Sue and Acquire: Evidence from Patent Lawsuits

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Abstract

We document a novel predation strategy through the U.S. patent system: firms strategically launch patent lawsuits against competitors to facilitate future acquisitions of those firms, a phenomenon we term “sue-and-acquire.” Initiating a patent lawsuit increases the likelihood of a subsequent M&A attempt by up to 13 times. Exploiting a U.S. Supreme Court ruling that exogenously constrains strategic lawsuits, we find more-affected firms reduce sue-and-acquire practices, establishing the causal link between strategic litigation and these practices. Cross-sectionally, these practices intensify when the patent lawsuits are ex ante more likely to be strategically motivated. Sue-and-acquire lawsuits exhibit systematic differences, such as lower legal merit, from other lawsuits, indicating that they are driven by strategic exploitation rather than genuine patent disputes. Consistent with sue-and-acquire strategies enhancing acquirers’ bargaining power, we find these acquisitions generate, on average, $87 million in additional shareholder value for acquiring firms. Our findings reveal how intellectual property rights can be used to influence innovation competition and entrepreneurial outcomes, with important implications for entrepreneurial strategy and technology policy.

Keywords: Product Market Predation, Mergers and Acquisitions, Patent Litigation

JEL Classifications: G34, G38, K21, L41

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Abstract

We document a novel predation strategy through the U.S. patent system: firms strategically launch patent lawsuits against competitors to facilitate future acquisitions of those firms, a phenomenon we term "sue-and-acquire." Initiating a patent lawsuit increases the likelihood of a subsequent M&A attempt by up to 13 times. Exploiting a U.S. Supreme Court ruling that exogenously constrains strategic lawsuits, we find more-affected firms reduce sue-and-acquire practices, establishing the causal link between strategic litigation and these practices. Cross-sectionally, these practices intensify when the patent lawsuits are ex ante more likely to be strategically motivated. Sue-and-acquire lawsuits exhibit systematic differences, such as lower legal merit, from other lawsuits, indicating that they are driven by strategic exploitation rather than genuine patent disputes. Consistent with sue-and-acquire strategies enhancing acquirers' bargaining power, we find these acquisitions generate, on average, \$87 million in additional shareholder value for acquiring firms. Our findings reveal how intellectual property rights can be used to influence innovation competition and entrepreneurial outcomes, with important implications for entrepreneurial strategy and technology policy.

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1 Introduction

Predatory strategies have long been employed by incumbent firms to undermine emerging competitors and suppress entrepreneurial activities (e.g., Milgrom and Roberts, 1982; Bolton and Scharfstein, 1990). While prior literature has traditionally centered on predatory pricing (e.g., Burns, 1986), recent work highlights how incumbent firms acquire innovative start-ups solely to kill their projects (Cunningham, Ederer and Ma, 2021). However, as business landscapes evolve and intellectual property becomes paramount in many industries (e.g., Bessen and Meurer, 2009), 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. Understanding these patent litigation strategies has become particularly urgent amid growing evidence on how incumbents in innovation-driven industries are stifling entrepreneurial activities (e.g., House Judiciary Committee, 2020).

In this study, we document a novel predatory strategy facilitated by patent litigation: the practice of firms filing strategic patent 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 ulterior motives, such as for competition elimination, rather than for genuine patent disputes. This strategy is facilitated by the patent system's widely criticized characteristics — being "too broad, too loose, and too expensive" (Becker and Posner, 2013).

First, patents have broad and ambiguous boundaries, in stark contrast to tangible properties (such as land), where property boundaries are clearly marked, and infringement can thus be readily determined with minimal costs (e.g., Bessen and Meurer, 2009). This ambiguity enables strategic lawsuits, as even tenuous claims can force defendants into costly litigation. Second, defending against a patent lawsuit is exorbitantly expensive, even when they are meritless (e.g., Boldrin and Levine, 2013). While direct legal costs alone amount to several million dollars (AIPLA, 2019), the total economic burden on a defendant firm can reach ten times the legal costs, through business disruptions and operational challenges (e.g., Bessen et al., 2018). These strategic patent lawsuits thus can significantly weaken defendants, especially small and resource-constrained firms, potentially coercing them into acquisition terms they 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 (*The 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." Vlingo again declined. Nuance then filed a patent lawsuit against Vlingo. Although Vlingo ultimately won, the company eventually agreed to sell itself to Nuance due to the significant financial strain. 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 just anecdotal: a *Wall Street Journal* article reports several such 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" (*The Wall Street Journal*, 2011).

To systematically investigate this sue-and-acquire phenomenon, we analyze the link between patent lawsuits and subsequent merger and acquisition (M&A) attempts by the plaintiff toward the defendant firm. Before diving into a natural experiment to draw the causal inference, we first identify this phenomenon by comparing the likelihood of M&A attempts between actual plaintiff-defendant pairs and matched control pairs without prior patent disputes. Our analysis reveals that initiating a patent lawsuit increases the baseline likelihood of a subsequent M&A attempt by up to 13 times, demonstrating a statistically and economically significant association. Importantly, the results are consistent across various model specifications: (i) the inclusion of a host of control variables, including firm-pair product similarity, and (ii) the use of entropy balancing to ensure comparability between actual plaintiff-defendant and control pairs (Hainmueller, 2012). Collectively, our baseline findings suggest a strong association between patent lawsuits and subsequent M&A attempts, providing empirical evidence consistent with the sue-and-acquire phenomenon.

We next investigate the causal link between strategic lawsuits and sue-and-acquire tactics by exploiting an exogenous shock to the U.S. patent system: the Supreme Court's decision on *Alice Corp. v. CLS Bank International* (hereafter, the Alice decision).[1] The Alice decision provides an ideal shock for our analysis, as it exogenously constrains firms' ability to file strategic patent lawsuits (e.g., Gugliuzza, 2017, 2018). Specifically, the Alice decision set new, more stringent standards for what can be patented, especially limiting patents on abstract ideas lacking tangible applications (hereafter, "abstract patents"). These abstract patents are widely believed to contribute to strategic lawsuits due to their broad and often vague nature (e.g., *The Atlantic*, 2014; Lefstin, Menell and Taylor, 2018). Crucially, the Alice decision allowed defendant firms to quickly and inexpensively end meritless lawsuits based on these abstract patents, thereby avoiding the substantial costs typically associated with prolonged patent litigation (e.g., Gugliuzza, 2017, 2018).[2] This increased protection against meritless lawsuits effectively weakens their coercive power and deters strategic lawsuits.

Accordingly, we predict a decrease in sue-and-acquire practices post-Alice, for firms more impacted by the decision (hereafter, "Alice-impacted firms"), as the ruling curtailed their ability to file strategic lawsuits using abstract patents. We identify these Alice-impacted firms as those whose patent portfolios are more heavily weighted toward abstract patents (see Section 5.2 for detailed methodology on identifying Alice-impacted firms). We identify the causal effects on sue-and-acquire activities using a triple-difference approach, comparing the M&A attempt likelihood between actual plaintiff-defendant pairs and matched control pairs (first difference), before and after the Alice decision (second difference), and between more-

[1]We thank Michael Meurer and Samantha Zyontz for providing valuable institutional knowledge on the Alice decision.

[2]For example, Gugliuzza (2017) notes that the Alice decision, along with other policy changes, allow courts to "quickly and cheaply dismiss infringement claims so plainly lacking merit."

Alice-impacted and less-impacted plaintiffs (third difference). Our triple-difference analysis reveals a statistically significant decline in sue-and-acquire activities post-Alice among more-Alice-impacted firms, relative to less-impacted firms. This decline, in response to arguably exogenous constraints on strategic lawsuits, provides causal evidence of strategic lawsuits driving the sue-and-acquire activities.

Having established the causal link between strategic lawsuits and the sue-and-acquire tactic, we next use larger and more comprehensive data on lawsuit-filing events to examine important cross-sectional heterogeneities of this tactic. If firms launch patent lawsuits for predatory acquisitions, these lawsuits stem from strategic intent — rather than genuine patent disputes. Consequently, sue-and-acquire activities should intensify when strategic lawsuits are, a priori, more likely. We test this prediction in three independent scenarios.

First, the sue-and-acquire strategy is likely more common among direct product market competitors, where firms are more incentivized to launch this tactic to gain a competitive advantage. Consistent with this prediction, we find that for patent lawsuits involving direct product competitors, plaintiffs are 120% more likely to subsequently attempt to acquire or merge with the defendant, compared to less directly competing pairs.[3] Importantly, this heightened acquisition activity does not merely reflect higher M&A propensities among product competitors (e.g., Hoberg and Phillips, 2010). The economic magnitude of patent lawsuits dominates product similarity in predicting M&A likelihood: the coefficient on patent lawsuits is up to seven times larger than that on product similarity, and the interaction effect between patent lawsuits and product similarity is up to ten times larger than the standalone effect of product similarity.[4]

Second, the phenomenon should be more prevalent in jurisdictions favorable to strategic lawsuits. Accordingly, we predict heightened sue-and-acquire activities for lawsuits filed in

[3]We measure product similarity between firm pairs using the pairwise language similarity score of their business descriptions, following Hoberg and Phillips (2016).

[4]We note that patent infringement lawsuits might be more frequent among firms with similar products. Our analysis, however, takes the existence of a patent lawsuit as given and investigates the likelihood that this particular lawsuit is strategically motivated and its association with a subsequent acquisition attempt. As such, it is independent of the frequency of patent lawsuits among competitor pairs.

the Eastern District of Texas, a venue widely regarded for its plaintiff-friendly rules and a known hub for strategic lawsuits (e.g., Klerman and Reilly, 2015; Love and Yoon, 2017).[5] Indeed, we find that lawsuits in this district are associated with a 100% higher likelihood of subsequent M&A than in other districts.

Third, the sue-and-acquire strategy should be more pronounced in industries prone to strategic patent lawsuits. Drawing on legal and innovation literature (e.g., Lemley and Shapiro, 2006; Bessen and Meurer, 2009), we identify two such industry groups: (i) the IT industry, known for its "vague and overly broad" patents that facilitate strategic litigation (Shapiro, 2010); and (ii) "patent-thicket" industries, characterized by dense and overlapping patent rights (Shapiro, 2000). In patent-thicket industries, a single product could potentially infringe upon thousands of patents. Consequently, in these industries, even a single patent dispute could jeopardize an entire production line of the defendant firm, imposing significant tolls on it. The potential for such significant disruption tilts the balance in favor of plaintiffs, giving rise to launching strategic lawsuits for predatory purposes. Our analyses reveal a concentration of sue-and-acquire activities in these industries: patent lawsuits filed by firms in the IT industry (patent-thicket industries) are associated with a 67% (40%) higher likelihood of subsequent M&A attempts than other industries.

To further establish the economic rationale for the sue-and-acquire strategy, we investigate its potential economic benefits to the acquirer. Suing-and-acquiring firms benefit from this tactic because it enhances their bargaining power in negotiations by imposing substantial financial and operational costs on target firms through patent litigation. While directly measuring these benefits is empirically challenging, stock market reactions to acquisition announcements provide a useful proxy for the anticipated economic gains. We find that sue-and-acquire deals generate announcement returns that are 2.3% to 3.1% higher than acquisitions without a preceding patent lawsuit. This premium translates to an economically

[5]This reputation is underscored by the fact that 63% of patent lawsuits initiated by "patent trolls" were filed in this district (Chien and Risch, 2017), earning it monikers such as "haven for patent pirates" (Williams, 2006) and "the town that trolls built" (*Bloomberg*, 2017).

sizable gain of \$64-\$87 million in shareholder value for suing-and-acquiring firms, suggesting possible significant economic benefits and validating the strategic value of this tactic.[6]

Lastly, to further establish the strategic nature of sue-and-acquire tactics, we examine the systematic differences between lawsuits followed by M&A attempts and "regular" patent disputes: lawsuit outcomes and patent boundaries — two characteristics that should differ systematically between strategic and genuine patent litigation. First, lawsuits initiated to facilitate acquisitions rather than resolve genuine patent disputes should exhibit lower legal merit and thus lower victory rates for plaintiffs. Consistent with this prediction, we find that plaintiffs in sue-and-acquire cases have a noticeably lower win rate (23%) than those in comparable disputes (46%). Second, patents with broad, ambiguous boundaries are widely documented in the legal literature as a key characteristic facilitating strategic patent litigation (e.g., Noel and Schankerman, 2013; Steensma, Chari and Heidl, 2015). Therefore, if these sue-and-acquire lawsuits are strategically motivated, they should systematically involve patents with broader, more ambiguous boundaries. Indeed, we find that patents in sue-and-acquire cases are more likely to have overly broad boundaries compared to patents in other lawsuits. These systematic differences in both lawsuit outcomes and patent characteristics further corroborate that sue-and-acquire practices represent a deliberate strategic exploitation of the patent system, rather than genuine patent disputes.

We address one alternative explanation of our findings. A priori, the sue-and-acquire phenomenon could reflect plaintiffs gaining valuable information about defendants during litigation ("information acquisition mechanism"), rather than a strategic decision to sue and then acquire at a cheaper valuation ("predatory lawsuit"). These mechanisms generate distinct predictions. Unlike the predatory lawsuit hypothesis, the information acquisition mechanism predicts no systematic pattern indicative of strategic intent in lawsuits leading to M&As, as these lawsuits were not ex ante strategically-motivated. Our earlier analyses, however, reveal patterns consistent with strategic intent behind the sue-and-acquire lawsuits:

[6] These figures are calculated by multiplying the acquirers' median market capitalization in this analysis (\$2.8 billion) by the range of abnormal returns (2.3% to 3.1%) we document.

(i) substantially lower success rates in court, (ii) patents with systematically more broad and ambiguous boundaries, and (iii) more pronounced presence in venues known for a concentration of strategic lawsuits. Together, these systematic patterns support the predatory lawsuit hypothesis over the information acquisition mechanism.

Our paper contributes to the emerging literature on the interaction between innovation-driven acquisitions and entrepreneurial exit paths, by being the first to document that firms exploit patent litigation to facilitate future M&As. While prior studies largely view acquisitions of entrepreneurial firms as efforts to integrate and foster innovation, recent work has begun to challenge this conventional wisdom. Closely related to our study, Cunningham, Ederer and Ma (2021) uncover "killer acquisitions," where pharmaceutical incumbents acquire innovative startups solely to discontinue their drug development projects. Kamepalli, Rajan and Zingales (2020) document that acquisitions by large tech incumbents create a "kill zone" that deters future entrepreneurial entry. Distinct from these papers, our paper documents *how* incumbents use patent lawsuits to facilitate acquisitions, enhancing our understanding of the comprehensive picture of this interaction.[7]

Furthermore, we contribute to the literature on the frictions of the patent system and their economic implications. Much of this research has focused on nonpracticing entities or "patent trolls," entities that own patents but do not produce commercial products (e.g., Tucker, 2014; Cohen, Gurun and Kominers, 2019; Appel, Farre-Mensa and Simintzi, 2019; Mezzanotti, 2021).[8] By contrast, our paper shifts the focus to practicing entities, which are uniquely positioned and incentivized to launch patent lawsuits to predate competitors, since their revenue stems mainly from using patents to produce goods (e.g., Lemley and Melamed, 2013). This distinction is crucial, as incumbents can strategically exploit patent litigation to suppress emerging competitors, unlike nonpracticing entities whose primary goal is to

[7]Relatedly, acquisitions facilitated by patent lawsuits may not end up as "killer acquisitions," since the target may not be discontinued, further distinguishing this paper from the aforementioned studies.

[8]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 products.

maximize licensing revenues. By documenting the sue-and-acquire tactics, this paper offers novel insights for ongoing policy discussions on patent system reform, particularly regarding how the current system may inadvertently enable strategic predation through litigation (e.g., *The Washington Post*, 2021; *The New York Times*, 2022).

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, Roberts and Gedge, 2020), our study demonstrates that the strategic use of patent litigation can achieve similar objectives. These findings are crucial for entrepreneurs and managers of emerging ventures who must navigate an increasingly complex intellectual property landscape (e.g., Shapiro and Varian, 1999), particularly in today's economy, where intellectual property becomes paramount across industries.

2 Exploitable Features of the U.S. Patent System: Why Is Sue-and-Acquire Feasible?

Although designed to promote innovation, the patent system in the United States has several features that make it susceptible to strategic exploitation, as argued by many prominent economists and legal scholars (e.g., Bessen and Meurer, 2009; Becker and Posner, 2013).[9] This section discusses two key features enabling the sue-and-acquire strategy: (i) the broad and loose boundaries of patents (Section 2.1) and (ii) the high costs of patent litigation (Section 2.2). We argue that these features create an environment where it is feasible for incumbent firms to strategically exploit the system through sue-and-acquire practices.

[9]The literature on the patent system is vast. For brevity, we focus 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.

2.1 *Patents with Broad and Loose Boundaries*

Patents, unlike tangible assets, often have broad and vague boundaries, which can lead to disputes and strategic lawsuits. The abstract nature of ideas makes it challenging to clearly define the scope of patents, allowing patent holders to potentially exploit this ambiguity and assert their rights against others. This lack of clarity in patent boundaries creates opportunities for firms to engage in strategic lawsuits, using litigation as a tool to eliminate competition.

The case of J.M. Smucker Co., a large food manufacturer, against Albie's Foods, Inc., a small grocery store, illustrates how the broad scope of patents can be exploited to squash competition. Smucker sued Albie's for infringing its patent (U.S. Patent No. 6,004,595) on a sealed, crustless peanut butter and jelly sandwich—a basic culinary concept. By asserting its patent rights over such a broad idea, Smucker was able to threaten legal action against essentially anyone for making a peanut butter sandwich. This case demonstrates how patents can be used as a powerful tool to limit competition, even in industries far removed from the traditional tech sector.

The Smucker's case is more than anecdotal and is "symptomatic of the larger and more profound problems with the patent system," as noted by Jaffe and Lerner (2011). The ambiguity in patent scope creates opportunities for firms to limit competition through litigation. In the context of the sue-and-acquire strategy, this ambiguity allows incumbent firms to target potential competitors with patent lawsuits, even if the claims are tenuous.

2.2 *Costly Patent Litigation*

In addition to the broad and loose boundaries of patents, the high costs of patent litigation further exacerbate the potential for strategic exploitation. Indeed, patent lawsuits are exorbitantly expensive to defend against (e.g., Allison, Lemley and Schwartz, 2017) and impose sizable direct costs: a 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).[10]

Beyond the direct costs, patent litigation also imposes significant indirect costs (i.e., the economic losses and business disruptions incurred beyond the direct legal expenses) on defendants (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 10 times the typical legal expenses. These high costs can be financially devastating for defendant firms, particularly smaller ones with limited resources.

These indirect costs can 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). A famous case that illustrates 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, and illustrates how defendants can be forced into costly settlements even when the asserted patents are of questionable validity.

Second, patent litigation can also disrupt a defendant firm's entire business ecosystem, beyond the firm itself. The broad scope of patent infringement liability allows plaintiffs to sue defendants' customers and suppliers as well (Bessen and Meurer, 2012). For example, a Vermont technology firm had to cancel two projects after a patent holder threatened to sue its clients (*The Washington Post*, 2013; Appel, Farre-Mensa and Simintzi, 2019). Moreover, ongoing litigation can deter customers from purchasing or upgrading products, as showcased by customers' reluctance to upgrade and purchase Blackberry products during the lengthy

[10]For instance, Vlingo spent a staggering \$3 million defending itself against one lawsuit, despite the eventual ruling of non-infringement.

litigation between NTP and RIM (*The Wall Street Journal*, 2006). These disruptions can have far-reaching consequences for a defendant's business relationships and market position.

Third, ongoing patent lawsuits discourage follow-on innovations and thus product competitiveness, as they cast significant uncertainty over the survival of disrupted products. For instance, Tucker (2014) found that a firm sued for patent infringement halted the release of new product variations during its litigation, leading to a roughly one-third revenue decline for affected products. Lastly, patent lawsuits can distract corporate professionals from their core duties, requiring substantial time for 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 10 times greater than the direct costs (Bessen et al., 2018). Second, the suing-and-acquiring 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. Mapping the intuition back to the sue-and-acquire setting, even if launching a patent litigation might be costly for the plaintiff, the plaintiff can benefit in the long term by deterring future market entrants.

The high costs of patent litigation (both direct and indirect), coupled with the ambiguity in patent scope, create a system that is ripe for strategic exploitation. Incumbent firms can leverage costly lawsuits to pressure smaller competitors or potential entrants into accepting acquisition offers they might otherwise reject. In sum, we conjecture that the current "too broad, too loose, and too expensive" patent system facilitates the sue-and-acquire practice as a predatory strategy.

3 Sample Construction and Data

3.1 *Data Sources*

We obtain data from five main sources. First, we obtain patent litigation data from the Stanford Non-Practicing Entity (NPE) Litigation Database, which comprehensively tracks patent lawsuits filed by practicing entities, non-practicing entities, and patent assertion entities from 2000 onwards (see more details from Miller, 2018). Second, for firms covered by the Compustat database, we obtain financial and accounting data directly from Compustat. This data include time-varying firm characteristics, such as total sales revenue and number of employees. Third, we obtain data from Dun and Bradstreet's National Establishment Time-Series (NETS) database for firms not covered by Compustat. NETS is a commercial database that aims to cover the universe of business establishments (both public and private) in the U.S. (see, e.g., Farre-Mensa, Hegde and Ljungqvist, 2020). Our subscription to the NETS database provides access to three key firm-level variables: the 4-digit Standard Industrial Classification (SIC) code, the total number of employees, and total sales. Fourth, we obtain M&A data from SDC and Capital IQ, augmented with data from the Bing web search engine, following the methodology of Mei (2020). Lastly, we obtain business description data from Capital IQ to measure product similarity between firms.

3.2 *Sample Construction*

We test the sue-and-acquire phenomenon using a baseline sample of (i) actual plaintiff-defendant pairs involved in patent lawsuits (i.e., the treated sample) and (ii) matched control pairs without a patent dispute (i.e., the control sample). The control sample serves as a benchmark for unconditional M&A likelihood in the absence of a patent lawsuit. We identify the sue-and-acquire phenomenon by comparing the M&A likelihood between the treated and control samples, which helps isolate the effect of patent lawsuits on subsequent

M&A attempts while controlling for other influential factors.

To construct the treated sample, we follow a three-step process. First, we obtain all U.S. patent lawsuits filed between 2000 and 2020 from the Stanford NPE Litigation Database.[11] The patent lawsuit sample starts in 2000 as the Stanford NPE Litigation Database began 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 apply only to firms that compete with other firms in the product or service market. By contrast, nonpracticing entities, which do not manufacture products or provide services, would have no competitors (e.g., Miller, 2018). Lastly, we restrict our sample to lawsuits filed by patent asserters covered in Compustat. We achieve this by matching the Stanford NPE Litigation Database with Compustat using name-matching algorithms. We impose this restriction for two reasons. First, for the plaintiff firms, it ensures the availability of essential financial and size control variables, such as the number of employees, total sales, and profitability. Second, since the determination of whether the plaintiff attempts to merge or acquire the defendant firm involves manual data collection (as explained in Section 3.3), putting some limitations on the scope of the sample is necessary. These steps yield a treated sample of 41,361 plaintiff-defendant pairs.

Next, we construct the control sample consisting of control pairs without a preceding patent dispute, following Bena and Li (2014), by identifying industry- and size-matched control firms. We proxy industry using the 2-digit SIC code and size using the number of employees, respectively.[12] To obtain the matching information for defendant firms, we match them with Compustat or NETS (if not covered by Compustat) data using a fuzzy matching algorithm.

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

[12]We use the number of employees as a proxy for firm size, due to the limited data availability on total assets for private defendant firms in our sample. This approach allows for a consistent matching method across all firms. Our results remain robust when using total assets as a size measure for public firms and the number of employees for private firms.

For each plaintiff firm, we identify up to 10 firms in the same industry that are closest to it in terms of size. These firms serve as the control firms for the actual plaintiff and are paired with the actual defendant firm. We repeat this process for each defendant firm, identifying up to 10 firms in the same industry that are closest to it in terms of size. These firms serve as the control firms for the actual defendant and are paired with the actual plaintiff firm. This process results in up to 20 control pairs for each actual plaintiff-defendant pair.[13] These steps yield a final treated sample of 38,100 plaintiff-defendant pairs, as 3,261 pairs (approximately 7.9%) were excluded due to the lack of suitable control pairs.[14]

Finally, our final sample consists of 625,963 firm pairs, with (i) 38,100 pairs involved in patent disputes serving as the treated sample and (ii) 587,863 industry- and size-matched control pairs without a preceding patent dispute serving as the control sample. Note that the vast majority (roughly 70%) of the defendant firms in our sample are private companies, for which data availability is limited. As such, the sample sizes vary across different tests due to the data availability of the control variables, such as product similarity between firm pairs. Given the nature of the analysis of the Alice decision, we describe its exact sample in Section 5.

Before proceeding with our detailed variable construction, we first examine the industry composition of our treated sample (i.e., the 38,100 plaintiff-defendant pairs involved in patent disputes) and the subset that later involves acquisition attempts. Table 1 presents the distribution of plaintiffs' industries using the Fama-French 12 classification. It shows that patent lawsuits are concentrated in innovation-intensive sectors, with Business Equipment (28.50%) and Healthcare (27.23%) accounting for over half of all patent litigation. Panel B reveals an even stronger concentration of sue-and-acquire cases in these sectors, with Business

[13]The decision to include a large number of control pairs is driven by data availability constraints for the control variables. For example, the data on product similarity between firm pairs is rather limited, resulting in a 50% reduction in the number of observations when included as a control variable. By starting with a relatively larger sample, we aim to mitigate the impact of data attrition and ensure a sufficient sample size for all our analyses.

[14]The primary reason for not finding control pairs is the unavailability of data on size and industry information for both the plaintiff and defendant firms.

Equipment and Healthcare representing 33.33% and 28.57% of such cases, respectively.

3.3 *Measure of M&A Attempts*

We construct the outcome variable, *Acquire*, to capture (i) whether a plaintiff firm attempts to merge with or acquire its defendant firm after the filing of a patent lawsuit and (ii) whether such an attempt exists between the control pairs. The variable construction involves a multi-step process that includes manual data collection. First, we obtain M&A information from SDC and Capital IQ, augmented with data from the Bing web search engine, following the methodology of Mei (2020). This approach ensures that we have broad coverage of M&A attempts. Following prior studies (e.g., Bena and Li, 2014; Fathollahi, Harford and Klasa, 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.

Second, because the Stanford NPE Litigation Database, SDC, and Capital IQ use different firm identifiers, we manually 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. Similarly, we manually match the control plaintiffs (control defendants) with acquirers (targets) to identify whether an M&A attempt exists among the control pairs. This process involves using fuzzy-matching algorithms to generate potential matches, which we then verify using the Bing web search engine. Lastly, to further validate the accuracy of the name matching, we conduct additional manual checks on all potential matches.

3.4 *Control Variables*

We employ several control variables. A key variable is the product similarity between each firm pair (*Prod_Sim*), as prior literature suggests that the M&A likelihood correlates with product similarity between companies (e.g., Hoberg and Phillips, 2010; Bena and Li, 2014). Measuring product similarity can be challenging for private firms, because it requires a business description (available in a 10-K form) to calculate this variable and thus is often limited to public firms. To overcome this limitation, we obtain business descriptions from Capital IQ, which covers both public and private firms. Its wide coverage allows us to compute this variable for a more comprehensive set of firm pairs.

To measure product similarity, we follow Hoberg and Phillips (2016) and compute the pairwise language similarity score of business descriptions between firm pairs.[15] For ease of interpretation, we normalize the product-similarity variable to a value ranging from 0 to 1. A higher value indicates that the two firms have more similar business descriptions, implying greater proximity in the product space.

In addition to product similarity, we include several control variables to capture the characteristics of both plaintiffs and defendants. For plaintiffs, we include the following variables: book-to-market ratio (BM_P), leverage ($Leverage_P$), profitability (ROA_P), total sales ($LnSales_P$), and the number of employees ($LnNumEmpl_P$). For defendants, due to the limited data availability for the majority of defendant firms in our sample, which are primarily private companies, we include the number of employees ($LnNumEmpl_D$) and total sales ($LnSales_D$). These two are the only relevant variables available through our NETS subscription.[16] The definitions of all control variables are in the Appendix A.1.

Panel A of Table 2 presents summary statistics for the full sample, including the treated and control firm pairs. The mean value of *Sued* is 6%, indicating that 6% of the full sample consists of actual plaintiff-defendant pairs (treated sample). The 0.1% sample mean of *Acquire* suggests that the unconditional likelihood of an acquisition attempt between a plaintiff (actual or control) and a defendant (actual or control) is relatively rare. The

[15] 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). 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/`.

[16] We use the number of employees and sales as proxies for firm size, due to the limited availability of total assets data for private defendant firms in our sample. This approach ensures a consistent measure of size across plaintiffs and defendants. Our results remain robust when including the total assets of plaintiff firms in the regressions.

summary statistics also reveal notable differences between plaintiffs and defendants in patent lawsuits. Plaintiff firms are significantly larger than defendant firms, with plaintiffs having an average of 31,624 employees (median = 8,000) and defendants having 12,657 employees (median = 1,000). These size differences suggest that, in our sample, firms initiating patent lawsuits tend to be substantially larger than the firms they sue.

3.5 *Entropy Balancing*

To enhance the comparability of our treated and control samples, we employ an entropy-balancing technique (Hainmueller, 2012). This method allows us to reweight the control sample so that the first moment (means) of each covariate is equalized across the treated and control groups. The entropy-balancing procedure is applied to all control variables used in our baseline analysis (in Section 4). By equalizing the means of these covariates, we mitigate potential selection bias arising from differences in firm characteristics between the two groups. To ensure the robustness of our findings, we report our results using both the unweighted sample (i.e., the treated sample plus the control sample) and the entropy-balanced sample.

The entropy-balancing procedure is applied to all control variables used in our baseline analysis (in Section 4), including the product-similarity measure ($Prod\_Sim$). Panel B of Table 2 reports the covariate balance statistics after we apply the entropy-balancing procedure. We find that the standardized differences in the means between the treated and control groups are insignificant and clustered around zero, indicating that the weighted control group closely resembles the treated group in terms of the included covariates, including $Prod\_Sim$. By equalizing the means of $Prod\_Sim$ and other covariates, we mitigate potential selection bias arising from differences in firm characteristics between the two groups. Although we do not explicitly balance the second (variance) moment of the covariate distributions to avoid assigning extreme weights, we observe that the variance ratios are largely balanced and clustered around 1.0.

We note that the number of observations (N) in Panel A of Table 2 (the full sample) is greater than the combined number of treated and control groups in Panel B. This is because the entropy-balancing procedure used in Panel B requires the availability of data for all control variables to perform the re-weighting. By contrast, Panel A includes all observations, regardless of the availability of control variable data.

4 Patent Lawsuits Leading to Acquisitions: Evidence of Sue-and-Acquire

This section systematically investigates the prevalence of the sue-and-acquire phenomenon by comparing the likelihood of M&A activity between plaintiff-defendant pairs and matched control pairs. Specifically, we estimate the following regression using our baseline sample:

$$
\begin{aligned}
Acquire_{ijm,t+3} = \gamma_0 + \gamma_1 Sued_{ijm,t} + \gamma_2 Prod\_Sim_{ijm,t} + \gamma_3 Plaintiff\_Characteristics_{im,t-1} \\
+ \gamma_4 Defendant\_Characteristics_{jm,t-1} + Lawsuit\_Group\_FE_m + \epsilon_{ijm,t}. \quad (1)
\end{aligned}
$$

The dependent variable, $Acquire_{ijm,t+3}$, is an indicator variable that takes the value of one if plaintiff firm i attempted to merge with or acquire defendant firm j within three years after the filing of the lawsuit. 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), we select a three-year cutoff window to comprehensively capture follow-on acquisition attempts. 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. $Prod\_Sim_{ijm,t}$ denotes the product similarity between firms i and j, derived from the linguistic similarity of business descriptions between two firms. A higher score indicates a greater overlap in product markets, indicating more direct competition between the pair.

We include several control variables to capture the characteristics of both plaintiffs and defendants. For plaintiffs, we control for the book-to-market ratio (BM_P), leverage ($Leverage_P$), profitability (ROA_P), total sales ($LnSales_P$), and the number of employees ($LnNumEmpl_P$). These variables account for the plaintiff's valuation, financial health, operating performance, size, and human capital. For defendants, due to the limited data availability for the majority of defendant firms in our sample, which are private companies, we include the number of employees ($LnNumEmpl_D$) and total sales ($LnSales_D$) to control for the defendant's size and operating scale. See the detailed variable definitions from Appendix A.1.

Each lawsuit group m consists of one observation for the plaintiff-defendant pair and its 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). This fixed-effects structure allows us to identify the sue-and-acquire phenomenon by comparing the M&A likelihood of each actual plaintiff-defendant pair against its matched control pairs. This within-group comparison controls for unobserved heterogeneity across lawsuit groups and isolates the effect of patent lawsuits on M&A likelihood. We cluster the standard errors at the lawsuit group m level.

Table 3 presents results estimated from Equation (1), using both OLS and entropy-balanced-weighted regressions. In column (1), the coefficient on $Sued$ is positive and statistically significant ($t = 15.72$), indicating that firms involved in patent lawsuits are more likely to engage in subsequent M&A attempts than those not involved in such lawsuits. Column (2) shows that the positive relationship between $Acquire$ and $Sued$ remains statistically significant ($t = 11.35$) and becomes even stronger when controlling for the product similarity between firm pairs ($Prod\_Sim$), alleviating concerns of potential omitted variable bias related to product similarity. Column (3) demonstrates the robustness of these results using the entropy-balanced-weighted regression analysis, which helps ensure that the treated and control groups have similar distributions of observable characteristics. In Column (3), the coefficient on $Sued$ remains positive and statistically significant ($t = 10.97$), with a magnitude of 1.33%. This result indicates that even after balancing the treated and control groups on observable characteristics, firms involved in patent lawsuits are still more likely to engage in subsequent M&A attempts than those not involved in such lawsuits. The consistency of the results across both the unweighted and entropy-balanced-weighted regressions underscores the robustness of the sue-and-acquire phenomenon.

As for the economic significance, we find that the filing of patent lawsuits results in an increase in the likelihood of M&A activity, with the magnitude of this increase ranging from 0.68% to 1.33%, depending on model specifications. This effect is economically substantial, as it represents an increase of up to 13 times the baseline likelihood of M&A within three years, which stands at 0.1%. The heightened propensity of firms to merge with or acquire firms they have sued confirms the presence of the sue-and-acquire phenomenon, lending preliminary support to the use of this tactic.

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.

Overall, the results in Table 3 provide empirical evidence that supports the use of sue-and-acquire tactics. The findings are robust to (i) the inclusion of control variables, including plaintiff-defendant product similarity and time-varying characteristics of both plaintiffs and defendants, and (ii) the use of entropy-balance-weighted regressions.

5 Exogenous Shock: Sue-and-Acquire Practices after the Alice Decision

In this section, we exploit the 2014 Alice decision as an exogenous shock to establish the causal link between strategic lawsuits and sue-and-acquire activities. The Alice decision exogenously limited the ability to file strategic lawsuits, allowing us to sharpen the identification of this link by examining changes in sue-and-acquire activities in response to this decision.

5.1 *The Alice Decision and Its Impact on Strategic Lawsuits*

The 2014 Alice decision fundamentally changed the patent litigation landscape by ruling that abstract ideas, lacking tangible invention, are not patentable. This ruling specifically targeted patents without concrete applications ("abstract patents"), which are prevalent in fields such as computer science, information technology, and business methods (e.g., Kesan and Wang, 2020). The decision created a natural experiment to study strategic patent litigation by significantly deterring strategic patent lawsuits involving abstract patents.

This deterrence effect stems from two key economic mechanisms. First, the decision substantially reduces defendant firms' costs to fend off meritless lawsuits, allowing them to "end those weak cases quickly and cheaply" (e.g., Gugliuzza, 2018; World Intellectual Property Organization, 2019). This change allows defendant firms to avoid the significant financial burdens typically associated with protracted patent litigations, thereby diminishing the coercive power of strategic lawsuits. Second, the decision increased the risks for plaintiffs filing strategic lawsuits using abstract patents, as it enables defendants to more easily seek and obtain patent invalidity rulings (e.g., *The Atlantic*, 2014; Gugliuzza, 2017). This aspect is crucial because challenging the validity of disputed patents is a common counter-strategy employed by defendant firms (e.g., Lemley and Shapiro, 2006). If successful, such challenges not only result in the plaintiff losing the lawsuit, but more importantly, lead to the invalidation of their patents. Indeed, 66% of patents challenged citing the Alice decision were invalidated after the decision (Tran, 2016).

These effects fundamentally changed the risk-reward of strategic patent lawsuits. Before Alice, the vague boundaries of abstract patents enabled broad interpretations of patent rights, making strategic lawsuits a low-risk strategy (e.g., *The Atlantic*, 2014; Lefstin, Menell and Taylor, 2018). Post-Alice, plaintiff firms considering strategic litigation using abstract patents face a less favorable risk-reward trade-off: diminished ability to cause harm to the defendants combined with increased risk of invalidation (i.e., losing) their patents.[17]

Consequently, the Alice decision provides a natural experiment that allows us to identify the causal relationship between strategic litigation and sue-and-acquire practices. By comparing more Alice-impacted firms (i.e., whose patent portfolios are more heavily weighted toward these abstract patents) to less impacted firms, before and after the ruling, we can isolate the causal effect of strategic patent litigation on subsequent M&A activity.

5.2 *Measuring Firm-Level Exposure to the Alice Decision*

Our empirical strategy aims to identify the impact of the Alice decision based on each firm's existing patent portfolios before the decision, closely following the methodology detailed in Acikalin et al. (2022). Briefly, this approach takes three steps.[18] First, we use the Longformer deep-learning model — a cutting-edge machine-learning algorithm — to estimate the probability that a patent could be invalidated due to the Alice ruling. To train the model, we construct a dataset containing two samples: a positive sample of patent applications rejected due to the Alice decision (obtained from Lu, Myers and Beliveau (2017)), and a negative sample comprising patents granted thereafter. To form the negative sample, we pair each positive patent application (rejected due to the Alice decision) with three negative patents, each from the same CPC group, subclass, and class, respectively. See more details from the method outlined in Experiment C by Acikalin et al. (2022).[19] In terms of performance, the model achieves an accuracy rate of 72% when applied to a testing sample, roughly in line with Acikalin et al. (2022).

[17] While the Alice decision primarily impacts strategic lawsuits, it might also change the incentives to file patent lawsuits in general. The deterrence effects, however, are more pronounced for strategic lawsuits, due to their inherently weaker legal merits and their greater reliance on the ambiguous boundaries of abstract patents that the Alice decision specifically targeted. This differential impact allows us to identify the causal effect of strategic patent litigation on subsequent M&A activity.

[18] The algorithm is complicated, and the summary here is inherently brief; see Acikalin et al. (2022) for details.

[19] While Acikalin et al. (2022) develop a multi-tiered approach for creating negative samples, we select Experiment C's method to achieve a balance between representativeness and manageability of our dataset.

Second, we use the trained model to assign an *AliceScore* to each patent, capturing the likelihood of it being rejected due to the Alice decision. Lastly, we aggregate the patent-level *AliceScore* to the firm level, capturing a firm's exposure to the Alice decision, using the following equation:

$$AliceExposure_i = \frac{\sum_{j=1}^{N_i} PatentValue_{i,j} \times AliceScore_{i,j}}{Sales_{i,2013}}, \tag{2}$$

where $PatentValue_{i,j}$ denotes the dollar value of firm i's patent j, with data obtained from the KPSS database (Kogan et al., 2017). The patent values are depreciated using an annual 20% rate with the year 2014 as the base year (Li and Hall, 2020; Acikalin et al., 2022). $Sales_{i,2013}$ denotes firm i's total sales in the year 2013. N_i denotes the total number of patents owned by firm i before the Alice decision.

5.3 *Empirical Analyses on the Impact of the Alice Decision*

To assess the impact of the Alice decision on sue-and-acquire practices, we conduct a lawsuit-level triple-difference analysis. We first start with the sample used in our baseline analysis (see Table 3). We then limit the sample period to 2011 through 2017, which provides a balanced sample that spans three years before and after the Alice decision. Lastly, we exclude 2014 (the decision year) to avoid the classification ambiguity and transitional effects typically associated with significant policy changes. We then estimate the following regression:

$$\begin{aligned} Acquire_{ijm,t+3} = \gamma_0 &+ \gamma_1 Sued_{ijm,t} * High\_AliceExposure_i * Post_t \\ &+ \gamma_2 Sued_{ijm,t} * High\_AliceExposure_i + \gamma_3 High\_AliceExposure_i * Post_t \\ &+ \gamma_4 Sued_{ijm,t} * Post_t + \gamma_5 Sued_{ijm,t} + \gamma_6 High\_AliceExposure_i + \gamma_7 Post_t \\ &+ \gamma_8 Prod\_Sim_{ijm,t} + \gamma_9 Plaintiff\_Characteristics_{im,t-1} \\ &+ \gamma_{10} Defendant\_Characteristics_{jm,t-1} + Lawsuit\_Group\_FE_m + \epsilon_{ijm,t}. \end{aligned} \tag{3}$$

The variable $High\_AliceExposure_i$ is an indicator variable that takes the value of one if firm i's exposure to the Alice decision ($AliceExposure$) is above the sample median, and zero otherwise. The variable $Post_t$ is an indicator variable that takes the value of one if the patent lawsuit is filed after 2014, and zero otherwise. All other variables are defined the same as those in Equation (1).[20]

Table 4 presents the estimated results. The key variable of interest is the triple interaction term $Sued * High\_AliceExposure * Post$, whose coefficient captures the change in sue-and-acquire intensity for firms more impacted by the Alice decision during the post-ruling period. We employ this triple-difference specification to compare the change in the likelihood of M&A attempts between actual plaintiff-defendant pairs and matched control pairs (first difference), before and after the Alice decision (second difference), and between firms more impacted by the Alice decision versus those less impacted (third difference). Columns (1) and (2) show that this coefficient is consistently statistically negative at the 1% level, indicating a significant decline (around 1.37% to 3.14%) in sue-and-acquire practices among Alice-impacted firms after the decision. This finding is consistent with the hypothesis that the Alice decision effectively curtails strategic lawsuits, consequently reducing sue-and-acquire activities, which hinges on the ability of firms to file such lawsuits.

It is important to note that this specification holds the occurrence of a patent lawsuit constant and investigates how the Alice decision impacts the likelihood of a follow-on M&A attempt, conditional on the existence of a patent lawsuit. As such, this approach mitigates the potential concern that the Alice decision might lead to an overall decline in patent litigations, which could confound the interpretation of our results. In other words, by focusing on the likelihood of M&A attempt — given that a lawsuit has been filed — we can more accurately assess the impact of the Alice decision on sue-and-acquire strategies, independent of any general trends in patent litigation.

The arguably exogenous nature of the Alice decision offers a valuable opportunity for

[20] Our results are robust to alternative specifications, including using a continuous variable for $AliceExposure$ or employing quartile regressions. These additional analyses are available upon request.

causal analysis of the link between strategic litigation and M&A activities. The noticeable decline in sue-and-acquire practices among impacted firms following the decision substantiates this causal connection, reinforcing the idea that sue-and-acquire practices are indeed a strategic use of patent lawsuits.

6 Strategically Motivated Lawsuits and the Prevalence of Sue-and-Acquire Practices

Having established the strategic relation between patent lawsuits and subsequent M&A using the Alice decision as a quasi-natural experiment, we now examine the prevalence of sue-and-acquire practices in a larger sample. Specifically, we examine whether these practices intensify when the patent lawsuits are ex ante more likely to be strategically motivated. More specifically, we investigate whether these practices are more common (1) when the 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.

6.1 *Direct Product Market Competitors*

First, we examine whether the sue-and-acquire practices are more prevalent when the plaintiff and the defendant more closely compete in the same product space. This test is motivated by the intuition that firms are more incentivized to eliminate direct competitors compared to other firms. Consequently, we conjecture that lawsuits filed against these direct competitors are more likely to be strategically motivated than those filed against firms outside their competitive space. To test this prediction, we conduct a cross-sectional test by interacting the main independent variable of interest $Sued$ with $High\_Prod\_Sim$, an indicator variable taking the value of one if the product similarity between firm i and firm j

is above the sample median, and zero otherwise. The regression model is as follows:

$$\begin{aligned} Acquire_{ijm,t+3} = \gamma_0 &+ \gamma_1 Sued_{ijm,t} * High\_Prod\_Sim_{ijm,t} + \gamma_2 Sued_{ijm,t} + \gamma_3 High\_Prod\_Sim_{ijm,t} \\ &+ \gamma_4 Plaintiff\_Characteristics_{im,t-1} + \gamma_5 Defendant\_Characteristics_{jm,t-1} \\ &+ Lawsuit\_Group\_FE_m + \epsilon_{ijm,t}. \end{aligned} \tag{4}$$

Table 5 reports the estimated results. Across all three specifications, the interaction term $Sued * High\_Prod\_Sim$ loads with a positive coefficient that is significant at the 1% level. In terms of economic significance, we find that the likelihood of a subsequent M&A attempt by the plaintiff firm is approximately 120% (= 0.0075/0.0059) higher when the product similarity of the plaintiff-defendant pair is above the sample median. These effects are robust to the inclusion of a host of control variables (column (2)) and the use of an entropy-balance-weighted sample (column (3)), which ensures that the treated and control groups have similar distributions of observable characteristics.

The results also help alleviate concerns that the sue-and-acquire phenomenon might be confounded by product similarity. In other words, firms operating in the same market space may be more likely to engage in both acquisitions and patent lawsuits. Our findings suggest that this is unlikely the case. Specifically, we find that the coefficient on $Sued$ is much larger than that on $High\_Prod\_Sim$ — up to seven times larger. Moreover, the coefficient on the interaction term between $Sued$ and $High\_Prod\_Sim$ is at least nine times larger than that on $High\_Prod\_Sim$ alone. This substantial difference in magnitudes suggests that sue-and-acquire behavior represents a distinct strategic choice, rather than being merely an artifact of firms operating in similar product domains.

Overall, the results in Table 5 show that the sue-and-acquire practice is indeed more pronounced among pairs that compete more directly in the product space. This finding is consistent with the intuition that strategic lawsuits aimed at facilitating competitor eliminations are more common among direct rivals, resulting in a higher prevalence of sue-and-acquire practices in these cases.

6.2 *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 notorious for its high concentration of strategic lawsuits (e.g., *The New York Times*, 2006). This reputation 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 this District is home to around 1% of the US population and is not commonly considered a major technology hub.

Anecdotal evidence also supports this notion of strategic patent lawsuits being prevalent in the Eastern District of Texas. For instance, Nuance, the firm that sued and later acquired Vlingo, launched its patent lawsuits in the Eastern District of Texas, despite both firms being based in Massachusetts. According to Vlingo, Nuance had been purposely filing lawsuits in this jurisdiction to drive up the litigation costs for defendant firms, including but not limited to Vlingo (Kile, 2011). The Eastern District of Texas has gained this reputation for being particularly favorable to plaintiff firms in patent litigation. This is due to several factors that collectively make it "predictably expensive" for accused infringers to defend against patent lawsuits in this jurisdiction, thus creating an environment that is conducive to strategic litigation (Love and Yoon, 2017).

Given the prevalence of strategic patent lawsuits in the Eastern District of Texas, we conjecture that firms seeking to weaken competitors through patent litigation are more likely to file lawsuits in this district. Consequently, lawsuits filed in this jurisdiction are more likely to be strategically motivated, resulting in a higher likelihood of being followed by an M&A attempt.[21] To test this prediction, we augment Equation (1) by including the interaction

[21]One might wonder why not all patent plaintiffs file lawsuits in the Eastern District of Texas, given

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 6 reports the results. The main variable of interest, $Sued * Eastern\_Texas$, loads with a positive and statistically significant coefficient. For example, column (3) shows that when a patent lawsuit is filed in the Eastern District of Texas, the likelihood of subsequent M&A attempts increases from 1.25% to 2.5% (i.e., 0.0125 + 0.0124). This represents a roughly 100% increase in M&A propensity compared to patent lawsuits filed elsewhere. Similar to other results, this result is robust to the inclusion of product similarity and other characteristics of plaintiffs and defendants as controls (column (2)) and the use of an entropy-balance-weighted sample (column (3)).

Overall, the results in Table 6 show that the sue-and-acquire practice is indeed more prevalent when patent lawsuits are filed in the Eastern District of Texas. Given this jurisdiction has a well-known reputation for being a hub of strategic lawsuits, this finding reinforces the link between strategic lawsuits and sue-and-acquire practices.

6.3 *IT and Patent-Thicket Industries*

We next investigate whether sue-and-acquire practices are more pronounced in industries prone to strategic patent lawsuits, namely, IT and patent-thicket industries. These industries are known to attract a high number of strategic lawsuits due to the unique characteristics of their patents. First, in the IT industry, patents are "notoriously difficult to interpret" (Bessen and Meurer, 2013) and often "vague and overly broad" (Shapiro, 2010). These features facilitate opportunistic litigation, because plaintiffs can exploit the overly ambiguous boundaries of IT patents (Bessen and Meurer, 2009; Burk and Lemley, 2009).

its reputation for being plaintiff-friendly. Based on our discussions with legal experts, we find two primary reasons. First, defendants in patent infringement cases can employ a counterattack strategy by filing their own patent infringement lawsuits against the original plaintiff in the same venue. Because courts typically consolidate related cases for efficiency, both the original lawsuit and the countersuit would likely be heard in the Eastern District of Texas. This could potentially backfire on plaintiffs who file meritless lawsuits in this jurisdiction. Second, filing a lawsuit in a district known for its plaintiff-friendly reputation could be perceived as an attempt to exploit the patent system's weaknesses, potentially damaging the plaintiff's reputation and credibility.

Second, for patent-thicket industries, patent rights are characterized by a dense web of overlapping patent rights such that one product can infringe upon thousands of patents (e.g., Lemley and Shapiro, 2006). Consequently, even a dispute over a single patent can jeopardize a firm's entire production line, imposing significant costs and risks on defendants. This vulnerability weakens defendants' bargaining power, fostering an environment conducive to strategic lawsuits, where plaintiffs can exploit the threat of protracted litigation to extract favorable terms.

To test this prediction, we augment Equation (4) by interacting $Sued$ with $IT\_Industry$, an indicator variable that equals one for firms in the IT industry (2-digit SIC codes 35 or 73), and zero otherwise (e.g., Bessen and Meurer, 2013). Panel A of Table 7 reports the results. Across all specifications, we find the interaction term $Sued{*}IT\_Industry$ consistently loads with a positive and statistically significant coefficient. In terms of the economic significance, we find IT firms are approximately 67% (i.e., = 0.0081/0.0121) 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.

We then investigate the prevalence of sue-and-acquire practices in patent-thicket industries. Similarly, we augment Equation (4) with the interaction term of $Sued$ and $Thicket\_Industry$, an indicator variable taking the value of one for firms with two-digit SIC codes of 35, 36, 38, or 73, and zero otherwise (e.g., Bessen and Meurer, 2013; Cohen, Gurun and Kominers, 2019).

The results, presented in Panel B of Table 7, reveal a consistent pattern. Across all three columns, the key interaction term $Sued * Thicket\_Industry$ exhibits a positive and statistically significant coefficient. Assessing the economic significance, we find that following an initial patent lawsuit, the likelihood of a subsequent M&A attempt is heightened by approximately 40% (i.e., = 0.0045/0.0117) for plaintiffs in patent-thicket industries as compared with other industries. The results are consistent with our prediction that the sue-and-acquire practice is particularly common in patent-thicket industries.

Taken together, our cross-sectional analyses provide strong evidence that the sue-and-acquire phenomenon is particularly pronounced in settings where the strategic motives behind patent lawsuits are more likely. In particular, we find that the sue-and-acquire tactic is more prevalent among (i) product market competitors, where the incentives to eliminate rivals are stronger; (ii) lawsuits filed in a jurisdiction known for its high concentration of strategic litigation; and (iii) industries more prone to strategic lawsuits, such as the IT and patent-thicket industries. The heightened propensity for sue-and-acquire practices in these settings reinforces the notion that strategic lawsuits are the driving force behind this phenomenon.

7 Benefits of the Sue-and-Acquire Strategy

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. Measuring the direct benefits of this strategy is a challenge, especially since the information about the strategy and its likelihood of success is revealed to the market over time. One way to assess the potential benefits is to compare the acquisition announcement effects for acquirers that employ this strategy with those that do not.

To this end, we first construct a treated 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 three years. The control sample consists of M&A deals without such preceding lawsuits. To ensure treatment-control comparability while preserving reasonable sample sizes, we construct two control groups, each with a varying degree of selection stringency. The first control group includes all other M&A deals in the US announced from 2000 to 2020. The second group is restricted to deals announced in the same year as those in the treated group and involving acquirers from the same industry (based on 2-digit SIC code). Similar to the baseline analyses, we also report the estimates from entropy-balance-weighted regressions, which reweight the control sample to closely match the treated sample's distribution of observable characteristics. Given the nature of the experiment, the usual caveats apply, since the decision to engage in the strategy is not a result of random assignment. We then estimate the following regression model:

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

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 $Sued_{ijm,t-1tot-3}$. It equals one if acquiring firm i sued target firm j for patent infringement within three years before t, and zero otherwise. Following prior M&A literature (e.g., Harford, Humphery-Jenner and Powell, 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*acquirer industry fixed effects. The standard errors are also clustered at the year*acquirer industry level.

Table 8 presents the results estimated from Equation (5). As previously discussed, to balance treatment-control comparability and maintain reasonable sample sizes, we construct two distinct control groups. The regressions for columns (1) and (2) include the first control group, while the regressions for columns (3) and (4) include the second control group. We report OLS regression results in columns (1) and (3) and entropy-balance-weighted regression results in columns (2) and (4). Across all specifications, the coefficients on *Sued* are consistently positive and statistically significant (at least at the 5% level), ranging from 2.3% to 3.1%. The results indicate a significantly more favorable response from the market to acquiring firms when the acquisitions were preceded by a patent dispute against the target firm. As previously discussed, given that the median market capitalization of acquiring firms in this analysis is $2.8 billion, this translates into an approximately $56 million to $87 million in additional shareholder value for the acquiring firm. This finding suggests possible economically sizable gains for firms engaging in this strategy. Importantly, the results remain robust when we use entropy-balance-weighted regressions, suggesting that the observed effects are more likely to be driven by the impact of the sue-and-acquire tactics than the differences between the treated and control groups. Overall, these results are consistent with the sue-and-acquire strategy yielding tangible benefits for acquiring firms, strengthening the validity of this strategy.

8 Strategic Intent in Patent Lawsuits

We examine whether sue-and-acquire lawsuits differ systematically from other "regular" patent lawsuits in ways that suggest strategic intent. Specifically, we analyze whether these lawsuits (i) have lower success rates in court, indicating less legal merit, and (ii) involve patents with broader and looser boundaries, a characteristic commonly believed to facilitate strategic litigation (e.g., Jaffe and Lerner, 2011; Becker and Posner, 2013).

8.1 *Lawsuit Outcomes*

The use of sue-and-acquire tactics suggests those lawsuits have less merit than "regular" lawsuits based on patent infringements. 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.

To empirically test this prediction, we compare the success rates of plaintiffs in sue-and-acquire (SA) cases against those in non-sue-and-acquire (NSA) cases. An SA pair is identified when the plaintiff firm attempts to acquire the defendant within three years of filing a patent lawsuit, whereas an NSA pair is defined by the absence of any acquisition attempt in the same period. To establish the NSA group (the control group), we first match up to five potential control plaintiffs for each SA plaintiff based on industry (using the SIC 2-digit code) and firm size (measured by the total number of employees).[22] We then identify all lawsuits filed by these control plaintiffs within the same year as the SA lawsuits. To maintain the validity of the NSA classification, we include only cases without any M&A activity within three years following the lawsuit. Our final sample comprises 163 SA pairs and 879 NSA pairs. Note that the average number of NSA pairs is slightly above five per SA pair, due to some plaintiffs initiating multiple lawsuits in a year.

Next, we create an indicator variable, *Plaintiff_Win*, to measure lawsuit outcomes. We follow legal studies in coding the patent lawsuit outcomes (e.g., Janicke and Ren, 2006; Allison, Lemley and Schwartz, 2013). Given the complexity of coding lawsuit outcomes in patent disputes, we focus on lawsuits with definitive outcomes, treating those with mixed results as indecisive. We follow the legal literature, basing our coding on rulings across three dimensions: validity, infringement, and enforceability. Specifically, a defendant in a patent lawsuit can mount a defense by (i) challenging the patent's validity (i.e., arguing that the patent(s) should not have been issued in the first place); (ii) claiming non-infringement (i.e., they did not infringe on the disputed patent, even if it is valid); or (iii) arguing for non-enforceability, suggesting that, despite potential infringement, the patent cannot be enforced due to the plaintiff's misconduct. Accordingly, *Plaintiff_Win* takes the value of 1 when (i) at least one of the plaintiff's patents is confirmed to be infringed upon and (ii) none are deemed invalid or unenforceable. In all other cases, it takes the value of 0.

Table 9 reports the differences in lawsuit outcomes between the SA and NSA pairs, focusing on the subset of patent lawsuits that conclude with definitive outcomes. It reveals a

[22] Given the need to manually collect and code lawsuit outcomes for each lawsuit, we construct this control sample to ensure a manageable dataset while maintaining statistical power.

notable difference in plaintiff victory rates: 23% for SA cases compared to 47% for NSA cases, indicating that SA cases are approximately 50% less likely to result in a plaintiff victory. This finding is consistent with our conjecture that sue-and-acquire lawsuits are more likely to be driven by ulterior motives, rather than genuine patent disputes, leading to a lower success rate for the plaintiffs. The majority of patent lawsuits are settled before reaching trial, with only a small fraction advancing to the trial stage (e.g., Janicke and Ren, 2006; Lemley, 2010). This pattern significantly reduces our sample size (by almost 90% to $N = 125$), which impacts the statistical power of this analysis (t-stat = 1.58). Nevertheless, the economic significance of this finding remains substantial and supports the strategic use of sue-and-acquire tactics.

In summary, our analysis reveals that plaintiffs in SA lawsuits are significantly less likely to win their lawsuits in court than plaintiffs in NSA cases. This finding corroborates the notion that firms employ sue-and-acquire tactics as a means to pressure defendant firms into accepting acquisition offers, rather than to resolve genuine patent disputes.

8.2 *Patent Boundary Broadness*

We next examine whether patents in sue-and-acquire lawsuits have overly broad boundaries, a feature that facilitates strategic patent lawsuits (e.g., Noel and Schankerman, 2013; Steensma, Chari and Heidl, 2015). The economic intuition is straightforward: patents with broad, ambiguous boundaries create uncertainty about the scope of protection, allowing patent holders to assert infringement claims against a wider range of potential competitors. This uncertainty, combined with the high costs of patent litigation defense, creates an exploitable mechanism for strategic lawsuits. As such, when patent boundaries are broad and loose, even tenuous infringement claims can force defendants into costly litigation. By contrast, patents with clearly defined boundaries are less useful for strategic lawsuits, as non-infringement can be more easily determined, and accordingly the defendants cannot be forced into costly litigation. Therefore, if sue-and-acquire practices represent strategic exploitation, we expect the patents involved to have systematically broader boundaries than those in other regular lawsuits.

While the patent system has been widely criticized for allowing overly broad and ambiguous claims (e.g., Becker and Posner, 2013), it is challenging to capture this looseness empirically. To overcome this challenge, we create a novel measure of patent boundary looseness, building upon the machine learning approach used in Section 5.2. Briefly, our method proceeds in three steps. First, we construct a training dataset consisting of (i) a positive sample of patent applications rejected for having "not clearly delineated" boundaries under 35 U.S.C. § 112(b) (hereafter 112(b)), and (ii) a negative sample of carefully matched granted patents. Specifically, we match each rejected patent to one granted patent based on three criteria: same CPC group, same patent examiner, and same grant year.[23] Second, using this training dataset, we train a Longformer deep-learning model to distinguish between patents with clearly and poorly delineated boundaries. Lastly, we apply the trained model to estimate a "boundary looseness" score for each patent involved in the lawsuits in our sample. This score represents the likelihood that the patent's claims fail to clearly define the scope of protection. In terms of performance, the model achieves an accuracy rate of 65% when applied to a test sample.

Using this measure, we then test whether patents involved in sue-and-acquire cases are more likely to have overly broad boundaries. We construct a sample consisting of all patents involved in patent lawsuits in our main sample, and then we estimate the following model:

$$TooBroad_{i,j,t} = \beta_0 + \beta_1 SueAcquire_{i,j,t} + \gamma X_{i,j,t} + \delta_t + \theta_c + \varepsilon_{i,j,t}, \tag{6}$$

where $TooBroad_{i,j,t}$ is our measure of patent boundary breadth for patent i in lawsuit j in year t, ranging from 0 to 1 with higher values indicating broader, more ambiguous claims.

[23]We adopt this stringent matching principle to account for examiner-specific variation in leniency (e.g., Dyer et al., 2023) and potential systematic changes in patent quality over time, as documented in prior literature. This approach ensures that the matched granted patent serves as a strong benchmark, likely having more clearly delineated boundaries than its rejected counterpart.

$SueAcquire_{i,j,t}$ is an indicator variable equal to one if the lawsuit is followed by the acquisition of the defendant by the plaintiff within three years, and zero otherwise. $X_{i,j,t}$ is a vector of control variables including the number of claims and the time since patent grant, following Mann (2018). We include year fixed effects (δ_t) to account for time trends and technology class fixed effects (θ_c) to control for differences across technology fields.

Table 10 presents the estimation. The coefficient on $SueAcquire$ is positive (0.0418) and statistically significant at the 5% level (t-statistic = 2.29), indicating that patents in sue-and-acquire cases are 4.18% more likely to be classified as "too broad" compared to patents in other lawsuits. Our results are robust to the inclusion of control variables and fixed effects, which account for patent characteristics, technology fields, and time trends in patent granting and litigation. These findings suggest that patents involved are systematically different from those in "regular" patent litigation, having overly broad boundaries, a characteristic commonly believed to contribute to strategic exploitation of the patent system.The systematic difference in patent characteristics corroborate that sue-and-acquire tactics are strategic in nature, as firms appear to deliberately select patents with broader boundaries to facilitate strategic lawsuits.

9 Conclusion

This paper uncovers a distinct predatory strategy within the patent system — the sue-and-acquire strategy. We first document that initiating a patent lawsuit increases the likelihood of a subsequent M&A attempt by the plaintiff toward the defendant by up to 13 times. To strengthen our identification, we exploit the Alice decision, which exogenously curtails the ability to file strategic lawsuits using abstract patents, as a quasi-experiment. Consistent with strategic litigation driving sue-and-acquire activities, we show a post-Alice decline in these activities among more-Alice-impacted firms, whose ability to file strategic lawsuits was more constrained by the decision. We further document that this sue-and-acquire practice intensifies when the initial patent lawsuit is ex ante more likely to be strategically motivated.

Next, our analysis of acquisition announcements reveals that suing-and-acquiring firms earn up to 3.1% higher abnormal returns, which translates to an average gain of $87 million, suggesting potential sizable benefits from this tactic. Supporting the strategic nature of these lawsuits, we find that (i) patents in sue-and-acquire cases have systematically broader boundaries and (ii) these cases have a lower success rate in court compared to other patent lawsuits. Collectively, these findings demonstrate the sue-and-acquire tactic as a distortion of the patent system used for predatory purposes.

These findings have important implications for policy-makers as they fine-tune relevant policies to protect entrepreneurial activities and foster innovation. First, this paper documents a novel predatory strategy that poses a significant risk for emerging ventures in innovation-driven industries. This risk is especially salient given the recent phenomenon of incumbent technology firms using various predatory approaches to eliminate competition and suppress entrepreneurial activities (e.g., House Judiciary Committee, 2020). Second, by documenting how the patent system can be strategically exploited, our findings add empirical evidence to the recent widespread demands for a modification of the patent system (e.g., *The Washington Post*, 2021; *The 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 broader economic costs of the patent system and corresponding implications for innovation and entrepreneurship activities.[24]

In interpreting our findings, it is important to note that this paper focuses on M&As, because they offer a uniquely suitable setting to examine the predatory effects of patent lawsuits. While predatory lawsuits could lead to other outcomes (such as market exits or bankruptcy of defendants), the generally very observable and well-documented nature of M&A events offers two empirical advantages: allowing us to (i) document the complete sequence of strategic actions (sue and then acquire), and (ii) conduct market reaction analyses

[24] Our findings do not imply that all patent lawsuits are predatory. Rather, they highlight that some firms exploit the patent system for predatory purposes, highlighting a potential loophole that warrants further examination.

in response to M&A announcements to identify the economic gains. For clarity, we thus focus on M&As and note that this focus likely results in conservative estimates of the full predatory effects of patent litigation.

Our study documents a significant number of patent lawsuit defendant-plaintiff pairs followed by M&A attempts: 373 cases within five years of the lawsuit, and 287 cases within three years. These cases correspond to an estimated economic loss of $15.4 billion and $11.9 billion for the defendants, respectively.[25] While these figures are economically sizable in themselves, they likely represent only a fraction of the full economic impact of this phenomenon for two reasons. First, each predation can create significant deterrent effects. Milgrom and Roberts (1982) and Kreps and Wilson (1982) demonstrate that observed instances of predatory behavior are rare precisely because of their strong deterrent effects — even a small chance of predation deters market entry. Similarly, the mere threat of patent litigation can deter competition without any lawsuits being filed. Second, patent litigation can facilitate predation through additional channels beyond M&As, such as forcing defendant firms into bankruptcy or market exit. Our documented effects focusing on M&A thus likely represent a conservative estimate of the full economic impact.

[25]This estimation is based on Bessen et al. (2018), which estimated the average economic loss for defendants in patent litigation to be $41.4 million per lawsuit.

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Table 1

Industry Distribution: All Patent Lawsuits versus Sue-and-Acquire Lawsuits

Industry Classification	% Among All Lawsuits	% Among Sue-and-Acquire Lawsuits
Consumer Non-Durables (Food, Tobacco, Textiles, Apparel, Leather, Toys)	6.53%	9.52%
Consumer Durables (Cars, TVs, Furniture, Household Appliances)	5.10%	0.00%
Manufacturing	12.74%	9.52%
Energy (Oil, Gas, and Coal Extraction and Products)	2.55%	4.76%
Chemicals and Allied Products	5.41%	9.52%
Business Equipment (Computers, Software, and Electronic Equipment)	28.50%	33.33%
Telecommunications	2.55%	0.00%
Shops (Wholesale, Retail, and Some Services like Laundries, Repair Shops)	6.37%	0.00%
Healthcare, Medical Equipment, and Drugs	27.23%	28.57%
Finance (Banks, Insurance, and Real Estate)	0.48%	0.00%
Other (Mines, Construction, Transportation, Hotels, Business Services)	2.55%	4.76%

Notes. This table presents the industry distribution of plaintiffs' industries in patent lawsuits in our sample from 2000 to 2020, classified using the Fama-French 12 industry categories. The second column reports the percentage distribution of all patent lawsuits across industries. The third column presents the distribution of sue-and-acquire cases, defined as instances where the plaintiff attempts to acquire the defendant within three years of filing a patent lawsuit.

Table 2

Summary Statistics and Covariate Balance for Treatment and Control Samples

Panel A: Summary Statistics for the Full Sample

	N	Mean	SD	Q1	Median	Q3
Acquire	625,963	0.001	0.027	0.000	0.000	0.000
Sued	625,963	0.061	0.239	0.000	0.000	0.000
$NumEmpl_P$ *(thousands)*	590,991	31.624	42.236	0.873	8.000	52.300
$NumEmpl_D$ *(thousands)*	501,067	12.657	27.825	0.152	1.000	11.900
$Sales_P$ *(millions)*	593,046	13326.44	19991.72	215.27	2573.18	19680.02
$Sales_D$ *(millions)*	500,715	4703.29	11701.76	25.91	289.78	3173.25
$LnNumEmpl_P$	590,991	8.561	2.623	6.773	8.987	10.865
$LnNumEmpl_D$	501,067	7.084	2.601	5.030	6.909	9.384
$LnSales_P$	593,046	21.147	2.979	19.187	21.668	23.703
$LnSales_D$	500,715	19.320	3.361	17.070	19.485	21.878
Prod_Sim	339,440	0.576	0.224	0.425	0.593	0.746
BM_P	467,547	0.386	0.552	0.185	0.333	0.555
$Leverage_P$	484,431	0.261	0.227	0.116	0.226	0.340
ROA_P	485,533	0.147	0.747	0.049	0.166	0.296
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. Covariate Balance after Entropy Balancing: Treated Group vs. Control Group

	Treated group (N=10,493)			*Control group* (N=159,230)				
	Mean	Variance	Skewness	Mean	Variance	Skewness	Standardized Mean Diff.	Variance Ratio
$LnNumEmpl_P$	8.893	5.877	-0.774	8.893	5.913	-0.689	0.000	0.994
$LnNumEmpl_D$	7.618	6.126	-0.288	7.618	6.561	-0.257	0.000	0.934
$LnSales_P$	21.741	6.395	-0.785	21.741	6.460	-0.805	0.000	0.990
$LnSales_D$	19.952	9.963	-1.360	19.952	12.274	-1.827	0.000	0.812
Prod_Sim	0.680	0.040	-0.604	0.680	0.046	-0.737	0.000	0.862
BM_P	0.338	0.313	-2.262	0.338	0.331	-2.432	-0.000	0.946
$Leverage_P$	0.252	0.051	2.164	0.252	0.059	2.341	-0.000	0.865
ROA_P	0.089	0.549	-0.838	0.089	0.521	0.186	-0.000	1.052

Notes. This table presents summary statistics and covariate balance for the treatment (actual plaintiff-defendant pairs) and control (industry- and size-matched control pairs) samples used in the main analysis. Panel A reports the summary statistics for the full sample, and Panel B compares the characteristics of the treatment and control groups after applying entropy balancing. The entropy-balancing procedure assigns weights to the observations to equalize the first moment (means) of each covariate across the treatment and control samples. The entropy-balancing procedure is applied to all control variables used in Equation (1). Standardized Mean Diff. are calculated as the difference in means divided by the standard deviation of the control group for each covariate, with values closer to 0 indicating better balance. Variance ratios, computed as the ratio of the variance in the control group to the variance in the treatment group for each covariate, are presented to assess balance on the second moment (variance). The number of observations in Panel A is greater than the combined number of treated and control groups in Panel B. This is because for the entropy-balance-weighted sample, we require the availability of all control variables to perform the re-weighting, whereas in Panel A, all observations are included. Variable definitions are in Appendix A.1.

Table 3

Do Firms Engage in Sue-and-Acquire Practices?

	Dependent Variable=Acquire		
	OLS		Entropy-Balance-Weighted
	(1)	(2)	(3)
Sued	0.0068***	0.0132***	0.0133***
	(15.72)	(11.35)	(10.97)
Prod_Sim		0.0043***	0.0063**
		(6.83)	(2.40)
BM_P		0.0002*	0.0000
		(1.84)	(0.03)
$Leverage_P$		-0.0009***	-0.0051***
		(-3.92)	(-3.96)
ROA_P		-0.0000	-0.0003
		(-0.59)	(-0.81)
$LnNumEmpl_P$		0.0005*	0.0027*
		(1.93)	(1.69)
$LnNumEmpl_D$		-0.0009***	0.0005
		(-3.13)	(0.48)
$LnSales_P$		0.0001	-0.0005
		(0.87)	(-1.12)
$LnSales_D$		0.0002*	-0.0004
		(1.92)	(-0.76)
Lawsuit FE	Yes	Yes	Yes
R^2	0.060	0.068	0.464
N	625,963	169,694	169,694

Notes. This table presents the 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 three years after year t. The sample consists of the treated sample (i.e., actual plaintiff-defendant pairs) and the control sample (i.e., size- and industry-matched control pairs without a preceding patent dispute). A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. Column (1) reports the results of the OLS regression with the lawsuit group fixed effects included. The regression for column (2) includes additional control variables. The sample size becomes smaller due to the data availability of the control variables. Column (3) presents the results of entropy-balance-weighted regression to ensure covariate balance between treated and control groups. 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. Variable definitions are in Appendix A.1.

Table 4
Exogenous Shock: Sue-and-Acquire Practices after the Alice Decision

	Dependent Variable=Acquire	
	(1)	(2)
*Sued*High_AliceExposure*Post*	-0.0137***	-0.0314***
	(-3.63)	(-4.14)
*Sued*High_AliceExposure*	0.0114***	0.0296***
	(3.36)	(4.49)
*High_AliceExposure*Post*	0.0000	0.0009
	(0.01)	(1.37)
*Sued*Post*	-0.0011	0.0047
	(-0.51)	(1.26)
Sued	0.0041**	-0.0013
	(2.54)	(-0.69)
High_AliceExposure	0.0007***	0.0006
	(2.67)	(1.02)
Prod_Sim		0.0094***
		(5.40)
BM_P		0.0016***
		(2.74)
$Leverage_P$		-0.0018***
		(-2.59)
ROA_P		0.0001
		(0.81)
$LnNumEmpl_P$		0.0014
		(1.09)
$LnNumEmpl_D$		0.0013**
		(2.34)
$LnSales_P$		0.0004*
		(1.90)
$LnSales_D$		0.0001
		(0.58)
Lawsuit FE	Yes	Yes
R^2	0.077	0.078
N	114,734	38,263

Notes. This table presents the results from our investigation into the Alice decision's impact on sue-and-acquire activities. The unit of observation in this analysis is at the lawsuit level. This analysis uses a subset of the sample used in our main analysis (see Table 3), focusing on the years 2011–2017 while excluding 2014, the year of the Alice decision. The dependent variable, *Acquire*, is an indicator variable that takes the value of 1 if firm i attempts to merge with or acquire firm j within three years after year t. *High_AliceExposure* is an indicator variable that takes the value of 1 if the plaintiff company's exposure to the Alice decision (*AliceExposure*) is above the sample median, and 0 otherwise; *Post* is an indicator variable taking the value of 1 if the patent lawsuit occurs after the Alice decision, and 0 otherwise; *Sued* is an indicator variable that takes the value of 1 if firm i filed a patent lawsuit against firm j in year t, and 0 otherwise. The coefficient on the stand-alone term *Post* is not reported because it is subsumed by the lawsuit fixed effects. All other variables are defined in the same way as the ones in Table 3. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. Variable definitions are in Appendix A.1.

Table 5

Prevalence of Sue-and-Acquire among Direct Product Market Competitors

	Dependent Variable=Acquire		
	OLS		Entropy-Balance-Weighted
	(1)	(2)	(3)
*Sued*High_Prod_Sim*	0.0075***	0.0089***	0.0088***
	(5.00)	(4.11)	(3.76)
Sued	0.0059***	0.0072***	0.0072***
	(5.73)	(4.75)	(4.23)
High_Prod_Sim	0.0007***	0.0011***	0.0000
	(6.40)	(6.26)	(0.07)
BM_P		0.0002*	-0.0000
		(1.80)	(-0.05)
$Leverage_P$		-0.0009***	-0.0053***
		(-3.99)	(-4.05)
ROA_P		-0.0000	-0.0003
		(-0.59)	(-0.89)
$LnNumEmpl_P$		0.0005*	0.0026
		(1.93)	(1.64)
$LnNumEmpl_D$		-0.0009***	0.0004
		(-3.11)	(0.43)
$LnSales_P$		0.0001	-0.0005
		(0.85)	(-1.03)
$LnSales_D$		0.0002**	-0.0004
		(1.99)	(-0.76)
Lawsuit FE	Yes	Yes	Yes
R^2	0.079	0.069	0.464
N	339,401	169,694	169,694

Notes. This table presents the estimation of the prevalence of sue-and-acquire practices among direct product market competitors. *High_Prod_Sim* is an indicator variable that is set to 1 if the product similarity of the firm-pair exceeds the sample median, and 0 otherwise. *Sued* is an indicator variable that takes the value of 1 if firm i filed a patent lawsuit against firm j in year t, and 0 otherwise. The dependent variable, *Acquire*, is an indicator variable that takes the value of 1 if firm i attempts to merge with or acquire firm j within three years after year t. A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. Column (1) reports the results of the OLS regression analysis with the lawsuit group fixed effects included. Column (2) includes additional control variables. The sample size becomes smaller due to the data availability of the control variables. Column (3) presents the results of entropy-balance-weighted regression analysis to ensure covariate balance between treatment and control groups. 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. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. Variable definitions are in Appendix A.1.

Table 6

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

	Dependent Variable=Acquire		
	OLS		Entropy-Balance-Weighted
	(1)	(2)	(3)
*Sued*Eastern_Texas*	0.0044*	0.0115*	0.0124**
	(1.86)	(1.94)	(1.97)
Sued	0.0065***	0.0124***	0.0125***
	(15.00)	(10.58)	(10.24)
Prod_Sim		0.0043***	0.0061**
		(6.81)	(2.32)
BM_P		0.0002*	0.0000
		(1.87)	(0.10)
$Leverage_P$		-0.0009***	-0.0051***
		(-3.90)	(-3.95)
ROA_P		-0.0000	-0.0003
		(-0.52)	(-0.71)
$LnNumEmpl_P$		0.0005**	0.0028*
		(1.98)	(1.74)
$LnNumEmpl_D$		-0.0009***	0.0004
		(-3.17)	(0.39)
$LnSales_P$		0.0001	-0.0005
		(0.82)	(-1.16)
$LnSales_D$		0.0002*	-0.0004
		(1.87)	(-0.82)
Lawsuit FE	Yes	Yes	Yes
R^2	0.060	0.069	0.464
N	625,963	169,694	169,694

Notes. This table presents the estimation of the prevalence of sue-and-acquire practices when the initial lawsuit if filed in the Eastern District of Texas. *Eastern_Texas* is an indicator variable that takes the value of 1 if the lawsuit was filed in the Eastern District of Texas, and 0 otherwise. *Sued* is an indicator variable that takes the value of 1 if firm i filed a patent lawsuit against firm j in year t, and 0 otherwise. The dependent variable, *Acquire*, is an indicator variable that takes the value of 1 if firm i attempts to merge with or acquire firm j within three years after year t. Note that the coefficient on *Eastern_Texas* is subsumed by the lawsuit fixed effects. A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. Column (1) reports the results of the OLS regression analysis with the lawsuit group fixed effects included. Column (2) includes additional control variables. The sample size becomes smaller due to the data availability of the control variables. Column (3) presents the results of entropy-balance-weighted regression analysis to ensure covariate balance between treatment and control groups. 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. *T*-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. Variable definitions are in Appendix A.1.

Table 7

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

Panel A: IT industry

	Dependent Variable=Acquire		
	OLS		Entropy-Balance-Weighted
	(1)	(2)	(3)
*Sued*IT_Industry*	0.0074***	0.0081**	0.0089**
	(4.10)	(2.05)	(2.16)
Sued	0.0059***	0.0121***	0.0121***
	(13.77)	(10.00)	(9.64)
Prod_Sim		0.0042***	0.0056**
		(6.74)	(2.16)
BM_P		0.0002*	-0.0000
		(1.79)	(-0.05)
$Leverage_P$		-0.0009***	-0.0050***
		(-3.81)	(-3.84)
ROA_P		-0.0000	-0.0003
		(-0.53)	(-0.76)
$LnNumEmpl_P$		0.0005**	0.0030*
		(2.11)	(1.89)
$LnNumEmpl_D$		-0.0009***	0.0004
		(-3.16)	(0.41)
$LnSales_P$		0.0000	-0.0006
		(0.64)	(-1.36)
$LnSales_D$		0.0002*	-0.0004
		(1.91)	(-0.77)
Lawsuit FE	Yes	Yes	Yes
R^2	0.060	0.068	0.464
N	625,963	169,694	169,694

Continued on next page

Table 7 (cont.)

Panel B: Patent Thicket Industries			
	Dependent Variable=Acquire		
	OLS		Entropy-Balance-Weighted
	(1)	(2)	(3)
*Sued*Thicket_Industry*	0.0060***	0.0045*	0.0056**
	(5.33)	(1.77)	(2.07)
Sued	0.0051***	0.0117***	0.0114***
	(11.52)	(8.54)	(8.13)
Prod_Sim		0.0042***	0.0056**
		(6.70)	(2.07)
BM_P		0.0002*	0.0000
		(1.83)	(0.01)
$Leverage_P$		-0.0009***	-0.0052***
		(-3.94)	(-4.02)
ROA_P		-0.0000	-0.0003
		(-0.59)	(-0.78)
$LnNumEmpl_P$		0.0005**	0.0030*
		(2.09)	(1.89)
$LnNumEmpl_D$		-0.0009***	0.0004
		(-3.16)	(0.41)
$LnSales_P$		0.0001	-0.0006
		(0.76)	(-1.28)
$LnSales_D$		0.0002*	-0.0004
		(1.91)	(-0.77)
Lawsuit FE	Yes	Yes	Yes
R^2	0.060	0.068	0.464
N	625,963	169,694	169,694

Notes. This table presents the estimation of the prevalence of sue-and-acquire practices among industries prone to strategic patent lawsuits. Panel A (B) reports the estimation for firms in IT industries (patent-thicket industries). In Panel A, *IT_Industry* is an indicator variable that takes the value of 1 if the plaintiff is in the IT industry (defined as firms with 2-digit SIC codes in 35 or 73), and 0 otherwise. In Panel B, *Thicket_Industry* is an indicator variable that takes the value of 1 if the plaintiff is in a patent-thicket industry (defined as those with two-digit SIC codes in 35, 36, 38, or 73), and 0 otherwise. For both panels, *Sued* is an indicator variable that takes the value of 1 if firm i filed a patent lawsuit against firm j in year t, and 0 otherwise. The dependent variable, *Acquire*, is an indicator variable that takes the value of 1 if firm i attempts to merge with or acquire firm j within three years after year t. A lawsuit group comprises one actual plaintiff-defendant pair along with its matched control pairs. Column (1) reports the results of the OLS regression analysis with the lawsuit group fixed effects included. Column (2) includes additional control variables. The sample size becomes smaller due to the data availability of the control variables. Column (3) presents the results of entropy-balance-weighted regression analysis to ensure covariate balance between treatment and control groups. 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. T-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. Variable definitions are in Appendix A.1.

Table 8
Benefits of the Sue-and-Acquire Practices

	Dependant Variable=Acq_CAR			
	All M&A deals		Industry matched deals	
	OLS	Entropy-Balance-Weighted	OLS	Entropy-Balance-Weighted
	(1)	(2)	(3)	(4)
Sued	0.0227***	0.0310***	0.0227**	0.0268**
	(2.92)	(2.64)	(2.06)	(2.05)
Acq_Size	-0.0037***	-0.0024**	-0.0032***	-0.0022**
	(-12.65)	(-2.25)	(-4.43)	(-2.24)
Acq_BM	-0.0007	-0.0183*	0.0038	-0.0097
	(-0.47)	(-1.95)	(0.97)	(-0.67)
Acq_Run_Up	0.0006	-0.0075	0.0064*	0.0027
	(0.39)	(-0.49)	(2.01)	(0.10)
Private_Target	0.0177***	0.0225***	0.0234***	0.0246**
	(11.01)	(2.71)	(5.71)	(2.59)
Acquiror Industry*Year FE	Yes	Yes	Yes	Yes
R^2	0.067	0.448	0.034	0.207
N	30,398	30,398	5,695	5,695

Notes. This table presents the results of the analysis estimating the incremental market returns for firms engaging in sue-and-acquire tactics around their acquisition announcements, compared with other acquiring firms. The analysis is conducted at the M&A deal level and includes both treatment and control groups. The treated group ("sued") comprises all M&A deals preceded by patent lawsuits filed within a three-year period. The control groups consistently include M&A deals not preceded by a patent lawsuit, with specific criteria applied for each column: Columns (1) and (2) include all relevant M&A deals during 2000 to 2020 from the SDC database with available data. Columns (3) and (4) are limited to deals in the same year as the treatment group and involving acquirers from the same industry (2-digit SIC code). Columns (1) and (3) report the results of the OLS regression analysis. Columns (2) and (4) presents the results of entropy-balance-weighted regression analysis. The dependent variable, *Acq_CAR*, represents the three-day ([-1,+1]) market-adjusted cumulative abnormal returns of the acquirer around the M&A announcement date. The key independent variable, *Sued*, is an indicator set to 1 for M&A deals preceded by a patent lawsuit filed by the acquirer against the target within three years prior to the M&A announcement. Control variables include acquirer characteristics (*Acq_Size*, *Acq_BM*, and *Acq_Run_Up*), and the indicator *Private_Target*, denoting whether the target firm is privately held. All models include industry*year fixed effects. Standard errors are clustered at the industry*year level. *T*-statistics are in parentheses. Significance levels: ***, **, and * denote 1%, 5%, and 10%, respectively. See Appendix A.1 for variable definitions.

Table 9
Sue-and-Acquire Lawsuits Outcomes

	(1) *Sue-and-Acquire Pairs*	(2)	(3) *Non-Sue-and-Acquire Pairs*	(4)	(5)	(6)
	N	Mean(%)	N	Mean(%)	Diff.	T-stats
Plaintiff_Win	12	23.2%	113	46.9%	-23.7%	-1.58

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 consist of plaintiff-defendant pairs in which the plaintiff firm attempts to acquire or merge with the defendant within three years following a patent lawsuit, whereas NSA pairs involve no such acquisition or merger attempts. See the detailed steps in identifying NSA pairs in Section 8.1. The sample includes patent lawsuits with definitive outcomes. *Plaintiff_Win* takes the value of 1 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 0 otherwise. Columns (1) and (2) present the number of plaintiff-defendant pairs and the average *Plaintiff_Win* likelihood for SA pairs, and Columns (3) and (4) provide the same measures 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. Variable definitions are in Appendix A.1.

Table 10
Broadness of Patents

	Dependent Variable=TooBroad
SueAcquire	0.0418**
	(2.29)
LnNumClaims	0.0354
	(0.89)
LawsuitYr-GrantYr	-0.0094
	(-1.07)
$(LawsuitYr - GrantYr)^2$	0.0002
	(1.02)
Technology Class FE	Yes
Lawsuit Year FE	Yes
Grant Year FE	Yes
R^2	0.159
N	119,103

Notes. This table presents the results from an analysis examining whether sue-and-acquire lawsuits involve patents that are more likely to be too broad. The sample consists of all patents included in the patent lawsuits from our main sample. The dependent variable, *TooBroad*, is an indicator variable that measures the likelihood that a patent's claims fail to clearly define its scope of protection, as estimated by a Longformer deep-learning model trained on patents rejected under 35 U.S.C. § 112(b) for having "not clearly delineated" boundaries. The main independent variable, *SueAcquire*, is a binary indicator equal to 1 if the lawsuit is followed by the acquisition of the defendant by the plaintiff within three years. The three control variables capture patent characteristics.*LnNumClaims* is defined as the natural logarithm of one plus the number of claims in a patent. *LawsuitYr-GrantYr* represents the difference in years between the patent's grant year and the lawsuit initiation year. *(LawsuitYr-GrantYr)*^{2} is defined as the squared value of *LawsuitYr-GrantYr*. The model also includes technology-class fixed effects, lawsuit initiation year fixed effects, and the patent grant year fixed effects. Standard errors are clustered at the technology-class level. *T*-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively. Variable definitions are 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 three years following the filing of the lawsuit, and zero otherwise.	SDC, Capital IQ, and Bing Web Search Engine
Acq_CAR	The three-day ([-1,+1]) cumulative market-adjusted abnormal returns of the acquiring firm around the deal announcement date.	CRSP 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 8), it denotes whether the acquirer sued the target within three years prior to the acquisition.	Stanford NPE litigation database
High_Prod_Sim	An indicator variable that takes the value of one if the *Prod_Sim* of the plaintiff-defendant pair is above the sample median, and zero otherwise. *Prod_Sim* denotes the pairwise product similarity score derived from the linguistic similarity of business descriptions between two firms, following Hoberg and Phillips (2016). A higher score indicates a greater overlap in product markets, indicating more direct competition between the pair.	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 NPE litigation database
IT_Industry	An indicator variable that takes the value of one if the plaintiff firm is in the IT industry (SIC 2-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, Gurun and Kominers (2019), patent-thicket industries are defined as industries with the SIC 2-digit codes 35, 36, 38 and 73.	Compustat
Baseline Control Variables		
BM_P	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
$Leverage_P$	The plaintiff firm's total debt scaled by total assets.	Compustat
ROA_P	The plaintiff firm's operating profits scaled by total assets.	Compustat
$LnSales_P$	Natural logarithm of one plus the plaintiff firm's sales. For firm-years available in Compustat, we use the *REVT* variable. When Compustat data are 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

$LnNumEmpl_P$	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 are 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
$LnSales_D$	Natural logarithm of one plus the defendant's sales. For firm-years available in Compustat, we use the $REVT$ variable. When Compustat data are 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
$LnNumEmpl_D$	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 are 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
Variables in exogenous shock analysis		
High_AliceExposure	An indicator variable that takes the value of 1 if a firm's exposure to the Alice decision (*AliceExposure*) is above the sample median.	KPSS and Compustat
AliceExposure	A firm-level measure of exposure to the Alice decision, calculated as the weighted average of the *AliceScore* of the firm's patents, scaled by the firm's total sales in 2013. Specifically, $AliceExposure_i = \frac{\sum_{j=1}^{N_i} PatentValue_{i,j} \times AliceScore_{i,j}}{Sales_{i,2013}}$. $PatentValue_{i,j}$ denotes the dollar value of firm i's patent j, obtained from the KPSS database (Kogan et al., 2017). Patent values are depreciated using an annual 20% rate. $AliceScore_{i,j}$ is the probability of patent j being rejected due to the Alice decision, estimated following Acikalin et al. (2022). $Sales_{i,2013}$ denotes firm i's total sales in the year 2013. N_i denotes the total number of patents owned by firm i before the Alice decision.	KPSS and Compustat
Post	An indicator variable that takes the value of one for patent lawsuits after 2014, and zero otherwise.	Stanford NPE litigation database
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

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