the variables used in the study. Eff. R&D Tax Credit is the effective R&D tax credit that firms could maximally receive as calculated by Wilson (2009). The nominal rate was 8% since 1987. Patents is the total number of eventually granted patents applied for in a given year. Future Cites is the total number of future cites collected by patents applied in year t. Average Future Cites is the average number of future cites collected by patents applied in year t. Stock Market Value is the total private value of patents applied in year t, measured as the sum of all market reactions to publications of these patents (data from Kogan et al. (2017)). Patents New Tech is the number of patents that are filed in a 3-digit technology classes where the given firm has never filed beforehand in that class (note that this measures new to the firm technologies and not necessarily new to the world technologies). Patents Known Tech is the number of patents that are filed in a 3-digit technology classes where the given firm has filed beforehand in that class. SM Value Known Tech is the total private value of patents filed in a 3-digit technology class where the given firm has filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. SM Value New Tech is the total private value of patents filed in a 3-digit technology classes where the given firm has not filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. % Value New Tech is the proportion of the latter two variables in percent. Backward Cites is the total number of backward cites made by patents applied in year t. Backward Self-Cites is the total number of self-backward cites made by patents applied in year t. Blocked EPO Patents is the total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report). Strategic patents is the total number of patents that fall into the top 10% of the stock market value reactions in a given year but not into the top 10% of future citations. Sales New to the Firm are sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand in that industry, measured in t+3. New Industries Entered is the total number of SIC 3-digit industries where the given firm has never generated sales beforehand in that industry, measured in t+3.

Table A2: R&D Tax Credit Introductions 1978 to 2006

State	Year of introduction	Nominal rate	Effective rate
Minnesota	1982	2.50%	2.50%
Indiana	1985	5.00%	5.00%
Iowa	1985	6.50%	6.50%
West Virginia	1986	10.00%	10.00%
Wisconsin	1986	5.00%	4.60%
California	1987	15.00%	13.70%
Kansas	1988	6.50%	0.40%
North Dakota	1988	4.00%	4.00%
Oregon	1989	5.00%	5.00%
Illinois	1990	6.50%	0.50%
Massachusetts	1991	10.00%	10.00%
Connecticut	1993	6.00%	6.00%
Arizona	1994	11.00%	11.00%
Missouri	1994	6.50%	0.50%
New Jersey	1994	10.00%	10.00%
Rhode Island	1994	16.90%	16.90%
Maine	1996	5.00%	0.40%
North Carolina	1996	5.00%	5.00%
Pennsylvania	1997	10.00%	0.90%
Georgia	1998	10.00%	10.00%
Montana	1999	5.00%	5.00%
Utah	1999	6.00%	6.00%
Delaware	2000	10.00%	0.90%
Hawaii	2000	20.00%	20.00%
Maryland	2000	10.00%	0.90%
Idaho	2001	5.00%	5.00%
South Carolina	2001	5.00%	5.00%
Texas	2001	5.00%	5.00%
Louisiana	2003	8.00%	8.00%
Vermont	2003	10.00%	0.90%
Ohio	2004	7.00%	0.50%
Nebraska	2006	3.00%	0.20%

The table reports the by state introduction of R&D tax credits (year of introduction, nominal and effective rates). Source: Wilson (2009), tax rates reflect the most recent rate.

Table A3: The Impact of R&D Tax Credits on Patents, Cites, and Stock Market Value

	a	b	c	d	e	f
	R&D	Patents	Future cites	Av. future cites	Value	Average value
R&D		0.074***	0.117***	0.050**	0.121***	0.054***
		(0.023)	(0.043)	(0.022)	(0.034)	(0.014)
log(age)	-0.001	0.138***	0.470***	0.279***	-0.025	-0.087***
	(0.043)	(0.029)	(0.051)	(0.036)	(0.032)	(0.017)
log(total assets)	0.439***	0.227***	0.355***	0.151***	0.366***	0.172***
	(0.034)	(0.022)	(0.029)	(0.012)	(0.026)	(0.008)
R&D tax credit rate$_{t\text{-}3}$	2.272***	1.259**	0.745	-0.565	1.882***	0.485***
	(0.496)	(0.619)	(0.565)	(0.444)	(0.607)	(0.180)
N	70839	70839	70839	70839	70839	70839
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.383	0.089	0.103	0.082	0.115	0.083

Notes: The table reports the effect of R&D tax credits on firm's R&D expenditures, total number of patents applied for in year t, citations and economic value of innovation. R&D tax credit is measured as effective R&D tax credit rate at $t-3$ following **?**. (Average) Future Cites is the (average) total number of future cites collected by patents applied for in year t. Value is the total private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents following Kogan et al. (2017). Average value is the average market reaction to publications of firm's patents applied in year t following Kogan et al. (2017). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table A4: The Impact of R&D Tax Credits on Patents in New vs. Known to the Firm Technologies

	a	b	c	d	e	f
	Patents known	Patents new	New classes	Value known	Value new	Fraction value new
R&D	0.064***	0.034***	0.031***	0.098***	0.063***	-0.126***
	(0.018)	(0.012)	(0.011)	(0.028)	(0.020)	(0.043)
log(age)	0.150***	0.063***	0.069***	0.031	-0.020	-0.773***
	(0.026)	(0.019)	(0.018)	(0.037)	(0.017)	(0.076)
log(total assets)	0.212***	0.084***	0.078***	0.298***	0.152***	-0.169***
	(0.027)	(0.006)	(0.006)	(0.038)	(0.012)	(0.016)
R&D tax credit rate$_{t-3}$	1.532**	0.093	0.094	2.479***	0.223	-3.089***
	(0.719)	(0.136)	(0.125)	(0.664)	(0.241)	(0.845)
N	70839	70839	70839	70839	70839	70839
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.100	0.030	0.031	0.059	0.032	0.213

Notes: The table reports the effect of R&D tax credits on firm's patenting activity within the known and new to the firm technological classes. Patents Known is the number of patents that are filed in a 3-digit technology classes where the given firm has filed beforehand in that class. Patents New is the number of patents that are filed in a 3-digit technology classes where the given firm has never filed beforehand in that class (note that this measures new to the firm technologies and not necessarily new to the world technologies). New classes is the number of 3-digit technology classes where the given firm has never filed beforehand in that class. Value Known is the total private value of patents filed in a 3-digit technology class where the given firm has filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Value New is the total private value of patents filed in a 3-digit technology classes where the given firm has not filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Fraction Value New is the proportion of the latter two variables in percent. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table A5: The Impact of R&D Tax Credits on Blockings, Strategic Patents, and Markups

	a	b	c
	Blocked EPO patents	Strategic patents	Markup
R&D	0.034*	0.013**	-0.075***
	(0.019)	(0.005)	(0.025)
log(age)	-0.415***	-0.157***	0.050
	(0.048)	(0.023)	(0.032)
log(total assets)	0.164***	0.053***	0.086***
	(0.013)	(0.007)	(0.017)
R&D tax credit rate $_{t\text{-}3}$	1.133***	0.388**	1.234**
	(0.391)	(0.146)	(0.463)
N	70839	70839	69653
Firm fixed effects	Yes	Yes	Yes
R^2	0.231	0.230	0.079

Notes: The table reports the effect of R&D tax credits on patent blocking, strategic patenting and firm's markups. R&D tax credit is measured as effective R&D tax credit rate at $t-3$ following Wilson (2009). Blocked EPO Patents is the total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report). Strategic patents is the total number of patents that fall into the top 10% of the stock market value reactions in a given year but not into the top 10% of future citations. Markups are defined as prices over marginal costs following De Loecker et al. (2020). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table A6: Number of Patents that Fall into the Top 1%, 5%, 10% etc. Category in Terms of Future Cites

	a	b	c	d	e	f
	Top 1%	Top 5%	Top 10%	Top 25%	Top 50%	Zero cites
R&D	0.008***	0.020**	0.022***	0.037***	0.045***	0.028***
	(0.003)	(0.008)	(0.008)	(0.012)	(0.012)	(0.010)
log(age)	0.005	0.011	0.008	0.033	0.094***	-0.115***
	(0.006)	(0.014)	(0.015)	(0.021)	(0.020)	(0.019)
log(total assets)	0.020***	0.054***	0.064***	0.114***	0.132***	0.094***
	(0.004)	(0.011)	(0.013)	(0.018)	(0.017)	(0.014)
R&D tax credit rate$_{t\text{-}3}$	0.056	0.333	0.442	0.833*	0.947**	0.975*
	(0.127)	(0.305)	(0.298)	(0.434)	(0.432)	(0.531)
N	70839	70839	70839	70839	70839	70839
R^2	0.009	0.027	0.033	0.051	0.096	0.098

Notes: The table reports the effect of R&D tax credits on firm's number of patents applied for in year t that fall into the top X% category of the distribution of patent total future citations. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table A7: Number of Patents that Fall into the Top 1%, 5%, 10% etc. Category in Terms of Market Value

	a	b	c	d	e	f	g	h	i
	Top 1%	Top 5%	Top 10%	Top 25%	Top 50%	Low 25%	Low 10%	Low 5%	Low 1%
R&D	0.006***	0.015***	0.018***	0.031***	0.039***	0.031***	0.007*	0.001	0.001***
	(0.002)	(0.005)	(0.007)	(0.010)	(0.012)	(0.011)	(0.004)	(0.001)	(0.000)
log(age)	-0.032**	-0.068***	-0.070***	-0.063**	0.039	0.247***	0.164***	0.015***	-0.002
	(0.013)	(0.019)	(0.020)	(0.024)	(0.033)	(0.039)	(0.018)	(0.004)	(0.002)
log(total assets)	0.019***	0.049***	0.061***	0.097***	0.109***	0.078***	0.018***	0.003*	0.002***
	(0.003)	(0.007)	(0.010)	(0.016)	(0.022)	(0.011)	(0.006)	(0.002)	(0.001)
R&D tax credit rate$_{t-3}$	0.100	0.255***	0.448**	0.813*	0.921	0.639	-0.264**	-0.056**	-0.018
	(0.066)	(0.091)	(0.172)	(0.406)	(0.612)	(0.421)	(0.130)	(0.025)	(0.011)
N	70839	70839	70839	70839	70839	70839	70839	70839	70839
R^2	0.011	0.028	0.033	0.047	0.046	0.042	0.049	0.042	0.035

Notes: The table reports the effect of nominal R&D tax credit rate on firm's number of patents applied for in year t that fall into the top X% category of the distribution of patent total market value, measured as the sum of all market reactions to publications of those patents following Kogan et al. (2017). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

B.2 Nominal Tax Credit Rate

The following tables B1 to B7 show estimations of the models introduced above for the California experiment but with nominal R&D tax credit rate instead of the effective R&D effective credit.

Table B1: The Impact of the Nominal R&D Tax Credit Rate on Patents, Cites and Stock Market Value

	a	b	c	d	e	f
	R&D	Patents	Future cites	Av. future cites	Value	Average value
R&D tax credit rate$_{t\text{-}3}$	3.641***	2.125***	3.316***	0.545	2.996***	0.666***
	(0.352)	(0.210)	(0.535)	(0.368)	(0.330)	(0.200)
N	22257	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.306	0.089	0.065	0.029	0.131	0.097

Notes: The table reports the effect of nominal R&D tax credit rate on firm's R&D expenditures, total number of patents applied for in year t, citations and economic value of innovation. (Average) Future Cites is the (average) total number of future cites collected by patents applied for in year t. Value is the total private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents following Kogan et al. (2017). Average value is the average market reaction to publications of firm's patents applied in year t following Kogan et al. (2017). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table B2: The Impact of the Nominal R&D Tax Credit Rate on Patents in New vs. Known to the Firm Technologies

	a	b	c	d	e	f
	Patents known	Patents new	New classes	Value known	Value new	Fraction value new
R&D tax credit rate$_{t-3}$	2.664***	0.366***	0.342***	3.119***	0.755***	-3.225***
	(0.216)	(0.117)	(0.107)	(0.298)	(0.235)	(0.662)
N	22257	22257	22257	22257	22257	6210
Firm fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.097	0.028	0.029	0.062	0.044	0.185

Notes: The table reports the effect of nominal R&D tax credit rate on firm's patenting activity within the known and new to the firm technological classes. Patents Known is the number of patents that are filed in a 3-digit technology classes where the given firm has filed beforehand in that class. Patents New is the number of patents that are filed in a 3-digit technology classes where the given firm has never filed beforehand in that class (note that this measures new to the firm technologies and not necessarily new to the world technologies). New classes is the number of 3-digit technology classes where the given firm has never filed beforehand in that class. Value Known is the total private value of patents filed in a 3-digit technology class where the given firm has filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Value New is the total private value of patents filed in a 3-digit technology classes where the given firm has not filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Fraction Value New is the proportion of the latter two variables in percent. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table B3: The Impact of the Nominal R&D Tax Credit Rate on Backward Citations

	a	b
	Back cites	Back self-cites
R&D tax credit rate $_{t\text{-}3}$	5.120***	5.357***
	(0.910)	(0.702)
N	22257	22257
Firm fixed effects	Yes	Yes
R^2	0.081	0.114

Notes: The table reports the effect of nominal R&D tax credit rate on firm's total number of backward cites and total number of backward self-cites made by patents applied for in year t. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table B4: The Impact of the Nominal R&D Tax Credit Rate on the Patent Citation Distribution

	a	b	c	d	e	f
	Top 1%	Top 5%	Top 10%	Top 25%	Top 50%	Zero cites
R&D tax credit rate$_{t\text{-}3}$	-0.040	0.700***	1.010***	1.683***	2.119***	0.478***
	(0.061)	(0.095)	(0.095)	(0.138)	(0.153)	(0.046)
N	22257	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.011	0.034	0.037	0.056	0.071	0.021

Notes: The table reports the effect of nominal R&D tax credit rate on firm's number of patents applied for in year t that fall into the top X% category of the distribution of patent total future citations. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table B5: The Impact of the Nominal R&D Tax Credit Rate on the Patent Market Value Distribution

	a	b	c	d	e	f	g	h	i
	Top 1%	Top 5%	Top 10%	Top 25%	Top 50%	Low 25%	Low 10%	Low 5%	Low 1%
R&D tax credit rate$_{t\text{-}3}$	-0.093	0.258***	0.542***	1.290***	1.833***	1.987***	-0.125	-0.152***	-0.043
	(0.071)	(0.070)	(0.108)	(0.141)	(0.127)	(0.204)	(0.178)	(0.034)	(0.029)
N	22257	22257	22257	22257	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.011	0.016	0.019	0.036	0.050	0.041	0.040	0.044	0.032

Notes: The table reports the effect of nominal R&D tax credit rate on firm's number of patents applied for in year t that fall into the top X% category of the distribution of patent total market value, measured as the sum of all market reactions to publications of those patents following Kogan et al. (2017). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table B6: The Impact of the Nominal R&D Tax Credit Rate on Blockings, Strategic Patents, and Markups

	a	b	c
	Blocked EPO patents	Strategic patents	Markup
R&D tax credit rate $_{t\text{-}3}$	3.747***	0.473***	0.791***
	(0.492)	(0.109)	(0.196)
N	22257	22257	22033
Firm fixed effects	Yes	Yes	Yes
R^2	0.312	0.027	0.010

Notes: The table reports the effect of nominal R&D tax credit rate on patent blocking, strategic patenting and firm's markups. R&D tax credit is measured as effective R&D tax credit rate at $t-3$ following Wilson (2009). Blocked EPO Patents is the total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report). Strategic patents is the total number of patents that fall into the top 10% of the stock market value reactions in a given year but not into the top 10% of future citations. Markups are defined as prices over marginal costs following De Loecker et al. (2020). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table B7: The Impact of the Nominal R&D Tax Credit Rate on the Sales in New to the Firm Markets

	a	b
	Sales in new to the firm industries in t+3	New industries entered in t+3
R&D tax credit rate $_{t-3}$	-0.866**	-0.081
	(0.328)	(0.050)
N	20225	20225
Firm fixed effects	Yes	Yes
R^2	0.033	0.035

Notes: The table reports the effect of nominal R&D tax credit rate on firm's entry into the new market as measured using numbers of new industries entered and sales generated in those industries. Sales New to the Firm are sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t + 3$. New Industries Entered is the total number of SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t + 3$. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

B.3 R&D User Costs

The following tables C1 to C7 show estimations of the models introduced above for the California experiment but with R&D user costs as defined in Wilson (2009) and often previously used in the literature instead of the effective R&D effective credit. Note that R&D tax credits lowered the costs of R&D such that a negative sign implies a positive effect of R&D tax credit introductions and vice versa.

Table C1: The Impact of R&D User Costs on Patents, Cites and Stock Market Value

	a	b	c	d	e	f
	R&D	Patents	Future cites	Av. future cites	Value	Average value
R&D tax credit rate$_{t-3}$	-4.071***	-2.759***	-4.448***	-1.131**	-4.078***	-1.212***
	(0.595)	(0.389)	(0.596)	(0.479)	(0.655)	(0.308)
N	22257	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.307	0.090	0.066	0.029	0.133	0.097

Notes: The table reports the effect of R&D user costs on firm's R&D expenditures, total number of patents applied for in year t, citations and economic value of innovation. (Average) Future Cites is the (average) total number of future cites collected by patents applied for in year t. Value is the total private value of patents applied in year t, measured as the sum of all market reactions to publications of those patents following Kogan et al. (2017). Average value is the average market reaction to publications of firm's patents applied in year t following Kogan et al. (2017). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table C2: The Impact of R&D User Costs on Patents in New vs. Known to the Firm Technologies

	a	b	c	d	e	f
	Patents known	Patents new	New classes	Value known	Value new	Fraction value new
R&D tax credit rate$_{t-3}$	-3.111***	-0.841***	-0.816***	-4.541***	-2.025***	3.302***
	(0.525)	(0.122)	(0.106)	(0.511)	(0.262)	(1.081)
N	22257	22257	22257	22257	22257	6210
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.098	0.029	0.030	0.064	0.045	0.185

Notes: The table reports the effect of R&D user costs on firm's patenting activity within the known and new to the firm technological classes. Patents Known is the number of patents that are filed in a 3-digit technology classes where the given firm has filed beforehand in that class. Patents New is the number of patents that are filed in a 3-digit technology classes where the given firm has never filed beforehand in that class (note that this measures new to the firm technologies and not necessarily new to the world technologies). New classes is the number of 3-digit technology classes where the given firm has never filed beforehand in that class. Value Known is the total private value of patents filed in a 3-digit technology class where the given firm has filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Value New is the total private value of patents filed in a 3-digit technology classes where the given firm has not filed beforehand in that class, measured as the sum of all market reactions to publications of these patents. Fraction Value New is the proportion of the latter two variables in percent. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table C3: The Impact of R&D User Costs on Backward Citations

	a	b
	Back cites	Back self-cites
R&D tax credit rate $_{t-3}$	-6.876***	-6.308***
	(1.169)	(1.219)
N	22257	22257
Firm fixed effects	Yes	Yes
R^2	0.082	0.115

Notes: The table reports the effect of R&D user costs on firm's total number of backward cites and total number of backward self-cites made by patents applied for in year t. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table C4: The Impact of R&D User Costs on the Patent Citation Distribution

	a	b	c	d	e	f
	Top 1%	Top 5%	Top 10%	Top 25%	Top 50%	Zero cites
R&D tax credit rate$_{t-3}$	0.058	-0.761***	-1.028***	-1.907***	-2.640***	-0.639***
	(0.093)	(0.170)	(0.212)	(0.336)	(0.360)	(0.184)
N	22257	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.011	0.034	0.037	0.057	0.073	0.021

Notes: The table reports the effect of R&D user costs on firm's number of patents applied for in year t that fall into the top X% category of the distribution of patent total future citations. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table C5: The Impact of R&D User Costs on the Patent Market Value Distribution

	a	b	c	d	e	f	g	h	i
	Top 1%	Top 5%	Top 10%	Top 25%	Top 50%	Low 25%	Low 10%	Low 5%	Low 1%
R&D tax credit rate$_{t\text{-}3}$	0.048	-0.421***	-0.639***	-1.597***	-1.946***	-2.215***	-0.158	0.151***	0.089
	(0.099)	(0.104)	(0.155)	(0.267)	(0.378)	(0.418)	(0.206)	(0.041)	(0.052)
N	22257	22257	22257	22257	22257	22257	22257	22257	22257
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.011	0.016	0.019	0.037	0.049	0.042	0.040	0.043	0.032

Notes: The table reports the effect of R&D user costs on firm's number of patents applied for in year t that fall into the top X% category of the distribution of patent total market value, measured as the sum of all market reactions to publications of those patents following Kogan et al. (2017). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table C6: The Impact of R&D User Costs on Blockings, Strategic Patents, and Markups

	a	b	c
	Blocked EPO patents	Strategic patents	Markup
R&D tax credit rate $_{t-3}$	-4.443***	-0.687***	-0.735**
	(0.915)	(0.137)	(0.280)
N	22257	22257	22033
Firm fixed effects	Yes	Yes	Yes
R^2	0.313	0.027	0.009

Notes: The table reports the effect of R&D user costs on patent blocking, strategic patenting and firm's markups. Blocked EPO Patents is the total number of blocked patent applications at the European Patent Office (EPO), defined as patent applications that were eventually denied by the EPO and referred to at least one US patent of the focal firm applied in year t, which was classified as potentially blocking (X or Y citations in the EPO examiner search report). Strategic patents is the total number of patents that fall into the top 10% of the stock market value reactions in a given year but not into the top 10% of future citations. Markups are defined as prices over marginal costs following De Loecker et al. (2020). All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

Table C7: The Impact of R&D User Costs on the Sales in New to the Firm Markets

	a	b
	Sales in new to the firm industries in t+3	New industries entered in t+3
R&D tax credit rate $_{t-3}$	0.555	0.029
	(0.340)	(0.049)
N	20225	20225
Firm fixed effects	Yes	Yes
R^2	0.033	0.035

Notes: The table reports the effect of R&D user costs on firm's entry into the new market as measured using numbers of new industries entered and sales generated in those industries. Sales New to the Firm are sales generated in SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t + 3$. New Industries Entered is the total number of SIC 3-digit industries where the given firm has never generated sales beforehand, measured in $t + 3$. All dependent variables are measured in logarithmic form. All models are OLS regressions. Heteroscedasticity-robust standard errors are clustered at the state level and shown in parentheses. All specifications control for firm fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively.

B.4 Estimation of Markups

The estimation of markups is based on production functions and follows De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2020). De Loecker and Scott (2016) and De Loecker, Eeckhout, and Unger (2020) provide evidence that markups from this approach are similar to those from a more commonly employed demand approach in selected industries where prices and quantities are available. An advantage of the production-based approach is that it can be estimated using standard balance sheet data that is available across a broad set of firms, industries and time periods, which is essential for our application. Our starting point is an industry-specific production function ($F(.)$) where output (Q, measured as sales) of firm i in industry j and time t is a function of variable production factors (V, measured as cost of goods sold) and capital:

$$Q_{it} = F_j(V_{it}, K_{it})\Omega_{it}$$

Assuming firms minimize costs, the first order condition yields and expression for a firm's markup, defined as the ratio of price to marginal costs:

$$\mu_{it} = \frac{\partial Q_{it}}{\partial V_{it}} \frac{V_{it}}{Q_{it}} \frac{P_{it}Q_{it}}{P_{it}^V V_{it}} = \frac{\theta_{it}}{\alpha_{it}}$$

The revenue share (α) is observed, and the output elasticity of variable inputs (θ) can be estimated from a production function.

We experiment with alternative functional forms of $F(.)$. In our baseline specification, we rely on a Cobb Douglas production:

$$q_{it} = \beta_\nu \nu_{it} + \beta_k k_{it} + \omega_{it} + u_{it}$$

where the lower case letters denote logarithms, ω_{it} is total factor productivity and u_{it} captures measurement error in output. This yields a constant elasticity across firms within industries: $\theta_{it} = \beta_\nu$. Although restrictive, the Cobb Douglas production function has the advantage that any bias in elasticities (which could for instance stem from using sales instead of quantities), and thus markups, is constant across firms within industries and time periods. For the Cobb Douglas specification, all variation in markups within industries over time stems from variation in the revenue share of variable inputs. Since we are interested in relative variation in markups within firms across time rather than a cross-sectional comparison of firms, the remaining bias is of minor importance in our application.

However, we also estimate translog production functions, which allows elasticities to vary with input use and therefore across firms and time periods. We use a version of the translog production function proposed by De Loecker, Eeckhout, and Unger (2020):

$$q_{it} = \beta_\nu \nu_{it} + \beta_k k_{it} + \beta_{2\nu} \nu_{it}\nu_{it} + \beta_{2k} k_{it}k_{it} + \omega_{it} + u_{it}$$

For estimation, we use the two-step estimation method proposed by Ackerberg, Caves, and Frazer (2015). Demand for variable inputs is assumed to depend on a function of capital, R&D, and total factor productivity which can be inverted. This allows specifying a first stage equation which controls for productivity using a nonparametric function in R&D, capital and variable inputs: $q_{it} = \phi(\nu_{it}, k_{it}, rd_{it}) + u_{it}$. This stage does not identify any coefficients from the production function but allows to net out measurement error u_{it}. We approximate $\phi(.)$ using a 4th order polynomial in ν, k and R&D.

Following Doraszelski and Jaumandreu (2013), we allow the law of motion for the productivity process to depend on R&D: $\omega_{it} = g(\omega_{i,t-1}, rd_{it}) + \varsigma_{it}$ where we approximate the unknown function $g(.)$ by a forth order polynomial. The law of motion yields the following moment condition for variable inputs: $\mathbb{E}[\varsigma_{it}(\theta_{it})\nu_{i,t-1}] = 0$.

A potential concern with the estimated elasticities is that they might be affected by unobserved price variation across firms. To address this problem, we follow two alternative approaches. First, De Loecker, Eeckhout, and Unger (2020) show that the output price bias can be addressed by controlling for the determinants of markups, which are captured by market shares and time in the first stage. Second, we use an alternative approach developed by Forlani, Martin, Mion, and Muûls (2016), which allows the estimating of elasticities from a function that explicitly relates sales to input factors. A drawback of their approach is that they have to impose additional assumptions on the demand side and – in the absence of price data – can only identify markups up to scale (or precisely under constant returns to scale). Due to these additional assumptions, we do not use their method as our baseline equation but employ it as a robustness check.