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Escaping the patent trolls: The impact of non-practicing entity litigation on firm innovation strategies

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Abstract

Research Summary: Non-practicing entities (NPEs) are firms that accumulate and acquire patents but do not further develop or implement the patented inventions (known as patent trolling). NPEs seek to receive royalties or profits through out-of-court settlements in patent infringement cases. We examine how firms targeted by NPEs in NPE-initiated litigations (i.e., target firms) shift their innovation strategies and trajectories in response to heightened litigation risks. We theorize and show that after the initial lawsuit, target firms draw more upon their in-house technologies to reduce the legal ground for further lawsuits. Furthermore, nontarget firms in related technology areas shift their innovation activities away from those of target firms under high NPE litigation risks. These effects are more pronounced with higher innovation costs and under more competitive product markets.

Managerial Summary: Non-practicing entities (NPEs) are known as patent trolls that accumulate and acquire patents but do not further develop or implement these patented inventions. These patent trolls aim to obtain royalties or profits through out-of-court settlements in patent infringement cases. We investigate how firms targeted by patent trolls in litigations (i.e., target firms) change their innovation strategies and trajectories to deal with increased NPE litigation risks. After the initial lawsuit, we find that these target firms use their in-house technologies more to reduce the legal ground for future lawsuits. Moreover, nontarget firms in related technology areas move their innovation activities away from those of target firms under high litigation risks. These effects are stronger when innovation costs are higher and under more competitive product markets.

KEYWORDS

innovation strategy and trajectory, litigation, non-practicing entity, patent troll, technology management and policy

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 (IP) rights facilitate and increase firms' incentives to innovate by providing formal legal protection against expropriation (Arora & Gambardella, 2010a, 2010b; Hsu et al., 2021; Hu & Png, 2013; Huang, 2010; Huang et al., 2017; Levin et al., 1987). We have witnessed significant innovation-driven economic growth in developed economies such as that of the United States (US) over the past several decades, in which the patent system provides vital protection and incentives for important technological breakthroughs (Ahuja & Katila, 2001; Huang et al., 2024; Mazzoleni & Nelson, 1998; Miric et al., 2023; Steil et al., 2002). 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 seek to accumulate and acquire patents and build their portfolios to enforce their IP rights and litigate against potential infringers but do not further develop or implement the patented inventions in any products, processes, or services.[1] NPEs often do not seek to stop patent infringements, but instead aim at receiving royalties or earn monetary profits through private remedies or out-of-court settlements (Cohen et al., 2016, 2019).

[1]By contrast, practicing entities (PEs), such as Intel and IBM, file litigations for patent infringements so as to protect their rights in the future development of products and/or processes and applications of the focal patent.

Recent studies have shown that NPEs harm the collective welfare of society and reduce firms' research and development (R&D) investment. Bessen et al. (2011) find that NPE litigations have cost defendants about half a trillion US dollars of wealth between 1990 and 2010. Cohen et al. (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.

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 (henceforth, target firms). Building upon insights from the transaction cost theory, prior studies have found that *ex ante*, under fragmented patent market, firms patent aggressively to avoid potential hold-up problems (Huang & Murray, 2009; Ziedonis, 2004). In addition, when firms' intellectual assets could not be well protected by IP rights, they develop more internal linkages and use more internal technologies (Zhao, 2006). Drawing upon and extending this theoretical perspective, we theorize that *after* the first (unexpected) litigation by the NPE, it could become difficult, risky or no longer feasible for the firms targeted by NPE to practice or patent aggressively in the areas of NPE litigation because the NPE has already owned and claimed many of the patents in those areas, thus creating hold-up problems. To avoid future hold-up problems in the face of rising threat of litigations by NPEs, a logical and plausible response is therefore for the target firms to avoid these specific areas of high hold-up risks by shifting to a more "inward" innovation strategy 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 future 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. Finally, these effects should be more pronounced when the patented technologies are costlier 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 firms 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

[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/).

[3]Blank Rome LLP, an IP law firm, indicated, "Unfortunately, no one has been able to come up with a patentable method for avoiding being sued for patent infringement (by patent troll)" https://www.blankrome.com/siteFiles/Defending_Against_Patent_Trolls.pdf.

(e.g., Fishwick, 2013).[4] 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 plausibly exogenous event. We find that compared with their coarsened exact matched control firms, which have never experienced any NPE litigation, the firms in the treatment group show 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 nontarget firms in related technology areas will shift their locus of innovation away from those of the target firms. In other words, these nontarget 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 the innovation costs for the patented technologies is higher and when the product markets are more competitive. Our qualitative semi-structured interviews with 20 senior executives, technology/R&D managers, lead engineers and patent attorneys in 19 firms across different technology sectors corroborate our findings.

This study makes several contributions. First, we contribute to the heated debate on how patent trolling and litigation lawsuits affect the innovation activities of target firms and potential reactions of peer firms. 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 strategies and trajectories. Drawing upon and extending the theoretical perspective of the hold-up problem from transaction cost theory, our study fills this important gap by investigating the *ex post* responses of the target firms to the (unexpected) litigation by the NPEs.[5] Importantly, we show that litigation can actually shape firms' innovation strategies and trajectories. Prior literature has focused on how firms' strategies shape their behaviors and actions and hence their chance of being involved in litigations. Our study contributes to this research stream by providing a novel and different perspective and shows that the impact of litigation on firms' strategic behavior is just as salient.

Second, we document the potentially detrimental effects of NPE litigations 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 et al. (2013) find that the positive spillover created by corporate R&D investment outweighs its negative effects on product market competition. Other scholars argue that the

[4]The occurrence of NPE litigation is largely unpredictable (Fishwick, 2013). We note that although NPE lawsuits are commonly preceded by a cease-and-desist letter, the warning time a firm receives before a lawsuit is generally not too long. Specifically, the cease-and-desist letters usually demand the target firms to respond within a very short time frame, such as 2 weeks (Grinvald, 2015).

[5]Our study is substantially different from prior studies such as Kiebzak et al. (2016) and Lemley and Feldman (2016). Kiebzak et al. (2016) examine the effect of NPEs on venture capital investments. Lemley and Feldman (2016) conduct a qualitative study and explore whether NPEs may either directly or indirectly contribute to the creation of new products of a society. They suggest that there is little evidence to support the notion that NPEs could have a positive impact. Unlike these studies, the focus of our paper is on the innovation strategies and trajectories of the NPE-target firms, and the moderating effects of innovation costs for the patented technologies and competitiveness of the product markets.

spillover effects could be related to post-R&D long-run stock performance, role of government and trade secret laws (e.g., Chen et al., 2013; Jia et al., 2019; Rathje & Katila, 2021; Wang, 2023). Our study shows that NPE litigation threats induce target firms to build more upon their prior patented knowledge and compel their peer firms to move away from potentially useful and important technology areas under NPE litigation risks. This could reduce the positive knowledge spillover beneficial to their industries and society and be detrimental for innovation-driven economies relying on cumulative knowledge production for growth.

Third, our study advances our understanding of the effects of US anti-patent troll legislation and its policy implications. Most states in the United States 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. This large-scale empirical evidence provides strong justification for the adoption and implementation of anti-patent troll legislation across different states in the United States, 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, which could help guide policymaking and decisions.

2 | CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

2.1 | NPE lawsuits and their costs to target firms

NPEs seek to accumulate and acquire patents and build their portfolios to enforce their IP rights and litigate against potential infringers but do not further develop or implement the patented inventions in their products, processes, or services. NPEs often do not seek to stop the patent infringements, but instead aim at receiving royalties or earn monetary profits through private remedies or out-of-court settlements (Cohen et al., 2016, 2019; Giordano-Coltart & Calkins, 2008; Luxardo, 2006; Reitzig et al., 2007).

NPEs acquire patents strategically and frequently assert ownership over important components of specific products and technologies of the target firms through patent litigations. 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 IP Lawyer's Association, litigation costs per patent related to claim construction could reach 2.4 million US dollars or more.[6,7] In addition, based on the PwC 2018 Patent Litigation Study, the median damages

[6]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.
[7]https://blueironip.com/what-are-the-costs-to-enforce-or-defend-a-patent/.

award for NPEs was 14.8 million US dollars from 2013 to 2017.[8] 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).

2.2 | The hold-up problem in transaction cost theory and effects of NPE litigation

When NPEs file for infringement of the patents, they own and initiate patent litigations against target firms, these target firms could run the risks of being "held up" and incur its associated costs after investing in and developing the technologies patented by the NPEs. The hold-up problem, which has been long studied in transaction cost theory, occurs when one party has made specific investments in a transaction and thus becomes vulnerable to be expropriated by the other party (e.g., Torrisi et al., 2016). A key insight derived from transaction cost theory is that conventional market contracts are insufficient in providing adequate protection against expropriation when investments are made in specific assets. In other words, when these assets cannot be easily repurposed or transferred to another user without substantial loss of value, simple market contracts provide inadequate safeguards (Klein et al., 1978). In the context of patenting, firms need to adopt a different set of strategy when they face the threat of being "held up" by NPEs (Galetovic et al., 2015). Based on transaction cost theory (Williamson, 1985), firms tend to adopt one of two strategies: (i) internalize transactions that involve highly specific assets (e.g., choosing to "make" rather than "buy") or (ii) reduce investments in areas where the risks of expropriation are high.

Building upon these insights from the transaction cost theory, prior studies have found that *ex ante*, firms patent aggressively to avoid potential hold-up problems under fragmented patent market (Ziedonis, 2004). On the other hand, when firms' intellectual assets could not be well protected by IP rights, they develop more internal linkages and use more internal technologies (Zhao, 2006). Drawing upon and extending this theoretical perspective, we theorize that *after* the initial (unexpected) litigation by the NPE, which is highly unpredictable (Fishwick, 2013), it becomes difficult or no longer feasible for the target firms to practice or patent aggressively in the areas of NPE litigation because of the hold-up problem which arises from NPE already owning and claiming many of the patents in those areas. To avoid future hold-up problems in the face of rising threat and potential future litigations by the NPEs, a logical and plausible response is therefore for the target firms to avoid these specific areas of high hold-up risks by shifting to a more "inward" innovation strategy to protect themselves from further advances of NPEs after the initial NPE lawsuit. This would allow the target firms to substantially reduce the

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

risks of being targeted by NPEs again and incurring further direct and indirect patent litigation costs.

This inward innovation strategy is practical and feasible as it allows the target firms to conduct a more focused examination of their existing and typically limited patent portfolio (e.g., dozens of patents) for continued innovation development of their patents that are not susceptible to the patents of the NPE. This approach would also be less costly in terms of time and resources than an avoidance approach whereby target firms simply avoid all technology areas where NPEs hold and assert patents, which could involve a comprehensive examination of a large and extensive number of patents (e.g., hundreds or thousands of patents) from other firms. Nevertheless, we argue that adopting an inward innovation strategy does not preclude the use of avoidance approach. Specifically, target firms could draw more upon their in-house technologies to reduce the potential legal ground for NPE lawsuits in the future while avoiding technology areas (in their patent portfolio) with high-NPE litigation risks.

Indeed, a senior manager in a computer and electronics manufacturer (Gigabyte Technology) articulated in an interview that "our company was sued by patent trolls … and we focus on our existing technologies as a way to avoid the litigation risk posed by patent trolls." A similar inward strategy was also confirmed by at least two other lead engineers in the semiconductor sector whose companies (Intel and Quanta) have been sued by patent trolls, as well as a compliance officer from biotechnology industry (Grape King Bio Ltd.), who pointed out that after their companies have been sued by NPEs, focusing on existing (in-house) technologies is one of their strategies (see Section 4.5 for details).

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). A higher number of self-citations indicate that a firm internalizes more knowledge created by its own R&D efforts, which suggests a strong competitive position in a 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 holdups from outside patent owners (Alcacer & Gittelman, 2006; Zhao, 2006).

Therefore, we postulate that after the target firms have become the defendants in NPE-initiated lawsuits, they will adopt an inward innovation strategy. Specifically, target firms will draw more upon their in-house technologies (as reflected by an increase in the proportion of backward self-citations to their patents) to reduce the potential legal ground for further NPE lawsuits. This leads to our first hypothesis:

> **Hypothesis (H1).** After the initial NPE lawsuit, target firms will draw more upon their in-house patented innovations.

The null hypothesis associated with H1 is that the target firms just accept the risk of being held up and 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.

The potential risk of litigations initiated by patent trolls and being held up by them 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 et al. (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 target firm imposes the same restriction on all other firms using the same technology when those parties are part of the same lawsuit and a verdict is reached in court for the dispute. Nevertheless, such precedent ordered by the court may alter the expectations of other firms that they could face the cease-and-desist letters or be sued by the NPE following the successful verdict against the target firm. 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 (nontarget 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.

Therefore, we hypothesize that after observing the occurrence of NPE lawsuits, the nontarget peer firms in related technology areas will shift the locus of their innovation activities away from those of the target firms (as reflected by a decrease in the proportion of forward non-self-citations to their patents) to avoid the areas with high NPE litigation risks.[9] This leads to the following prediction:

> **Hypothesis (H2).** After the initial NPE lawsuit, target firms' patented innovations will be used less by nontarget peer firms.

2.3 | Moderating role of innovation costs

Based on the hold-up problem in transaction cost theory, the following factors significantly influence a firm's contracting problem in markets for technologies: (i) the costs associated with being "held up" after investing in technologies NPEs later claimed in their patents and (ii) the additional problems posed by a competitive product market where multiple firms compete in similar technological areas. We discuss in turn each of these factors that may influence the effect of the heightened NPE litigation risks on firms' decision to shift their innovation strategy.

First, the costs associated with being "held up" by NPEs will be higher when the target firms have invested more in technologies later claimed in the NPE's patents. Indeed, the target firms would be in a much weaker negotiation position if they have only learned about the patented technology, which have already incurred a large amount of innovation investments, after embedding the technology in their firms' operation and processes that are difficult or costly to redeploy. Here, the patented technology has become a highly specific asset (based on transaction cost theory) as the target firms do not know that NPEs would claim the ownership of this intellectual asset before their innovation investment decision.

[9]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, due to potential hold-up risks in the future and given 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.

Accordingly, we posit that target firms may respond to NPE litigation risks more vigorously when they undertake costlier innovation development. Since inventors generally get a temporary reward of annual earnings for a given patent (Toivanen & Väänänen, 2012), firms commonly spend more on producing each patent involving more inventors hired to develop such a patent/technology project. A patent/technology project involving more inventors is typically also more complex and thus costlier (Huang, 2017; Huang & Murray, 2009). Thus, to assess the potential costs going into individual patented technology, we construct the measure, number of inventors per patent, as a proxy for the innovation development cost of a given patent.[10]

Firms which have incurred a high cost for developing a more complex patented innovation would suffer more loss than those firms which have invested little in producing an incremental patented innovation if the costlier patents were targeted by NPEs in litigations, potentially creating a more serious hold-up problem. In other words, if such litigations on costlier patents are upheld and focal firms can no longer use their patents which have incurred high innovation costs, these firms would suffer more than firms with less costly patents targeted by the NPE litigations. These firms are also more vulnerable when being held up by NPEs and have higher incentive to accept out-of-court settlements in NPE litigations. Therefore, when the investment on technology innovation is costlier, 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 (H3a).** The increase in the use of target firms' in-house patented innovations after the initial NPE lawsuit will be more pronounced when the costs for such patented innovations are greater.

Following similar logic, when the innovation cost of a particular technology area is high, suggesting higher costs when being "held up," it not only attracts more NPE litigations but also makes the outcome of the litigations, such as out-of-court settlements, costlier for the nontarget firms in related technology areas. These nontarget firms are thus more likely to shun such technological areas. Therefore, the hypothesized relationship depicted in H2 will be more pronounced when the costs of such patented innovations are greater. This leads to the next prediction:

> **Hypothesis 3b (H3b).** The effect that target firms' patented innovations are used less by nontarget peer firms will be more pronounced when the costs for such patented innovations are greater.

2.4 | Moderating role of product market competition

The risk and cost of being held up would be higher in a competitive product market in which the target firms operate, where multiple firms compete in similar technological areas. 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 NPE litigations particularly in a hold-up problem (Baggs & De Bettignies, 2007). Therefore,

[10]The *average R&D expenditure per patent* provides another measure of the R&D expenditure/cost on average for each patent at the firm level. We describe the operationalization of this measure in a robustness analysis in subsequent sections.

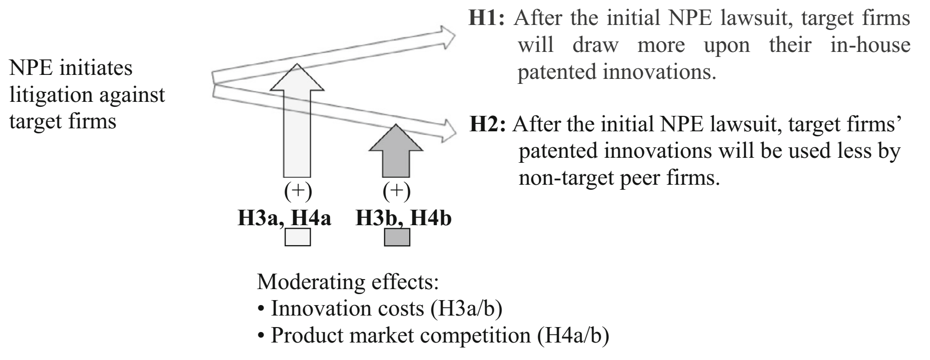

FIGURE 1 Conceptual framework.

these firms must respond quickly to any emerging threats in their operating environment to survive and outperform their competitors, a notion that has been studied and affirmed in prior papers (e.g., Hoisl et al., 2017). 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 nontarget firms in related technology areas (as depicted in H1 and H2, respectively) should be more pronounced in a competitive product market. Thus, we make the following predictions (H4a and H4b, which correspond to H1 and H2, respectively):

> **Hypothesis 4a (H4a).** The increase in the use of target firms' in-house patented innovations after the initial NPE lawsuit will be more pronounced when competition in the product market in which the target firms operate is stronger.

> **Hypothesis 4b (H4b).** The effect that target firms' patented innovations are used less by nontarget peer firms will be more pronounced when competition in the product market in which the target firms operate 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 the innovation costs (number of inventors) and product market competition.

3 | METHODOLOGY

3.1 | Empirical context and strategy

There is a growing trend in NPE litigations over the past decade, which is of vital concern to managers and policymakers. This is shown in Figure 2 which plots the number of patent

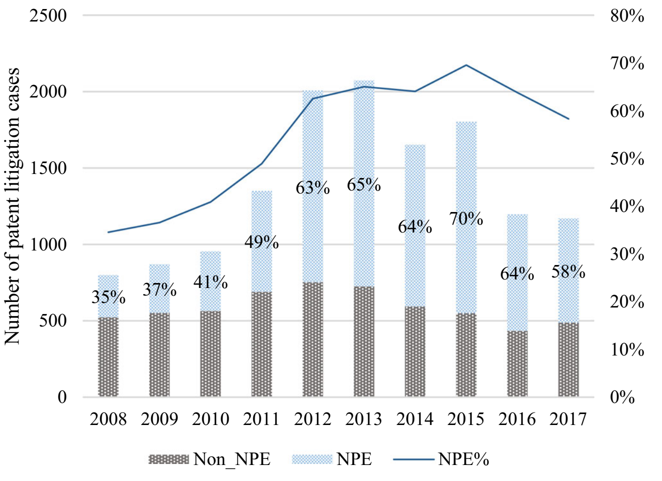

FIGURE 2 Patent litigation cases against publicly listed firms.

litigation cases by NPE and non-NPE against publicly listed firms on NYSE/NASDAQ/AMEX.[11]

In our empirical analyses, we focus on the effect of the initial NPE litigation filed against a target firm in the United States. We consider this a plausibly exogenous event and perform a staggered difference-in-differences analysis that relies 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.[12]

We match firms in the treatment group to firms in the control group by coarsened exact matching (CEM) using the following variables: *firm age*, *firm size*, *cash level*, *industry*, and *year*. *Firm age* is defined as the number of years since a firm was publicly listed. *Firm size* is the natural logarithm of total assets, that is, ln(assets). *Cash level* is the natural logarithm of cash level, that is, ln(cash). *Industry* denotes the industry indicator based on two-digit SIC code and *year* is the year of observation. The CEM process allows us to obtain a highly comparable group of control firms to the treatment group of firms (see Section 3.3 for the descriptive statistics) (e.g., Jain & Huang, 2022). As a robustness check, we find qualitatively similar and consistent results using the propensity score matching procedure (details available upon request).

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

[11]The figure of patent litigation cases against all firms shows a similar trend.
[12]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).

3.2 | Data

To test our predictions, we construct a longitudinal dataset of publicly listed firms in the United States 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.[13] 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 US 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).

Finally, 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 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 CEM procedure as described in Section 3.1, the sample contains 1379 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 proportion 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) to the total number of all citations (self or external) made in 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 drawing and building upon its own in-house technologies relative to technologies from other firms.

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

The second dependent variable is *forward non-self-citations*, which is the proportion of the total number of forward non-self-citations 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 (nontarget) 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 nontarget 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 innovation costs per patent, we construct *more* (*less*) *inventors per patent*, which is an indicator variable that equals 1 if the average of numbers of inventors per patent for the firm is above (below) the median and 0 if otherwise. When *more inventors per patent* takes on the value of 1, it indicates that the innovation cost of developing a patented technology for a firm is relatively high. As a robustness check, we construct the variables, *high* (*low*) *R&D per patent*, using the ratio of R&D expenditures to the number of patents of a firm as another proxy of innovation costs at the firm level.[14] We find consistent empirical results when using R&D expenditures per patent (more details in Section 4.2).

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. Specifically, Hoberg and Phillips (2010, 2016) utilize the unique words employed by firms in describing their products within the business description sections of their 10-K reports, and then reduce the high-dimensional word vectors into a concise matrix, which represents the pairwise similarity scores among the firms. This year-by-year product similarity measures allow us to generate a set of industries in which firms can have their own distinct set of competitors. The product similarity score should be low for a diversified firm facing tough competition in each of its industries. 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.[15] *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.

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[14] *High* (*low*) *R&D per patent* 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 3 years divided by the total number of patents in the same period.

[15] 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.

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 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 *cumulative patents*, defined as the cumulative amount of innovation output produced by the firm in the recent 3 years.[16] 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 3 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. *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 include firm fixed effects and year fixed effects in all regression models to control for unobserved time-invariant firm characteristics and unobserved changes over time, respectively.

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.

In Table 3, we show the descriptive statistics of our CEM sample by comparing the treatment and control firms. Specifically, we report the mean of the key variables for the treatment and control groups and perform the two-sample test. None of the mean (except *firm age*) differ between treatment and control firms at the 5% significance level. Overall, the CEM process yields a well-matched treatment group and control group of firms for the empirical analysis.

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 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*,

[16]The results remain consistent when we operationalize *cumulative patents* as ln(1 + patents) instead of ln(1 + cumulative patents).

TABLE 1 Variable definitions and summary statistics.

Variable	Definition	Mean	Std. dev.	Median	Min	Max
Dependent variables						
Backward self-citations	The proportion of the total number of self-citations a firm cited in all its patent applications filed in a given year (which are eventually granted) 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	The proportion of the total number of forward non-self-citations 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
Cash level	Natural logarithm of cash level (i.e., ln(cash)).	4.949	1.289	4.929	0.000	7.684
Cumulative patents	Natural logarithm of one plus firm's cumulative number of patents in last 3 years (i.e., ln(1 + cumulative patents)).	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

TABLE 1 (Continued)

Variable	Definition	Mean	Std. dev.	Median	Min	Max
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
More inventors per patent	An indicator variable that equals 1 if the average of the numbers of inventors for a given patent for the firm is above the median and 0 otherwise.	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	20
1	Backward self-citations	1.000																			
2	Forward non-self-citations	−0.348	1.000																		
3	Post-NPE	0.155	−0.086	1.000																	
4	Ligation window dummy	0.024	0.026	0.459	1.000																
5	Firm age	−0.045	−0.026	0.000	−0.065	1.000															
6	Firm size	−0.123	0.002	−0.016	−0.068	0.398	1.000														
7	Cash level	0.005	−0.066	−0.024	−0.043	0.194	0.800	1.000													
8	Cumulative patents	0.344	−0.272	0.069	−0.039	0.184	0.351	0.355	1.000												
9	R&D intensity	0.265	−0.069	0.138	0.059	−0.386	−0.429	−0.085	0.030	1.000											
10	Tobin's Q	0.203	−0.072	−0.035	−0.019	−0.224	−0.216	−0.013	0.038	0.291	1.000										
11	Sales growth	0.110	−0.122	−0.130	−0.036	−0.355	−0.128	−0.020	−0.001	0.173	0.374	1.000									
12	Cash ratio	0.282	−0.142	−0.012	0.040	−0.375	−0.453	0.073	−0.035	0.625	0.401	0.236	1.000								
13	Capital intensity	0.081	0.018	−0.044	−0.033	−0.065	0.132	0.080	0.123	0.081	0.027	0.058	−0.021	1.000							
14	Return-on-assets	−0.079	0.013	0.142	0.024	0.178	0.392	0.313	0.141	−0.352	−0.163	−0.031	−0.232	−0.033	1.000						
15	Leverage	−0.041	0.026	−0.064	−0.019	0.142	0.274	0.134	0.093	−0.180	0.005	−0.074	−0.177	0.079	−0.118	1.000					
16	Z-score	0.161	−0.040	−0.016	−0.022	−0.124	−0.090	0.079	0.145	0.137	0.464	0.278	0.339	0.071	0.240	−0.394	1.000				
17	Industry Tobin's Q	0.196	−0.214	0.161	0.010	−0.251	−0.083	0.009	−0.056	0.277	0.343	0.156	0.222	0.029	−0.098	0.061	0.005	1.000			
18	More inventors per patent	−0.055	0.081	−0.032	−0.023	0.060	0.150	0.225	−0.027	−0.003	0.041	0.023	−0.028	0.027	0.004	0.029	−0.007	0.020	1.000		
19	High rival similarity	0.128	−0.002	0.152	0.119	−0.299	−0.097	0.095	0.003	0.436	0.063	0.079	0.282	−0.057	−0.091	−0.015	−0.043	0.217	0.051	1.000	
20	More rivals	0.089	0.013	0.143	0.110	−0.354	−0.134	0.049	−0.028	0.448	0.056	0.109	0.281	−0.090	−0.124	−0.004	−0.052	0.253	0.029	0.880	1.000

Note: 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
Cash level	4.955	4.988	−0.033	.514
Firm size	6.563	6.611	−0.047	.402
Firm age	24.691	26.242	−1.551	.007
R&D intensity	0.282	0.253	−0.029	.802
Sales growth	0.159	0.178	−0.019	.618
Capital intensity	0.044	0.046	−0.002	.192

Note: None of the mean (except firm age) differ between treatment and control firms at the 5% significance level.

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 (OLS) regression model in Equation (1):

$$\begin{aligned}
&\text{Backward self}-\text{citation}_{i,t}(\text{forward non}-\text{self}-\text{citations}_{i,t})\\
&\quad=\alpha+\beta_1\,\text{post}-\text{NPE}_{i,t}+\beta_2\,\text{litigation window dummy}_{i,t}+\beta_3\,\text{firm age}_{i,t-1}\\
&\qquad+\beta_4\,\text{firm size}_{i,t-1}+\beta_5\,\text{cumulative patents}_{i,t-1}+\beta_6\,\text{R\&D intensity}_{i,t-1}\\
&\qquad+\beta_7\,\text{Tobin's Q}_{i,t-1}+\beta_8\,\text{sales growth}_{i,t-1}+\beta_9\,\text{cash ratio}_{i,t-1}\\
&\qquad+\beta_{10}\,\text{capital intensity}_{i,t-1}+\beta_{11}\,\text{return}-\text{on}-\text{assets}_{i,t-1}+\beta_{12}\,\text{leverage}_{i,t-1}+\beta_{13}\,\text{Z}\\
&\qquad-\text{score}_{i,t-1}+\beta_{14}\,\text{industry Tobin's Q}_{i,t-1}+\text{firm fixed effects}+\text{year fixed effects}+\varepsilon_{i,t}
\end{aligned}\tag{1}$$

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

In all models, we include robust standard errors to account for possible heteroscedasticity and lack of normality in the error terms (Greene, 2004). All models include firm fixed effects and year fixed effects. Robustness check using a double-censored Tobit model yields consistent results in terms of statistical significance and effect sizes to the OLS models (details available upon request).

4 | RESULTS

4.1 | 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* in Model 3. 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 = .017).

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 (.017)	−0.030 (.000)	0.007 (.048)	−0.040 (.003)
Litigation window dummy					0.004 (.401)	0.022 (.253)
Firm age	−0.000 (.969)	0.324 (.440)	−0.001 (.899)	0.319 (.454)	−0.001 (.893)	0.319 (.458)
Firm size	0.005 (.239)	0.031 (.010)	0.004 (.292)	0.032 (.011)	0.004 (.306)	0.031 (.015)
Cumulative patents	0.006 (.072)	0.029 (.195)	0.007 (.048)	0.025 (.251)	0.007 (.050)	0.025 (.253)
R&D intensity	−0.248 (.048)	0.346 (.405)	−0.250 (.048)	0.347 (.399)	−0.249 (.048)	0.346 (.407)
Tobin's Q	0.000 (.798)	0.012 (.004)	0.000 (.887)	0.012 (.003)	0.000 (.882)	0.012 (.003)
Sales growth	−0.008 (.684)	0.069 (.100)	−0.009 (.644)	0.068 (.110)	−0.009 (.663)	0.070 (.103)
Cash ratio	−0.034 (.074)	0.086 (.035)	−0.034 (.070)	0.081 (.034)	−0.034 (.070)	0.080 (.022)
Capital intensity	−0.057 (.293)	0.504 (.015)	−0.058 (.262)	0.509 (.016)	−0.059 (.256)	0.505 (.018)
Return-on-assets	−0.066 (.013)	0.184 (.356)	−0.066 (.013)	0.186 (.349)	−0.066 (.015)	0.188 (.348)
Leverage	−0.014 (.365)	−0.078 (.075)	−0.014 (.362)	−0.075 (.072)	−0.014 (.365)	−0.075 (.062)
Z-score	0.000 (.616)	−0.002 (.076)	0.000 (.492)	−0.002 (.063)	0.000 (.484)	−0.002 (.059)
Industry Tobin's Q	0.000 (.182)	0.008 (.000)	0.000 (.185)	0.008 (.000)	0.000 (.155)	0.008 (.000)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1379	1034	1379	1034	1379	1034
Adj. R^2	.611	.530	.613	.530	.613	.530

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

Given that the mean and standard error of the variable *backward self-citations* are 0.051 and 0.104, respectively, it represents a 17.6% increase relative to the sample mean or 8.65% increase relative to the standard error (also see footnote 28). By contrast, we find a *negative* effect of *post-NPE* on *forward non-self-citations* in Model 4. Specifically, after the first NPE case, *forward non-self-citations* decrease by 3% ($p = .000$). Given that the mean and standard error of the variable *forward non-self-citations* are 0.723 and 0.327, respectively, it represents a 4.15% decrease relative to the sample mean or 9.17% decrease relative to the standard error. In the most stringent (and preferred) Models 5 and 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 Models 3 and 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 0.7% ($p = .048$). Therefore, results from Models 3 and 5 lend support to Hypothesis H1. 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 4% ($p = .003$).[17] Therefore, results from Models 4 and 6 provide support for Hypothesis H2.[18]

We examine the temporal trends of the effects of the initial NPE lawsuit on target firms' *backward self-citations* and *forward non-self-citations*, as shown in Figures 3 and 4, respectively. 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, nontarget 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.

4.2 | Moderating effects of innovation costs

We first investigate how the costs of patented innovation, as proxied by the number of inventors for a given patent, moderate 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 *more* (*less*) *inventors per patent* in our regression Models 1 and 2 in Table 5.[19] The coefficient of the interaction variable *post-NPE* × *more* (*less*) *inventors per patent* captures the moderating effect. As shown in Model 1 of Table 5, the coefficient of *post-NPE* × *more inventors per patent* is positive and significant ($\beta = .018$, $p = .017$) while the coefficient of *post-NPE* × *less inventors per patent* is not significant ($\beta = .013$, $p = .204$). By comparing these two coefficients, our results support Hypothesis H3a. That is, the increase in the

[17]We use the *number of forward non-self-citations* and *number of backward self-citations* as alternative dependent variables in separate regressions for robustness checks and find consistent results (see Section 5.8).

[18]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.

[19]Note that a "constrained" model is a standard approach in econometrics, which compares two sets of constrained interactions (e.g., Huang & Murray, 2009; Murray & Stern, 2007), for example, *Post-NPE* × *More inventors per patent* versus *Post-NPE* × *Less inventors 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.

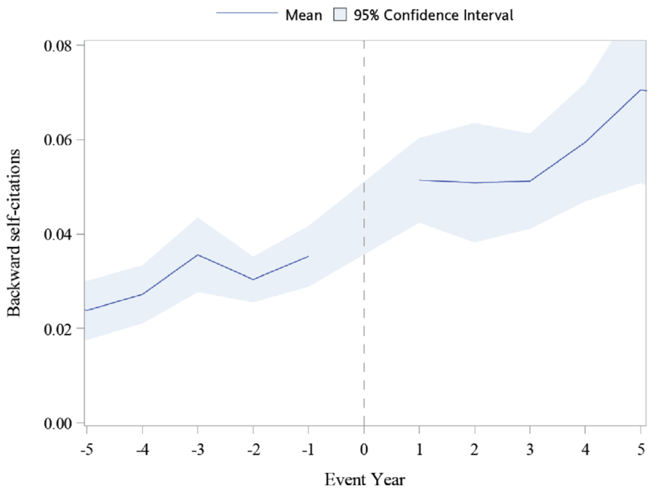

FIGURE 3 Estimated effect of non-practicing entities (NPEs) lawsuit on backward self-citations.

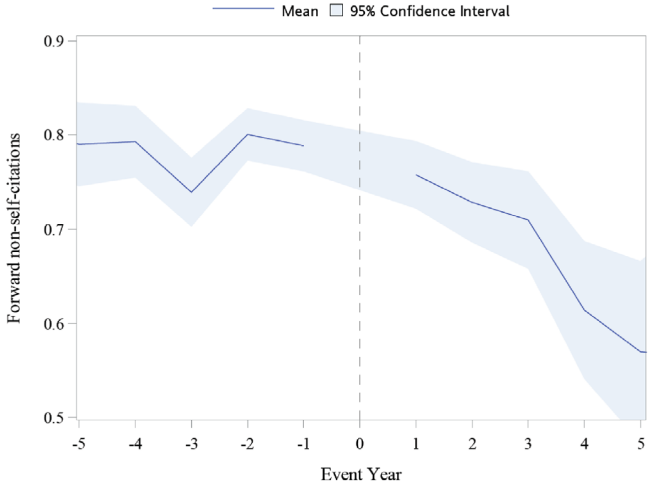

FIGURE 4 Estimated effect of non-practicing entities (NPE) lawsuit on forward non-self-citations.

proportion of backward self-citations to patented innovations of the target firm after the initial NPE lawsuit will be more pronounced when the number of inventors for the patented innovation is higher.

On the other hand, as shown in Model 2, the coefficient of *post-NPE* × *more inventors per patent* is negative and significant ($\beta = -.045$, $p = .072$), but the coefficient of *post-NPE* × *less inventors per patent* is not significant ($\beta = -.039$, $p = .462$). Therefore, our results support Hypothesis H3b. 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 number of inventors for the patented innovation is higher.

As previously mentioned, we perform a robustness check by substituting *post-NPE* × *more* (*less*) *inventors per patent* with *post-NPE* × *high* (*low*) *R&D per patent* in Models 1 and 2 of Table 5, respectively. The results are highly consistent (details available upon request).

TABLE 5 Moderating effects of number of inventors 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 × More inventors per patent	0.018 (.017)	−0.045 (.072)				
Post-NPE × Less inventors per patent	0.013 (.204)	−0.039 (.462)				
Post-NPE × High rival similarity			0.008 (.087)	−0.040 (.093)		
Post-NPE × Low rival similarity			0.009 (.208)	−0.039 (.182)		
Post-NPE × More rivals					0.008 (.054)	−0.047 (.019)
Post-NPE × Fewer rivals					0.005 (.349)	−0.066 (.121)
Litigation window dummy	−0.000 (.951)	0.023 (.620)	0.004 (.459)	0.024 (.470)	0.004 (.362)	0.039 (.224)
Firm age	−0.001 (.765)	0.783 (.004)	−0.006 (.695)	−0.003 (.911)	−0.040 (.000)	0.000 (1.000)
Firm size	−0.001 (.968)	0.071 (.067)	0.002 (.798)	0.039 (.277)	0.005 (.379)	0.030 (.405)
Cumulative patents	0.013 (.033)	0.052 (.278)	0.008 (.026)	0.027 (.382)	0.006 (.091)	0.018 (.604)
R&D intensity	−0.088 (.152)	0.067 (.187)	−0.266 (.004)	0.008 (.604)	−0.128 (.050)	0.148 (.564)
Tobin's Q	0.000 (.983)	0.019 (.003)	0.001 (.196)	0.011 (.395)	0.001 (.373)	0.009 (.408)
Sales growth	0.021 (.453)	0.114 (.060)	−0.018 (.419)	0.019 (.049)	−0.014 (.385)	0.012 (.342)
Cash ratio	−0.026 (.086)	0.199 (.001)	−0.040 (.005)	0.056 (.374)	−0.022 (.089)	0.066 (.321)
Capital intensity	0.037 (.765)	0.569 (.576)	−0.056 (.057)	0.187 (.743)	−0.034 (.355)	0.475 (.153)
Return-on-assets	−0.039 (.442)	0.085 (.291)	−0.017 (.043)	0.079 (.264)	−0.013 (.169)	0.073 (.378)
Leverage	−0.023 (.464)	−0.023 (.837)	−0.010 (.549)	−0.150 (.457)	−0.009 (.381)	−0.053 (.357)
Z-score	−0.000 (.997)	−0.005 (.000)	0.000 (.498)	−0.002 (.420)	0.000 (.361)	−0.001 (.454)
Industry Tobin's Q	0.083 (.131)	0.076 (.117)	0.000 (.370)	0.008 (.000)	−0.000 (.641)	0.008 (.000)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1126	870	1366	1025	1366	1025
Adj. R^2	.529	.518	.594	.523	.624	.532

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

4.3 | 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*.[20] As shown in Model 3 of Table 5, the coefficient of the interaction term *post-NPE* × *high rival similarity* is positive and significant ($\beta = .008$, $p = .087$), whereas the coefficient of *post-NPE* × *low rival similarity* is not significant ($\beta = .009$, $p = .208$). 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 ($\beta = .008$, $p = .054$), whereas the interaction term *post-NPE* × *fewer rivals* is not significant ($\beta = .005$, $p = .349$). Taken together, these results lend support to Hypothesis H4a. 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.[21]

As shown in Model 4 of Table 5, the coefficient of the interaction term *post-NPE* × *high rival similarity* is negative and significant ($\beta = -.040$, $p = .093$), while the coefficient of the interaction term of *post-NPE* × *low rival similarity* is not significant ($\beta = -.039$, $p = .182$). Similarly, in Model 6, the coefficient of the interaction term *post-NPE* × *more rivals* is negative and significant ($\beta = -.047$, $p = .019$) but the coefficient of *post-NPE* × *fewer rivals* is not significant ($\beta = -.066$, $p = .121$). Taken together, our results support Hypothesis H4b. 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.

4.4 | Additional analyses of other moderating effects

We discuss and perform further analyses of the moderating effects of standard essential patents (SEPs), product life cycle, firm size, and information computer technology (ICT)-related sectors. We provide the details in the Appendix. In summary, we find that (i) firms in SEP-related industries are less likely to shift their innovation strategies when facing patent trolling; (ii) despite having different product life cycles (and therefore varying product development speeds), there is no significant difference in terms of how these firms shift their innovation strategies in response to NPE threats; (iii) the effects on *backward self-citations* and *forward non-self-citations* are more salient for small firms compared with large firms; and (iv) the effect of NPE litigation is stronger in ICT-related sectors than in non-ICT sectors.

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

[21] 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.

4.5 | Qualitative evidence from interviews

Our qualitative semi-structured interviews with 20 senior executives, technology/R&D managers, lead engineers and patent attorneys in 19 firms across different technology sectors corroborate our findings. Their job titles of our interviewees include process supervisor, compliance officer, lead engineers, project managers and patent attorneys. To help us obtain a better understanding across different types/sizes of firms, many of the interviewees work in large and well-established firms, such as Intel, Taiwan Semiconductor Manufacturing Company (TSMC) and Quanta Computer Inc., while others work in smaller firms and startups in electronics, computer science and biotechnology. Appendix Table A1 shows some examples of the quotes taken from these interviews and the corresponding job titles and industries of the interviewees. During the interviews, we asked the interviewees what their companies' responses were after being sued by an NPE and if their companies have any strategies in place should they be sued by an NPE. Our theory posits that after firms are sued by NPEs, they tend to shift their focus to developing in-house R&D projects to reduce the threat of future NPE litigation. The responses we gathered from these interviews are generally consistent with our predictions. For instance, a process supervisor in TSMC replied: "our company has been bothered by patent trolling… and the company plans to identify the risky technological areas that are vulnerable to patent trolling so we can avoid them." A senior manager in a computer and electronics manufacturer (Gigabyte Technology) mentioned that "our company was sued by patent trolls … and we focus on our existing technologies as a way to avoid the litigation risk posed by patent trolls." A similar strategy was also confirmed by at least two other lead engineers in the semiconductor sector whose companies (Intel and Quanta) have also been sued by patent trolls. A patent attorney concurred and added that "companies may change their product or commercialization strategy, depending on whether there are any blocking third party patents… Not only does it affect their R&D and commercialization plans, investors will also ask about it during IP due diligence for financing rounds."

Another implication of our theoretical predictions is that a firm would have lower incentive of escaping patent trolling if it or its main competitor has not yet been involved in an NPE litigation. The response from a compliance officer working in a biotechnology firm (Grape King Bio Ltd.) from our interview is supportive of such an implication. The compliance officer offered the following discussion: "our company has not been sued by any patent trolls. The top management of the firm does not seriously consider the threat of patent trolls as a factor when developing our patent portfolio…. However, another company that I previously worked for (FSP Group) had the experience of being involved in NPE litigation. Hence, that firm considered patent trolling as a serious threat and implemented a so-called 'patent landscape' project, whereby it constructed the patent portfolio carefully in order to avoid the areas with high litigation risk. I presume this is the so-called 'once bitten, twice shy' effect." A similar discussion is provided by another compliance officer in technological firm Egis Technology Inc.

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 (2SLS) regression analysis (Section 5.1) and (ii) a difference-in-differences estimation using the difference in the timing of the enactment of the anti-patent troll law across different US states as a plausibly exogenous event (Section 5.2). In Section 5.3, we provide further analyses of how an inward innovation strategy is associated with fewer subsequent NPE litigations. In Section 5.4, we discuss the avoidance and inward innovation strategies. In Section 5.5, we conduct a supplementary analysis of the effect of NPE litigation on target firms' patenting behavior. In Section 5.6, we perform a supplementary analysis of NPE litigation risk and technology competition. In Section 5.7, we discuss the effect of NPE litigation on alternative measures of citations in the same patent class as the patents of the target firms. In Section 5.8, we perform robustness checks using alternative dependent variables and subsample analyses. In Section 5.9, we conduct robustness analyses on citations added by patent examiner versus applicant. Finally, in Section 5.10, we discuss whether firms just focus on their areas of core competencies in response to the NPE lawsuit.

5.1 | 2SLS regression analysis

In 2012, the US passed the America Invents Act (AIA), which significantly increased the litigation costs for patent trolls. Accordingly, NPEs turn to the court of the Eastern District of Texas—the court that is known to be generally friendly to plaintiffs, leading to a remarkable increase in the number of patent infringement cases filed in the court of the Eastern District of Texas since 2012 (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. Further, since the passage of the AIA is exogenous to the firms and not influenced by the firm managers, this potential instrument meets the criteria of a suitable instrumental variable (Bettis et al., 2014). 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 2SLS regression analysis to mitigate the potential endogeneity issue and find consistent result in Appendix Table A2.

5.2 | Difference-in-differences analysis of anti-patent troll laws

Anti-patent troll laws are legislations that punish bad faith patent assertions in an attempt to halt patent trolling. 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, to a certain degree, exogenous to the firms, we use it as a plausibly exogenous event in a difference-in-differences regression analysis.[22] We present the results of the difference-

[22]We acknowledge the limitations of a staggered difference-in-differences model per discussion in Baker et al. (2022).

in-differences regression analysis in Appendix Table A3. The results suggest that when the threat of patent trolling reduces after the passage of the anti-patent troll laws, firms rely less on in-house technologies, and nontarget 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.

5.3 | Inward 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 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 A4. The dependent variable is an indicator variable, which takes the value of 1 if the firm was sued by an NPE between year $t + 1$ and $t + 5$ and 0 otherwise. We regress the binary dependent variable on *backward self-citations* together with the control variables. We find that the adoption of a more inward innovation strategy (i.e., greater *backward self-citations*) is associated with less future risk of a given firm being sued by an NPE, whether we use the number of backward self-citations (Model 1) or the proportion of backward self-citations (Model 2). More importantly, we elaborate on the economic significance of the results. We find that 1% increase in the proportion of backward self-citations reduces 3% of NPE takeover probability. This reduction can lead to an expected cost reduction of $4.22 million for an innovating firm.[23]

As a related issue, we also examine whether there is a significant change in the mix of IPC classes in which a target's patents are filed. We construct a new variable, *shifting technology classes* that measures the extent to which a firm shifts its technology class and moves into new technology areas. Specifically, for a given year, this variable is constructed as the inverse of the percentage of the patents that are in the same three-digit IPC classes with the patents this firm has applied 3 years ago (for instance, for the event year set as 0, this measure shows the percentage of overlap of the IPC classes between the patent portfolios in the year 0 and year −3). Robustness checks using year −1 and year −2 yield consistent results. Using *shifting technology classes* as the dependent variable, we find a negative and significant coefficient on *Post-NPE*, indicating that firms are *less* likely to enter new technology areas after initial NPE lawsuits. This result is consistent with our main finding that the NPE-targeted firm engages in more inward innovations.

5.4 | Inward innovation strategy and avoidance approach

We further discuss and empirically test the inward innovation strategy and avoidance approach in this section. Technology-based firms that aim to mitigate NPEs' litigation threat

[23]Based on Bessen et al. (2011), the average cost per NPE litigation case is about $140.6 million based on an estimation of changes in market capitalization of the defendant. Therefore, the expected cost reduction for an innovation firm is $140.6 million × 0.03 = $4.22 million. When we use the number of backward self-citations as the explanatory variable, the economic significance is even stronger, where 1% increase in the number of backward self-citations reduce 4% of NPE takeover probability.

could undertake one of the following approaches as a response to the NPE threat—that is, (i) both inward and avoidance strategy; (ii) only inward strategy; and (iii) only avoidance strategy. To test which one of the three strategic approaches receives the strongest empirical support, we construct two new variables associated with parts of the backward self-citation proportion, depending on whether the cited patent is in the same technological area (three-digit IPC class) as those asserted by NPEs in the first litigation case (our plausibly exogenous event). The part that overlaps with NPE-asserted areas is denoted as *backward self-citations overlapped with NPE-asserted IPC classes*; the part that does not overlap is denoted as *backward self-citations independent from NPE-asserted IPC classes*. We then re-estimate the baseline regression model using these two new dependent variables, and report the results in Appendix Table A5. Our results suggest that in response to NPE threat, target firms adopt an inward innovation strategy while choosing those areas (in their patent portfolio) away/independent from the high-NPE litigation risk areas (option i). We provide related discussion in the Appendix.

5.5 | 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 after being sued by NPEs (see Appendix Table A6 Model 1). The result is consistent if we use the dependent variable, *Change in number of patents*, as shown in Appendix Table A6 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.

5.6 | 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 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). 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. We perform regression analysis that compares 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* (details are available upon request). We find that the reaction of target firms to NPE lawsuits is significantly stronger when firms operate in industries with a high level of technology competition compared with those firms not operating in these industries.

5.7 | 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.

5.8 | Alternative dependent variables and subsample analyses

We perform the following robustness checks. The main dependent variables, *backward self-citations* and *forward non-self-citations*, in our analyses are constructed as proportions to control for the influence of firms with more (less) patents and hence more (less) citations. To ensure that our results are not purely driven by the inclusion of more forward self-citations over time, we first perform a robustness check using the *number of forward non-self-citations* and *number of backward self-citations* as alternative dependent variables in separate regression models and continue to find consistent results.

Second, we also reexamine our main regression analysis using a subsample in which we exclude the firms ever sued by PEs. Specifically, before we start the matching using CEM procedure, we removed all the firms in both treatment and control groups that were ever sued by PE at any given point of time during our sample period. Therefore, it is safe to say that any results drawn from the analyses using such a subsample should be free of the influence of PE litigations. The results are largely consistent with our main findings (details available upon request), which lend support to the notion that our findings are not driven by PE litigations.

Third, we note that most of the NPE lawsuit cases in our dataset (more than 75%) involved only one defendant. As a robustness check, we drop the sample involving more than one defendant which yields consistent results as those shown in Table 4 (details available upon request). Furthermore, we estimate the regression using the standard error clustered at the case-level (i.e., clustering the standard error across treatment firms and their corresponding matching firms if they are sued in the same NPE case). We find consistent results in this analysis.

5.9 | Citations added by the applicant versus citations added by the examiner

We collect examiner citations data that allow us to separate our citations into applicant- and examiner-added citations. We then investigate to what extent the NPE lawsuits may affect these two types of citations. We find that the results on *backward self-citations by applicants* and *forward non-self-citations by applicants* as the dependent variables, respectively, are consistent with our main results (Table 4). The result on *forward non-self-citations by examiners* as the dependent variable shows a consistent direction although it is not significant. The result on *backward self-citations by examiners* as the dependent variable is also not significant. We provide the empirical results and related discussion in Table A7 of the Appendix.

5.10 | Focusing on core competencies

When a focal target firm adopts an inward innovation strategy, as manifested in an increase in the backward self-citations, it could also mean that firms focus on their core competencies, that is, that they focus on technology areas in which they are particularly strong. To explore whether the target firm focuses on their core competencies, we separate *backward self-citations* into two groups—that is, the cited patents that are in the core technology/IPC class of the target firm and the cited patents that are in other IPC classes. To determine a target firm's core IPC class, we count the number of patents the firm applied for in each IPC class over the past 5 years and calculate its proportion to the total number of patents applied for. The IPC class with the highest proportion is defined as the core class (using more or fewer number of years as cut-off or including the top two or three IPC classes yield similar results). If an IPC class is not the firm's core IPC class, it is considered its other IPC class. We then reconstruct the backward self-citations proportions using such self-citations in the firm's core and other IPC classes, respectively. Empirical results in Table A8 of the Appendix shows that the effects of *post-NPE* on *backward self-citations in core IPC class* and on *backward self-citations in other IPC classes* are both significant and positive, suggesting that the target firms do not merely focus on their areas of core competencies in response to the NPE lawsuit.

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, nontarget 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 the innovation costs (numbers of inventors) for the patented technologies are greater 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 moving away from potentially useful technological areas they used to build upon.

Our study echoes the seminal work by Cohen et al. (2019) in several ways. First, our study extends Cohen et al. (2019) by extending their findings, which advances our understanding of how patent trolls affect corporate innovation. Cohen et al. (2019) find that the target firms reduce R&D activities (as shown in their Table 7). We further explore the target firms' strategic responses to NPE litigations and find that they not only invest less in innovation but also adjust their innovation strategies by shifting the locus of their innovation. Second, we find that although cash holding is an important factor in how NPEs choose their target, firms with relatively low amount of cash still face substantial NPE litigation risk.[24] Therefore, given that a reduction in cash level cannot mitigate NPE threats entirely, NPE-targeted firms could be

[24]To examine how NPE litigation risk is related to cash holding, we divide the entire sample (of firm-year observations) obtained from Compustat between 2008 and 2018 into quartiles based on cash holdings. We then study the percentage of firms that experienced NPE lawsuits in each quartile. Consistent with the findings in Cohen et al. (2019), we find a positive relationship between cash holding and NPE litigations. Nevertheless, we also observe that the percentages of firms targeted by NPEs remain sizeable for firms with relatively low cash holdings. Specifically, the percentages of NPE litigation are 4.47 and 7.03% for the lowest and second lowest cash level quartiles, respectively.

incentivized to respond in other ways, such as adopting a more inward innovation strategy as theorized and empirically tested in this study.

The findings from this article 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. Indeed, decision-makers and managers in firms should be cognizant of the impact of NPE litigations and how anti-patent troll laws can potentially help enhance collaborative activities 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 United States. Prior research has proposed an automatic process of administrative review at the threshold of infringement lawsuits in US district courts (Cohen, Golden, et al., 2017; Cohen, Gurun, & Kominers, 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. These laws regulating the behavior of NPEs are indeed vital to facilitate technological progress in the industry and in society.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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