# Essays on Property Rights and Financing

by

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For God,
who watches over me every step of the way
and gives me the strengths to persevere.

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# ABSTRACT

This dissertation comprises of two essays on property rights and financing. The two essays have tight relationship under the broad theme of intellectual property rights of firms. The first essay focuses on property rights *within* firms, between firms and employees, whereas the second essay focuses on property rights *between* firms.

The first essay examines how increasing firms' ownership of employee patents affects debt financing. I exploit a Court of Appeals Federal Circuit ruling that shifted property rights to employee patents from employees to firms, and find that firms' debt financing increases by 18%. The increase is attributable to firms' more efficient and productive use of patents, which improves the pledgeability of patents as collateral. I further show that a reduction in holdup problems increases synergistic value of patents through enhanced asset complementarity, inventor collaboration, and innovation productivity.

The second essay uses novel hand-collected patent litigation data from 2000-2006 to show that patent litigation has important financial and real impacts on firms. We find that defendant firms experience declining financial flexibility and innovation activities, and shift innovation strategy to pursue more exploitative projects. The product market overlap exacerbates financial constraints of defendants in intra-industry litigation, whereas a large reduction of litigation probability when pursuing exploitative innovation intensifies narrower innovation scope for defendants in inter-industry litigation. We sharpen our results by instrumenting the probability of being sued and the timing of patent litigation using China's participation in TRIPS (Trade-Related Aspects of Intellectual Property Rights) agreement. Lastly, we find suggestive evidence that patent litigation has spillover effects on other non-litigated firms in the industry.

# CHAPTER I

# Property Rights and Debt Financing

## 1.1 Abstract

I examine how increasing firms' ownership of employee patents affects debt financing. I exploit a Court of Appeals Federal Circuit ruling that shifted property rights to employee patents from employees to firms, and find that firms' debt financing increases by 18%. The increase is attributable to firms' more efficient and productive use of patents, which improves the pledgeability of patents as collateral. I further show that a reduction in holdup problems increases synergistic value of patents through enhanced asset complementarity, inventor collaboration, and innovation productivity.

## 1.2 Introduction

Patents are important assets to knowledge-intensive firms in part because of the growing use of patents as collateral to access debt financing.[1] The ownership of patents produced by corporate inventor-employees is determined by invention assignment agreements in practice. These contracts are inherently incomplete given the highly complex, uncertain, and long innovation processes, and, as a result, induce holdup problems and inefficiencies in how

[1] *Loumioti* (2013) documents that the percentage of secured syndicated loans collateralized by intangible assets grew from 11% to 24% over the 1997-2005. *Mann* (2017) reports that 38% of US patenting firms had pledged their patents as collateral at some point in 2013.

the patents are managed and utilized depending on who owns the patents. Therefore, the allocation of patent ownership is important for debt financing not only because firms need to be in possession of the patents to pledge them as collateral but also because the ownership structure changes the efficiency and productivity of underlying innovation processes, which in turn affect the pledgeability and value of patents to lenders.

The goal of this paper is to empirically examine how the property rights allocation between firms and employees affects debt financing. The patent assignment agreement between firms and inventor-employees provides a well-defined setting for examining property rights on a narrower subset of corporate assets. However, an empirical identification of the effect of property rights on debt financing poses a key challenge. The potential endogeneity issues arise because property rights are not randomly assigned, and any unobserved variables that drive property rights allocation may also be correlated with firms' debt financing decisions. In particular, firms with greater investment opportunities may enforce their property rights more and, at the same time, require greater financing to materialize the opportunities. Without a clean empirical setting, an observed correlation between property rights and debt financing is difficult to interpret.

To overcome the identification challenge, I exploit a Court of Appeals for the Federal Circuit (CAFC) ruling in 2008, which, *de facto*, shifted property rights to patents from inventor-employees to firms in eight pro-employee invention assignment states.[2]. The main regression relies on state-level variation in the property rights enforcement through invention assignment agreements in a difference-in-difference setting. The regression estimate captures an increase in the leverage ratio of the treated firms in the eight states relative to control firms after the court ruling. Both the timing and context in which the decision was made were relatively free from the influence of lobbying, political pressure, or local economic conditions, and thus provide a plausible causal interpretation of the regression estimates.

I first estimate the effect of increasing property rights on firms' debt financing, as mea-

[2]The eight states include CA, DE, IL, KS, MN, NC, UT, WA. The background under which these eight states became pro-employee state is explained in Section 1.3.1.

sured by total debt-to-assets ratio. I find that firms in the eight treatment states affected by the CAFC decision increase total debt-to-assets ratio by 2.5 percentage points relative to firms located in control states. The economic magnitude of the difference-in-difference coefficient is equivalent to an additional $62 million total debt for firms in the treated states, following the increase in property rights. For a pre-treatment average total debt-to-assets ratio of 0.14 for the treated firms, it is an 18% increase in the ratio. This key result stands up to a range of robustness checks. To show that the actual issuance increases, I reestimate the regressions using new long-term debt issuances as a dependent variable, and I find about a 23% increase in the issuance. In a falsification test, I verify that the debt financing results are not found in non-patenting firms, which should not be affected by the court ruling for their lack of use of invention assignment agreements. In addition, I show that my results stand up to robustness tests on a subsample of firms located only in the headquarter state to rule out spurious effects by multi-state firms.

I further examine what types of debt are issued after patent ownership shifts to firms. As the number of pledgeable patents increases, firms' access to bank debt secured by assets would increases as large banks appear most frequently as security interest holder on assignments of pledged patents. Consistently, I find that long-term debt increases significantly while short-term debt barely changes. The move away from short-term debt to long-term debt is indicative of creditors' willingness to extend long-term debt as the existence of collateral mitigates borrower risk, such as opportunistic behaviors by managers, for lenders. I then explore whether heterogeneity in access to debt financing prior to the court decision matters and find that the existence of some debt helps more when patent ownership shifts to firms. It appears that the underlying innovation process that generate pledgeable patents is important, whereas the marginal effects from financial constraints prior to treatment is minimal. The firm ownership of patents reduce holdup costs of innovation, and firms benefit from more synergistic use of patents in innovation process. Consistently, I find that multi-segment firms that benefit from the scope of underlying innovation process also experience greater increase in debt financing. This result leads to further investigation of changes in underlying innovation process.

Next, I provide additional tests on underlying channels that reinstate the main result. The firm ownership of patents is likely to increase the return from the innovation process and pledgeability of patents for two reasons. First, firms have comparative advantages in managing, providing resources, and commercializing patents. Second, firms' common ownership of patents reduces holdup cost and allows firms to maximize synergies from larger portfolio of patents. This is much so in today's innovation environment, where a final product incorporates many different components,[3] and large value is derived from synergies among patents. In support, I find stronger increasing debt financing effects on firms operating with multiple business segments, which benefit from the economies of scope. Thus, I further examine how synergistic innovation process is gauged from growing asset complementarity, which in turn helps increase patent pledgeability both in quantity and quality.

One way to measure the improvement in asset complementarity under the firm ownership of patents is to use patent citations because they convey information about linkages between innovations, inventors, and assignees (*Hall, Jaffe, and Trajtenberg*, 2005). I use self-citation (citation made to patents owned by the same assignee) to capture how firms tap into its own resources and utilize existing technology collectively. I find that, post treatment, the self citation rises by 15% for an average treated firm. Another measure of complementarity is how inventors collaborate on producing patents. *Hart* (1995) points out that integration changes the incentives of parties to reveal information and cooperate. I use the number of inventors assigned to each patent as an inventor collaboration measure and find that it increases by 5% for an average firm in treatment states after the shift in the property rights to firms.

Next, I show that both the rising asset complementarity and inventor collaboration bolster pledgeability of patents by increasing productivity, efficiency, and economic value of

[3] The average number of patents to make one product varies from five for small molecule drugs in pharmaceuticals (*Ouellette*, 2010) to hundreds for a laptop computer (WIPO).

patents. I use the number of granted patents, the number of granted patents per dollar spent on R&D, and counts of external patent citations as measures of productivity, innovation efficiency, and patent quality. I find that the number of granted patents and per dollar number of granted patents increases by 15% and 0.14 for the treated firms relative to the control firms. The citations received from other firms prove the economic value of the cited patents to external innovation (*Parchomovsky and Wagner*, 2005) and also confer redeployability value as collateral (*Chava, Nanda, and Xiao* 2017, *Hochberg, Serrano, and Ziedonis* 2017). I find that citations received by the existing patents and the new patents increase by 51% and 8% per patent, respectively. Overall, the citation results exhibit the growing economic value of existing and new patents, based on the changes in patent quality, and the increasing productivity captures the growing number of pledgeable patents as collateral. The rise in patent pledgeability is corroborated by larger increase in the average number of patent pledged as collateral by treated firms in comparison to control firms, shown in Figure 1.2.

In sum, this paper presents results indicative benefits arising from the firm ownership of patents. The firm ownership leads to more productive and efficient use of the patents, and the resulting increased value of patents to lenders allows the firms to raise more debt financing. These results are broadly consistent with the main implication of the property rights theory (*Hart*, 1995), that a party with greater influence on the value of the asset should own it. However, it is difficult to provide clear predictions on the optimal form of financing contracts or optimal capital structures under the current setting, where the invention assignment agreement describes the relationship between the firm and its employees, not between the firm and financiers. Nonetheless, it may still be of some interest to explore whether the increase in property rights also affects the issuance of new equity. In unreported analysis, I find that there is no sizable statistically significant effect on seasoned equity offerings of the sample firms.

This paper contributes to a few strands of related literature. Recent property rights studies that focus on innovation use firm-level vertical integration decisions with regards to the relative importance of R&D investment. Using a sample of UK firms, *Acemoglu, Aghion, Griffith, and Zilibotti* (2004) explicitly show the diverging incentives for integration, depending on the relative ex ante investment intensity. They find that a backward integration is negatively correlated with higher (lower) supplying (producing)-industry technology intensity. Similarly, *Fresard, Hoberg, and Phillips* (2017) show that a vertical integration is less likely in the industries where innovation is in an early stage and R&D spending is large, since the returns are best protected under separate ownership when the investment by technology developers is more important. Whereas both studies focus on the ex ante determinants of integration, this paper highlights ex post changes in innovation processes subsequent to a shift in asset ownership structure.

This paper also builds on the growing literature in patent collateral and debt financing. *Mann* (2017) documents the use of patent collateral and empirically shows that, everything else constant, stronger creditor rights on patent collateral lead to greater access to debt financing and R&D investment for knowledge-intensive firms. *Chava et al.* (2017) provide complementary results that provide evidence on how the value of patent collateral is priced in bank loans. *Hochberg et al.* (2017) document an increasing venture lending to startup firms when the liquidity of secondary markets for patents increases. The key distinction in this paper is that the improved access to debt financing critically hinges on the ownership structure of the patents and also depends on organization structure.

Lastly, this paper is related to inventor incentives and innovation. In a closely related paper by *Hvide and Jones* (2016), the authors exploit a similar empirical setting in Norway and conclude that the shift in property rights to patents from researcher to university led to a large decline in the rate of start-ups by university researchers. The quantity and quality of innovative output by university researchers also declined. These divergent results may be attributable to the institutional differences between universities and corporations. The relationship-specific nature of innovation, inventor-specific employment contract, and compensation schemes between the firm and inventor-employees may have limited decline in inventor-employee incentives from outweighing the benefits of reducing holdup costs borne by firms. This paper is also consistent with claims that inventor human capital is an important input into firms' innovation process (*Liu, Mao, and Tian*, 2017) and that the lack of inventor-specific union may have limited the reduction in inventor-employee incentives (*Bradley, Kim, and Tian*, 2017), resulting in a net benefit in terms of patent pledgeability.

The remainder of the paper is structured as follows. Section 1.3 explains empirical strategy of this paper using pre-invention assignment agreements. Section 1.4 outlines the hypotheses. Section 1.5 describes the data in detail. Section 1.6 presents main results, Section 1.7 provides discussions about the results, and Section 1.8 presents additional robustness tests. Section 1.9 concludes the paper.

## 1.3 Empirical Strategy

### 1.3.1 Pre-invention Assignment Agreements

In this paper, I focus on the property rights to patents arranged by a contract written between corporate inventor-employees and their employer firms. A pre-invention assignment agreement is an employment contract that obligates an employee to assign to the employer all interest in any future inventions conceived during the employment term. This contract is prevalently used and required to be signed by technical employees, engineers, and researchers (*Cherensky* 1993, *Pisegna-Cook* 1994, *Mattioli* 2011). The scope of the pre-invention assignment agreements may be broad enough to cover more categories of inventions than just employer-specified inventions and extend beyond the terms of employment, for a reasonable period after employment has ended. As a part of employment contracts, the pre-invention assignment agreements are governed by state laws. When present, pre-invention assignment agreements supersede common laws (the default rule in absence of such agreement), and courts generally honor the agreements.

In the early 1990s, eight states enacted state legislation[4] to protect inventor-employees from employers' abuse of their superior negotiation positions, limit the scope of employers' claims on employee inventions, and help clarify conditions under which a pre-invention assignment agreement is considered effective (*Pisegna-Cook* 1994, *Howell* 2012). The inventions that fall under the protection of the state legislations most likely arise from the "general inventive employees[5] (e.g. software engineers)," who perform general research or design work and are subject to specific inventive employment, but no specific inventions or end results are contemplated. The inventions from general inventive employees tend to be a gray area because these employees may be encouraged by the employer to pursue their creative instincts, even though they may diverge from assigned work.[6]

There are several advantages of using pre-invention assignment agreements in this paper. First, although property rights to any assets used for production nevertheless provide implications for debt financing, as highlighted in the introduction, the growing role of knowledge assets as collateral for securing financing motivates patents as a timely and appropriate venue for this study. Second, pre-invention assignment agreements are prevalently used in knowledge-intensive firms, and explicitly define the division of ownership over patents. Lastly, the existence of a plausibly exogenous shock on the interpretation of invention assignment contracts helps establish a causal inference and quantify the effect of strengthening firm ownership of employee patents. Empirically showing the equilibrium outcome and establishing a causal relationship between property rights and debt financing of a firm are challenging because the allocation of property rights is endogenous. Before I explain the

[4]California, Cal. Lab. Code §§2870-72 (1994); Delaware, Del.Code Ann. tit. 19, §805 (1993); Illinois, Ill. Ann. Stat. ch. 765, para. 1060/2 (1994); Kansas, Kan. Stat. Ann. §44-130 (1993); Minnesota, Minn. Stat. Ann. §181.78 (1994); North Carolina, N.C. Gen. Stat. §§66-57.1-2 (1994); Utah, Utah Code Ann. §§43-39-1 to -3 (1994); Washington, Wash. Rev. Code §§49.44.140-.150 (1994)

[5]The other ends of the employment type spectrum are "specific inventive" or "employed-to-invent" employees and "non-inventive" employees (*Gullette*, 1980). Since specific inventive employees' work serves specific purpose of inventing defined process or product, once the goal is achieved, the employer is entitled to the invention. On the other hand, the work of non-inventive employees, such as shop or manufacturing as well as non-technical employees, does not involve any expectation of inventive activity.

[6]For example, Google is known for encouraging its engineers 20 percent of their paid time to work on pet projects.

quasi-experiment setting in Section 1.3.2 and 1.3.3, I provide an example of a use of pre-invention assignment agreements.

Recently, pre-invention assignment agreements have become widely used throughout an organization regardless of an employee's likelihood of inventing (*Mattioli*, 2011), and overwhelming employer claims on employee inventions[7] have raised concerns. Firms increasingly take advantage of the protection provided by pre-invention assignment agreements. For example, Ford has initiated a companywide innovation challenge and encourages its employees from any part of the business to participate by submitting invention ideas on new products or changes to the company's existing offerings.[8] The contest rules require a submission of an invention disclosure form (a pre-invention assignment agreement), which says "Each entrant will assign and Sponsor will hold exclusive right, title and interest in all inventions or other materials submitted and, in all revenue, profits and Net Proceeds generated as a result of commercialization of a Submision[...]."[9] The company claims that, from the start of the first challenge in January 2015, more than 4,500 Ford employees have submitted invention ideas and nearly 3,500 *first-time* inventors have participated in the event. This example illustrates two important aspects of the pre-invention assignment agreements. The first is the broad use of the agreement across all employment types, and the second is the important role of the law's interpretation of such agreements when disputes over property rights on aforementioned general inventive employee inventions arise.

### 1.3.2 Institutional Setting

An analysis of how the property rights allocation causally affects firms' debt financing requires a plausibly exogenous change in property rights that is uncorrelated with firms' debt financing decisions. In 2008, the Court of Appeals Federal Circuit (CAFC) made a decision

[7] *The Economist*, Dec. 14, 2013. "Ties that bind"; *The New York Times*, Apr. 13, 2014. "My Ideas, My Boss's Property"

[8] *The Washington Post*, Dec. 14, 2016. "How Ford turned thousands of employees into inventors"

[9] The Ford innovation contest rules are available on http://henryfordinnovation.com/challenge/contestrules/

in *DDB Technologies LLC v. MLB Advanced Media, LP*[10] on a pre-invention assignment agreement case that shifted property rights to employee inventions from employees to firms, resulting in more pro-employer trends toward invention assignment agreements. CAFC cases are heard by a panel comprised of three judges who are selected randomly, which minimizes potential political influences. In addition, CAFC case sessions are generally held in Washington, D.C., which further limits the possible impact of local state economies on the court's ruling.

The CAFC decision on *DDB Technologies LLC v. MLB Advanced Media, LP* had three main parts (*Hedvat*, 2011). First and foremost, despite the fact that employment contracts are governed by state laws, the court ruled that provisions regarding patent assignment will be regulated under federal law. The significance of this statement is that this would preempt the pro-employee state legislations of the eight states and create uniform standards on patent assignment provisions. Second, employers are granted authority over patents when express language is provided in employment contracts. This means that making claims over employee inventions would become easier by including expressive terms, such as "agrees to and does hereby grant and assign...," "assignment of inventions," and "ownership of discoveries," in the invention assignment agreements. The practical influence of the court's ruling can easily be found on law firms' advice at the time to corporate clients. The law firms explicitly recommended that their corporate clients include express phrases in invention assignment agreements.[11] For example,

> "The *DDB Technologies* decision should provide comfort to employers that the effect of language assigning patents in employment agreements will be interpreted uniformly pursuant to federal law and will not be subject to differing interpretation under varying state law. The decision creates a roadmap to which employers

[10] 517 F.3d 1284, 1290 Fed. Cir. 2008

[11] For additional discussions written by law firms, see "Employer and employee ownership of intellectual property. Not as easy as you think" available at http://legalsolutions.thomsonreuters.com/law-products/news-views/corporate-counsel/employer-and-employee-ownership-of-intellectual-property-not-as-easy-as-you-think; "Ruling Will Guide Employers' Rights to Inventions" available at https://www.law360.com/articles/48989/rulingwillguideemployersrightstoinventions

can be reasonably certain that if their employment agreements contain language that expressly assigns rights in existing and future inventions, this assignment language will be interpreted under federal law to vest automatically ownership of the inventions with the employer, regardless of the state law governing the agreement or the domicile of the employee."[12]

Third, the fact that CAFC has nationwide jurisdiction and that the court categorized DDB Technologies case as a precedential case indicate that the effects of the decision made in *DDB Technologies LLC v. MLB Advanced Media, LLP* have impacts on immediate future pre-invention assignment agreement cases. In summary, the decision ruled by the CAFC effectively increased property rights to employee inventions for firms in the eight formerly pro-employee states. In the following section, I explain the implementation of this empirical setting in regression analyses.

### 1.3.3 Methodology

I exploit the CAFC decision in 2008 as an exogenous shock in a difference-in-difference framework. I define firms with headquarters located in the eight states affected by the court's decision as treated firms. I use the state of headquarter as a definition of state because "Generally, the state where the employer is located or where the job duties are performed will be a reasonable choice of law and likely be honored" (American Bar Association, 2014). I present a few example cases in the Appendix A.2 to verify that the headquarter state is indeed a reasonable indicator for treatment state. For all firms, post-treatment period is defined as years on and after 2008.

The main regression specification is as follows.

$$Total\ debt/Assets_{it} = \alpha + \beta\, treat_i \times post_t + \delta_i + \gamma_t + \epsilon_{it}$$

[12]The full discussion is available at http://www.kramerlevin.com/Federal-Circuit-Supplants-State-Law-to-Interpret-Patent-Assignments-in-Employment-Agreements-11-06-2008/

The main regression dependent variable is total debt-to-assets ratio as a measure of a firm's level of debt financing. The total debt is a sum of long-term debt and short-term debt. *treat* and *post* terms are included in the regression but both get dropped because each term is collinear with firm fixed effects and year fixed effects, respectively. An important identification assumption for the difference-in-difference (DD) estimate, $\beta$, to be consistent is that, absent treatment, the change in the total debt-to-assets ratio for firms in the treatment states would not have been different than the change in the same ratio for firms in the control states. To provide some evidence of this parallel trend assumption, I present a visual inspection of the parallel trends in Figure 1.1.

Under the identification assumption, the DD coefficient captures the additional changes for firms in the treatment states, relative to firms in the control states, following the shift in property rights after the 2008 CAFC decision. In addition to firm and year fixed effects presented in the above specification, I use firm and industry-year fixed effects to rule out potential unobserved heterogeneity across industries over time and get a more precise estimate. Lastly, I include error clustering at state level to correct for potential error correlation within the same state and account for serial correlations in the dependent variable.

## 1.4 Hypothesis Development

### 1.4.1 Debt Financing

An important implication of the property rights theory (*Hart*, 1995) is that, when assets are complementary, some form of integration is better than separate-ownership. However, the trade-offs in the incentives of parties acquiring and relinquishing the asset ownership make the optimal asset ownership structure dependent on whose ownership makes better use of the assets and increases the total surplus from the relationship-specific investments. Therefore, the net benefit of shifting patent ownership from employees to firms depends highly on whether the firms or employees make more efficient use the patents.

We can easily imagine that patents are complementary assets to the extent that each component patents must be combined to make firm-specific final products. *Merges* (2009) highlights that the required integration of many components makes individual ownership more costly for the modern complex innovation processes. There are also benefits from the integration of patent ownership due to the synergies among the patents as explained in detail in the following sub-section 1.4.2. The reduction in cost of separate ownership and rise in benefits from synergistic values would be maximized under firm ownership of patents due to firms' comparative advantages in managing, utilizing collective resources, commercializing, and attracting funding for innovation (*Gruner*, 2006). Therefore, acknowledging that the lenders are able to properly assess the improved patent values (*Chava et al.*, 2017), I predict that the superior integration of patents under firm ownership by firms improves firms' access to debt financing by enhancing the pledgeability of the patents as collateral.

### 1.4.2 Asset Complementarity and Inventor Collaborations

The most important benefit of integration of patent ownership is that there is a reduction in holdup problem, which leads firms to maximize the synergistic value of patents from more efficient and productive use of patents. The value of patent portfolios over individual patents emphasizes the significance of synergistic values of patents created by the economies of scope, which arise from different business applications of a firm's underlying expertise and direct transfer of knowledge between the firm's businesses (*Helfat* 1997, *Henderson and Cockburn* 1996). I measure the changes in the synergistic value of patents by asset complementarity and inventor collaboration. The former captures the reduction in holdup problem which invigorates the complementary use of patents, whereas the latter captures the changes in inventor incentives to promote collaboration rather than competing against each other.

To measure asset complementarity, I use self-citation of patents. *Hall et al.* (2005) suggest that citations, in general, convey technological and economically significant information embodied in patents by disclosing information about linkages between inventions, inventors, and assignees. In particular, self-citations represent transfers of knowledge that are mostly internalized and provide a signal regarding the value to the firm of the subsequent down-the-line, technologically connected innovations (*Hall, Jaffe, and Trajtenberg*, 2001). The authors additionally highlight that self-citations are a reflection of the knowledge accumulation and suggestive of the firms' incentives to internalize some of the knowledge spillovers created by its own developments. It is also important to note that self-citations, in fact, capture cross-citations among different inventors within the same firm. Thus, an increase in self-citation would indicate a greater integration of a firm's overall internal resources and technology.

Another measure of complementarity is inventor collaboration. The complex nature of today's innovations values inventor collaborations and explains a shift from "hero-inventor" to team production environment (*Cherensky* 1993, *Merges* 1999). The integration changes the incentives of the employees and encourages them to share information and co-operate given relatively small return but also small cost of doing so (*Hart*, 1995). I use the number of inventors assigned to each patent as a proxy for such collaborative efforts, since the integration is likely to promote collaboration rather than competition that stresses individual efforts. I expect that both the asset complementarity and inventor collaboration measures to rise subsequent to the treatment.

### 1.4.3 Pledgeability of Patents

The asset complementarity and inventor collaboration improve patent pledgeability by enhancing productivity and value of patents resulting from the better integrative innovation processes. *Helfat* (1997) finds that firms with larger amounts of complementary technological knowledge and physical assets undertook larger amounts of R&D, which suggests that the asset complementarity reinforces productivity. I first measure productivity by counting the number of granted patents. For any concerns with raw counts capturing excessive attempts through larger number of applications, I employ the percentage of successful patent applications as the second measure. These measures capture how fruitful was a firm's innovative efforts under the improved asset integration and inventor collaboration. I expect both measures to increase after the treatment.

One of the limitations with plain patent count is that it is inherently limited in the extent to which it can capture heterogeneity in value and importance of each patent (*Griliches, Pakes, and Hall*, 1987). Hence, I use citations received from other firms as a measure of the quality and economic value of patents. Citations do not only convey quality of patents but also suggest redeployability of patents in the secondary market (*Hochberg et al.*, 2017) by proxying for potential use by others, both of which are important for the assessment of the patent values by lenders.

I first compare the citations before and after the treatment on *existing* patents granted prior to the treatment. More productive use of the existing patents under firm ownership of patents would attract greater external interests due to changes in the perception of intrinsic values of the patents. Then, to compare across old and new patents, I compute the citations received in the first 3-years post grant[13] to capture whether patents that are granted post treatment additionally benefit from the improved integration. I hypothesize that these citation measures increase subsequent to the increased property rights. Overall, the improvement in patent productivity and quality would represent the enhanced pledgeability of patents that lead to incremental access to debt financing.

## 1.5 Data

Although pre-invention assignment agreements are commonly required as a part of employment contract, whether or not a firm uses the contract is only partially observable.[14] However, it is widely accepted that the pre-invention assignment agreements are typically presented to engineers and almost all technical employees. To ensure that sample firm employees are bound by such contract, I restrict my sample to patenting US public firms

[13] *Mehta, Rysman, and Simcoe* (2009) find that patent citations peak 2-3 years after grant date.

[14] Sometimes firms disclose the use of pre-invention assignment agreement on annual financial statements such as 10-K, but firms are not required to do so.

(country of incorporation is United States) in Compustat. I also exclude financial firms (SIC code 6000-6999) and utilites (SIC codes 4900-4999) for the reasons that these firms may be affected by capital requirements or regulatory supervision. I drop observations with missing total assets and replace missing values of debt with zero.

Next, I collect patent application and grant data from United States Patent and Trademark Office (USPTO). USPTO provides US patent applications and grant documents from 1926 to present. I download each document between 2003-2016. Each document contains information about the patent, application and grant dates, names and locations of inventors and assignees, and citations. I keep only the utility patents[15] assigned to US domicile corporations so that I can make sure the empirical setting applies to the sample firms. Then, I name-match the collected data to the Compustat sample firms. One advantage of the USPTO data is that it also provides application documents that are not eventually granted. This makes it possible to compute success rate of patent applications used in the analyses. A detailed description of how the data was collected is in the Appendix A1.

The final sample consists of 1,959 unique patenting firms during the sample period of 2003-2013. Table 1.1 describes the sample firms. The main dependent variable is total debt-to-assets ratio, computed by dividing the sum of short-term and long-term debt by total assets. Panel A describes financial characteristics of all sample firms during the entire sample period from 2003-2013. Notice that the total debt-to-assets ratio is slightly smaller than the average of all Compustat firms. This is consistent with the stylized fact that knowledge-intensive firms tend to carry less debt. The ratio is even smaller for firms in the treatment states presented in Panel B. Panel B compares the firm characteristics by treatment and control state firms only during the pre-treatment period between 2003-2007. The treatment state firms are smaller in size and have relatively lower total debt-to-assets ratio. The treatment state firms also in general seem to be involved in slightly greater patent activities. The p-values in the last column show that both the financial and patent activity characteristics

[15]Utility patents are inventions of a new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement thereof.

are statistically different between the treatment state firms and control state firms.

The fact that the treated and control firms are different on observable dimensions may raise concerns for endogeneity issues in the empirical analyses given the possibility that they may also differ on unobservable dimensions in a way that violates parallel trends assumption. These concerns are mitigated in the following ways. First, the difference-in-difference setting fully accounts for any observable level difference between the treatment and control groups using the *treat* indicator. Second, although there is no way to formally test the parallel trends assumption, I show in Figure 1.1 that the treatment and control groups during the pre-treatment period seem to have parallel trends. In addition, I include firm fixed effects in all of my regression specifications to mitigate potential confounding effects of the time-invariant unobservables. Lastly, I do a robustness check with matching on observable regressions at the end of the results section.

## 1.6 Results

The results are organized as follows. I first show debt financing results from difference-in-difference regressions. I also present a graphical illustration of the difference-in-difference regression coefficients in Figure 1.1. After presenting the main results on debt financing, I explore underlying mechanisms using the same difference-in-difference framework.

### 1.6.1 Increasing Debt Financing

Table 1.2 presents the main difference-in-difference regression results on debt financing. In Columns (1) and (2), the dependent variable is total debt-to-assets ratio. Column (1) includes firm and year fixed effects to remove any time-invariant unobservable firm characteristics and year-specific macroeconomic effects. Column (2) sharpens the specification by including firm and industry-year fixed effects by further removing industry-year specific shock that may cause differential leverage outcome. The DD coefficients show that an average treated firm increases the total debt-to-assets ratio by about 2.5 percentage points subsequent to the increasing firm property rights to employee inventions. The estimated increase is 18% relative to an average of 0.14, which is equivalent to $62 million increase in total debt for an average firm with $2.46 billion total assets.

To give some economic contents to this number, I compare it to some of the results from the creditor rights and debt financing literature. *Bae and Goyal* (2009) find that better enforceability of contracts in 49 countries over 1994-2003 increases the loan amounts by $57 million. *Loumioti* (2013) finds that firms using patents as collateral during 1996-2005 increase secured syndicated loan amount by $51 million. *Mann* (2017), by exploiting an exogenous changes in creditor rights, finds that strengthening creditor rights increases total debt by $26 million per quarter. Although each paper derives variations from different sources, the key underlying mechanism is relaxing market frictions for borrowers using collateral, and find roughly similar changes in the level of debt financing.

To ensure that the treated firms experience increase in access to debt financing and thus issue more new debt, I use new issuance of long-term debt (dltis) scaled by total assets at the beginning of the year as a dependent variable in Columns (3) and (4). The estimates show that an average treated firm increases new long-term debt issuance by approximately 1.5 percentage points. This is equivalent to as large as 23% ($37 million) increase in the ratio (dollar amount of long-term debt issuance), which accounts for about half of the total debt increase. The results support that the increase in property rights to employee patents enhances treated firms' ability to raise additional debt financing.

Figure 1.1 adds graphical illustration of the difference-in-difference results. The graph plots the DD coefficient estimates by event years. The negative numbers are years prior to the treatment in 2008, zero in treatment year, and positive numbers are years post of the treatment in 2008. The horizontal axis shows the event time, and the vertical axis shows DD coefficient estimates. There are four key observations to be made in this figure. First, the graph shows that, during the pre-treatment years, the DD estimates that capture the level difference in the outcome variable stay flat and relatively close to zero, supporting the evidence that the pre-trends assumption holds. Second, the treatment effect is concentrated on the event year. Recall that the CAFC decision was made early in Febrary of 2008, allowing enough time for firms to adjust and show concentrated treatment effects in the year of the event. There seems to be a slight increase in the latter years, which merits further investigation of the timing of changes that takes effect in increasing the level of debt. I explain this timing of changes in Section 1.6.4. Third, the gray plots represent statistically insignificant estimates, whereas the yellow plots represent statistically significant estimates. The plots show that the estimates are close to zero *and* statistically insignificant during the pre-treatment years, but as soon as the treatment takes effect in event year zero, the estimates increase in magnitude, as well as become statistically significant. Lastly, there is no reversal of the effect in the post-treatment period.

I further provide a falsification test to check the internal validity and run additional analyses to eliminate a few potential alternative stories. To ensure that the court ruling is only relevant for the patenting firms' debt financing through its impact on invention assignment agreements, I run the baseline regressions in Table 1.2 for *non-patenting* firms. The results are reported in Table A1 in the Appendix A. The DD coefficient on total debt-to-assets ratio is not only statistically insignificant, but the magnitude is substantially smaller for non-patenting firms that have higher average pre-treatment total debt-to-assets ratio of 0.28. Furthermore, the DD coefficients on long-term debt issuance are slightly negative and statistically indistinguishable from zero. The internal validity of the empirical setting and the results further reinforce that the observed changes in the level of debt financing is likely due to the treatment effect of increasing property rights to firms after CAFC ruling.

Next, if firms have geographic subsidiaries located in multiple states and thus are exposed to multiple state laws governing the invention assignment agreements, the effect of the treatment may be less clear and raise concerns that the results found in Table 1.2 capture some spurious effects. First, I verify from the data that approximately 90% of patents are issued to the state of headquarters. Second, I only use firms operating in single state and run the same regressions from Table 1.2. The results are presented in the Appendix Table A2. Each column presents results for zero, fewer than or equal to one, or fewer than or equal to two geographic subsidiaries, respectively.[16] The results still hold, but the statistical significance weakens, possibly attributable to significantly reduced number of observations.

I avoid including time-varying control variables that may be affected by the treatment and give inconsistent estimates of the treatment effect. However, In Table A3 in the Appendix A shows that I find similar results when include common controls in the leverage literature in Columns (1)-(6) and also when include a measure of stock of innovation and R&D expenditures in Columns (7) and (8), respectively. In unreported table, I also confirm that the new long-term debt issuance results also stay robust to inclusion of these controls.

### 1.6.2 Types of Debt and Firms

In previous section, I show that the increase in firm ownership of employee patents increase firms' debt financing. Access to which types of debt increase? Table 1.3 presents the results on different types of debt. *Kerr and Nanda* (2015) emphasizes in their survey of financing for innovation wide use of bank debt by innovative firms from small startups to public firms. Therefore, I look into the changes in amount of bank debt, particularly as bank debt is highly likely backed by collateral. Consistently, Column (1) shows that the bank debt of treated firms increases relative to that of control firms by about 19%.

I further investigate whether increasing property rights also affect maturity of increasing debt financing by substituting for borrower risk. Within the incomplete framework, lenders can better control borrower risk if they know they will be able to seize collateralized assets, or credibly threaten to take these assets, ex post, in default. The transfer of control rights upon default allow greater bargaining power for lenders, who in turn extend credit on more favorable terms, such as lower interest rates or longer maturities.[17] Therefore, an increased

[16] The data is provided on Professor Scott Dyreng through https://sites.google.com/site/scottdyreng/Home/data-and-code

[17] *Qian and Strahan* (2007) also finds in a cross-country setting that under stronger creditor protection, loans have longer maturities, highlighting debt maturity is an effective contracting tool in environments with

capacity to pledge assets makes collateral more effective and increase creditor protection and enhancing loan availability. Whereas the long-term debt increases significantly in Column (3), short-term debt in Columns (4)-(6) are statistically indistinguishable from zero. In sum, increasing property rights allow firms to use more secured debt financing and also benefit from the access to long-term debt by securing creditor protection through pledged collateral.

As pointed out in Section 1.5, the overall sample firms tend to be small and hold low debt compared to an average Compustat firm. The summary statistic in Table 1.1 Panel A indeed shows that about 25% of sample firms have zero total debt-to-assets ratio. The estimates presented in the baseline regression shows the average effect of increase in firm ownership of employee inventions subsequent to the court ruling. Given the skewed distribution of total debt-to-assets ratio, looking into which firms are more conducive to raising more debt in a response to changes in property rights helps with understanding the effects better. Therefore, I present a quantile regression framework in Table 1.4 Panel A and examine heterogeneous impact of increasing property rights on firms with different starting levels of debt.

The first column reports a baseline estimate with industry and year fixed effects to be consistent with the rest of quantile regression specifications. The quantile estimates are reported staring with the 30th percentile because many observations in the lower quantiles are zero in both the treated and control distributions. The median estimate is closest to the baseline estimate. I find larger beneficiaries of shifting property rights arise among firms that had some level of debt to start with. The results are suggestive of some degree of economies of scope and scale required in the underlying channel. This is because synergies in the underlying innovation process is more likely for firms with some useful existing resources.

The quantile regression results raise question on whether increasing property rights help relax financial constraints of a subset of treated firms. In Table 1.4 Panel B, I use size and age as rough proxies of financial constraints interaction terms. Interestingly, the results in Columns (1) and (2) show that the triple interaction term is statistically insignificant,

weak legal protection and costly contract enforcement (*Diamond*, 2004).

suggesting there is no evident benefits of higher property rights based on the financial constraints. However, Column (3) shows that the effect of firm ownership of patent is statistically significantly higher for firms with multiple business segment. This is consistent with the quantile regression results, where there is greater chance for synergistic underlying innovation process where firms can leverage from different business segments.

Overall, these results suggest that the increasing debt financing seems to be attributable to changes in innovation processes that makes patents become more pledgeable. I further investigate underlying channels in the next section.

### 1.6.3 Asset Complementarity and Inventor Collaboration

In Table 1.5, I present two sets of results on improved integrative innovation processes. In Columns (1) and (2), the dependent variable is log number of self-citation. It is computed as the sum of all self-citations made to the firm's existing patents granted within the last ten years by a cohort of patent applications submitted in the same year. *Hall et al.* (2005) find that the median backward citation lag is 10 years, so I limit the age of pool of cited patents to ten years so that the relationship is not merely picking up the size of existing pool of patents, particularly for older firms. Furthermore, I control for the number of applications submitted in Column (2) to avoid the possibility that the increase in citations is driven mechanically by more applications submitted.

In the context of this paper, self-citation captures the internal transfers of knowledge and complementary use of firms' existing patents in current innovation activities. In the post-treatment period, an average treated firm's self-citation rises by 15%. To give some economic meaning to this number, note that the average total number of self-citations made per year during the pre-treatment period is 38. Post-treatment, an average treated firm makes 6 additional self-citations to the firm's existing patents from its own patent pool. This means that the treated firms make greater use of its own assets and benefit from the cumulative stock of patents.

The complementarity exists not only in assets but also among the inventors of the patents. In Columns (3) and (4), I measure the inventor collaboration as average number of inventors assigned per patent. This is to capture the possibility that firms also promote research environment in which more inventors collaborate in a team (*Merges* 1999, *Cherensky* 1993). The inventor collaboration increases by 5%. Overall, consistent with patent portfolio theory and the hypothesis in Section 1.4.2, the shift in ownership of employee inventions to firms seems to enhance how firms use existing portfolio of assets together. Next, to further identify how the improvements in asset complementarity and inventor collaboration affect the pledgeability of patents, I examine productivity and changes in the economic value of patents.

### 1.6.4 Productivity and Pledgeability

Figure 1.2 compares the increase in use of patent as collateral between the treated and control firms, measuring the average number of patent reassignment transactions identified as "security interest" per firm by pre-treatment and post-treatment period. The average number of patents pledged as collateral stays about the same for control firms but increases for treated firms. The increase in the use of patents as collateral can be driven by changes not only in quantity but also in quality of patents under firm ownership of patents. So I turn to examining different measures of changes in patents pledgeability.

I use two measures of productivity. In Columns (1) and (2) in Table 1.6, the dependent variable is log number of granted patents, which measures the productivity level. In Columns (3) and (4), the dependent variable is number of granted patents scaled by R&D expenses.[18] In the first two columns, I find that an average treated firm is granted 15% more patents compared to a control firm after gaining more property rights to employee patents. This is equivalent to about 3 more patents granted for a treated firm. Given the mean (median) number of granted patents for treated firms during the pre-treatment period is 18 (2), this is

[18]The productivity result using 2 years lagged patent grant measure, accounting for the time it takes for innovation effort to materialize, remains statistically strong and similar in magnitude.

a sizable increase in patent productivity. In Columns (3) and (4), I find that the innovation efficiency measured by the number of granted patents per dollar spent on R&D increases by 0.14. This means that for every $100 spent, an average treated firm is granted 14 additional patents, after the increase in property rights.

Lastly, in Table 1.7, I show the increase in the quality of patents in terms of citation measures to capture the changes in the economic value of patents. The intuition is that the internal knowledge transfers induced by an enhanced integration triggers greater external innovative interests in the use of patents, and the citation counts embody economic values of these linkages among patent uses. The dependent variable in Columns (1) and (2) is average total number of citations received per *existing* patents that had been granted prior to the treatment year. This is to isolate the changes in citations for the same patents before and after the treatment. To do so, I create the measure using only the patents that had been granted prior to the treatment year. The estimated additional increase is 51% *per patent* and translates to 12 additional citations received by the existing patents of an average treated firm. Given the number of citations received tends to diminish with time, finding the strong increase in the citations to existing patents suggests a significant changes in firms' incentives to make greater use of its asset pool.

In Columns (3) and (4), I use the average number of total citations received per patent in the first 3-years post grant. This measure is to compare the existing patents with newly granted patents on the same ground since older patents have more time to accrue citations. I use three years as the comparison window because patent citations peak 2-3 years after grant date (*Mehta et al.*, 2009), and thus capture the most of meaningful citations during the first three years. Since this takes care of the concerns with older patents mechanically accruing more citations, I do not include patent age in the first two columns. The number of citations received by newly granted patents to an average treated firm grows by 8% *per patent* in the post-treatment period. This is equivalent to 6 additional citations for newly granted patents. The interpretation requires some attention because the first 3-years citations measure for patents that are granted 2-3 years prior to the court ruling would overlap with post-treatment period. However, finding a strong positive effect, despite the fact that the overlapping period should work against finding a strong increase, implies a sharp changes around the treatment.

This section provides additional channel evidence on improved productivity and success of innovation efforts that reinforce the the collateral value of the patents for debt financing.

### 1.6.5 Progression of changes

In this section, I further layout some detailed tests on the timing of material impacts found in the previous sections. By the nature of R&D process, it may take some time for the treated firms to integrate assets to its full capacity. Therefore, I further distinguish changes that are immediately reflected in debt financing from changes that gradually incorporated with some time lag. In Figure 1.1, I show that the majority of treatment effect is concentrated around the event year in 2008, and there is some additional increase in latter years. This prompts a question on the time progression of the channel effects found in the previous sections. To examine the changes in detail, I run the same difference-in-difference by replacing *post* with year before, event year, and post-event years. The results are intuitive. In Table 1.8, Column (1) shows an immediate effect of complementary asset uses measured by total number of self-citations as a percentage of all citations made by new applications submitted in a year. The point estimate is insignificant in the year prior to the treatment, but the estimates become statistically significant and large starting in the event year. The immediate improvement in complementarity is intuitive because firms make use of assets that are already in place.

On the other hand, I would expect a mechanical lag in patent grants and inventor collaboration, given the patent grant process takes about 2-3 years (*Hall et al.*, 2001), and firms need some time to reorganize the inventor groups. Consistent with this prediction, Columns (2) and (3) show changes that happen with some time lags. Although the effect is somewhat positive prior to the treatment, in Column (2), there is a slightly negative effect around the treatment year, then the estimates become stronger and positive starting in the second year and onwards. The temporary decline around the event year may suggest that, with the shift of property rights to firms, the employee inventor incentives may be adversely affected for some time, but recover with some time lag. Column (3) also shows some time lag in patent productivity measured by the number of granted patents. These lagged effects may, in turn, explain why some of the main debt financing effect has additional increase in the latter years in the post-treatment period. That is, the treated firms gradually incorporate the changes in the asset holdings and enhance efficient integration of the assets that result in the improvement in pledgeability of patents as collateral.

## 1.7 Discussion

Incomplete contract is an important friction considered in this paper. In practice, contractual provisions on decisions over innovation processes are highly complex. As emphasized in *Aghion and Tirol* (1994), "the exact nature of the innovation is ill-defined ex ante, and two parties cannot contract for delivery of a specific innovation." This is because contracting on all contingencies, such as changing product market conditions, competition dynamics, demands, or technology shocks, is impossible. Moreover, firms and employees cannot communicate and negotiate about all possibilities or write a clear contract that courts can then enforce. Therefore, fully specifying the usage of patents in every state of the world in a contract ex ante is too costly for firms.

Instead, specifying property rights which allow an asset owner to decide the usage of patents increases her ex ante incentives to make relationship-specific investments. The investment here represents an asset owner's non-physical investment decisions about how to make the asset more productive.[19] The CAFC court ruling in the empirical setting changes the ownership of patents but not the uncertainties inherent in the innovation processes. The

[19]The R&D spending is actually unaffected in data.

patent ownership, in turn, improves the firm's innovation productivity, more than market transactions due to greater marginal returns from relationship-specific innovation processes.

More productive innovation processes help improve pledgeability of patents in two ways. For a patent to have useful value as collateral when a borrower defaults, redeployability and quality of the patent are the two most important factors for lenders. The firm ownership of patents enhances both redeployability and quality of patents because firms have comparative advantages in making greater resources (financially and organizationally), attracting wider interests in technology, and thus increasing demand for the technology. Therefore, the firm ownership of patents increases the availability of pledgeable patents for greater access to secured debt financing, as shown in the main regression results.

Shifting property rights creates tension between incentives of firms and employees in opposite directions, although the overall effect appears to be *net* positive. I further investigate the changes in inventor-employee incentives after the court ruling and find statistically indistinguishable changes in inventor-level productivity (untabulated), possibly for two reasons. First, the inventor productivity is measured by the number of granted patents per inventor, which only captures observable efforts. Second, when patents are complementary, an employee's patent alone is useless without other patents, so giving up her patent does not change the employee's marginal return absent a relationship-specific investment with the firm. The second possibility helps explain why this paper finds contrasting results from *Hvide and Jones* (2016), which finds negative innovation incentives when researchers affiliated with universities lose their property rights. In the university setting, both the relationship-specific innovation and asset complementarity are absent. Also, university compensation schemes with regards to innovation are highly likely be different from that of corporations.

I further look into state-level aggregate innovation effects of the court ruling. The results are reported in Appendix Table A5. I use the universe of patents on USPTO patent grant records, which allows me to compare changes in innovation level by different groups of inventors. Column (1) shows that the general effect of the court ruling on corporations, which in this analysis is comprised of the sample firms and private companies, is consistent with the main results. This highlights that the tension in property rights between firms and employees exists in a broader sample. However, the positive innovation incentive is absent for the government (Column (2)) and individuals (Column (3)). The government-assigned patent result is not surprising given that contract and agreement terms are heavily regulated by different property rights allocation standards. Also, since patents assigned to individuals do not suffer from ownership allocation issues, it is reasonable not to find any effects on them.

Is there a possibility for firms to rewrite contracts with their employees after the court ruling to circumvent the changes in property rights? It is not likely given higher contracting and enforcement costs under the old patent ownership structure. The overall effect of shifting property rights from employee patents to firms seems to have enhanced underlying innovation efficiency. However, the overall firm value effect is less clear,[20] particularly when inventor-level incentives seem to have remained unchanged. One possibility is that firms may have increased employee compensation for shifted patent ownership, which would increase outflows of cash and offset the efficiency gains. This calls for further investigation of property rights and compensation of inventor-employees, which is outside the scope of this paper.[21]

## 1.8 Robustness

### 1.8.1 Matching Regressions

To ease concerns for the time-varying differences in observable firm characteristics, I rerun the main regressions using matched samples on observable firm characteristics. Table 1.9 reports the propensity score matching diagnostics. As with any endogeneity problems, a matching regression itself does not fully resolve identification concerns, but, used in con-

[20] In unreported result of event study on a comparison of return changes between the treated and control group around the court's ruling, I do not find differences of returns.

[21] This would require employee-level wages data, specifically for those who are identified as corporate inventors.

junction with the difference-in-difference setting, can provide a useful robustness test for earlier regression results. There are observable and statistically significant differences between the treatment and control group during the pre-treatment period shown in the pre-match columns. It is important to note that the difference in average leverage growth rates between the treatment and control group is statistically insignificant, reinforcing the parallel trends assumptions. The next three columns compare the same variables after the matching on propensity scores. The p-values reported on the pairwise mean differences between treatment and control groups become all statistically insignificant, assuring that the matching process has removed meaningful differences on observable dimensions. In sum, the main results of this paper remain robust to matching away the observable differences.

Table 1.10 presents the matching regression results using the matched sample. I use propensity score matching using the observable differences between the treated and control firms reported in Table 1.1. In addition, to ensure that the matching process embodies parallel trend assumption of the difference-in-difference framework, I include the annual growth rate of the total debt-to-assets ratio in the propensity score (*Lemmon and Roberts*, 2010). The matching regression coefficients decrease slightly but remain robust to both nearest neighbor matching with $n = 1$ and $n = 2$ with replacement.

### 1.8.2 Alternative Explanations

In this section, I evaluate potential alternative explanations stemming from the fact that firms can choose the state of their corporate headquarters, which is used to assign treatment indicator in the empirical setting. Then, I address a possibility of concurrent effects of financial crisis around the CAFC decision in 2008.

#### 1.8.2.1 Non-random Selection of Headquarter State

Since firms choose in which state to locate their headquarters, I cannot completely rule out the possibility that the results may be affected by unobserved factors that are correlated with both the headquarter state decision and financing decision. However, for the non-random treatment to be consistent with the results, it would need an omitted variable that not only relates to firm's headquarter choice but also explains why the level of debt financing for the firms in the eight treatment states responds differently from that of firms in the control states, specifically around 2008.

The major determinants of a firm's state of headquarter choice are natural resources, unionization levels, input-output relationships, state taxes, founder's home location, energy costs, and environmental regulation (*Garmaise*, 2011). One likely confounding factor is the state corporate tax rates. That is, firms choose to locate in one of the eight treated states for corporate tax reasons, particularly with regards to debt tax shields. If this is so, then the differential debt financing responses between treated firms and control firms may be found, even in the absence of the property rights shock. In Table A4, I verify that the pre-treatment trends assumption holds for the state corporate tax rates, and that the year-by-year changes in corporate tax rate during the entire sample period are not statistically different between the treatment and control states.[22] The regression results reported in Columns (3) of Table A3 are robust to controlling for the state-level corporate tax rates and, thus, rule out the state tax story.

Second, following the enactment of employee protection state legislations in the early 1990s, innovative firms that are more protective of their legal rights over patents may have selected *out* of the eight treatment states, leaving only the firms with relatively higher fraction of tangible assets, such as plants and equipment, that are easily pledged as collateral. This may cause the differential access to debt financing over time. To eliminate the possibility that a difference in pre-treatment level of tangible assets drives the result, I augment the baseline specification by including pre-treatment level of tangible assets, measured by pre-treatment average level of plants and equipment scaled by total assets, interacted by the *post* indicator. In Columns (4) of Table A3, I verify that the results remain robust.

[22]The corporate tax rates are collected from Tax Foundation. The data is available at https://taxfoundation.org/state-corporate-income-tax-rates/

Lastly, I check to see if firms with relatively high future innovation investment opportunities selected into the eight treatment states to take advantage of the employee rights protection, and thus increase their debt financing to materialize the opportunity. In Figure A1 Panel (b) in the Appendix A, I show that the distribution of intellectual property-intensive firms (or employments) are not all concentrated in the eight treated states. Therefore, if the main results were driven by ex-ante investment opportunity differences, I should find the similar results in firms in untreated states as well. This is not so. In untabulated regression without year fixed effects, I find that the coefficient on *post* is very close to zero and statistically insignificant, showing that the level of debt financing for firms in control states remained about the same over time. In addition, I include the pre-treatment level of innovation to control for the ex ante innovation opportunities and again find the results are robust.

#### 1.8.2.2 Financial Crisis

I address potential concerns with the overlapping period of the CAFC ruling with the financial crisis in 2008. The concern here is that the main results may be driven by some unobservable state-specific factor that causes treatment states to react differently to the financial crisis. Ideally, I would repeat my analysis by including state-year fixed effects to control for state-year specific shock that would account for differential effect of the financial crisis. However, the treatment variable is state-level, and the state-year fixed effects would absorb the $treat \times post$ effect. I handle this problem in two ways. First, in Appendix Table A4, I report the differences in means of important state-level economic variable growth rates between treated and untreated states. I show that the GDP growth, GDP per capita growth, and unemployment rate growth are all statistically indifferent from zero for all years during the sample period, ensuring that the trends in state economic conditions of the treatment and control states are similar both before and after 2008.

Second, I mitigate this concern by additionally including state with industry-year fixed effects or state-industry with year fixed effects. The former specification captures variation among same-state firms, whereas the latter is more stringent model that captures variation only among the same industry firms in the same states. Tables 1.11-1.14 reports the additional results. The main regression results in Table 1.11 are remain similar, both economically and statistically significantly, for the total debt-to-assets ratio and strengthens for the long-term debt issuance after including the state fixed effects. In Table 1.12, the self-citation results are robust, whereas the magnitude and statistical significance of inventor collaboration results weaken slightly to about 3% increase. The number of granted patents in Table 1.13 and citations to existing patents in Table 1.14 strengthens, whereas the results on percentage of successful applications and citations to new patents weakens and become statistically insignificant.

## 1.9 Conclusion

In this paper, I consider how property rights allocation alleviates some inefficiencies in firms' economic relationship with inventor-employees in innovation processes and affect knowledge-intensive firms' debt financing. This is an important issue not only because property rights increase pledgeability of patents but more importantly because the asset ownership improves firms' incentives to maximize synergistic values of patents, which are valuable to firms' lenders.

I empirically investigate the effects of firms' increasing property rights to employee patents on debt financing capacity. To mitigate endogeneity concerns, I exploit the Court of Appeals Federal Circuit ruling on invention assignment agreements that exogenously increased firms' property rights to inventor-employee patents. I find that the pro-*employer* interpretation of the invention assignment agreement increases total debt by an average $62 million. I also provide evidence that the increased access to debt financing is attributable to firms' improved integration of existing patents, inventor collaboration, and innovation productivity.

Overall, this paper highlights an optimal patent ownership structure under incomplete contracting from the firms' perspective. Recognizing that corporate inventor-employees are accountable for about 90% of all patentable inventions in the US (*Pisegna-Cook* 1994, *Gruner* 2006), whether the firm ownership of employee patents is optimal for the social level of innovation in the economy is an interesting question but beyond the scope of this paper. A detailed data on inventor-employee employment, moves, and wages would provide the opportunity to expand the current research to implications of property rights on entrepreneurial spawning and firms' investment in human capital to address comprehensive impact of property rights allocation.

Figure 1.1: Difference in Leverage Ratio by Years to Treatment

This figure presents the regression coefficients in event time. The horizontal axis indicates event time, where negative numbers are pre-treatment years, zero is the year in which CAFC ruling was made, and positive numbers are post-treatment years. The vertical axis shows the coefficient estimates, $\beta_k$ in the regression specification below. The gray dots show statistically insignificant coefficients, whereas the yellow dots show statistically significant at 1%-level coefficients. The dotted lines are confidence intervals at 10%-level. All standard errors are clustered by state.

$$Total\ debt/Assets_{it} = \alpha + \sum_k \beta_k treat_i \times event_k + \delta_i + \gamma_t + \epsilon_{it}$$

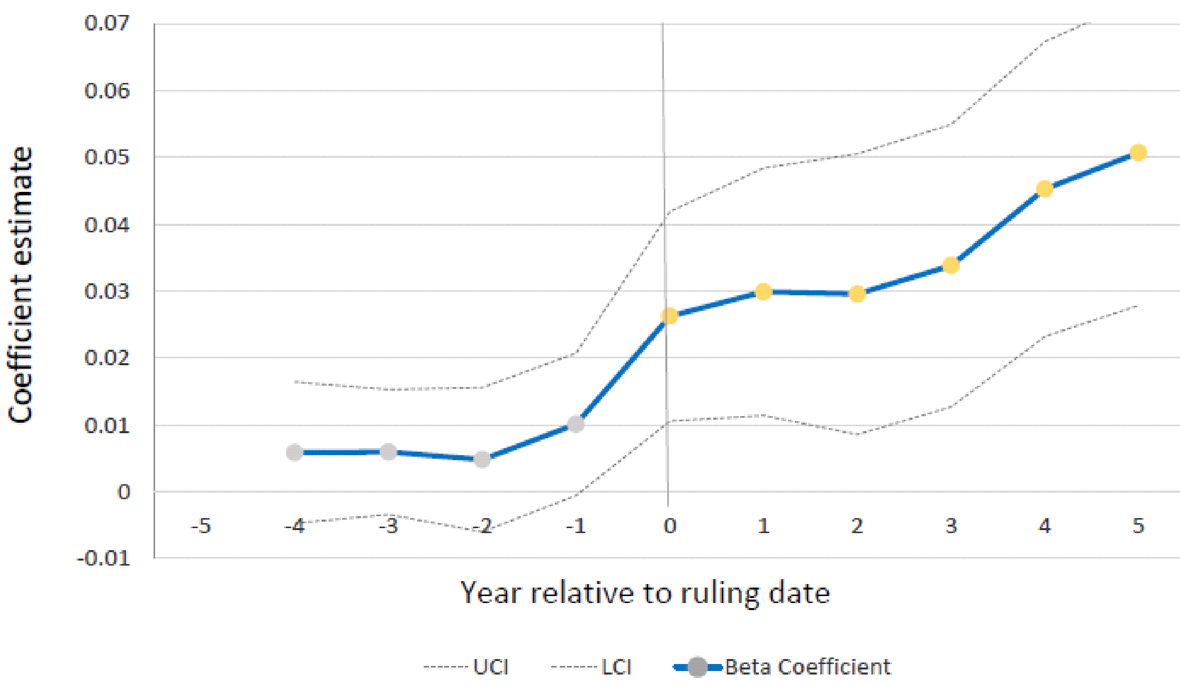


Figure 1.2: Number of Patents Pledged as Collateral

This figure compares the changes in the average number of patents pledged as collateral between treated and control group. The data comes from USPTO Patent Assignment files. The vertical axis measures the average number number of patent pledged as collateral *per* firm. The patents pledged as collateral is identified using assignment transactions marked as "security interest."

Table 1.1: Summary Statistics

This table reports summary statistics for firms in my sample, which comprises of actively patenting firms during the sample period of 2003-2013. I also exclude firms in financials and regulated industries. Panel A provides descriptive characteristics of all sample firms between 2003-2013. Panel B summarizes key variables used in the empirical analyses by treatment and control group firms during the pre-treatment period between 2003-2007. The last column shows p-value of difference in means. The outcome variable in the main regression is *Total debt/Assets*, which is winsorized between zero and one. For variable definitions and details of their construction, see Appendix A3. Observations with missing asset are dropped.

Panel A: All Sample Firms Summary (2003-2013)

| | Mean | Std. dev. | p25 | p50 | p75 | N |
|---|---|---|---|---|---|---|
| Assets ($ mil) | 5,046 | 26,667 | 70 | 333 | 1,850 | 16,540 |
| Ln(Assets) | 5.92 | 2.32 | 4.25 | 5.81 | 7.52 | 16,540 |
| Total debt/Assets | 0.18 | 0.22 | 0.00 | 0.11 | 0.28 | 16,540 |
| R&D exp/Assets | 0.12 | 0.19 | 0.01 | 0.06 | 0.15 | 16,540 |
| Ppent/Assets | 0.17 | 0.16 | 0.06 | 0.12 | 0.24 | 16,540 |

Panel B: Pre-treatment Comparisons (2003-2007)

| | Treatment State* | | Control State | | |
|---|---|---|---|---|---|
| Variables | Mean | N | Mean | N | p-value |
| Assets ($ mil) | 2,460 | 3,630 | 5,062 | 5,123 | 0.000 |
| Ln(Assets) | 5.48 | 3,630 | 5.88 | 5,123 | 0.000 |
| Total Debt/Assets | 0.14 | 3,630 | 0.20 | 5,123 | 0.000 |
| LTD issuance | 0.07 | 3,630 | 0.10 | 5,123 | 0.000 |
| R&D exp/Assets | 0.15 | 3,630 | 0.10 | 5,123 | 0.000 |
| Ppent/Assets | 0.14 | 3,630 | 0.20 | 5,123 | 0.000 |
| Granted patents | 18.26 | 3,630 | 16.74 | 5,123 | 0.551 |
| Patent applications | 33.60 | 3,630 | 28.34 | 5,123 | 0.357 |
| % successful application | 74.20 | 2,644 | 72.52 | 3,435 | 0.039 |
| Avg. First 3-yrs citations | 2.43 | 2,413 | 1.98 | 2,988 | 0.000 |
| Avg. citations | 0.84 | 3,630 | 0.71 | 5,123 | 0.000 |
| Number of inventors | 2.78 | 3,017 | 2.70 | 3,960 | 0.027 |
| Number of self-citation | 38.40 | 3,475 | 43.52 | 4,818 | 0.558 |

*Treatment states include CA, DE, IL, KS, MN, NC, UT, and WA.

Table 1.2: Increasing Debt Financing

This table reports the results of estimating the main difference-in-difference regressions below to examine how shifting property rights to patents from employees to firms affects firms' debt financing. The dependent variable in Columns (1) and (2) is *Total debt/Assets*. The dependent variable in Columns (3) and (4) is *LTD issuance*. The odd-numbered columns include firm and year fixed effects, and the even-numbered columns use more stringent specification including firm and industry-year fixed effects. For variable definitions and details of their construction, see Appendix A3. All standard errors are clustered by state.

$$y_{it} = \alpha + \beta_1 treat_i \times post_t + \delta_i + \gamma_t + \epsilon_{it}$$

$$y_{it} = \alpha + \beta_1 treat_i \times post_t + \beta_2\, post_t + \delta_i + \theta_{jt} + \epsilon_{it}$$

| | (1)<br>Total debt/Assets | (2)<br>Total debt/Assets | (3)<br>LTD issuance | (4)<br>LTD issuance |
|---|---|---|---|---|
| treat×post | 0.026*** | 0.024** | 0.018*** | 0.013* |
| | (0.009) | (0.010) | (0.006) | (0.007) |
| post | | -0.018 | | 0.011 |
| | | (0.012) | | (0.019) |
| Firm FE | Y | Y | Y | Y |
| Year FE | Y | – | Y | – |
| Industry-year FE | N | Y | N | Y |
| Observations | 16,540 | 16,184 | 16,540 | 16,184 |
| Adjusted $R^2$ | 0.610 | 0.605 | 0.279 | 0.276 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.3: Types of Debt

The table reports the results of estimating the difference-in-difference regressions below to examine how shifting property rights to patents from employees to firms affects different types of debt. The data on different types of debt is collected from Capital IQ. *Bank Debt/AT*, *Conv. Debt/AT*, *LTD/AT*, and *Short-term Debt* are bank debt, convertible debt, long-term debt (dltt), and short-term debt (dlc) scaled by total assets, respectively. *Mature in 1 yr* (dd1) and *Mature in 1 or 2 yrs* (dd2) are current portion long-term debt due in one or two years. For variable definitions and details of their construction, see Appendix A3. All standard errors are clustered by state.

$$Types\,of\,Debt_{it} = \alpha + \beta_1 treat_i \times post_t + \delta_i + \gamma_t + \epsilon_{it}$$

| | | | | Short-term debt | | |
|---|---|---|---|---|---|---|
| | Bank Debt | Conv. Debt | Long-term Debt | Short-term Debt | Mature in 1 yr | Mature in 1 or 2 yrs |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| treatXpost | 0.007* | 0.009** | 0.027*** | 0.001 | 0.001 | 0.004 |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.002) | (0.003) |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 13,991 | 13,991 | 13,991 | 16,540 | 16,540 | 16,540 |
| Adjusted $R^2$ | 0.501 | 0.511 | 0.610 | 0.300 | 0.169 | 0.195 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.4: Which Firms Benefit the Most?

Panel A presents quantile regression analysis where the dependent variable is Total debt-to-assets ratio. The estimates are obtained without firm fixed effects (which cannot be combined with quantile regressions) but instead with firm and industry fixed effects. Standard errors are obtained by bootstrapping using 100 repetitions each time. For comparison, the first column reports an baseline estimate from a specification including firm and industry fixed effects only. Panel B reports the cross-sectional results on the main difference-in-difference regression by including additional interaction terms. $d_3$ proxies financial constraints using firm size, age, and unprofitability in Columns (1) - (3), respectively. Each financial constraint indicator is equal to 1 if the proxy is below the median among treated firms during pre-treatment period for size and age, or if the proxy is below zero for unprofitable firms. The last interaction term, multi-segment, counts the number of business segments and is equal to 1 if the number of business segment is greater than zero. For simplicity, only the interaction terms of interest are reported in the table. All specifications include firm and year fixed effects. All standard errors are clustered by state.

$$\mathcal{Q}(Total\ debt/Assets_{it} \mid \tau) = \alpha(\tau) + \beta(\tau)\, treat_i \times post_t + \delta_i(\tau) + \gamma_t(\tau) + \epsilon_{it}(\tau)$$

Panel A: Quantile Regressions

| | Baseline | q30 | q40 | q50 | q60 | q70 | q80 | q90 |
|---|---|---|---|---|---|---|---|---|
| treatXpost | 0.026*** | 0.002 | 0.006 | 0.026*** | 0.047*** | 0.045*** | 0.042*** | 0.040** |
| | (0.007) | (0.002) | (0.006) | (0.010) | (0.009) | (0.011) | (0.013) | (0.017) |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

$$Total\ debt/Assets_{it} = \alpha \quad + \quad \beta_1\, treat_i \times post_t \times d_3 + \beta_2\, treat_i \times post_t + \beta_3\, post_t \times d_3 + \delta_i + \gamma_t + \epsilon_{it}$$

Panel B: Financial Constraints and Organization Structure

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| treatXpostX $d_3$ | -0.010 | 0.021 | 0.080 | 0.032** |
| | (0.021) | (0.014) | (0.124) | (0.012) |
| treatXpost | 0.029*** | 0.017* | 0.024*** | 0.012 |
| | (0.009) | (0.009) | (0.009) | (0.013) |
| $d_3$ | Small Firms | Young Firms | Unprofitable | Multi-segments |
| Firm FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Observations | 16,540 | 16,540 | 16,540 | 16,540 |
| Adjusted $R^2$ | 0.610 | 0.610 | 0.610 | 0.610 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.5: Asset Complementarity and Inventor Collaboration

The table reports the results of estimating the difference-in-difference regressions below to examine the asset complementarity and inventor collaboration as underlying channel of the main debt financing results. Columns (1) and (2) examine changes in the asset complementarity measured with self-citation. In Column (2), I include pre-treatment average count of submitted applications (absorbed by firm fixed effects) and its interaction term the *post* dummy to control for any mechanical relationship between number of applications submitted and self-citations driving the difference in response of asset complementarity. Columns (3) and (4) examine inventor collaboration. Column (3) includes firm and year fixed effects, and Columns (1), (2), and (4) use more stringent specification including firm and industry-year fixed effects. For variable definitions and details of their construction, see Appendix A3. All standard errors are clustered by state.

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2\, post_t + \delta_i + \theta_t + \epsilon_{it}$$

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2\, post_t + \beta_3\, Control_i \times post_t + \delta_i + \theta_{jt} + \epsilon_{it}$$

| | Log(1+self citation) | | Avg. inventors | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| treat×post | 0.144** | 0.156** | 0.127*** | 0.141*** |
| | (0.071) | (0.071) | (0.038) | (0.035) |
| post | -0.416 | -0.393 | | -0.517 |
| | (0.351) | (0.345) | | (0.709) |
| Firm FE | Y | Y | Y | Y |
| Year FE | – | – | Y | – |
| Industry-year FE | Y | Y | N | Y |
| Control | – | Avg.app count | – | – |
| Observations | 14,956 | 14,956 | 13,095 | 12,882 |
| Adjusted $R^2$ | 0.806 | 0.807 | 0.338 | 0.344 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.6: Increase in Patent Productivity

The table reports the results of estimating the difference-in-difference regressions below to examine the patent productivity as underlying patent productivity channel that supports the main debt financing results. In Columns (1) and (2), I measure the productivity using log of number of granted patents. The results still hold when using *lagged* granted patents measure. In Columns (3) and (4), I measure innovation efficiency by scaling the number of patent grants by dollar spent on R&D. Column (3) uses only expensed R&D spending (XRD), and Column (4) uses both expensed and capitalized R&D expenses (XRD+RDIP). The number of observations in Columns (3) and (4) declines because due to data limitation from lagging the measure, I use only 3 periods before and after the treatment. For all specifications, I include the firm age dummy (absorbed by firm fixed effects) and its interaction with the *post* dummy to control for differential trends by firm age and experience in patenting driving the differential outcomes. Columns (1), (3), and (4) include firm and year fixed effects, and Column (2) uses more stringent specification including firm and industry-year fixed effects. The efficiency results using more stringent specification are unreported but remains robust. For variable definitions and details of their construction, see Appendix A3. All standard errors are clustered by state.

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2\, Control_i \times post_t + \delta_i + \gamma_t + \epsilon_{it}$$

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2 post_t + \beta_3\, Control_i \times post_t + \delta_i + \theta_{jt} + \epsilon_{it}$$

| | Log(1+grant) | | Grant/R&D Exp | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| treatXpost | 0.145*** | 0.144*** | 0.140* | 0.137* |
| | (0.052) | (0.045) | (0.083) | (0.080) |
| post | | -0.540*** | | |
| | | (0.040) | | |
| Firm FE | Y | Y | Y | Y |
| Year FE | Y | – | Y | Y |
| Industry-year FE | N | Y | – | – |
| Application year FE | Y | Y | – | – |
| Control | Firm age | Firm age | – | – |
| Observations | 10,330 | 10,169 | 8,687 | 8,692 |
| Adjusted $R^2$ | 0.861 | 0.865 | 0.061 | 0.061 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.7: Citations on New and Old Patents

The table reports the results of estimating the difference-in-difference regressions below to examine the improvement in economic value of new and existing patents.In Columns (1) and (2), I measure the average citations received *per* existing patent to compare citations received on the same portfolio of patents over time. In Columns (3) and (4), I measure the average citations received *per* patent in the first 3-years after the grant year to compare across patents of different age. In the odd-numbered columns, I allow for differential trends by average age of pre-treatment patent portfolio. In the even-numbered columns, I further allow for differential trends by average age of pre-treatment patent portfolio and size of patent portfolio. For each patent portfolio age and patent stock size controls, I include the variables alone (absorbed by firm fixed effects) and their interaction term with the *post* dummy. For variable definitions and further details of their construction, see Appendix A3. All specification include firm and industry-year fixed effects. All standard errors are clustered by state.

$$Citations_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2\, Control_i \times post_t + \delta_i + \theta_{jt} + \epsilon_{it}$$

| | Avg. citations | | Avg. first 3-yr citations | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| treat×post | 0.434*** | 0.432*** | 0.205** | 0.204** |
| | (0.143) | (0.143) | (0.087) | (0.088) |
| post | 2.038*** | 2.038*** | 0.629** | 0.629** |
| | (0.372) | (0.371) | (0.309) | (0.309) |
| Firm FE | Y | Y | Y | Y |
| Industry-year FE | Y | Y | Y | Y |
| Application year FE | Y | Y | Y | Y |
| Controls | Portfolio Age | Portfolio Age<br>Patent Stock | Portfolio Age | Portfolio Age<br>Patent Stock |
| Observations | 10,695 | 10,695 | 10,695 | 10,695 |
| Adjusted $R^2$ | 0.490 | 0.490 | 0.404 | 0.404 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.8: Immediate and Lagged Changes

The table reports progression of changes over time in asset complementarity and productivity presented in Tables 1.5 and 1.6. $t + 0$ is the year in which CAFC decision is made in 2008. The dependent variable in Column (1) is the a total number of self citations as a percentage of all citations made by new applications each year. Columns (2) and (3) show lagged effects. The dependent variable in Column (2) is the average number of inventors assigned per patent. The dependent variable in Column (3) is the log of number of granted patents. For variable definitions and further details of their construction, see Appendix A3. All standard errors are clustered by state.

$$y_{it} = \alpha + \sum_k \beta_k \, treat_i \times event_k + \delta_i + \epsilon_{it}$$

| | Immediate | Lagged | |
|---|---|---|---|
| | (1)<br>% self citation | (2)<br>Avg. inventors | (3)<br>Log(1+grant) |
| treat × t-1 | 0.295 | 0.121** | 0.015 |
| | (0.181) | (0.046) | (0.028) |
| treat × t+0 | 0.789*** | -0.030 | 0.007 |
| | (0.269) | (0.028) | (0.042) |
| treat × t+1 | 0.492* | 0.000 | 0.067 |
| | (0.264) | (0.076) | (0.062) |
| treat × t+2 | 0.529** | 0.171*** | 0.237*** |
| | (0.199) | (0.031) | (0.067) |
| treat × t+$3_+$ | 1.844*** | 0.240*** | 0.217*** |
| | (0.605) | (0.025) | (0.078) |
| Firm FE | Y | Y | Y |
| Application year FE | – | – | Y |
| Control | – | – | Firm age |
| Observations | 10,234 | 13,095 | 10,330 |
| Adjusted $R^2$ | 0.364 | 0.336 | 0.859 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.9: Propensity Score Matching Diagnostics

This table presents pairwise comparisons of the variables on which the nearest neighbor matching (n=2) with replacement is performed. The summarized variable are mean values in the pre-treatment periods. Leverage growth is included to ensure the pre-treatment trend in the main outcome variable, total debt-to-assets ratio, is matched. Each of the last columns in Pre-Match and Post-Match are p-value of difference in means between Control and Treatment. The table shows that the post-matched variables are statistically indifferent from zero. For variable definitions and further details of their construction, see Appendix A3.

| | Pre-Match | | | Post-Match | | |
|---|---|---|---|---|---|---|
| Variable | Control | Treatment | p-value | Control | Treatment | p-value |
| Leverage growth | 10.988 | 5.378 | 0.478 | 1.874 | 5.403 | 0.182 |
| LTD issuance growth | 22.728 | 41.658 | 0.563 | 33.956 | 41.848 | 0.839 |
| Size growth | 0.323 | 0.490 | 0.188 | 0.433 | 0.362 | 0.369 |
| Assets | 4,808 | 2,527 | 0.066 | 2,733 | 2,533 | 0.707 |
| R&D exp. | 0.119 | 0.162 | 0.000 | 0.169 | 0.161 | 0.458 |
| Ppent | 0.181 | 0.133 | 0.000 | 0.137 | 0.133 | 0.581 |
| Log(1+ grant) | 1.247 | 1.522 | 0.000 | 1.514 | 1.514 | 0.996 |
| Log(1+ application) | 1.588 | 1.920 | 0.000 | 1.945 | 1.913 | 0.694 |
| % successful application | 0.696 | 0.709 | 0.383 | 0.701 | 0.708 | 0.608 |

Table 1.10: Increasing Debt Financing - Propensity Score Matching Regressions

The table reports the results of the difference-in-difference estimation using the propensity score matched sample to ensure the results reported in Table 1.2 are not driven by observable differences between the treated and control firms. The dependent variable is *Total debt/Assets*. The odd-numbered columns include firm and year fixed effects, and the even-numbered columns use more stringent specification including firm and industry-year fixed effects. All standard errors are clustered by state. Columns (1) and (2) uses nearest neighbor matching with n=1, and Columns (3) and (4) uses nearest neighbor matching with n=2 with replacement. All standard errors are clustered by state.

| | NN=1 | | NN=2 | |
|---|---|---|---|---|
| | Total debt/Assets<br>(1) | LTD issuance<br>(2) | Total debt/Assets<br>(3) | LTD issuance<br>(4) |
| treat×post | 0.024** | 0.015* | 0.021** | 0.016** |
| | (0.011) | (0.009) | (0.010) | (0.007) |
| Firm FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Observations | 9,340 | 9,340 | 10,798 | 10,798 |
| Adjusted $R^2$ | 0.582 | 0.232 | 0.588 | 0.236 |

Standard errors in parentheses
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

Table 1.11: Increasing Debt Financing - State Robustness

The table reports the results of estimating the main difference-in-difference regressions with state or state-industry fixed effects. The dependent variable in Columns (1) and (2) is *Total debt/Assets*. The dependent variable in Columns (3) and (4) is *LTD issuance*. The odd-numbered columns include state and industry-year fixed effects, and the even-numbered columns use more stringent specification additionally including year and state-industry fixed effects. For variable definitions and further details of their construction, see Appendix A3. All standard errors are clustered by state.

$$y_{it} = \alpha + \beta_1 treat_i \times post_t + \delta_s + \theta_{jt} + \epsilon_{it}$$

$$y_{it} = \alpha + \beta_1 treat_i \times post_t + \beta_2 post_t + \gamma_t + \lambda_{sj} + \epsilon_{it}$$

| | (1)<br>Total debt/Assets | (2)<br>Total debt/Assets | (3)<br>LTD issuance | (4)<br>LTD issuance |
|---|---|---|---|---|
| treat×post | 0.023** | 0.027*** | 0.018*** | 0.020*** |
| | (0.009) | (0.008) | (0.006) | (0.006) |
| post | -0.001 | | -0.193*** | |
| | (0.154) | | (0.034) | |
| Year FE | N | Y | N | Y |
| State FE | Y | N | Y | N |
| Industry-year FE | Y | N | Y | N |
| State-industry FE | N | Y | N | Y |
| Observations | 16,540 | 16,540 | 16,540 | 16,540 |
| Adjusted $R^2$ | 0.099 | 0.235 | 0.036 | 0.116 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.12: Asset Complementarity and Inventor Collaboration - State Robustness

The table reports the results of asset complementarity and inventor collaboration channel with state or state-industry fixed effects. Columns (1) and (2) examine changes in the asset complementarity using self-citation as the measure. In Column (2), I include pre-treatment average count of submitted applications and its interaction with the *post* dummy to control for any mechanical relationship between number of applications submitted and self-citations driving the difference in response of asset complementarity. Columns (3) and (4) examine inventor collaboration. Columns (1), (2), and (3) include state and industry-year fixed effects, and Column (4) includes year and state-industry fixed effects. For variable definitions and details of their construction, see Appendix A3. All standard errors are clustered by state.

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \delta_s + \theta_{jt} + \epsilon_{it}$$

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2 post_t + \beta_3\, Control_i + \beta_4\, Control_i \times post_t + \gamma_t + \lambda_{sj} + \epsilon_{it}$$

| | Log(1+self citation) | | Avg. inventors | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| treat×post | 0.191** | 0.121* | 0.075** | 0.081*** |
| | (0.076) | (0.066) | (0.037) | (0.029) |
| post | 0.846 | 0.503** | -0.155 | |
| | (1.337) | (0.223) | (0.409) | |
| Year FE | N | N | N | Y |
| State FE | Y | Y | Y | N |
| Industry-year FE | Y | Y | Y | N |
| State-industry FE | N | N | N | Y |
| Control | – | Avg.app count | – | – |
| Observations | 15,489 | 15,489 | 13,095 | 13,095 |
| Adjusted $R^2$ | 0.051 | 0.639 | 0.078 | 0.122 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.13: Patent Productivity and Successful Patent Applications - State Robustness

The table reports the results of underlying patent productivity channel with state-industry fixed effects. In Columns (1) and (2), I measure the productivity using log of number of granted patents. In Columns (3) and (4), I scale the number of eventually granted patents by total number of applications submitted in a year to measure the percentage of successful patents, then multiply the ratio by 100. For all specifications, I include the firm age and its interaction term with the *post* dummy to control for firm's age and experience in patenting driving the differential outcomes. The odd-numbered columns include state and industry-year fixed effects, and the even-numbered columns use more stringent specification including year and state-industry fixed effects. For variable definitions and details of their construction, see Appendix A3. All standard errors are clustered by state.

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2\, Control_i + \beta_3\, Control_i \times post_t + \delta_s + \theta_{jt} + \epsilon_{it}$$

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2 post_t + \beta_3\, Control_i + \beta_4\, Control_i \times post_t + \gamma_t + \lambda_{sj} + \epsilon_{it}$$

| | Log(1+grant) | | % successful app | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| treat×post | 0.144** | 0.152*** | 1.353 | 2.066 |
| | (0.055) | (0.055) | (1.579) | (1.712) |
| post | -0.379 | | -65.238*** | |
| | (1.514) | | (12.345) | |
| Year FE | N | Y | N | Y |
| State FE | Y | N | Y | N |
| Industry-year FE | Y | N | Y | N |
| State-industry FE | N | Y | N | Y |
| Application year FE | Y | Y | – | – |
| Control | Firm age | Firm age | Firm age | Firm age |
| Observations | 10,330 | 10,330 | 10,976 | 10,976 |
| Adjusted $R^2$ | 0.140 | 0.283 | 0.128 | 0.178 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 1.14: Citations on New and Old Patents - State Robustness

The table reports the results of improvement in economic value of new and existing patents with state-industry fixed effects. In Columns (1) and (2), I measure the average citations received *per* patent in the first 3-years after the grant year to compare across patents of different age. In Columns (3) and (4), I measure the average citations received *per* existing patent to compare citations received on the same portfolio of patents over time. In the odd-numbered columns, I allow for differential trends by average age of pre-treatment patent portfolio. In the even-numbered columns, I further allow for differential trends by average age of pre-treatment patent portfolio and size of patent portfolio. For each patent portfolio age and patent stock size controls, I include the variables alone and their interaction term with the *post* dummy. For variable definitions and further details of their construction, see Appendix A3. All specification include firm and industry-year fixed effects. All standard errors are clustered by state.

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2\, Control_i + \beta_3\, Control_i \times post_t + \delta_s + \theta_{jt} + \epsilon_{it}$$

$$y_{it} = \alpha + \beta_1\, treat_i \times post_t + \beta_2\, post_t + \beta_3\, Control_i + \beta_4\, Control_i \times post_t + \gamma_t + \lambda_{sj} + \epsilon_{it}$$

| | Avg. citations | | First 3-yr citations | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| treat×post | 0.585*** | 0.526*** | 0.176 | 0.134 |
| | (0.199) | (0.187) | (0.109) | (0.085) |
| post | 5.664*** | | 3.572*** | |
| | (1.278) | | (0.960) | |
| Year FE | N | Y | N | Y |
| State FE | Y | N | Y | N |
| Industry-year FE | Y | N | Y | N |
| State-industry FE | N | Y | N | Y |
| Controls | Portfolio Age<br>Patent Stock | Portfolio Age<br>Patent Stock | Portfolio Age<br>Patent Stock | Portfolio Age<br>Patent Stock |
| Observations | 10,695 | 10,695 | 10,695 | 10,695 |
| Adjusted $R^2$ | 0.203 | 0.215 | 0.066 | 0.090 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

## CHAPTER II

# Patent Litigation and Innovation Competition

## 2.1 Abstract

Using novel hand-collected patent litigation data from 2000-2006, we show that patent litigation has important financial and real impacts on firms. We find that defendant firms experience declining financial flexibility and innovation activities, and shift innovation strategy to pursue more exploitative projects. The product market overlap exacerbates financial constraints of defendants in intra-industry litigation, whereas a large reduction of litigation probability when pursuing exploitative innovation intensifies narrower innovation scope for defendants in inter-industry litigation. We sharpen our results by instrumenting the probability of being sued and the timing of patent litigation using China's participation in TRIPS (Trade-Related Aspects of Intellectual Property Rights) agreement. Lastly, we find suggestive evidence that patent litigation has spillover effects on other non-litigated firms in the industry.

## 2.2 Introduction

The importance of intellectual property for firms has increased over time, and patent litigation has become an important means of actively protecting firms' valuable patent intellectual property. Costly patent litigation[1] hurts firms' financial health and, more importantly, deters firms' subsequent innovation activities and product market competition by aggravating investment frictions. A sharp increase in non-practicing entity (NPE)[2] patent litigation has attracted much attention from the academia and led to a number of important papers (e.g., *Mezzanotti* (2015), *Cohen, Gurun, and Kominers* (2016)) that focus directly on NPE litigation. However, a limitation of NPE litigation is that NPE litigation cannot, by nature, address how interactions of operating firms directly contribute to innovation and product market competition.

In this paper, we use our hand-collected patent litigation data to examine the real consequences of patent litigation on operating firms. Existing studies (*Bhagat, Brickley, and Coles* (1994), *Bhagat, Bizjak, and Coles* (1998), *Mezzanotti* (2015)) have found substantial negative value impact of corporate litigation in general. Building on these earlier studies, we add substantial details of how firms' investments and innovation strategy change in the context of product market competition, both of which help explain what underlying changes induce the declining firm values. In order to highlight the industry dynamics of patent litigation, we further divide our sample cases into intra- and inter-industry cases to capture the significance of product market relevance of patent litigation consequences. The product market relevance also differentiate patent litigation from securities litigation, where the latter is about disputes between firm and its investors with regards to governance, frauds, and disclosure rule violations.

We derive our economic intuition of patent litigation from *Lanjouw and Lerner* (1997) model and identify legal expense, damages awards, and the probability of winning case as important key parameters in the endogenous enforcement process. We first find that patent litigation costs decrease financial flexibility of firms. Since defendants are likely to bear

[1]The median litigation costs and damage awards have reached $5 million and $17 million per case *AIPLA* (2015). These financial burdens and subsequent product market difficulties are well-described in the examples in the Appendix B1.

[2]Non-practicing entities amass patents not fro producing commercial products, but in order to claim license fees and/or litigate infringement on their patent portfolios.

greater financial burden of paying damages awards, we find that defendant firms experience larger decline in financial flexibility than plaintiff firms do. We show that defendant firms' cash level falls by $20 million after patent litigation. The number of firms paying dividends also decline by 5.6% following litigation.

Next, we show how litigation costs curtail innovation activities relatively more for defendant firms. The costs associated patent litigation push up the hurdle for taking positive NPV project. We measure firms' innovation activities by the number of patent applications and find that it declines by 35%. The number of citations received by defendants also falls by 4%. This may be due to the increase in perceived costs of potential patent litigation for firms using technology related to the asserted patent, in case it is found invalid. These results lead us to investigate industry spillover effect of patent litigation. We indeed find that a greater number of firms targeted as defendants decreases industry-wide innovation, as measured by the number of patent applications.

The first part of the analyses relies on a difference-in-difference framework to capture the relative effects of patent litigation between plaintiffs and defendants. However, we acknowledge that the types of litigant and the timing of patent litigation are both endogenous variables. For example, the weakening financial health may have attracted more patentees to target alleged infringers to take advantage of relative financial flexibility, thus resulting in reverse causality. Therefore, we attempt to mitigate such confounding effects by using instrumental variable approach. We use the passage of TRIPS agreement between China and the US in 2001, which strengthened the incentive of the US firms to enforce intellectual property rights against potential US rival entrants to the China market. We find qualitatively consistent results using the instrumental variable approach.

As emphasized in the beginning, the essence of patent litigation entails product market competition. Therefore, we further divide our sample depending on whether plaintiffs and defendants are in the same industry or not to further understand how the product market relevance plays out in patent litigation. We define intra-industry litigation cases as a dispute between two opposing firms in the same 3-digit SIC. We first re-characterize the key patent litigation parameters by intra- and inter-industry case and generally find that there are greater product market overlap between intra-industry litigants and larger damages awards, which amplify the financial damages and deteriorating innovation activities. In regression results, we verify that the negative financial and innovation activities results we found earlier strengthen substantially for intra-industry cases.

Finally, we provide details of how patent litigation change firms' innovation strategy. We find that firms generally pursue safer innovation strategy in narrower scope. On a patent-level, firms develop more exploitative patents. On a firm-level, firms cut down on general acquisitions but increase same-industry acquisitions by 56%, which is indicative of firms focusing on the core business and technology. We further investigate the types of external R&D investments. The corporate venture capital (CVC) investments decrease by 10%, consistent with pursuing safer innovation strategy, as CVC investments are known as a means to explore and experiment with new technology outside of firms' boundaries. Lastly, we find that the breadth of business segments decline by 7.7% for defendant firms after patent litigation, suggesting that the narrower focus may have caused defendant firms to close down on remotely related business segments.

The last part of the analyses with firms' exploitative innovation strategy seem to reflect that higher uncertainty associated with innovation activities discourages the pursuit of long-term risky R&D projects (*Cohen, Levin, and Mowery* (1987), *Nohria and Gulati* (1996), *Gao, Hsu, and Li* (2018), *Aghion, Angeletos, Banerjee, and Manova* (2010)). This is also consistent with *Lerner* (1995) that higher uncertainty about the quality of patent litigation increases the chance of disputes reaching trial instead of settlement. We provide additional evidence that given being involved in a patent litigation as a defendant in year $t$, shifting towards exploitative innovation strategy in year $t+1$ reduces the probability of being targeted as a defendant in the same year $t+1$. This result supports that the exploitative innovation strategy is an effective way to hedge away future patent litigation risks.

This paper contributes to a few related literature. This paper expands patent litigation literature by showing important inter-firm dynamics and innovation competition between operating entities. Our paper differentiates from the patent litigation studies focusing on NPE patent litigation (*Cohen et al.* (2016), *Mezzanotti* (2015),*Appel, Farre-Mensa, and Simintzi* (2017)) in three important ways. First, by focusing on patent litigation between operating firms, we provide evidence of inter-firm dynamics that form innovation and product market competition, which are absent in NPE patent litigation by nature. Second, whereas the NPE litigation is largely driven by monetary gains from suing cash rich defendants, we do not find evidence of such cash-driven motives. The diverging litigation effects between plaintiffs and defendants and stronger intra-industry litigation effects clearly differentiate the motivation of litigation of operating firms from that of NPE firm. Lastly, building on previous studies, we do not only show the adverse effects of patent litigation, but we also additionally focus on providing in-depth analyses of how affected firms' innovation strategies change in terms of both internal and external R&D efforts.

This paper also builds on broader corporate litigation literature. Existing corporate litigation studies focus on corporate fraud (e.g., *Karpoff and Lott Jr.* (1993), *Dyck, Morse, and Zingales* (2010)), shareholder litigation (e.g., *Lin, Liu, and Manso* (2016)), environmental-related litigation (*Karpoff, Lott, and Rankine* (1999)), antitrust litigation (*Bizjak and Coles* (1995)) and general inter-firm litigation (*Bhagat et al.* (1994)). Unlike corporate fraud or shareholder litigation that stem from managerial agency problem, patent litigation highlights operating risk for firms with large intellectual properties. This paper shows findings consistent with *Bhagat et al.* (1994) that litigation leads to decline in financial flexibility. However, we provide additional important details on changes in the types, modes, and breadth of firms' innovation strategies specific to patent litigation.

The rest of the paper is organized as follows. Section 2.3 develops hypotheses. Sample data, variable definitions, and summary statistics are reported in Section 2.4. Section 2.5 describes our empirical approach. Section 2.6 presents the main results, and Section 2.7

concludes.

## 2.3 Hypothesis Development

In this section, we derive our economic framework from *Lanjouw and Lerner* (1997) model and develop our hypotheses from the key parameters identified in the model. A patentee makes a decision on whether to go trial or to settle a patent dispute with an infringer. The decision is based on comparing the settlement payoff with the expected payoff from going to trial, which depends on the probability of winning the case ($W$, $w$), damages awards ($j$), and legal expenses ($L$, $l$). The patentee's decision comes down to weighing between litigation costs saved when settle and expected damages awards earned when reaching a trial. Equation (9) in *Lanjouw and Lerner* (1997) describes a patentee's decision from patentee's expected payoff, $(Y + W\alpha j - L) + Max\{0, \theta[(L + l) - j(W\alpha - w)]\}$. If the settlement profit in the term in the bracket is negative, the case will go to trial, and if it is positive, the case will settle. Therefore, we focus on the damages awards, legal costs, and the probability of winning trial to develop our empirical predictions in the following hypotheses on the real consequences of patent litigation using the comparative statics on these key parameters.[3]

*Hypothesis 1: Patent litigation costs decrease financial flexibility.*

Patent litigation is costly. According to *AIPLA* (2015), the median patent litigation costs ($L$, $l$) has increased from \$4.5 million to \$5.0 million between 2005 and 2015 for firms with more than \$25 million risk. Also, the median damages (j) awarded range from \$2 million to \$17 million over 1997-2016, and as much as \$2.5 billion for mega-award granted in 2016 ($PWC$, 2017). Damages awards are not required to be reported on dockets. There are 112 cases with reported damages awards in our data. Breaking down into different types of damages awards, our data shows that the lost profits range between \$2.2 million and

[3]We are mainly interested in comparative statics with respect to damages awards on financial variables (i.e. $\frac{\partial Cash}{\partial j}$, $\frac{\partial Div}{\partial j}$, $\frac{\partial Leverage}{\partial j}$, $\frac{\partial Growth}{\partial j}$) and innovation output outcome variables (i.e. $\frac{\partial NumApplication}{\partial j}$, $\frac{\partial Citations}{\partial j}$). Innovation strategy variables are considered with respect to actions that change the probability of winning case $W$ and $w$ (i.e. $\frac{\partial InnovationScope}{\partial W}$).

\$57.4 million. The reasonable royalty ranges from \$88,000 to \$45.3 million. We expect that both plaintiffs and defendants to experience financial constraints post litigation, but since defendants are accountable for damages awards, if found to have infringed the patentee's technology, defendants' financial burden will be larger. It is also important to note that if legal expenses ($L$, $l$) are substantially larger than the damages awards ($j$), then cases are likely to be settled most of the time. The median lost profits and reasonable royalty are \$8.9 million and \$4.6 million, respectively, both of which are comparable or larger than the median legal expenses of \$5 million.

*Hypothesis 2: Litigation costs reduce innovation activities.*

As litigation costs increase, the threshold for taking positive NPV innovation project also rises, forcing firms to forgo some of low return innovation projects on both firm- and industry-level. As a result, we predict that the number of patent applications decrease after patent litigation. Furthermore, as patent citations capture the intricate web technology users, we expect that patent litigation decreases the number of citations received by the defendant patents. This reflects the increased perceived of cost of citing the asserted patent for citing firms for the possibility of the asserted patent resulting in invalidity. This hints at a potential industry spillover effects of patent litigation aggregate industry-level. We predict that the greater the number of defendants in a given year in a given industry, the larger reduction in industry-level innovation activities.

*Hypothesis 3: The decrease in financial flexibility and innovation activities is more pronounced in intra-industry case.*

We divide our sample cases into intra- and inter-industry case in order to emphasize that patent litigation is closely related to industry dynamics. We define categorize a case as an intra-industry case when plaintiffs and defendants share the same 3-digit SIC code. By doing so, we can re-characterize the key patent litigation parameters by intra- and inter-industry cases.

Our data shows that intra-industry case plaintiffs and defendants indeed overlap to a larger degree in terms of technology and product market. The patent proximity, which measures the distance between vectors of patent classes of plaintiff and defendant pair, is higher in intra-industry case (0.42) than in inter-industry case (0.31). *Hoberg and Phillips* (2016) measure of text-based industry classification of product market rivals also is greater for intra-industry cases. The score is 0.42 for intra-industry and 0.31 for inter-industry, which indicate that the pair of firms in intra-industry cases are closer rivals in the product market. These two measures ensure that intra-industry case litigants have greater product market overlap. Therefore, the average damages award is larger in intra-industry cases ($9.60 million) compared to inter-industry cases ($8.29 million), as damages awards account for the harm done by an infringer on sales of the product related to an asserted patent.

The summary of key parameters above by intra- and inter-industry case alludes to a greater chance of observing intra-industry case as the key parameters increase patentees' incentives to go to trial. We confirm that there are greater number of intra-industry cases (441) than inter-industry cases (390) in our data. These observations lead us to expect also to find more pronounced negative effects of financial and innovation activities results for intra-industry cases. This is mainly due to larger damages awards when there is greater product market overlap as we have shown above.

*Hypothesis 4: Firms choose exploitative innovation strategy after patent litigation to avoid future litigation risks.*

*Lerner* (1995) finds that greater uncertainty about the quality of case (i.e. the perceived probability of winning the case) impedes settlement. Therefore, in order to avoid future litigation risks, we expect firms to choose incremental patent development to stay closer to the core technology that reduces the uncertainty about the quality of cases. In other words, after patent litigation, firms will follow an exploitative innovation strategy.

We use a few proxies of narrower innovation scope. First, on a patent-level, we measure the breadth of patents using the citations. An *Exploitative* patent uses existing patents and patents cited by those to capture how narrow is the trajectory of related technologies. On a firm-level, we expect firms to focus more on *same*-industry acquisitions for external innovation.

Another way to measure firms' incentives to pursue exploitative innovation project is to look at changes in corporate venture capital (CVC) investments. It is widely accepted that firms use CVC to search for new technologies outside of firm boundaries (*Fulghieri and Seville* (2009)) and to become more receptible to experimentation and exploration (*Fulghieri and Seville* (2014), *Ma* (2016)). Therefore, we predict that firms trim down on CVC investments after patent litigation. The reduction of relatively distanced projects may also result in a decrease in the number of business segments. Lastly, we verify that the variety of ways of pursuing exploitative innovation strategy lowers near future litigation risks when conditioning on firms learning towards exploitative innovation projects after the patent litigation.

## 2.4 Data and Summary Statistics

### 2.4.1 Data Source and Sample Selection

Our sample consists of S&P 500 firms that had at least one patent litigation during our sample period between 2000 and 2006. We restrict our sample period to 2006 due to significant structural changes in intellectual property rights after 2006. Particularly, patent troll related litigations soared after 2006. *Bessen and Meurer* (2014) show that aggregate direct costs[4] of NPE patent litigations grew rapidly from about $7 billion in 2005 and 2006, to $11 billion in 2007 and $29 billion in 2011. The NPE patent assertions account for about 70% of patent litigations in 2012, a 270% increase over 26% in 2006. In 2006, a patent dispute by NPT Inc., a patent holding company, nearly caused the shutdown of BlackBerry wireless service, and reached a $612.5 million settlement. This successful NPE

[4]Aggregate director cost includes all legal costs, settlement costs, and other full costs for currently unresolved lawsuits.

suit, which was quite rare before 2006, gained Congress attention and media spotlight.[5] In the information and communication technology (ICT) segment, furthermore, there were many structural changes in product market and regulations around 2007 with the introductions of new technologies such as iPhone, cloud computing service infrastructure, and flash-based hard drive. Given many confounding factors causing a spurious relation between patent litigation and real consequence in product market competition, our sample period is a clearer setting for examining the implications of patent litigation on product market competition.

There are two main sources of data. The first is *Lex Machina*. *Lex Machina* provides patent litigations in detail starting in January, 2000. The database leverages primary data source from PACER, the USPTO, and ITC, and offers comprehensive information about each patent litigation. We hand-collect information on litigants and asserted patents involved in a case, damage amounts,[6] judges, courts, and final decisions. We keep cases that involve at least one S&P 500 firm in the litigation.[7] The second source of data is NBER patent database (*Hall et al.*, 2001). We match our sample firms to NBER's *pdpass* firm identifier and obtain detailed patents owned by our sample firms. Since NBER data ends in 2006 and *Lex Machina* starts in 2000, our sample period is restricted between 2000 to 2006.

Overall, our sample data consists of 473 unique S&P 500 firms, 1,692 unique cases, and 2,620 unique firm-case observations. The number of unique firm-case observation implies that some cases involve non-S&P 500 firm as counterparty. In the next section, we describe our sample litigations in detail and characteristics of firms by plaintiff and defendant.

[5]See more "BlackBerry Maker Reaches Deal in Patent Dispute," The New York Times, 2006 March and the government hearing in 2006, "Patent Trolls: Fact or Fiction," 2006 June

[6]Not all cases disclose the damage amount. We leave the unreported damages as missing in the data.

[7]Surprisingly, none of our sample cases seems to involve litigation against non-practicing entities (NPEs or "trolls"). One possible reason is that since the objective of NPEs centers around monetary gains, these cases may settle before reaching a trial.

### 2.4.2 Summary Statistics

#### 2.4.2.1 Patent Litigation Summary

Table 2.1 Panel A describes our sample patent litigation cases. There are total 1,692 S&P 500 firm associated cases in our sample. We exclude 16 cases that are still on-going lawsuits without case termination date.[8] In our sample, 76% cases are initiated by S&P 500 plaintiff firms. Of these cases, only 18% of the cases reach final verdict, and around 70% of cases are dismissed after being filed. Conditional on reaching verdict, about 65% of cases are won by the plaintiffs, which suggests that firms are more likely to reach trial if there is high probability of winning ex ante.

The average length of litigation is about 2 years, and each case has on average 1.31 plaintiffs and 1.90 defendants.[9] About 60% of cases are intra-industry cases, where plaintiffs and defendants are in the same industry based on two-digit SIC. The average total damage awards in our sample is $7.3 million,[10] which is also consistent with the previously referenced number for *PWC* (2017). Note that damage awards are not always reported in case dockets, and we only have 112 cases with reported damage awards.

We acknowledge that many patent assertions can reach to the settlement before actual trials. Those settlements that are not observed in our litigation sample. In our litigation sample, 18% of trials end up with a verdict during our sample and about 70% of trials are dismissed. We expect that patent litigations ending up in actual trials are the ones that face fiercer product market competition. Usually damage rewards are three times larger than settlement costs, and thus firms will settle before reaching trials if the expected payoff/cost of litigation is greater than settlement costs. Therefore, it is likely that our litigation sample may capture the cases with greater economic importance.

[8] The results are robust after including those on-going lawsuits.

[9] Since our sample include only litigants who can be identified in Compustat, these numbers constitute the lower bounds.

[10] In untabulated table, we also report damages from litigation, computed as a net amount. Damages paid are negative numbers and received are positive number. The average net damage amount is positive given our sample firms are more likely to be plaintiffs in sample cases, and they are also more likely to win, receiving damages from their opponent firms.

#### 2.4.2.2 Firm Characteristics Summary

Table 2.1 Panel B reports summary statistics of patent portfolios on firm-level as of 2006. The number of unique firms in our sample is 159 and 271, with and without non-S&P 500 opponent firms, respectively. Our sample firms have mean (median) of 1,450 (139) patents in their portfolio and a mean (median) age of 10.9 (10.4) years-old. The average number of claims on patents and truncation-adjusted citations received are 18.6 and 16.4, respectively. Lastly, our sample firms hold relatively more of explorative patents that uses and are related to a wide variety of technology fields.

Panel C describes financial characteristics of our sample firms. The average leverage of 0.21 is relatively large for R&D-intensive firm. However, keep in mind that our sample firms consist of S&P 500 firms, therefore the leverage ratio of 0.21 may actually be on the lower end compared to other non R&D-intensive firms. Also, note that our sample firms have relatively high average Q and are in highly competitive industries.

In order to give some reference statistics, we also report comparisons between litigated firms and never-litigated firms, using all S&P 500 firms between 2000 and 2006 in Table 2.2 Panel A. In terms of financials, litigated and never-litigated firms are similar, except for the size and acquisitions. The innovation dimensions shows stark differences, however. Litigated firms have statistically significantly higher R&D expenses and Tobin's Q and are more profitable. These are intuitive differences because patent litigation would be common among firms actively pursuing innovation. Also, highly profitable firms have the financial ability to bear the high litigation costs as well as more likely to attract potential litigants. Furthermore, Litigated firms have much larger patent portfolios and generally higher quality patents. Note that the raw number of citations seems to be higher for never-litigated firms due to skewness. When we take the log of the number of citations, litigated firms have statistically significantly greater number of citations received.

### 2.4.3 Determinants of Patent Litigation

As we emphasized in the introduction, patent litigation is likely related to firms' innovation strategies and product market relationships, beyond the individual patent characteristics. The goal of this paper is to capture such firm-level characteristics and interactions of firms in the product market together which lead to patent litigation. Earlier studies of patent litigation has focused and identified the patent-level determinants of patent litigation. Before we present our main firm-level analyses, we briefly describe the determinants of patent litigation and ensure that our data exhibits similar characteristics to earlier small sample patent litigation studies.

In Appendix Table B1, we report regression of different types of patent litigation on firms' innovation, financials, and industry characteristics. It is important to note that this table presents the probability of different types of patent litigation, and not the probability of *any* litigation, because our sample consists only of firms involved patent litigation.

Table B1 suggests that firms with high quality and original patents are likely to become plaintiffs and take initiative in protecting patents (Column (1)). Also, firms with greater cash-to-assets ratio are likely to become defendants. Both results are consistent with previous studies that the economic value of patents as well as the level of cash stock are important determinants of patent litigation (*Lanjouw and Schankerman* 2004, *Allison, Lemley, and Walker* 2009). In column (3), we find that large firms with highly original patents, though not necessarily large stock of patents, large R&D spending, and relatively low industry-median Q tend to be involved in within industry cases. The results suggest that large innovative firms are likely to lean on patent litigation to protect its proprietary technology and secure competitive position in the product market.

## 2.5 Empirical Approach

Our main analysis approach is difference-in-difference regressions. We define our "treatment" group as defendant firms[11] and compare the *relative* changes in outcome variables two years before and after patent litigation.[12] We use difference-in-difference analysis to capture the differential impact of patent litigation on different types of litigant around the patent litigation.

$$Y_{i,j,t} = \beta_0 + \beta_1 After_{i,j,t} \times Defendant_{i,j,t} + \beta_2 After_{i,j,t} + \beta_3 Defendant_{i,j,t} \\ + \beta' X_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,j,t}$$

where $i$ indexes portfolio firms, $j$ indexes litigation cases, $t$ indexes years, $Y_{i,j,t}$ is a dependent variable. *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if a firm is defendant in litigation case, otherwise zero. The year fixed effects and firm fixed effects to remove common time trend in corporate policy and time-invariant unobservables, respectively. We cluster standard errors at case level.[13] The resulting difference-in-difference coefficient captures the changes in defendant firm outcome variables relative to the changes in plaintiff firm outcome variables, post-treatment.

We acknowledge that our "treatment" is non-random (also discussed in Section 2.4.3 Determinants of Patent Litigation), and also have shown that the defendant firms are somewhat different from the plaintiff firms from Panel B of Table 2.2. The non-random treatment and the endogenous timing of patent litigation can cause several limitations in drawing causal inference. For example, firms with strong innovation outcome may attract more asserted claims because rival firms using similar technology may wait until the profits from the al-

[11] The designation of treatment group is arbitrary. Since our sample data consists of firms with at least one patent litigation, the difference-in-difference coefficients can be interpreted in exactly the opposite way with defining plaintiff firms as a treatment group.

[12] For robustness, we also use different windows for treatment period. The results are robust.

[13] Our main results are qualitatively robust to firm-level clustering.

legedly infringing patent build up to maximize the expected profit from patent litigation. The unobservable drivers of decision to initiate patent litigation that are correlated with firms' financial health, innovation strategy, or product market position would cause differential outcome even without patent litigation. Given these limitations, we try to provide comparisons of pre-litigation trends in the set of outcome variables to ensure that the defendant and plaintiff firms have similar trends in observable dimensions prior to litigation to understand the direction of any possible bias on the difference-in-difference estimate.

## 2.6 Results

### 2.6.1 Financial and Innovation Outcomes

#### 2.6.1.1 Financial Outcome

In this section, we present firm-level financial and innovation activities consequences of patent litigation. Again, the main coefficients of interests describe the additional changes in the outcome variables of defendant firms relative to plaintiff firms. In Table 2.3 Columns (1) and (2), we find that defendant firms' cash level declines sharply by 1 percentage point, or by 5.8%, and the number of defendant firms paying dividend declines by 4 percentage points, or by 5.6%. The results confirm that firms experience mounting financial constraints as they go through costly patent litigation.

In Columns (3)-(5), we also find an increase in leverage by 4 percentage points and decreases in asset growth and market share by 7 percentage points and 20%, respectively. The leverage seems to increase rather due to shrinking asset size, which is likely to be associated with firms' exploitive innovation strategy by cutting down on investments and business segments remotely related to firms' core technologies. We document changes in firms' innovation activities and strategies in the next two sections. We avoid including controls that may also be affected by patent litigation in our main regressions. Including them will cause our estimates to be biased and inconsistent. However, we report regressions that include a few controls in the Appendix Table B2 as a reference.

We briefly comment about the magnitude of our finding before discussing about potential selection issues. The decrease in cash translates to \$105 million. The most relevant study to ours is **?**, which finds that firm values of the plaintiff and defendant jointly drop by about 1%, or \$20 million, after upon the announcement of inter-firm litigation related to corporate control, breach of contract, patent infringement, antitrust, and others between 1981 and 1983. The authors also find that patent infringement-specific lawsuits result in decrease of firm value by 1.89% (\$80 million) for defendants, 0.09% (\$3.5 million) for plaintiffs, and 3.13% for pairs. Compared to these, our financial results, although not directly comparable, may seem too large. However, given that our sample firm market equity is ten-times larger, the magnitude of changes in our result seems reasonable, particularly as we focus on the S&P 500 firms.

We acknowledge that the baseline regression may suffer from endogeneity. First, one may be concerned that financially weaker firms tend to be attacked by rivals. This is unlikely because defendants that are unable to raise capital to finance litigation would be forced to settle the dispute regardless of the ultimate merit of the case. This means that firms with deteriorating pre-treatment financial condition is *less* likely to show up in our sample. Second, firms with higher chance of intellectual property (IP) legal dispute may be more likely to protect their risk through IP insurance, which reimburses the litigation expenses either to enforce IP against infringers or defend against charges of infringing other companies' IP rights. However, this endogenous selection would likely bias our results toward finding no effect of the treatment and thus it is unlikely to drive our results.

#### 2.6.1.2 Innovation Activities

We further explore how firms' innovation activity changes. The financial costs of patent litigation limit firms' ability to take on all positive NPV projects, which then slows down innovation activities. We measure innovation activity by the number of application because the effects measured by the number of granted patents show up with some time lags. Table 2.4 Column (1) and (2) show that defendants' number of patent applications declines by 35%, and the number of citations also declines by 4%. The decrease in citation is indicative of the citing firms' fear of finding the asserted patents invalid, which would increase patent litigation risks and reduce the citing firms' expected profit. To check if the patent application, citations, and particularly patent grant have delayed response, we run the regressions again by focusing on the effects in the first, second, and third year after litigation individually in each columns of Table B5. Our results are consistent with the main regression results.

It appears that patent litigation does not only affect firms in-house R&D but also external acquisitions of technology. The results are presented in Columns (3) and (4). We find defendant firms' number and size of acquisitions fall by 10% and 45%, respectively.[14] Again, it is important to note that the reduction in the number and size of acquisitions is related to firms' post-litigation innovation strategies to pursue exploitive innovation projects that we discuss in Section 2.6.4 later.

The citation result hints at potential industry-level spillover effects of patent litigation, as patents are intricate web of related technology users. Panel A Table 2.5 presents how patent litigation has spillover effects to non-litigant firms in the same industry in terms of innovation activities. The more firms involved in patent litigation as defendants in a given industry, the lower the industry-level innovation productivity by 20%. Similarly, Panel B shows that the industry-wide external acquisitions decline by 3%. This negative externality can be socially inefficient because it may cause a holdup problem where excessive IP rights lead rival firms to underinvestment in innovation and hurt consumers (*Galetovic, Haber, and Levine* (2015)). Overall, the results in this section show that patent litigation has economically significant financial impact on defendant firms, and thus reduce litigant firms' incentives to innovate.

[14]The declining acquisition results are reflective of the example of Johnson & Johnson's and Boston Scientific case in the Appendix B1, where after settling a series of patent disputes in losses, Boston Scientific experienced financial difficulties that led to fewer acquisitions.

### 2.6.2 Matching and Instrumental Variable Approach

The observable level differences between defendant and plaintiff firms are not problematic for consistency of our regression coefficient because the level differences between defendant and plaintiff firms are fully accounted for by the treatment indicator. However, to provide robustness of our previous results that these results are not driven by the observable differences, we use propensity score matching and re-estimate our difference-in-difference regressions for robustness.

#### 2.6.2.1 Propensity Score Matching Regressions

We first estimate propensity scores using a probit regression, where the outcome variable is equal to one in the year a firm is involved in patent litigation as a defendant and zero otherwise. We use all the S&P 500 sample firms that had at least one patent litigation for the period of 2000-2006, but exclude sample firms that were involved as plaintiff and defendant in separate patent litigations in a certain year. To calculate the propensity score, we use variables including firm-level patent portfolio characteristics (Number of Patent, Number of Claims, Assigned Number, Originality, Adjusted Citation) and financial characteristics (Size, R&D, Profitability, Tangibility, Market/Book ratio, Cash Flow Volatility). It is important to note that we also use the pre-litigation period growth rate of the outcome variables to ensure that we take into account the parallel trend assumption. We then match one controlled firm that involved in litigation as a plaintiff for each treated firm based on the predicted probability of being a defendant. After the propensity score matching, the difference in average propensity score between the treated and control groups decreases significantly from 44% to 15%. In appendix, we report probit regression result, and report post-match result and verify that most covariates become statistically insignificant, suggesting a successful matching process.

The results using a propensity score matching sample are reported in Table 2.6. The results are qualitatively consistent with Table 2.3 and Table 2.4. Both the Panel A and

Panel B show that the financial and innovation activity results remain robust although the number of observation decreases due to matching. The similar matching coefficients ensure that the matched covariates above did not cause the differential trends in each of the outcome variables in Table 2.3 and Table 2.4.

#### 2.6.2.2 Instrumental Variable Regressions

In this section, we attempt to further sharpen our tests by addressing the endogeneity by exploiting an exogenous shock on the timing and probability of becoming a patent litigation defendant. In 2001, China overhauled the patent law to fulfill the obligations under Trade-Related Aspects of Intellectual Property Rights (TRIPS) (*Hu and Jefferson* (2009)). *Delgado, Kyle, and McGahan* (2010) find that implementation of TRIPS is related to an increase in trade in IP-dependent products compared with other sectors, indicating that owners of IP received better profit protection with the implementation of TRIPS. Therefore, we use our sample firm exposures to sales in China as an instrument variable.

An important identification assumption in instrumental variable regression is that the shock affects firms' financial and innovation policies only through the patent litigation. The TRIPS shock has two important aspects. First, the timing of TRIPS agreement, and specifically the timing of China's patent law overhaul is relatively free from any U.S. firm's lobbying towards particular financial policy. Also, given we measure exposure by the sales, which largely depends on factors not under direct influence of the firm, for example demands in China, it is less likely that, in anticipation of Chinese patent law overhaul, firms suddenly increased exposures to China. Therefore, the effects we find in difference-in-difference regression should account for the effects of patent litigation only through the TRIPS shock.

In column (1) of Panel A Table 2.7, the first stage regression shows that TRIPS increases the probability of a sample firm becoming a defendant. The instrument variable *Post TRIPS* takes the value of one after China's TRIPS participation, for firms that any of their competitors in the same industry have China exposure before 2001, and zero otherwise.[15] The first-stage regression has difference-in-difference interpretation. The coefficient on *Post TRIPS* captures the relative changes in the probability of being sued in patent litigation for firms with sales exposure in China. In untabulated table, we also control for covariates and find that most of the covariates are statistically significant, alleviating concerns for weak instruments, and the adjusted R-square is high, which suggests that the TRIPS shock is relevant. This probit result ensures that the TRIPS shock is a valid instrument. The following regression results are reported in Table 2.7. The results are strengthened and qualitatively consistent with difference-in-difference results. We find that defendant firms still experience weakened patent outcomes, take on less innovative projects and acquisitions, which implies losing competitive position in the product market.

### 2.6.3 Intra- and inter-industry Patent Litigation

The important driver of patent litigation is to protect the boundary of a firm's intellectual boundary, which also determines the competitiveness of the firm's position in the product market. To emphasize the product market relevance of patent litigation, we categorize cases into intra- and inter-industry. A case is categorized as intra(inter)-industry if plaintiffs and defendants share the same (different) 3-digit SIC. Consistent with our predictions, Table 2.8 Panel A shows that most of patent litigation effects come from intra-industry cases. As we described in the hypothesis development section, intra-industry case litigants indeed have greater product market overlap, as measured by technology proximity and text-based industry classification rival scores, and the greater product market overlap predicts more pronounced patent litigation effects for intra-industry cases due to larger litigation costs exacerbating financing constraints and thus even lower innovation activities. Table 2.8 emphasizes the importance of patent litigation as a means of innovation competition by highlighting the role of financial fatness partly related to predation motive of patentees. This

[15] We obtain regional sales distribution data for S&P500 sample firms from Factset database.

is also clearly different from NPE patent litigation motives.

### 2.6.4 Innovation Strategy

This section provides substantial details of how firms change their investments and innovation strategy following patent litigation with variety of proxies for the scope of innovation. First, we quantitatively capture the changes in firms' innovation strategies following *Gao et al.* (2018) measures of innovation. A patent is categorized as exploitative if 80% or more of its citations are based on a firm's existing patents and the citations made by those patents, whereas a patent is categorized as exploratory if 80% more more of its citations are based on new knowledge outside of a firm's existing patents or the citations made by those patents. Then we scale the total number of exploitative/exploratory patents over year t-2 to year t by the total number of patent application over the same period, which gives us continuous time-varying measure of innovation strategy. Table 2.9 Column (1) and (2) show that defendant firm patents become more exploitative.

Column (3)-(5) presents narrower scope of innovation projects in terms of innovation done outside the firm's boundary. In relation to cutting down on acquisitions in Columns (3) and (4) in Table 2.4, Column (3) in Table 2.9 shows that defendant firms appear to trim down less-related industry acquisitions and focus more on same-industry acquisitions, which is indicative of technologically-driven acquisitions suggested by *Bena and Li* (2014). More interestingly, we find firms invest 10% less in corporate venture capital (CVC).[16] Innovative firms often use CVC as means to be more open to experimentation and exploration (*Fulghieri and Seville* (2009)) and to undertake R&D investments outside of firms' boundaries

[16]We obtain Corporate VC fund- and portfolio firm-specific information from Thomson Reuters VentureXpert database for the period 1995-2010. VentureXpert, which has been used extensively in the prior literature (*Fulghieri and Seville* (2014), *Bernstein, Giroud, and Townsend* (2015)), provides detailed firm-specific funding information. We calculate the CVC investment variable that captures the total number/investment amount of CVC on entrepreneurial firms.

to exploit new technologies (*Fulghieri and Seville* (2014), *Ma* (2016)).[17] Therefore, the decrease in CVC investment captures defendant firms reduction of scope of innovation that increases potential probability of future patent litigation. We also find that defendant firms reduce the number of business segments after litigation. This is consistent with the negative asset growths shown in Table 2.3 as defendant firm's cutting down on less related business segments both inside and outside the firm.

Lastly, we provide evidence that the exploitative innovation strategy indeed seems to hedge some of the future patent litigation risks. Table 2.10 tests whether pursuing exploitative innovation strategy in the year following patent litigation for a defendant reduce the probability of begin accused as an infringer in the near future. The result shows that defendant firms that narrow down the scope of innovation in the year following patent litigation becomes defendant in future patent litigation less frequently.

## 2.7 Conclusion

In this paper, we examine the real consequences of patent litigation on corporate financial flexibility, innovation output, and innovation strategy. We consider patent litigation as a form of product market competition. Hence, we emphasize the product market relevance in understanding the effects of patent litigation.

To derive our predictions on the impact of patent litigation, we borrow the stylized model of patent enforcement from *Lanjouw and Lerner* (1997). The model allows us to focus our analyses around the key parameters that determine the patentee's decision to go to trial against an infringer. We are able to build our hypotheses on the comparative statics on the key patent litigation parameters that are observable in our hand-collected data.

We show that patent litigation weakens firms' financial health, particularly more for

[17] In 2014, CVC investors participated in 656 deals totaling \$12.31 billion. For example, *Intel Capital* invested 1100 start-up companies, and 189 of these portfolio firms went public and 258 of them are acquired. *Dow Venture* extends to agriculture, consumer and life-stlye, energy, infrastructure and transportation through CVC and *Samsung Venture* extensively invested in clean-tech and medical-tech.

defendants who need to bear the burden of damages awards. We also find that such deterioration in financial health reduces firms' innovation output. More importantly, we show that the intra-industry litigation that involves litigants with substantial overlap in the product market has more pronounced effects. Additionally, we find evidence that firms choose more exploitative innovation strategies to avoid future patent litigation risks by reducing the uncertainty about the quality of potential cases.

Overall, using our novel hand-collected patent litigation data, we highlight the essence of patent litigation as innovation competition for firms in innovation-intensive industries and further extend the existing literature by providing detailed analyses of subsequent changes in firms' investment and innovation types.

Table 2.1: Summary Statistics

The table presents summary statistics for sample firms that have patent litigation records. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. Panel A describes the patent litigation case characteristics in our sample. Panel B is a summary of firm-level patent portfolio summary based on 2004. Panel C is financial and investment summary of all sample firms in our sample.

| | Mean | Std.dev | Min | Med | Max | Obs. |
|---|---|---|---|---|---|---|
| **Panel A: Litigation Summary** | | | | | | |
| Plaintiff (dummy) | 0.76 | 0.43 | 0.00 | 1.00 | 1.00 | 1692 |
| Defendant (dummy) | 0.24 | 0.43 | 0.00 | 0.00 | 1.00 | 1692 |
| Case with verdict | 0.17 | 0.38 | 0.00 | 0.00 | 1.00 | 1692 |
| Win case (conditional) | 0.64 | 0.48 | 0.00 | 1.00 | 1.00 | 294 |
| Dismissed case | 0.70 | 0.46 | 0.00 | 1.00 | 1.00 | 1676 |
| Transferred case | 0.04 | 0.19 | 0.00 | 0.00 | 1.00 | 1676 |
| Consolidated case | 0.08 | 0.28 | 0.00 | 0.00 | 1.00 | 1676 |
| Case duration in years | 1.98 | 1.86 | 0.01 | 1.00 | 13.00 | 1677 |
| Num. of plaintiffs | 1.31 | 0.65 | 1.00 | 1.00 | 5.00 | 1691 |
| Num. of defendants | 1.90 | 2.70 | 1.00 | 1.00 | 59.00 | 1691 |
| Total damage (mil) | 7.32 | 17.71 | -1.76 | 0.15 | 101.23 | 112 |
| Intra-ind. case | 0.60 | 0.49 | 0.00 | 1.00 | 1.00 | 838 |
| **Panel B: Patent Summary** | | | | | | |
| Number of patents | 1450 | 3925 | 1.00 | 139 | 45213 | 401 |
| Patent age | 10.94 | 6.30 | 1.00 | 10.44 | 31.00 | 401 |
| Assignee sequence number | 1.01 | 0.03 | 1.00 | 1.00 | 1.33 | 401 |
| Grant year | 1996 | 6.30 | 1976 | 1996 | 2006 | 401 |
| Application year | 1993 | 5.90 | 1975 | 1994 | 2004 | 401 |
| Number of claims | 18.60 | 6.93 | 1.00 | 17.47 | 76.00 | 401 |
| Adj. #Citations | 16.43 | 22.68 | 0.00 | 11.83 | 386.50 | 401 |
| Log(1+#Citations) | 2.54 | 0.82 | 0.00 | 2.55 | 5.96 | 401 |
| Exploitive | 0.19 | 0.20 | 0.00 | 0.14 | 1.00 | 141 |
| Explorative | 0.70 | 0.25 | 0.00 | 0.75 | 1.00 | 141 |
| **Panel C: Financial and Investment Summary** | | | | | | |
| Log(Assets) | 8.96 | 1.27 | 5.65 | 8.84 | 13.53 | 880 |
| Cash | 0.17 | 0.18 | 0.00 | 0.10 | 0.88 | 880 |
| Dividend | 0.71 | 0.45 | 0.00 | 1.00 | 1.00 | 880 |
| Leverage | 0.21 | 0.15 | 0.00 | 0.20 | 1.33 | 880 |
| Assets growth | 0.14 | 0.52 | -0.61 | 0.06 | 9.72 | 880 |
| Log(1+Number of Total Acquisition) | 0.20 | 0.42 | 0.00 | 0.00 | 2.56 | 880 |
| Log(1+Average Acquisition Size) | 1.24 | 2.45 | 0.00 | 0.00 | 10.99 | 880 |
| Same Industry Acquisition | 0.09 | 0.40 | 0.00 | 0.00 | 6.00 | 880 |
| Log(1+Number of CVC Deal) | 0.37 | 0.82 | 0.00 | 0.00 | 5.38 | 880 |
| Number of Segments | 4.55 | 2.66 | 1.00 | 5.00 | 17.00 | 769 |
| R&D Exp. | 0.06 | 0.05 | 0.00 | 0.04 | 0.60 | 880 |
| Profitability | 0.14 | 0.08 | -0.21 | 0.14 | 0.48 | 880 |
| Tangibility | 0.81 | 0.15 | 0.24 | 0.84 | 1.00 | 880 |
| Tobin's Q | 2.25 | 1.94 | 0.08 | 1.64 | 29.32 | 880 |
| CF Vol | 0.03 | 0.05 | 0.00 | 0.02 | 1.10 | 880 |
| 1 - HHI | 0.84 | 0.15 | 0.02 | 0.87 | 0.97 | 880 |

Table 2.2: Univariate Analysis

The table presents summary statistics for the firms that have patent litigation records vs never-litigated (Panel A) during the sample period of 2000-2006, and pre-treatment characteristics for the firms that are plaintiff vs defendant (Panel B) in our sample patent litigation cases. In Panel A, the sample consists of 1,737 firm-year observations of S&P 500 firms during the period of 2000-2006. In Panel B, the sample consists of 1,692 cases by 137 S&P 500 firms during the sample period of 2000-2006. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**Panel A: Comparison between litigated and never-litigated firms**

| | Litigated | | Never-litigated | | |
|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Mean Difference |
| Log(Assets) | 8.96 | 8.84 | 8.44 | 8.21 | 0.53*** |
| Cash | 0.17 | 0.10 | 0.17 | 0.10 | 0.00 |
| Dividend | 0.71 | 1.00 | 0.52 | 1.00 | 0.19*** |
| Leverage | 0.21 | 0.20 | 0.22 | 0.22 | -0.01 |
| Assets growth | 0.14 | 0.06 | 0.15 | 0.05 | -0.01 |
| R&D Expense | 0.06 | 0.04 | 0.05 | 0.03 | 0.01** |
| Profitability | 0.14 | 0.14 | 0.13 | 0.13 | 0.02*** |
| Tangibility | 0.81 | 0.84 | 0.81 | 0.85 | 0.00 |
| Tobin's Q | 2.25 | 1.64 | 2.02 | 1.40 | 0.23** |
| CF Vol | 0.03 | 0.02 | 0.03 | 0.02 | -0.00 |
| 1 - HHI | 0.84 | 0.87 | 0.84 | 0.89 | 0.00 |
| Number of patents | 2,982 | 999 | 601 | 94 | 2,380*** |
| Observations | 880 | | 857 | | |

**Panel B: Pre-treatment comparison between plaintiff and defendant**

| | Plaintiff | | Defendant | | |
|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Mean Difference |
| Log(Assets) | 9.00 | 8.90 | 9.29 | 9.52 | -0.29*** |
| Cash | 0.17 | 0.10 | 0.18 | 0.12 | -0.02 |
| Dividend | 0.70 | 1.00 | 0.71 | 1.00 | -0.01 |
| Leverage | 0.22 | 0.22 | 0.22 | 0.21 | 0.00 |
| Assets growth | 0.13 | 0.06 | 0.14 | 0.06 | -0.00 |
| R&D Expense | 0.06 | 0.04 | 0.06 | 0.05 | -0.01** |
| Profitability | 0.14 | 0.14 | 0.14 | 0.13 | 0.00 |
| Tangibility | 0.82 | 0.85 | 0.85 | 0.90 | -0.03*** |
| Tobin's Q | 2.30 | 1.61 | 2.26 | 1.61 | 0.05 |
| CF Vol | 0.03 | 0.02 | 0.03 | 0.02 | -0.00 |
| Number of patents | 3,239 | 1,024 | 4,949 | 2,461 | -1,709*** |
| Observations | 614 | | 286 | | |

Table 2.3: The Effects of Patent Litigation: Financial Outcomes

The table examines the effects of patent litigation on corporate financial outcomes. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. For each litigation case, we restrict the sample period from t-3 to t+3 year around the litigation filing date. In columns (1)-(5), the dependent variables are corporate financial policy: total cash scaled by total assets (*Cash*), dividend payer dummy (*Dividend*), leverage ratio using book value of total debt (*Leverage*)), assets growth rate (*Asset growth*), and the market share based on 3-digit SIC (*Mkt Share*). In Panel A, we present results from difference-in-difference analysis and in Panel B, we report the dynamics of the litigation effects. *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. The variable t-1 year is an indicator variable equal to one if the observation is recorded in the year preceding the litigation. t-3, t-2, t+1, t+2, t+3 year are dummy variables defined analogously. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

**Panel A: Diff-in-Diff Analysis on Financial Policies**

| | (1) Cash | (2) Dividend Dummy | (3) Leverage | (4) Asset growth | (5) Market Share |
|---|---|---|---|---|---|
| After X Defendant | -0.01*** | -0.04*** | 0.04*** | -0.07*** | -0.20 |
| | (-2.95) | (-3.03) | (3.03) | (-4.94) | (-1.34) |
| Defendant | 0.01** | 0.01 | -0.02*** | 0.03*** | 0.21** |
| | (2.41) | (1.00) | (-3.29) | (3.35) | (2.32) |
| After | 0.00* | 0.00 | -0.00 | 0.02*** | 0.41*** |
| | (1.81) | (0.21) | (-0.90) | (3.33) | (5.27) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,099 | 10,099 | 10,099 | 10,099 | 10,099 |
| Adjusted $R^2$ | 0.871 | 0.882 | 0.670 | 0.159 | 0.979 |

**Panel B: Dynamic Effects on Financial Policies**

| | (1) Cash | (2) Dividend Dummy | (3) Leverage | (4) Asset growth | (5) Market Share |
|---|---|---|---|---|---|
| t-3 year X Defendant | 0.01 | -0.00 | -0.01 | 0.01 | -0.42** |
| | (0.92) | (-0.27) | (-0.99) | (0.36) | (-2.22) |
| t-2 year X Defendant | 0.00 | 0.03** | -0.00 | 0.11*** | 0.06 |
| | (0.71) | (2.27) | (-0.70) | (2.84) | (0.46) |
| t-1 year X Defendant | -0.00 | 0.01 | -0.00 | -0.01 | -0.09 |
| | (-0.12) | (0.83) | (-0.89) | (-0.63) | (-1.06) |
| t+1 year X Defendant | -0.01*** | -0.02 | 0.04*** | -0.06*** | 0.09 |
| | (-2.67) | (-1.63) | (2.97) | (-3.58) | (1.02) |
| t+2 year X Defendant | -0.01** | -0.04** | 0.03** | -0.01 | -0.21 |
| | (-2.40) | (-2.27) | (2.52) | (-0.34) | (-1.49) |
| t+3 year X Defendant | -0.01 | -0.04* | 0.03*** | -0.07*** | -0.80*** |
| | (-1.44) | (-1.96) | (3.16) | (-3.41) | (-4.10) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,099 | 10,099 | 10,099 | 10,099 | 10,099 |
| Adjusted $R^2$ | 0.871 | 0.882 | 0.671 | 0.162 | 0.979 |

Table 2.4: The Effects of Patent Litigation: Innovation Outcomes

The table examines the effects of patent litigation on corporate innovation outcomes. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. For each litigation case, we restrict the sample period from t-3 to t+3 year around the litigation filing date. In columns (1)-(4), the dependent variables are corporate innovation outcome and strategy: the log of one plus number of patent applications at a certain year ((*Log(1+Number of Patent Application)*), the log of one plus adjusted citation (Log(1+Number of Adj. Citations)), the log of one plus number of acquisitions (*Log(1+Number of Acquisitions)*), and the log of average transaction size of acquisitions (*Log (1+Average Deal Size)*) at a certain year. In Panel A, we present results from difference-in-difference analysis and in Panel B, we report the dynamics of the litigation effects. *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. The variable t-1 year is an indicator variable equal to one if the observation is recorded in the year preceding the litigation. t-3, t-2, t+1, t+2, t+3 year are dummy variables defined analogously. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

**Panel A: Diff-in-Diff Analysis on Innovation Outcome**

| | (1) Log(1+Number of Patent Application) | (2) Log(1+Number of Adj. Citations) | (3) Log(1+Number of Total Acquisitions) | (4) Log(1+Average Acquisition Size) |
|---|---|---|---|---|
| After X Defendant | -0.35*** | -0.04*** | -0.10** | -0.45* |
| | (-5.63) | (-3.53) | (-2.48) | (-1.85) |
| Defendant | 0.13*** | 0.01 | 0.05** | 0.29** |
| | (3.90) | (1.47) | (2.29) | (2.04) |
| After | 0.14*** | 0.01* | 0.01 | -0.00 |
| | (3.88) | (1.85) | (0.51) | (-0.01) |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 9,973 | 10,099 | 10,099 | 10,099 |
| Adjusted $R^2$ | 0.919 | 0.960 | 0.370 | 0.346 |

**Panel B: Dynamic Effects on Innovation Outcome**

| | (1) Log(1+Number of Patent Application) | (2) Log(1+Number of Adj. Citations) | (3) Log(1+Number of Total Acquisitions) | (4) Log(1+Average Acquisition Size) |
|---|---|---|---|---|
| t-3 year X Defendant | 0.24** | 0.03 | -0.05 | -0.25 |
| | (2.37) | (1.54) | (-0.56) | (-0.54) |
| t-2 year X Defendant | 0.27*** | 0.04*** | -0.02 | -0.27 |
| | (3.01) | (2.70) | (-0.31) | (-0.61) |
| t-1 year X Defendant | 0.22** | 0.02 | -0.04 | -0.54 |
| | (2.43) | (1.15) | (-0.60) | (-1.41) |
| t+1 year X Defendant | -0.11 | -0.01 | -0.13** | -0.60 |
| | (-1.16) | (-0.76) | (-2.22) | (-1.55) |
| t+2 year X Defendant | -0.18* | -0.02 | -0.09 | -0.56 |
| | (-1.91) | (-1.15) | (-1.23) | (-1.29) |
| t+3 year X Defendant | -0.26** | -0.02 | -0.17** | -0.99** |
| | (-2.36) | (-1.49) | (-2.30) | (-2.37) |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 9,973 | 10,099 | 10,099 | 10,099 |
| Adjusted $R^2$ | 0.920 | 0.960 | 0.371 | 0.348 |

Table 2.5: Patent Litigation and Industry Outcome

The table examines the effect of patent litigation on industry-level product market competition outcome. The sample comprises of all S&P 500 firms for the period of 2000-2006 at 3-digit SIC level. The dependent variables are industry-level fluidity measure, industry median profitability, industry median R&D expense scaled by total assets, the log of one plus the industry average adjusted citations received, and the log of one plus the total number of firms in industry. The main independent variable is *Log(1+#Ind. Defendant)*, the log of one plus total number of patent litigations in a 3-digit SIC industry in a certain year. Rival firm and year fixed effects are included. *t-statistics* (in parenthesis) are robust. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

**Panel A: Industry Analysis on Innovation Outcome**

| | (1) Log(1+Number of Patent Application) | (2) Log(1+Number of Adj. Citations) | (3) Exploitive | (4) Explorative |
|---|---|---|---|---|
| Log(1+#Ind. Defendant) | -0.20*** | -0.03*** | 0.01 | -0.01 |
| | (-6.97) | (-4.66) | (1.23) | (-1.05) |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,536 | 2,536 | 842 | 842 |
| Adjusted $R^2$ | 0.823 | 0.963 | 0.482 | 0.572 |

**Panel B: Industry Analysis on External Innovation Outcome**

| | (1) Log(1+Number of Total Deal) | (2) Log(1+Average Deal Size) | (3) Same Industry Acquisition | (4) Log(1+Number of CVC Deal) | (5) Number of Segments |
|---|---|---|---|---|---|
| Log(1+#Ind. Defendant) | -0.01* | -0.07 | -0.00 | -0.04*** | -0.02 |
| | (-1.69) | (-0.89) | (-0.08) | (-3.10) | (-0.52) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,536 | 2,536 | 2,536 | 2,536 | 2,083 |
| Adjusted $R^2$ | 0.372 | 0.171 | 0.171 | 0.706 | 0.788 |

Table 2.6: The Effects of Patent Litigation: Propensity Matching Analysis

The table examines the effects of patent litigation on corporate internal and external innovation outcomes using propensity score matching. The propensity score for being defendant is calculated based on firm-year patent portfolio characteristics, Size, R&D expense, Profitability, Tangibility, Market/Book, and Industry HHI. The sample comprises of all S&P 500 firms that had at least one patent litigation for the period of 2000-2006. In Panel A, the dependent variables are corporate financial policy: total cash scaled by total assets (*Cash*), dividend payer dummy (*Dividend*), leverage ratio using book value of total debt (*Leverage*)), assets growth rate (*Asset growth*), and the market share based on 3-digit SIC (*Mkt Share*). In Panel B, the dependent variables are corporate innovation outcome: the log of one plus number of patent applications at a certain year ((*Log(1+Number of Patent Application)*), the log of one plus adjusted citation (Log(1+Number of Adj. Citations)), the log of one plus number of acquisitions (*Log(1+Number of Acquisitions)*), the log of average transaction size of acquisitions (*Log (1+Average Deal Size)*) at a certain year. *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

**Panel A: Propensity Score Matching Analysis on Financial Outcome**

| | (1)<br>Cash | (2)<br>Dividend Dummy | (3)<br>Leverage | (4)<br>Asset growth | (5)<br>Mkt Share |
|---|---|---|---|---|---|
| After X Defendant | -0.01 | -0.06*** | 0.04*** | -0.08*** | -0.08 |
| | (-0.89) | (-2.96) | (2.76) | (-4.49) | (-0.29) |
| Defendant | 0.01*** | 0.00 | -0.02*** | 0.05*** | 0.22 |
| | (2.94) | (0.12) | (-3.55) | (3.13) | (1.22) |
| After | 0.00 | 0.00 | 0.00 | 0.05*** | 0.67*** |
| | (0.65) | (0.35) | (0.20) | (3.49) | (3.50) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,023 | 5,023 | 5,023 | 5,023 | 5,023 |
| Adjusted $R^2$ | 0.873 | 0.838 | 0.636 | 0.168 | 0.955 |

**Panel B: Propensity Score Matching Analysis on Innovation Outcome**

| | (1)<br>Log(1+Number of<br>Patent Application) | (2)<br>Log(1+Number of<br>Adj. Citations) | (3)<br>Log(1+Number<br>of Total Acquisitions) | (4)<br>Log(1+Average<br>Acquisition Size) |
|---|---|---|---|---|
| After X Defendant | -0.34*** | -0.02*** | -0.15*** | -0.72*** |
| | (-7.99) | (-2.68) | (-6.41) | (-5.47) |
| Defendant | 0.07** | 0.00 | 0.08*** | 0.42*** |
| | (2.58) | (0.36) | (5.74) | (5.61) |
| After | 0.23*** | 0.01 | 0.08*** | 0.44*** |
| | (7.14) | (1.42) | (5.66) | (4.91) |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 4,974 | 4,974 | 4,974 | 4,974 |
| Adjusted $R^2$ | 0.942 | 0.955 | 0.397 | 0.353 |

Table 2.7: The Effects of Patent Litigation: IV approach

The table examines the effects of patent litigation on corporate internal and external innovation outcomes using instrument variable approach. We use China's TRIPS participation in 2001 as an instrument and apply a diff-in-diff estimation. The variable *Post TRIPS* takes the value of one after China's TRIPS participation, for firms that any of their competitors in the same industry have China exposure before 2001, and zero otherwise. We restrict the sample period from t-2 to t+2 year around the litigation filing date. The sample comprises of all S&P 500 firms that had at least one patent litigation for the period of 2000-2002. In Panel A, column (1) presents the relation between our instrument and the probability of being a defendant. In columns (2)-(5), the dependent variables are corporate financial outcome: Cash scaled by total assets (*Cash*), dividend payer (*Dividend Dummy*), leverage ratio (*Leverage*), asset growth (*Asset growth*), and market share (*Market Share*). In Panel B, the dependent variables are corporate innovation outcome and strategy: the log of one plus number of acquisitions (*Log(1+Number of Acquisitions)*), the log of average transaction size of acquisitions (*Log (1+Average Deal Size)*) at a certain year, and the dummy variable that equals one if the acquisition is between the same industry (*Same Industry Acquisition*), the log of one plus number of CVC transaction (*Log(1+Number of CVC Deal)*), the number of business segments (Number of Segments). Case, year and firm fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

**Panel A: Instrument Variable Analysis on Financial Policies**

| | (1) Defendant | (2) Cash | (3) Dividend Dummy | (4) Leverage | (5) Asset growth | (6) Market Share |
|---|---|---|---|---|---|---|
| Post TRIPS | 0.05* | -0.02*** | 0.09*** | 0.03*** | -0.54*** | -0.84** |
| | (1.73) | (-3.30) | (4.40) | (3.06) | (-4.65) | (-2.53) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,746 | 1,746 | 1,746 | 1,746 | 1,746 | 1746 |
| Adjusted $R^2$ | 0.128 | 0.956 | 0.962 | 0.909 | 0.269 | 0.986 |

**Panel B: Instrument Variable Analysis on Innovation Outcome**

| | (1) Log(1+Number of Patent Application) | (2) Log(1+Number of Adj. Citations) | (3) Log(1+Number of Total Acquisitions) | (4) Log(1+Average Acquisition Size) |
|---|---|---|---|---|
| Post TRIPS | -0.01 | -0.03** | 0.04 | 0.45 |
| | (-0.21) | (-2.25) | (0.61) | (1.31) |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,383 | 1,383 | 1,383 | 1,383 |
| Adjusted $R^2$ | 0.968 | 0.988 | 0.263 | 0.224 |

Table 2.8: The Effects of Patent Litigation on Financial Policies and Innovation: Intra- vs. Inter-industry

The table examines the effects of patent litigation on corporate financial, and innovation outcomes. We use sub-sample where cases are between intra-industry rivals in Panel A and inter-industry firms in Panel B based on three-digit sic code. The sample comprises of all S&P 500 firms for the period of 2000-2006 at litigation case level. *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

**Panel A: Intra-Case Cases**

| | (1) Cash | (2) Dividend Dummy | (3) Leverage | (4) Log(1+Number of Patent Application) | (5) Log(1+Number of Adj. Citations) |
|---|---|---|---|---|---|
| After X Defendant | -0.02* | -0.20*** | -0.03*** | -0.17** | -0.03* |
| | (-1.93) | (-5.45) | (-3.99) | (-2.51) | (-1.68) |
| Defendant | 0.01* | 0.08*** | 0.01*** | 0.07** | -0.00 |
| | (1.79) | (4.75) | (3.07) | (2.16) | (-0.24) |
| After | 0.01* | 0.01 | 0.01*** | 0.11*** | -0.01* |
| | (1.93) | (0.93) | (2.91) | (2.95) | (-1.72) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,020 | 2,020 | 2,020 | 2,020 | 2,020 |
| Adjusted $R^2$ | 0.915 | 0.816 | 0.804 | 0.956 | 0.965 |

**Panel B: Inter-Case Cases**

| | (1) Cash | (2) Dividend Dummy | (3) Leverage | (4) Log(1+Number of Patent Application) | (5) Log(1+Number of Adj. Citations) |
|---|---|---|---|---|---|
| After X Defendant | 0.00 | 0.10** | -0.00 | -0.09 | 0.00 |
| | (0.30) | (2.12) | (-0.01) | (-1.23) | (0.34) |
| Defendant | 0.00 | -0.03** | 0.00 | 0.04 | 0.00 |
| | (0.95) | (-2.06) | (0.19) | (1.49) | (0.29) |
| After | 0.00 | -0.01 | 0.01* | 0.06 | -0.01 |
| | (0.79) | (-1.37) | (1.85) | (1.59) | (-1.54) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,848 | 1,848 | 1,848 | 1,848 | 1,848 |
| Adjusted $R^2$ | 0.930 | 0.880 | 0.813 | 0.944 | 0.981 |

Table 2.9: The Effects of Patent Litigation: Innovation Strategy

The table examines the effects of patent litigation on corporate external innovation. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. For each litigation case, we restrict the sample period from t-3 to t+3 year around the litigation filing date. In columns (1)-(5), the dependent variables are corporate innovation outcome and strategy: the exploitive innovation measure (*Exploitive*), the explorative innovation measure (*Explorative*)), the dummy variable that equals one if the acquisition is between the same industry (*Same Industry Acquisition*), the log of one plus number of CVC transaction (*Log(1+Number of CVC Deal)*), and the number of business segments (Number of Segments). In Panel A, we present results from difference-in-difference analysis, and in Panel B, we report the dynamics of the litigation effects. *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. The variable t-1 year is an indicator variable equal to one if the observation is recorded in the year preceding the litigation. t-3, t-2, t+1, t+2, t+3 year are dummy variables defined analogously. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. $^{***}$, $^{**}$, and $^{*}$ indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | (1) Exploitive | (2) Explorative | (3) Same Industry Acquisition | (4) Log(1+Number of CVC Deal) | (5) Number of Segments |
|---|---|---|---|---|---|
| After X Defendant | 0.04$^{***}$ | -0.03$^{**}$ | 0.05$^{***}$ | -0.10$^{**}$ | -0.35$^{**}$ |
| | (2.72) | (-2.11) | (3.27) | (-2.22) | (-2.31) |
| Defendant | -0.01$^{**}$ | 0.01 | -0.02$^{**}$ | 0.03 | 0.34$^{***}$ |
| | (-2.44) | (1.64) | (-2.49) | (0.92) | (3.63) |
| After | -0.01$^{*}$ | 0.01 | -0.01$^{*}$ | 0.01 | 0.22$^{***}$ |
| | (-1.84) | (1.40) | (-1.86) | (0.31) | (2.84) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,327 | 8,327 | 10,099 | 10,099 | 9,219 |
| Adjusted $R^2$ | 0.545 | 0.688 | 0.353 | 0.867 | 0.832 |

Table 2.10: The Hedging Effects of Innovation Strategy on Patent Litigation

The table examines the effects of corporate innovation strategy on future patent litigation. We test whether exploitive innovation strategy after a litigation in year $t$ affects the likelihood of litigation in year $t+1$. The sample comprises of all S&P 500 firms that had at least one patent litigation for the period of 2000-2006. The dependent variables are the log of one plus number of defendant case in year $t+1$ (*Log(1+num of defendant case in t+1)*), the log of one plus total number of defendant case from $t+1$ to $t+3$ year (*Log(1+total num of defendant case within 3yrs)*), a dummy variable that equals one if firm is a defendant in any litigation case in year $t+1$ (*Defendant t+1*), a dummy variable that equals one if firm is a defendant in any litigation case within $t+1$ to $t+3$ year (*Defendant within 3yrs*). *Exploitive t+1* is the exploitive innovation measure (*Exploitive*) after in year $t+1$. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | (1)<br>Log(1+num of<br>deft case in t+1) | (2)<br>Log(1+total num of<br>deft case within 3yrs) | (3)<br>Defendant t+1 | (4)<br>Defendant<br>within 3yrs |
|---|---|---|---|---|
| Exploitive t+1 X Defendant | -0.92* | -1.31*** | -0.59** | -0.70*** |
| | (-1.92) | (-3.49) | (-2.00) | (-2.79) |
| Exploitive t+1 | -0.25 | -0.35 | -0.23 | -0.20 |
| | (-1.17) | (-1.21) | (-1.46) | (-0.98) |
| Defendant | -0.07 | -0.27*** | -0.05 | -0.14*** |
| | (-0.65) | (-3.78) | (-0.77) | (-2.69) |
| Size | 0.02 | -0.12 | 0.03 | -0.08 |
| | (0.25) | (-0.90) | (0.52) | (-0.81) |
| R&D Exp. | -0.30 | -0.02 | -0.20 | 0.00 |
| | (-0.66) | (-0.03) | (-0.65) | (0.01) |
| Profitability | 0.40 | 0.70 | 0.27 | 0.33 |
| | (1.06) | (1.04) | (1.26) | (0.87) |
| Tangibility | -0.04 | -0.17 | -0.00 | -0.18 |
| | (-0.11) | (-0.36) | (-0.02) | (-0.51) |
| Tobin's Q | 0.00 | -0.00 | 0.00* | -0.00 |
| | (1.53) | (-0.30) | (1.70) | (-0.01) |
| CF Vol | 0.40 | 0.65 | 0.26 | 0.27 |
| | (1.25) | (1.06) | (1.41) | (0.94) |
| 1 - HHI | 0.36 | 0.52 | 0.80 | 0.90 |
| | (0.41) | (0.40) | (1.28) | (1.10) |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 756 | 756 | 756 | 756 |
| Adjusted $R^2$ | 0.207 | 0.645 | 0.163 | 0.530 |

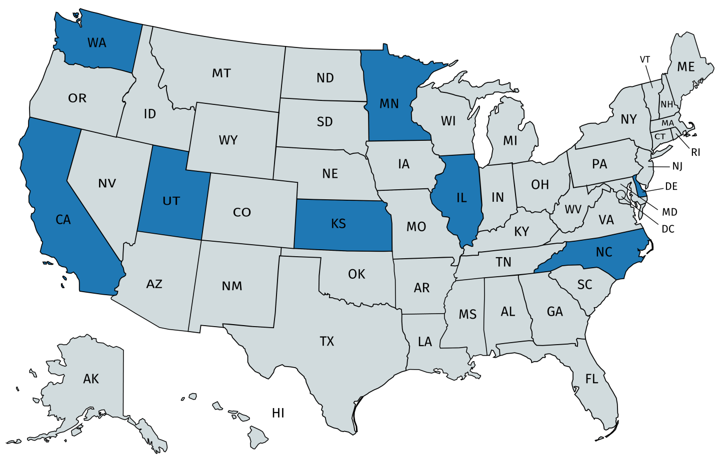
# APPENDICES

# APPENDIX A

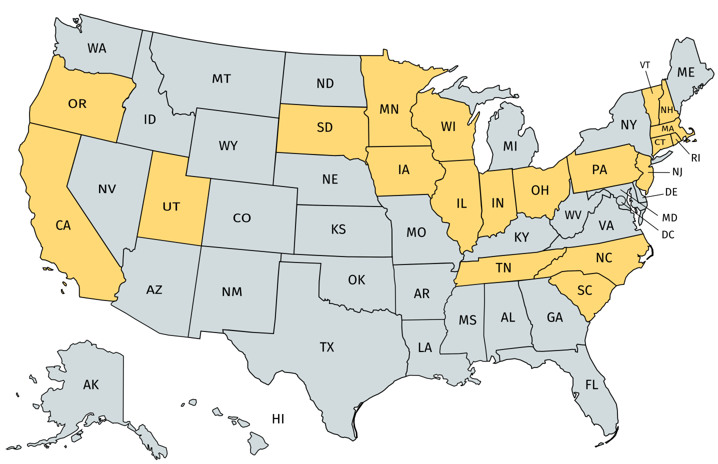
# Property Rights and Debt Financing

Figure A1: Geographic Distribution of Treated States and Patent-intensive States

The figures present the distribution of the treated states and patent-intensive industry employment to highlight that the patent-intensive firms are not concentrated only in the treated states. Figure (a) shows where the distribution of treated states. Figure (b) presents the states in which the fraction of employment from patent-intensive industry is above national average (USPTO Intellectual Property and the U.S. Economy Report, 2012) as of 2010. The comparison reinforces that the results are not driven by firms with relatively greater innovation investment opportunities sorting into the treated states. The distribution of patent-intensive firms are wider, but the effect of shift of property rights to employee invention is found only in the firms located in treated states.




(a) Treated States




(b) IP-intensive Employment State

## Table A1: Falsification Test Using Non-patenting Firms

This table presents baseline results in Table 2 for *non-patenting firms*. The dependent variable in Columns (1) and (2) is *Total debt/Assets*. The dependent variable in Columns (3) and (4) is *LTD issuance*. The odd-numbered columns include firm and year fixed effects, and the even-numbered columns use more stringent specification including firm and industry-year fixed effects. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

| | (1)<br>Total debt/Assets | (2)<br>Total debt/Assets | (3)<br>LTD issuance | (4)<br>LTD issuance |
|---|---|---|---|---|
| treat×post | 0.010 | 0.011 | -0.001 | -0.006 |
| | (0.013) | (0.012) | (0.006) | (0.007) |
| post | | -0.435** | | -0.151 |
| | | (0.179) | | (0.180) |
| Firm FE | Y | Y | Y | Y |
| Year FE | Y | – | Y | – |
| Industry-year FE | N | Y | N | Y |
| Observations | 35,619 | 35,567 | 35,619 | 35,567 |
| Adjusted $R^2$ | 0.663 | 0.665 | 0.396 | 0.396 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

## Table A2: Subsample with Single Subsidiary Location

The table reports the main regression results for subsample of firms operating in single or relatively limited number of states. The dependent variable is *Total debt/Assets*. The geographic subsidiary data is from *Dyreng, Lindsey, and Thornock* (2013). The data provides the count of geographic subsidiaries and the corresponding states. Column (1) reports the result for firms with single operating location in the headquarter state. Columns (2) and (3) report the results for firms with one or two geographic subsidiaries that may be located outside the headquarter state, but certainly limited in geographic presence of the firm. All specifications include firm and year fixed effects. All standard errors are clustered by state.

$$Total\ debt/Assets_{it} = \alpha + \beta_1\, treat_i \times post_t + \delta_i + \gamma_t + \epsilon_{it}$$

| | (1)<br>Total debt/Assets<br>(Zero sub) | (2)<br>Total debt/Assets<br>(One sub) | (3)<br>Total debt/Assets<br>(Two subs) |
|---|---|---|---|
| treat×post | 0.036* | 0.033* | 0.022* |
| | (0.020) | (0.020) | (0.013) |
| Firm FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| Observations | 3,084 | 6,001 | 8,799 |
| Adjusted $R^2$ | 0.485 | 0.509 | 0.565 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

## Table A3: Baseline Regression with Control Variables

This table presents baseline results with control variables. The dependent variable is *Total debt/Assets*. Each control variable dummy is equal to one if the pre-treatment average is greater than median, otherwise zero. The control variables are included as dummy variables interacted with *post* indicator. The stand-alone control variables are also included but absorbed by the firm fixed effects. Each control variable is static and computed from the pre-treatment period median. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| treatXpost | 0.025** | 0.028*** | 0.026*** | 0.025** | 0.025** | 0.024** | 0.026*** | 0.026** | 0.027*** |
| | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.011) | (0.010) |
| Size | -0.011 | | | | | | | | -0.007 |
| | (0.011) | | | | | | | | (0.011) |
| Age | | 0.004 | | | | | | | 0.008 |
| | | (0.008) | | | | | | | (0.009) |
| State-tax | | | 0.008 | | | | | | 0.007 |
| | | | (0.010) | | | | | | (0.012) |
| Tangibility | | | | -0.004 | | | | | -0.004 |
| | | | | (0.008) | | | | | (0.010) |
| Market-to-book | | | | | 0.010 | | | | 0.012 |
| | | | | | (0.008) | | | | (0.008) |
| Profitability | | | | | | -0.008 | | | -0.005 |
| | | | | | | (0.010) | | | (0.009) |
| Pre-patent stock | | | | | | | -0.000 | | 0.000 |
| | | | | | | | (0.010) | | (0.000) |
| R&D expenditure | | | | | | | | -0.000 | -0.009 |
| | | | | | | | | (0.010) | (0.008) |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 16,540 | 15,027 | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 | 15,027 |
| Adjusted $R^2$ | 0.610 | 0.611 | 0.610 | 0.610 | 0.610 | 0.610 | 0.610 | 0.610 | 0.611 |

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table A4: Pre-treatment State Economic Conditions

This table reports difference in means of state-level economic variable growth rates between treated states and untreated states by year. For simplicity, I report two years before and after the 2008 CAFC court ruling, but the differences in means are statistically insignificant for all sample years. The second and third column report means of corresponding economic variable, and the last column reports p-values on the difference in means. The objective of this table is to show that the difference-in-difference results are not driven by differential trends in state-level economics variables. The differences in state-level economic variables are small and are not statistically different from zero throughout my sample period.

| | Mean Comparison | | |
|---|---|---|---|
| Year | Treated States | Untreated States | p-value |
| **GDP growth, percent** | | | |
| 2006 | 5.313 | 4.742 | 0.576 |
| 2007 | 1.450 | 2.969 | 0.331 |
| 2008 | -1.487 | −2.013 | 0.671 |
| 2009 | 2.862 | 4.273 | 0.107 |
| 2010 | 4.275 | 4.100 | 0.879 |
| **GDP per capita growth, percent** | | | |
| 2006 | 2.425 | 1.691 | 0.384 |
| 2007 | 0.988 | 0.498 | 0.558 |
| 2008 | -1.613 | −0.495 | 0.316 |
| 2009 | -3.650 | −2.965 | 0.534 |
| 2010 | 0.400 | 1.477 | 0.183 |
| **Unemployment rate growth, percent** | | | |
| 2006 | -0.122 | −0.083 | 0.188 |
| 2007 | 0.013 | −0.016 | 0.332 |
| 2008 | 0.284 | 0.241 | 0.517 |
| 2009 | 0.637 | 0.569 | 0.306 |
| 2010 | 0.023 | 0.016 | 0.783 |
| **State corporate tax rate growth, percent** | | | |
| 2006 | 0 | −0.004 | 0.669 |
| 2007 | 0 | −0.002 | 0.671 |
| 2008 | 0 | 0.034 | 0.706 |
| 2009 | -0.005 | 0.002 | 0.555 |
| 2010 | 0 | −0.002 | 0.613 |

Table A5: State-level Aggregate Innovation

This table presents state-level aggregate innovation output. The dependent variable is 2-year lagged log number of patent grants. I lagged the variable to account for the time it takes for firm's underlying innovation changes to take effects. I use all granted patents in USPTO Patent Grant data that are assigned to entities in the US with role code 2 (US company or corporation), 4 (US individual), 6 (US Federal government), 8 (US county government), and 9 (US state government). Column (1) uses patents granted to corporations (role code 2). Column (2) uses patents granted to all government (role code 6,8 and 9). Column (3) uses patents granted to individuals (role code 4). *Treat* and *Post* indicators are defined as before. *Treat* is equal to one if assignee state is in CA, DE, IL, NC, MN, MS, UT, or WA, zero otherwise. *Post* is one if on and after 2008, zero otherwise. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

| | (1)<br>log(1+grant)<br>Corporations | (2)<br>log(1+grant)<br>Government | (3)<br>log(1+grant)<br>Individuals-only |
|---|---|---|---|
| treatXpost | 0.163* | 0.040 | 0.089 |
| | (0.095) | (0.072) | (0.091) |
| Firm FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| Observations | 450 | 44 | 405 |
| Adjusted $R^2$ | 0.987 | 0.988 | 0.886 |

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1

## A.1 USPTO Patent Data Collection

US patent data is important part of the empirical analyses because I use the firm-level patent characteristics, such as percentage of successful applications and patent citations, to provide evidence for the increasing patent pledgeability mechanism. In this section, I briefly describe the data collection process, and how I validate the data across different publicly available patent data sources.

USPTO publicly provides a bulk data download through Reed Tech. The database keeps patent application and patent grant data separately, and USPTO releases the data weekly in XML data format. I first download these weekly files and parse each XML files to obtain relevant information. The key information contained in each document is the assignee names, assignee state, assignee country, and assignee role code. For each set of patent application and patent grant data, I keep only documents with role code "02," which represents US corporation assignee. Then using assignee state and country, I limit my sample to only ones that are issued to US domicile US corporations. Next, I name-match the assignees to my patenting sample firms from Compustat. I use multiple ways for name-matching, and also verify with spot-checking with eyes given the number of sample firms is not too large.

Additionally, I performed validation of my data using existing sources. First, going through the universe of US patents allows me to verify the claim that about 80-90% of patentable inventions are created by the employee inventors (*Cherensky* 1993, *Pisegna-Cook* 1994, *Gruner* 2006). Consistent with these papers, using the role code categories, I verify that the composition of patent assignees in my data is also mainly composed of corporations, followed by individual and government. Second, I cross-checked with KPSS data (*Kogan, Papanikolaou, Seru, and Stoffman* (2017)). KPSS is an excellent data source for patents. However, there are few limitations with KPSS. One is that KPSS covers US patent data from 1926 to November of 2010, whereas my sample period is over 2003-2013. The other is that to measure the success rate of patent applications in the application year, I need to be able to verify whether the applied patents are eventually granted. This requires for me to see grant data unto 2016, given it takes on average about two to three years for a patent to go through the grant process. By using USPTO data, I can extend the patent data unto 2016 for computation purpose, and also use KPSS to cross-check my patent grant and citations data for the overlapping period between 2003-2009. I first verified raw number of grant documents parsed in each of KPSS and my dataset. For the period between 2003-2009, the counts match about 99.9% for most of the years. In 2010, KPSS data stops in November 2nd, 2010. The count gap between KPSS and my data is about 15,000 granted patents, which is plausible given the average number of patents granted each month. Lastly, I also validated that the number of citations on overlapping firms during the common time period is almost identical.

## A.2 Statutory Laws and Firm Headquarters

This section provides a few examples of cases to verify that pre-invention assignment agreements are governed by state law where a firm's headquarter is located. In the empirical analysis, the a sample firm's headquarter state is used to define the treatment indicator.

1. **DDB Technologies, LLC v. MLB Advanced Media**

   - Case no. 04-CV-352, 2006.
   - The initial case was heard in Western District of Texas.
   - The involved inventions by David Barstow assigned to Schlumberger Technology Corporation, whose headquarter is located in Texas.

2. **Evan Brown v. Alcatel USA, Inc (F/N/A DSC Communications Corporation)**

   - Case no. 05-02-01678-CV, 2004.
   - The case was heard in 199th Judicial District Court. Collin County, Texas.
   - DSC Communications was a Texas-based phone equipment maker.

3. **Banks v. Unisys Corporation and Burroughs Corporation**

   - Case no. 228 F.3d 1357, 2000.
   - The case was initially heard in District Court for the Eastern District of Michigan.
   - Gerald Banks and Kelly Banks were employed with Burroughs Corporation, now wholly-owned by Unisys Corporation.
   - Burroughs Corporation headquarter is located in Michigan.

## A.3 Variable Description

- **Total debt/Assets** = (Long-term debt (dltt) + Short-term debt (dlc))/ total assets. The missing observations were replaced with zero, then the ratio is winsorized between zero and one following *Lemmon, Roberts, and Zender* (2008).

- **LTD issuance** = Long-term debt issuance (dltis)/($Total\ assets_{t-1}$). The missing observations were replaced with zero, then the ratio is winsorized between zero and one following *Lemmon et al.* (2008).

- **Self-citation** = A total number of citations on a firm's own patents granted in the last 10 years by new applications. The median backward citation lag is around 10 years (*Hall et al.* (2005))

- **% successful app** = (Total number of eventually granted patents)/(Total number of patent applications submitted) X 100

- **Firm age**= Firm age is counted since date of incorporation obtained from Datastream.

- **First 3-yr citations** = Average number of total citations received during the first 3-years post-grant per patent.

- **Avg. citations** = Average annual number of citations received per existing patents granted prior to treatment year.

- **Portfolio Age**= Average age of all existing patents in firm's patent portfolio in the year prior to the CAFC ruling.

- **Patent Stock**= The total number of all existing patents in firm's patent portfolio in the year prior to the CAFC ruling.

- **% Self citation** = Sum of all self citations divided by the total number of citations made by new applications, then multiplied by 100.

- **Leverage growth** = Average of annual growth of debt-to-assets ratio.

- **Size growth** = Average of annual growth of total assets.

# APPENDIX B

# Patent Litigation and Innovation Competition

## Table B1: Determinant of Patent Litigation

The table examines the determinants of patent litigation probability. The sample comprises of all patents (to be updated) in our sample period, 1976-2006. The dependent variable *Litigation* is the dummy variable that equals to one if the firm is involved in a litigation at the given year. Firm, industry, and year fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for firm clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | (1) Defendant | (2) Log(# Defendant) | (3) Intra-ind. case | (4) Log(# Intra-ind. Case) | (5) Inter-ind. case | (6) Log(# Inter-ind. Case) |
|---|---|---|---|---|---|---|
| Log(1+# Patent) | -0.01 | 0.16*** | -1.20*** | 0.10* | 1.20*** | 0.51*** |
| | (-0.13) | (2.61) | (-4.86) | (1.70) | (4.86) | (8.51) |
| Log(1+# Adj. Citations) | -0.77*** | -0.52*** | -1.01 | 0.91*** | 1.01 | 0.99*** |
| | (-3.03) | (-3.30) | (-1.42) | (5.46) | (1.42) | (4.38) |
| Log(1+# Adj. Citing) | 0.84*** | 0.07 | -0.07 | -0.71*** | 0.07 | -0.33** |
| | (3.76) | (0.54) | (-0.13) | (-5.87) | (0.13) | (-2.11) |
| Portfolio Avg. Originality | -4.46*** | -2.88*** | 3.37* | 4.19*** | -3.37* | 0.48 |
| | (-4.47) | (-4.46) | (1.72) | (6.85) | (-1.72) | (0.61) |
| Log(Portfolio # Assignee) | -1.12 | 1.30 | 36.67 | -29.87*** | -36.67 | -24.45*** |
| | (-0.10) | (0.29) | (1.24) | (-5.43) | (-1.24) | (-4.27) |
| Size | 0.10 | -0.12* | 1.20*** | 0.19*** | -1.20*** | -0.58*** |
| | (0.89) | (-1.78) | (5.27) | (2.86) | (-5.27) | (-7.93) |
| Cash | 0.81 | 0.60** | -1.30 | -0.06 | 1.30 | -2.78*** |
| | (1.61) | (2.30) | (-1.15) | (-0.25) | (1.15) | (-10.18) |
| Leverage | -1.53** | -2.11*** | -3.71*** | -2.87*** | 3.71*** | -1.37*** |
| | (-2.14) | (-4.89) | (-2.92) | (-6.48) | (2.92) | (-3.29) |
| R&D Exp. | 0.32 | -0.96 | 17.61*** | 3.80*** | -17.61*** | -11.12*** |
| | (0.17) | (-0.86) | (3.60) | (3.57) | (-3.60) | (-9.19) |
| Profitability | 0.81 | 1.50** | -3.26 | -0.40 | 3.26 | 0.15 |
| | (0.73) | (2.19) | (-1.51) | (-0.54) | (1.51) | (0.18) |
| Tangibility | -0.95* | -1.31*** | 1.21 | 0.35 | -1.21 | -0.77** |
| | (-1.66) | (-4.44) | (1.22) | (1.22) | (-1.22) | (-2.28) |
| Tobin's Q | -0.06 | 0.02 | -0.18 | -0.09*** | 0.18 | 0.03** |
| | (-0.98) | (1.11) | (-1.55) | (-6.32) | (1.55) | (1.97) |
| CF Vol | -1.61 | -0.34 | -0.96 | -2.98** | 0.96 | -1.60 |
| | (-0.66) | (-0.23) | (-0.16) | (-2.01) | (0.16) | (-0.91) |
| Dividend Dummy | 0.18 | 0.07 | 1.17*** | 0.92*** | -1.17*** | -0.42*** |
| | (1.15) | (0.64) | (3.46) | (11.25) | (-3.46) | (-3.41) |
| 1 - HHI | 2.79 | 6.25** | 0.17 | 3.91 | -0.17 | -0.81 |
| | (0.54) | (2.52) | (0.02) | (1.54) | (-0.02) | (-0.32) |
| Ind. Med R&D | 4.67 | 7.37** | 7.59 | -2.06 | -7.59 | -4.56 |
| | (0.75) | (2.49) | (0.50) | (-0.69) | (-0.50) | (-1.48) |
| Ind. Med Q | 0.20 | -0.11 | -2.89*** | -0.03 | 2.89*** | 0.50** |
| | (0.45) | (-0.51) | (-3.01) | (-0.16) | (3.01) | (2.13) |
| Ind. Med Leverage | 0.45 | 3.52*** | -5.31 | 0.87 | 5.31 | -1.18 |
| | (0.14) | (3.16) | (-0.83) | (0.91) | (0.83) | (-1.07) |
| Ind. Med Profitability | 2.10 | 4.63*** | 3.09 | -2.93 | -3.09 | 0.24 |
| | (0.72) | (3.30) | (0.46) | (-1.64) | (-0.46) | (0.15) |
| Ind Med Tangibility | 7.40** | 0.65 | 9.87* | 6.23*** | -9.87* | 1.33 |
| | (2.27) | (0.47) | (1.78) | (4.75) | (-1.78) | (1.02) |
| Year FE | Yes | Yes | Yes | Yes | Yes | |
| Ind FE | Yes | Yes | Yes | Yes | Yes | |
| Observations | 1,149 | 1,270 | 561 | 1,270 | 561 | 1270 |
| Adjusted $R^2$ | | 0.496 | | 0.773 | | 0.615 |
| Pseudo $R^2$ | 0.183 | | 0.443 | | 0.443 | |

Table B2: The Effects of Patent Litigation: Financial Outcomes

The table examines the effects of patent litigation on corporate financial outcomes. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. For each litigation case, we restrict the sample period from $t-2$ to $t+2$ year around the litigation filing date. In columns (1)-(5), the dependent variables are corporate financial policy: total cash scaled by total assets (*Cash*), dividend payer dummy (*Dividend*), leverage ratio using book value of total debt (*Leverage*)), assets growth rate (*Asset growth*), and the market share based on 3-digit SIC (*Mkt Share*). *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | (1)<br>Cash | (2)<br>Dividend Dummy | (3)<br>Leverage | (4)<br>Asset growth | (5)<br>Market Share |
|---|---|---|---|---|---|
| After X Defendant | -0.01*** | -0.04*** | 0.03*** | -0.08*** | 0.30** |
| | (-2.98) | (-2.95) | (2.77) | (-5.77) | (2.54) |
| Defendant | 0.01*** | 0.01 | -0.02*** | 0.05*** | -0.10 |
| | (2.90) | (0.71) | (-2.99) | (6.93) | (-1.50) |
| After | 0.00* | -0.00 | 0.00 | 0.02*** | 0.18*** |
| | (1.80) | (-0.22) | (0.37) | (3.46) | (3.15) |
| Size | -0.01* | 0.09*** | -0.05*** | -0.27*** | 3.72*** |
| | (-1.92) | (5.06) | (-3.97) | (-9.48) | (13.16) |
| R&D Exp. | -0.29*** | 0.41*** | 0.32*** | 0.84*** | 4.36*** |
| | (-5.10) | (4.66) | (4.08) | (7.40) | (3.67) |
| Profitability | -0.06** | 0.25*** | 0.07 | -0.36*** | 6.62*** |
| | (-2.15) | (2.60) | (1.05) | (-3.16) | (8.52) |
| Tangibility | 0.15*** | 0.05 | -0.06*** | 0.74*** | -1.64*** |
| | (8.36) | (1.13) | (-2.60) | (11.51) | (-2.95) |
| Tobin's Q | -0.00*** | 0.00*** | -0.00*** | 0.10*** | 0.07*** |
| | (-4.21) | (2.96) | (-4.07) | (10.31) | (4.53) |
| CF Vol | 0.17*** | 0.40*** | 0.17 | -0.98*** | 3.95*** |
| | (5.05) | (4.67) | (1.17) | (-6.77) | (4.23) |
| 1 - HHI | -0.08 | 0.03 | 0.32*** | -0.10 | -62.36*** |
| | (-1.21) | (0.20) | (2.88) | (-0.47) | (-11.58) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,099 | 10,099 | 10,099 | 10,099 | 10,099 |
| Adjusted $R^2$ | 0.878 | 0.884 | 0.681 | 0.530 | 0.986 |

Table B3: The Effects of Patent Litigation: Innovation Outcomes

The table examines the effects of patent litigation on corporate innovation outcomes. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. For each litigation case, we restrict the sample period from $t-3$ to $t+3$ year around the litigation filing date. In columns (1)-(4), the dependent variables are corporate innovation outcome and strategy: the log of one plus number of patent applications at a certain year ((*Log(1+Number of Patent Application)*), the log of one plus adjusted citation (Log(1+Number of Adj. Citations)), the log of one plus number of acquisitions (*Log(1+Number of Acquisitions)*), and the log of average transaction size of acquisitions (*Log (1+Average Deal Size)*) at a given year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | (1) Log(1+Number of Patent Application) | (2) Log(1+Number of Adj. Citations) | (3) Log(1+Number of Total Acquisitions) | (4) Log(1+Average Acquisition Size) |
|---|---|---|---|---|
| After X Defendant | -0.35*** | -0.04*** | -0.10*** | -0.41*** |
| | (-9.88) | (-5.61) | (-4.65) | (-3.76) |
| Defendant | 0.13*** | 0.01*** | 0.05*** | 0.28*** |
| | (6.70) | (2.72) | (4.60) | (4.71) |
| After | 0.14*** | 0.01*** | 0.00 | -0.04 |
| | (6.35) | (3.24) | (0.29) | (-0.76) |
| Size | 0.38*** | -0.11*** | 0.17*** | 1.03*** |
| | (8.31) | (-8.52) | (8.18) | (7.54) |
| R&D Exp. | 2.32*** | 0.05 | -1.12*** | -7.19*** |
| | (5.10) | (1.00) | (-5.37) | (-6.93) |
| Profitability | 0.93*** | -0.35*** | 0.53*** | 3.10*** |
| | (5.14) | (-6.13) | (6.60) | (6.78) |
| Tangibility | 0.53*** | -0.09*** | 0.75*** | 5.70*** |
| | (4.19) | (-2.66) | (12.31) | (14.08) |
| Tobin's Q | -0.00 | 0.01*** | 0.01*** | -0.01 |
| | (-0.43) | (8.62) | (2.70) | (-1.15) |
| CF Vol | 0.84* | 0.49** | 0.79*** | 3.12** |
| | (1.91) | (2.37) | (2.68) | (2.27) |
| 1 - HHI | -0.67 | -0.36*** | 0.79*** | 2.16 |
| | (-1.31) | (-4.07) | (3.73) | (1.34) |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 9,973 | 10,099 | 10,099 | 10,099 |
| Adjusted $R^2$ | 0.921 | 0.965 | 0.395 | 0.372 |

Table B4: The Effects of Patent Litigation: Innovation Strategy

The table examines the effects of patent litigation on corporate external innovation. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. For each litigation case, we restrict the sample period from t-3 to t+3 year around the litigation filing date. In columns (1)-(5), the dependent variables are corporate innovation outcome and strategy: the exploitive innovation measure (*Exploitive*), the explorative innovation measure (*Explorative*)), the dummy variable that equals one if the acquisition is between the same industry (*Same Industry Acquisition*), the log of one plus number of CVC transaction (*Log(1+Number of CVC Deal)*), and the number of business segments (Number of Segments). *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| | (1) Exploitive | (2) Explorative | (3) Same Industry Acquisition | (4) Log(1+Number of CVC Deal) | (5) Number of Segments |
|---|---|---|---|---|---|
| After X Defendant | 0.04*** | -0.03*** | 0.05 | -0.10** | -0.33** |
| | (5.28) | (-3.73) | (1.20) | (-2.29) | (-2.24) |
| Defendant | -0.02*** | 0.01*** | -0.02 | 0.03 | 0.32*** |
| | (-5.20) | (2.97) | (-0.85) | (1.04) | (3.53) |
| After | -0.02*** | 0.01** | -0.02 | 0.01 | 0.22*** |
| | (-3.72) | (2.17) | (-1.42) | (0.41) | (2.96) |
| Size | -0.01 | 0.03* | 0.03 | 0.07 | 0.44* |
| | (-0.83) | (1.93) | (0.43) | (0.99) | (1.85) |
| R&D Exp. | -0.33*** | 0.24*** | -0.47 | 1.06* | 3.90** |
| | (-4.64) | (2.76) | (-0.90) | (1.92) | (2.01) |
| Profitability | 0.24*** | 0.05 | 0.60 | -0.44 | -2.87** |
| | (4.80) | (1.26) | (1.21) | (-1.22) | (-2.10) |
| Tangibility | -0.17*** | 0.14*** | 0.27 | 0.68* | 0.58 |
| | (-5.61) | (4.17) | (1.03) | (1.72) | (0.66) |
| Tobin's Q | -0.00 | 0.00** | 0.05* | 0.01 | 0.01 |
| | (-1.51) | (2.49) | (1.66) | (0.64) | (0.25) |
| CF Vol | 0.11* | -0.02 | -0.03 | -0.29 | -1.70 |
| | (1.90) | (-0.44) | (-0.06) | (-0.62) | (-1.11) |
| 1 - HHI | -0.50*** | -0.33** | 0.29 | 1.32 | 5.88* |
| | (-3.37) | (-2.19) | (0.51) | (1.31) | (1.96) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,327 | 8,327 | 10,099 | 10,099 | 9,219 |
| Adjusted $R^2$ | 0.554 | 0.691 | 0.436 | 0.869 | 0.837 |

## Table B5: The Effects of Patent Litigation: Innovation Strategy by Year

The table examines the effects of patent litigation on corporate innovation. The sample comprises of 1,692 litigation cases that S&P 500 firm associated for the period of 2000-2006. For each litigation case, we restrict the sample period from $t-3$ to $t+3$ year around the litigation filing date. In Panel A, the dependent variables are the log of one plus number of patent applications at a certain year ((*Log(1+Number of Patent Application)*). In Panel B, the dependent variables are the log of one plus adjusted citation (Log(1+Number of Adj. Citations)). In Panel C, the dependent variables are the log of one plus number of patent applications at a certain year ((*Log(1+Number of Patent Grant)*). In columns (1)-(3), we present results from difference-in-difference analysis with the dependent variables in $t+1$, $t+2$, and $t+3$ year after litigation. *After* is a dummy variable that equals one after litigation year, and zero before and including litigation year. *Defendant* is a dummy variable that equals one if firm is one of defendants in litigation case, otherwise zero. Year and firm fixed effects are included. *t-statistics* (in parenthesis) are robust and adjusted for Case clustering. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

**Panel A: Log(1+Number of Patent Application)**

| | (1) | (2) | (3) |
|---|---|---|---|
| After X Defendant | -0.27*** | -0.14** | -0.01 |
| | (-4.05) | (-2.22) | (-0.16) |
| Defendant | 0.08** | 0.03 | -0.04 |
| | (2.43) | (0.84) | (-1.29) |
| After | 0.05 | -0.04 | -0.03 |
| | (1.33) | (-1.33) | (-1.08) |
| Year FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Observations | 9,457 | 8,659 | 7,597 |
| Adjusted $R^2$ | 0.913 | 0.905 | 0.912 |

**Panel B: Log(1+Number of Adj. Citations)**

| | (1) | (2) | (3) |
|---|---|---|---|
| After X Defendant | -0.03*** | -0.02** | -0.01 |
| | (-3.35) | (-2.56) | (-1.25) |
| Defendant | 0.00 | 0.00 | -0.00 |
| | (0.99) | (0.12) | (-0.72) |
| After | 0.01 | 0.00 | 0.00 |
| | (1.63) | (0.94) | (0.24) |
| Year FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Observations | 8,327 | 8,327 | 10,099 |
| Adjusted $R^2$ | 0.554 | 0.691 | 0.436 |

**Panel C: Log(1+Number of Patent Grant)**

| | (1) | (2) | (3) |
|---|---|---|---|
| After X Defendant | -0.12** | -0.12** | -0.13** |
| | (-2.32) | (-2.40) | (-2.51) |
| Defendant | 0.07** | 0.06** | 0.04* |
| | (2.56) | (2.25) | (1.66) |
| After | 0.03 | -0.02 | -0.02 |
| | (0.83) | (-0.75) | (-0.92) |
| Year FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Observations | 9,940 | 9,478 | 8,757 |
| Adjusted $R^2$ | 0.887 | 0.885 | 0.890 |

## B.1 Case Example

**Symbol Technologies v. Proxim**

In December 2001, Symbol Technologies filed suit against Proxim for patent infringement. Symbol Technologies and Proxim were direct competitors wireless networking equipment for Wi-Fi and broadband wireless networks industry. The asserted patents in the litigation entailed a power saving feature in wireless local area network ("WLAN") communication protocols. During the trial, the jury found that Proxim's OpenAir products and 802.11 products infringed Symbol's patents. Around the time when Symbol's patents were granted between 1991 and 1995, Proxim began selling the OpenAir products under the RangeLAN2 name in 1994. Symbol's infringement expert had performed infringement analysis for the OpenAir products, but without joining Proxim's Wireless LAN Interoperability Forum, could not further determine direct infringement without Proxim's protocol and source code.

As a defense against patent infringement suit, Proxim contended that it is entitled to the defense of laches, arguing Symbol Technologies sustained both economic and evidentiary prejudice as a result of Symbol's unreasonable delay in bringing suit. However, Proxim failed to bring evidence that demonstrates Symbol had actual knowledge of Proxim's infringing activities and that Symbol Technologies failed on duty to inquire. As a result, in lieu of permanent injunction, Symbol Technologies was awarded a six percent royalty on sales of infringing products by Proxim in amount of $22,865,477 and damages in amount of $3,052,192, adding to approximately $26 million.

After the ordering of royalty and damages in July 2004, Proxim shortly announced that it plans to pay Symbol $22.75 million over the next two and a half years, starting with the quarter that ended September 30th. In a quarterly SEC filing in 2004, Proxim noted that "...we may be subject to significant and immediate liabilities in connection with our patent litigation case with Symbol Technologies, Inc. ("Symbol") which exceed our current cash resources." Proxim also warned that a large patent award to Symbol combined with difficulties in refinancing its Bridge Notes could force the company to "seek protection under applicable bankruptcy laws." Proxim was eventually acquired in 2005 by Terabeam Inc.[1]

**Johnson & Johnson v. Boston Scientific**

Johnson & Johnson and Boston Scientific's long history of myriad patent disputes date back to 2003. The asserted patent technology is used in making coronary artery stents. The market for coronary artery stents has grown into a $6.5 billion worldwide business in which profit margins can near 80 percent. Boston Scientific enjoyed a huge success, generating $2 billion sales, from Taxus stent introduced in the stents market dominated by the market pioneer, Cypher by Johnson & Johnson. Quickly, Boston Scientific became Johnson & Johnson's biggest rival in the stents market.

However, by 2005, a series of courtroom battles with Johnson & Johnson raised concerns by the stock market of Boston Scientific's ability to enhance Taxus line for further sales and casted doubt on the company's financial health from continuing legal expenses. The media and market analysts particularly expressed concerns with Johnson & Johnson's potential strategy of using appeals and cases to drag on the patent dispute given its size and financial flexibility to hurt Boston Scientific financially even more than by collecting royalties. In 2006, Johnson & Johnson acquires Conor Medsystems that uses paclitaxel, the drug that stent patent litigation centers on. The market viewed that Johnson & Johnson's deep pockets and long experience with stent litigation could strengthen Conor's legal position, and Boston Scientific's shares fell on the news of Johnson's and Johnson's acquisition of Conor.

The final blow on Boston Scientific came in 2010. Since 2003, Boston Scientific settled 17 lawsuits with Johnson & Johnson, and it finally settled on the on going patent litigation on stent by paying Johnson & Johnson $1.7 billion, which is the largest sum ever paid to resolve patent litigation over medical device. Even though Ray Elliot, president and chief executive of Boston Scientific, assured the market of Boston Scientific's resilience and ability

[1]See following sources for further information on Proxim's patent litigation news reports. https://www.law360.com/telecom/articles/2166/proxim-pays-23m-to-settle-symbol-s-wlan-patent-suit; http://query.nytimes.com/gst/fullpage.html?res=940DE5DD1E30F936A2575AC0A9629C8B63&mcubz=0; http://www.proxim.com/about-us/investor-information/investor-faqs

to manage the payments with some financial flexibility, the market and industry analysts suggested that the settlement's size would sharply curtail the company's ability to make major acquisitions in the near future or force the company to undergo layoffs. Consistent with the market's view, Boston Sceintific announced layoff plans during the same month, apparently due to large impairment charges and legal bills including payments to Johnson & Johnson.[2]

[2] See following sources for further information on Johnson & Johnson and Boston Scientific patent disputes. http://query.nytimes.com/gst/fullpage.html?res=990CEED9173EF93AA3575BC0A9639C8B63&pagewanted=all&pagewanted=print; http://www.nytimes.com/2006/11/18/business/18stent.html; http://www.nytimes.com/2007/10/04/business/04patent.html; http://www.nytimes.com/2010/02/02/business/02device.html; http://www.massdevice.com/update-boston-scientific-lay-1300-q4-2009-sales-rise-losses-narrow/.

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