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Media coverage and patent trolls: A study on US high-tech firms☆

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ABSTRACT

This paper investigates the impact of media coverage on a nonpracticing entity (NPE) patent litigation concerning the defendant firms. Using a sample of high-tech and patent-intensive firms from the US market between 2000 and 2020, we find that NPEs tend to target highly visible firms. This result is more pronounced when the firms are large and experience positive sentiment in the market. We ensure the causality of this relationship using the anti-troll law, which is targeted to curb the threat of NPE trolls, as a natural experiment and distance from the nearest news branch as an instrumental variable. We find that after suing the target firms, the return of the plaintiff, or the NPE firm, increases. Our results provide new insight into the effect of media coverage on firms' litigation environment.

1. Introduction

This study examines whether firms' higher visibility attracts nonpracticing entity (NPE) litigation. NPEs are a form of organization that has emerged as a significant driver of patent litigation in the last two decades. NPEs purchase patent rights not to produce commercial products but to claim license fees and litigation against infringement (Shrestha, 2010). To do so, they persistently send demand letters to rival firms.[1] Because litigation is too expensive for the defendant firms (Bessen and Meurer, 2013), they tend to come into early settlement by paying settlement fees, which is the main profit for NPE firms. NPEs rarely produce products; instead, their target is to optimize the settlement fees by frivolously suing the patent-intensive firm. The extant literature refers to them as patent trolls.

The increase in NPEs has yielded a debate about their impact on innovation (Cohen et al., 2019). Proponents claim that NPEs perform a key financial intermediary role. They police well-off firms' infringements that could otherwise infringe upon small inventors' patents without going through any consequences; however, most literature argues against NPEs in that they purposely raise the cost of innovation by exploiting the cost of the legal process. Additionally, the risk remains that imperfect courts may rule in NPEs' favor even if no infringement has occurred. Furthermore, even if the defendant can survive the validity test, the threat of a legal process can yield rents from the innovative firms. Bessen and Meurer (2013) find that NPE lawsuits led to almost half a trillion dollars in lost wealth to the defendants from 1990 to 2010 in the US market.[2] They also investigated that NPEs cost defendants around 29 billion USD in 2011, a 400% increase from over 7 billion US dollars (USD) in 2005. NPEs also impose indirect costs on firms. Appel et al. (2019) finds that frequent patent infringement claims made by NPEs affect US start-ups' ability to grow, create jobs, innovate, and raise capital. Kiebzak et al. (2016) argues that frivolous litigation from the NPEs deters entrepreneurial activity, and Chien (2011) discusses the severe effect of NPEs on small firms. Even though NPEs pose a significant threat to innovation and firm performance, little is known about the determinants of NPE litigation. Only Cohen et al.

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[1] MPHJ, which is one of the most notorious NPEs, sent demand letters to over 16,000 firms between 2012 and 2013 but never filed a lawsuit.

[2] In an event study of 1630 lawsuits on stock prices (4114 events using a 5 day window to measure returns), Bessen, Ford, and Meurer (2011) find that NPE lawsuits lead to almost half a trillion USD lost wealth to the defendants from 1990 to 2010 in the US market. During the last four years of this sample period, the lost wealth averaged at least 80 billion USD per year.

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(2019) investigate that NPEs strategically target cash-rich firms to optimize their expected litigation payoff. Our study investigates whether media coverage has any bearing on NPE litigation.

The media can significantly influence corporate behavior (Zyglidopoulos et al., 2012), as media works as a corporate governance mechanism. For example, Bushee and Miller (2012) argue that higher press coverage largely reduces the degree of information asymmetry during earnings announcement periods. Positive media coverage generates positive outcomes for the firms; for example, higher visibility leads to a lower cost of equity (Baker et al., 2002) and cost of debt (Cheng et al., 2006). Increasing media attention can also raise the firm's corporate social responsibility (CSR) strengths (Zyglidopoulos et al., 2012) and credit rating (Hao and Li, 2021). This paper hypothesizes that NPEs target firms with higher visibility and those more capable of paying settlement fees.

Our testable hypothesis is based on the signaling theory, which primarily discusses reducing the information asymmetry between two or more parties (Spence, 2002). The extant literature has used signaling theory to explain information asymmetry in various research contexts. For example, in a study of corporate governance, Zhang and Wiersema (2009) examine how chief executive officers (CEOs) signal the dormant quality of their firms to potential investors by the visible quality of their financial statements. Miller and Triana (2009) explain how firms use heterogeneous boards to signal adherence with social values to diverse organizational stakeholders. Our study is related to the literature examining how the media signals firms' financial and market outcomes. For example, Hao and Li (2021) argue that a firm's credit ratings increase with higher media visibility. Using the Spanish data from 2004 to 2019, Peña-Martel et al. (2021) find that media attention increases the firm's research and development (R&D) investment. Zyglidopoulos et al. (2012) argue that media attention as an awareness measure can significantly increase CSR investment. Cook et al. (2006) find that a firm's pre-IPO publicity predicts positive stock return on the day of its initial public offering (IPO). Concisely, more visible firms usually send a positive signal about their underperformance and capability to pay the settlement amount imposed by NPEs during litigation.

Cohen et al. (2019) posit that "NPEs sue cash-rich firms and target cash in business segments unrelated to alleged infringement at essentially the same frequency as they target cash in segments related to alleged infringement". In contrast, Miller (2010) finds that NPEs litigate relatively stronger patents than those litigated by practicing entities and individuals. The study also finds that NPE patent litigation is more prevalent in the technological areas characterized as new or permitting relatively broad patents. Therefore, NPEs choose their cases strategically, i.e., the financially strong firms, to optimize their expected litigation payoff. The sole purpose of NPE litigation is trolling, and NPEs are opportunistic in selecting their target to ensure their expected litigation payoff; therefore, it is legitimate to expect that they would troll highly visible firms, which should be able to pay the settlement amount imposed by NPEs during litigation. Therefore, the media signals the NPEs about the ability of the firms to pay settlement costs, and firms, which are more visible in the media, are targeted more frequently by NPEs.

We test the hypothesis by examining whether firm visibility increases the threat of NPE litigation. Our study's sample comprises 22,558 firm-year observations with 3326 NPE lawsuits from 2000 to 2020. The ordinary least squares (OLS) regressions show that firms with higher visibility are more likely to be sued by NPEs. A one-unit increase in visibility leads to a 9% chance for the firm to be sued by an NPE. Our result is economically significant as it is coherent with Cohen et al. (2019), who find that a one standard deviation increase in cash-level increases the probability of being sued by an NPE by 7.40%. The OLS results are robust to alternative estimation models, such as the probit and Cox-hazard models, and control for broader industry conditions and economy-wide effects.

To test the robustness of our baseline regression, we use measures of firm visibility, such as *Analyst coverage*, *Google SVI*, *Visibility rank*, *All news*, and *Firm visibility dummy*. Analysts act as informational intermediaries between firms and shareholders to increase the information quality and quantity (Chou and Shiah-Hou, 2010; Jiraporn et al., 2012). They analyze the publicly available data, including financial statements, earnings-related disclosure data, and other announcements, and allocate their analysis regarding the financial information to the public. The coefficient of the *Analyst coverage* is very similar to our primary independent variable, i.e., *Visibility*. We use *Google SVI,* i.e., the number of web-search about the companies by year, as a proxy of *Visibility* from the Google Trend website. We measure *Visibility rank* as the standard rank of the total number of product/patent-related news articles; *All news* is the natural logarithm of the number of all news plus one, and the *Firm visibility dummy* to be equal to 1 for the firm is covered by the RavenPack in a given year, and 0 otherwise. All of these variables show positive coefficients at a 1% significance level, which justifies the robustness of our baseline estimation.

As another form of robustness test, we examine whether firm size matters in NPE litigation. Casterella et al. (2010) examine the corporate litigation risk for audit firms. They find that firm size and growth are positively significant with litigation risk. The argument is that as larger firms have more clients than smaller firms, they are more known and vulnerable to litigation risk. Similarly, we argue that as large firms, such as Microsoft, Google, and IBM, receive greater media attention than smaller firms, we expect large firms to be exposed to higher rates of NPE trolling than smaller firms. By interacting the *Visibility* with the *Large firm* and *Small firm*, we find that when large firms are more visible, they are more threatened by the NPEs. In contrast, when a *Small firm* interacts with *Visibility*, the coefficient becomes negative and significant. Perhaps the *Visibility* of the *Small firm* makes the lower strength of the firm clearer to the NPEs. Therefore, NPEs troll the smaller firms less. All of the results prove that size matters regarding visibility and NPE threats.

Identifying a causal effect of firm visibility on NPE litigation is challenging. Jensen (1979) suggests that the business press inclines to accommodate the public's taste and report sensational news. Therefore, firms threatened by NPE litigation might be more visible in the media. To mitigate this endogeneity issue, we conduct a two-stage instrumental variable analysis using *Distance* from the firm headquarters to the nearest Dow Jones news branches. Gurun and Butler (2012) argue that a firm's media coverage and the content of this coverage are contingent on the distance between the firm and news outlets. To the extent that journalists incur higher costs by collecting and analyzing information from distant firms, longer travel time lowers the likelihood of news coverage. Second, long travel time between news outlets and a firm can reduce media attention and interest in the firm; *Distance* is negatively related to *Visibility* in the first regression stage. In the second stage, least square regression, the coefficient of the *Instrument visibility* on the NPE litigation is positive and statistically significant at 1%.

We conduct additional tests to investigate the endogeneity problem by including the anti-troll law as an interaction term. Beginning with Vermont in 2013, some US states adopted patent reforms through anti-troll law that protects local businesses from bad faith infringement claims. The main goal of the anti-troll law was to curb the NPEs' discretion in sending mass demand letters. The independent variable, *Visibility*, interacts with the *Antitroll*

dummy to differentiate the treatment and control firms. The coefficient of *Visibility* alone remains positive and statistically significant in the firm place; however, when *Visibility* interacts with the *Antitroll dummy*, we find a largely negative and statistically significant outcome. Therefore, after a state adopts the anti-troll law, the NPEs' effect abates enough to eliminate the positive effect of the *Visibility* on the *NPE* threat. Therefore, the baseline results remain robust even after controlling for the potential endogeneity between *Visibility* and *NPE* lawsuits.

Next, we investigate the economic channel through which firm visibility may attract NPE litigations. According to our NPE opportunism hypothesis, the relationship between firm visibility and NPE threat is built on the arguments that media coverage disseminates firm-specific information to the market participants and that NPEs are opportunistic as they target firms that are highly capable of paying off settlement fees. That is, firms with good performance are associated with more positive news coverage, and those firms, in turn, may attract more NPE trolls. To empirically test this hypothesis, we divide the firm news into four groups, i.e., negative sentiment and positive sentiment in the 25th percentile, 50th percentile, and 75th percentile. We find that negative sentiment is negatively related to the NPE litigation. Conversely, the significantly positive coefficient increases with the increase in the percentile of the positive sentiment news. This finding is consistent with our conjecture that NPEs are opportunistic and target stronger firms capable enough to pay the settlement cost.

Another economic channel that induces the NPEs to threaten the patent-intensive firms is the plaintiffs' willingness to establish their identity. According to identity theory (Burke, 1991), we conjecture that the NPEs aim to protect their interests and express/build their identity by targeting highly visible firms. Positioning oneself vis-à-vis a highly visible company is one of the easiest ways for NPEs to establish and signal their identity, suggesting that by taking legal action against a high-performance firm, NPEs may try to prove their identity similar to the sued firm in the market. Therefore, after the lawsuit, the NPE's (plaintiff) return is expected to rise because by suing a highly visible firm, NPEs try to prove that they are as strong as the targeted firm. Using the monthly return data from the Center for Research in Security Prices (CRSP), we find that the plaintiff firms' return rises significantly at 1% in the first and second months following the litigation. In contrast, the plaintiff or NPE stock return is insignificant before the lodgement of a lawsuit. Therefore, NPEs as plaintiffs are incentivized to sue a highly visible firm because it ensures the settlement costs and establishes their identity in the market.

Finally, we intend to test how detrimental NPE litigation is for the defendant firms by examining the impact of NPE litigation on the defendants' stock return. The extant literature argues that the NPEs create substantial wealth loss to the defendant firms by frivolously suing. In an event study of 1630 lawsuits on stock prices (4114 events using a five-day window to measure returns), Bessen and Meurer (2013) found that NPE lawsuits led to almost half a trillion dollars lost wealth to the defendants from 1990 to 2010 in the US market. To investigate the extent of distress NPEs cause to the defendant firms, we regress the *Visibility* on the cumulative abnormal returns (*CAR*) of the defendant firms following the NPE lawsuits. After being sued by the *NPE*s, *Visibility* is significantly and negatively associated with the defendant firms' CAR. Therefore, increasing the visibility of the defendant firm following NPE threats leads to a negative abnormal return, which justifies this study's primary motivation regarding the deterrent effect and determinants of NPEs.

This study contributes to two strands of literature. First, this is an addition to the literature on the real effects of media coverage. Zingales (2000) and Dyck and Zingales (2002) argue that the media plays a significant role in corporate policies and resource allocation decisions. For example, the literature discusses the business media's positive role in identifying accounting fraud (Miller, 2006; Dyck et al., 2010), reducing violations of governance (Dyck et al., 2008), revealing board ineffectiveness (Joe et al., 2009), being a watchdog of executive compensation (Kuhnen and Niessen, 2012), reducing the use of dual-class shares (Braggion and Giannetti, 2013), inducing managers' capital allocation decisions (Liu and McConnell, 2013), and increasing the probability of forced CEO turnover (You et al., 2018). Few papers discuss the dark side of media coverage. For example, Donelson et al. (2021a) state that more media coverage is more likely to have misconduct uncovered and escalate shareholder litigation. Caskurlu (2019) argues that going public makes firms vulnerable to litigation. In other words, firms become targets of excessive patent lawsuits shortly before IPO completions, and the litigation intensity remains after firms go public. Gurun and Butler (2012) suggest that a positive media slant is related to the firms' local media advertising expenditures. Dai et al. (2020) show the negative effects of media coverage on firms' long-term growth measured by innovation; however, the discussion of the association between media coverage and patent trolling at patent-intensive companies, such as high-tech firms, is non-extant. The analysis of NPE trolling is undoubtedly a novel addition to the media coverage literature.

Second, this study discusses the NPEs in the finance literature, which is limited because of data scarcity. Cohen et al. (2019) were the first to report the first large-sample evidence of the behavior and impact of NPEs on firm policies. They argue that NPEs behave as opportunistic "patent trolls", i.e., NPEs target cash-rich firms unrelated to alleged infringement to ensure the settlement fees. They also observe a negative impact of NPE litigation on the innovation of the defendant firms. Appel et al. (2019) use the staggered anti-troll law to examine the impact of NPEs on start-up employment. They find that anti-troll law increased the employment of the start-up firm, inferring that the NPEs are a threat to the start-up employment. Other literature from the field of law and science, such as Chen et al. (2019), Tucker (2014), Kiebzak et al. (2016), and Chien (2011), also discusses the detrimental effect of NPEs on the firm; however, the discussion of media coverage in the NPE literature is still an open question. Our study aims to fill this gap by using the Stanford NPE Litigation Database and investigating whether media coverage attracts NPE trolls. This study is critical because it would give policymakers an idea about the determinants of NPE litigation, which is detrimental to patent-intensive firms and impairs innovation.

The remainder of the paper is organized as follows. Section 2 provides the literature review on the media coverage and the detrimental effects of NPEs on the defendant firms. Section 3 discusses the hypotheses, Section 4 describes sample construction and reports summary statistics, Section 5 presents our empirical results, and Section 6 concludes and summarizes the paper.

2. Literature review

2.1. Firm visibility

Our study is related to the literature that examines how media visibility nurtures financial and market outcomes. The extant literature suggests that the financial media's creation and broadcasting of information can inform market participants (Bushee et al., 2010; Drake et al., 2014; Fang and Peress, 2009). The reduction of information asymmetry and disciplinary effect of media assist the investors in pinpointing the potential problems of the companies (Dai et al., 2015; Joe et al., 2009; Kuhnen and

Niessen, 2012; Miller, 2006). One stream of literature investigates the impact of a firm's media visibility on the cost of capital. For example, Baker et al. (2002) find a negative association between firm visibility and the cost of equity. They argue that after cross-listing, investors' recognition of the company increases through media coverage. This broader news coverage significantly reduces a firm's cost of equity capital. Similarly, Gao et al. (2020) and Cheng et al. (2020) find a negative relationship between press coverage and the cost of debt capital, arguing that media coverage impacts firms' debt structure by lessening the use of bank loans and enhancing their reliance on public bonds. Both of them rely on the concept of information asymmetry.

Another stream of research discusses the impact of media on the financial market. For example, Zyglidopoulos et al. (2012) find that while increases in media attention are related to increases in CSR strengths, CSR weaknesses are not sensitive to changes in media attention. Hao and Li (2021) investigate the relationship between a firm's information visibility, as proxied by the amount of its press coverage, and its credit ratings. They find a positive relationship between highly visible firms and credit ratings; this positive relationship is prominent in higher information asymmetry and weaker monitoring systems. In contrast, Bushee et al. (2010) argue that higher press coverage largely reduces the degree of information asymmetry during earnings announcement periods. They measure the information asymmetry by bid–ask spreads and market depth. Furthermore, Miller (2006) finds that firms with higher information visibility are more likely to have accounting frauds identified by press articles. Kölbel et al. (2017) find that negative media articles regarding environmental, social, and governance issues increase a firm's credit risk.

Recently, a fair share of media literature discusses the different types of litigation in the context of firm visibility. For example, Tan (2016) considers the relative prominence of the plaintiff over the defendant. Using data from the US semiconductor industry, they show that plaintiff firms that command much higher levels of media coverage than rivals can make the defendant firms agree to a settlement and avoid litigation. Donelson et al. (2021b) investigate the role of the media in shareholder litigation, using the setting of the stock option backdating scandal. Backdating denotes misrepresenting stock options' grate dates to make options more valuable to managers while evading taxes and compensation expenses. They find that more media coverage is more likely to have misconduct uncovered and escalate shareholder litigation. Caskurlu (2021) argues that going public makes firms vulnerable to litigation. In other words, firms become targets of excessive patent lawsuits shortly before IPO completions, and the litigation intensity remains after firms go public, suggesting that firms can face an increased likelihood of litigation when they are in the spotlight and vulnerable.

The finance literature has been concerned with shareholder and patent litigation; however, NPE litigation, a distinct form of patent litigation, is absent in the discussion of firm visibility. Our study aims to fill this gap by discussing the impact of firm visibility in attracting or driving away NPE litigation.

2.2. Nonpracticing entity

NPEs are "firms that rarely or never practice their patents" (Shrestha, 2010). They do not produce the product but purchase the patent rights on behalf of the small firms. NPEs aim to recover cash quickly above their investment in purchasing patents. They frivolously keep sending demand letters against their rivals. Because litigation is too expensive, defendant firms tend to come into early settlement by paying settlement fees, which is the main profit of the NPE firms.

The extant literature profoundly analyzes the negative impact of patent litigation on firm performance. The most discussed area is the effect of the NPE litigation is its impact on the stock return of the defendant firms. Using 4114 events in an event study of 1630 lawsuits on stock prices, Bessen and Meurer (2013) found that NPE lawsuits led to almost half a trillion USD in lost wealth to defendants from 1990 to 2010 in the American market. As NPE litigation imposes an inevitable amount of business cost to the high-tech firms, it decreases the profits that these firms could invest in innovation, meaning that NPE lawsuits reduce the incentives to innovate to a large extent. In a similar study, Chen et al. (2019) investigated the negative spillover effect of patent litigation on peer firms. Henry (2013) argues that firms lose 0.85% of their value following a claim that one of their patents is invalid. In contrast, Tucker (2014) empirically investigates how NPE trolling affects the sales of medical imaging technology. Using data from 4829 hospitals across the US, he finds that relative to similar products not covered by patents, sales of the imaging software of the medical industry decline by one-third when sued by the NPEs.

The effects of NPEs are also highly discussed on entrepreneurial and employment activity. Kiebzak et al. (2016) argues that frivolous litigation by the NPEs deters entrepreneurial activity. Appel et al. (2019) analyzes how frequent patent infringement claims by NPEs affect the start-ups' ability to grow, create jobs, innovate, and raise capital. He exploits the staggered adoption of anti-troll laws in 32 US states. The findings suggest that anti-troll laws, which restrict the patent infringement claim of bad faith by NPEs, lead to a 4.4% increase in employment at high-tech start-ups—a frequent target of NPEs. Using a database of 223 technology start-up companies, Chien (2011) argue that smaller companies are more affected by NPEs than the companies with over 100 million USD in revenue; however, in their sample, these large companies were litigated at a significantly higher frequency.

A handful of studies discuss the absolute value of the loss stemming from NPE threats. For example, Bessen and Meurer (2013) investigated that NPEs cost defendants around 29 billion USD in 2011, a 400% increase from over 7 billion USD in 2005. Jeruss et al. (2012) examined NPEs from 2007 to 2011, finding that NPE cases among all the patent litigation rose from 22% in 2007 to almost 40% of cases filed in 2011. Besson and Meurer (2008) argue that NPEs discourage innovation by heightened costs to the firms and VCs launching innovative products to the market as the litigation cost arises after product commercialization by threatening lawsuits; thus, NPEs affect the return on investment and innovation.

2.3. NPE-related laws

To reduce the threat of NPE trolls, the US federal government introduced the well-known state anti-troll law enacted in 2013. Beginning with Vermont in 2013, states adopted patent reforms that protect local businesses from bad faith infringement claims. The main goal of the anti-troll law was to curb the NPEs' discretion in sending mass demand letters. To this end, courts can consider "whether the letter had the required information, requested an unreasonable license fee, or demanded payment in an unreasonably short period of time" in deciding whether a patent demand letter was sent in bad faith (DeSisto, 2015). If such a determination is reached, the court can compel the NPE to post a bond equal to the target's expected litigation costs. In addition, the law establishes that if a court finds that a Vermont firm has been the target of bad faith patent infringement assertions, then the court may award it the following remedies: "(1) equitable relief; (2) damages; (3) costs and fees, including reasonable attorney's fees; and (4) exemplary damages in an amount equal to 50,000.00 USD or three times the total of damages, costs, and

fees, whichever is greater". To minimize the burden imposed on firms that NPEs target, the law allows the state's Attorney General to initiate legal actions against abusive NPEs. The Vermont law has served as a model for other states, and 34 states have passed anti-troll laws through 2017.

3. Hypothesis development

Our hypothesis about the impact of firm visibility on attracting the NPE trolls stems from a distinct concept of the literature, i.e., signaling theory.

3.1. Signaling theory

Signaling theory primarily discusses reducing the information asymmetry between two or more parties (Spence, 2002). Literature has used signaling theory to explain information asymmetry in a wide arena of research contexts. For example, in a study of corporate governance, Zhang and Wiersema (2009) examine how CEOs signal the dormant quality of their firms to potential investors by the visible quality of their financial statements. Miller and Triana (2009) explain how firms use heterogeneous boards to signal adherence to the social values of diverse organizational stakeholders. Spence (1983) demonstrated how high-quality prospective employees differentiate themselves from low-quality ones using the expensive signal of rigorous higher education. Signaling theory is often used in the finance literature, where literature has examined the signaling value of board characteristics (Certo, 2003), top management team characteristics (Lester et al., 2006), venture capitalist and angel investor presence (Elitzur and Gavius, 2003), and founder involvement (Busenitz et al., 2005).

Our study is related to the literature examining how the media signals firms' financial and market outcomes. For example, Hao and Li (2021) argue that media enhances the firms' credit ratings by providing richer information to the creditors and monitoring the managers' and large shareholders' strategic behavior. Using the Spanish data from 2004 to 2019, Peña-Martel et al. (2021) find that media attention increases the R&D investment of the firm. Zyglidopoulos et al. (2012) argue that media attention as an awareness measure increases CSR investment to a large extent. Cook et al. (2006) find that a firm's pre-IPO publicity predicts positive stock return on the day of its IPO. The literature also recognizes the business media's positive role in reversing governance violations (Dyck et al., 2008), exposing board ineffectiveness (Joe et al., 2009), monitoring executive compensation (Kuhnen and Niessen, 2012), limiting the use of dual-class shares (Braggion and Giannetti, 2013), influencing managers' capital allocation decisions (Liu and McConnell, 2013), and disciplining insiders' transactions (Dai et al., 2015). All of these suggest that firms more visible in the media positively signal their underperformance, suggesting they are highly capable of paying the settlement amount imposed by NPEs in the litigation.

Cohen et al. (2019) posit that "NPEs sue cash-rich firms and target cash in business segments unrelated to alleged infringement at essentially the same frequency as they target cash in segments related to alleged infringement". Nonetheless, cash is not a key driver of intellectual property lawsuits by practicing entities (e.g., IBM and Intel) or any other type of litigation against firms. Conversely, Miller (2010) finds that NPEs litigate relatively stronger patents than those litigated by practicing entities and individuals. He also finds that NPE patent litigation is more prevalent in the technological areas characterized as new or permitting relatively broad patents. Therefore, NPEs choose their cases strategically, i.e., the financially strong firms, to optimize their expected litigation payoff. The sole purpose of NPE litigation is trolling, and NPEs are opportunistic in selecting their target to ensure their expected litigation payoff. Therefore, it is legitimate to expect that they would troll the highly visible firms as they are supposed to be capable enough to pay the settlement amount imposed by NPEs in the litigation. Therefore, we propose the following:

Hypothesis. The media signals the NPEs about the ability of the firms to pay settlement costs, and firms that are more visible in the media are targeted more by NPEs.

4. Data and sample construction

Our sample focuses mainly on high-tech firms because (i) most innovation occurs in high-tech industries (Brown et al., 2009), and (ii) NPE litigations are concentrated in innovative industries. We define a firm as being in a high-tech industry based on the classification in Loughran and Ritter (2004). We collect the NPE litigation data from the Stanford NPE Litigation Database. These NPE litigation statistics are based on cases coded "830 Patent" in the PACER database, maintained by the Administrative Office of the US Courts. In most estimations, we are interested in the defendants, whom the NPEs troll.

Following Hao and Li (2021) and Dai et al. (2021), we use the number of media coverage as the proxy for firm visibility. We collect the media news data of the US firms from the RavenPack, which has increasingly become one of the leading global databases of press coverage (Hao and Li, 2021) and has been widely used in finance and accounting studies (Twedt, 2016; Dai et al., 2015; Drake et al., 2014). RavenPack brings together news from (1) Dow Jones Newswire, the Wall Street Journal, and Barron's, (2) national and local news and business publisher and government updates, and (3) press releases, such as PR Newswire, CNW Group, and Regulatory News Services. For the primary estimation, we collect only the product and patent-related news based on the hypothesis that patent and NPE litigators are supposed to sue the firms based on these types of news. RavenPack assigns relevance scores to every news article, ranging from 1 to 100, indicating how strongly a firm relates to the corresponding news story. Following Hao and Li (2021), we focus only on news articles with relevance scores of 100.

The patent information data is obtained from Kogan et al. (2017) (KPSS), which allows us to observe the patenting activity of each firm in our sample based on patents filed at the US Patent and Trademark Office (USPTO) from 1926 to 2020. The dataset provides information on the number of patents, the estimated market value of patents, and the number of citations received by each patent filed with the USPTO.

Our sample comprises companies at the intersection of NPE data, firm visibility data from RavenPack, financial data from Compustat, and stock return data from the CRSP from 2000 to 2020. We match the NPE litigation data with the merged CRSP-Compustat data by matching the names of the companies in the CRSP-Compustat data with the defendant names in the Stanford Non-Practicing Entity Litigation Database. All the continuous variables are winsorized at the 1st and 99th percentiles. The final sample comprises 2570 unique firms and 22,558 firm-year observations.

We also use analyst coverage, Google Search Volume Index (SVI), and Distance data for robustness tests. The analyst coverage data is collected from the Thompson Reuter I/B/E/S database, the Google SVI data is obtained from Google Trends, and Distance data is collected from gist.github.com.

Panel A of Table 1 represents the yearly distribution of the number of firms, the number of high-visibility firms, and those facing NPE litigation.

Table 1
Distribution of visibility and NPE lawsuits.

Panel A: Visibility and NPE lawsuits by year				
Year	(1) # of firms	(2) Visibility #	(3) Visibility # of times per firm	(4) NPE #
2000	1839	7999	4.35	80
2001	1693	11209	6.62	82
2002	1517	11456	7.55	84
2003	1363	11942	8.76	106
2004	1287	24283	18.87	128
2005	1270	24669	19.42	125
2006	1235	28670	23.21	133
2007	1215	38223	31.46	196
2008	1104	40514	36.70	186
2009	1024	50422	49.24	187
2010	1005	62410	62.10	248
2011	947	84213	88.93	251
2012	923	104231	112.93	256
2013	872	98611	113.09	223
2014	846	97007	114.67	199
2015	828	96060	116.01	184
2016	794	72351	91.12	182
2017	737	63085	85.60	144
2018	702	72206	102.86	140
2019	703	95815	136.29	159
2020	654	102958	157.43	33
Total	22558	1198334		3326
Panel B: Visibility and NPE lawsuits by industry				
Sector	(1) # of firms	(2) Visibility #	(3) # of times per firm	(4) # of NPE
Communication equipment	2108	326811	155.03	389
Communication services	1410	32370	22.96	163
Computer hardware	1327	62547	47.13	378
Electronics	3882	463005	119.27	1254
Measuring controlling devices	1832	55608	30.35	270
Medical instruments	2618	89788	34.30	355
Navigation equipment	441	47052	106.69	129
Software	6842	11045	1.61	98
Telephone equipment	2098	110108	52.48	290
Total	22558	1198334		3326

The table reports the firm Visibility and NPE lawsuits of the high-tech industry. Panel A reports the yearly frequency of the NPE lawsuits and the firm's Visibility from 2000 to 2020, and Panel B presents the same distribution across 4-digit SIC sectors. In Panel A, the NPE rate in column (5) is the number of NPE lawsuits in column (4) divided by the total number of firms in column (1). In column (3) of Panel A, the # of times per firm is the number of Visibility in column (2) divided by the total number of firms in column (1). Panel B reports a similar NPE rate and Visibility by industry.

Columns (2) and (3) show the continuous increase in the firm's visibility. The times of visibility per firm increased from 4.35 times in 2000 to 157.43 times in 2020. The NPE% in Column (5) equals the number of NPE lawsuits divided by the total number of firms in Column (1). The average NPE rate in the sample is 15%. The NPE rate peaked in 2012 before the anti-troll law was passed. The NPE rate then fell gradually from 26% in 2013 to 20% in 2018 before rising to 23% in 2019; however, the NPE rate fell exceptionally to 5% in 2020, the year the COVID-19 pandemic broke out.

Panel B of Table 1 shows the firm visibility and NPE lawsuit distribution across four-digit SIC industries. In Column (4), we observe that electronics were the highest target of the NPEs, followed by communication equipment and computer hardware. Overall, the rate of NPE lawsuits varies from 1% to 32% across different industries. Column (1)–(3) displays the times of visibility across different industries; the most visible industry is the electronics industry.

4.1. Summary statistics

Fig. 1 represents the times of visibility per firm and the percentage of NPE. From 2000 to 2015, visibility per firm increased continuously before dropping in 2016 and rising again in 2018. In contrast, the percentage of the firms sued by the NPEs steadily increased from 2000 to 2012. It then started falling in 2013 when the anti-troll law was adopted in different US states; however, in 2018, this percentage again increased. Both variables show an almost similar trend; however, 2020 shows a distinctive pattern of NPE rates, which fell sharply during the COVID-19 pandemic.

Table 2 reports the summary statistics of the key variables used in this study.

We find that the *NPE* lawsuits in the high-tech industry are 15% on average, somewhat higher than 8.6% of the NPE litigation in Cohen et al. (2019), who examined all industries. In contrast, we test only the high-tech industry. The *Number of NPE* shows that, on average, NPEs sue firms at least 1.55 times per year (based on the whole sample). The *Visibility count* finds that, on average, a firm is visible in the news at least 53 times a year, which Dai et al. (2021) find 66 times; however, Dai et al. (2021)

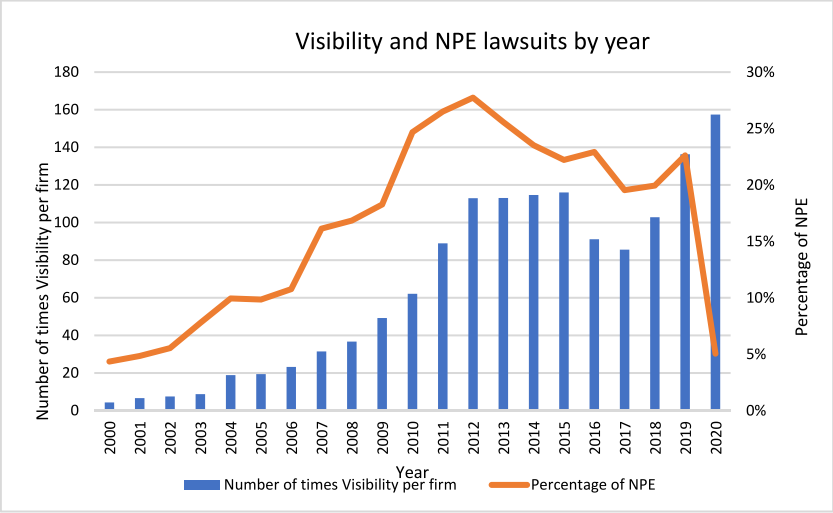

Fig. 1. Time series of the Visibility and NPE threats: This figure shows the average number of times a high-tech firm is visible in the news and the percentage of firms trolled by NPEs. The Number of time Visibility per firm is the total visibility of all the firms divided by the total number of firms per year. The Percentage of NPE is the total number of NPE litigation divided by the total number of firms in a year.

Table 2
Summary statistics.

	Mean	SD	25th percentile	50th percentile	75th percentile	N
NPE lawsuit						
NPE	0.138	0.344	0	0	0	14484
Number of NPE	1.550	9.820	0	0	0	14484
Visibility measures						
Visibility	2.479	1.827	0	2.565	3.784	14484
Visibility count	53.122	567.260	0	6	34	14484
Analyst coverage	1.5533	12.541	0	0	0	14484
Google SVI	5.672	0.950	5.201	5.837	6.357	4073
ESS	0.313	2.863	0.019	0.060	0.171	9732
CSS	0.029	0.032	0.015	0.028	0.042	9732
Firm characteristics						
Book to market	0.612	0.551	0.226	0.437	0.810	14484
Firm size	5.628	2.171	3.987	5.378	6.981	14484
Number of patents	1.174	1.732	0	0	1.946	14484
RD	0.121	0.122	0.043	0.088	0.153	14484
Cash ratio	0.323	0.323	0.220	0.142	0.284	0.471
Past return	0.130	0.743	−0.318	0.004	0.366	14484
Large firm	0.315	0.465	0	0	1	14484
Small firm	0.230	0.421	0	0	0	14484
Distance	2.158	3.038	0	0	5.776	11759
Anti-troll law	0.056	0.230	0	0	0	14484

The table reports the summary statistics of the main variables of this study; the sample period is from 2000 to 2020 and considers only the high-tech industry defined by Loughran and Ritter (2004). Variable definitions are provided in the Appendix. We use the NPE litigation data from the Stanford NPE Litigation Database and delisting data from the CRSP, and continuous variables are winsorized at 1% on both sides.

used all the industries while we focus on high-tech industries only.

The average *Book to market ratio* is 0.612. The *Firm size* (natural logarithm of total assets) is 5.628 on average. The *Number of patents* (natural logarithm of one plus the number of patents) is 1.174, *RD* is 0.121, and the 12 months rolling *Past return is* 0.13. These values are broadly consistent with Hao and Li (2021) and Cohen et al. (2019).

4.2. Empirical specification and control variables

To examine whether media visibility attracts higher NPE trolls in the US market, we estimate the following fixed effect model:

$$NPE_{i,t} = \alpha + (\beta \times Visibility_{i,t-1}) + \lambda X_{i,t} + \eta_j + \delta_t + \varphi_s + \varepsilon_{i,t} \quad (1)$$

where i indicates firms, j indicates industries, s indicates the state, and t indicates years. The dependent variable, $NPE_{i,t}$, is an indicator variable that equals 1 if a firm i is threatened by an *NPE* in a corresponding year t, and 0 otherwise. The independent variable $Visibility_{i,t-1}$ is the measure of firm visibility one year earlier. $Visibility_{i,t-1}$ is the natural logarithm of the total number of times a firm is visible in the news (data collected from the RavenPack) plus one. In Eq. (1), we are primarily concerned with coefficient β, which denotes the rate and magnitude of the relationship between firm *Visibility* and the chance of the defendant firms being trolled by an *NPE*. We hypothesize that the more visible firms are more likely to be trolled by the *NPEs*.

As NPE trolling can be driven by common unobserved year, industry, and state effects, we incorporate year-, industry-, and state-fixed effects (δ_t, η_j, and φ_s, respectively) in the models. The industry is defined by four digits SIC codes on Loughran and Ritter's (2004), and standard errors are clustered at the industry

level. This fixed effect is used to incorporate all the variables that do not vary within a given year and industry, such as business cycles and industry-wide investment opportunities. This effect includes industry-wide competition (Kahle and Stulz, 2017), merger waves (Doidge et al., 2017), VC financing cycles (Ljungvist et al., 2018), etc., ensuring that our study analyzes the propensity of the firm to be sued by NPEs while absorbing any unobserved heterogeneity that varies across industries and years over time.

$X_{i,t}$ includes time-varying firm-specific control variables that can affect the probability of firms' propensity to be sued by NPEs, such as *Book to market*, *Firm size*, *Number of patents*, *RD*, *Cash ratio*, and *Past return*.

We follow Cohen et al. (2019)—who measure whether the NPEs target cash-rich firms—and use *Book to market* as a control. To account for the fact that high-value and growth firms may attract more NPEs, we include *Book to market* and *Firm size* as controls. We measure *Firm size* by the natural logarithm of the total assets. Kim and Skinner (2012) assume that large and high-growth firms are more focused on the media and, therefore, more vulnerable to litigation risk. Miller (2010) argues that NPEs litigate relatively stronger patents than practicing entities and individuals. Based on the hypothesis that a higher number of patents increases the chance of NPE trolls and following Cohen et al. (2019), we control for the *Number of patents*.

Finally, *R&D* is deemed the innovation input that may increase the innovation quality and attract NPEs; Cohen et al. (2019) also establish that *NPEs* target cash-rich firms. Based on these assumptions, we use *R&D* and *Cash ratio* as the firm-level control variables for our estimation.

5. Empirical results

5.1. Association between firm visibility and NPE trolls—Baseline

The baseline regression test is the most basic form of our estimation, i.e., the impact of media visibility on the defendant firm's propensity to be litigated (or trolled) by the NPEs. Even though the dependent variable is binary, we use OLS as our baseline regression because our estimation holds many fixed effects and various dimensions. Lancaster (2000) argues that using maximum likelihood tests such as logit or probit in this regard may cause an unexpected problem. In Panels A and B of Table 3, the dependent variable *NPE* is an indicator variable equal to 1 if the firm is sued by an NPE and 0 otherwise. The independent variable *Visibility* is the natural logarithm of the total number of product and patent-related news plus one in Panel A. In Panel B of Table 3, the dependent variable, *Visibility count*, is the total number of related products and patents. Columns (1), (2), and (3) of both panels use the year-fixed effect, firm-fixed effect, and both year- and firm-fixed effects altogether, respectively.

The results suggest that the NPEs more troll firms that are highly visible in the media. In both panels and all the specifications in Table 3, the coefficients of *Visibility* and *Visibility count* are significantly positive at 1%. In the tightest form of our estimation, where both year-level controls and industry-fixed effects are considered, a 1% increase in *Visibility* increases the chance of *NPE* litigation by 8.9%. This result is consistent with Cohen et al. (2019), who show that NPEs are opportunistic and sue high-quality firms to ensure the receipt of the settlement payment.

All the other significant control variables show the expected signs. For example, *Firm size, Number of patents,* and *R&D* are significantly positively associated with the chance of being threatened by NPEs. In contrast, the *Cash ratio* shows a negative relation with the NPE threats. The *Book to market* shows a negative relation with NPE troll, following Cohen et al. (2019), even though it is insignificant. The positive and significant coefficient of *Firm size* indicates that NPEs are highly attracted to large firms and likely to troll them. Perhaps the bigger target size signals the NPEs of the firm's ability to pay the settlement fees. The *Number of patents* is positively and significantly (at 1%) related to NPE trolls suggesting that the higher the number of patents, the more likely the NPEs are to target the firm. Similarly, *R&D* is positively and significantly related to NPE trolls, supporting Mazzenotti (2021), who finds a positive relationship between R&D and patent litigation. *Cash ratio* is significantly but not positively related to NPE trolling, which contradicts Cohen et al. (2019). Finally, *Past return* is positively but insignificantly related to NPE.

Table 3
Baseline—The impact of Visibility on the NPE threat.

Panel A: Visibility (natural logarithm)			
	(1)	(2)	(3)
Visibility	0.100***	0.108***	0.089***
	(6.42)	(6.13)	(5.97)
Book to market	−0.001	0.002	−0.001
	(−0.37)	(0.60)	(−0.25)
Firm size	0.125***	0.149***	0.142***
	(7.99)	(8.02)	(8.81)
Number of patents	0.236***	0.233***	0.233***
	(14.54)	(12.71)	(15.13)
RD	0.215*	0.168*	0.192*
	(1.96)	(1.92)	(1.95)
Cash ratio	0.008	−0.120**	−0.115**
	(0.14)	(−2.17)	(−2.15)
Past return	0.003	0.014	0.004
	(0.17)	(0.50)	(0.19)
Year FE	Yes	No	Yes
Industry FE	No	Yes	Yes
Observations	14484	14484	14484
Adjusted R-squared	0.176	0.179	0.190
Panel B: Visibility count			
	(1)	(2)	(3)
Visibility count	0.006***	0.006***	0.005***
	(5.93)	(4.62)	(5.59)
Book to market	−0.003	0.002	−0.002
	(−0.55)	(0.48)	(−0.37)
Firm size	0.224***	0.275***	0.263***
	(8.00)	(8.14)	(8.86)
Number of patents	0.460***	0.448***	0.448***
	(14.21)	(11.45)	(14.66)
RD	0.410*	0.301*	0.362*
	(1.90)	(1.80)	(1.88)
Cash ratio	0.066	−0.184*	−0.192*
	(0.62)	(−1.77)	(−1.88)
Past return	0.005	0.032	0.007
	(0.15)	(0.54)	(0.17)
Year FE	Yes	No	Yes
Industry FE	No	Yes	Yes
Observations	14484	14484	14484
Adjusted R-squared	0.177	0.180	0.191

This table reports the fixed effect impact of the company visibility on the firms' propensity to be litigated by NPEs. The dependent variable NPE is an indicator variable equal to 1 if an NPE sues the firm. The independent variable in Panel A, Visibility, is the natural logarithm of the number of patent-related news in the prior year from RavenPack plus one. The independent variable in Panel B, Visibility Count, is the number of patent-related news in the prior year from RavenPack. Column (1) includes only the fixed effects, and Columns (2) and (3) report the control variables alongside. The control variables are defined in the Appendix. Standard errors are clustered at the firm level, and *t*-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

5.2. Robustness tests

5.2.1. Alternative robustness tests of the baseline

Table 4 employs other specification tests to examine whether the results are coherent with the baseline estimation. First, in

Table 4
Alternative robustness tests.

	Probit model				Cox model	
	(1)		(2)		(3)	(4)
	Coefficient	Marginal	Coefficient	Marginal		
Visibility	0.116***	0.021***	0.116***	0.021***	0.026***	0.025***
	(14.34)	(14.46)	(14.39)	(14.52)	(2.61)	(2.59)
Book to market	0.004	0.001	0.004	0.001	0.013*	0.012*
	(0.99)	(0.99)	(0.96)	(0.96)	(1.96)	(1.94)
Firm size	0.154***	0.028***	0.156***	0.029***	0.023	0.041**
	(15.10)	(15.25)	(15.19)	(15.35)	(1.41)	(2.46)
Number of patents	0.157***	0.029***	0.155***	0.028***	0.326***	0.301***
	(16.29)	(16.67)	(15.98)	(16.33)	(22.41)	(20.24)
RD	0.437***	0.080***	0.446***	0.081***	−0.183	−0.138
	(3.98)	(3.99)	(4.06)	(4.07)	(−0.86)	(−0.65)
Cash ratio	0.083	0.015	0.087	0.016	0.124	0.187
	(1.06)	(1.06)	(1.10)	(1.10)	(0.99)	(1.49)
Past return	0.027*	0.005*	0.029*	0.005**	0.001	0.034
	(1.79)	(1.79)	(1.94)	(1.95)	(0.02)	(1.08)
Industry sales growth			0.024	0.004		0.022
			(1.21)	(1.21)		(1.01)
GDP growth			1.906**	0.348***		12.69***
			(2.05)	(2.05)		(7.56)
Pseudo R-squared	0.188		0.189			
Log likelihood					−16051.8	−16018.436
Observations	14484	14484	14484	14484	13877	13877

This table shows different estimated effects of the visibility on a firm's propensity to be sued by an NPE. The dependent variable NPE is the indicator variable that equals 1 if the firm is sued by an NPE and 0 otherwise. Here we examine the probit and Cox models. The first probit model in Column (1) reports the estimate using year- and industry-fixed effect. The second probit model in Column (2) shows the estimate using year- and firm-fixed effect. The Cox model in Columns (3) and (4) reports the Cox-hazard ratios of the firm's Visibility on NPE threats. The control variables are defined in the Appendix. Standard errors are clustered at the industry level, and *t*-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Columns (1) and (3), following Broggard et al. (2021), we use the probit model to test whether the outcome is coherent with the baseline. The year and industry-fixed effects are not included in the probit model. We include the industry sale growth rate and real gross domestic product (GDP) growth rate as controls in Column (3) to control for the broader industry conditions and economy-wide effects. Like the OLS estimates, the coefficients from the probit model are positively and significantly related to the chance of NPE threats, which supports the OLS regression that media visibility increases the chance of NPE threats.

Columns (5) and (6) report the hazard ratios from the Cox model. In this case, the hazard ratio is the probability that an NPE will sue a firm in the next year. Survival models account for an event's occurrence and time (Fama and French, 2004). Moreover, a survival model is best when examining censored and time-series data with different time horizons (Shumway, 2001). Like the OLS estimate, the hazard ratio is also significantly and positively related to NPE lawsuits. Therefore, the probability of NPE threat increases following high visibility. Column (6) includes the industry sale growth-rate variables and real GDP growth rate. Overall, the coefficient of (SCA) remains robust to this alternative model specification.

5.2.2. Alternative measures of firm visibility

In this section, we use different firm visibility measures, such as *Analyst coverage*, *Google SVI*, *Visibility rank*, *All news*, and *Firm visibility dummy*, to test the robustness of the baseline regression.

Following Chun and Shin (2018), we use *Analyst coverage* as an alternative measure of visibility. Analysts act as informational intermediaries between firms and shareholders to increase the information quality and quantity (Chou and Shiah-Hou, 2010; Jiraporn et al., 2012). They analyze the publicly available data, including financial statements, earnings-related disclosure data, and other announcements, and allocate their analysis regarding the financial information to the public. We collect the *Analyst coverage* data from the I\B\E\S database, finding that the coefficient is positively and significantly related to the *NPE* lawsuits; this result is similar to the baseline regression.

Our second alternative measurement is the *Google SVI*. By searching the ticker number and name of the company together, we collect the data from Google Trends, which provides the number of web-search for the companies by year. Appel et al. (2019) and Dayani (2020) use Google SVI for the companies' patent troll-related web searches to examine the impact of the anti-troll law on patent troll-related news. Both of them find that the anti-troll law reduces the number of news about patent trolls. In this study, we find that the number of web searches about the company through Google SVI is positively and significantly (at 1%) associated with NPE lawsuits. This finding suggests that NPEs are attracted to companies whose product/patent-related news is frequently visible on the internet.

To resolve the influence of the outliers and to correct the skewness of data, we use the standard rank of the total number of product/patent-related news articles as another measure of firm visibility. Column (3) of Table 5 indicates that the coefficient of *Visibility rank* is positive and statistically significant at 1%. In Column (4), we construct another measurement of firm visibility using all types of news about the company. Using all the news information from the RavenPack, we calculate the natural logarithm of the number of all news plus one to be the independent variable *All news*. *All news* is also significantly and positively related to the *NPE* lawsuits. In addition, to ensure that our sample focuses on all firms covered by RavenPack and is not driven by the sample selection process, we create an indicator variable, *Firm visibility dummy*, which is equal to 1 for firms covered by RavenPack in a given year and 0 otherwise. In Column (5), we also find that the coefficient of the *Firm visibility dummy* is positive and significant at 1%, which implies that firms with non-zero media coverage are more prone to NPE litigation than those without media visibility. The results of the last three measurements comply with that of Hao and Li (2021).

All of these measurements in Table 5 suggest the robustness of our baseline results to alternative measures of company visibility.

Table 5
Alternative measurements of visibility.

	(1)	(2)	(3)	(4)	(5)
Analyst coverage	0.097***				
	(2.01)				
Google SVI		0.033***			
		(3.95)			
Visibility rank			0.001***		
			(6.38)		
All news				0.029***	
				(5.26)	
Firm visibility dummy					0.044***
					(4.33)
Book to market	−0.001	−0.005	0.001	−0.001	0.001
	(−0.10)	(−1.50)	(0.08)	(−1.04)	(0.08)
Firm size	0.031***	0.065***	0.030***	0.033***	0.032***
	(10.97)	(8.11)	(10.26)	(8.18)	(10.32)
Number of patents	0.051***	0.043***	0.049***	0.049***	0.050***
	(13.89)	(7.77)	(13.60)	(11.35)	(14.25)
RD	0.078***	0.498***	0.067***	0.080***	0.075***
	(4.66)	(7.91)	(4.38)	(3.99)	(4.62)
Cash ratio	−0.016	0.132**	−0.020	−0.017	−0.020
	(−1.17)	(2.81)	(−1.38)	(−0.89)	(−1.38)
Past return	0.007	−0.004	0.007	0.009	0.006
	(1.63)	(−0.20)	(1.53)	(1.57)	(1.55)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	13215	2877	13215	10030	13215
Adjusted R-squared	0.188	0.205	0.193	0.208	0.191

This table shows the robustness of different measures of firm visibility in NPE lawsuits. The dependent variable NPE is an indicator variable equal to 1 if an NPE sues the firm. This table uses five different independent variables as the firm Visibility measure. The Analyst coverage is the natural logarithm of the number of estimates given by the analysts for a given firm plus one. The Google SVI is the natural logarithm of the number of times the defendant firm appears in the Google search plus one, and the Visibility rank is the standardized rank of the total number of product-related news articles. All News is the natural logarithm of the number of all types of news plus one. Firm visibility dummy is an indicator variable that equals 1 if RavenPack covers the firm in a given year and 0 otherwise. The control variables are defined in the Appendix. Standard errors are clustered at the firm level, and t-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 6
Size effect on NPE litigation.

	(1)	(2)
Large firm	0.0208	
	(1.60)	
Large firm × Visibility	0.030***	
	(5.33)	
Small firm		0.070***
		(4.87)
Small firm × Visibility		−0.032***
		(−5.85)
Visibility	0.008***	0.014***
	(3.82)	(4.26)
Book to market	0.001	0.001
	(0.08)	(0.60)
Number of patents	0.044***	0.020***
	(11.95)	(4.04)
RD	0.026*	0.002
	(1.96)	(0.15)
Cash ratio	0.016***	0.008
	(6.36)	(1.60)
Past return	0.006	0.003
	(1.28)	(1.29)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	14484	14484
Adjusted R-squared	0.202	0.333

This table reports how the size of the firms impacts the association between Visibility and the NPE threat for the defendant firm. Large firm is an indicator variable equal to 1 if the natural logarithm of the firm's total assets is greater than the 75th percentile of all the firm's total assets. The Small firm is an indicator variable equal to 1 if the natural logarithm of the firm's total assets is less than the 25th percentile of all the firm's total assets. The dependent variable NPE is an indicator variable equal to 1 if an NPE sues the firm. Visibility is the natural logarithm of the number of patent-related news in the prior year from RavenPack plus one. The control variables are defined in the Appendix. Standard errors are clustered at the firm level, and t-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

5.3. Size effect

Cohen et al. (2019) argue that "NPEs sue cash-rich firms and target cash in business segments unrelated to alleged infringement at essentially the same frequency as they target cash in segments related to alleged infringement". Nevertheless, cash is not a key driver of intellectual property lawsuits by practicing entities (e.g., IBM and Intel) or any other type of litigation against firms. In contrast, Miller (2010) investigates that NPEs litigate relatively stronger patents than those litigated by practicing entities and individuals. The study also finds that NPE patent litigation is more prevalent in the technological areas characterized as new or permitting relatively broad patents; therefore, NPEs choose their cases strategically to optimize their expected litigation payoff. The sole purpose of NPE litigation is trolling, and NPEs are opportunistic in selecting their target to ensure their expected litigation payoff; thus, it is legitimate to expect that they would troll very large firms, which should be capable of paying the settlement amount imposed by NPEs in the litigation. This section investigates whether company size matters in attracting NPE trolls. As large firms, such as Microsoft, Google, IBM, etc., receive more media attention than smaller firms, we expect large firms to be exposed to higher rates of NPE trolling than smaller firms.

In this experiment, we define a large firm as an indicator variable 1 if the firm is in the 75th percentile of the total assets of all firms. Similarly, small firms are defined as an indicator variable equal to 1 if the firm's total asset belongs to the least 25th percentile of the total assets of all the firms. We employ the difference-in-difference (DiD) test by multiplying the size of the firms by the *Visibility* as follows:

$$NPE_{i,t} = \alpha + \beta_1 \times Firm\ size_{i,t-1} + \beta_2(Firm\ size_{i,t-1} \times Visibility_{s,t-1}) + \beta_3 \times Visibility_{s,t-1} + \lambda X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

$X_{i,t}$ is the vector of control variables, μ_i is the industry-fixed effect, and δ_t is the time-fixed effect. Column (1) of Table 6 shows that *Large firm* alone is not significantly related to the propensity of NPE troll; however, when interacted with *Visibility*, the coefficient becomes significantly positive. This result implies that it is not the size but the *Visibility* or charm of the firm that attracts higher patent trolls. Conversely, when a *Small firm* interacts with *Visibility*, the coefficient becomes negative and significant. Perhaps the *Visibility* of the *Small firm* makes the lower strength of the firm clearer to the NPEs; therefore, NPEs troll the smaller firms less. All of the results prove that size matters regarding visibility and NPE threats. Kim and Skinner (2012) assume that large and high-growth firms are more focused on the media and, therefore, more vulnerable to litigation risk.

5.4. Endogeneity test

5.4.1. Instrumental variable analysis

One potential concern of this study is endogeneity. Jensen (1979) suggests that the business press inclines to accommodate the public's taste and report sensational news; therefore, the NPE litigation news might increase the firm's visibility. Miller (2006) finds that journalists are more prone to follow firms with specific characteristics, such as firms with good profiles, large sizes, or

those requiring lower investigation costs. Unobservable factors can jointly determine firm visibility and NPE trolling; therefore, it is essential to control the omitted variable bias to validate the robustness of our results. Consequently, we next conduct a two-stage instrumental variable analysis, as set forth below, to alleviate this concern.

$$Visibility_{i,t} = \alpha + \beta\ IV_{i,t-1} + \lambda\ Control\ Variables_{i,t-1} + \eta\ Fixed\ Effects + \varepsilon_{i,t} \quad (3)$$

and

$$NPE_{i,t+1} = \alpha + \beta\ Instrumented\ visibility_{i,t} + \lambda Control\ Variables_{i,t} + \eta Fixed\ Effects + \varepsilon_{i,t} \quad (4)$$

where we include the same control variables as in Eq. (1) and industry- and year-fixed effects; standard errors are again clustered at the year level. We regress *Visibility* on our instrumental variable (*IV*) in the first-stage regression and then use the predicted value of *Visibility* in the second-stage regression.

Following Dai et al. (2015) and Hao and Li (2021), we use *Distance* to the news branches as the instrumental variable. To calculate *Distance*, we use location (headquarter states) information for firm headquarters from Compustat, location information for Dow Jones's US offices from the Dow Jones website, and detailed information on the distance between the different states from gist.github.com. The eight Dow Jones offices are in Boston, Chicago, Minneapolis, New York, Princeton, San Francisco, Waltham, and Washington.[3] We assume that the distance between a firm's headquarters and Dow Jones's eight offices reduces media coverage for two reasons. First, Gurun and Butler (2012) and You et al. (2018) argue that a firm's media coverage and content depend on the distance between the firm and news outlets. To the extent that journalists incur higher costs by collecting and analyzing information from distant firms, longer travel times lower the likelihood of news coverage. Second, long travel time between news outlets and firms can reduce the media's attention and interest.

Column (1) of Table 7 shows that our instrumental variable *Distance* is significantly and negatively related to *Visibility,* i.e., the higher the distance between the firm's headquarters and the nearest news branch of the Dow Jones, the lower the visibility of the firm in the news. Using the predicted value of *Visibility* and regression on the *NPE* in the second stage, we find a positive and statistically significant coefficient of the *Instrument visibility*. This finding suggests that firm visibility is important in attracting *NPE* trolls after controlling for endogeneity.

5.4.2. DiD test

We conduct additional tests to investigate the endogeneity by including the anti-troll law as an interaction term. Beginning with Vermont in 2013, some US states adopted patent reforms through anti-troll law that protects local businesses from bad faith infringement claims. The anti-troll law primarily aims to curb the NPEs' discretion in sending mass demand letters. To this end, courts can consider "whether the letter had the required information, requested an unreasonable license fee, or demanded payment in an unreasonably short period of time" in deciding whether a patent demand letter was sent in bad faith (DeSisto, 2015). If such a determination is reached, the court can compel the NPE to post a bond equal to the target's expected litigation costs. To minimize the burden imposed on firms that NPEs target, the law allows the state's Attorney General to initiate legal actions against abusive NPEs. The Vermont law has served as a model for other states, and 34 states have passed anti-troll laws through

[3] See http://www.dowjones.com/contact.

Table 7
Firm visibility on NPE threat: Instrumental variable approach.

	First stage (1) Visibility	Second stage (2) NPE
Distance	−0.409*	
	(−1.86)	
Instrumented visibility		0.012***
		(3.14)
Book to market	−0.078	−0.009
	(−0.74)	(−1.20)
Firm size	11.19***	0.277***
	(8.20)	(6.12)
Number of patents	13.74***	0.326***
	(10.76)	(6.06)
RD	27.46***	0.652***
	(4.12)	(2.99)
Cash ratio	0.289	−0.249
	(0.13)	(−1.68)
Past return	1.081**	0.021
	(2.62)	(0.40)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	11758	10082
Adjusted R-squared	0.424	0.200

This table reports the 2SLS regression of company visibility's impact on the firm's propensity to be litigated by NPEs. The first-stage regression in Column (1) uses Distance as the instrumental variable of Visibility. The instrumental variable Distance is measured as the minimum distance between the firm's headquarters and any news branch of the Dow Jones. Column (2) reports the impact of the Fitted Visibility from the first-stage regression on the firms' propensity to be litigated by NPEs. Visibility is the natural logarithm of the number of patent-related news in the prior year from RavenPack plus one. NPE is the dummy variable equal to 1 if the firm is sued by an NPE at least once a year; otherwise, it is 0. The control variables are defined in the Appendix. Standard errors are clustered at the firm level, and *t*-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

2017. To investigate the impact of the anti-troll act, we test the following equation:

$$NPE_{i,t} = \alpha + \beta_1 Visibility_{i,t-1} + \beta_2(Visibility_{i,t-1} \times Antitroll\ dummy_{s,t-1}) + \beta_3\ Antitroll\ dummy_{s,t-1} + \lambda X_{i,t} + \eta\ Fixed\ Effects + \varepsilon_{i,t} \quad (5)$$

where $Antitroll\ dummy_{s,t-1}$ is an indicator variable equal to 1 if the firm belongs to a state that has adopted the anti-troll law in the corresponding year. The independent variable, $Visibility_{i,t-1}$, interacts with the $Antitroll\ dummy_{s,t-1}$ to differentiate the treatment and control firms. As the anti-troll law is a state-wise law adopted in different years in different states, we use the state-fixed effect, μ_s, to absorb the variable among the states. In addition, there is variation in years by the states to adopt this law. To incorporate the time variation, we use the year-fixed effect δ_t.

In Columns (1) and (3) of Table 8, we use industry- and year-fixed effect, and in Column (2), we use state- and year-fixed effect. The results are very similar in all cases. The coefficient of *Visibility* is positive and statistically significant, whereas the coefficient of *Antitroll dummy* is insignificant in Columns (2) and (3); however, when *Visibility* interacts with the *Antitrolldummy*, we find a largely negative and statistically significant outcome. Therefore, after a state adopts the anti-troll law, the effect of NPE abates enough to eliminate the positive effect of the *Visibility* on the NPE threat. This result is consistent with Appel et al. (2019), who find that anti-troll law is positively related to the growth of start-up firms. The anti-troll law was adopted to assuage the business operation. The reduction of NPE trolls adds another rationale or accomplishment to this law.

The baseline results remain robust even after controlling for the potential endogeneity between *Visibility* and NPE lawsuits.

Table 8
The effect of the anti-troll law: Diff-n-diff test.

	(1)	(2)	(3)
Visibility	0.056***	0.026***	0.023***
	(14.87)	(9.53)	(9.05)
Visibility*Anti-troll law	−0.012*	−0.017**	−0.011*
	(−1.93)	(−2.49)	(−1.74)
Anti-troll law	0.006	0.035**	0.024
	(0.61)	(2.34)	(1.02)
Book to market		−0.001	−0.001
		(−0.57)	(−1.43)
Firm size		0.025***	0.024***
		(8.70)	(10.65)
Number of patents		0.051***	0.051***
		(11.21)	(14.49)
RD		−0.026*	−0.019
		(−1.85)	(−1.44)
Cash ratio		−0.0298*	−0.0211
		(−2.03)	(−1.47)
Past return		0.003	0.007
		(0.75)	(1.71)
Year FE	Yes	No	Yes
Industry FE	Yes	Yes	Yes
State FE	No	Yes	No
Observations	14484	14484	14484
Adjusted R-squared	0.096	0.185	0.192

This table reports the difference-in-difference impact of the anti-troll law on the defendant firm's propensity to be litigated by an NPE. The dependent variable NPE is the dummy variable equal to 1 if the firm is sued by an NPE at least once a year; otherwise, 0. The interaction between the Visibility and the Antitroll dummy shows how anti-troll law affects the propensity to be sued in the case of defendant firms. Anti-troll dummy is the indicator variable that equals 1 if the firm belongs to a state year that has adopted the anti-troll law. The control variables are defined in the Appendix. Standard errors are clustered at the industry level, and t-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

5.5. Economic channels or mechanism

5.5.1. Test on the news sentiment

Following Dai et al. (2021), we investigate the effect of news sentiment on the NPE litigation of the defendant firms. According to our NPE opportunism hypothesis, the relationship between firm visibility and NPE threat is built on the arguments that media coverage (1) disseminates the firm-specific information to the market participants and (2) NPE are opportunistic as they target those firms that are highly capable of paying off the settlement fees. That is, firms with good performance are associated with more positive news coverage, and those firms, in turn, may attract more NPE trolls.

To empirically test this hypothesis, we collect the sentiment data from the RavenPack database, which provides a composite sentiment score (CSS) and event sentiment score (ESS) for every news held in the database. The ESS ranges from +1.0 to −1.0; a score above 0 indicates a positive sentiment, those below 0 indicate a negative sentiment score, and those equal to 0 are neutral. In our estimation, $ESS_{negative}$ refers to scores below 0, $ESS_{percentile25}$ refers to scores in the top 25th percentile of all positive scores, $ESS_{percentile50}$ refers to scores that belong in the top 50th percentile of all positive scores, and $ESS_{percentile75}$ refers to scores that belong to the top 75th percentile of all positive scores. In contrast, the CSS ranges from 0 to 100, with a score above 50 indicating a positive sentiment, scores below 50 indicating a negative sentiment, and scores equal to 50 indicating a neutral sentiment. In our estimation, $CSS_{negative}$ refers to scores below 50, $CSS_{percentile25}$ refers to scores in the top 25th percentile of all positive scores, $CSS_{percentile50}$ refers to scores in the top 50th percentile of all the positive scores, and $CSS_{percentile75}$ indicates scores in the top 75th percentile of all positive scores.

Columns (1) and (5) of Table 9 show that both the negative ESS and CSS scores are negatively related to the propensity of NPE threat, and the coefficient of ESS and CSS increases significantly with the increase in percentiles. The sentiment variable's highest positive and most significant coefficient exists in the top 75th percentile of the respective scores, suggesting that NPEs are attracted mostly to the positive (at the top percentile) news and negatively associated with the negative sentiment news. This finding is consistent with our conjecture that NPEs are opportunistic and target stronger firms capable enough to pay the settlement cost.

Dai et al. (2021) find that negative news coverage (News G1t) and the most positive news coverage inhibits innovation. Their results indicate that news coverage with a highly positive tone significantly affects corporate innovation. Our result of the positive relationship between positive news and NPE litigation is consistent with Dai et al. (2021), as NPE trolls also damage innovation.

5.5.2. Plaintiff's return after the litigation

The stakeholder theory suggests that to succeed in the long term, firms must gratify the often-conflicting demands of diverse stakeholders (Freeman, 2010). As some stakeholders are more significant than others for the survival and success of the firm (Cummings and Doh, 2000; Mitchell et al., 1997), some firms are more vulnerable to stakeholder pressures than others (Fiss and Zajac, 2006; Oliver, 1991; Salancik and Pfeffer, 1978). Fiss and Zajac (2006) argue that firms that are more visible and receive more media attention are more vulnerable to stakeholder pressures because of the resulting exposure to multiple stakeholder groups and greater pressures to adapt the framing of their actions to pressure from multiple sources. Ettenson and Klein find that highly visible firms are more likely to become the campaign targets of social movement organizations and other non-profit organizations (NGOs), whose consumer influence has amplified significantly in recent decades. Targeting a highly visible firm brings a sense of identity to social movement organizations (Rowley and Moldoveanu, 2003). In other words, positioning oneself vis-à-vis a highly visible company is one of the easiest ways for a stakeholder group to establish and signal its identity.

According to identity theory, identity refers to labeling thyself as an occupant of a role and incorporating the meaning, expectation, and performance related to that role into the self (Burke and Tully, 1977; Thoits, 1986). These meanings and expectations from a set of standards direct behavior (Burke, 1991; Burke and Reitzes, 1981). In the innovation world, NPEs are the "firms that rarely or never practice their patents, and instead focus on earning licensing fees" (Shrestha, 2010). They usually purchase patenting licenses for small and weak firms to foster innovation. In addition to supporting small businesses, they keep threatening the strong and valuable patents of the other firms by sending sporadic demand letters. According to identity theory, we can explain this behavior as the NPEs' strategy to establish and signal their identity in the innovation world. In 2021, patent trolls filed more than 2900 infringement lawsuits in the US.

This suggests that by suing a high-performance firm, NPEs may try to prove their identity similar to the sued firm in the market. To investigate whether NPEs are better off by suing a highly visible firm, we investigate the pre- and post-returns of the NPE firms following their lawsuits again the highly visible defendant firms.

Columns (1) and (2) of Table 10 reveal the one- and two-month ex-post returns following the lawsuits. From Column (1), the monthly return following the NPE lawsuit is positive and significant at 1%. The return of the second month following the NPE lawsuit is also positive and significant at 10%. In contrast, the plaintiff returns ex-ante lawsuits are not significant. This result proves that NPEs as plaintiffs are incentivized to sue a highly visible firm because it ensures the settlement costs and establishes their identity in the market.

Table 9
News sentiment on NPE trolling.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESS_{negative}$	−0.057***							
	(−7.99)							
$ESS_{percentile25}$		−0.028***						
		(−3.68)						
$ESS_{percentile50}$			0.010					
			(1.13)					
$ESS_{percentile75}$				0.043***				
				(5.04)				
$CSS_{negative}$					−0.056***			
					(−5.60)			
$CSS_{percentile25}$						0.028*		
						(1.65)		
$CSS_{percentile50}$							0.020**	
							(2.08)	
$CSS_{percentile75}$								0.063***
								(6.12)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9375	9375	9375	9375	9375	9375	9375	9375
Adjusted R-squared	0.060	0.057	0.057	0.060	0.063	0.057	0.057	0.061

The table reports how the news sentiment impacts the defendant firms' propensity to be litigated by the NPEs, using different percentiles of ESS and CSS as the independent variables. ESS is the event sentiment score of the news. CSS is the composite sentiment score of news provided by RavenPack. The dependent variable NPE is an indicator variable equal to 1 if the firm is sued by an NPE and otherwise 0. The control variables are defined in the Appendix. Standard errors are clustered at the firm level, and *t*-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 10
Plaintiff return before and after litigation.

	(1) One-month return	(2) Two-months return	(3) $Return_{t-1}$	(4) $Return_{t-2}$
NPE	0.025***	0.026*	−0.003	0.005
	(3.58)	(1.94)	(−0.15)	(0.37)
Book to market	0.003**	0.002*	0.002	−0.002
	(2.95)	(1.92)	(1.34)	(−0.95)
Firm size	0.005	0.005	0.006**	0.004*
	(0.18)	(0.44)	(2.53)	(1.86)
Number of patents	0.004**	0.005**	0.004	−0.002
	(2.36)	(2.63)	(1.35)	(−0.92)
RD	−0.065***	−0.146***	−0.00	0.001
	(−4.42)	(−6.03)	(−0.16)	(0.23)
Cash ratio	−0.009	−0.005	−0.004**	−0.001
	(−0.54)	(−0.63)	(−2.75)	(−1.55)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2391	2100	2391	2110
Adjusted R-squared	0.032	0.045	0.026	0.025

This table shows the effect of NPE litigation on the plaintiff's stock return. In this case, the NPEs are the patent owners or plaintiffs. The dependent variables, one and two-month returns, are the plaintiff firm's one- and two-month cumulative returns, respectively, following the NPE lawsuits, and the dependent variable, $Return_{t-1}$ and $Return_{t-2}$, are the plaintiffs' one- and two-month stock returns, respectively before the NPE lawsuit. The independent variable NPE is the dummy variable equal to 1 if the plaintiff lodges a lawsuit. The control variables are defined in the Appendix. Standard errors are clustered at the firm level, and *t*-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 11
NPE Opportunism: Defendant's return after litigation.

	(1) CAR [0, 1]	(2) CAR [0, 2]	(3) CAR [0, 3]
Visibility	−0.009**	−0.005**	−0.004*
	(−1.98)	(−1.93)	(−1.72)
Book to market	0.001***	0.001***	0.001***
	(17.45)	(17.42)	(13.51)
Firm size	0.002	0.002	0.007
	(0.43)	(0.34)	(0.52)
Number of patents	0.003*	0.003*	0.012
	(1.81)	(1.82)	(1.53)
RD	0.066	0.066	−0.086
	(0.76)	(0.76)	(−0.46)
Cash ratio	0.005	0.005	0.003
	(0.43)	(0.33)	(0.54)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	945	945	945
Adjusted R-squared	0.074	0.075	0.083

This table reports the impact of the increase in company visibility on the defendant firm's return after being litigated by the NPEs. The dependent variables are the defendant firm's one-, two-, and three-month cumulative returns following the NPE lawsuits. The independent variable, Visibility, is the natural logarithm of the number of patent-related news in the prior year from RavenPack plus one. The control variables are defined in the Appendix. Standard errors are clustered at the firm level, and *t*-stats are reported in parentheses. Statistical significance at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

5.5.3. Defendant's return following NPE threat

Bhagat et al. (1998) discuss one of the most comprehensive analyses indicating a negative stock price reaction to the announcement of corporate litigation. They analyze different legal disagreements and find that corporate lawsuits cause the average corporate defendant to lose 0.97% of its market value, or 15.96 million USD, over a (−1, 0) event window; however, the magnitude and loss of market value differ enormously depending on several factors, specifically based on the type of violations (Karpoff and Lott, 1993). Fich and Shivdasani (2007) argue that the costliest type of litigation is the shareholder-initiated class action for which they report a −16% average cumulative abnormal return during the (−20, −3) window and a −5.95% abnormal return during the (−1, 0) window. Gande and Lewis (2009) confirm this outcome, documenting the average CAR of −4.66% and −14.45%, respectively, during the (−1, 1) and (−10, 1) windows.

On a similar note, the extant literature argues that by frivolously suing, the NPEs create a substantial wealth loss to the defendant firms. In an event study of 1630 lawsuits on stock prices (4114 events using a five-day window to measure returns), Bessen and Meurer (2013) found that NPE lawsuits led to the defendants losing almost half a trillion USD from 1990 to 2010 in the US market. During the last four years of this sample period,

Table A.12
Variable description.

Variable	Definition	Source
All news	The natural logarithm of the number of all types of news plus one	RavenPack
Anti-troll law	The dummy variable equals 1 if the firm belongs to a state in which the anti-troll law has been adopted in the respective year, otherwise 0.	Appel et al. (2019)
Analyst coverage	The natural logarithm of one plus the number of analysts issuing an annual forecast for a firm in the 12th month of its fiscal year	I/B/E/S database
Book to market	Book value of firm equity divided by market value of firm equity	Compustat
Cash ratio	Total cash and cash equivalent divided by total asset	Compustat
CSS	Composite sentiment score about the firm	RavenPack
Distance	The minimum distance between the firm headquarters and any news branch of the Dow Jones	gist.github.com
ESS	Event-related sentiment score	RavenPack
Firm size	Natural logarithm of total assets plus one	Compustat
Firm visibility dummy	The indicator variable equals 1 if the firm is covered by RavenPack in a given year and 0 otherwise.	RavenPack
Instrumented visibility	The predicted value of Visibility from the regression of Distance on Visibility	gist.github.com & RavenPack
GDP growth	The growth of the US GDP adjusted to 2010	BEA
Google SVI	Natural logarithm of the number of times the firm appeared on the Google Search Volume Index the Google Search Volume Index	Google Trends
Industry sales growth	The growth rate of the industry sales	Compustat-CRSP merged
Large firm	Large firm is an indicator variable equal to 1 if the natural logarithm of the firm's total assets is greater than the 75th percentile of all the firm's total assets.	Compustat
NPE	The indicator variable is equal to 1 if an NPE sues the firm.	Stanford NPE database
NPE%	The number of NPE litigation divided by the number of firms	Stanford NPE database
Number of patents	Natural logarithm of the number of patents a firm holds plus one	KPSS
One-month return	One-month cumulative stock return following the NPE lawsuit	CRSP
Past return	Firm's past 12-month stock return	CRSP
RD	Natural logarithm of R&D expenses plus one	Compustat
Return_{t-1}	Return of one month before the NPE lawsuit	CRSP
Return_{t-2}	Return of one month before the NPE lawsuit	CRSP
Small firm	The Small firm is an indicator variable equal to 1 if the natural logarithm of the firm's total assets is less than the 25th percentile of all the firm's total assets.	Compustat
Two-month return	Two-month cumulative stock return following the NPE lawsuit	CRSP
Three-month return	Three-month cumulative stock return following the NPE lawsuit	CRSP
# of times visibility per firm	The total number of visibility by all firms in a year divided by the number of firms	RavenPack
Visibility	Natural logarithm of the number of patent-related news in the prior year plus one	RavenPack
Visibility count	Number of times a firm's product-related news appeared	RavenPack
Visibility rank	The standardized rank of the total number of product-related news articles	RavenPack

the gone wealth averaged at least 80 billion USD per year. Their sample constituted the technology industry and invested heavily in R&D.

In Table 11, we regress the *Visibility* on the *CAR* of the defendant firms following the NPE lawsuits to investigate the extent of distress that NPEs cause to the defendant firms. Therefore, the sample consists of the firms that the NPEs already sue.

All columns in Table 11 show that after being sued by the NPEs, *Visibility* is significantly and negatively associated with the CAR. That said, investors have a negative sentiment about the companies that the NPEs threaten. Therefore, increasing the visibility of the defendant firm following NPE threats leads to a negative abnormal return, which justifies our study; this study's primary motivation is to establish the deterrent effect of NPEs and determine NPE determinants.

6. Conclusion

This paper documents a previously unexplored shadowy side of the media coverage: the NPE trolling. Using a novel database of NPE litigation from the Stanford NPE Litigation Database and the media coverage data from the RavenPack database, we find that highly visible firms frequently become the targets of frivolous NPE lawsuits. Our baseline finding is consistent with the signaling hypothesis that NPEs strategically target highly visible firms that can pay off the settlement fees, i.e., media exerts a positive signal about the firm's capability to pay the settlement fees, which the NPEs then target. This result is robust to alternative estimation models such as the probit and Cox-hazard models and alternative measures of firm visibility. Additionally, comparing the positive and negative news coverage finds that NPEs are positively and significantly attracted to the positive news of the defendant firms.

Moreover, we find support for the economic mechanism that underlies the impact of media coverage on NPE threat, namely the identity theory that by targeting the highly visible firms, the NPEs aim to protect their interests and express/build their identity. Positioning oneself vis-à-vis a highly visible company is one of the easiest ways for NPEs to establish and signal their identity.

We follow the two-stage instrumental variable analysis and the DiD test to identify the causal effect of firm visibility on NPE litigation. Using distance, i.e., the minimum distance between the firm headquarters and the closest Dow Jones Branch, we find that

the instrumented visibility variable is positively and significantly related to the NPE litigation. We use the anti-troll law adopted to curb the NPEs' discretion of sending mass demand letters to defendant firms as an exogenous shock in the DiD test. We find that after the anti-troll law was adopted in a state, the effect of NPEs abated enough to eliminate the positive effect of the *Visibility* on the NPE threat. Finally, the size effect suggests that when large firms are more visible, they are more trolled by NPEs than smaller firms.

Our study sheds light on how excessive media coverage may invite patent trolls and provide avenues for further research into the real effects of NPEs on long-term corporate policies.

Appendix

See Table A.12.

Anti-patent troll laws signing dates by states

State	Date
AL	4/02/2014
AZ	3/24/2016
CO	6/05/2015
CT	5/08/2017
FL	6/02/2015
GA	4/15/2014
ID	3/26/2014
IL	8/26/2014
IN	5/05/2015
KS	5/20/2015
LA	5/28/2014
ME	4/14/2014
MD	5/05/2014
MI	1/06/2017
MN	4/29/2016
MS	3/28/2015
MO	7/08/2014
MT	4/02/2015
NH	7/11/2014
NC	8/06/2014
ND	3/26/2015
OK	5/16/2014
OR	3/03/2014
RI	6/04/2016
SC	6/09/2016
SD	3/26/2014
TN	5/01/2014
TX	6/17/2015
UT	4/01/2014
VT	5/22/2013
VA	5/23/2014
WA	4/25/2015
WI	4/24/2014
WY	3/11/2016

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