Sue and Acquire: Evidence from Patent Lawsuits*

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Abstract

We investigate whether and how firms strategically launch patent lawsuits against competitors to facilitate future acquisitions of the same firm, a practice we define as sue-and-acquire. We find a heightened likelihood of mergers and acquisitions after the filing of a patent lawsuit. Notably, the sue-and-acquire practices are particularly pronounced when the initial patent lawsuit is likely to be strategically motivated, namely, (i) when the plaintiff and defendant firms more directly compete in a product market, (ii) when the lawsuit is filed in the Eastern District of Texas, a venue characterized by a high concentration of strategic patent lawsuits, and (iii) in IT and patent thicket industries, where strategic patent lawsuits are more common. Additional analyses of market responses to the acquisition announcements reveal that sue-and-acquire firms benefit from the practice. Lastly, we find some evidence that sue-and-acquire plaintiffs are less likely to prevail in court. Overall, our findings suggest that firms exploit the patent legal system to eliminate competition, a practice that should be of interest to patent and anti-trust regulators.

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1 Introduction

Predatory strategies have long been employed by firms aiming to undermine and potentially eliminate competitors. Prior literature has traditionally centered on predatory pricing, where incumbent firms temporarily slash prices to drive out competitors (e.g., Burns, 1986; Sweeting et al., 2020). However, as business landscapes evolve and intellectual property becomes paramount in many industries, new facets of predatory behavior emerge. Despite this transformation, the strategic use of patent litigation as a tool to exert market pressure remains notably under-explored in academic literature.

In this study, we document a novel predatory strategy facilitated by patent litigation: the practice of firms filing strategic lawsuits against potential competitors only to acquire them later, a phenomenon we term "sue-and-acquire." By "strategic lawsuits," we refer to those initiated primarily for competitor-weakening motives, rather than being driven by legitimate patent disputes. This strategy is feasible due to the unique natures of the patent system: First, patents protect intangible assets, which inherently possess ambiguous boundaries, making them susceptible to exploitation. Second, defending against a patent lawsuit is exorbitantly expensive—even when the underlying claim holds little merit (see more detailed discussions from Section 2). Such litigation can significantly weaken a defendant, potentially coercing it into an acquisition agreement it would otherwise reject.

A prominent example of the sue-and-acquire tactic is the lawsuit initiated by Nuance Communications against Vlingo, a start-up and rising competitor (New York Times, 2012). Nuance first offered to acquire Vlingo, and Vlingo declined this offer. Subsequently, Nuance countered with an ultimatum: either accept the acquisition or face patent lawsuits — "pay $20 million in legal fees vindicating themselves in intellectual property litigation."[1] Vlingo again declined. Nuance later indeed filed a patent lawsuit against Vlingo. While Vlingo

[1]See more details from the case document of a lawsuit filed by Vlingo against Nuance, accusing Nuance of unfair competition. Available at https://masslawyersweekly.com/wp-content/blogs.dir/1/files/2011/10/9-1-11-DO-1-Complaint-with-Jury-Demand-06005057.pdf.

ultimately won, the company eventually agreed to sell itself to Nuance due to the significant financial strains. According to a former Vlingo executive, "we had the better product, but it didn't matter, because this system is so completely broken." Such sue-and-acquire cases appear to be more than anecdotal. A Wall Street Journal article lists a series of these cases and concludes that "patent infringement claims in technology are less a sign that a start-up is engaged in nefarious or shady practices and more a sign that it has made it" (Wall Street Journal, 2011).

To systematically investigate the sue-and-acquire phenomenon, we analyze whether a patent lawsuit precedes an acquisition attempt by the plaintiff towards the defendant. We first obtain data on patent lawsuits filed in the United States between 2000 and 2020 from the Stanford Patent Lawsuits Database and identify plaintiff-defendant pairs. We then construct industry- and size-matched pseudo-lawsuits to serve as the control group. Lastly, we identify the sue-and-acquire phenomenon by comparing the likelihood of merger and acquisition (M&A) attempts between the actual plaintiff-defendant pairs and the industry- and size-matched pseudo pairs.

Our analysis reveals a positive association between the filing of patent lawsuits and the likelihood of a merger and acquisition. In terms of the economic significance, the likelihood of a merger and acquisition increases by 0.94% to 1.76%, depending on model specifications, when preceded by a patent lawsuit. This effect is economically sizable, as the unconditional mean of the merger-and-acquisition likelihood of our entire sample is 0.1%. Importantly, the results are robust to controlling for a host of variables, including product similarity between the plaintiff and defendant firms. Collectively, our main findings suggest that some firms indeed first initiate a patent lawsuit against a firm and later acquire that same firm, providing empirical evidence confirming the sue-and-acquire phenomenon.

To validate the use of the sue-and-acquire tactic, we conduct three cross-sectional analyses, examining if the "sue-and-acquire" phenomenon intensifies when the initial patent lawsuit is more likely to be strategically motivated. If firms indeed use this tactic to fa-

cilitate acquisitions, the lawsuits are more likely a result of strategic motives than genuine patent disputes. As such, we anticipate a surge in "sue-and-acquire" instances in these lawsuits. First, we expect a higher concentration of "sue-and-acquire" instances where the competitor-weakening incentive is stronger. We use the product market overlap between the defendant-plaintiff pairs as a proxy for the direct competition and accordingly the competition-eliminating incentives. Our findings reveal that the merger-and-acquisition likelihood is approximately 50% higher for pairs with above-median product similarity than those with below-median similarity.

Second, the phenomenon is also more prevalent for patent lawsuits in the Eastern District of Texas, a jurisdiction known for a high concentration of strategic lawsuits (e.g., Klerman and Reilly, 2015; Love and Yoon, 2017). Due to district-specific rules perceived to favor plaintiffs, it attracts numerous meritless lawsuits. Notably, lawsuits in this district are associated with a merger-and-acquisition likelihood about 100% higher than in other districts. Third, the sue-and-acquire practices stand out in the IT sector and industries characterized by "patent thickets"—complex webs of patent rights where a product might infringe on multiple patents (Shapiro, 2000). Given the unique nature of their patents, firms in these areas are frequent targets of strategic lawsuits (see, for example, Bessen and Meurer, 2009; Allison et al., 2015), and we conjecture that these firms are more vulnerable to sue-and-acquire practices, which rely on strategically exploiting the patent litigation system. Collectively, these patterns, where sue-and-acquire practices intensify with strategic motivation, indicate that coercing acquisitions drives patent lawsuits.

Next, to demonstrate the validity of the sue-and-acquire strategy, we examine market reactions to acquisitions following patent lawsuits. For this strategy to be rational, the sue-and-acquire firms must indeed gain from it, manifested in positive returns to these firms upon the announcements of the acquisitions. Consistent with this prediction, we find that these sue-and-acquire acquisitions elicit 2% higher abnormal returns than acquisitions without a preceding patent lawsuit. Additional analyses show that part of the benefit stems from

reduced product market competition, as shown by positive returns of the rival firms in response to the acquisitions (e.g., Eckbo, 1983; Fathollahi et al., 2022; Kepler et al., 2022).

Furthermore, we evaluate the returns of rival firms in response to acquisition announcements as a function of rival firm size. The validity of the sue-and-acquire strategy can be inferred from the announcement of acquisitions, which signals to other rival firms that this strategy can be used to coerce acquisitions. We conjecture that small rival firms, when compared to larger counterparts, are more likely to be the target of this predatory approach, resulting in a more negative market reaction. We find consistent empirical results, suggesting that this predatory approach likely harms small firms.

Lastly, to further validate the use of the sue-and-acquire strategy, we examine the outcomes of these patent lawsuits. If these lawsuits were indeed initiated to weaken competitors, they are less likely to be driven by legitimate patent disputes and should have a lower victory rate for plaintiffs. We find some evidence consistent with this prediction, supporting the strategic use of patent lawsuits to facilitate acquisitions.

Notably, the true prevalence of the sue-and-acquire phenomenon likely exceeds our estimation. This is due to the deterrent effects of patent litigation threats: the high costs of patent litigation could compel target firms to accept acquisitions merely at the *threat* of litigation, without an actual lawsuit. For instance, if Vlingo had acquiesced to an acquisition deal when faced with the litigation threat, this case would not have been included in our analyses. Such threaten-and-acquire cases are unobserved, likely underestimating the actual prevalence of the sue-and-acquire phenomenon.[2] Future research with more comprehensive data may provide greater insight into the full extent of this phenomenon.

It's worth mentioning that mergers and acquisitions provide a useful context for examining the predatory effects of patent lawsuits. While other outcomes from predatory lawsuits, such as market exits or bankruptcy of defendants, are possible, establishing the strategic intent behind them is challenging. This is because genuine patent disputes might also push the

[2]See, for example, Milgrom and Roberts (1982); Agarwal et al. (2009) for how credible threats would have strong deterring effects.

infringers out of the market or towards bankruptcy. However, the sue-and-acquire sequence reveals a contradiction: a plaintiff, who initially saw the defendant as merely copying its technology, later recognized the value of the defendant for acquisition. Importantly, these alternative outcomes are also consistent with the tenor of the predatory effects of patent lawsuits (see, for example, Forbes (2019)).[3] Moreover, these alternative outcomes would bias us against empirically establishing the prevalence of the sue-and-acquire practice.

This paper offers several contributions to finance and economics research. First, it contributes to the emerging literature on the interaction between M&As and product market competition, by being the first to document that incumbent firms exploit patent litigation to facilitate future mergers and acquisitions. These studies collectively show the anti-competitive effects of acquisitions: Cunningham et al. (2021) finds that pharmaceutical incumbents acquire innovative start-ups solely to "kill" their projects; Kepler et al. (2022) shows that firms strategically manage acquisitions terms to evade antitrust oversight; Kamepalli et al. (2020) documents that large tech incumbents' acquisitions of entrants deter future entries, creating a "kill zone." Distinct from the previous papers, our paper documents *how* incumbents use patent lawsuits to facilitate acquisitions, enhancing our understanding of anti-competitive conduct.

Second, we expand a growing literature in finance and economics that examines the frictions in the patent system and their economic implications. Much of this research has largely focused on nonpracticing entities (NPEs, also colloquially known as "patent trolls"), entities that own patents but do not produce commercial products.[4] These studies largely find that patent trolls hurt firms' ability to innovate and grow (e.g., Tucker, 2014; Cohen et al., 2019; Appel et al., 2019; Mezzanotti, 2021). In contrast, our paper shifts the focus to practicing entities, whose revenue stems mainly from using their patents to produce goods.

[3]As reported by Forbes (2019), Nielsen pursued a patent infringement lawsuit against Sorenson Media, which subsequently led to Sorenson's bankruptcy. Nielsen later acquired Sorenson during the ensuing bankruptcy proceedings.

[4]The primary business model of nonpracticing entities is collecting licensing fees and litigating against other firms for patent infringement — in stark contrast to practicing entities, such as Apple Inc., whose revenues are mainly from sales of products.

Unlike NPEs, practicing entities often launch patent lawsuits to weaken competitors, such as inflating competitors' production costs or delaying their product releases (e.g., Lemley and Melamed, 2013), which raises anti-competitive concerns and has implications for consumers and antitrust regulators.

Relatedly, we contribute to the policy debates on the welfare effects of the patent system and the potential solutions. The scholarly debate on the patent system presents a spectrum of perspectives. For example, while Boldrin and Levine (2013) advocates for the abolition of the patent system due to a lack of evidence supporting its role in motivating innovation, Gilbert (2011) proposes reforms to address its imperfections. Recent studies highlight positive aspects, showing benefits for startups with lenient patent examiners Farre-Mensa et al. (2020) and protection for small firms (Acikalin et al., 2022). By documenting the novel mechanism of using patent lawsuits to coerce acquisitions, our paper provides valuable insights for policy discussions on patent system refinement.

Lastly, this paper adds to the large literature on predatory practices by unveiling a unique predatory strategy in the realm of intellectual property rights: the "sue-and-acquire" tactic. While traditional predatory literature has predominantly focused on pricing mechanisms (e.g., Burns, 1986; Sweeting et al., 2020), our study demonstrates the strategic use of patent litigation to achieve similar objectives. As such, this study complements prior studies and underscores the need for a broader understanding of predatory practices, given the increasing significance of intellectual property in the modern economy.

2 Institutional Background

The patent system is designed to provide economic incentives, in the form of temporary monopoly rights, to promote innovation and invention.[5] However, many prominent

[5]The literature on the patent system is vast. For brevity, our discussion focuses on aspects that are most relevant to this study. See, for example, Bessen and Meurer (2009),Burk and Lemley (2009), and Boldrin and Levine (2013) for comprehensive reviews. Furthermore, given the well-recognized importance of motivating innovation, a large literature focuses on how to motivate innovation (e.g., Manso, 2011; Ferreira et al., 2014).

economists and legal scholars argue that the current system is "too broad, too loose, and too expensive" (e.g., Bessen and Meurer, 2009; Becker and Posner, 2013). These features can result in firms exploiting the patent system to eliminate competition (e.g., Jaffe and Lerner, 2011). The "broad and loose" boundaries of patents can enable companies to threaten or initiate litigation against competitors, even if the underlying claims are tenuous (a detailed example is provided in Section 2.1). Furthermore, the costly patent litigation system often makes it rational for firms targeted by these lawsuits to abandon their products rather than fight, even when they believe they are not infringing (e.g., Jaffe and Lerner, 2011).

Further detailed discussions of the "too broad, too loose, and too expensive" features are provided in Section 2.1 and Section 2.2.

2.1 Patents with Broad and Loose Boundaries

Unlike tangible assets, patents have broad and vague boundaries, leading to disputes. To understand the impact of this difference, consider the analogy of patents and real estate. The boundaries of land rights are generally well-defined, making it unlikely for one to accidentally encroach on others' property. In contrast, the abstract and complex nature of ideas makes it challenging to clearly establish the boundaries of patents. This often results in disputes over rights, and, in some cases, strategic lawsuits where patent holders seek to expand the scope of their patents for excessive profits.

One prominent example demonstrating how the broad scope of patents can be exploited is a patent lawsuit filed by J. M. Smucker Co., a large jam and jelly maker, against Albie's Foods, Inc., a grocery and caterer in Michigan (e.g., Jaffe and Lerner, 2011). Smucker accused Albie's of infringing its patent (U.S. Patent No. 6,004,595) for their sale of crustless peanut butter and jelly sandwiches. Specifically, Smucker's patent protected their "sealed crustless sandwich" concept — namely an invention of having fillings between two pieces of bread and crimping the edges to seal the fillings. This broad patent enabled Smucker to assert its patent

right against any firms selling crustless peanut butter and jelly sandwiches.[6] This patent essentially granted Smucker exclusive rights over a basic culinary concept—the sealed, crustless sandwich—highlighting the potential overreach and vagueness of some patent claims. As Jaffe and Lerner (2011) notes, this lawsuit over peanut butter sandwiches is more than anecdotal and instead is "symptomatic of the larger and more profound problems with the patent system."

2.2 Costly Patent Litigation

Patent lawsuits are known to be exorbitantly expensive (e.g., Allison et al., 2017). A recent survey by the American Intellectual Property Law Association estimates that the median litigation cost ranges from $2.7 million for smaller cases to $4 million for larger ones (AIPLA, 2019). For instance, Vlingo spent a staggering $3 million defending itself against one lawsuit, despite the eventual ruling of non-infringement.

While the direct costs of patent lawsuits are significant, they often do not capture the full economic costs borne by the defendant firms. This is because patent lawsuits also impose significant indirect costs (e.g., Lerner, 1995; Bessen and Meurer, 2012; Bessen et al., 2018). For instance, Bessen et al. (2018) estimate the average loss per lawsuit to be $41.4 million, about ten times the typical legal expenses. Furthermore, Bessen and Meurer (2012) estimate that the annual aggregated economic costs of patent litigation average around 14% of total R&D expenditures.

Indirect costs from patent litigation arise in many forms. First, a primary concern is the potential shutdown of a defendant's operations due to the disputed technology, even if it covers only a minor aspect of the product (Lemley and Melamed, 2013). This risk is exacerbated by court rulings that grant preliminary injunctions—halting the defendant's

[6]The patent abstract states the following: "The sandwich includes a lower bread portion, an upper bread portion, an upper filling and a lower filling between the lower and upper bread portions, a center filling sealed between the upper and lower fillings, and a crimped edge along an outer perimeter of the bread portions for sealing the fillings therebetween. The upper and lower fillings are preferably comprised of peanut butter, and the center filling is comprised of at least jelly."

operations even before a trial starts—if the plaintiff is deemed likely to win the case and suffer irreparable harm (Jaffe and Lerner, 2011). Such shutdowns, potentially lasting years until a final verdict, amplify the patentee's bargaining power (Lanjouw and Lerner, 2001; Lemley and Shapiro, 2006; Shapiro, 2016). As such, many defendants choose to settle, even when they view the lawsuit as meritless (Jaffe and Lerner, 2011; Boldrin and Levine, 2013).

A famous case that illustrates the power of injunction and the significant costs of patent litigation is the patent lawsuit by NTP Inc. against Research in Motion (RIM), the manufacturer of Blackberry cellphones. Despite the disputed patents covering only a minor fraction of the Blackberry system, NTP's legal victory allowed it to seek a shutdown of RIM's entire operation. Consequently, RIM settled for over $610 million. Ironically, the disputed patents were later invalidated by the USPTO, suggesting that they were of little merit and should not have been granted in the first place. This case highlights the economic stakes in patent disputes.

Second, patent litigation can disrupt not just the defendant firm, but its entire business ecosystem. The broad scope of patent infringement liability allows patent plaintiffs to sue not just the defendants but also their customers and suppliers (Bessen and Meurer, 2012). For instance, a Vermont technology firm had to cancel two projects after a patent holder threatened to sue its clients (The Washington Post, 2013; Appel et al., 2019). Additionally, the mere shadow of ongoing litigation can deter customers, as showcased by customers' reluctance to upgrade and purchase Blackberry products during the lengthy litigation between NTP and RIM (Wall Street Journal, 2006).

Third, ongoing patent lawsuits discourage follow-on innovations and thus product competitiveness, as they cast significant uncertainty over the survival of the disrupted products. For instance, Tucker (2014) found that a firm sued for patent infringement halted the release of new product variations for two years during the litigation, leading to a revenue decline of about one-third for affected products. Lastly, patent lawsuits can distract corporate professionals from their core duties, as they must allocate substantial time to legal documentation,

depositions, and court testimonies.

One might wonder whether patent lawsuits are equally costly for the plaintiff firms and about the rationality of the sue-and-acquire strategy. First, while both plaintiff and defendant firms bear the direct litigation costs, the defendant firm alone bears the substantial indirect costs, estimated to be ten times greater than the direct costs (Bessen et al., 2018). Second, the sue-and-acquire firm benefits not only from acquiring the defendant per se, but also from deterring future entrants. In their seminal work, Milgrom and Roberts (1982) demonstrate that predatory practices create a reputation that deters future entrants, making it a rational long-term strategy, despite the high costs in the short-term.

In summary, within the current "too broad and too expensive" patent system, incumbent firms might find it feasible to exploit the high costs and uncertainties of patent litigation, strategically using lawsuits to facilitate acquisitions.

3 Sample Construction and Data

3.1 Sample Construction

We test the sue-and-acquire phenomenon using a sample that includes actual patent lawsuits (i.e., the treatment sample) and a matched control group of pseudo lawsuits (i.e., the control sample). The construction of the treatment sample involves the following three steps. First, we obtain all patent lawsuits filed between 2000 and 2020 from the Stanford Non-Practicing Entity (NPE) Litigation Database.[7] The patent lawsuit sample starts in 2000 as the Stanford NPE Litigation Database begins its coverage from that year. Second, we limit the sample to lawsuits initiated by practicing entities — that is, firms that make products and/or offer services. This is because the sue-and-acquire tactics only apply to firms that compete with other firms in the product or service market. By contrast, nonpracticing

[7]This database is the first publicly available database to track comprehensively how practicing entities, nonpracticing entities, and patent assertion entities use patents in litigation. See more details from Miller (2018).

entities, which do not manufacture products or provide services, would have no competitors (e.g., Miller, 2018). Finally, we restrict our sample to lawsuits filed by publicly listed patent asserters to ensure data availability for our return analyses.

Next, we construct the control sample consisting of pseudo plaintiff-defendant pairs, following Bena and Li (2014). First, for each actual plaintiff (defendant), we identify up to ten corresponding pseudo plaintiffs (defendants) within the same industry and with the closest size in terms of employees. We define industry based on the two-digit SIC code. We use the number of employees as a proxy for the firm size, given the absence of data on total assets for private defendant firms in our sample. Using the number of employees allows us to implement a consistent matching method for all the firms in our sample.[8] Second, we pair each plaintiff in the actual lawsuits with up to ten of the closest matches for the defendant and pair each defendant with up to ten of the closest matches for the plaintiff. We exclude actual plaintiff-defendant pairs from the analyses if neither the plaintiff nor the defendant has any matches.

Lastly, we reach our final sample, which consists of the actual plaintiff-defendant pairs and the pseudo pairs (i.e., the treatment and control samples). Our final sample consists of 625,963 observations, with 38,100 lawsuits between actual plaintiff-defendant pairs and 587,863 pseudo lawsuits between control pairs. Note that the vast majority (roughly 70%) of the defendant firms in our sample are private companies, for which data availability is limited. The sample sizes may vary across specific tests due to the data availability of the control variables.

3.2 Measure of M&A Attempts

We construct the outcome variable, *Acquire*, to capture whether the plaintiff attempts to merge with or acquire the defendant after the filing of a patent lawsuit. The variable

[8] In an untabulated analysis, we construct our control sample by using total assets to measure the size of the public firms and the number of employees for private firms. Our results are robust to this alternative sample construction method.

construction takes the following three steps. First, we obtain M&A information from SDC and Capital IQ to ensure that we have comprehensive coverage of all M&A attempts. Following prior studies (e.g., Bena and Li, 2014; Fathollahi et al., 2022), we restrict our analysis to M&A deals with acquirers seeking to own more than 50% of shares after the deals, to ensure the acquirers have controlling interests in the target firms after the deals. We also require the acquiring firms to be publicly listed to be consistent with the selection criteria used for the patent lawsuits sample. Second, because the Stanford Lawsuits Database, SDC, and Capital IQ use different firm identifiers, we use fuzzy-matching algorithms to match plaintiffs (defendants) with acquirers (targets) based on firm names, to identify whether a plaintiff attempts to acquire a defendant after initiating a patent lawsuit. Lastly, to ensure the accuracy of name matching, we use the Bing web search engine following Mei (2020) and manually verify all potential matches.

3.3 Control Variables

We include a host of control variables in our regression models. First, we control for product similarity of each plaintiff-defendant pair (*Prod_Sim*) in our empirical analysis, as prior literature suggests that the likelihood of mergers and acquisitions is a function of product similarity between two companies (e.g., Bena and Li, 2014; Hoberg and Phillips, 2010). To measure product similarity, we follow Hoberg and Phillips (2016) and compute the pairwise similarity score of business descriptions of firm-pairs to gauge the language similarity when describing their products. We employ the textual analysis algorithm provided by WRDS, which modifies Hoberg and Phillips (2016)'s algorithm by incorporating recent advances in machine learning (e.g., Le and Mikolov, 2014).[9] For ease of interpretation, we normalize the product similarity variable to a value ranging from zero to one. A higher value denotes the two firms have more similar business descriptions, implying greater proximity in the product space.

[9]The algorithm can be accessed on WRDS at https://wrds-www.wharton.upenn.edu/pages/support/applications/textual-analysis/textual-analysis-on-sp-500-companies/.

Besides product similarity, we also include the following variables to capture the characteristics of plaintiffs: book-to-market ratio (*Pltf_BM*), leverage (*Pltf_Leverage*), profitability (*Pltf_ROA*), total sales (*Log(Pltf_SLS)*), and the number of employees (*Log(Pltf_Num_Empl)*). For defendants, we include two control variables: total sales (*Log(Def_SLS)*) and the number of employees (*Log(Def_Num_Empl)*). We note that we employed a distinct set of control variables for the defendant firms as the majority of defendant firms in our sample are private and have limited data availability. We detail the definitions of all control variables in Appendix A.1.

We obtain data from three sources to measure the characteristics of plaintiff and defendant firms. First, we obtain data on business descriptions from Capital IQ. Second, for companies covered by Compustat, we obtain time-varying firm characteristics, such as total sales, from Compustat. Third, for firms not covered by Compustat, we obtain data from Dun and Bradstreet's NETS database (NETS). NETS is a commercial database that aims to cover all business establishments in the United States, akin to the U.S. Census Bureau's Longitudinal Business Database (LBD).[10] Our subscription to NETS provides us with access to the following variables on firm characteristics: four-digit SIC code, consolidated-level number of employees, and total sales.

3.4 Descriptive Statistics

Panel A of Table 1 presents the descriptive statistics on all variables used in our main empirical analyses. We find that patent asserters tend to be larger than the alleged infringers, with more employees and generating higher sales than the alleged infringers. Panel B of Table 1 presents the descriptive statistics of the treatment (actual plaintiff-defendant pairs) and control (matched pseudo plaintiff-defendant pairs) groups, respectively. The differences in firm characteristics between these two groups and the t-statistics of the differences are presented in the last two columns of Panel B. As described in Section 3.1, the control group

[10] See Farre-Mensa et al. (2020) for more details.

is matched with the treatment group based on size, proxied by the number of employees, and industry, based on two-digit SIC codes. We find that the actual plaintiffs have higher sales, higher profitability (proxied by ROA), lower B/M ratios, and lower leverage than their size- and industry-matched controls. The defendant firms have higher sales than their matched control firms. Furthermore, the product similarity between actual plaintiff-defendant pairs is on average higher than that between pseudo pairs.

Table 2 presents the correlation matrix of variables used in our main empirical analyses. The patterns from the correlation matrix are generally similar to those from Table 1, except for the following observations. First, we find a significant correlation between *Acquire* and *Sued*, which provides preliminary and comforting support to the sue-and-acquire phenomenon. Second, we find a high correlation between the number of employees and total sales for both patent asserters and alleged infringers, presumably due to both variables likely capturing the size effect. Specifically, the correlation between *Log(Pltf_SLS)* and *Log(Pltf_Num_Empl)* is 0.957 (Pearson) and 0.857 for *Log(Def_SLS)* and *Log(Def_Num_Empl)*. Lastly, we find a positive correlation between *Sued* and *Prod_Sim*, suggesting that patent lawsuits are more common among product market competitors.

4 Do Firms Engage in Sue-and-Acquire Practices?

In this section, we investigate whether patent lawsuits are associated with an increased likelihood of follow-on M&A attempts. Specifically, we estimate the following regression model using our main sample (see Section 3.1 for detailed sample construction):

$$\begin{aligned} Acquire_{ijm,t+5} = \gamma_0 + \gamma_1 Sued_{ijm,t} + \gamma_2 Prod\_Sim_{ijm,t} + \gamma_3 Plaintiff\_Characteristics_{im,t-1} \\ + \gamma_4 Defendant\_Characteristics_{jm,t-1} + Lawsuit\_Group\_FE_m + \epsilon_{ijm,t}. \quad (1) \end{aligned}$$

The dependent variable, $Acquire_{ijm,t+5}$, is an indicator variable that takes the value of one if the plaintiff firm i attempted to merge with or acquire the defendant firm j within

five years after the filing of the lawsuit. To comprehensively capture follow-on acquisition attempts, we select a five-year cutoff window, given that patent lawsuits take on average two and a half years to reach the trial stage (e.g., Lemley, 2010; Love and Yoon, 2017).[11] The independent variable of interest, $Sued_{ijm,t}$, is an indicator variable that takes the value of one if firm i filed a patent lawsuit against firm j in year t, and zero otherwise. Each lawsuit group m contains one observation for the plaintiff-defendant pair and several industry- and size-matched control pairs. We include $Lawsuit\_Group\_FE_m$, the lawsuit group fixed effects for each group of a plaintiff-defendant pair and its matched control pairs, following Bena and Li (2014). We cluster the standard errors at the lawsuit group m level.

Table 3 presents results estimated from Equation (1). In column (1), we find that *Sued* is positively associated with *Acquire*, suggesting a positive relationship between the likelihood of M&A and the existence of preceding patent lawsuits. Columns (2) and (3) show that the relation between *Acquire* and *Sued* remains statistically positive and is even stronger when controlling for *Prod_Sim*, as shown in columns (2) and (3). This alleviates concerns of potential bias due to omitted variables related to product similarity. Turning to the economic significance, we find that the filing of patent lawsuits increases the likelihood of M&A by 0.94% to 1.76%, depending on the model specifications. The effect is economically sizable, as it is around ten times greater than the unconditional mean of the likelihood of M&A within five years (i.e., 0.1%). The heightened propensity of firms to merge with or acquire firms they've sued confirms the presence of sue-and-acquire phenomenon, lending preliminary support to the use of sue-and-acquire tactics.

Turning to the control variables, we find a positive and statistically significant coefficient on *Prod_Sim*, consistent with prior studies (e.g., Hoberg and Phillips, 2010; Bena and Li, 2014) that document a higher likelihood of M&A transactions between product market competitors. Due to the high correlation between the number of employees and total sales, as shown in Table 2, they are not included in the same regression.

[11] Our results are robust to using a shorter (i.e., three-year) window to capture M&A attempts after patent lawsuits.

Overall, the results in Table 3 provide empirical evidence that supports the use of sue-and-acquire tactics. The findings are robust to the inclusion of control variables, including product similarity between the plaintiffs and the defendants, time-varying characteristics of both plaintiffs and defendants, and the lawsuit group fixed effects.

5 Are Sue-and-Acquire Practices More Prevalent Among Strategically Motivated Lawsuits?

Next, we further explore the nature of the sue-and-acquire practices by examining whether these practices intensify when the initial patent lawsuits are likely to be strategically motivated. Specifically, we examine whether these practices are more common (1) when the patent plaintiff and defendant compete more directly in the product market, (2) when the lawsuits are filed in a venue known for a high concentration of strategic patent litigation, and (3) when the underlying industries are prone to strategic patent lawsuits.

5.1 Product Market Competitors

First, we examine whether the sue-and-acquire practices are more prevalent when the plaintiff and the defendant more aggressively compete in the same product space. To test this, we conduct a cross-sectional test by augmenting Equation (1) with the interaction term between the main independent variable of interest, *Sued*, and our measure of product similarity, *Prod_Sim*. The regression model is as follows:

$$\begin{aligned} Acquire_{ijm,t+5} = \gamma_0 + \gamma_1 Sued_{ijm,t} * Prod\_Sim_{ijm,t} + \gamma_2 Sued_{ijm,t} + \gamma_3 Prod\_Sim_{ijm,t} \\ + \gamma_4 Plaintiff\_Characteristics_{im,t-1} + \gamma_5 Defendant\_Characteristics_{jm,t-1} \\ + Lawsuit\_Group\_FE_m + \epsilon_{ijm,t}. \end{aligned} \tag{2}$$

Columns (1) to (3) of Table 4 report the results estimated from Equation (2). Across

all three specifications, the interaction term, $Sued * Prod\_Sim$, loads with a positive coefficient that is significant at the 1% level. Next, to simplify the interpretation of economic significance, we repeat the analysis using an indicator variable ($High\_Prod\_Sim$), instead of a continuous variable, to capture product similarity. $High\_Prod\_Sim$ takes the value of one if the product similarity between firm i and firm j is above the sample median, and zero otherwise. The results are reported in columns (4) to (6) of Table 4. We continue to find a positive and statistically significant coefficient on the interaction variable, $Sued * Prod\_Sim$. In terms of the economic significance, we find that the likelihood of a subsequent merger and acquisition attempt by the plaintiff is roughly 49% (i.e., = 0.0065/0.0134) higher when the product similarity of the plaintiff-defendant pair is above the sample median. Overall, the results in Table 4 show that the sue-and-acquire practice is indeed more pronounced among pairs that more directly compete in the product space.

5.2 The Eastern District of Texas

Second, we examine whether the sue-and-acquire practice is more prevalent when the initial lawsuit is filed in the Eastern District of Texas, a venue characterized by its high concentration of strategic lawsuits. The notion that the Eastern District of Texas is notorious for its high concentration of strategic lawsuits is supported by mounting empirical and anecdotal evidence. For instance, a striking 63% of patent lawsuits initiated by "patent trolls" were filed in the Eastern District of Texas in 2015 (Chien and Risch, 2017). This concentration is particularly noteworthy considering that the Eastern District of Texas is home to around 1% of the US population and is not considered as a major technology hub.

Anecdotal evidence also supports the notion that strategic patent lawsuits are more prevalent in the Eastern District of Texas. For instance, Nuance, the previously discussed firm that sued and later acquired Vlingo, launched its patent lawsuit in the Eastern District of Texas, despite the fact that both firms were based in Massachusetts. According to Vlingo, Nuance had been purposely filing lawsuits in this jurisdiction to drive up the litigation costs

for defendants, including Vlingo (Kile, 2011).

Given the prevalence of strategic patent lawsuits in the Eastern District of Texas, we anticipate that firms seeking to weaken competitors through patent litigation are more likely to file lawsuits in this district. Consequently, these lawsuits are likely to be followed by corporate acquisitions.[12] To test this prediction, we augment Equation (1) by including the interaction term between $Sued$ and $Eastern\_Texas$, an indicator variable that takes the value of one if the patent lawsuit is filed in the Eastern District of Texas, and zero otherwise.

Table 5 reports the results. The main variable of interest, $Eastern\_Texas * Sued$, loads with a positive and statistically significant coefficient. The result is robust to the inclusion of product similarity and other characteristics of plaintiffs and defendants as controls. For example, column (3) shows that the likelihood of subsequent M&A attempts increases from 1.65% to 3.19% (i.e., =0.0154+0.0165), when a patent lawsuit is filed in the Eastern District of Texas, equivalent to a roughly 100% increase in M&A propensity compared to patent lawsuits filed elsewhere. Overall, the results in Table 5 demonstrate that the sue-and-acquire practice is more likely when a patent lawsuit is filed in the Eastern District of Texas, a jurisdiction widely perceived to attract plaintiffs that intentionally exploit the patent litigation system.

5.3 IT and Patent Thicket Industries

Third, we examine whether sue-and-acquire practices are especially common among industries where strategic patent lawsuits are more common, namely IT and patent thicket industries. These two groups of industries are commonly believed to attract many strategic

[12] One might wonder why all patent plaintiffs do not file suits in the Eastern District of Texas. Based on our conversations with legal scholars, there are two main reasons. First, alleged patent infringers could leverage the pro-patentee nature of the Eastern District of Texas by counter-suing the original plaintiff in the same venue. Specifically, one common counterattack strategy adopted by patent defendants is to sue the original plaintiffs for patent infringement to force a cease-fire. Importantly, for legal efficiency, both cases are likely to be heard in the same venue, namely the venue where the initial lawsuit was filed. Thus, filing a meritless patent lawsuit in the Eastern District of Texas might backfire. Second, filing a patent lawsuit in this infamous "renegade district" is indicative of exploiting the loopholes of the patent legal system and would cause a loss of reputation capital.

lawsuits, due to the unique natures of their patents. First, ample empirical evidence reveals that IT firms are targeted in lawsuits of dubious merits "through no fault of their own" (e.g., Bessen and Meurer 2009; Bessen and Meurer 2013; Feng and Jaravel 2016). This particular prevalence of opportunistic lawsuits is believed to arise from the industry's patents, which are "notoriously difficult to interpret" (Bessen and Meurer, 2013) and often "vague and overly broad" (e.g., Bessen and Meurer, 2009; Shapiro, 2010; Jaffe and Lerner, 2011; Bessen and Meurer, 2013; Appel et al., 2019). Patent thicket industries are likewise characterized by a high concentration of opportunistic patent lawsuits (Allison et al., 2015; Hall et al., 2021). This is because patentees can claim overly broad rights of their patents, given the dense web of patents with overlapping rights in these industries. This means a firm's entire production line might be endangered by only a few patents. As a result, patent lawsuits can impose a great toll on defendants, giving rise to strategic exploitation by plaintiffs.

To test this prediction, we modify Equation (2) by interacting $Sued$ with $IT\_Industry$, which is an indicator variable that takes the value of one for those firms with the two-digit SIC code equal to 35 or 73 and zero otherwise. Panel A of Table 6 reports the results with the same set of control variables in Table 3. Across all specifications, we consistently find the main interaction term $IT\_Industry * Sued$ loads with a positive and statistically significant coefficient. In terms of the economic significance, we find IT firms are approximately 49% (i.e., $= 0.0082/0.0165$) more likely to engage in sue-and-acquire practices than non-IT firms. The results support our prediction that the sue-and-acquire phenomenon is more severe in the IT industry, relative to other industries.

Next, we identify patent thicket firms following prior studies (e.g., Bessen and Meurer, 2013; Cohen et al., 2019). Specifically, we create an indicator variable $Thicket\_Industry$, that takes the value of one if a firm is in an industry with the SIC two-digit code equal to 35, 36, 38, or 73 and zero otherwise. We then modify Equation (2) by interacting $Sued$ with $Thicket\_Industry$.

Panel B of Table 6 reports the results. The main variable of interest $Thicket\_Industry*$

Sued consistently loads with a positive and statistically significant coefficient across the three columns. Turning to the economic magnitude, we find that, following an initial patent lawsuit, the likelihood of a subsequent merger and acquisition attempt is heightened by approximately 40% (i.e., = 0.0062/0.0155) for patent thicket industries as compared to other industries. The results are consistent with our prediction that the sue-and-acquire practice is particularly common in patent thicket industries.

Taken together, the results in Table 6 show that firms in industries with more strategic patent lawsuits are more likely to initiate a patent lawsuit and later attempt to acquire the sued firm.

6 Do Sue-and-Acquire Firms Benefit from the Practice?

In this section, we further corroborate the use of sue-and-acquire tactics by examining whether firms that adopt this strategy derive any benefits, a critical assumption behind the rationale of this tactic.

6.1 Benefits to the Sue-and-Acquire Firms

In this section, we measure the benefits gained by firms engaging in the practice of sue-and-acquire by analyzing the abnormal returns of these firms around the announcement of acquisitions. To conduct this empirical analysis, we first construct a treatment sample (i.e., a "sued" sample) that consists of all M&A deals from our main sample that are preceded by patent lawsuits filed within five years. We then include all other U.S. M&A deals announced during the time period from 2000 to 2020 as the control sample. The data on these control deals are obtained from the SDC Database.[13] Given that the return analysis requires stock

[13]For the construction of the control sample, we apply the same selection criteria as in our main sample. Specifically, only those deals are included where the deal form was coded as a merger, an acquisition of majority interest, or an acquisition of asset, following Bena and Li (2014).

return data, only deals involving publicly traded acquirers are considered. The final sample for this analysis includes 30,555 deals for which all data required for variable construction are available. The regression model is as follows:

$$Acq\_CAR_{im,t} = \gamma_0 + \gamma_1 Sued_{ijm,t-1tot-5} + \gamma_2 Acq\_Size_{i,q-1} + \gamma_3 Acq\_BM_{i,q-1} + \gamma_4 Acq\_Run\_Up_{i,t} + \gamma_5 Private\_Target_{jm,t} + Year\_FE + AcquirerIndustry\_FE + \epsilon_{im,t}. \quad (3)$$

The dependent variable, $Acq\_CAR_{im,t}$, is the three-day ([-1,+1]) market-adjusted cumulative abnormal return of acquirer i around the M&A announcement date t. The main independent variable of interest is $Sued_{ijm,t-1tot-5}$, and it takes the value of one if acquiring firm i had previously sued target firm j for patent infringement within the five years leading up to t, and zero otherwise. Following prior M&A literature (e.g., Harford et al., 2012), we incorporate several control variables: Acq_Size, which represents the natural logarithm of the market value of acquirer i as of the last fiscal quarter preceding t; Acq_BM, denoting the book-to-market ratio of acquirer i as of the last fiscal quarter before t; Acq_Run_Up, measured as the cumulative market-adjusted abnormal return of acquirer i over the 200 trading days ([-210, -10]) leading up to t; and $Private\_Target$, indicating whether the target firm is privately held. Lastly, to account for time trends and industry-specific factors, we incorporate year and acquirer industry fixed effects. The standard errors are clustered at the acquirer level.

Table 7 reports the results estimated from Equation (3). Specifically, column (1) presents results incorporating both year and industry fixed effects, while column (2) only includes year fixed effects. Across both specifications, our main independent variable, $Sued$, consistently exhibits a positive and statistically significant coefficient. In terms of the economic magnitude, acquisitions following a patent lawsuit yield abnormal returns that are 2% higher compared to other acquisitions. These findings indicate that the capital market responds more positively to sue-and-acquire firms compared to other acquiring entities. Our

results demonstrate that sue-and-acquire firms indeed derive benefits from such tactics.

6.2 Are Part of the Benefits from the Reduced Competition?

In this section, we examine whether part of the benefits accruing to the sue-and-acquire firms stems from reduced competition. As previously noted, eliminating competitors likely motivates the sue-and-acquire practice. To probe the anti-competitive effects, we follow existing studies to examine the abnormal returns of industry rivals around the acquisition announcement (e.g., Eckbo, 1983; Fathollahi et al., 2022; Kepler et al., 2022). The intuition is that anti-competitive mergers could reduce product market competition, leading to elevated product prices, which in turn benefits all rivals of the merging firms.

To test this prediction, we begin by analyzing the portfolio returns of industry competitors. We conduct the analysis at the individual M&A deal level. Specifically, for the acquirer of each deal in Table 7, we identify industry rivals as those firms that share the same four-digit SIC code as the acquirer. We then estimate the following regression model.

$$\begin{aligned} Rivals\_CAR_{i,t} = \gamma_0 + \gamma_1 Sued_{ijm,t-1tot-5} + \gamma_2 Private\_Target_{j,t} \\ + \gamma_3 Log(Num\_Rivals)_{i,t} + Year\_FE + AcquirorIndustry\_FE + \epsilon_{i,t}. \end{aligned} \quad (4)$$

The dependent variable, $Rivals\_CAR_{i,t}$, is the three-day ([-1,+1]) buy-and-hold abnormal (market-adjusted) value-weighted portfolio returns of acquirer i's industry rivals around the M&A announcement date.[14] The main independent variable, $Sued_{ijm,t-1\,to\,t-5}$, is an indicator variable set to one if the acquirer i had previously filed a patent lawsuit against the target firm j before the acquisition, and zero otherwise. As in Equation (3), we include $Private\_Target$ as a control. We also control for the number of rivals ($Log(Num\_Rivals)$) following prior studies (e.g., Kepler et al., 2022). The standard errors are clustered at the acquiring firm level.

[14] Each rival is weighted by its market value measured at the end of June of the preceding year, following Fama and French (1996).

Panel A of Table 8 reports the results estimated from Equation (4). We find that the main independent variable, *Sued*, loads with a positive and statistically significant coefficient in both columns (1) and (2). This result suggests that acquisitions preceded by patent litigation induce higher abnormal returns for industry rivals relative to acquisitions without such preceding litigation, consistent with an anti-competitive effect.

Next, we investigate whether the market reactions documented in Panel A of Table 8 vary across rivals of different sizes. Rival firms are identified using the same approach described for Panel A of Table 8. The sample of this analysis is constructed at the deal-rival firm level. The regression model is as follows:

$$\begin{aligned} Individual\_Rival\_CAR_{r(i),t} = \gamma_0 + \gamma_1 Sued_{ijm,t-1tot-5} + \gamma_2 Sued_{ijm,t-1tot-5} * Small\_Rival_{r(i),q-1} \\ + \gamma_3 Small\_Rival_{r(i),q-1} + \gamma_4 Rival\_BM_{r(i),q-1} + \gamma_5 Rival\_Run\_Up_{r(i),t} \\ + \gamma 6 Private\_Target_{jm} + Year\_FE + AcquirerIndustry\_FE + \epsilon_{r(i),t}. \end{aligned} \tag{5}$$

The dependent variable, $Individual\_Rival\_CAR_{r(i),t}$, is the three-day market-adjusted abnormal returns of firm $r(i)$, namely the industry rival of acquirer i, around the M&A announcement date. The main independent variable, $Sued_{ijm,t-1,to,t-5}$, is defined as it is in Panel A of Table 8. *Small_Rival* is an indicator variable that takes the value of one if the market value of a rival firm is below the median of all rival firms of the focal acquirer, and zero otherwise. The market value is measured as of the most recent fiscal quarter before t. We include the same set of controls as those in Equation (3). The standard errors are clustered at the acquirer industry level.

Panel B of Table 8 reports the results estimated from Equation (5). Column (1) includes acquirer-industry fixed effects and year fixed effects, and Column (2) includes year fixed effects only. For both specifications, we find the interaction term, $Sued * Small\_Rival$ loads with a negative coefficient, statistically significant at the 1% level. Moreover, we find the variable *Sued*, which captures the average market reactions to all rival firms, loads with

a statistically significant coefficient in both columns. Our findings show that small rival firms have a more negative reaction to the announcement of acquisitions preceded by patent litigation, consistent with the announcement validating the sue-and-acquire strategy, which likely harms small firms.

Collectively, the results in Tables 7 and 8 support the key assumption behind the use of the sue-and-acquire tactics — that is, firms indeed benefit from this tactic. Importantly, a part of the benefits likely results from reduced product competition.

7 Are Sue-and-Acquire Lawsuits More Frivolous?

In this section, we provide additional evidence for the use of sue-and-acquire tactics by examining whether firms that initiate sue-and-acquire lawsuits are less likely to be successful in court. Given that this tactic involves firms launching patent lawsuits against competitors for strategic reasons, rather than on the merits of the case, such lawsuits should have a lower likelihood of success in court.

We compare the likelihood of plaintiff win of the plaintiff-defendant pairs in the sue-and-acquire (SA) pairs to that of matched non-sue-and-acquire (NSA) pairs. In the SA pairs, the plaintiff firm acquires the defendant firm within five years after initiating a patent lawsuit, whereas in the NSA pairs, it does not. To identify the NSA pairs, i.e., the control group, we first identify up to five control plaintiffs for each plaintiff in the SA pairs, based on the SIC 2-digit code and firm size. Similar to the way we identify control firms in the main analysis, we proxy firm size using the total number of employees. Then, we identify all the lawsuits initiated by the identified control plaintiff in the same year as those initiated by the SA pairs. Third, to ensure that the control pairs are indeed NSA pairs, we only consider lawsuits not succeeded by M&A within the subsequent five years. The final sample for this analysis consists of 163 SA pairs and 879 NSA pairs. Note that a plaintiff can initiate lawsuits against multiple defendants in a given year. Thus, the average number of NSA pairs

matched to each SA pair is slightly higher than five.

Next, we create an indicator variable, *Plaintiff_Win*, to measure the lawsuit outcomes. We follow legal studies in coding the patent lawsuit outcomes (e.g., Janicke and Ren, 2006; Allison et al., 2013). Given the complexity of coding lawsuit outcomes, especially in patent cases, we concentrate on lawsuits with definitive outcomes, treating those with mixed results as indecisive. Specifically, we follow the legal literature, basing our coding on rulings across three dimensions: validity, infringement, and enforceability. Note that a defendant in a patent case can defend itself through three defenses: (i) challenging the validity of the disputed patent(s) by arguing that the patent(s) should not have been issued in the first place; (ii) claiming non-infringement by proving that, even if the disputed patent is valid, the defendant firm did not infringe on it; or (iii) claiming non-enforceability by proving that, even if the disputed patent is valid and the defendant firm infringed, the patent is unenforceable because the patentee has engaged in inequitable conduct. Accordingly, *Plaintiff_Win* takes the value of one if (1) at least one of the plaintiff's claims or patents is deemed to have been infringed and (2) no claims or patents are judged invalid or unenforceable, and zero otherwise.

The majority of patent lawsuits are resolved before going to trial (e.g., Janicke and Ren, 2006),[15] leading to indecisive outcomes and posing significant empirical challenges for our analysis. Accordingly, we employ two different samples to compare lawsuit outcomes between SA and NSA pairs: (i) the first sample includes patent lawsuits with definitive outcomes and (ii) the second sample includes all patent lawsuits. For the latter sample, when a lawsuit yields an ambiguous outcome, *Plaintiff_win* is coded as zero, as it does not represent a decisive victory for the plaintiff firm.

Panel A of Table 9 reports the differences in lawsuit outcomes between the SA and NSA pairs, focusing on the sample of patent lawsuits that have definitive outcomes. As noted earlier, a limited number of patent lawsuits yield definitive outcomes. Excluding lawsuits

[15]For example, Lemley (2010) finds that on average only 2.8% of patent cases reached the trial stage.

with indecisive outcomes reduces our sample size by almost 90%, significantly limiting the statistical power of this analysis. Nonetheless, our analysis shows that plaintiffs in the SA pairs are 14% less likely to prevail in the patent lawsuits compared to plaintiffs in the NSA pairs, consistent with our prediction. While presumably, due to the small sample size ($N = 158$), the results lack statistical significance ($t - stat$ =1.11), yet the economic magnitude remains substantial. The findings provide some evidence supporting the use of the sue-and-acquire tactics.

Panel B of Table 9 presents the differences in lawsuit outcomes between the SA and NSA pairs for the sample of all patent lawsuits. We continue to find that plaintiffs in the SA pairs are less likely to prevail in the patent lawsuits, relative to plaintiffs in the NSA pairs. The difference is statistically significant at the 5% level.

Taken together, we find that SA plaintiffs are less likely to prevail in the court than their NSA counterparts. The results confirm that sue-and-acquire lawsuits are more strategically-motivated and less driven by genuine patent disputes, consistent with the use of sue-and-acquire tactics.

8 Robustness Analysis

In our main analysis, we investigate the likelihood of M&A announced within five years after the filing of a patent lawsuit, because of the long period–on average two and a half years–a patent lawsuit usually takes to reach trial (Lemley, 2010; Love and Yoon, 2017). In this section, we conduct a robustness analysis by focusing on a three-year window. In other words, we re-estimate Equation (1) after replacing the dependent variable, *Acquire*, with *Acquire_within3yr*.

Table 10 reports the results. Consistent with our main results in Table 3, we find that the main independent variable, *Sued*, loads with a positive coefficient that is statistically significant at the 1% level across the three columns. In economic terms, the results suggest

an increase in the likelihood of M&A by 0.7% to 1.3% when a patent lawsuit is preceded by a merger or acquisition in the past three years. This impact is still economically sizable, given that the unconditional mean of $Acquire\_within3yr$ is 0.07%.

9 Conclusion

We uncover a novel strategy adopted by incumbent firms to facilitate acquisitions of competitors — via strategic patent lawsuits. We first show that patent lawsuits are likely to be followed by plaintiffs' attempts to acquire defendant firms. We then show that this sue-and-acquire practice is more pronounced when the initial patent lawsuit is likely to be strategically motivated, supporting the notion that some firms strategically exploit the patent system to facilitate acquisitions. Next, focusing on the announcements of the acquisitions, we confirm that sue-and-acquire firms indeed benefit from this practice, validating that it is a rational strategy. A further examination of the market responses of rival firms reveals that part of the benefit is from reduced market competition. Lastly, our findings provide some evidence that in cases of sue-and-acquire lawsuits, plaintiffs have a lower likelihood of success in court, confirming that these lawsuits are likely driven by strategic motives.

The findings in this paper have important policy implications for both anti-trust and patent regulators. First, by documenting that incumbent firms can strategically exploit the patent system to weaken other firms and facilitate acquisitions of those firms, this paper informs the concurrent debates about abusive conduct by incumbent firms to stifle competition (e.g., House Judiciary Committee, 2020). Second, the findings also illuminate the strategic exploitation of the patent system, suggesting that the recent widespread demands for patent reform are plausibly warranted (e.g., The Washington Post, 2021; New York Times, 2022). Our study, along with related papers on the economic implications of the patent system, provides an avenue for future research into the strategic exploitation of the patent system for anti-competitive purposes.

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Table 1
Descriptive Statistics

Panel A: Summary Statistics

	N	Mean	SD	Q1	Median	Q3
Acquire	625,963	0.001	0.033	0.000	0.000	0.000
Sued	625,963	0.061	0.239	0.000	0.000	0.000
Log(Pltf_Num_Empl)	590,991	8.561	2.623	6.773	8.987	10.865
Log(Def_Num_Empl)	501,067	7.084	2.601	5.030	6.909	9.384
Log(Pltf_SLS)	593,046	21.147	2.979	19.187	21.668	23.703
Log(Def_SLS)	500,715	19.320	3.361	17.070	19.485	21.878
Pltf_BM	467,547	0.386	0.552	0.185	0.333	0.555
Pltf_ROA	485,533	0.147	0.747	0.049	0.166	0.296
Pltf_Leverage	484,431	0.261	0.227	0.116	0.226	0.340
Prod_Sim	339,440	0.576	0.224	0.425	0.593	0.746
Thicket_Industry	625,963	0.270	0.444	0.000	0.000	1.000
IT_Industry	625,963	0.117	0.321	0.000	0.000	0.000
Eastern_Texas	625,963	0.055	0.227	0.000	0.000	0.000

Panel B. Treatment Group vs. Control Group

	Treatment group		*Control group*			
	N	Mean	N	Mean	Diff.	T-stats
Log(Pltf_SLS)	35,073	21.293	557,973	21.138	0.154***	9.42
Log(Def_SLS)	26,696	19.370	474,019	19.317	0.053**	2.50
Pltf_BM	27,736	0.354	439,811	0.388	-0.034***	-10.03
Pltf_ROA	28,610	0.122	456,923	0.149	-0.027***	-5.91
Pltf_Leverage	28,517	0.255	455,914	0.261	-0.006***	-4.46
Prod_Sim	17,742	0.671	321,698	0.571	0.101***	58.67

Notes. Panel A presents the summary statistics for the entire sample. The unit of observation is at the lawsuit level. Panel B compares the characteristics of plaintiffs and defendants between the treatment and control samples. The treatment sample comprises all actual patent lawsuits, while the control sample consists of matched pseudo lawsuits. See Section 3.1 for the detailed procedures taken to reach the treatment and control samples. The last two columns of the table report the differences between the treatment and control groups, along with the t-statistics from t-tests. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 2
Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Acquire*	1	0.066***	0.014***	0.015***	0.013***	0.014***	0.008***	-0.001	-0.003**	0.038***
(2) *Sued*	0.066***	1	0.013***	0.010***	0.006***	0.006***	-0.008***	-0.028***	-0.017***	0.103***
(3) *Log(Pltf_SLS)*	0.013***	0.012***	1	0.064***	0.961***	0.054***	-0.065***	0.280***	0.105***	0.041***
(4) *Log(Def_SLS)*	0.010***	0.004**	0.050***	1	0.059***	0.941***	-0.029***	0.015***	0.023***	0.101***
(5) *Log(Pltf_Num_Empl)*	0.012***	0.004***	0.957***	0.047***	1	0.056***	-0.035***	0.270***	0.076***	0.060***
(6) *Log(Def_Num_Empl)*	0.014***	0.006***	0.050***	0.857***	0.052***	1	-0.023***	0.019***	0.010***	0.107***
(7) *Pltf_BM*	0.004***	-0.015***	0.001	-0.016***	0.014***	-0.010***	1	-0.261***	-0.207***	-0.012***
(8) *Pltf_ROA*	0.002	-0.008***	0.185***	0.006***	0.171***	0.012***	-0.075***	1	0.229***	-0.016***
(9) *Pltf_Leverage*	-0.004***	-0.006***	-0.033***	0.018***	-0.050***	0.008***	-0.366***	0.139***	1	-0.034***
(10) *Prod_Sim*	0.038***	0.100***	0.054***	0.104***	0.069***	0.115***	0.004**	-0.009***	-0.026***	1

Notes. Table 2 presents Pearson (Spearman) correlations above (below) the diagonal of the matrix. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 3
Do Firms Engage in Sue-and-Acquire Practices?

	Dependent Variable=Acquire		
	(1)	(2)	(3)
Sued	0.0094***	0.0175***	0.0176***
	(18.51)	(12.99)	(13.13)
Prod_Sim		0.0060***	0.0059***
		(9.56)	(9.46)
Pltf_BM		0.0002*	0.0002*
		(1.80)	(1.74)
Pltf_Leverage		-0.0011***	-0.0011***
		(-3.99)	(-4.10)
Pltf_ROA		-0.0000	-0.0000
		(-0.18)	(-0.05)
Log(Pltf_SLS)		0.0003***	
		(3.40)	
Log(Def_SLS)		-0.0002	
		(-1.45)	
Log(Pltf_Num_Empl)			0.0009***
			(3.41)
Log(Def_Num_Empl)			-0.0004
			(-1.62)
Lawsuit Group FE	Yes	Yes	Yes
R^2	0.067	0.083	0.083
N	625,963	224,987	224,850

Notes. This table presents the OLS regression results of whether a firm first initiates patent lawsuits against and later attempts to merge with or acquire the same firm. The main independent variable, *Sued*, is an indicator variable that takes the value of one if firm i filed a patent lawsuit against firm j in year t, and zero otherwise. The dependent variable, *Acquire*, is an indicator variable that takes the value of one if firm i attempts to merge with or acquire firm j within five years after year t. The sample consists of the treatment sample (i.e., actual plaintiff-defendant pairs) and the control sample (i.e., pseudo plaintiff-defendant pairs matched by size and industry). See Section 3.1 for the detailed steps taken to reach the treatment and control samples. Column (1) reports the main results with the lawsuit group fixed effects included. A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. In columns (2) and (3), we include additional controls. The sample size varies across the three columns due to the data availability of the control variables. All tests in this table include lawsuit group fixed effects, with standard errors clustered at the lawsuit group level. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 4
Prevalence of Sue-and-Acquire Among Direct Product Market Competitors

	Dependent Variable=Acquire					
	(1)	(2)	(3)	(4)	(5)	(6)
*Prod_Sim*Sued*	0.0233***	0.0219***	0.0223***			
	(5.40)	(3.57)	(3.62)			
Prod_Sim	0.0038***	0.0050***	0.0049***			
	(8.68)	(8.70)	(8.57)			
*High_Prod_Sim*Sued*				0.0072***	0.0063**	0.0065**
				(3.90)	(2.37)	(2.42)
High_Prod_Sim				0.0011***	0.0015***	0.0015***
				(8.09)	(8.62)	(8.45)
Sued	-0.0006	0.0026	0.0025	0.0103***	0.0133***	0.0134***
	(-0.21)	(0.66)	(0.64)	(7.65)	(6.52)	(6.55)
Pltf_BM		0.0002*	0.0002*		0.0002*	0.0002*
		(1.82)	(1.76)		(1.75)	(1.68)
Pltf_Leverage		-0.0011***	-0.0011***		-0.0011***	-0.0011***
		(-4.05)	(-4.17)		(-4.02)	(-4.14)
Pltf_ROA		-0.0000	-0.0000		-0.0000	-0.0000
		(-0.26)	(-0.13)		(-0.24)	(-0.11)
Log(Pltf_SLS)		0.0003***			0.0003***	
		(3.51)			(3.28)	
Log(Def_SLS)		-0.0002			-0.0002	
		(-1.44)			(-1.33)	
Log(Pltf_Num_Empl)			0.0009***			0.0009***
			(3.42)			(3.44)
Log(Def_Num_Empl)			-0.0004			-0.0004
			(-1.64)			(-1.52)
Lawsuit Group FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.089	0.083	0.083	0.088	0.083	0.083
N	339,401	224,987	224,850	339,401	224,987	224,850

Notes. This table presents the OLS regression results of whether sue-and-acquire practices are more prevalent when the plaintiff and the defendant more directly compete with each other in the product space. In columns (1) to (3), we employ a continuous measure, specifically *Prod_Sim*, to gauge the product similarity between the plaintiff and defendant. The value of this continuous measure ranges from zero to one; a higher value denotes that the firm-pair has closer competition in the product space. The main variable of interest is $Prod\_Sim * Sued$. In columns (4) to (6), we substitute the continuous measure with an indicator variable, $High\_Prod\_Sim$, which is set to one if the product similarity exceeds the sample median and zero otherwise. The main variable of interest is $High\_Prod\_Sim * Sued$. We use the same sets of controls as those in Table 3. All tests in this table include lawsuit group fixed effects, with standard errors clustered at the lawsuit group level. A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 5
Sue-and-Acquire Prevalence in the Eastern District of Texas

	Dependent Variable=Acquire		
	(1)	(2)	(3)
*Eastern_Texas*Sued*	0.0082***	0.0151**	0.0154**
	(2.80)	(2.24)	(2.26)
Sued	0.0090***	0.0164***	0.0165***
	(17.53)	(12.08)	(12.19)
Prod_Sim		0.0060***	0.0059***
		(9.55)	(9.44)
Pltf_BM		0.0002*	0.0002*
		(1.82)	(1.76)
Pltf_Leverage		-0.0011***	-0.0011***
		(-3.97)	(-4.08)
Pltf_ROA		-0.0000	0.0000
		(-0.10)	(0.03)
Log(Pltf_SLS)		0.0003***	
		(3.40)	
Log(Def_SLS)		-0.0002	
		(-1.51)	
Log(Pltf_Num_Empl)			0.0009***
			(3.45)
Log(Def_Num_Empl)			-0.0004*
			(-1.71)
Lawsuit Group FE	Yes	Yes	Yes
R^2	0.067	0.083	0.083
N	625,963	224,987	224,850

Notes. This table presents the OLS regression results of whether sue-and-acquire practices are more common when the initial lawsuit is filed in the Eastern District of Texas. The main independent variable is the interaction term between *Sued* and*Eastern_Texas*, an indicator variable that takes the value of one if the lawsuit was filed in the Eastern District of Texas, and zero otherwise. We employ the same control sets as outlined in Table 3. All tests in this table include lawsuit group fixed effects, with standard errors clustered at the lawsuit group level. A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. *T*-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 6
Sue-and-Acquire Prevalence in Industries Prone to Strategic Patent Litigations

Panel A: IT industry			
	Dependent Variable=Acquire		
	(1)	(2)	(3)
*IT_Industry*Sued*	0.0072***	0.0081*	0.0082*
	(3.67)	(1.87)	(1.89)
Sued	0.0086***	0.0163***	0.0165***
	(16.55)	(11.56)	(11.68)
Prod_Sim		0.0059***	0.0059***
		(9.51)	(9.41)
Pltf_BM		0.0002*	0.0002*
		(1.76)	(1.70)
Pltf_Leverage		-0.0010***	-0.0010***
		(-3.91)	(-4.01)
Pltf_ROA		-0.0000	-0.0000
		(-0.13)	(-0.01)
Log(Pltf_SLS)		0.0003***	
		(3.32)	
Log(Def_SLS)		-0.0002	
		(-1.47)	
Log(Pltf_Num_Empl)			0.0009***
			(3.51)
Log(Def_Num_Empl)			-0.0004*
			(-1.66)
Lawsuit Group FE	Yes	Yes	Yes
R^2	0.067	0.083	0.083
N	625,963	224,987	224,850

Continued on next page

Table 6 (cont.)

Panel B: Patent Thicket Industries

	Dependent Variable=Acquire		
	(1)	(2)	(3)
*Thicket_Industry*Sued*	0.0072***	0.0059**	0.0062**
	(5.50)	(2.00)	(2.11)
Sued	0.0075***	0.0155***	0.0155***
	(13.87)	(9.76)	(9.81)
Prod_Sim		0.0059***	0.0059***
		(9.45)	(9.34)
Pltf_BM		0.0002*	0.0002*
		(1.78)	(1.73)
Pltf_Leverage		-0.0011***	-0.0011***
		(-4.00)	(-4.11)
Pltf_ROA		-0.0000	-0.0000
		(-0.18)	(-0.05)
Log(Pltf_SLS)		0.0003***	
		(3.39)	
Log(Def_SLS)		-0.0002	
		(-1.48)	
Log(Pltf_Num_Empl)			0.0009***
			(3.56)
Log(Def_Num_Empl)			-0.0004*
			(-1.69)
Lawsuit Group FE	Yes	Yes	Yes
R^2	0.068	0.083	0.083
N	625,963	224,987	224,850

Notes. This table presents the OLS regression results of whether firms in industries prone to strategic patent lawsuits are more likely to engage in sue-and-acquire practices. Panel A (B) reports the estimation for firms in IT industries (patent thicket industries). In Panel A, the main independent variable is the interaction term between *Sued* and *IT_Industry*, an indicator variable that takes the value of one if the patent asserter is in the IT industry, and zero otherwise. The IT industry is defined as those firms with two-digit SIC codes in 35 or 73. In Panel B, the main independent variable is the interaction term between *Sued* and *Thicket_Industry*, an indicator variable that takes the value of one if the patent asserter is in a patent-thicket industry, and zero otherwise. The patent-thicket industry is defined as those with two-digit SIC codes in 35, 36, 38, or 73. All regression models include the baseline controls outlined in Table 3. Lawsuit group fixed effects are included, and standard errors are clustered at the lawsuit group level. A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. *T*-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 7
Do Sue-and-Acquire Firms Benefit from the Practice?

	Dependant Variable=Acq_CAR	
	(1)	(2)
Sued	0.0173**	0.0199***
	(2.05)	(2.63)
Acq_Size	-0.0037***	-0.0037***
	(-14.93)	(-15.16)
Acq_BM	-0.0009	-0.0010
	(-0.63)	(-0.72)
Acq_Run_Up	0.0010	0.0011
	(0.82)	(0.91)
Private_Target	0.0173***	0.0174***
	(12.12)	(12.81)
Acquiror Industry FE	Yes	No
Year FE	Yes	Yes
R^2	0.031	0.026
N	30,525	30,555

Notes. This table presents the OLS regression results, examining whether sue-and-acquire firms earn more positive abnormal returns around the announcement of the acquisition compared to other acquiring firms. The sample consists of two groups of mergers and acquisitions. The first group is the "sue-and-acquire" group (i.e., the treatment group), consisting of all mergers and acquisitions preceded by patent lawsuits filed within five years before the M&A announcement date. The other group is the control group, consisting of all other U.S. M&A deals announced during the time period from 2000 to 2020 without preceding patent lawsuits filed within five years before the M&A announcement. For the control group, we restrict our analysis to deals with publicly-listed acquirers to ensure consistency with the construction of our treatment group. We also restrict to deals with the form of the deal coded as a merger, an acquisition of majority interest, or an acquisition of asset, following Bena and Li (2014). The unit of observation is at the M&A deal level. The dependent variable is *Acq_CAR*, measured as the three-day market-adjusted cumulative abnormal returns of the acquiring firm around the M&A announcement date. The main independent variable of interest is an indicator, *Sued*, which is set to one if the M&A deal is preceded by a patent lawsuit filed by the acquiring firm against the target, within five years prior to the M&A. The control variables include the characteristics of acquiring firms (i.e., *Acq_Size*, *Acq_BM*, and *Acq_Run_Up*), and an indicator variable *Private_Target* capturing whether the target firm is privately held. Regarding the fixed effects, column (1) includes both acquirer industry fixed effects, constructed based on two-digit SIC code, and year fixed effects. Column (2) includes the year fixed effects only. Both tests cluster standard errors at the acquiring firm level. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 8
Are Part of the Benefits from the Reduced Market Competition?

Panel A: Portfolio Returns of Industry Rivals		
	Dependent Variable=Rivals_CAR	
	(1)	(2)
Sued	0.0044***	0.0042**
	(2.76)	(2.46)
Controls	Yes	Yes
Acquiror Industry FE	Yes	No
Year FE	Yes	Yes
R^2	0.006	0.001
N	29,114	29,115
Panel B: Large Rivals vs. Small Rivals		
	Dependent Variable=Individual_Rival_CAR	
	(1)	(2)
Sued	0.0077***	0.0074***
	(3.82)	(3.92)
*Sued*Small_Rival*	-0.0100***	-0.0100***
	(-8.14)	(-8.16)
Small_Rival	-0.0007**	-0.0006*
	(-2.17)	(-1.99)
Controls	Yes	Yes
Acquiror Industry FE	Yes	No
Year FE	Yes	Yes
R^2	0.001	0.001
N	1,876,984	1,876,984

Notes. Panel A of this table presents the results estimated from Equation (4), which examines whether part of the benefits accruing to the suing-and-acquiring firms is due to a reduction in product market competition. The sample is at the deal level. The dependent variable *Rivals_CAR* is the value-weighted three-day market-adjusted portfolio returns of industry rivals of the acquirer around the M&A announcement date. Rival firms are those that share the same four-digit SIC code as the acquirer. The main independent variable of interest is *Sued*, an indicator variable that takes the value of one if the M&A deal is preceded by a patent lawsuit within five years before the M&A announcement date, and zero otherwise. Panel B presents how the market reactions to industry rivals vary across rivals of different sizes, estimated from Equation (5). The unit of observations is at the deal-rival firm level. *Small_Rival* is an indicator variable that takes the value of one if the rival firm's market value is below the median of all rival firms of the focal acquirer, and zero otherwise. The dependent variable *Individual_Rival_Ret* is measured as market-adjusted three-day abnormal returns of individual rival firms around the deal announcement. Across both panels, column (1) presents estimates from the regression models incorporating both acquirer industry fixed effects and year fixed effects, while column (2) only includes year fixed effects. Standard errors are clustered at the acquirer industry level. Estimated coefficients on control variables are omitted for brevity. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 9
Are Sue-and-Acquire Patent Lawsuits More Meritless?

Panel A: Comparison of Outcomes for SA and NSA Pairs for Lawsuits with Definitive Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Sue-and-Acquire Pairs		*Non-Sue-and-Acquire Pairs*			
	N	Mean	N	Mean	Diff.	T-stats
Plaintiff_Win	16	0.313	142	0.458	-0.145	-1.11

Panel B: Comparison of Outcomes for SA and NSA Pairs for All Lawsuits

	(1)	(2)	(3)	(4)	(5)	(6)
	Sue-and-Acquire Pairs		*Non-Sue-and-Acquire Pairs*			
	N	Mean	N	Mean	Diff.	T-stats
Plaintiff_Win	163	0.031	879	0.074	-0.043**	-2.03

Notes. This table presents the differences in lawsuit outcomes between the *Sue-and-Acquire* (SA) and *Non-Sue-and-Acquire* (NSA) pairs. The unit of observation is at the plaintiff*defendant pair level. The SA pairs represent plaintiff-defendant pairs where the plaintiff firm attempts to acquire or merge with the defendant within five years post-initiation of patent lawsuits, while NSA pairs do not have such an attempt. See the detailed steps in identifying NSA pairs in Section 7. Panel A and B differ in sample composition: Panel A focuses on patent lawsuits with definitive outcomes, whereas Panel B includes all patent lawsuits. *Plaintiff_Win* takes the value of one if (1) at least one claim or one patent of the plaintiff is ruled to have been infringed and (2) no claims or patents are ruled to be invalid or unenforceable, and zero otherwise. The first two columns present the number of plaintiff-defendant pairs and the average likelihood of *Plaintiff_Win* for SA pairs, while the subsequent two columns do so for NSA pairs. Column (5) reports the value of the mean difference of the likelihood of *Plaintiff_Win* between SA pairs and NSA pairs, and column (6) reports the t-statistics of the difference. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively. See the detailed definitions of all variables in Appendix A.1.

Table 10
Alternative Measure: Acquire within Three Years

	Dependent Variable=Acquire_within3yr		
	(1)	(2)	(3)
Sued	0.0068***	0.0131***	0.0133***
	(15.72)	(11.29)	(11.46)
Prod_Sim		0.0040***	0.0040***
		(7.67)	(7.73)
Pltf_BM		0.0002*	0.0002*
		(1.76)	(1.86)
Pltf_Leverage		-0.0008***	-0.0008***
		(-3.94)	(-4.05)
Pltf_ROA		-0.0000	-0.0000
		(-0.61)	(-0.45)
Log(Pltf_SLS)		0.0002***	
		(3.04)	
Log(Def_SLS)		-0.0000	
		(-0.02)	
Log(Pltf_Num_Empl)			0.0004**
			(2.09)
Log(Def_Num_Empl)			-0.0007***
			(-2.75)
Lawsuit Group FE	Yes	Yes	Yes
R^2	0.060	0.072	0.072
N	625,963	224,987	224,850

Notes. This table presents the results estimated from Equation (1) after replacing the dependent variable *Acquire* with *Acquire_within3yr*. Specifically, we examine the likelihood of acquisition within three years after the initial patent lawsuit, rather than five years. Lawsuit group fixed effects are included, and standard errors are clustered at the lawsuit group level. A lawsuit group includes one actual plaintiff-defendant pair and matched control pairs. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. See the detailed definitions of all variables in Appendix A.1.

A Appendix

A.1 Variable Definitions

Variable	Definition	Source
Dependent Variables		
Acquire	An indicator variable that is set to one if patent asserter i attempts to merge with or acquire firm j within five years following the filing of the lawsuit, and zero otherwise.	SDC, Capital IQ, and Bing Web Search Engine
Acquire_within3yr	An indicator variable that is set to one if patent asserter i attempts to merge with or acquire firm j within three years following the filing of the lawsuit, and zero otherwise.	SDC, Capital IQ and Bing Web Search Engine
Acq_CAR	The three-day cumulative market-adjusted abnormal returns of the acquiring firm around the deal announcement date.	CRSP and SDC
Rival_CAR	The value-weighted three-day market-adjusted portfolio returns of the acquirer's industry rivals around the M&A announcement date. Rival firms are those sharing the same four-digit SIC code as the acquirer in the deal. Each rival firm's value is determined by its market value as of June from the previous year.	CRSP, Compustat, and SDC
Main Independent Variables		
Sued	An indicator variable that is set to one if patent asserter i files a lawsuit against firm j in year t, and zero otherwise. In the return analyses (Table 7 and Table 8), it denotes whether the acquirer sued the target within five years prior to the acquisition.	Stanford Lawsuits Database
High_Prod_Sim	An indicator variable that takes the value of one if the *Prod_Sim* is above the sample median, and zero otherwise.	Capital IQ
Eastern_Texas	An indicator variable that takes the value of one if the lawsuit is filed in the Eastern District of Texas, and zero otherwise.	Stanford Lawsuits Database
IT_Industry	An indicator variable that takes the value of one if the plaintiff firm is in the IT industry (SIC two-digit code 35 and 73), and zero otherwise.	Compustat
Thicket_Industry	An indicator variable that takes the value of one, if the plaintiff firm is in a patent thicket industry and zero otherwise. Following Bessen and Meurer (2013) and Cohen et al. (2019), patent thicket industries are defined as industries with the SIC two-digit codes 35, 36, 38 and 73.	Compustat
Baseline Control Variables		
Prod_Sim	Pairwise product similarity score between two firms based on their business descriptions. A higher score suggests a greater overlap in the product market, indicating more direct competition between the firms. The similarity score algorithm was obtained from WRDS.	Capital IQ

$Pltf\_BM$	The book-to-market ratio for the plaintiff firm, calculated as the book value of common equity divided by the market value of common equity.	Compustat
$Pltf\_Leverage$	The plaintiff firm's total debt scaled by total assets.	Compustat
$Pltf\_ROA$	The plaintiff firm's operating profits scaled by total assets.	Compustat
$Log(Pltf\_SLS)$	Natural logarithm of one plus the plaintiff firm's sales. For firm-years available in Compustat, we use the $REVT$ variable. When Compustat data is missing, the consolidated-level sales from the NETS database are employed. To align Compustat's $REVT$ (in millions) with NETS, we multiply $REVT$ by 1,000,000.	Compustat and NETS
$Log(Pltf\_Num\_Empl)$	Natural logarithm of one plus the number of the plaintiff firm's employees. For firm-years available in Compustat, we use the EMP variable. When Compustat data is missing, we use the consolidated-level number of employees in the NETS database. To ensure consistency between Compustat and NETS, we multiply the EMP (reported in thousands) by 1,000.	Compustat and NETS
$Log(Def\_SLS)$	Natural logarithm of one plus the defendant's sales. For firm-years available in Compustat, we use the $REVT$ variable. When Compustat data is missing, we use the consolidated-level sales data from the NETS database. To ensure consistency between Compustat and NETS, we multiply the $REVT$ (reported in millions) by 1,000,000.	Compustat and NETS
$Log(Def\_Num\_Empl)$	Natural logarithm of one plus the number of the defendant's employees. For firm-years available in Compustat, we use the EMP variable. When Compustat data is missing, we use the consolidated-level number of employees in the NETS database. To ensure consistency between Compustat and NETS, we multiply the EMP (reported in thousands) by 1,000.	Compustat and NETS
Control Variables in the return analyses		
Acq_Size	Natural logarithm of the acquiring firm's market value at the most recent fiscal quarter end.	CRSP and Compustat
Acq_BM	The acquiring firm's book-to-market ratio at the most recent fiscal quarter end.	CRSP and Compustat
Acq_Run_Up	The cumulative market-adjusted abnormal returns of the acquiring firm in the 200 trading days preceding (-210, -10) the announcement date.	CRSP
$Private\_Target$	An indicator variable that takes the value of one if the target firm of the merger or acquisition is not publicly listed, and zero otherwise.	SDC
$Log(Num\_Rivals)$	Natural logarithm of the number of rivals.	CRSP and Compustat
Variable in the lawsuit outcome analysis		
$Plaintiff\_Win$	An indicator variable that takes the value of one if (1) at least one claim or patent of the plaintiff has been ruled as infringed and (2) no claims or patents have been ruled as invalid or unenforceable, and zero otherwise.	Docket Navigator