Escaping the Patent Trolls: The Impact of Non-Practicing Entity Litigation on Firm Innovation Strategies

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Abstract

Non-practicing entities (NPEs) are firms that amass patents to assert their intellectual property rights but have little or no intention of further developing these patents (a practice known as patent trolling). NPEs tend to initiate lawsuits not for actual patent infringements but for the potential profits derived from out-of-court settlements. In this study, we examine how firms shift their innovation strategies in response to heightened NPE litigation risks. We theorize that firms targeted by NPEs who become defendants in NPE-initiated litigation (i.e., target firms) will subsequently draw more upon their in-house technologies to reduce the potential legal ground for such lawsuits. We further hypothesize that the non-target firms in related technology areas will shift the locus of their innovation activities away from those of the target firms to avoid the areas with high NPE litigation risks. These effects are more pronounced when research and development (R&D) expenses for the patented technologies are higher and when the product markets are more competitive. Results from our difference-in-differences estimates and instrumental variable regression analyses provide support for these hypotheses. Overall, our results suggest that firms facing NPE litigation risks would shift their follow-on innovation trajectories and distance themselves from the existing network of innovation activities in an attempt to escape patent trolling. Our study yields important managerial and policy implications for firms and policymakers.

Keywords: Patent Troll; Non-Practicing Entity; Litigation; Innovation Strategy

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1. Introduction

Innovation contributes to economic growth by creating new knowledge and increasing productivity in society (Arrow, 1962; Brown et al., 2009; Rivera-Batiz & Romer, 1991; Sorenson & Fleming, 2004). Intellectual property rights facilitate and increase firms' incentives to innovate by providing formal legal protection against expropriation (Arora & Gambardella, 2010a, 2010b; Hu & Png, 2013; Levin et al., 1987). Over the past three decades, we have witnessed innovation-driven economic growth in developed economies like that of the United States (US), which is fueled by technological breakthroughs under the protection of the patent system. At the same time, observers have noted that patent litigations initiated by non-practicing entities (NPEs) have surged since the 2000s (Bessen & Meurer, 2013; Liang, 2010). NPEs, also commonly known as "patent trolls," are firms that amass patents and build their portfolios to enforce their intellectual property rights and litigate against potential infringers but have little or no intention of further developing these patents.[1] Therefore, NPEs often initiate patent infringement lawsuits with little or no genuine intent of developing or implementing their intellectual property rights. Their primary goal is to earn monetary profits through private remedies or out-of-court settlements (Cohen et al., 2016, 2019).

Recent studies have shown that NPEs harm the collective welfare of society and reduce firms' research and development (R&D) investment. Bessen, Ford, and Meurer (2011) find that NPE litigations have cost defendants about half a trillion US dollars of wealth between 1990 and 2010. Cohen, Gurun, and Kominers (2016, 2019) find that firms reduce their innovation activities after being targeted by NPEs. Recent anecdotal evidence has also shown that NPEs may also hurt public health and downstream research by suing medical device testing companies that develop devices used in COVID-19 testing.[2] However, there is scant empirical evidence of the consequence of rising NPE litigation threats on firm innovation strategies and trajectories.

[1] By contrast, practicing-entities (PEs), such as Intel and IBM, file litigations for real patent infringements so as to protect their rights in future development and application of the focal patent.
[2] As an example of controversial NPE lawsuit, Labrador Diagnostics, a "patent troll", sued a medical device testing company, BioFire, for patent infringement in March 2020, where BioFire was working on a coronavirus test and Labrador Diagnostics asked for an injunction against the sales and usages of BioFire's testing device. See more details in https://www.patentprogress.org/2020/03/18/patents-in-the-time-of-coronavirus/.

In this study, we investigate the important question of how heightened NPE litigation risks impact the innovation strategies and trajectories of firms that are targeted by NPEs. We theorize that facing the rising threat of patent trolls, firms targeted by patent trolls (henceforth, target firms) would shift their innovation strategies to protect themselves from the advances of NPEs.[3] Specifically, we hypothesize that after target firms have become the defendants in NPE-initiated lawsuits, they will draw more upon their in-house technologies to reduce the potential legal ground for NPE lawsuits. Furthermore, we hypothesize that after observing the occurrence of NPE lawsuits, the peer firms operating in related areas will shift the locus of their innovation activities away from those of target firms to avoid areas with high NPE litigation risks. Lastly, these effects should be more pronounced when the patented technologies are costlier in terms of R&D expenses and when the product markets in which the firms operate are more competitive.

To test our predictions, we construct a longitudinal dataset of US public companies with comprehensive patent litigation data between 2008 and 2016 from the following datasets: (i) patent litigation cases from the Lex Machina database; (ii) NPE data from the Stanford NPE litigation dataset (Miller, 2018); (iii) patent and related patent data from the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT, 2018 edition); and (iv) firm financial data and other attributes from the Compustat database.

To perform our empirical analyses, we focus on the effect of the first NPE litigation filed against a target firm, given that the reaction of target firms to subsequent NPE litigations might be affected by the reaction to the first NPE litigation. The patent lawsuits initiated by NPEs are usually sudden and unanticipated by the target firms as target firms have little or no idea whether and when an NPE might initiate a patent lawsuit against them. Therefore, we perform a staggered difference-in-differences analysis using the timing of the first patent lawsuit by an NPE against a given target firm (treatment group) as a plausible exogenous event. We find that compared with their propensity-score matched control firms, which have never experienced any NPE litigation, the firms in the treatment group show

[3] Shah IP Law, an IP law firm, indicated, "how can a startup deter patent trolls? Unfortunately, there is not much that you can do to prevent trolls from filing lawsuits against you." https://www.shahiplaw.com/can-startups-deter-patent-trolls/.

an increase in the number of backward self-citations to their patented innovations post-NPE litigation. We also find that these firms experience a decrease in the number of forward non-self-citations. The first set of results is consistent with our predictions that, post-NPE litigation, these target firms draw more upon their in-house technologies to reduce the potential legal ground for NPE lawsuits. The second set of results suggests that the non-target firms in related technology areas will shift their locus of innovation away from those of the target firms. In other words, these non-target firms distance themselves from the existing innovation activities at risk of NPE litigation in an attempt to "escape" the patent trolls. These effects are more pronounced when R&D expenses for the patented technologies are higher and when the product markets are more competitive.

This paper makes the following contributions. First, we contribute to the heated debate on how patent trolling and litigation lawsuits affect the innovation activities of firms and potential firm collaboration. While proponents have argued that NPEs serve society by "policing" the patent infringement, the opponents believe that they exploit the legal process and disrupt innovation activities (Cohen et al., 2016, 2019). However, few or no studies have examined how NPE lawsuits affect target firms' innovation strategy. Our study fills this important gap. Specifically, we show that NPE litigations hamper inter-firm collaboration and technology developments by making firms adopt more inward-looking innovation strategies and distance themselves from the existing network of innovation activities. In other words, patent litigation threats deter potential collaboration among innovating firms in related areas and hinder the exchange and accumulation of knowledge.

Second, we document the potentially detrimental effects of NPE litigation on knowledge externality resulting from technological innovation and adoption (i.e., knowledge spillover). Prior studies have provided evidence on the importance of knowledge spillover. Jaffe (1986) shows that the productivity of a firm is affected by the R&D investment made by its peer firms. Fosfuri and Rønde (2004) show that, to benefit from technology spillovers, firms have stronger incentive to cluster in an industrial district when the growth potential of an industry is high. Bloom, Schankerman, and Van Reenen (2013) ascertain that the positive spillover created by corporate R&D investment outweighs its negative effects on product market competition. Chen, Chen, Liang, and Wang (2013) find that firms benefiting more from spillover experience higher post-R&D long-run stock performance. Our study shows that the threat of NPE litigation induces firms to isolate themselves from their usual network of innovation, thereby reducing the positive knowledge spillover beneficial to their industries and society.

Third, our study advances our understanding of the effects of US anti-patent troll legislation and its policy implications. Most states in the US have passed anti-patent troll laws between 2013 and 2016. While some prior studies in law have looked at the usefulness of the adoption of anti-patent troll law (e.g., Hrdy, 2018; Martyn, 2014; Mezzanotti & Simcoe, 2019; Thoman, 2014; Vogel, 2015), few or no studies have examined its impact on the innovation and business activities of firms. Consistent with our predictions, we show that after the passage of the state-level anti-patent troll laws, firms significantly lower the reliance on their own technology and increase technology collaboration among firms. This large-scale empirical evidence provides strong justification for the adoption and implementation of anti-patent troll legislation across different states in the US, as well as support for policymakers imposing greater restrictions on NPE litigation. For example, Cohen, Gurun, and Kominers (2017) propose an automatic process of the administrative review of infringement lawsuits in US district courts that meets the minimum threshold of patent litigations as a way of providing feedback and information for the evaluation and adjustment of the patent system. Our paper provides the theoretical and empirical reasons for why these proposed policies are vital and needed.

2. Conceptual Framework and Hypotheses Development

2.1 Main Effects of NPE Lawsuits

NPEs amass patents and build their patent portfolios to enforce their intellectual property rights and initiate patent infringement lawsuits against potential infringers, but, unlike practicing entities, they have little or no intention of further developing these patents. Their primary goal is to earn monetary profits through private remedies or out-of-court settlements (Cohen et al., 2016, 2019).

NPEs frequently purchase unused patents and strategically claim the ownership of basic components of certain products of the target firms. Patent litigation cost consists of direct and indirect parts. The major component of direct cost is the legal fee. According to a survey of IP-related costs of the American Intellectual Property Lawyer's Association, litigation costs per patent related to claim construction could reach 2.4 million US dollars or more.[4,5] In addition, based on the PwC 2018 Patent Litigation Study, the median damages award for NPEs was 14.8 million US dollars from 2013 to 2017.[6] Indirect patent cost is typically even higher than direct cost, including the drop in stock price around the announcement of patent lawsuits and the reduction of revenue resulting from the risk that the court might rule in favor of the plaintiff. For instance, a court might order a damage payment or an injunction interrupting the production of products claimed by the patents (Bessen & Meurer, 2012). To avoid being trapped in a long, costly legal process, many target firms might accept settlement agreements when facing NPE-initiated lawsuits. NPE-initiated lawsuits are inconsistent with the commonly known deterrence model, which describes that the patenting system should function in a way that deters potentially unfounded patent lawsuits (Chen, 2013). This is because NPEs do not utilize their patents to produce goods and services, hence bearing little, if any, indirect patent litigation costs, such as prohibited sales and loss of customer trust (LaLonde & Gilson, 2017; Urbanek, 2008; Yun et al., 2017).

To the extent that the occurrence of NPE litigation is unpredictable (Fishwick, 2013), the first NPE litigation against a target firm could alarm the firm, raising awareness of the possibility of litigation. Therefore, to reduce the risks of being targeted by NPEs again and incurring further direct and indirect patent litigation costs, firms that are targeted by NPEs are likely to adopt an inward innovation strategy after the initial NPE lawsuit to reduce future litigation threats from NPEs. In other words, target firms will draw more upon their in-house technologies to reduce the potential legal ground for NPE lawsuits in the future. Prior studies have used the proportion of citations to those patents belonging to the same firm to represent internalized knowledge use and proportion of the benefits captured by the original firm (Hall et al., 2001, 2005; Zhao, 2006). Indeed, the number of self-citations to a firm's focal patents reflects the firm's strategy of resources allocation between investing in internal development and the external acquisition of technologies. A higher number of self-citations indicates that a firm internalizes more knowledge created by its own R&D efforts, which suggests a strong competitive position in a

[4] Claim construction is defined as "the process in which courts interpret the meaning and scope of a patent's claims." Given that the claims in patent lawsuits define the invention to which the patentee is entitled the right to exclude, claim construction generally determines the possible outcome of patent litigations. See more detailed definition of claim construction at https://www.finnegan.com/en/insights/articles/claim-construction.html

[5] https://blueironip.com/what-are-the-costs-to-enforce-or-defend-a-patent/

[6] https://www.ipwatchdog.com/wp-content/uploads/2018/09/2018-pwc-patent-litigation-study.pdf

particular technology area as the firm relies more on itself and less on other firms (Hall et al., 2005). Furthermore, firms with a high level of self-citations to their own patents can better appropriate their intellectual assets by reducing potential threats and hold-ups from outside patent owners (Alcacer & Gittelman, 2006; Zhao, 2006). Thus, we postulate that the target firms' inward-looking innovation strategy would be reflected in an increase in the proportion of backward patent self-citations. This leads to our first hypothesis:

Hypothesis 1 (H1): After the initial NPE lawsuit, target firms will increase the proportion of backward self-citations to their patented innovations.

The null hypothesis associated with H1 is that the target firms just accept the cost of NPE lawsuits as an inevitable operating cost and do not significantly alter their innovation strategies as a response. However, we will show empirically later that target firms and peer firms actually respond to the potential threat posed by NPEs by shifting their innovation strategies and trajectories, thereby rejecting the null hypothesis.

Moreover, the potential risk of litigations initiated by patent trolls may also keep innovators away from certain areas of technology. Prior studies have provided evidence that firms learn about their operating environment by observing their peers in the same industry. Cho, Kim, and Rhee (1998) show that firms could learn from the mistakes of early movers in similar product categories. Prince and Rubin (2002) argue that a lawsuit against a firm could be seen as an indication of a heightened litigation risk by other firms in the same industry. Specifically, NPE lawsuits may affect peer firms that invest in similar or related technology areas as the defendant firm. In the common law system, an unfavorable precedent ordered by a court against one firm imposes the same restriction on all other firms using the same technology. An NPE lawsuit thereby presents litigation risk not only to the defendant firm but also to all other peer firms using similar technology (Prince & Rubin, 2002). As such, after observing the occurrence of NPE lawsuits, even firms not directly sued by NPEs (non-target firms) may also be incentivized to rework their innovation strategy and shift the locus of their innovation activities away from those of the target firms to avoid areas with potentially high NPE litigation risks.

As a consequence, once targeted by NPEs, the target firm may receive *less* forward (non-self-) citations for its affected patents because other firms divert their resources and innovation activities away from the targeted technology area.[7] Therefore, we hypothesize that the non-target firms in related technology areas will shift the locus of their innovation activities away from those of the target firms to avoid the areas with high NPE litigation risks. This leads to the following prediction:

Hypothesis 2 (H2): After the initial NPE lawsuit, the proportion of forward non-self-citations received by a target firm's focal patented innovations will decrease.

2.2 Moderating Role of R&D Expenses

Next, we explore the internal and external factors that may influence the effect of the heightened NPE litigation risks on firms' decision to shift their innovation strategy. First, we argue that target firms might respond to NPE litigation risks more vigorously when they undertake costlier research and technology development. When a court orders a damage payment, firms that had incurred a high cost for developing expensive patents tend to suffer the greatest loss. These firms are also most vulnerable to NPE litigations and have the highest incentive to accept out-of-court settlements. Therefore, when R&D on technology innovation is more expensive, NPE-targeted firms tend to increase the reliance on their in-house technologies, hence exacerbating the hypothesized relationship in H1. This leads to the following hypothesis:

Hypothesis 3a (H3a): The increase in the proportion of backward self-citations to patented innovations of the target firm after the initial NPE lawsuit will be more pronounced when the R&D expense for the patented innovation is higher.

Following similar logic, when the R&D cost of a particular technology area is high, it not only attracts more NPE litigations but also makes the outcome of the litigations, such as out-of-court

[7] We acknowledge the possibility that a firm may see an NPE lawsuit against its competitor as an opportunity to gain the leading position (Rubin & Bailey, 1994) and further increase their investment in the same technology. However, to the extent that NPE lawsuits are becoming increasingly more commonplace and affect all firms working in similar technology areas, the diversion of resources and innovation activities is becoming the predominant strategy.

settlements, costlier for the non-target firms in related technology areas. These non-target firms are thus more likely to shun such technological areas. Therefore, the hypothesized relationship depicted in H2 will be more pronounced when R&D expenses on a given patented technology are higher. This leads to the next prediction:

Hypothesis 3b (H3b): The decrease in the proportion of forward non-self-citations received by a target firm's focal patented innovations will be more pronounced when the R&D expense for the patented innovation is higher.

2.3 Moderating Role of Product Market Competition

An important external factor to consider is the competition in the product market in which the target firms operate. In a highly competitive market, firms can only earn normal profits, which are typical profits that firms can earn in a (close to) perfectly competitive product market. Such profits are particularly sensitive to and are adversely affected by any additional costs, such as those incurred through litigations (Baggs & De Bettignies, 2007). Therefore, these firms must respond quickly to any emerging threats in their operating environment to survive, a notion that has been studied and affirmed in prior papers. For example, it has been argued that greater competition may reduce the firm's profits and increase the probability that the firm might face financial distress, thus compelling managers to work harder toward cost reduction to avoid firm liquidation (Schmidt, 1997). Moreover, responding to an increase in product market competition, firms tend to undertake more aggressive merger and acquisition strategies to maintain their competitive advantage (Chatain, 2014; Chen et al., 2020).

As such, we hypothesize that firms' response and change in their innovation strategies to heightened NPE litigation risk for both target firms and non-target firms in related technology areas (as depicted in H1 and H2, respectively) should be more pronounced in a competitive product market. Therefore, we make the following predictions (H4a and H4b, which correspond to H1 and H2, respectively):

Hypothesis 4a (H4a): The increase in the proportion of backward self-citations to patented innovations of the target firm after the initial NPE lawsuit will be more pronounced when competition in the product market in which the target firm operates is stronger.

Hypothesis 4b (H4b): The decrease in the proportion of forward non-self-citations received by a target firm's focal patented innovations will be more pronounced when competition in the product market in which the target firm operates is stronger.

We illustrate our conceptual framework in Figure 1, which depicts the effects of NPE litigation on firm innovation strategies, manifested in the backward self-citations and forward non-self-citations to target firms' patents, as well as the moderating effects of R&D expenses and product market competition.

[Insert Figure 1 about here]

3. Methodology

3.1 Empirical Context and Strategy

NPE litigation provides an important context for our study. Indeed, there is a rising trend in NPE litigation over the past decade, which is of growing concern to managers and policymakers (Figure 2). Figure 2 shows the patent litigation cases against publicly listed firms on NYSE/NASDAQ/AMEX.[8]

[Insert Figure 2 about here]

In our empirical analyses, we focus on the effect of the initial NPE litigation filed against a target firm. This approach allows us to assess the effect of NPE litigation more effectively because the reactions of the target firm to subsequent NPE litigations might be affected by the reaction to the first NPE litigation. To the target firm, the initial patent lawsuit initiated by an NPE is usually sudden and largely unanticipated as the target firm has little or no idea whether and when the NPE might initiate a patent lawsuit against it and for which particular technology or patent (Fishwick, 2013). Furthermore, NPEs often take advantage of vague, difficult-to-interpret words and phrases in patents to make claims that otherwise were difficult to predict. Even if the accused infringer has read the patent closely, it was difficult to understand how an infringement had happened (Samuels, 2013). Therefore, we consider this event as a plausibly exogenous one and perform a staggered difference-in-differences analysis that relies

[8] The figure of patent litigation cases against all firms shows a similar trend.

on the different timings of the first patent lawsuit initiated by an NPE against given target firms. Our treatment group consists of firms that have ever been sued by NPEs for patent infringement in any year after 2008, while our control group consists of firms that have never been sued by NPEs.[9]

We match firms in the treatment group to firms in the control group using propensity score matching (PSM) using the following variables: *Firm age*, *Firm size*, *Book-to-market ratio*, *Return-on-assets*, *R&D-to-assets ratio*, *Ln(1+ patents)*, *Ln(1+cumulative patents)* and *Year of observation*.[10] *Firm age* is the number of years since a firm was publicly listed. *Firm size* is the natural logarithm of total assets, i.e., ln(assets). *Book-to-market ratio* is the book value of equity divided by the market value of equity. *Return-on-assets* is the net income divided by total assets. *R&D-to-assets ratio* is the amount of R&D expense divided by total assets. *Ln(1+patents)* is the natural logarithm of one plus a firm's total number of the United States Patent and Trademark Office (USPTO) patent applications in a given year that are eventually granted, while *Ln(1+cumulative patents)* is the natural logarithm of one plus a firm's cumulative number of patents filed with the USPTO in the last three years. Specifically, using the entire sample, we estimate the propensity score as the predicted value of a logistics regression where the dependent variable is an indicator variable taking the value of 1 if a firm is a treatment firm and 0 if otherwise. For each treatment firm, we find the firm from the control group in the same Standard Industrial Classification (SIC) code that is closest to it in terms of propensity score as its control firms. This is a rigorous matching process that yields a quality sample where both firms with and without the experience of being targeted by NPEs receive comparable representation.

While an NPE-initiated litigation is typically sudden and unanticipated, we cannot completely exclude the possibility that certain NPE litigation cases might not be fully exogenous as specific firm characteristics like cash holding might influence the likelihood of being sued by NPEs. In addition to controlling for these potential variables, to mitigate this issue, we employ an instrumental variable regression analysis and a quasi-experimental analysis using the enactment of anti-patent troll laws as

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[9] The firms in our control group have never been sued by NPEs since 2001, the beginning year of Lex Machina's lawsuit database. Note that the concept and definition of "patent troll" were initially discussed in 2001 (Osenga 2014).

[10] We find qualitatively similar and consistent results using coarsened exact matching (detailed results are available upon request).

the setting, as described in the Supplementary and Robustness Analyses Section. Results are consistent with those in the staggered difference-in-differences analysis.

3.2 Data

To test our predictions, we construct a longitudinal dataset of US public companies with comprehensive patent litigation data between 2008 and 2016 from the following datasets: (i) patent litigation cases from the Lex Machina database; (ii) NPE data from the Stanford NPE litigation dataset (Miller, 2018); (iii) patent and patent-related data from the Worldwide Patent Statistical Database (PATSTAT, 2018 edition); and (iv) firm financial data and other attributes from the Compustat database.

We construct our sample through the following procedure. First, we obtain comprehensive patent infringement lawsuit data from Lex Machina, a part of LexisNexis. Our dataset includes detailed information on the lawsuit cases filed in US courts from 2008 to 2018, including the case title, case filing date, the names of plaintiffs and defendants, and the patents asserted by plaintiffs. Second, we obtain the NPE data from Stanford University's NPE Patent Data Project to determine which lawsuit cases were initiated by NPEs.[11] The Stanford Project identifies 13 categories of patent asserters and labels each patent asserter accordingly based on to which category an asserter belongs. To identify NPEs, Miller (2018) recommends that "those who use the term … 'patent troll' are generally referring to entities that fall within Category 1 (acquired patents), Category 4 (corporate heritage), or Category 5 (individual-inventor-started company)." We thus follow the same approach and identify a firm being sued by NPEs if the firm is involved as a defendant in a lawsuit initiated by an NPE. As a result, of the 43,122 lawsuit cases filed during 2008–2018, there are 19,251 cases of which at least one plaintiff is identified as an NPE. Third, we collect detailed patent and patent-related data from the EPO Worldwide Patent Statistical Database (PATSTAT, 2018 edition).

Lastly, we conduct a matching process to identify the public company defendants as reported in Compustat or the Center for Research in Security Prices (CRSP) database. Specifically, we first perform the separate matching of defendant names to corporate names in the Compustat and to the corporate

[11] The details of the Stanford NPE Litigation Database can be found at https://npe.law.stanford.edu/.

names in CRSP, respectively. Then, we conduct manual checks for those observations that have high but imperfect matching quality to ensure correct matching. This process yields 11,529 lawsuit cases in all of which at least one defendant is a public company. We then construct a firm-year panel dataset including the entire Compustat/CRSP dataset between 2008 and 2016. After performing the PSM procedure as described in Section 3.1, the sample contains 2,205 firm-year observations, including both treatment and control group firms within a seven-year window surrounding a target firm's first NPE lawsuit.

3.3 Variables and Measures

We describe our variables and measures in this section. First, we construct the following two dependent variables to shed light on firm innovation strategy and trajectory. The first dependent variable is *Backward self-citations*, which is the ratio of the total number of self-citations that a firm has cited in all its patent applications filed in a given year (which are eventually granted) relative to the total number of all citations (self or external) made to the firm's patent applications filed in the same year (which are eventually granted). *Backward self-citation* captures a firm's tendency to undertake an inward innovation strategy by investing and drawing upon its own in-house technologies relative to technologies from other firms.

The second dependent variable is *Forward non-self-citations*, which is the ratio of the total number of forward non-self-citations relative to the total number of all forward citations (self or external). To be specific, a patent's forward non-self-citation refers to the citations made by the applicants who are not the patent holders themselves. *Forward non-self-citations* captures other (non-target) firms' tendency to undertake follow-on R&D on the patented technologies held by the target firm. A higher value indicates a greater tendency for a non-target firm to conduct follow-on R&D in a similar technology area as the target firm.

The key independent variable *Post-NPE* is an indicator variable that takes the value of 1 if, in and after the first year, a firm is targeted by an NPE-initiated lawsuit as a defendant (i.e., for the treatment group) and 0 if otherwise. For the control group of firms, *Post-NPE* always takes on the value of 0. *Post-NPE* is our main difference-in-differences variable of interest.

We construct the following moderating variables. To measure R&D expenditure for each patented technology, we construct *High (Low) R&D per patent*, which is an indicator variable that equals 1 if a firm's R&D expenses per patent are above (below) the median and 0 if otherwise. Specifically, R&D expenses per patent are defined as the total R&D expenses (in millions of dollars) in the recent three years divided by the total number of patents in the same period. When *High R&D per patent* takes on the value of 1, it indicates that the R&D cost of developing a patented technology for a firm is relatively high.

For the empirical measure of product market competition, we rely on the product similarity measure provided by Hoberg and Phillips (2010; 2016), which is widely used in the innovation literature (e.g., Angus, 2019; Chen et al., 2020; Frésard et al., 2020). This measure is constructed based on the notion of how "similar" the product descriptions are as provided in the 10-K filings of any pair of firms. A higher similarity score indicates that two firms are similar in product space and are likely to be competitors. Specifically, we construct the following two sets of alternative variables: *High (Low) rival similarity* and *More (Fewer) rivals*. *High (Low) rival similarity* is an indicator variable that equals 1 if a firm's total similarity is above (below) median and 0 if otherwise, where total similarity is a score that gauges the product similarity between paired firms based on Text-based Network industry classification (TNIC) and is negatively related to pricing power in the framework of product differentiation theory.[12] *More (Fewer) rivals* is an indicator variable that equals 1 if a firm's number of rivals in the same TNIC industry is above (below) median and 0 if otherwise. When *High rival similarity* or *More rivals* equals 1, it suggests that the firms face a relatively high level of competition in the product market.

For the control variables, we include a set of variables at the firm level including those related to firm innovation characteristics and financials. First, a control variable that we include in the more stringent regression models is *Litigation window dummy*, which is an indicator variable that equals 1 in the year when a firm is sued by an NPE and 0 if otherwise. *Litigation window dummy* always takes on the value of 0 for the control group of firms. This variable allows us to account for the possibility that

[12] We thank Professors Hoberg and Phillips for making the TNIC data publicly available on their website: https://hobergphillips.tuck.dartmouth.edu/. More detailed descriptions of these variables are available on their website as well.

the effect NPE litigation on firm innovation strategy in the actual year of litigation might be noisy.

Consistent with prior studies, we control for *Firm age* and *Firm size,* which affect firm performance in terms of its growth and amount of resources respectively. We control for *Ln(1+cumulative patents)*, the cumulative amount of innovation output produced by the firm in the recent three years.[13] We also control for *R&D intensity*, which is the firm's investment in R&D calculated as the amount of R&D expenses divided by sales. In addition, we control for the following financial variables. *Tobin's Q* is the ratio of the market value of assets to book assets. *Sales growth* is the average change in sales in percent over the last three years. *Cash ratio* is the amount of cash holding defined as the sum of cash and short-term investments divided by book assets. *Capital intensity* is the property, plant, and equipment divided by the number of employees. *Return-on-assets* is the net income divided by total assets. *Leverage* refers to financial leverage defined as the total debts divided by assets. *Z-score* refers to the Altman's Z-score, which is a measure of creditworthiness. Lastly, *Industry Tobin's Q* is the industry-level growth opportunity defined as the median Tobin's Q of firms in a given three-digit SIC industry.

We provide the variable definitions and summary statistics of the firm-year panel dataset in Table 1. In Table 2, we provide the pairwise correlations for these variables. The low correlation between *Backward self-citations* and *Forward non-self-citations* lends further support to the notion that these two variables capture distinct types of innovation strategies as described above.

[Insert Tables 1 and 2 about here]

3.4 Model Specification and Estimation

To capture the effect of NPE lawsuits, we estimate baseline regressions as follows. The dependent variables are *Backward self-citations* and *Forward non-self-citations*, and the key independent variable is the indicator variable *Post-NPE* that takes the value of 1 since the first year in which a company was targeted by NPEs (i.e., the year in which a firm was involved in an NPE-initiated lawsuit case as a defendant for the first time) and 0 if otherwise. The coefficient of *Post-NPE* as an independent variable

[13] The results remain consistent when we substitute *Ln(1+cumulative patents)* by *Ln(1+patents)*.

in these regressions hence represents the change in a firm's innovation strategy after it was targeted by NPEs. In these regression models, we also include the following control variables: *Litigation window dummy, Firm age*, *Firm size*, *Ln(1+cumulative patents)*, *R&D intensity*, *Tobin's Q*, *Sales growth*, *Cash ratio*, *Capital intensity*, *Return-on-assets*, *Leverage*, *Z-score*, and *Industry Tobin's Q*. We specify the ordinary least squares regression model in equation (1) below:

$$\begin{aligned}
&\textit{Backward self-citation}_{i,t}\ (\textit{Forward non-self-citations}_{i,t}) \\
&= \alpha + \beta_1\ \textit{Post-NPE}_{i,t} + \beta_2\ \textit{Litigation window dummy}_{i,t} + \beta_3\ \textit{Firm age}_{i,t-1} + \beta_4\ \textit{Firm size}_{i,t-1} \\
&\quad + \beta_5\ \textit{Ln(1+cumulative patents)}_{i,t-1} + \beta_6\ \textit{R\&D intensity}_{i,t-1} + \beta_7\ \textit{Tobin's Q}_{i,t-1} \\
&\quad + \beta_8\ \textit{Sales growth}_{i,t-1} + \beta_9\ \textit{Cash ratio}_{i,t-1} + \beta_{10}\ \textit{Capital intensity}_{i,t-1} + \beta_{11}\ \textit{Return-on-assets}_{i,t-1} \\
&\quad + \beta_{12}\ \textit{Leverage}_{i,t-1} + \beta_{13}\ \textit{Z-score}_{i,t-1} + \beta_{14}\ \textit{Industry Tobin's Q}_{i,t-1} \\
&\quad + \textit{Firm fixed effect} + \textit{Year fixed effect} + \varepsilon_{i,t}, \qquad (1)
\end{aligned}$$

where *i* refers to firm and *t* refers to year.

4. Results

4.1 Descriptive Statistics

Table 3 provides the descriptive statistics of our PSM sample by comparing the treatment and control firms. For each variable used to estimate the propensity score, we present the mean of the variable for the treatment and control groups respectively and perform the two-sample test. The differences between the treatment and control firms are small and not significant for most of the variables. Overall, the PSM process yields a well-matched treatment group and control group of firms for the empirical analysis.

[Insert Table 3 about here]

We first inspect the temporal trend of the effects of the initial NPE lawsuit on target firms' *Backward self-citations* and *Forward non-self-citations*, as presented in Figure 3 and 4. Prior to the initial NPE lawsuit event, there are no significant pre-trends in both graphs. However, there is a significant jump in *Backward self-citations* after the initial NPE lawsuit event as shown in Figure 3. By contrast, there is a significant decline in *Forward non-self-citations* after the NPE lawsuit event as shown in Figure 4. These temporal changes in *Backward self-citations* and *Forward non-self-citations* are consistent with our hypotheses. Firms targeted by NPE lawsuits subsequently draw more upon their in-house technologies to reduce the potential legal ground for future NPE lawsuits. Furthermore, non-target firms in related technology areas seem to shift the locus of their innovation activities away from those of the target firms to avoid the areas with high NPE litigation risks.

[Insert Figures 3 and 4 about here]

4.2 Main Effect of NPE Lawsuits on Target Firms' Innovation Strategies

We start our multivariate analyses by investigating whether a firm shifts its innovation strategy after being targeted by NPEs for the first time. As shown in Models 1 and 2 of Table 4, we regress the dependent variables, *Backward self-citations* and *Forward non-self-citations*, on only the control variables, including firm fixed effects and year fixed effects. In Models 3 and 4, we include the key difference-in-differences variable of interest, *Post-NPE*. We find a positive effect of *Post-NPE* on *Backward self-citations*. When the value of *Post-NPE* changes from 0 to 1 (i.e., the first NPE lawsuit occurs), *Backward self-citations* increase by 0.9% (p = .001). By contrast, we find a *negative* effect of *Post-NPE* on *Forward non-self-citations*. After the first NPE case, *Forward non-self-citations* decrease by 1.7% (p = .069). In the most stringent (and preferred) Model 5 and Model 6, we include *Litigation window dummy* as an additional control variable. The results of Model 5 and Model 6 are consistent with those shown in Model 3 and Model 4, respectively. In Model 5, we find a positive effect of *Post-NPE* on *Backward self-citations*. After the first NPE case, *Backward self-citations* increase by 0.8% (p = .021) or 7.69% relative to the standard error. Therefore, results from Models 3 and 5 lend support to Hypothesis 1. In Model 6, we find a *negative* effect of *Post-NPE* on *Forward non-self-citations*. After the first NPE case, *Forward non-self-citations* decrease by 1.9% (p = .024) or 5.81% relative to the standard error. Therefore, results from Models 4 and 6 provide support for Hypothesis 2.[14]

[Insert Table 4 about here]

[14] As a supplementary analysis, we study the effect of NPE litigation on target firms' patenting behavior. Please refer to Section 5.4 on "NPE litigation risk and firm patenting" for more details.

4.3 Moderating Effects of R&D Expenditures

We first investigate how R&D expenditure on a patented technology moderates the effects of NPE litigation risk on firm innovation strategy. Following Murray and Stern (2007) and Huang and Li (2019), we employ a "constrained model" by including the pair of variables *High (low) R&D per patent* in our regression Models 1 and 2 in Table 5.[15] The coefficient of the interaction variable *Post-NPE* × *High (low) R&D per patent* captures the moderating effect. As shown in Model 1 of Table 5, the coefficient of *Post-NPE* × *High R&D per patent* is positive and significant (β = 0.035, p = .018) while the coefficient of *Post-NPE* × *Low R&D per patent* is not significant (β = 0.008, p = .464). By comparing these two coefficients, our results support Hypothesis 3a. That is, the increase in the proportion of backward self-citations to patented innovations of the target firm after the initial NPE lawsuit will be more pronounced when the R&D expense for the patented innovation is higher.

On the other hand, as shown in Model 2, the coefficient of *Post-NPE* × *High R&D per patent* is negative and significant (β = -0.058, p = .014), but the coefficient of *Post-NPE* × *Low R&D per patent* is not significant (β = 0.009, p = .377). Therefore, our results support Hypothesis 3b. It suggests that the decrease in the proportion of forward non-self-citations received by a target firm's focal patented innovations will be more pronounced when the R&D expense for the patented innovation is higher.

[Insert Table 5 about here]

4.4 Moderating Effects of Product Market Competition

We predict that the effects of NPE litigation risk should be particularly strong when the target firm operates in a competitive market because firms are under great pressure to avoid any direct or indirect costs resulting from potential infringement lawsuits. To assess product market competition, we employ these two sets of indicator variables: *High (Low) rival similarity* and *More (Fewer) rivals*.[16]

[15] A "constrained" model is a standard approach in econometrics, which compares two sets of constrained interactions (e.g., Huang & Murray 2009; Murray & Stern 2007), i.e., *Post-NPE* × *High R&D per patent* versus *Post-NPE* × *Low R&D per patent*. As is standard for such constrained models, we are not able to add the main effect term, *Post-NPE*, in the regression model further because it is fully partialed out and included in the two separate interaction variables.

[16] We derive qualitatively similar results when employing the Herfindahl-Hirschman Index (HHI) constructed for each three-digit SIC code industry as an alternative measure of product market competition. HHI is defined as the sum of the squared market shares of all firms in the same industry, where market share is a firm's annual sales

As shown in Model 3 of Table 5, the coefficient of the interaction term *Post-NPE* × *High rival similarity* is positive and significant (β = 0.016, p = .009), whereas the coefficient of *Post-NPE* × *Low rival similarity* is not significant (β = 0.007, p = .318). This finding is further supported by the result in Model 5 where the coefficient of the interaction term *Post-NPE* × *More rivals* is positive and significant (β = 0.016, p = .011), whereas the interaction term *Post-NPE* × *Fewer rivals* is not significant (β = 0.009, p = .244). Taken together, these results lend support to Hypothesis 4a. That is, the increase in the proportion of backward self-citations to patented innovations of the target firm after the initial NPE lawsuit will be more pronounced when competition in the product market is stronger.[17]

As shown in Model 4 of Table 5, the coefficient of the interaction term *Post-NPE* × *High rival similarity* is negative and significant (β = -0.042, p = .045), while the coefficient of the interaction term of *Post-NPE* × *Low rival similarity* is not significant (β = 0.012, p = .661). Similarly, in Model 6, the coefficient of the interaction term *Post-NPE* × *More rivals* is negative and significant (β = -0.044, p = .038) but the coefficient of *Post-NPE* × *Fewer rivals* is not significant (β = -0.013, p = .732). Taken together, our results support Hypothesis 4b. It suggests that the decrease in the proportion of forward non-self-citations received by a target firm's focal patented innovations will be more pronounced when competition in the product market is stronger.

5. Supplementary and Robustness Analyses

The initial patent lawsuit initiated by an NPE is usually sudden and largely unanticipated as the target firm has little or no idea whether and when the NPE might initiate a patent lawsuit against them and for which particular technology or patent. Nevertheless, we cannot completely exclude the possibility that certain NPE litigation cases might not be fully exogenous due to particular firm attributes. In addition to controlling for these potential variables, we mitigate this concern by undertaking two supplementary analyses: (i) a two-stage least squares regression analysis (Section 5.1) and (ii) a

divided by the total sales of all firms in the same industry.

[17] Our results are conservative in the sense that under higher product competition, we should observe less litigation from NPEs due to potentially lower profit from the firms. Nevertheless, the effects of NPE litigation on our results are significant and robust.

difference-in-differences estimation using the difference in the timing of the enactment of the anti-patent troll law across different US states as an exogenous event (Section 5.2).

In Section 5.3, we provide further analyses of how an inward-looking innovation strategy is associated with fewer subsequent NPE litigations. In Section 5.4, we conduct a supplementary analysis of the effect of NPE litigation on target firms' patenting behavior. In Section 5.5, we perform a supplementary analysis of NPE litigation risk and technology competition. Lastly, in Section 5.6, we discuss the effect of NPE litigation on alternative measures of citations in the same patent class as the patents of the target firms.

5.1 Two-Stage Least Squares (2SLS) Regression Analysis

In 2012, the US passed the America Invents Act (AIA), which significantly increased the litigation costs for patent trolls. For example, the cost for patent trolls is higher because the listing of multiple targeted defendants in one litigation case is prohibited.[18] To cope with the higher litigation costs, NPEs turn to the court of the Eastern District of Texas—the court that is known to be generally friendly to plaintiffs.[19] As a result, there has been a remarkable increase in the number of patent infringement cases filed in the court of the Eastern District of Texas since 2012, as well as in the share of cases filed in this court relative to all cases nationwide (Love & Yoon, 2017). Therefore, firms headquartered in Texas since 2012 should be subject to a significantly high level of NPE litigation risk because lawsuit filing in Texas is less costly than that in other states.[20] Further, since the passage of the AIA is exogenous to the firms and not influenced by the firm managers, this potential instrument meets the following criteria (Bettis et al., 2014). First, it does not directly affect the dependent variable other than through the

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[18] Patent trolls often target multiple defendants in one case to save costs before the AIA. The AIA prohibits such a speculative strategy that "hits many birds with one stone" (Schwartz, 2012). See details at https://btlj.org/2011/10/patent-trolls-under-the-patent-reform-act/

[19] For example, even though the AIA prohibits plaintiffs from prosecuting multiple defendants in one litigation case, in the Eastern District of Texas, it is still quite common for the individual patent cases filed by the same NPE to be consolidated into what is effectively a single suit (Love & Yoon, 2017). Such a practice reduces the litigation costs for NPEs.

[20] According to the decision of TC Heartland LLC v. Kraft Foods Group Brands LLC, 581 U.S. ___ (2017), after 2017: "patent lawsuits can only be brought in the state where the defendant is incorporated", or "where the defendant has committed acts of infringement and has a regular and established place of business." As such, the filing cases in Texas started to drop after 2017. Nevertheless, such legal environment change does not affect our argument as our sample period ends in 2016. See details at https://supreme.justia.com/cases/federal/us/581/16-341/

potentially endogenous variable. Second, it is exogenous to the system (i.e., unaffected by other variables in the system). Third, it has a logical relationship with endogenous variables. Therefore, we construct the instrumental variable, *Texas HQ after 2011*, which equals 1 if a firm-year observation satisfies both the following conditions: (i) this firm is headquartered in the state of Texas, and (ii) this observation is in any year after 2011; and equals 0 if otherwise. We use this instrumental variable in the two-stage least squares (2SLS) regression analysis to mitigate the potential endogeneity issue.

In Table 6, we report the results of the 2SLS regression. In the first stage, we regress *Post-NPE* on *Texas HQ after 2011*, including all of the control variables, firm fixed effects and year fixed effects in the regression model. The positive coefficient on *Texas HQ after 2011* (β = 0.070, p < .000) supports the notion that firms headquartered in Texas are subject to higher litigation risk. In addition, *Texas HQ after 2011* passes the weak identification test with the F-value of about 11.341, greater than the rule-of-thumb value of 10 (Stock & Yogo, 2005). These results show that our instrument satisfies the relevance restriction. Importantly, Model 1 and Model 2 show the results of the second-stage regressions. Here, we continue to find that *Post-NPE* has a positive effect on *Backward self-citations* (β = 0.032, p = .085) and a negative effect on *Forward non-self-citations* (β = -0.783, p = .041). These results are consistent with the results from the main analyses, as shown in Table 4.

[Insert Table 6 about here]

5.2 Difference-in-Differences Analysis of Anti-Patent Troll Laws

Although patent laws such as the AIA are executed at the federal level, state governments can still take initiatives in combatting NPEs by enacting state-level anti-patent troll laws. Anti-patent troll laws are legislations that punish bad faith patent assertions in an attempt to halt patent trolling.[21] Figure 5 presents a map of the different enactment years of the anti-patent troll laws across the different states in the US. As of 2016, 29 states have enacted the anti-patent troll laws, with Vermont as the first state to pass such a law in 2013. In terms of Vermont, for instance, 9 VSA § 4195 explicitly expressed its

[21] The information of anti-patent troll law can be found on the website of National Conference of State Legislatures (NCSL), namely, https://www.ncsl.org/research/financial-services-and-commerce/2015-patent-trolling-legislation.aspx and https://www.ncsl.org/research/financial-services-and-commerce/patent-trolling-legislation.aspx.

ambition to protect Vermont from abusive and bad faith assertions of patent infringement. In 9 VSA § 4197, a set of key factors is provided for courts to consider as evidence to determine whether a plaintiff has made a bad faith assertion. These factors include the information specified in the demand letter, such as payments of license fee within an unreasonable short period of time, and actions taken or not taken by the plaintiff prior to sending the demand letter, such as failing to conduct a comparison analysis of the claims in the patent and the target's products or technology.[22] Given that the anti-patent troll laws are designed to prevent deceptive and aggressive patent assertions, we expect that firms located in the states that passed anti-patent troll laws face lower litigation risks from NPEs and thus are less compelled to shift their innovation strategies. Since the passage of the anti-patent troll laws is a top-down regulatory change made by the state governments, which occurs in different years across different states and is largely exogenous to the firms, we use it as an exogenous event in a difference-in-differences regression analysis.

[Insert Figure 5 about here]

To construct our sample for this difference-in-differences analysis, we first construct a new treatment group of firms, which are those headquartered in the states with anti-patent troll laws. Next, using the PSM approach we find a group of control firms which are headquartered in the states without anti-patent troll laws. We then combine the treatment and control groups with firm-year observations as our sample for analyses. Lastly, we construct the difference-in-differences variable of interest, *Post-state law*, which is an indicator variable that equals 1 if a firm is headquartered in the states that have passed the anti-patent troll laws and if the year of observation falls on or after the year in which the law is passed. Otherwise, the variable equals 0. For control firms headquartered in the states without the anti-patent troll laws, *Post-state law* always equals 0.

We present the results of the difference-in-differences regression analysis in Table 7. The coefficient of *Post-state law* has a negative effect on *Backward self-citations* (β = -0.007, p = .039) and a positive effect on *Forward non-self-citations* (β = 0.009, p = .085). These results suggest that when the threat of patent trolling reduces after the passage of the anti-patent troll laws, firms rely less on in-

[22] See https://legislature.vermont.gov/statutes/section/09/120/04195 for 9 VSA § 4195 and https://legislature.vermont.gov/statutes/section/09/120/04197 for 9 VSA § 4197.

house technologies, and non-target firms in related technology areas continue to build on the patented innovations of the target firms. These results provide further support to H1 and H2.

[Insert Table 7 about here]

5.3 Inward-Looking Innovation Strategy and NPE Litigation Risk

We have shown that when firms are initially sued by NPEs, target firms will draw more upon their in-house technologies to reduce the potential legal ground for NPE lawsuits. While it is not the focus of our study, a related question is to what extent such inward-looking innovation strategy would be associated with fewer NPE litigations. To answer this question, we perform a logit regression analysis of NPE litigations using a sample consisting of firms with the first NPE litigation as shown in Appendix Table 1. In Model 1, the dependent variable is a binary variable, which takes the value of 1 if the firm was sued by an NPE starting from year t+1 and 0 if otherwise. We regress the binary dependent variable on *Backward self-citations* together with the control variables: *Firm age, Firm size*, *Ln(1+cumulative patent)*, *R&D intensity*, *Tobin's Q*, *Sales growth*, *Cash ratio*, *Capital intensity*, *Return-on-assets*, *Leverage*, *Z-score*, and *Industry Tobin's Q* (all lagged by one year). As expected, we find that the adoption of a more inward-looking innovation strategy (i.e., greater *Backward self-citations*) is associated with less (β = -3.014, p = .056) future risk of a given firm being sued by an NPE. As shown in Model 2, the result is consistent (β = -2.702, p = .076) if we use the dependent variable that equals 1 if the firm was sued by an NPE between year t+1 and t+5 and 0 if otherwise.

5.4 NPE Litigation Risk and Firm Patenting

As a supplementary analysis, we study the effect of NPE litigation on target firms' patenting behavior. We find that the number of patent applications (which were eventually granted) of the target firms reduced (β = -0.038, p = .087) after being sued by NPEs (see Appendix Table 2 Model 1). The result is consistent (β = -0.572, p = .005) if we use the dependent variable, *Change in number of patents*, as shown in Model 2. This suggests that NPE litigations not only influence the innovation strategy of target firms to be more inward-looking (i.e., increase the proportion of backward self-citations to their patented innovations) but also reduce the quantity of patented innovations.

5.5 NPE Litigation Risk and Technology Competition

Considering that the NPE-initiated patent infringement litigation is common in technology-intensive industries, it may be worthwhile looking into whether the reaction of target firms to NPE lawsuits is stronger in industries with a higher level of technology competition. We note that a firm does not need to be a technology-intensive firm (or compete in the same technology space) to own patents or be sued by NPEs for patent infringement. Nevertheless, to provide supplementary evidence, we construct an indicator of technology competition and examine whether the effect of NPE lawsuits on innovation strategy varies with technology competition. Following Eisdorfer and Hsu (2011), we define an industry as possessing a high level of technology competition if the rate of successful technology patent application within this industry is higher than 30%. This is denoted by the binary variable *Technology-intensive*, which equals 1 if a firm is in an industry with a high level of technology competition and equals 0 if otherwise. On the other hand, *Non-technology-intensive* is a binary variable that equals 1 if a firm is not in an industry with a high level of technology competition and equals 0 if otherwise. As shown in Appendix Table 3, our regression analyses compare the coefficients of the two sets of interaction terms—*Post-NPE* × *Technology-intensive* and *Post-NPE* × *Non-technology-intensive*—in a constrained model with the dependent variable *Backward self-citations* in Model 1 and *Forward non-self-citations* in Model 2. We find that the reactions of target firms to NPE lawsuits—in terms of both *Backward self-citations* ($\beta = 0.012$, $p = .030$) and *Forward non-self-citations* ($\beta = -0.064$, $p < .000$)—are stronger when firms operate in industries with a high level of technology competition compared with those firms not operating in these industries.

5.6 NPE Litigation Effect on Target Firms' Innovation Strategies - Alternative Measures using the Same Patent Class

One might predict that the shift in innovation strategy following NPE litigation should be particularly observable for the citations made in technological areas that a company is already familiar with. Thus, to examine this notion, we replicate Table 4 using a set of alternative measures of the dependent variables, where we restrict the cited and citing patents to be in the same IPC code as the patents held by the target firms. The results remain largely consistent, implying that target firms are likely to implement an inward innovation strategy by producing new patents in the same technological class as their existing patents.

6. Discussion

In this study, we theorize and show how firms targeted by NPEs can reduce their litigation risk by shifting their innovation strategy. Specifically, after the initial NPE lawsuits, target firms will draw more upon their in-house technologies to reduce the potential legal ground for NPE lawsuits. Furthermore, non-target firms in related technology areas tend to shift the locus of their innovation activities away from those of the target firms to avoid the areas with high NPE litigation risks. The effects are more pronounced when R&D expenses for the patented technologies are higher and when the product markets are more competitive. Taken together, these results lend further support to the notion that firms seek to escape the patent trolls by isolating themselves in the network of technology.

The findings from this paper yield important managerial implications. This study sheds light on the impact of patent infringement lawsuits initiated by NPEs on firm innovation strategies and inter-firm innovation activities. Our results show that NPE litigations could interrupt the accumulation and build-up of follow-on technology, which disrupts technological development in the industry and is detrimental to inter-firm collaboration and society. Indeed, decision-makers and managers in firms should be cognizant of the impact of NPE litigations and how anti-patent troll laws can help enhance collaboration among firms and facilitate the systematic development of valuable technologies by allowing firms to build on one another's patented technologies. This would allow them to make better plans and more informed decisions.

This study also yields important policy implications. This study provides the theoretical and empirical support for governments to engage in anti-patent troll regulations. The US government enacted the AIA in 2012, which largely increased the litigation costs of NPEs. Indeed, many US state governments have adopted anti-patent troll laws since 2012. Nevertheless, there is still much-heated policy discussion on how to regulate NPE litigations and improve the effectiveness of patent infringement lawsuits in the US. Prior research has proposed an automatic process of administrative review at the threshold of infringement lawsuits in US district courts (Cohen et al., 2017), which can provide policymakers with the information to evaluate and improve the performance of their patent system. Our study contributes to this discussion by shedding light on the underlying theoretical mechanisms and providing a detailed assessment of the impact of anti-patent troll laws and patent infringement lawsuits initiated by NPEs on firm innovation activities and collaboration. These laws regulating the behavior of NPEs are indeed vital and necessary to facilitate technological progress in the industry and in society.

References

Alcacer, J., & Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics, 88*(4), 774-779.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*(4), 589-609.

Angus, R. W. (2019). Problemistic search distance and entrepreneurial performance. *Strategic Management Journal, 40*(12), 2011-2023.

Arora, A., & Gambardella, A. (2010a). Ideas for rent: an overview of markets for technology. *Industrial and Corporate Change, 19*(3), 775-803.

Arora, A., & Gambardella, A. (2010b). The market for technology. Hall BH, Rosenberg, eds. *Handbook of the Economics of Innovation*, 1 (Elsevier, Amsterdam), 641-678.

Arrow, K. J. (1962). Economic welfare and the allocation of resources for invention. Nelson RR, ed. *The Rate and Direction of Inventive Activity: Economic and Social Factors* (Princeton University Press, Princeton, NJ), 609-626.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research, 46*(3), 399-424.

Baggs, J., & De Bettignies, J. E. (2007). Product market competition and agency costs. *The Journal of Industrial Economics, 55*(2), 289-323.

Bessen, J., Ford, J., & Meurer, M. J. (2011). The private and social costs of patent trolls. *Regulation, 34*(4), 26-35.

Bessen, J., & Meurer, M. J. (2012). The private costs of patent litigation. *Journal of Law, Economics and Policy, 9*, 59-80.

Bessen, J., & Meurer, M. J. (2013). The direct costs from NPE disputes. *Cornell Law Review, 99*(2), 387-424.

Bettis, R., Gambardella, A., Helfat, C., & Mitchell, W. (2014). Quantitative empirical analysis in strategic management. *Strategic Management Journal, 35*(7), 949-953.

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica, 81*(4), 1347-1393.

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance, 64*(1), 151-185.

Chatain, O. (2014). How do strategic factor markets respond to rivalry in the product market?. *Strategic Management Journal, 35*(13), 1952-1971.

Chen, E. H. (2013). Making abusers pay: Deterring patent litigation by shifting attorneys' fees. *Berkeley Technology Law Journal, 28*, 351-381.

Chen, S., Chen, Y., Liang, W., & Wang, Y. (2013). R&D spillover effects and firm performance following R&D increases. *Journal of Financial and Quantitative Analysis, 48*(5), 1607-1634.

Chen, I. J., Hsu, P. H., Officer, M. S., & Wang, Y. (2020). The Oscar goes to…: High-tech firms' acquisitions in response to rivals' technology breakthroughs. *Research Policy, 49*(7), 104078.

Cho, D. S., Kim, D. J., & Rhee, D. K. (1998). Latecomer strategies: evidence from the semiconductor industry in Japan and Korea. *Organization Science, 9*(4), 489-505.

Cohen, L., Golden, J. M., Gurun, U. G., & Kominers, S. D. (2017). "Troll" check: A proposal for administrative review of patent litigation. *Boston University Law Review, 97*(5), 1775-1841.

Cohen, L., Gurun, U. G., & Kominers, S. D. (2016). The growing problem of patent trolling. *Science, 352*(6285), 521-522.

Cohen, L., Gurun, U. G., & Kominers, S. D. (2017). Patent Trolling Isn't Dead—It's Just Moving to Delaware. *Harvard Business Review (website)*.

Cohen, L., Gurun, U. G., & Kominers, S. D. (2019). Patent trolls: Evidence from targeted firms. *Management Science, 65*(12), 5461-5486.

Eisdorfer, A., & Hsu, P. H. (2011). Innovate to survive: The effect of technology competition on corporate bankruptcy. *Financial Management, 40*(4), 1087-1117.

Fishwick, L. (2013). Mediating with non-practicing entities. *Harvard Journal of Law & Technology, 27*, 331-348.

Frésard, L., Hoberg, G., & Phillips, G. M. (2020). Innovation activities and integration through vertical acquisitions. *The Review of Financial Studies, 33*(7), 2937-2976.

Fosfuri, A., & Rønde, T. (2004). High-tech clusters, technology spillovers, and trade secret laws. *International Journal of Industrial Organization, 22*(1), 45-65.

Hall, B. H., Jaffe, A. B. & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools. Working Paper 8498, NBER, Cambridge, MA.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics, 36*, 16-38.

Hoberg, G., & Phillips, G, (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies, 23*(10), 3773-3811.

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy, 124*(5), 1423-1465.

Hu, A. G. Z., & Png, I. P. L. (2013). Patent rights and economic growth: Evidence from cross-country panels of manufacturing industries. *Oxford Economic Papers, 65*(3), 675-698.

Huang, K. G., & Li, J. (2019). Adopting knowledge from reverse innovations? Transnational patents and signaling from an emerging economy. *Journal of International Business Studies, 50*(7), 1078-1102.

Huang, K. G., & Murray, F. E. (2009). Does patent strategy shape the long-run supply of public knowledge? Evidence from human genetics. *Academy of Management Journal, 52*(6), 1193-1221.

Hrdy, C. A. (2018). The Reemergence of State Anti-Patent Law. *University of Colorado Law Review, 89*(1), 133-218.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review, 76*(5), 984–1001.

LaLonde, A., & Gilson, J. (2017). Adios to the irreparable harm presumption in the trademark law. *The Trademark Reporter, 107*(5), 913-959.

Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G., Gilbert, R., & Griliches, Z. (1987). Appropriating the returns from industrial R&D. *Brookings Papers on Economic Activity*, *1987*(3),783-831.

Liang, M. (2010). The aftermath of TS Tech: The end of forum shopping in patent litigation and implications for non-practicing entities. *Texas Intellectual Property Law Journal, 19*(1), 29-78.

Love, B. J., & Yoon, J. (2017). Predictably expensive: A critical look at patent litigation in the Eastern District of Texas. *Stanford Technology Law Review, 2*0(1), 1-38.

Martyn, S. (2014). I'll have a latte, scone, and your online data, please. *Colorado Technology Law Journal, 12*(2), 499-522.

Mezzanotti, F., & Simcoe, T. (2019). Patent policy and American innovation after eBay: An empirical examination. *Research Policy, 48*(5), 1271-1281.

Miller, S. P. (2018) Who's suing us: Decoding patent plaintiffs since 2000 with the Stanford NPE litigation dataset. *Stanford Technology Law Review, 21*(2), 235-275.

Murray, F., & Stern, S. (2007). Do formal intellectual property rights hinder the free flow of scientific knowledge?: An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior & Organization, 63*(4), 648-687.

Osenga, K. (2014). Formerly manufacturing entities: Piercing the patent troll rhetoric. *Connecticut Law Review, 47*(2), 435-480.

Prince, D. W., & Rubin, P. H. (2002). The effects of product liability litigation on the value of firms. *American Law and Economics Review, 4*(1), 44-87.

Rivera-Batiz, L. A., & Romer, P. M. (1991). Economic integration and endogenous growth. *The Quarterly Journal of Economics, 106*(2), 531-555.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician, 39*(1), 33-38.

Rubin, P. H., & Bailey, M. J. (1994). The role of lawyers in changing the law. *The Journal of Legal Studies, 23*(2), 807-831.

Samuels, J. (2013). Patent trolls hurt innovation. *Politico*. March, 6. https://www.politico.com/story/2013/03/patent-trolls-are-draining-our-innovation-economy-088517

Schmidt, K. M. (1997). Managerial incentives and product market competition. *The Review of Economic Studies, 64*(2), 191-213.

Schwartz, D. L. (2012). The rise of contingent fee representation in patent litigation. *Alabama Law Review*, *64*(2), 335-388.

Sorenson, O., & Fleming, L. (2004). Science and the diffusion of knowledge. *Research policy*, *33*(10), 1615-1634.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. Andrews DWK, Stock JH, eds. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (Cambridge University Press, Cambridge, UK), 80-108.

Thoman, E. M. (2014). A modern adaptation of three Billy Goats Gruff: Is Vermont's bad faith assertions of patent infringement statute strong enough to help patent owner's safely cross the bridge?. *University of Cincinnati Law Review, 83*(3), 989-1008.

Urbanek, J. H. (2008). A Postmortem for permanent injunctions against business method patent infringement in the wake of EBay v. MercExchange. *DePaul Law Review, 57*(2), 607-638.

Vogel, N. (2015). Patently Preempted. *The John Marshall Review of Intellectual Property Law*, *14*(2), 6.

Yun, W., Kim, D., & Kim, J. (2017). Multi-categorical social media sentiment analysis of corporate events. *Proceedings of the International Conference on Electronic Commerce, 2017*, 1-8.

Zhao, M. (2006). Conducting R&D in countries with weak intellectual property rights protection. *Management Science*, 52(8), 1185-1199.

Table 1. Variable Definitions and Summary Statistics

Variable	Definition	Mean	STD	Median	Min	Max
Dependent Variables						
Backward self-citations	A ratio of the total number of self-citations a firm cited in all its patent applications filed in a given year (which are eventually granted) relative to the total number of all citations (self or external) to the firm's patent applications filed in the same year (which are eventually granted).	0.051	0.104	0.014	0.000	1.000
Forward non-self-citations	A ratio of the total number of forward non-self-citations relative to the total number of all forward citations (self or external), where a patent's forward non-self-citation refers to the citations made by the applicants who are not the patent holders themselves.	0.723	0.327	0.859	0.000	1.000
Explanatory, Interaction and Control Variables						
Post-NPE	For the treatment group (*NPE target* = 1), *Post-NPE* takes the value of 1 since the first year a firm becomes an NPE target, and 0 in the years before that; for the control group (*NPE target* = 0), *Post-NPE* takes on the value of 0 throughout the sample period.	0.160	0.367	0.000	0.000	1.000
Litigation window dummy	A dummy variable that equals one in the first year of the patent litigation.	0.034	0.180	0.000	0.000	1.000
Firm age	The number of years since a firm is publicly listed in Compustat database.	24.122	16.943	19.000	4.000	66.000
Firm size	Natural logarithm of book assets (i.e., ln(assets)).	6.203	2.071	6.019	2.707	11.292
Ln(1+cumulative patents)	Natural logarithm of one plus firm's cumulative number of patents in last three years.	1.468	1.515	1.099	0.000	5.606
R&D intensity	R&D expenses divided by sales.	0.958	5.040	0.038	0.000	43.978
Tobin's Q	The ratio of the market value of assets to book assets, where the market value of assets is defined as the book value of assets minus the book common equity plus the market value of common equity.	2.302	1.916	1.659	0.844	12.283
Sales growth	The average of percent changes of the sales over the last 3 years.	0.229	0.806	0.064	-0.182	6.345
Cash ratio	The sum of cash and short-term investments divided by book assets.	0.284	0.260	0.198	0.009	0.962

Capital intensity	Property, plant and equipment divided by the number of employees.	0.147	0.428	0.038	0.005	3.298
Return-on-assets	Net income divided by book assets.	-0.065	0.236	0.023	-0.732	0.298
Leverage	The sum of long-term and short-term debts divided by the book assets.	0.181	0.216	0.120	0.000	1.181
Z-score	Altman's (1968) Z-score, a measure of creditworthiness.	3.766	7.027	3.107	-8.468	36.951
Industry Tobin's Q	The median Tobin's Q of firms in a three-digit SIC industry.	1.960	0.795	1.686	1.065	4.273
High R&D per patent	An indicator variable that equals 1 if a firm's R&D expenses per patent are above the median and 0 if otherwise. Specifically, R&D expenses per patent are defined as the total R&D expenses (in millions of dollars) in the recent three years divided by the total number of patents in the same period.	0.500	0.500	1.000	0.000	1.000
High rival similarity	An indicator variable that equals 1 if a firm's total similarity is above median and 0 if otherwise, where total similarity is a score that gauges the product similarity between paired firms based on Text-based Network industry classification (TNIC).	0.501	0.500	1.000	0.000	1.000
More rivals	An indicator variable that equals 1 if a firm's number of rivals in the same TNIC industry is above median and 0 if otherwise.	0.502	0.500	1.000	0.000	1.000

Table 2. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Backward self-citations	1																		
2	Forward non-self-citations	-.328	1																	
3	Post-NPE	.044	-.066	1																
4	Ligation window dummy	.013	.013	.426	1															
5	Firm age	-.097	.088	.077	.007	1														
6	Firm size	-.085	.051	.251	.089	.430	1													
7	Ln(1+cumulative patents)	.083	-.118	.129	.056	.000	.171	1												
8	R&D intensity	.123	-.141	-.069	-.031	-.132	-.159	-.005	1											
9	Tobin's Q	.170	-.213	.008	.017	-.206	-.231	.085	.179	1										
10	Sales growth	.125	-.091	-.057	-.015	-.171	-.104	.018	.083	.174	1									
11	Cash ratio	.254	-.240	-.072	-.014	-.427	-.440	.111	.317	.380	.268	1								
12	Capital intensity	-.034	.050	-.023	.009	.177	.290	-.098	-.021	-.100	-.022	-.196	1							
13	Return-on-assets	-.155	.113	.140	.054	.291	.457	.041	-.359	-.272	-.180	-.424	.052	1						
14	Leverage	-.004	-.013	.014	-.013	.136	.223	-.015	-.019	.057	-.001	-.285	.154	-.112	1					
15	Z-score	.036	-.067	.043	.037	-.028	.060	.080	.034	.323	.023	.163	-.065	.341	-.361	1				
16	Industry Tobin's Q	.255	-.347	.027	-.017	-.245	-.234	.028	.239	.419	.212	.467	-.128	-.275	-.053	.097	1			
17	High R&D per patent	-.045	.147	.018	.011	.070	.151	-.707	.004	-.072	-.019	-.105	.068	.002	.133	-.155	.108	1		
18	High rival similarity	-.114	.016	-.046	-.037	.302	.062	-.095	-.170	-.176	-.184	-.343	-.085	.112	.120	-.092	-.225	-.004	1	
19	More rivals	-.114	.009	-.077	-.055	.308	.095	-.138	-.178	-.199	-.174	-.382	-.056	.118	.165	-.117	-.257	.038	.868	1

Notes. All correlation coefficients with a magnitude of 0.02 or greater are significant at the 0.05 level.

Table 3. Descriptive Statistics of the Attributes of Treatment Firms and Control Firms

Variable	Treatment (Mean)	Control (Mean)	Diff.	*p*-value
Firm age	24.195	25.476	-1.281	.343
Firm size	6.876	6.742	0.134	.331
Book-to-market ratio	0.446	0.454	-0.007	.897
Return-on-assets	0.010	-0.004	0.013	.387
R&D-to-assets ratio	0.092	0.077	0.015	.104
Ln(1+patent)	1.496	1.277	0.219	.056
Ln(1+cumulative patents)	2.040	1.832	0.208	.117

Table 4. Main Effects of NPE Litigation on Target Firm Innovation Strategies

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Backward self-citations	Forward non-self-citations	Backward self-citations	Forward non-self-citations	Backward self-citations	Forward non-self-citations
Post-NPE			**0.009**	**-0.017**	**0.008**	**-0.019**
			(.001)	**(.069)**	**(.021)**	**(.024)**
Litigation window dummy					0.004	0.005
					(.322)	(.563)
Firm age	-0.006	-0.072	-0.006	-0.073	-0.006	-0.073
	(.132)	(.176)	(.104)	(.177)	(.103)	(.177)
Firm size	0.004	-0.058	0.004	-0.058	0.004	-0.059
	(.240)	(.000)	(.218)	(.000)	(.225)	(.000)
Ln(1+cumulative patents)	0.003	0.013	0.003	0.013	0.003	0.013
	(.253)	(.731)	(.223)	(.731)	(.209)	(.730)
R&D intensity	-0.109	0.001	-0.121	0.027	-0.121	0.027
	(.061)	(.974)	(.045)	(.524)	(.043)	(.515)
Tobin's Q	0.000	-0.001	0.000	-0.001	0.000	-0.001
	(.611)	(.740)	(.765)	(.827)	(.728)	(.850)
Sales growth	0.016	0.030	0.014	0.032	0.014	0.032
	(.295)	(.420)	(.361)	(.390)	(.362)	(.387)
Cash ratio	-0.013	0.060	-0.012	0.056	-0.012	0.055
	(.406)	(.261)	(.455)	(.286)	(.440)	(.299)
Capital intensity	-0.001	0.472	-0.001	0.476	-0.001	0.476
	(.380)	(.078)	(.452)	(.077)	(.425)	(.077)
Return-on-assets	-0.033	0.151	-0.034	0.154	-0.034	0.155
	(.061)	(.017)	(.049)	(.015)	(.048)	(.014)
Leverage	0.008	-0.019	0.009	-0.021	0.009	-0.021
	(.619)	(.424)	(.568)	(.383)	(.571)	(.377)
Z-score	0.000	0.000	0.000	0.000	0.000	0.000
	(.878)	(.903)	(.813)	(.906)	(.808)	(.905)
Industry Tobin's Q	-0.000	0.008	-0.000	0.008	-0.000	0.008
	(.538)	(.000)	(.502)	(.000)	(.542)	(.000)
Constant	0.160	2.846	0.168	2.851	0.168	2.851
	(.122)	(.064)	(.094)	(.065)	(.092)	(.065)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2205	1728	2205	1728	2205	1728
Adj. R^2	0.619	0.550	0.621	0.550	0.622	0.550

Notes. Exact *p*-values in parentheses. Coefficients are based on robust standard errors clustered by firm. All tests are two-tailed.

Table 5. Moderating Effects of R&D Expenses and Product Market Competition

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Backward self-citations	Forward non-self-citations	Backward self-citations	Forward non-self-citations	Backward self-citations	Forward non-self-citations
Post-NPE × High R&D per patent	**0.035** **(.018)**	**-0.058** **(.014)**				
Post-NPE × Low R&D per patent	0.008 (.464)	0.009 (.377)				
Post-NPE × High rival similarity			**0.016** **(.009)**	**-0.042** **(.045)**		
Post-NPE × Low rival similarity			0.007 (.318)	0.012 (.661)		
Post-NPE × More rivals					**0.016** **(.011)**	**-0.044** **(.038)**
Post-NPE × Fewer rivals					0.009 (.244)	-0.013 (.732)
Litigation window dummy	0.003 (.656)	-0.012 (.220)	0.003 (.518)	0.006 (.415)	0.003 (.616)	0.013 (.148)
Firm age	-0.016 (.278)	0.000 (.986)	-0.014 (.222)	-0.007 (.346)	-0.027 (.245)	-0.007 (.166)
Firm size	0.006 (.508)	-0.069 (.002)	0.002 (.636)	-0.061 (.001)	0.002 (.587)	-0.049 (.000)
Ln(1+cumulative patents)	0.003 (.444)	0.013 (.732)	0.002 (.517)	0.012 (.761)	0.003 (.095)	0.002 (.951)
R&D intensity	-0.211 (.158)	0.058 (.504)	-0.160 (.168)	0.039 (.559)	-0.194 (.055)	0.003 (.969)
Tobin's Q	-0.001 (.639)	-0.005 (.364)	-0.001 (.615)	-0.004 (.285)	-0.000 (.958)	0.012 (.200)
Sales growth	0.017 (.382)	0.034 (.439)	0.017 (.387)	0.038 (.385)	0.021 (.379)	0.003 (.927)
Cash ratio	0.013 (.680)	0.014 (.718)	-0.009 (.666)	0.040 (.390)	-0.006 (.679)	0.023 (.575)
Capital intensity	-0.016 (.716)	0.627 (.085)	-0.002 (.291)	0.501 (.062)	-0.003 (.225)	0.502 (.061)
Return-on-assets	-0.051 (.135)	0.191 (.002)	-0.035 (.102)	0.143 (.015)	-0.036 (.017)	0.120 (.030)
Leverage	0.002 (.962)	-0.019 (.616)	0.017 (.541)	-0.047 (.179)	0.019 (.496)	-0.047 (.282)
Z-score	-0.000 (.730)	0.001 (.519)	0.000 (.952)	0.001 (.383)	0.000 (.757)	0.001 (.699)
Industry Tobin's Q	0.003 (.627)	-0.004 (.698)	-0.000 (.959)	0.008 (.000)	0.000 (.756)	0.008 (.000)
Constant	0.393 (.269)	1.129 (.040)	0.394 (.186)	1.259 (.001)	0.667 (.222)	1.162 (.001)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2205	1728	2205	1728	2205	1728
Adj. R^2	0.622	0.550	0.465	0.542	0.583	0.549

Notes. Exact *p*-values in parentheses. Coefficients are based on robust standard errors clustered by firm. All tests are two-tailed.

Table 6. Two-Stage Least Squares Regression Analysis

	First stage	Second stage	
	Post-NPE	Model 1: Backward self-citations	Model 2: Forward non-self-citations
Texas HQ after 2011	0.070 (.000)		
Post-NPE		**0.032** **(.085)**	**-0.783** **(.041)**
Firm age	0.046 (.393)	-0.013 (.188)	-0.089 (.060)
Firm size	-0.019 (.662)	0.004 (.288)	-0.065 (.219)
Ln(1+cumulative patents)	0.004 (.816)	0.003 (.311)	0.002 (.954)
R&D intensity	0.004 (.000)	0.001 (.006)	0.002 (.221)
Tobin's Q	0.013 (.206)	0.001 (.588)	0.014 (.186)
Sales growth	0.012 (.017)	0.003 (.019)	0.010 (.054)
Cash ratio	-0.074 (.467)	-0.009 (.610)	-0.182 (.188)
Capital intensity	-0.032 (.223)	-0.001 (.421)	0.550 (.080)
Return-on-assets	0.100 (.247)	-0.017 (.131)	0.252 (.032)
Leverage	-0.118 (.187)	0.011 (.334)	-0.005 (.978)
Z-score	-0.001 (.802)	-0.000 (.927)	0.001 (.364)
Industry Tobin' Q	0.016 (.639)	0.001 (.871)	0.043 (.431)
Constant	-0.945 (.547)		
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	3748	2205	1728
Log likelihood	238.5	4641.9	42.1
F-value for weak IV test	11.341		

Notes. Exact *p*-values in parentheses. Coefficients are based on robust standard errors clustered by firm. All tests are two-tailed.

Table 7. Effects of Anti-Patent Troll Law on Innovation Strategy

	Model 1	Model 2
	Backward self-citations	Forward non-self-citations
Post-state law	**-0.007**	**0.009**
	(.039)	**(.085)**
Firm age	-0.007	-0.009
	(.458)	(.607)
Firm size	-0.000	0.047
	(.996)	(.017)
Ln(1+cumulative patents)	0.008	-0.020
	(.091)	(.004)
R&D intensity	0.035	0.241
	(.725)	(.014)
Tobin's Q	0.002	0.011
	(.657)	(.113)
Sales growth	-0.020	0.016
	(.221)	(.008)
Cash ratio	0.009	-0.060
	(.536)	(.090)
Capital intensity	-0.011	0.106
	(.224)	(.004)
Return-on-assets	0.032	0.011
	(.585)	(.417)
Leverage	0.015	-0.002
	(.786)	(.563)
Z-score	-0.000	-0.001
	(.496)	(.118)
Industry Tobin's Q	0.000	-0.004
	(.261)	(.740)
Constant	0.183	-0.048
	(.252)	(.898)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
N	4444	4444
Adj. R^2	0.734	0.598

Notes. Exact *p*-values in parentheses. Coefficients are based on robust standard errors clustered by firm. All tests are two-tailed.

Figure 1. Conceptual Framework

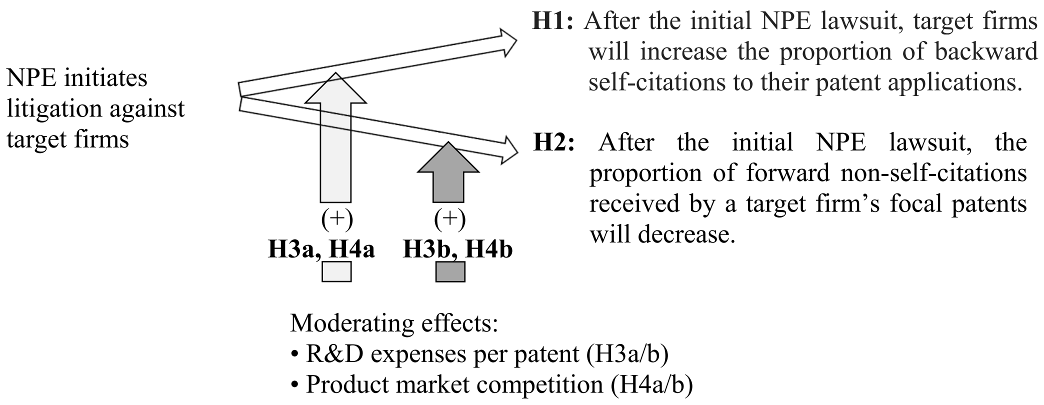


Figure 2. Patent Litigation Cases against Publicly Listed Firms

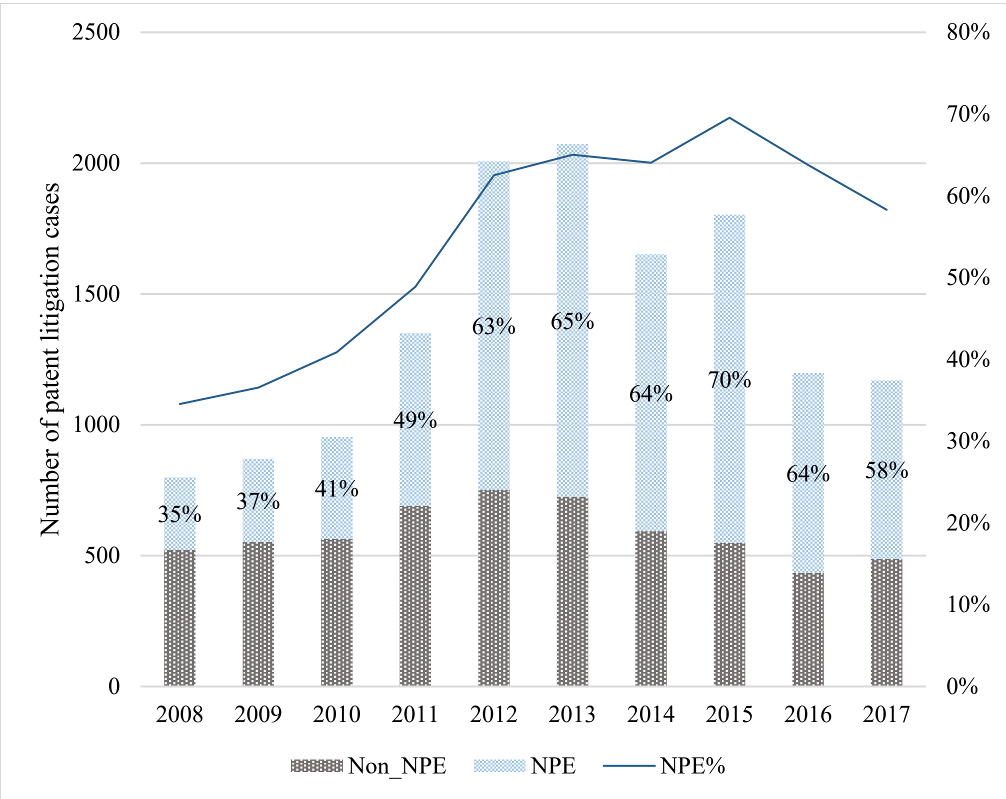


Figure 3. Estimated Effect of NPE Lawsuit on Backward Self-Citations

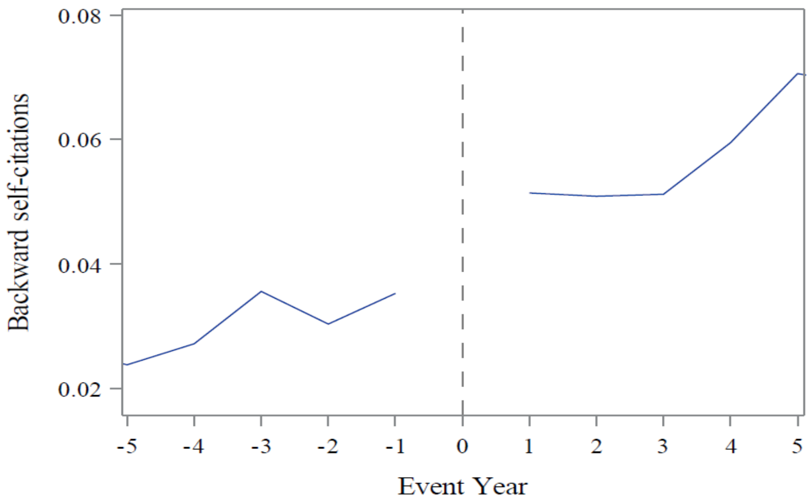


Figure 4. Estimated Effect of NPE Lawsuit on Forward Non-Self-Citations

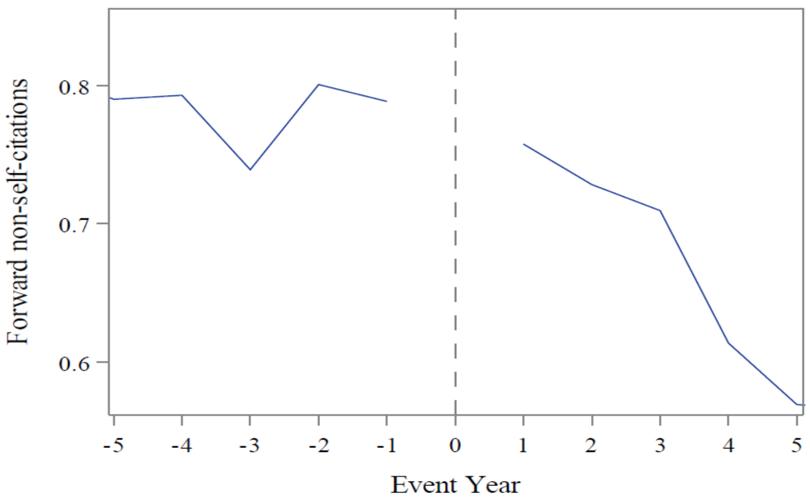
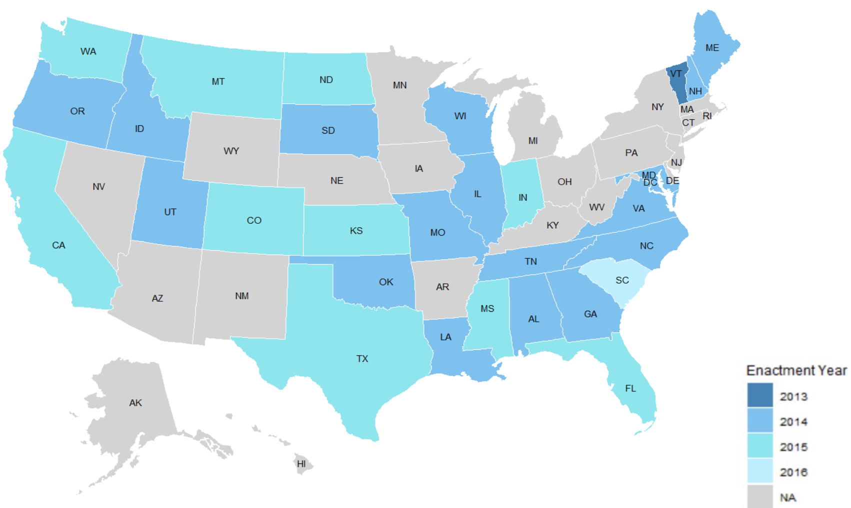


Figure 5. Enactment of the Anti-Patent Troll Law across Different States in the US



Appendices

Appendix Table 1. Inward-Looking Innovation Strategy and NPE Litigation Risk

	Model 1	Model 2
	Indicator of Sued by NPE starting from year t+1	Indicator of Sued by NPE between year t+1 and t+5
Backward self-citations	**-3.014**	**-2.702**
	(.056)	**(.076)**
Firm age	-0.037	-0.036
	(.000)	(.000)
Firm size	0.640	0.614
	(.000)	(.000)
Ln(1+cumulative patents)	0.437	0.372
	(.000)	(.000)
R&D intensity	-3.086	-2.893
	(.012)	(.015)
Tobin's Q	-0.017	0.012
	(.857)	(.897)
Sales growth	-0.534	-0.832
	(.313)	(.155)
Cash ratio	2.182	1.941
	(.007)	(.013)
Capital intensity	-0.100	0.010
	(.922)	(.992)
Return-on-assets	-0.892	-0.752
	(.422)	(.487)
Leverage	-0.899	-0.950
	(.356)	(.315)
Z-score	-0.026	-0.025
	(.315)	(.320)
Industry Tobin's Q	0.015	-0.020
	(.936)	(.911)
Constant	-6.305	-5.826
	(.000)	(.000)
Year fixed effects	Yes	Yes
N	528	528
-2 Log L	724.666	720.986

Notes. Exact p-values in parentheses. Coefficients are based on robust standard errors clustered by firm. All tests are two-tailed.

Appendix Table 2. NPE Litigation Risk and Firm Patenting

	Model 1	Model 2
	Number of patents	Change in number of patents
Post-NPE	**-0.038**	**-0.572**
	(.087)	**(.005)**
Litigation window dummy	0.074	0.594
	(.022)	(.305)
Firm age	-0.011	0.025
	(.768)	(.870)
Firm size	0.235	-0.239
	(.000)	(.599)
R&D intensity	0.004	1.139
	(.962)	(.104)
Tobin's Q	0.029	0.248
	(.000)	(.000)
Sales growth	0.074	1.635
	(.205)	(.110)
Cash ratio	-0.485	0.979
	(.008)	(.481)
Capital intensity	-0.264	0.461
	(.000)	(.026)
Return-on-assets	0.239	3.133
	(.045)	(.025)
Leverage	-0.170	-0.971
	(.349)	(.358)
Z-score	-0.003	0.011
	(.501)	(.638)
Industry Tobin's Q	-0.015	0.002
	(.363)	(.001)
Constant	2.064	-0.540
	(.052)	(.798)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	3845	3845
Adj. R^2		0.033
pseudo R^2	0.833	

Notes. Exact *p*-values in parentheses. Coefficients are based on robust standard errors clustered by firm. All tests are two-tailed.

Appendix Table 3. NPE Litigation Risk and Technology Competition

	Model 1	Model 2
	Backward self-citations	Forward non-self-citations
Post-NPE × Technology-intensive	**0.012** **(.030)**	**-0.064** **(.000)**
Post-NPE × Non-Technology-intensive	0.005 (.177)	0.014 (.539)
Litigation window dummy	0.004 (.520)	0.006 (.547)
Firm age	-0.006 (.085)	-0.072 (.178)
Firm size	0.004 (.015)	-0.062 (.000)
Ln(1+cumulative patents)	0.003 (.067)	0.010 (.775)
R&D intensity	-0.123 (.011)	0.023 (.671)
Tobin's Q	0.000 (.718)	-0.001 (.872)
Sales growth	0.014 (.522)	0.001 (.042)
Cash ratio	-0.012 (.242)	0.051 (.421)
Capital intensity	-0.001 (.548)	0.442 (.078)
Return-on-assets	-0.035 (.008)	0.168 (.007)
Leverage	0.008 (.558)	-0.020 (.350)
Z-score	0.000 (.779)	0.000 (.822)
Industry Tobin's Q	-0.000 (.535)	0.008 (.000)
Constant	0.162 (.075)	2.863 (.061)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	2205	1728
Adj. R^2	0.622	0.551

Notes. Exact *p*-values in parentheses. Coefficients are based on robust standard errors clustered by firm. All tests are two-tailed.