I examine how increasing firms’ ownership of employee patents affects debt financing. I exploit a Court of Appeals Federal Circuit ruling that increased firms’ property rights to employee patents. I find that firm ownership of patents increases firms’ total debt-to-assets ratio by 18%, which is equivalent to a $62 million increase in total debt. Firms’ residual control over patents improves pledgeability of patents as collateral, by raising firms’ incentives to make more productive and synergistic use of patents. This, in turn, leads to reduction in holdup problems, as evident from enhanced complementarity of patents and inventor-employees.

*JEL classification:* D23, G32, O32, O34.

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1. Introduction

Patents are important assets to knowledge-intensive firms in part because of the growing use of patents as collateral to access debt financing. 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 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 patent ownership structure changes the productivity of underlying innovation processes, which in turn affect the pledgeability of patents as collateral.

The goal of this paper is to empirically examine how 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 a property rights shift within firms. However, an empirical identification of the effect of property rights on debt financing poses a key challenge. 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 opportunities. Without a clean empirical setting, an observed correlation between property rights and debt financing is difficult to interpret.

To overcome this identification challenge, I exploit a Court of Appeals for the Federal Circuit (CAFC) ruling in 2008, which, de facto, shifted patent property rights from inventor-employees to firms in eight pro-employee invention assignment states. The main regression

\footnote{Lounioti (2013) documents that the percentage of secured syndicated loans collateralized by intangible assets grew from 11% to 24% over the 1997-2005. Mann (2018) reports that 38% of US patenting firms had pledged their patents as collateral at some point in 2013.}

\footnote{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 2.}
relies on state-level variation in property rights enforcement through invention assignment agreements in a difference-in-difference setting. The regression estimate captures an increase in the leverage ratio of 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, and 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 measured 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 property rights shift. 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 flow of debt increases, I reestimate the regressions using new long-term debt issuances as a dependent variable and find about a 23% increase in the new 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. Firm ownership of patents facilitates debt financing as pledged patents increase liquidation values by shifting control rights on collateralized patents to lenders when a borrower firm defaults. Hence, pledged patents allow lenders to extend credit on more favorable terms. Consistently, I find that treated firms’ use of bank debt, which is often secured by assets, increases. Also, while the level of long-term debt increases substantially, short-term debt hardly changes. Therefore, shifting property rights to firms also helps alleviate financing
friction between firms and financiers.

Next, I provide underlying channel evidence to show that the increase in debt financing is driven by enhancement in pledgeability of patents as collateral and reduction in holdup problems in innovation processes under the firm ownership of patents. In relationship-specific investments like corporate innovation, an integration of ownership boosts synergies and productivity. These synergies, in turn, improve both the quantity and quality of pledgeable patents. First, I find that the number of pledgeable patents, as measured by the number of granted patents, rises by about 8%. Also, treated firms’ propensity to patent, which measures the number of patents produced for every million dollars spent on R&D, increases by as much as 65%.

Second, improvement in the quality of firms’ existing and new patents, as measured by change in the number of external citations received per patent, increases by 40% and 6.5%, respectively. Patent citation is also an important measure of pledgeability of patents because it indicates patent redeployability and external interests in the cited firms’ technologies (Chava, Nanda, and Xiao 2017; Hochberg, Serrano, and Ziedonis 2017), both of which are critical in attracting lenders’ willingness to take patents as collateral for secured debt financing.

It is important to note that greater access to debt financing is not merely driven by a growing asset size when property rights shift. Accordingly, I first provide results that show the actual number of pledged patents as collateral increases by 2.4% for treatment firms relative to control firms. However, the increase in the number of pledged patent is positively correlated for the subsample with the greater improvement in quality but not for the subsample with the larger increase in the number of granted patents. These subsample analyses highlight important interpretations of the main debt financing results. As suggested by the cross-sectional significance of quality improvement, the main debt financing results are not reflective of a mechanical rise in debt capacity due to increasing asset size when property rights shift.
Lastly, I attempt to show a reduction in holdup problems, which is the key insight that differentiates this paper from the literature on creditor rights. Integration of ownership reduces potential opportunistic behaviors that lead to ex ante underinvestments. Since innovative efforts and non-physical investments are unobservable, I use self-citation and inventor collaboration as proxies for measuring reduction in holdup problems. These measures convey how firm ownership of patents strengthens complementarity among patents and inventor-employees. I find that treated firms’ self-citation counts increase by 12.5%, and inventor collaboration, as measured by the number of inventors assigned to each patent, increases by 5%.

In sum, firm ownership of patents facilitates firm’s debt financing by improving pledgeability of patents as holdup problems in underlying innovation processes subside. Furthermore, this paper tightly links the growing importance of property rights on knowledge-assets to firm financing and highlights the tension arising from the knowledge-asset ownership structure as firms move toward knowledge-based production. This paper focuses on knowledge-intensive firms’ debt financing, however, it is difficult to draw implications on the optimal form of financial contracts or capital structure, as invention assignment agreements are restricted to the relationship between firms and employees, not between firms and financiers (Hart and Moore 1998). Nonetheless, it may still be of some interest to explore whether the increase in property rights also affects the issuance of new equity. In an 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. First, this paper builds on the growing literature in patent collateral and debt financing. Loumioti (2013) and Mann (2018) document the increase in the use of patents as collateral. Mann (2018) further empirically shows that, everything else constant, stronger creditor rights on patent collateral lead to greater access to debt financing and R&D investments. Chava et al. (2017) provides complementary results on how the value of patent collateral is priced in bank loans.
Hochberg et al. (2017) provides evidence to show that venture lending to startup firms increases with redeployability of patents when the liquidity of secondary markets for patents rises. In contrast, by exploiting the change in patent ownership structure, this paper shows the fundamental source of patent pledgeability and draws important implications on both debt financing and innovation processes.

Recent studies that focus on property rights and firm innovations show that firms’ integration decisions vary negatively with the strength of protection on returns from innovation. Using a sample of UK firms, Acemoglu, Aghion, Griffith, and Zilibotti (2004) shows that incentives for integration are high(low) for firms in a relatively lower(higher) ex ante R&D investment intensity, as R&D investments are easy to be expropriated. Similarly, Fresard, Hoberg, and Phillips (2017) shows that vertical integration is less likely in industries where innovation is in early stages and R&D spending is high, since returns are best protected under separate ownership when the investments by technology developers are 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.

Lastly, this paper is related to inventors and innovation and finds inventors’ human capital as important input in innovation processes (Liu, Mao, and Tian 2017; Islam and Zein 2018). In a closely related paper by Hvide and Jones (2016), the authors find that a shift in patent property rights from researchers to universities in Norway led to a large decline in the rate of startups, quantity, and quality of innovation by university researchers. These contrasting results may be attributable to institutional differences between universities and corporations. Complementarity of firm-employee relationship-specific innovation processes, corporate inventor employment contracts, and employee compensation schemes may limit the deterioration of employee incentives when property rights shift in a corporate setting. Therefore, although inventors provide key human capital, the institutional structure also plays an important role in the outcome of innovation.

The remainder of the paper is structured as follows. Section 2 explains empirical strategy
of this paper using pre-invention assignment agreements. Section 3 outlines the hypotheses. Section 4 describes the data in detail. Section 5 presents main results, Section 6 provides discussions about the results, and Section 7 presents additional robustness tests. Section 8 concludes the paper.

2. Empirical Strategy

2.1. Pre-invention Assignment Agreements

In this paper, I focus on 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 pre-invention assignment agreements may be broad enough to cover categories of inventions beyond employer-specified inventions and extend past the terms of employment for a reasonable period after employment has ended. As part of employment contracts, pre-invention assignment agreements are governed by state laws, and when present, supersede common laws (the default rule in the absence of such agreement). Generally, courts honor these agreements.

In the early 1990s, eight states enacted state legislation 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). Inventions

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3 Absent invention assignment agreements, the court considers the nature of the employment, the subject matter of the invention, and the resource contribution of the employer to determine the extent of firms’ ownership or the shop-rights according to the common law principles (Pisegna-Cook 1994).

that fall under the protection of state legislation most likely arise from “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. Inventions from general inventive employees tend to be a grey area because these employees may be encouraged by their employers to pursue creative projects that 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 asset used for production nevertheless have implications for debt financing as highlighted in the introduction, the growing role of knowledge assets as collateral for securing financing suggests patents as a timely and appropriate venue for this study. Second, pre-invention assignment agreements are prevalently used in knowledge-intensive firms and somewhat pre-define the division of ownership of patents. Lastly, the existence of a plausibly exogenous shock on the interpretation of pre-invention assignment contracts helps establish 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 firms’ debt financing are challenging tasks because property rights allocation is endogenous. Before I explain the quasi-experiment setting in Section 2.2 and 2.3, I provide an example of how pre-invention assignment agreements are used.

Recently, pre-invention assignment agreements have become widely used throughout an organization regardless of an employee’s likelihood of inventing (Mattioli 2011). For example, Ford has initiated a companywide innovation challenge and encouraged its employees from any part of the business to participate by submitting invention ideas on new products

\(^5\)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.
or changes to the company’s existing offerings. 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 Submission[...].” 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 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. Recently, however, the overwhelming employer claims on employee inventions have raised concerns. Firms increasingly take advantage of the protection provided by pre-invention assignment agreements, and thus invention assignment agreements highlight the significant value of knowledge assets to firms.

2.2. Institutional Setting

In 2008, the Court of Appeals Federal Circuit (CAFC) made a decision in *DDB Technologies LLC v. MLB Advanced Media, LP* on a pre-invention assignment agreement case that shifted employee invention property rights 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

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8 The Ford innovation contest rules are available on http://henryfordinnovation.com/challenge/contestrules/
10 517 F.3d 1284, 1290 Fed. Cir. 2008
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 pro-employee state legislation in 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 the presence of expressive terms, such as “agrees to and does hereby grant and assign...,” in invention assignment agreements. The expressive terms put the assignment in the present tense, and thus even without any inventions in the present, future inventions are automatically and immediately assigned to firms, under the court’s interpretation (Baniak and Dawson, 2009). The practical influence of the court’s ruling can easily be found in law firms’ advice to corporate clients at the time. Law firms recommended that their corporate clients include express phrases in invention assignment agreements. 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 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.”


Third, since CAFC has nationwide jurisdiction and the court categorized *DDB Technologies LLC v. MLB Advanced Media, LLP* as a precedential case, the decision impacts future pre-invention assignment agreement cases.\(^\text{13}\)

In summary, the CAFC decision effectively increased firms’ property rights to employee inventions in the eight formerly pro-employee states by preempting existing state legislation on protecting inventor-employee interests regarding invention assignment agreements.\(^\text{14}\) In the following section, I explain the implementation of this empirical setting in regression analyses.

2.3. 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 C 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.

\[
\text{Total debt/Assets}_{ist} = \alpha + \beta \text{treat}_s \times \text{post}_t + \delta_i + \gamma_t + \epsilon_{ist}\tag{1}\]

\(^\text{13}\)Hedvat (2011) shows (in the footnote 63) that the subsequent courts have adopted the reasoning and holding of *DDB Technologies LLC v. MLB Advanced Media, LLP* case in Board of Trustees of the Leland Stanford Junior Univ. v. Roche Molecular Sys., Inc. (Fed. Cir. 2009), Rothschild v. Cree, Inc. (D. Mass. 2010), EMD Crop Bioscience, Inc. v. Becker Underwood, Inc. (W.D. Wis. 2010), and STMicroelectronics, Inc. v. Harari (N.D. Cal. Aug. 2008).

\(^\text{14}\)It is a possibility that the ruling discourages invention disclosures by inventor-employees for the fear of losing ownership after the ruling. However, if there is any intention to profit from an invention, the incentives to hide inventions and not patent them would be low given the required protection on property and cashflow rights under the patent system.
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. An important identification assumption for the difference-in-difference 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 Section 4.

Under the identification assumption, the difference-in-difference 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.

3. Hypothesis Development

3.1. Debt Financing

Corporate innovation processes entail much uncertainties, such as technological shocks, success of projects, and even changes in business directions. These uncertainties make explicitly contracting on non-physical investments in innovation difficult, which leads to incomplete contracts with inefficiency in relationship-specific corporate innovation processes and holdup problems. Patent ownership is important because it alters the degree of holdup problem by encouraging firms’ to make productive use of patents, which in turn, foster pledgeability of patents as collateral for debt financing.

Under modern complex innovation processes, the integration of many components makes
individual ownership more costly (Merges 2009). Particularly, when assets are complementary, such as patents that make up different parts of the same end-product, some form of integration is better than separate-ownership (Hart 1995). A transfer of patent ownership encourages investment by firms but discourages investment by inventor-employees, resulting in a tradeoff that makes it difficult to predict the outcome. However, since firms have comparative advantages in collectively managing, commercializing, and providing resources for innovation (Gruner 2006), I predict that shifting property rights to firms facilitates firms’ access to debt financing by enhancing pledgeability of patents as collateral, as holdup problems that stem from incomplete contract subside.

3.2. Pledgeability of Patents and Holdup Problems

In relationship-specific processes like corporate innovation, synergies build up, where various patents are integrated toward the firm’s end-products. These synergies, in turn, increase innovation productivity and also improve the quality of patents. After the CAFC decision, patent pledgeability may increase for two reasons. First, the court ruling mechanically increases the number of potentially pledgeable patents for firms as a result of ownership transfers. Second, firm ownership of patents reduces holdup problem in innovation processes and thus helps improve the production of pledgeable patents. Although the court’s ruling is also applicable retroactively, given that invention assignment agreements also govern any future inventions conceived during the employment term, post-treatment changes in innovation processes carry prominent impacts on debt financing.

Increase in productivity is also accompanied by improvements in the quality of pledgeable patents. That is, firms’ greater ability to attract interests in their technology and to commercialize patents increases the redeployability of patents, which in turn raises lenders’ interests in taking the patents as collateral. Hence, I predict that firm ownership of patents enhances patent pledgeability and helps firms raise debt financing provided that lenders are able to properly assess patent values (Chava et al. 2017).
Lastly, the increase in patent pledgeability is induced by a reduction in holdup problems. Residual ownership lessens concern for opportunistic behaviors in innovation processes and thus enhances complementarity among firms’ patents and inventor-employees. That is, the reduction in holdup also promotes greater knowledge transfer and information sharing within firms. Therefore, I further predict that firm ownership of patents reduces holdup problems, an effect that is evident in improved patent complementarity and inventor-employee collaboration.

4. 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.\textsuperscript{15} 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 \textit{patenting} US public firms (country of incorporation is United States) in Compustat. I also exclude financial firms (SIC code 6000-6999) and utilities (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 grant data from United States Patent and Trademark Office (USPTO). USPTO provides US patent 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\textsuperscript{16} assigned to US domicile corporations so that I can make sure the empirical setting applies to the sample firms. Then, I name-match the

\textsuperscript{15}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.

\textsuperscript{16}Utility patents are inventions of a new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement thereof.
collected data to the Compustat sample firms. A detailed description of how the data was collected is in the Appendix B.

The final sample consists of 1,959 unique patenting firms during the sample period of 2003-2013. Table I 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 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 I 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.

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17 The sample period is 2003-2013. However, a few important outcome variables, such as count of citations, suffer from truncation problem. To avoid such issue, I collect patent data up to 2016.
5. Results

5.1. Increasing Debt Financing

Table 2 reports the main baseline 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 firm-specific time-invariant effects and aggregate time trends. Column (2) uses more stringent specification by additionally including the industry-year fixed effects to absorb potential industry-year-specific shocks. The difference-in-difference estimates are similar. Following the court’s ruling that shifted employee patent property rights to firms, treatment firms’ total debt increases by about 2.5 percentage points, relative to control firms. This is an 18% increase in the total debt-to-assets ratio for an average treated firm with $2.46 billion pre-treatment total assets and total debt-to-assets ratio of 0.14. The estimate translates into about a $62 million increase in total debt.\textsuperscript{18} In columns (3) and (4), I confirm that the actual flow of debt, as measured by the long-term debt issuances (dltis) scaled by total assets at the beginning of the year, also increases by 1.5 percentage points (23% increase in the ratio), or by $37 million in long-term debt issuances.

The impact of the ruling was immediate and easily perceptible to firms. Following the CAFC ruling, law firms promptly informed and advised their corporate clients about the ruling’s new interpretation of existing invention assignment agreements favoring firms’ rights (see Section 2.2.). The practicality and significance of who owns employee inventions are evident in media discussions.\textsuperscript{19} Furthermore, the economic magnitude of debt changes caused by the shift in property rights to patents is comparable to those in the creditor rights literature, which finds a sizable impact of law on debt financing. Bae and Goyal\textsuperscript{2009} finds that better enforceability of loan contracts in 49 countries over 1994-2003 increases loan

\textsuperscript{18}The increase in debt financing is not likely driven by an increase in future cash flows from transferred patents because such an increase should instead reduce the use of debt. Also, Lian and Ma\textsuperscript{2018} documents that a cashflow-based borrowing is less common among small firms, given their low profits and that for small public firms, the median share of cashflow-based borrowing is 7% compared to asset-based borrowing of 61%.


\textsuperscript{20}Bae and Goyal (2009)
amounts by $57 million. [Loumioti (2013)] documents that firms using patents as collateral during 1996-2005 increase secured syndicated loan amounts by $51 million. [Mann (2018)], by exploiting exogenous changes in creditor rights, finds that strengthening creditor rights increases total debt by $26 million per quarter.

Figure 1 traces the difference-in-difference coefficient (vertical axis) estimates over the years to treatment (horizontal axis). The key observation is that, prior to the treatment in \( t = 0 \), the coefficients are statistically indistinguishable from zero and only become positive and statistically significant following the court’s ruling in 2008. This graphical illustration provides some visual inspection of parallel trends, where the flat line prior to the treatment is suggestive of no pre-existing differential trends in total debt-to-assets. The graph also emphasizes the sharp change in debt financing for treatment firms relative to control firms. There is no reversion of the effects, but there seems to be a slight additional increase in the latter years, which merits further investigation of the timing of underlying changes provided in Section 5.5.

The falsification test in Table [A1] further helps establish the internal validity of the empirical setting. To ensure that the court ruling is only relevant for patenting firms’ debt financing through its impact on invention assignment agreements, I re-run the baseline regressions in Table 2 using only non-patenting firms. The coefficients on total debt-to-assets ratio are statistically insignificant. The magnitudes are also substantially smaller for non-patenting firms, which have a higher average pre-treatment total debt-to-assets ratio of 0.28. The coefficients on long-term debt issuance are even slightly negative and statistically indistinguishable from zero. Therefore, the observed increase in the level of debt financing found in the main regressions is likely caused by the treatment effect of increasing property rights of firms after the CAFC ruling.

Lastly, I ensure that the main results do not capture some spurious changes in debt. If firms have geographic subsidiaries located in multiple states and thus are exposed to multiple state laws governing invention assignment agreements, the effect of the treatment may be less
clear. Table A2 in the Appendix shows that this is not the case. Each column presents baseline regression estimates for zero, fewer than or equal to one, or fewer than or equal to two geographic subsidiaries, respectively. The results still hold, but the statistical significance weakens, possibly attributable to the significant reduction in the number of observations. In Table A3, I run the baseline regression by each treatment state against control states and show that the main result in Table 2 is also not driven solely by California.

I avoid including time-varying control variables that may be affected by the treatment and give inconsistent estimates of the treatment effect. However, Table A4 in the Appendix shows similar results when I include common controls in the leverage literature in columns (1) through (6) and also when I include measures of innovation stock and R&D expenditures in columns (7) and (8), respectively. In an unreported table, I confirm that the new long-term debt issuance results also stay robust with the inclusion of these controls.

5.2. Types of Debt and Firms

Firm ownership of patents facilitates debt financing as pledged patents increase the liquidation value by shifting control rights on collateralized patents when a borrowing firm defaults (Aghion and Bolton 1992; Hart and Moore 1994; Benmelech and Bergman 2009). Particularly, Kerr and Nanda (2015) emphasizes the wide use of bank debt by innovative firms, from small startups to public firms, in a survey on financing for innovation. Consistent with the theory and survey results, column (1) in Table 3 shows that bank debt, which is likely to be secured by assets, increases by 16%, where the pre-treatment average ratio is 0.037. However, convertible debt, reported in column (2), continues to be a viable means of accessing debt financing for high R&D-intensive firms (Stein 1992; Julio, Kim, and Weisbach 2007). This suggests that patent-secured debt financing may not completely substitute for all other types of debt financing.

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20 The data is provided on Professor Scott Dyreng through https://sites.google.com/site/scottdyreng/Home/data-and-code
21 Lerner and Seru (2017) warns of regional biases of patent data, particularly with California and Massachusetts, where innovative activities are concentrated.
Next, I explore how debt maturity is affected. The transfer of control rights on pledged assets upon default allows greater bargaining power for lenders, who in turn may extend credit on more favorable terms, such as lower interest rates or longer maturities. Earlier studies find that firms in stronger secured creditor rights and enforcement have longer maturity loans (Giannetti 2003; Diamond 2004; Qian and Strahan 2007). I also find consistent results, where an increased capacity to pledge assets makes collateral more effective and increases loan availability. Whereas long-term debt increases significantly in column (3), the estimates on short-term debt in columns (4)-(6) are statistically indistinguishable from zero.

Table A5 in the Appendix examines whether there is heterogeneity in effects conditional on ex ante financial constraints proxied by size and age. One may expect to find stronger effects on smaller and younger firms as they are more likely to be ex ante financially constrained. However, I find similar effects across the tercile groups. This is not surprising given that my sample consists already of relatively small and young patenting firms. Overall, I find that the increase in firms’ property rights to employee patents allows firms to raise greater bank debts and long-term debts.

5.3. Improvement in Pledgeability of Patents

Firm ownership of employee patents gives firms control over all patents. Residual control over future uses of patents increases firms’ incentives to make more productive use of patents and thus changes innovation processes.\textsuperscript{22} I further investigate the underlying channel and provide strong evidence that firm ownership of patents enhances pledgeability of patents as collateral.

The results are reported in Table 4. In columns (1) and (2), I measure the number of granted patents two-years ahead of time to account for the grant review process, which takes an average of two years (Hall, Jaffe, and Trajtenberg 2001). Following the court’s ruling, theoretical, employees incentives may be affected negatively as the property rights shift from employees to firms. However, absent more detailed employee-level data, it is difficult to clearly confirm that employee incentives changed one way or the other. Additional discussion on employee incentive changes can be found in the Discussion Section.
treatment firms’ number of granted patents increases by 7.7% \( (e^{0.074} - 1) \), relative to control firms. Also, the return from each million dollars spent on R&D (also known as patent propensity), measured by the two-year ahead number of granted patents scaled by R&D expenditure, is about 65% higher for treatment firms, with pre-treatment ratio of 0.38.\(^{23}\)

The significant increase in the number of pledgeable patents is accompanied by improvements in the quality of existing and new patents. Chava et al. (2017) shows that lenders are able to differentiate the quality of pledged patents, based on the number of citations per patent.\(^{24}\) Therefore, improvement in the quality of patents would also enhance pledgeability of patents as collateral. The dependent variable in columns (1) and (2) of Table 5 is the number of average citations per patent. The regression estimates show that the number of citations increases by 40%. This is surprising given that patent citations tend to decrease over time. It is important to note that patent citations measure not only the quality of patents but also redeployability of patents as they indicate interests from external users of the technology.\(^{25}\)

In Table 6, I examine how the number of actually collateralized patents changes after the treatment, providing direct evidence of how enhanced pledgeability of patents under firm ownership of patents results in the actual growth of the number of patents pledged as collateral.

\(^{23}\)Hall et al. (2001) finds an average patent propensity of 1.25 (median of 0.51) among the positive R&D spending U.S. firms between 1979-1988. More recently, the National Science Foundation National Center for Science and Engineering Statistics reported a national aggregate patent propensity of 0.42 in 2008 (see https://www.nsf.gov/statistics/infbrief/nsf13307/)

\(^{24}\)Patent citation is a well-established and widely-used measure of patent quality for its conveyance of both technological and economically significant information that signify the economic value of the cited patents (Trajtenberg 1990; Hall et al. 2001; Hall, Jaffe, and Trajtenberg 2005).

\(^{25}\)I use only the first 3-year count of citations to do a fair comparison of citations counts between existing and new patents as citations accrue over time. Therefore, the measure is fuzzy for patents that are granted around the treatment, where the three years include both years prior and post treatment. However, this would work against finding strong increase in citations post treatment.
collateral. I collect patent assignment data from USPTO and identify patent reassignments marked as “security interest.” The dependent variable is computed as the logarithm of total number of collateralized patents per firm-year. The full sample regressions in columns (1) and (2) show that, under firm ownership of patents, treated firms are able to pledge about 2.4% more patents as collateral relative to control firms.

In the next four columns, I exploit cross-sectional differences in changes in the number of granted patents and citations received to provide some evidence that the increase in debt financing result is not entirely mechanically driven by a sudden increase in the size of assets from shifting property rights to employee patents. I divide the full sample into high and low levels of changes in the number of citations (columns (3) and (4)) and the number of granted patents (columns (5) and (6)) post treatment. Whereas the effects of increasing firms’ property rights to employee patents on the number of collateralized patents are virtually the same across treated firms that experienced high and low changes in the number of granted patents, there is a significant difference in the effects when looking across the changes in the quality of patents measured by citations. The estimate for the high citation increase group in column (3) is statistically significant and about three times larger than the estimate for the low citation increase group in column (4). That is, the high patent quality improvement group is associated with an additional 3.5% increase in the number of pledged patents for treated firms.

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26USPTO assignment files show which patents are reassigned under security interests, but since the amount of borrowings associated with each security interest is not reported, I cannot explicitly identify patent secured debt in the previous section.

27I do not use a triple-difference regression specification because the changes in the number of granted patents and citations happens simultaneously with the changes in the number of pledged patents to firms. Using the triple interaction term would lead to bad control problem and result in an inconsistent estimate. However, I acknowledge that the subsample analyses only show strong correlations as there might be a confounder that affects both the degree of changes in patent quantity/citation and the number of collateralized patents.
5.4. Reduction in Holdup Problem

A key implication of property rights theory (Hart, 1995) is that an integration of owner-
ship reduces holdup problems, which ex ante cause underinvestments. This is also the key
insight that differentiates this paper from the creditor rights literature. However, in the con-
text of corporate innovation, holdup or non-physical investments are hard to observe. Hence,
I use two proxies that measure integrative innovation efforts, or the reduction in holdup.

In Table 7 columns (1) and (2), the dependent variable is the logarithm of number of
self-citations. 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. Self-citations are a reflection of knowledge accumulation and suggestive of
firms’ incentives to internalize knowledge spillovers created by their own developments (Hall
et al., 2001). Self-citation increases by about 12.5%. This estimate captures the degree of
changes in firms’ complementary use of patents following the shift of patent property rights
to firms, which also confirms that the integration of many components makes individual
ownership more costly for modern complex innovation processes (Merges, 2009).

Similarly, there is greater collaboration among inventor-employees, proxied by the aver-
age number of inventor-employees assigned per patent, around the court ruling. Columns
(3) and (4) show that inventor collaboration increases by 5%, where the pre-treatment mean
is 2.78 inventors per patents. There may be some variation across industries in how R&D
is conducted. Column (4) includes industry-year fixed effects to remove such variation, and
the result strengthens even more. Therefore, consistent with property rights theory, firm
ownership of patents seems to lower holdup problems in innovation processes, which in turn
contributes to improving productivity and pledgeability of patents as found in the previous
section.

Hall et al. (2001) 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.
5.5. Progression of Changes

In this section, I briefly layout some detailed tests on the progression of shifting property rights effects. In Figure 1, I show that the majority of the treatment effect is concentrated around the event year in 2008, with some additional increase in latter years. However, by the nature of the R&D process, there may be some time lags for the treated firms to integrate assets to their full capacity. Therefore, in Table 8, I use the same regression specifications from Table 4 and Table 7 and trace the effect of the treatment over time. All time interaction terms are included in the regression, but for simplicity, I report only years close to the treatment.

Treatment effects on self-citation appear immediately, though not as sharp as the debt results. Making citations does not require time and thus picks up immediate changes. However, changes in patent grants and inventor collaboration appear with some time lag. The change in the number of granted patents already accounts for the average 2-3 year patent review process, and thus seeing the effects starting at year $t+0$ can be interpreted as capturing lagged effects. Likewise, firms may need some time to reorganize inventor groups and corporate-level innovation processes, and thus the effects on inventor collaboration materialize within two years of the treatment. These lagged effects likely explain why some of the main debt financing effect increase further in the latter years of the post-treatment period.

6. Discussion

Incomplete contract is an important friction in this paper. In practice, contractual provisions on decisions in innovation processes are highly complex. As emphasized in Aghion and Tirole (1994), “the exact nature of the innovation is ill-defined ex ante, and two parties cannot contract for delivery of a specific innovation.” Therefore, contracting on all contingencies, or specifying the usage of patents in every state of the world is impossible, and thus writing a complete invention assignment agreement becomes too costly for firms. The ex
ante non-contractibility of non-physical investments in innovation leads to holdup problems and ex ante underinvestment in innovation.

In the context of incomplete contracts, the court ruling in the empirical setting changes the scope for opportunistic behavior of firms and inventor-employees by affecting the patent ownership structure. Firm ownership of patents is effective in not only reducing holdup but also creating synergies under relationship-specific investments like corporate innovation. That is, there are firm-specific synergies in innovation processes if firm and employee economic relationship holds but not if they split up. This implies that arms-length patent transactions in market are incomparable and, more importantly, that a mechanical increase in the number of pledgeable patents alone does not drive the results (Table 6).

The findings of this paper speak only to firms’ debt financing and cannot come to a conclusion on the optimal patent ownership structure. The implications for firm values would depend on knowing how innovation incentives of both firms and employees change after the court’s ruling. However, due to a lack of detailed inventor employee-level data, an explicit test of firm values is difficult. Therefore, I look into an indication for how inventor-employee incentives might change, based on inventor-level productivity measures and I postulate how inventor-employee incentives may be affected in a corporate setting, where strong complementarity exists in patents and firm-employee relationships.

Despite shifting property rights to patents away from employees to firms, in a untabulated...
result, I find statistically indistinguishable change in inventor-level productivity following the court ruling. This result is somewhat consistent with the theory that complementarity should yield benefits but no costs because marginal returns from owning part of the asset are the same as marginal returns from not owning any assets (Hart, 1995). This also 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 to universities. In the university setting, both relationship-specific innovation and asset complementarity are absent. However, beyond complementarity, there may still be other possibilities for seeing no change in inventor innovation incentives. For example, firms may have increased employee compensation for shifted patent ownership, which would increase cash outflows and offset gains from innovation productivity and access to debt. This calls for further investigation of property rights and compensation of inventor-employees, which is outside the scope of this paper.

Lastly, I further explore state-level aggregate innovation effects of shifting patent ownership to firms, which further corroborate the main results of the previous section. I use the universe of patents on USPTO patent grant records, which include public and private firms, government, and individuals. In Table A6 columns (1) and (2), I confirm that there is a general property rights effect on state-level aggregate innovation, which is also illustrated in Figure A2. In columns (3), (4), and (5), I further divide the state-level sample into different assignee groups. Columns (3) and (4) capture state-level aggregate innovation effect only on firms and government, where the tension from shifting the property rights to employee patents exists. Although there seems to be some degree of group-specific effects, the estimates are positive and statistically significant, showing that the increase in property rights to employee patents boosts both firm and government innovation. In contrast, the estimate

However, I cannot rule out the possibility of limitation of the employee incentive measure because the inventor productivity is measured by the number of granted patents per inventor, which only captures observable efforts.

This would require employee-level wages data, specifically for those who are identified as corporate inventors.
in column (5) is small and statistically insignificance, where individual inventors should not have been affected by the court’s ruling. Subgroup analyses again confirm the validity of the empirical setting on an aggregate-level, where the court ruling is only relevant for subgroups that experience tension in patent ownership structure through invention assignment agreements.

7. Robustness

7.1. Matching Regressions

To ease concerns for the time-varying differences in observable firm characteristics, I re-run the main regressions using matched samples on observable firm characteristics. Table 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 conjunction 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 groups 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 groups is statistically insignificant, reinforcing the parallel trends assumptions. The next three columns compare the same variables after propensity score matching. 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 observable differences.

Table 10 presents the matching regression results using the matched sample. I use propensity score matching using observable differences between the treated and control firms reported in Table 1. In addition, to ensure that the matching process embodies the parallel trends 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.

7.2. 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 a treatment indicator in the empirical setting. Then, I address a possible concurrent effects of the 2008 financial crisis around the CAFC decision.

7.2.1. 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 the 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 choice of headquarter state 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 regard 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 a shock to the property rights. In Table A7 I verify that the pre-treatment trends assumption holds for state corporate tax rates, and that the year-by-year changes in corporate tax rates during the entire sample period are not statistically different
between treatment and control states. The regression results reported in columns (3) of Table A4 are robust to controlling for 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 firms with a 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 aforementioned results, 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 column (4) of Table A4, I verify that the results remain robust.

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, thereby increasing their debt financing to materialize these opportunities. In Figure A1 Panel (b) in 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 similar results in firms in untreated states, as well. This is not so. In an 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 ex ante innovation opportunities and again find robust results.

34The corporate tax rates are collected from Tax Foundation. The data is available at https://taxfoundation.org/state-corporate-income-tax-rates/
7.2.2. Financial Crisis

I address potential concerns with the overlapping period of the CAFC ruling and the financial crisis in 2008, such 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 a state-year specific shock that would account for the differential effect of the financial crisis. However, the treatment variable is state-level, and the state-year fixed effects would absorb the \textit{treat} \times \textit{post} effect. I handle this problem in two ways. First, in Appendix Table A7, I report the differences in means of important state-level economic variable growth rates between treated and untreated states. I show that 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 treatment and control states are similar both before and after 2008.

Second, I mitigate the above concerns by additionally including states 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 a more stringent model that captures variation only among the same industry firms in the same states. Tables 11, 12, 13, and 14 report these additional results. The main regression results in Table 11 remain similar, both economically and statistically significant, for the total debt-to-assets ratio, and strengthen for the long-term debt issuance after including state fixed effects. In Table 12, the number of granted patents, patent propensity, and the number of pledged patents are robust both in magnitude and statistical significance. The estimate for the average number of citations per patent in Table 13 strengthens from about 0.4 to 0.5, while the first 3-year citation measure becomes statistically insignificant. Lastly, in Table 14, self-citation strengthens in magnitude, whereas the inventor collaboration measure weakens but is still statistically significant. Overall, the inclusion of state-level fixed effects changes a few estimates, but the results remain qualitatively consistent.
8. Conclusion

In this paper, I consider how property rights allocation alleviates some inefficiencies in firms’ economic relationship with inventor-employees in innovation processes and affects knowledge-intensive firms’ debt financing. The results not only highlight the tension in patent ownership structure between firms and inventor-employees, but also address how property rights ease knowledge-intensive firms’ access to debt financing.

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 invention assignment agreements increases total debt by an average $62 million. I also provide strong evidence that firm ownership of patents improves pledgeability of patents by reducing holdup problems and promoting complementarity in corporate innovation processes.

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


Hvide, Hans, and Benjamin Jones, 2016, University innovation and the professor’s privilege, Working paper.


Figure 1. Difference in Leverage Ratio by Years to Treatment

This figure presents the coefficient estimates from the regression equation below over the years to treatment. The horizontal axis indicates event time. The negative numbers are pre-treatment years; zero is year 2008 in which CAFC ruling was made; and positive numbers are post-treatment years. The vertical axis shows the coefficient estimates, \( \beta_k \)'s from the baseline specification with firm and year fixed effects. 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.

\[
\frac{Total\ debt}{Assets_{ist}} = \alpha + \sum_k \beta_k \text{treat}_{ist} \times \text{event}_k + \delta_i + \gamma_t + \epsilon_{ist}
\]
Table 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 D. Observations with missing asset are dropped.

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

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets ($ mil)</td>
<td>5,046</td>
<td>26,667</td>
<td>70</td>
<td>333</td>
<td>1,850</td>
<td>16,540</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>5.92</td>
<td>2.32</td>
<td>4.25</td>
<td>5.81</td>
<td>7.52</td>
<td>16,540</td>
</tr>
<tr>
<td>Total debt/Assets</td>
<td>0.18</td>
<td>0.22</td>
<td>0.00</td>
<td>0.11</td>
<td>0.28</td>
<td>16,540</td>
</tr>
<tr>
<td>R&amp;D exp/Assets</td>
<td>0.12</td>
<td>0.19</td>
<td>0.01</td>
<td>0.06</td>
<td>0.15</td>
<td>16,540</td>
</tr>
<tr>
<td>Ppent/Assets</td>
<td>0.17</td>
<td>0.16</td>
<td>0.06</td>
<td>0.12</td>
<td>0.24</td>
<td>16,540</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Variables</th>
<th>Treatment State*</th>
<th>Control State</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>N</td>
</tr>
<tr>
<td>Assets ($ mil)</td>
<td>2,460</td>
<td>3,630</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>5.48</td>
<td>3,630</td>
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<tr>
<td>Total Debt/Assets</td>
<td>0.14</td>
<td>3,630</td>
</tr>
<tr>
<td>LTD issuance</td>
<td>0.07</td>
<td>3,630</td>
</tr>
<tr>
<td>R&amp;D exp/Assets</td>
<td>0.15</td>
<td>3,630</td>
</tr>
<tr>
<td>Ppent/Assets</td>
<td>0.14</td>
<td>3,630</td>
</tr>
<tr>
<td>Granted patents</td>
<td>18.26</td>
<td>3,630</td>
</tr>
<tr>
<td>Patent applications</td>
<td>33.60</td>
<td>3,630</td>
</tr>
<tr>
<td>Avg. First 3-yrs citations</td>
<td>2.43</td>
<td>2,413</td>
</tr>
<tr>
<td>Avg. citations per patent</td>
<td>0.84</td>
<td>3,630</td>
</tr>
<tr>
<td>Number of patent collateral</td>
<td>0.13</td>
<td>3,630</td>
</tr>
<tr>
<td>Number of inventors</td>
<td>2.78</td>
<td>3,017</td>
</tr>
<tr>
<td>Number of self-citation</td>
<td>38.40</td>
<td>3,475</td>
</tr>
</tbody>
</table>

* treatment states include CA, DE, IL, KS, MN, NC, UT, and WA.
Table 2: Increasing Debt Financing

This table reports the results of estimating the main difference-in-difference regressions 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, which is computed as the long-term debt issuance scaled by one year-lagged total 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. Industry is 2-digit SIC. For variable definitions and details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Total debt/Assets</th>
<th>Total debt/Assets</th>
<th>LTD issuance</th>
<th>LTD issuance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>treat×post</td>
<td>0.026***</td>
<td>0.024**</td>
<td>0.018***</td>
<td>0.015**</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.006)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>–</td>
<td>Y</td>
<td>–</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>16,540</td>
<td>16,540</td>
<td>16,540</td>
<td>16,540</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.007</td>
<td>0.004</td>
<td>0.004</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1
Table 3: Types of Debt

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

<table>
<thead>
<tr>
<th>treat×post</th>
<th>Bank Debt (1)</th>
<th>Conv. Debt (2)</th>
<th>Long-term Debt (3)</th>
<th>Short-term Debt (4)</th>
<th>Mature in 1 yr (5)</th>
<th>Mature in 1 or 2 yrs (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.006*</td>
<td>0.008**</td>
<td>0.024***</td>
<td>0.001</td>
<td>0.001</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

| Firm FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 | 16,540 |
| $R^2$ (within) | 0.010 | 0.001 | 0.005 | 0.002 | 0.001 | 0.001 |

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 4: Increase in Pledgeability of Patents

The table reports the results of estimating the difference-in-difference regressions below to examine the number of pledgeable patents as underlying patent productivity channel that supports the main debt financing results. In columns (1) and (2), the dependent variable is 2-year lead log number of patent grants to account for the time it takes for firms’ underlying innovation changes to take effects. The results are robust to replacing missing patent grant with zeros. In columns (3) and (4), the dependent variable is the 2-year lead number of granted patents scaled by current R&D expense ($ million) to measure the changes in underlying innovation productivity. 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. Industry is 2-digit SIC. For variable definitions and details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Log$(1 + grant)_{t+2}$</th>
<th>Grant$_{t+2}$/R&amp;D Exp</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>treat$\times$post</td>
<td>0.074**</td>
<td>0.074**</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>–</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>11,893</td>
<td>11,893</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.060</td>
<td>0.076</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
***$p<0.01$, **$p<0.05$, *$p<0.1$
Table 5: Improvement in Citations and Quality of Patents

The table reports the results of estimating the difference-in-difference regressions to examine the improvement in the quality of new and existing patents. In columns (1) and (2), I measure the average number of citations received per existing patent to compare citations received by the same portfolio of patents over time. In columns (3) and (4), I measure the average number of citations received per patent in the first 3-years after the grant-year to compare across patents of different age. In all specifications, I allow for differential trends by the average age of patents in pre-treatment patent portfolio. For the patent portfolio age control, I include the variables alone (absorbed by firm fixed effects) and their interaction term with the post dummy. 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. Industry is 2-digit SIC. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Avg. citations</th>
<th></th>
<th>Avg. first 3-yr citations</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>treat × post</td>
<td>0.336**</td>
<td>0.434***</td>
<td>0.158*</td>
<td>0.205**</td>
</tr>
<tr>
<td></td>
<td>(0.135)</td>
<td>(0.129)</td>
<td>(0.080)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>–</td>
<td>Y</td>
<td>–</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Application year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls</td>
<td>Portfolio Age</td>
<td>Portfolio Age</td>
<td>Portfolio Age</td>
<td>Portfolio Age</td>
</tr>
<tr>
<td>Observations</td>
<td>10,695</td>
<td>10,695</td>
<td>10,695</td>
<td>10,695</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.252</td>
<td>0.283</td>
<td>0.026</td>
<td>0.024</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 6: Increase in the Number of Pledged Patents

The table reports the results of estimating the difference-in-difference regressions below to examine the changes in the number of patents pledged as collateral. The dependent variable is logarithm of one plus the total number of patents pledged as collateral. The data comes from USPTO Patent Assignment files. The patents pledged as collateral is identified using assignment transactions marked as “security interest.” All specifications controls for the pre-treatment level of R&D spending and size of patent stock and their interaction terms with Post. Column (1) uses full sample with firm and year fixed effects. Column (2) also uses full sample and include firm and industry-year fixed effects to account for potential industry-year specific variation in pledgeability of patents. Columns (3) and (4) divide the full sample into high and low changes in the number of citations measuring quality, respectively. Columns (5) and (6) divide the full sample into high and low changes in the number of granted patents, respectively. The change is “high” if the difference between post-treatment and pre-treatment level of the respective variables is greater than the median and “low” otherwise. All columns include firm and year fixed effects. Industry is 2-digit SIC. For variable definitions and details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: Log(1+number of patent collateral)</th>
<th>( \Delta \text{Cite} )</th>
<th>( \Delta \text{Grant} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>High (3)</td>
<td>Low (4)</td>
</tr>
<tr>
<td>treat( \times )post</td>
<td></td>
<td>0.024*</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.012)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Firm FE</td>
<td></td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td></td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td></td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>16,540</td>
<td>9,299</td>
<td>7,241</td>
</tr>
<tr>
<td>( R^2 ) (within)</td>
<td>0.016</td>
<td>0.016</td>
<td>0.017</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 7: Asset Complementarity and Inventor Collaboration

The table reports the results of estimating the difference-in-difference regressions 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 by self-citation, which counts the number of citations made on previous inventions patented by firms. Columns (3) and (4) examine inventor collaboration. The odd columns include firm and year fixed effects, and the even columns use more stringent specification including firm and industry-year fixed effects. Industry is 2-digit SIC. For variable definitions and details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Log(1+self citation)</th>
<th>Avg. inventors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>treat×post</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.117*</td>
<td>0.138**</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>–</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>15,489</td>
<td>15,489</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.003</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 8: Immediate and Lagged Changes

The table reports progression of changes over time in patent pledgeability and asset complementarity. For simplicity, I only report coefficients of two years prior to the treatment year in 2008, $t + 0$, and four years following the treatment to show some lagged effects in columns (2) and (3). The dependent variable in Column (1) is the 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 D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Immediate</th>
<th>Lagged</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log(1+self citation)</td>
<td>Log$(1 + grant)_{t+2}$</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>treat $\times t - 2$</td>
<td>0.021</td>
<td>0.057</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>treat $\times t - 1$</td>
<td>0.175**</td>
<td>0.104</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.074)</td>
</tr>
<tr>
<td>treat $\times t + 0$</td>
<td>0.136*</td>
<td>0.142**</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>treat $\times t + 1$</td>
<td>0.137*</td>
<td>0.134**</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.056)</td>
</tr>
<tr>
<td>treat $\times t + 2$</td>
<td>0.127*</td>
<td>0.188**</td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>treat $\times t + 3$</td>
<td>0.219*</td>
<td>0.212**</td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.081)</td>
</tr>
<tr>
<td>treat $\times t + 4$</td>
<td>0.223</td>
<td>0.205**</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.077)</td>
</tr>
</tbody>
</table>

Firm FE: Y, Year FE: Y, Application year FE: –, Observations: 15,489, 9,737, 13,095

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1
Table 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 D.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre-Match</th>
<th></th>
<th></th>
<th>Post-Match</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Control</td>
<td>Treatment</td>
<td>p-value</td>
<td>Control</td>
<td>Treatment</td>
<td>p-value</td>
</tr>
<tr>
<td>Leverage growth</td>
<td>10.988</td>
<td>5.378</td>
<td>0.478</td>
<td>1.874</td>
<td>5.403</td>
<td>0.182</td>
</tr>
<tr>
<td>LTD issuance growth</td>
<td>22.728</td>
<td>41.658</td>
<td>0.563</td>
<td>33.956</td>
<td>41.848</td>
<td>0.839</td>
</tr>
<tr>
<td>Size growth</td>
<td>0.323</td>
<td>0.490</td>
<td>0.188</td>
<td>0.433</td>
<td>0.362</td>
<td>0.369</td>
</tr>
<tr>
<td>Assets</td>
<td>4,808</td>
<td>2,527</td>
<td>0.066</td>
<td>2.733</td>
<td>2.533</td>
<td>0.707</td>
</tr>
<tr>
<td>R&amp;D exp.</td>
<td>0.119</td>
<td>0.162</td>
<td>0.000</td>
<td>0.169</td>
<td>0.161</td>
<td>0.458</td>
</tr>
<tr>
<td>Ppent</td>
<td>0.181</td>
<td>0.133</td>
<td>0.000</td>
<td>0.137</td>
<td>0.133</td>
<td>0.581</td>
</tr>
<tr>
<td>Log(1+ grant)</td>
<td>1.247</td>
<td>1.522</td>
<td>0.000</td>
<td>1.514</td>
<td>1.514</td>
<td>0.996</td>
</tr>
<tr>
<td>Log(1+ application)</td>
<td>1.588</td>
<td>1.920</td>
<td>0.000</td>
<td>1.945</td>
<td>1.913</td>
<td>0.694</td>
</tr>
<tr>
<td>% successful application</td>
<td>0.696</td>
<td>0.709</td>
<td>0.383</td>
<td>0.701</td>
<td>0.708</td>
<td>0.608</td>
</tr>
</tbody>
</table>
Table 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 2 are not driven by observable differences between the treated and control firms. The dependent variable is Total debt/Assets. 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. 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.

<table>
<thead>
<tr>
<th></th>
<th>NN=1</th>
<th></th>
<th>NN=2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total debt/Assets (1)</td>
<td>LTD issuance (2)</td>
<td>Total debt/Assets (3)</td>
</tr>
<tr>
<td>treat×post</td>
<td>0.024**</td>
<td>0.015*</td>
<td>0.021**</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>9,340</td>
<td>9,340</td>
<td>10,798</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.582</td>
<td>0.232</td>
<td>0.588</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 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. Industry is 2-digit SIC. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>(1) Total debt/Assets</th>
<th>(2) Total debt/Assets</th>
<th>(3) LTD issuance</th>
<th>(4) LTD issuance</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat$\times$post</td>
<td>0.023*** (0.009)</td>
<td>0.027*** (0.008)</td>
<td>0.018*** (0.006)</td>
<td>0.020*** (0.006)</td>
</tr>
<tr>
<td>Year FE</td>
<td>–</td>
<td>Y</td>
<td>–</td>
<td>Y</td>
</tr>
<tr>
<td>State FE</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>State-industry FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>16,540</td>
<td>16,540</td>
<td>16,540</td>
<td>16,540</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.098</td>
<td>0.235</td>
<td>0.036</td>
<td>0.116</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 12: Increase in Pledgeability of Patents - State Robustness

The table reports the results of underlying patent pledgeability channel with state-industry fixed effects. In columns (1) and (2), the dependent variable is 2-year lead log number of patent grants to account for the time it takes for firms’ underlying innovation changes to take effects. In columns (3) and (4), the dependent variable is the 2-year lead number of granted patents scaled by current R&D expense to measure the changes in underlying innovation productivity. In columns (5) and (6), the dependent variable is logarithm of one plus the total number of patents pledged as collateral. The data comes from USPTO Patent Assignment files. The patents pledged as collateral is identified using assignment transactions marked as “security interest.” Columns (5) and (6) additionally control for the pre-treatment level of R&D spending and size of patent stock and their interaction with Post. 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. Industry is 2-digit SIC. For variable definitions and details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Log(1 + grant)_{t+2} (1)</th>
<th>Log(1 + grant)_{t+2} (2)</th>
<th>Grant_{t+2}/R&amp;D Exp (3)</th>
<th>Grant_{t+2}/R&amp;D Exp (4)</th>
<th>Log(1+Patent Collateral) (5)</th>
<th>Log(1+Patent Collateral) (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat×post</td>
<td>0.085*</td>
<td>0.103**</td>
<td>0.293**</td>
<td>0.295***</td>
<td>0.023*</td>
<td>0.024*</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.043)</td>
<td>(0.120)</td>
<td>(0.085)</td>
<td>(0.013)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Year FE</td>
<td>–</td>
<td>Y</td>
<td>–</td>
<td>Y</td>
<td>–</td>
<td>Y</td>
</tr>
<tr>
<td>State FE</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>State-industry FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Control</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>11,893</td>
<td>11,893</td>
<td>10,584</td>
<td>10,584</td>
<td>16,540</td>
<td>16,540</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.091</td>
<td>0.233</td>
<td>-0.026</td>
<td>-0.015</td>
<td>0.101</td>
<td>0.137</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 13: Citations on New and Old Patents - State Robustness

The table reports the results of improvement in quality 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 all specifications, I allow for differential trends by average age of pre-treatment patent portfolio. For the patent portfolio age control, I include the variables alone and their interaction term with the post dummy. Industry is 2-digit SIC. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Avg. citations</th>
<th>First 3-yr citations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>treat×post</td>
<td>0.590***</td>
<td>0.527***</td>
</tr>
<tr>
<td></td>
<td>(0.197)</td>
<td>(0.186)</td>
</tr>
<tr>
<td>Year FE</td>
<td>–</td>
<td>Y</td>
</tr>
<tr>
<td>State FE</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>State-industry FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Application year FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls</td>
<td>Portfolio Age</td>
<td>Portfolio Age</td>
</tr>
<tr>
<td>Observations</td>
<td>10,695</td>
<td>10,695</td>
</tr>
<tr>
<td>R² (within)</td>
<td>0.203</td>
<td>0.215</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table 14: 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 measured by self-citation, which counts the number of citations made on previous inventions patented by firms. Columns (3) and (4) examine inventor collaboration. Columns (1) and (3) include state and industry-year fixed effects, and columns (2) and (4) include year and state-industry fixed effects. Industry is 2-digit SIC. For variable definitions and details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>Log(1+self citation)</th>
<th>Avg. inventors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>treat×post</td>
<td>0.194**</td>
<td>0.163*</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Year FE</td>
<td>–</td>
<td>Y</td>
</tr>
<tr>
<td>State FE</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Industry-year FE</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>State-industry FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>15,489</td>
<td>15,489</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.052</td>
<td>0.639</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Appendix A. Robustness

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

The figures present the distribution of the treated states in Figure (a) and states in which the fraction of employment from patent-intensive industry is above the national average (USPTO Intellectual Property and the U.S. Economy Report, 2012) as of 2010 in Figure (b). The comparison shows that the results are not driven only by the firms with relatively greater innovation investment opportunities sorting into the treated states. If the results were driven only by such firms sorting into high-innovation states, then the changes in the outcome variables for treated firms relative to control firms would not have been as profound, as control states also include many high-innovation states.
Figure A2. State-level Aggregate Innovation

This table presents state-level aggregate innovation output by treated and control states. I use all granted patents in USPTO Patent Grant data that are assigned to entities in the US, which subsumes the Compustat sample firms used in the main regression analyses. The horizontal axis indicates time, where the vertical line is drawn on year 2008 when CAFC ruling was given. The vertical axis shows the 2-year lead log number of patent grants to account for the time it takes for firms’ underlying innovation changes to take effects. There seems to be a parallel trend in the log number of patent grants between the treated and control states prior to 2008. However, subsequent to the CAFC ruling, whereas the control state patent grant levels off, treated states show larger growth in patent grants. The graph corresponds to regression result in column (1) of Table A6. For variable definitions and further details of their construction, see Appendix D.
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. Industry is 2-digit SIC. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th>treat×post</th>
<th>Total debt/Assets (1)</th>
<th>Total debt/Assets (2)</th>
<th>LTD issuance (3)</th>
<th>LTD issuance (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.010</td>
<td>0.012</td>
<td>-0.001</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
</tbody>
</table>

Firm FE: Y, Y, Y, Y
Year FE: Y, Y, Y, Y
Industry-year FE: N, Y, N, Y
R^2 (within): 0.006, 0.017, 0.003, 0.006

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.

<table>
<thead>
<tr>
<th>Dependent variable: Total debt/Assets</th>
<th>Zero sub (1)</th>
<th>One sub (2)</th>
<th>Two subs (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat×post</td>
<td>0.036*</td>
<td>0.033*</td>
<td>0.022*</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.012)</td>
</tr>
</tbody>
</table>

Firm FE: Y, Y, Y
Year FE: Y, Y, Y
Observations: 3,084, 6,001, 8,799
R^2 (within): 0.005, 0.010, 0.004

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1
Table A3: Baseline Regression by Treatment States

This table presents baseline results by treatment states. The dependent variable is Total debt/Assets. Column(1) is the baseline result from Table 2 column (1). Each of columns (2)-(9) runs the baseline regression using one treatment state against the rest of control states. Notice that the number of observations changes accordingly. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th>Dependent variable: Total debt/Assets</th>
<th>Baseline</th>
<th>CA</th>
<th>DE</th>
<th>IL</th>
<th>NC</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>treat×post</td>
<td>0.026***</td>
<td>0.032***</td>
<td>0.002</td>
<td>0.028***</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>16,540</td>
<td>14,167</td>
<td>9,781</td>
<td>10,519</td>
<td>10,062</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.007</td>
<td>0.007</td>
<td>0.002</td>
<td>0.003</td>
<td>0.003</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dependent variable: Total debt/Assets</th>
<th>KS</th>
<th>MN</th>
<th>UT</th>
<th>WA</th>
</tr>
</thead>
<tbody>
<tr>
<td>(6)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>treat×post</td>
<td>0.069***</td>
<td>0.013*</td>
<td>0.033***</td>
<td>-0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>9,796</td>
<td>10,297</td>
<td>9,870</td>
<td>10,130</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table A4: 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. Only the interaction terms are reported below. 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.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat×post</td>
<td>0.025***</td>
<td>0.028***</td>
<td>0.026***</td>
<td>0.025***</td>
<td>0.026***</td>
<td>0.026**</td>
<td>0.025***</td>
<td>0.024**</td>
<td>0.027***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.011</td>
<td></td>
<td>-0.007</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
<td>(0.010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.004</td>
<td></td>
<td>0.008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td></td>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State-tax</td>
<td></td>
<td>0.008</td>
<td></td>
<td>0.007</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.010)</td>
<td></td>
<td>(0.011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tangibility</td>
<td>-0.004</td>
<td></td>
<td>-0.004</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td></td>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market-to-book</td>
<td></td>
<td></td>
<td></td>
<td>0.010</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.008</td>
<td></td>
<td>-0.005</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td></td>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-patent stock</td>
<td></td>
<td>-0.000</td>
<td></td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.010)</td>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D expenditure</td>
<td></td>
<td>-0.000</td>
<td></td>
<td>-0.009</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.010)</td>
<td></td>
<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Firm FE: Y Y Y Y Y Y Y Y Y Y
Year FE: Y 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

$R^2$ (within): 0.007 0.007 0.007 0.007 0.007 0.007 0.007 0.007 0.007

Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1
Table A5: Financial Constraints

Panel A and B present the baseline regression analyses, where firms are sorted into terciles according to ex ante proxies for financial constraint, size and age, as measured in the year prior to the treatment, respectively. The dependent variable is Total debt-to-assets ratio. All specifications include firm and year fixed effects. For variable definitions and details of their construction, see Appendix D. All standard errors are clustered by state.

Panel A: Terciles by Firm Sizes

<table>
<thead>
<tr>
<th>Dependent Variable: Total debt/Assets</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat×post</td>
<td>0.017</td>
<td>0.037***</td>
<td>0.019*</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.009)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>4,877</td>
<td>5,150</td>
<td>5,564</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.003</td>
<td>0.007</td>
<td>0.022</td>
</tr>
</tbody>
</table>

Panel B: Terciles by Firm Age

<table>
<thead>
<tr>
<th>Dependent Variable: Total debt/Assets</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>treat×post</td>
<td>0.030**</td>
<td>0.020</td>
<td>0.031**</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>4,885</td>
<td>5,002</td>
<td>5,140</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.009</td>
<td>0.004</td>
<td>0.012</td>
</tr>
</tbody>
</table>
Table A6: State-level Aggregate Innovation

This table presents state-level aggregate innovation output. The dependent variable is 2-year lead log number of patent grants to account for the time it takes for firms’ 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). Columns (1) and (2) use all observations. Column (1) include only state and year fixed effects. Column (2) additionally includes group fixed effects (group equals to zero for patents granted to individuals and one otherwise). Columns (3) and (4) use subset of non-individual patents granted to US company or corporation (role code=2) and all US government (role code=6, 8 and 9), which likely have employer-employee tension in ownership. Column (3) includes state and year fixed effects, and column (4) additionally include role fixed effects. Column (5) uses only patents granted to individuals (role code=4) and includes state and year fixed effects. For variable definitions and further details of their construction, see Appendix D. All standard errors are clustered by state.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Firms and Government</th>
<th>Individuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>treat x post</strong></td>
<td>0.303**</td>
<td>0.394**</td>
<td>0.644***</td>
</tr>
<tr>
<td></td>
<td>(0.147)</td>
<td>(0.148)</td>
<td>(0.195)</td>
</tr>
<tr>
<td>State FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Group FE</td>
<td>N</td>
<td>Y</td>
<td>–</td>
</tr>
<tr>
<td>Role FE</td>
<td>–</td>
<td>–</td>
<td>N</td>
</tr>
<tr>
<td>Observations</td>
<td>1,115</td>
<td>1,115</td>
<td>613</td>
</tr>
<tr>
<td>(R^2) (within)</td>
<td>-0.005</td>
<td>0.660</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table A7: Pre-treatment State Economic Conditions

This table reports difference in means of state-level economic variable growth rates between treated states and control 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 columns 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.

<table>
<thead>
<tr>
<th>Year</th>
<th>Treated States</th>
<th>Untreated States</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP growth, percent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>5.313</td>
<td>4.742</td>
<td>0.576</td>
</tr>
<tr>
<td>2007</td>
<td>1.450</td>
<td>2.969</td>
<td>0.331</td>
</tr>
<tr>
<td>2008</td>
<td>-1.487</td>
<td>-2.013</td>
<td>0.671</td>
</tr>
<tr>
<td>2009</td>
<td>2.862</td>
<td>4.273</td>
<td>0.107</td>
</tr>
<tr>
<td>2010</td>
<td>4.275</td>
<td>4.100</td>
<td>0.879</td>
</tr>
<tr>
<td>GDP per capita growth, percent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>2.425</td>
<td>1.691</td>
<td>0.384</td>
</tr>
<tr>
<td>2007</td>
<td>0.988</td>
<td>0.498</td>
<td>0.558</td>
</tr>
<tr>
<td>2008</td>
<td>-1.613</td>
<td>-0.495</td>
<td>0.316</td>
</tr>
<tr>
<td>2009</td>
<td>-3.650</td>
<td>-2.965</td>
<td>0.534</td>
</tr>
<tr>
<td>2010</td>
<td>0.400</td>
<td>1.477</td>
<td>0.183</td>
</tr>
<tr>
<td>Unemployment rate growth, percent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>-0.122</td>
<td>-0.083</td>
<td>0.188</td>
</tr>
<tr>
<td>2007</td>
<td>0.013</td>
<td>-0.016</td>
<td>0.332</td>
</tr>
<tr>
<td>2008</td>
<td>0.284</td>
<td>0.241</td>
<td>0.517</td>
</tr>
<tr>
<td>2009</td>
<td>0.637</td>
<td>0.569</td>
<td>0.306</td>
</tr>
<tr>
<td>2010</td>
<td>0.023</td>
<td>0.016</td>
<td>0.783</td>
</tr>
<tr>
<td>State corporate tax rate growth, percent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>0</td>
<td>-0.004</td>
<td>0.669</td>
</tr>
<tr>
<td>2007</td>
<td>0</td>
<td>-0.002</td>
<td>0.671</td>
</tr>
<tr>
<td>2008</td>
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<td>0.034</td>
<td>0.706</td>
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<tr>
<td>2009</td>
<td>-0.005</td>
<td>0.002</td>
<td>0.555</td>
</tr>
<tr>
<td>2010</td>
<td>0</td>
<td>-0.002</td>
<td>0.613</td>
</tr>
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</table>
Appendix B. 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.
Appendix C. 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
   - 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.
Appendix D. Variable Description

- **Assets** = Total assets. Observations with missing assets are dropped.
- **Total debt/Assets** = \((\text{Long-term debt (dltt)} + \text{Short-term debt (dlc)}) / \text{Total Assets}\). 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 \((\text{dltis}) / (\text{Total assets}_{t-1})\). The missing observations were replaced with zero, then the ratio is winsorized between zero and one following [Lemmon et al. (2008)].
- **R&D exp/Assets** = R&D expenditure \((\text{xrd})\) scaled by total assets.
- **Ppent/Assets** = Plant, property and equipment \((\text{ppent})\) scaled by total assets.
- **Bank and Convertible Debt** = The data is obtained from Capital IQ Capital Structure. The missing bank debt and convertible debt observations are replaced with zero, then the ratio is winsorized between zero and one.
- **Firm age** = Firm age is counted since date of incorporation obtained from Datastream.
- **Log\((1 + \text{grant}_{t+2})\)** = Logarithm of one plus the number of granted patents in year \(t + 2\). The lead grant number is used to account for the average of two-years it takes for the patent grant process.
- **Grant_{t+2}/R&D Exp** = The number of granted patents in year \(t + 2\) scaled by the total R&D expenditure in year \(t\). The lead grant number is used to account for the average of two-years it takes for the patent grant process.
- **Avg. citations** = Average annual number of citations received per existing patents granted prior to treatment year.
- **Avg. First 3-yr citations** = Average number of total citations received during the first 3-years post-grant per patent.
- **Portfolio Age** = Average age of all existing patents in firm’s patent portfolio in the year prior to the CAFC ruling.
- **Log\((1+\text{number of patent collateral})\)** = Logarithm of one plus the total number of patents pledged as collateral, measured from the USPTO Patent Assignment data classified as security interests.
- **Patent Stock** = The total number of all existing patents in firm’s patent portfolio in the year prior to the CAFC ruling.
- **Log\((1+\text{self citation})\)** = Logarithm of one plus the 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)])
- **Avg. inventors** = The average number of inventors listed on a given patent document.
- **Leverage growth** = Average of annual growth of debt-to-assets ratio.
- **Size growth** = Average of annual growth of total assets.