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Patent remedies and technology licensing: Evidence from a supreme court decision

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Abstract

Research Summary: Remedies for infringement are important determinants of the strength of patent protection. However, there has been little emphasis on the role of patent remedies in profiting from innovation via licensing. To address this gap, we examined the impact of patent remedies on technology licensing. Our study exploited a US Supreme Court decision that reduced the probability of issuing injunctions as a remedy to compare US firms' licensing propensity with that of a matched control group of European firms. We found that the decision reduced, on average, US firms' propensity to license. This effect is driven mainly by small firms and especially those in discrete technology industries. This research contributes to the literature on profiting from innovation and presents several implications for firms' licensing strategies.

Managerial Summary: This study demonstrates how patent remedies (i.e., injunctions vs. ongoing royalties) differentially influence firms' incentives to engage in technology licensing. We suggest that injunctions cast a credible threat to potential licensees' product market activities, enhance the bargaining power of licensors in negotiations, and increase the likelihood of making a deal. Our research shows that when the probability of obtaining an injunction declines, firms are less likely to capture value by out-licensing their technological innovations. Especially for small firms, profiting from innovation via licensing becomes challenging. This effect exacerbates when small firms operate in discrete technology industries. These findings imply that in such conditions, firms may benefit from other value capture mechanisms, such as entering the product market or forming partnerships with industry incumbents.

KEYWORDS

injunctions, ongoing royalties, patent remedies, profiting from innovation, technology licensing

1 | INTRODUCTION

For over three decades, management scholars and practitioners have been interested in how firms can profit from technological innovation. Understanding the conditions of value capture from innovation has an unwavering pertinence for the strategic management field (Gambardella, Heaton, Novelli, & Teece, 2021). The seminal work by Teece (1986) was among the first to identify the factors that impact firms' ability to appropriate returns. One way of generating revenue from innovation is licensing internally developed ideas in technology markets (Arora, Fosfuri, & Gambardella, 2001b; Arora, Fosfuri, & Ronde, 2013; Gans & Stern, 2003). A recent study estimated that the revenue gains from technology transactions for the period from 1990 to 2014 were larger than $1 trillion per year, corresponding to over 10% of the total revenue generated by US public firms (Arque-Castells & Spulber, 2022). Technology commercialization via licensing is argued to work best when the appropriability regime is tight (Teece, 1986, 2006). The basic premise is that strong patent protection discourages imitation and increases innovators' incentives to engage in technology trade (Gans, Hsu, & Stern, 2002; Gans & Stern, 2003; Teece, 1986). Although prior research has advanced our understanding of the relationship between patent protection and technology licensing, studies in this field have mainly considered patent effectiveness as a summary measure of the factors that shape an appropriability environment (e.g., Arora & Ceccagnoli, 2006). Consequently, there has been little emphasis on the mechanisms underlying the strength of patent protection. We suggest that *patent remedies* play an important role in profiting from technological innovation via licensing. Thereby, we distinguish between the two types of remedies available in patent law and examine their diverse impacts on technology licensing and implications for firm strategies.

Patent remedies indemnify a patentee for their losses due to infringement and regenerate the conditions in which a patentee would have been absent from infringement (Lemley, 2009). Remedies are governed by two main rules: (a) *property rules* devised to retain the entitlement of the patentee, unless they are willing to transfer it—achieved by court order for an *injunction* as a remedy—and (b) *liability rules* designed to allow for infringement as long as the infringer compensates the patentee for the damages caused—performed by court order for *compensatory damages* (for incurred losses, such as lost profits) and *ongoing royalties* (for future harm) as remedies (Calabresi & Melamed, 1972; Kieff, 2011; Schankerman & Scotchmer, 2001). These remedies present serious implications for innovators' licensing strategies. While the threat of an injunction may increase an innovator's bargaining power in licensing negotiations and the likelihood of making a deal, the threat of collecting damages, such as ongoing royalties, might be less effective in incentivizing *ex ante* licensing and deterring infringement. We aim to shed more light on how patent remedies impact innovative firms' technology licensing strategies by incorporating insights from the extant literature on patent remedies (e.g., Cotter & Golden, 2019; Denicolo, Geradin, Layne-Farrar, & Padilla, 2008; Kieff, 2011; Sandrik, 2012; Schankerman & Scotchmer, 2001; Shapiro, 2016) with prior work on technology licensing (e.g., Arora et al., 2001b; Arora & Ceccagnoli, 2006; Fosfuri, 2006; Gans & Stern, 2003; Teece, 1986).

Our empirical analyses are built on a regulatory change in patent law regarding the issuance of injunctions. In 2006, the US patent system witnessed a shift from property rules toward liability rules with the Supreme Court's decision on the *eBay* versus *MercExchange* patent dispute case (Gupta & Kesan, 2016). Specifically, the Supreme Court removed the substantial precedent for the automatic issuance of permanent injunctions[1] based on a finding of patent infringement. Instead, the court introduced a four-factor test to determine eligibility to obtain an injunction. In effect, this ruling reduced the probability of obtaining an injunction for infringed patents by about 25% (Chien & Lemley, 2012). Exploiting this shift in patent remedies in the United States, we drew on a quasi-natural experimental setting to explore the subsequent impact on US firms' propensity to license, namely the rate of licensing per patent, compared to a matched control group of European firms. We also examined which types of firms were affected by this change. Our analyses showed that the shift in patent remedies diminished US firms' propensity to license, on average. In addition, this effect was mainly driven by small firms and intensified in discrete technology industries.

The regulatory change in patent remedies was introduced largely due to a growing concern about nonpracticing entities (NPEs) and aimed at preventing their patent-trolling activities (Sandrik, 2012). To date, research on the consequences of this ruling has analyzed the changes in injunction rates, comparing the success rate of NPEs with that of practicing entities in the United States (Gupta & Kesan, 2016; Seaman, 2016). Other studies focused on patenting, R&D spending, venture capital investment outcomes (Mezzanotti, 2021; Mezzanotti & Simcoe, 2019), and industry-level acquisition activities (Caskurlu, 2019). We inform and contribute to this literature by presenting its impact on firms' propensity to license, evidencing which types of firms are more reliant on certain patent remedies for technology licensing.

This study also contributes to the existing literature on profiting from technological innovation. Research in this stream has advanced around the three pillars of value capture from innovation (Teece, 2006). Some studies focused on the dominant design paradigm and entry timing (e.g., Suarez, Grodal, & Gotsopoulos, 2015; Utterback, 1994; Utterback & Suarez, 1993), while others explored the role of complementary assets (e.g., Helfat, 1997; Rothaermel, 2001; Shane, 2001; Tripsas, 1997). Thus far, research on the appropriability regime has mostly been interested in its impact on licensing in technology markets, associating strong protection with high value capture (e.g., Arora & Ceccagnoli, 2006; Gans, Hsu, & Stern, 2008; Gans & Stern, 2003). Recent work has extended this framework to profiting from innovation in the digital economy (Teece, 2018) and enabling technologies (Gambardella et al., 2021). We contribute to the appropriability regime research by going beyond the dichotomy of strong versus weak protection. Indeed, we provide a more nuanced approach to the mechanisms underlying the

[1]A *permanent injunction* is a court order granted after a trial hearing is complete to stop the infringer from producing goods that infringe on an established patent right. Throughout our study, we use the word *injunction*, instead of *permanent injunction*, for the sake of brevity.

strength of patent protection and theorize about the diverse effects of patent remedies on firms' propensity to license. We also discuss the implications of patent remedies for firms' licensing strategies.

2 | THEORETICAL BACKGROUND

2.1 | Patent remedies

Remedies are defined by patent law and have several implications for innovative firms (Shapiro, 2016). They are guided by either property rules or liability rules (Lemley & Weiser, 2007). Property rules refer to a situation in which an intellectual property (IP) right is transferred from a patentee to a buyer in a discretionary transaction, and the value of the IP is determined by a mutual agreement (Calabresi & Melamed, 1972). Whereas liability rules refer to a situation in which infringement of an IP right is allowed if the infringer compensates the patentee with a payment objectively determined by a court (Calabresi & Melamed, 1972). Essentially, remedies available under each ruling differ. Under property rules, courts issue an injunction to enjoin the infringer from producing, using, or selling a product that reads on an infringed patent[2] (Cotter & Golden, 2019). An injunction is a forward-looking remedy in the sense that it aims to prevent future harm to the patentee. Under liability rules, courts issue two types of remedies: (a) compensatory damages for past infringement that have already taken place at the time of a court's final verdict and (b) ongoing royalties for prospective infringement, that is, for the harm that will be caused by future infringement (Cotter, 2013).

Much of the extant literature on patent remedies focuses on the desirable conditions for property rules versus liability rules and designing optimal remedies for patent infringement (e.g., Calabresi & Melamed, 1972; Heald, 2008; Kaplow & Shavell, 1996; Merges, 1994, 1996; Schankerman & Scotchmer, 2001; Shapiro, 2016). A comprehensive review of this literature reveals certain patterns regarding the relative desirability of patent remedies. The classical approach to IP rights, supported by early theoretical work, suggests that a property rule is more favorable when the transaction costs in *ex ante* negotiations are expected to be lower than the costs associated with potential errors and hardships involved in the process of a court determining the appropriate value of an IP (Calabresi & Melamed, 1972; Cotter, 2013; Sterk, 2008). In the absence of accurate information on the level of harm, a damages award might be set too low, and this might motivate the infringer to engage in further infringement (Merges, 1994). Moreover, property rules are argued to entail informational benefits that incentivize a patentee to develop, use, and disseminate information on the potential use of an invention (Smith, 2004, 2007). Property rules are also recognized as superior to liability rules in encouraging private negotiations (Kaplow & Shavell, 1996).

In the past two decades, the traditional approach to property rules versus liability rules has been subjected to substantial criticism. These criticisms revolve around two main themes. First, the threat of obtaining an injunction is alleged to increase a patentee's bargaining power in licensing negotiations, thus leading to hold-up problems and excessive royalty rates beyond the

[2]Injunctions are of two types: (a) *permanent injunctions* are issued after a final determination that one or more patent claims is/are infringed and (b) *preliminary injunctions* are issued prior to a final determination of the merits of such cases. Preliminary injunctions are more difficult to obtain because there is a level of uncertainty surrounding a patent's scope or validity during a trial. Please see Lanjouw and Lerner (2001) for a detailed discussion of preliminary injunctions. In this study, we focus on permanent injunctions due to the recent changes set by the US Supreme Court's decision on the *eBay* versus *MercExchange* case regarding the eligibility for and issuance of permanent injunctions.

market value of a patented invention (Lemley & Shapiro, 2006). Second, the strategic use of patents under property rules is argued to inflate patent litigations (Bessen & Meurer, 2005; Galasso & Schankerman, 2010) and patent-trolling activities (Bessen, Ford, & Meurer, 2011; Fischer & Henkel, 2012; Reitzig, Henkel, & Heath, 2007). Overall, due to the major emphasis on optimal policy design and legal doctrine rather than on technology transactions, this literature has thus far been developed around a policy debate on remedies and has overlooked the relationship between patent remedies and technology licensing.

2.2 | Technology licensing

Technology licensing has long been investigated by management and innovation scholars (e.g., Anand & Khanna, 2000; Arora et al., 2001b; Arora & Nandkumar, 2012; Fosfuri, 2006). Prior research on licensing concentrates on two broad areas: the appropriability regime and firm characteristics (Conti, Gambardella, & Novelli, 2013). Studies examining appropriability regimes point to the fact that strong patent protection facilitates market transactions (e.g., Arora et al., 2001b; Arora & Merges, 2004; Gans & Persson, 2013; Gans & Stern, 2003; Teece, 1986). Typically, the disclosure of information involves a risk of expropriation, which is regarded as a major impediment to technology transfer (Arrow, 1962). However, strong patent protection enhances market safety and enables the disclosure of an invention to multiple third parties to increase the expected deal amount and the probability of making an agreement without the risk of expropriation or user reproduction by providing an *ex post* mechanism to alleviate such behavior (Gans & Stern, 2010; Mohammadi & Khashabi, 2021). Empirical evidence also supports the idea that strong patent protection has a positive impact on licensing as a technology commercialization strategy (Arora & Ceccagnoli, 2006; Gans et al., 2002). In sum, research in this field asserts that strong patent protection is a precondition for and a facilitator of technology licensing (Arora & Gambardella, 2010; Gans & Stern, 2010).

2.3 | Patent remedies and incentives to license

Regarding the incentives created by various remedies, it is essential to study them from both supply and demand perspectives. In the United States, remedies are issued as follows: When a court determines that a patent is valid and infringed, it first issues compensatory damages for past infringement. The court then orders either an injunction to prevent future infringement or ongoing royalties to compensate the patentee for future infringement (Shapiro, 2016). The relationship between patent remedies and technology licensing depends on the potential threats these remedies cast in negotiations. They create either a *threat to exclude* or a *threat to collect damages* (Schankerman & Scotchmer, 2001). How these threat points materialize for potential licensors and licensees is of great interest in understanding the incentives to license.

For a patentee of an invention, excludability is the key to profitability when the disclosure of the underlying idea is necessary for technology trade (Gans & Stern, 2003). Typically, disclosure involves the risk of expropriation, imitation, and user reproduction (Gans & Stern, 2010). However, a patentee can leverage an injunction's threat to exclude to freely reveal the information about a patented technology to multiple potential licensees, preserving the right to make an exclusive agreement with the licensee that offers the highest amount or end the negotiations at any time. In this respect, an injunction enhances a patentee's bargaining power and provides informational benefits and incentives to develop, use, and disseminate information on the potential use of an invention (Smith, 2004, 2007). The availability of an injunction also ensures that the patentee will be adequately compensated for their loss if an infringement occurs. Usually, it is difficult to objectively determine the amount of true harm to a patentee (Calabresi & Melamed, 1972). Under property rules, rather than a court intervention for determining the value of the loss, the parties are left to make a mutual agreement; this helps the patentee set the asking price and attain an amount equal to the perceived value of the IP (Merges, 1994). Thus, injunctions are expected to enhance a patentee's ability to capture value from technological innovation and increase their incentives to license.

Compared to injunctions, ongoing royalties are likely to decrease a patentee's incentives to license. Principally, liability rules allow for infringement on an IP right if the infringer pays an objectively determined royalty to the patentee (Calabresi & Melamed, 1972). This characteristic of liability rules provides a patentee with little protection when they disclose patented ideas in licensing negotiations. Liability rules also severely limit a patentee's ability to negotiate a license with multiple parties, offer an exclusive deal to one party, or withdraw from negotiations. Similarly, the threat to collect damages creates little incentive to license, considering the risk of undercompensation if litigation occurs (Kieff, 2011; Merges, 1994). When a court faces hardships in determining the appropriate value of an IP, a patentee may be undercompensated for their loss (Cotter, 2013). Therefore, ongoing royalties are likely to hamper a patentee's ability to capture value from licensing and decrease their incentives to engage in technology trade.

For a potential licensee, incentives to in-license are influenced by the risks of patent litigation (Somaya, 2012) and the costs associated with various patent remedies. An injunction is likely to inflate an infringer's risk of being enjoined from the production of a good that reads on an IP right. Property rules also increase litigation costs for an infringer, given the prospect of adequately compensating the patentee if the patent is upheld as valid and infringed. Moreover, the threat to exclude induces an infringer to incur the cost of inventing around, especially if the firm has made sunk-cost investments in production. Therefore, under property rules, a potential licensee is expected to have high incentives to secure the freedom to operate by undertaking thorough patent clearance before investing in production and seeking an *ex ante* license agreement. Conversely, ongoing royalties are likely to reduce the cost of infringement by removing the risk of ceasing production. Liability rules also eliminate the cost of inventing around by enabling the infringer to continue production on an infringed patent. Moreover, potential errors and hardships in determining the appropriate value of an IP may favor the infringer (Cotter, 2013). The infringer may find it less costly to pay *ex post* damages to the patentee rather than to make an *ex ante* licensing deal. Especially if the damages award is equated by a court to the amount the parties would have agreed upon *ex ante*, the infringer merely pays the accrued sum to the patentee (Carlton, 2009). This renders ongoing royalties ineffective in deterring infringement (Kaplow & Shavell, 1996).

Overall, we argue that injunctions are more effective than ongoing royalties in deterring infringement and incentivizing potential licensors and licensees to engage in the technology trade. Thus, following the shift from property rules toward liability rules, we expect to observe a decline, on average, in firms' propensity to license.

2.4 | Patent remedies and firm characteristics

Prior research on licensing suggests that one of the main determinants of technology trade is a firm's size (Gambardella, Giuri, & Luzzi, 2007). In general, large firms have fewer incentives to license their technologies (Arora, Fosfuri, & Gambardella, 2001a). Owing to the immense volume of their downstream operations, large firms risk losing a sizable share of their profits with the entry of a new competitor into the product market (Arora & Gambardella, 2010). In contrast, small firms are more likely to license their innovations. For firms that have a small market share, the revenue generated by license fees is larger than the revenue dissipation resulted from adding a new competitor (Arora & Fosfuri, 2003; Fosfuri, 2006). Although small firms are more likely to engage in licensing, they rely more heavily on the strength of patent protection in their market transactions (Arora & Gambardella, 2010), especially when they lack alternative mechanisms of protection such as complementary assets for downstream production (Teece, 1986). In the absence of complementary assets, strong patent protection is shown to positively affect firms' propensity to license (Arora & Ceccagnoli, 2006).

Regarding patent remedies, we assert that the regulatory shift mainly hampers small firms' incentives to license, as opposed to those of large firms, for the following reasons. First, ironclad protection from expropriation facilitated by an injunction is essential for firms that lack complementary assets. The threat to exclude is likely not only to shield the innovator from imitation, but also to provide the innovator with enough time to gain access to or build complementary assets for production, whereas the threat to collect damages is unlikely to protect against imitation. Following the regulatory change, the possession of complementary assets is expected to be the key to shielding from imitation and capturing value from innovation. Typically, small firms face high costs in accessing or controlling these complementary assets (Gans et al., 2002). Therefore, small firms are expected to experience a reduction in their bargaining power in licensing negotiations and a decline in their propensity to license. However, by owning and controlling access to complementary assets, large firms can still leverage them to deter imitation and retain their bargaining power in licensing negotiations (Teece, 1986, 2006).

Second, due to the high cost of litigation, small firms with limited financial resources may find it difficult to enforce their IPs and prefer *ex ante* licensing to a lengthy and uncertain litigation process (Thomas, 2006). One way of facilitating *ex ante* licensing is to use the threat to exclude to encourage potential licensees to engage in negotiations, which is possible for small firms under property rules (Thomas, 2006). Another way to facilitate *ex ante* licensing is to have a reputation for aggressive patent enforcement (Agarwal, Ganco, & Ziedonis, 2009). Research shows that aggressive patent enforcement can enhance firms' ability to capture value (Somaya, 2012). Arguably, large firms with deep pockets can litigate their IPs more aggressively than small firms. Following the regulatory change, small firms' bargaining power in *ex ante* licensing negotiations is likely to decline, while large firms can use their reputation for aggressiveness in patent enforcement as an alternative credible threat to deter infringement and facilitate license deals.

Third, new criteria regarding eligibility to obtain an injunction mostly favor large firms (Everding, 2007; Holte, 2015). Based on the new ruling, being or not being a product market competitor with the infringer is considered by the courts in determining the patentee's eligibility for an injunction (Diessel, 2007). Specifically, when a patentee is a direct product market competitor with an infringer, they usually secure an injunction (Seaman, 2016). However, if a patentee is not in direct competition with the infringer (e.g., small firms with no downstream production, specialized technology firms, or individual inventors), an injunction is generally denied (Seaman, 2016). Thus, following the Supreme Court's ruling, it has become harder for small firms to obtain injunctions, while large firms with downstream operations remain mostly eligible (Denicolo et al., 2008; Holte, 2015).

To sum up, we posit that small firms are more reliant on the excludability provided by injunctions in technology market transactions, while large firms can shield themselves from imitation via alternative mechanisms of protection. Additionally, with the new eligibility rules, small firms are less likely to obtain an injunction than large firms. Therefore, we expect to observe the decline in firms' propensity to license to be mainly driven by small firms.

2.5 | Patent remedies and industry characteristics

Industry characteristics are another important determinant of the incentives to license (Cohen, Nelson, & Walsh, 2000). Prior literature on innovation contends that patent protection varies across industries (Cohen et al., 2000; Cohen, Goto, Nagata, Nelson, & Walsh, 2002; Merges & Nelson, 1990). Specifically, this body of literature distinguishes between discrete and complex technology industries (Kusunoki, Nonaka, & Nagata, 1998; Levin, Klevorick, Nelson, & Winter, 1987; Von Graevenitz, Wagner, & Harhoff, 2013). Discrete technology industries are characterized by the use of technologies that can be protected with a single or a few patents, such as the chemical and pharmaceutical industries, whereas complex technology industries build on technologies that involve many distinctly patentable inventions that constitute an end product (Cohen et al., 2000). The computer, semiconductor, and electronic industries are illustrative of complex technologies. Studies on discrete versus complex technology industries acknowledge discrepancies in the effectiveness of patent protection in these industries (Levin et al., 1987). While discrete technology industries rely heavily on patent protection to prevent imitation, ensure freedom to operate, and generate licensing revenues, complex technology industries largely depend on alternative mechanisms of protection, such as lead time and complementary assets, to reap their investments in R&D (Cohen et al., 2000). Figure 1 depicts discrete versus complex technology industries with respect to a firm's size.

Regarding patent remedies, we have thus far argued that the regulatory shift mainly hampers small firms' propensity to license. We further suggest that the impact of patent remedies on small firms' propensity to license varies by industry. Thereby, we compare the licensing propensity of small firms in discrete technology industries with that of small firms in complex technology industries—quadrants I and II in Figure 1. In discrete technology industries, patents are important sources of information that reveal valuable technological details of an underlying invention. Competitors and potential licensees in such industries carefully study patent documents to ensure patent clearance and freedom to operate (Knight, 2012). Because patents disclose important information about an invention, firms in discrete technology industries are prone to a high risk of expropriation (Anton & Yao, 1994). Especially, small firms in these

		Industry Characteristics	
		Discrete Technology Industry	Complex Technology Industry
Firm Size	Small Firm	**I** (9,538) [1,785]	**II** (81,076) [13,941]
	Large Firm	**III** (5,690) [1,258]	**IV** (31,178) [5,508]

FIGURE 1 2 × 2 matrix of industry characteristics and firm size with the number of observations in parentheses and the number of firms in brackets.

industries lacking alternative mechanisms of protection, such as complementary assets, are likely to rely on the threat to exclude to alleviate such risk and facilitate licensing negotiations. Conversely, in complex technology industries, patents have fuzzy boundaries (Lemley & Shapiro, 2005), that is, patent scopes are unclear (Bessen & Meurer, 2008), and patent claims reveal relatively less information about the underlying invention. In addition, IP rights are highly fragmented, which renders it more difficult to perform patent clearance and secure freedom to operate (Ziedonis, 2004). Due to these characteristics, patents have traditionally been less effective in protecting innovation in complex technology industries (Cohen et al., 2000). Small firms in these industries rely on alternative mechanisms of protection, such as speed to market, to shield from imitation and appropriate returns from innovation (Leiponen & Byma, 2009). Therefore, we contend that the excludability provided by an injunction is critical, particularly for small firms in discrete technology industries compared to those in complex technology industries.

In sum, injunctions are expected to be more influential in incentivizing licensing by small firms in discrete technology industries vis-à-vis small firms in complex technology industries. Thus, following the regulatory shift, we expect the decline in small firms' propensity to license to be magnified in discrete technology industries.

3 | EMPIRICAL EVIDENCE

3.1 | Data and sample

To test our theoretical arguments, we employed several difference-in-difference (DiD) estimations to compare US firms' propensity to license with that of European (i.e., German and Swiss) firms in the pre- versus post-eBay period. The rationale for using European firms as a control group is as follows: First, the Supreme Court's decision is effective for all US firms. To ensure that the firms in our control group were unaffected by the Supreme Court's decision, we sampled firms from different institutional contexts. To the best of our knowledge, there was no major legislative change in the control firms' patent systems during the study period. Second, European countries (i.e., Germany and Switzerland) have a sizable technology market. To illustrate, two recent surveys of inventors, namely PatVal-EU II and PatVal-US, show that 13.72% of patents are licensed in the United States, while in Switzerland and Germany, 8.89 and 6.5% of patents are licensed, respectively.[3] Similarly, research has found that Switzerland and Germany have the second largest number of IP intermediary firms in Europe (following the United Kingdom) (Benassi, D'Angelo, & Geenen, 2012), indicating a vibrant technology market in these countries.

As for the timeframe of our analyses, we considered a 2001–2010 window. This choice placed the Supreme Court's decision at the midpoint of the analysis period. It also provided sufficient observations around the event to estimate its impact on the outcomes of interest. Longer time windows, while providing more statistical power, would have made our analyses prone to potential contamination effects. Specifically, our choice to end the sample by the end of 2010 is because the America Invents Act, a legislation that brought several changes to the US patent system, came into effect in 2011. Given that the Supreme Court's decision took place in mid-2006 (i.e., argued on March 29th, and decided on May 15th), we excluded this year from our analyses.

[3]https://www.academia.edu/1449640/InnoS_and_T_Final_Report_on_Inventors.

Regarding the exogeneity of the Supreme Court's decision, a myriad of briefs was submitted to the Supreme Court by various industry stakeholders, providing similar degrees of support for eBay and MercExchange (Beckerman-Rodau, 2007). For instance, corporations, law scholars, and bar associations were split in their support of eBay (e.g., the Bar Association of the City of New York, American Innovators' Alliance, various IP professors, Research in Motion, Time Warner, Yahoo!, etc.) and MercExchange (e.g., the American Bar Association, Biotechnology Industry Organization, various Law & Economics professors, General Electric, Qualcomm, Tessera, etc.) (Beckerman-Rodau, 2007). Although one may argue that the industry stakeholders might have had an expectation about the Supreme Court's decision, such as approving or reverting the Appeals Court's verdict, it was not anticipated that the Supreme Court would have completely altered the injunctive relief policy by introducing the principles of equity for injunction eligibility decisions.[4] The unexpected change in the policy increased our confidence in the exogeneity of this ruling.

Since the beginning of the Supreme Court's case hearing (July 2005),[5] there has been much media coverage (Dolak & Bettinger, 2008), and this case received a lot of attention from the industry, as was also reflected in a multitude of briefs submitted by several industry participants to the Supreme Court during the 2005–2006 period. To account for the potential chilling effect on firms' licensing activities during the Supreme Court's hearing process, we excluded 2005 as a robustness check in our restricted sample to retest the main effect on firms' propensity to license. In Section 3.4, we further discuss and assess the underlying assumptions of our empirical approach.

In this study, we gathered an initial sample of 90,249 firms in five IP-intensive industries: chemicals, machinery, computer/electronics, electrical equipment, and medical devices.[6] We obtained our sample of firms from the Orbis and Amadeus databases. One advantage of these databases is that they allow firms to be matched with their patenting information, which was gathered from the Patstat database. The Patstat database is widely used to identify patent characteristics (e.g., Grimpe & Hussinger, 2014; Nandkumar & Srikanth, 2016; Wagner, Hoisl, & Thoma, 2014).

Firm–patent information was available for 55,015 firms. We further restricted this data by focusing on firms that had at least one patent application before the Supreme Court's decision, which resulted in a dataset of 25,807 firms. We then complemented this dataset by compiling information on license agreements. The license agreements of US firms were extracted from ktMINE, which provides a comprehensive database of license agreements in the United States (Arque-Castells & Spulber, 2022; Fosfuri, Helmers, & Roux, 2012) gathered from the Securities and Exchange Commission, the United States Patent and Trademark Office reassignment database, and federal records.[7] We also hand collected information on European firms' license agreements via a company name search and a manual match in the Factiva database.

To improve the comparability between the treatment and control groups (Bettis, Gambardella, Helfat, & Mitchell, 2014), we conducted a one-to-one match between our US

[4]See the news articles and legal opinions on how the Supreme Court's decision was taken by surprise: "eBay Gets Troll Call: An unexpected Supreme Court patent win fails to lift the stock" (https://www.thestreet.com/technology/ebay-gets-troll-call-10285681).

[5]https://www.supremecourt.gov/search.aspx?FileName=/docketfiles/05-130.htm.

[6]Industry NAICS codes: 325, 333, 334, 335, 3391. This industry specification focuses on the manufacturing industries and excludes NPEs.

[7]In a few cases where firms appeared to have no patents, but announced licensing deals, we further searched and hand collected additional information about their patenting activities from ktMINE database and supplemented our dataset.

TABLE 1 *T*-tests of the mean values of matching variables used in k2k CEM

Mean			
Matched variables	**United States (treatment)**	**European (control)**	***T*-test *p*-value**
Small firm	0.71	0.71	1.00
Large firm	0.29	0.29	1.00
Chemical	0.12	0.12	1.00
Machinery	0.45	0.45	1.00
Computer	0.26	0.26	1.00
Electric	0.11	0.11	1.00
Medical devices	0.06	0.06	1.00
Profit margin	0.27	0.35	.00

Note: The table compares the means of matching variables for the sample of treatment and control groups. Two-sided *t* tests on the difference between mean values are depicted. The variable year is also fully matched but not reported above.
Abbreviation: CEM, coarsened exact matching.

and European firms using coarsened exact matching (CEM) on four dimensions (i.e., size, industry, year, and profit margin) and balanced the treatment and control groups.[8] This matching method is widely used in similar studies (e.g., Aggarwal & Hsu, 2013; Azoulay, Stuart, & Wang, 2013). The process coarsens the data over these four dimensions to find a suitable match. Compared to alternative approaches, such as matching based on the mean of the pretreatment variables, CEM matching is more precise and provides efficient matching.

Table 1 presents the mean values for the variables used in CEM to match the treatment and control groups. The two-sided t-test of mean differences shows no significance, except for profit margin. Notably, US firms have lower profit margins than their European counterparts, which could be due to macroeconomic or institutional factors. To account for this difference, in all the empirical analyses, we controlled for profit margin, which showed a small and insignificant effect in the majority of specifications. Our matched dataset comprised 129,796 firm-year observations.

3.2 | Measures

3.2.1 | Dependent variable

To test the impact of the shift in patent remedies on firms' propensity to license, we examined the rate of firms' license agreements per patent. Our dependent variable, *Licensing per patent*, is

[8]The number of variables included in matching the treatment and control groups typically involves a trade-off between precision and generalizability. Specifically, as the number of variables included in matching increases, the number of one-to-one matched pairs declines, leading to a small sample size. This could raise generalizability concerns. Thus, we have matched our treatment and control groups on the four most relevant variables for licensing. Including further variables in the matching process, such as a firm's age, creates an imbalance in the matching among the aforementioned variables.

the log transformation of the number of out-license agreements per year by each firm divided by the cumulative number of firm's patents by that year, that is, log (1 + the number *of out-license agreements /firm's cumulative number of patents*). Generally, firms are not compelled to publicly report such agreements. Therefore, our license agreement data are limited to publicly available information. In the ktMINE database, licensing agreements are categorized with respect to the type each deal represents. Our variable consisted of technology transfer agreements. In the Factiva database, technology transfer agreements were gathered manually. Given that the number of license agreements was heavily skewed in our sample, we used the log transformation of this variable in our specifications.

3.2.2 | DiD variables

The DiD variables in our analyses were two dummy variables: *US*, indicating whether the firm is a US (and therefore treated) versus European firm, and the *Post-eBay Period*, which takes the value of 0 for 2001–2005 and 1 for 2007–2010. Table 2 summarizes the descriptions of the variables in our analyses.

3.2.3 | Key independent variables

The key independent variables in our analyses—used in the split samples and interactions—were a firm's size and industry characteristics (discrete vs. complex). For the *Firm Size* variable, we used the categorization of firms provided by the ORBIS/AMADEUS databases. These databases cluster firms depending on their public/private status, operating revenue, assets, and number of employees. In our data, a firm is considered large when it matches at least one of the following conditions: (a) public firm, (b) operating revenue ≥10 million EUR, (c) total assets ≥20 million EUR, or (d) employees ≥150. A firm is considered small when it is not included in the large category. For industry characteristics, a dummy variable, indicating a *Discrete* industry, equaled 0 if the focal firm is operating in machinery, computer/electronics, electrical equipment, or medical devices industries. *Discrete* equaled 1 if the firm was operating in the chemical industry.

3.3 | Model

To test the impact of the regulatory shift on firms' licensing propensity, we used several DiD estimations. A standard DiD model that estimates the effect on the treatment group is formulated as follows:

$$Y_{it} = \beta_0 + \beta_1\, US_i + \beta_2\, PosteBay_t + \beta_3\, US_i \times PosteBay_t + \beta_k \mathbf{X}_{it} + \varepsilon_{it} \tag{1}$$

where Y_{it} indicates the log (number of out-license agreements per year t by firm i *divided by firm's cumulative number of patents* + 1); US_i is a dummy variable taking the value of 1 if the firm is in the United States (treated) or if the firm is European, 0; and *Post-eBay*$_t$ is a dummy variable taking the value of 1 in the posttreatment period (2007–2010) and 0 in the pretreatment

TABLE 2 Variable descriptions

Variable	Description	Source
LICENSING PER PATENT	log(1 + the # of number of out-license agreements per year by each firm divided by the firm's cumulative # of patents) Firm's cumulative # of patents refer to the total number of patent applications by each firm up to 1 yr before the focal year of observation	*ktMINE*, *FACTIVA* *PATSTAT*, *ORBIS*, *AMADEUS*
POST-EBAY PERIOD	A dummy variable taking the value of 1 in the period 2007–2010, and 0 in 2001–2005 (2001–2004 in the robustness tests)	
US	A dummy variable taking the value of 1 if the firm is in the United States (treated) and 0 if the firm is a European firm	*ORBIS*, *AMADEUS*
OPERATING REVENUE	The yearly revenue amount (in thousand $) reported by each firm in the sample	*ORBIS*, *AMADEUS*
PROFIT MARGIN	The yearly percentage of [(profit before tax/operating revenue) × 100] reported by each firm in the sample	*ORBIS*, *AMADEUS*
FIRM AGE CATEGORY	A categorization of firm age in deciles. Firm age is calculated as the difference of each year observed from the year of incorporation.	*ORBIS*, *AMADEUS*
FIRM SIZE	A categorization of firms under four original categories according to ORBIS/AMADEUS firm size tags. Small, medium, large, and very large firms depending on: Operating revenues, total assets and number of employees. In our split sample analyses, small and medium firms are grouped as "small," and large and very large firms are grouped as "large." In our data, a firm is considered to be large when it matches at least one of the following conditions: (a) listed (public firm), (b) operating revenue > = 10 million EUR, (c) total assets > = 20 million EUR, or (d) employees > = 150. A firm is considered to be small when it is not included in the large category.	*ORBIS*, *AMADEUS*
NUMBER OF EMPLOYEES	The yearly cumulative number of employees reported by each firm	*ORBIS*, *AMADEUS*
INDUSTRY	Dummy variables for each industry specified in the analyses: Chemical, machinery, computer/electronics, electrical equipment, and medical devices	*ORBIS*, *AMADEUS*
DISCRETE/ COMPLEX INDUSTRY	Dummy variable, indicating "complex" as machinery, computer/electronics, electrical equipment, medical devices, and "discrete" as chemical, following the discrete vs. complex industry definition by Cohen et al. (2000).	*ORBIS*, *AMADEUS*
YEAR	Dummy variables for each year specified in the analysis: 2001–2010	

period (2001–2005). The year 2006 is omitted because this is the year the US Supreme Court announced its decision. $\mathbf{X}_{it}$ is a vector of the controls. The coefficient of interest is β_3, which shows the treatment effect.

Given that we are interested in estimating a fixed-effect model—and thus control for the firm and year fixed effects—the first-order terms indicating *US* and *Post-eBay* in Equation (1) cannot be estimated.[9] Thus, we report the point estimates for the following fixed-effect model, with robust *SE*s clustered around firms:

$$Y_{it} = \beta\, US_i \times PosteBay_t + \beta_k \mathbf{X}_{it} + \varepsilon_{it} \tag{2}$$

We chose a fixed-effects (within) ordinary least squares regression because of the short panel (i.e., many individual units and only a few periods) characteristic of the dataset.

3.4 | Internal validity of the DiD analysis

A valid estimation of a DiD specification is based on several assumptions. A DiD estimator assumes the exogeneity of the treatment event. This implies that the components of the independent variables are not influenced by the treatment; therefore, the outcome variable is not affected in the pretreatment period. The exogeneity assumption could be violated if agents anticipate treatment and adjust their behavior accordingly. As discussed in Section 3.1, we argue that in our sample, firms could not have anticipated the details of the Supreme Court's decision. Therefore, we believe that the exogeneity assumption is justified for our treatment event.

Another key assumption of a DiD is the comparability of the treatment and control groups. This assumption has several implications. First, the treatment and control groups should be relatively balanced over the relevant observable variables, and if not, the unbalanced variables should be controlled for in the regressions (Roberts & Whited, 2013).[10] According to Table 1, our treatment and control groups are well balanced over all the matching variables, except for profit margin, which is included as a control variable in our estimation models. The second implication of the comparability assumption is that pretreatment dynamics in the outcome variables across the treated and control groups are similar, on average. To investigate this, we conducted an event study and plotted the differences in *Licensing per patent* between treated and control firms by year. Figure 2 plots the event study outcome, where each dot corresponds to the estimated yearly difference in the average log licensing per patent between US firms (treated) and European firms (control). The vertical bars show a 90% confidence interval. Time (in years) is indicated on the horizontal axis; 2006 was excluded. The vertical dashed line indicates the timing of the treatment event.[11]

As depicted in Figure 2, the common trend assumption for the *Licensing per patent* variable holds in the pretreatment period. There were no significant differences across the treatment and control groups before the Supreme Court's decision, which validates our DiD approach. The significant difference between the two categories materialized only after the treatment. Despite a supportive visual representation, there may still be factors that influence the parallel

[9]In the online appendix, we report estimates that exclude the firm and year-fixed effects.

[10]The matching process is based on the *observable* variables. Therefore, a balanced sample may still be prone to heterogeneity among unobservables. We discuss this limitation in Section 4.

[11]The estimation model for Figure 2 includes firm, year, and age-category fixed effects, besides all the controls used in Table 5. To show the robustness of this trend to exclusion of controls, we present the plotted event study from a specification that does not include the controls. We also exclude the year 2005 from the model. The plotted results are similar and presented in the online appendix (Figure A1).

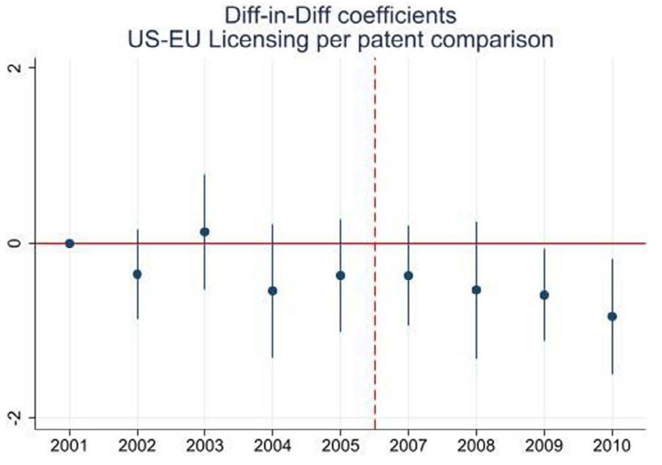

FIGURE 2 Event study plot for licensing per patent coefficients of US versus European firm comparison. Event study plot, where each dot is the estimated difference in average log licensing propensity between the treatment and control firms by year—that is, *log*(*1 + # license agreements*/*patents*). The estimated coefficients and errors on the Y axis are multiplied by 10^3. The model includes firm, year, and age-category fixed effects, besides all the controls in Table 5. Vertical bars are 90% confidence intervals. Time (in year) a is plotted on the horizontal axis—2006 excluded. The vertical dashed line indicates the timing of the treatment event. The value at the first period (2001) is set as baseline.

trend assumptions. Thus, besides the visual representation provided in Figure 2, we performed two alternative approaches as robustness checks to increase our confidence in the results. First, we eliminated 2005 to build a restricted sample and repeated the analyses on this sample. Second, to account for a potential failure of the parallel trends assumption, we used a *fully flexible group-specific dynamics* estimation (Mora & Reggio, 2017), an extension of Equation (2), which allowed for different pretreatment trends in the treated and control groups. We report the results of these analyses in the following sections.

3.5 | Descriptive statistics

The descriptive statistics for the matched sample are depicted in Table 3. In our pooled sample, most firms did not engage in licensing activities, which created a skewed distribution of *Licensing per patent*, with a mean of 0.001. The maximum number of *Licensing per patent* per year is 8. In terms of mean numbers, operating revenue was about \$59.4 million, the number of employees was above 152, and the profit margin was 32%. The US firms constituted 50% of our matched sample (treatment group), German firms represented 41%, and Swiss firms represented 9%. In addition, 71% of our sample were small firms, and around 29% were large firms. Around 11.9% of the sample consisted of firms in discrete industries. The machinery industry was the most represented in the data, at 46.3%, followed by the computer industry, at 25.2%. The medical devices industry, at 5.7%, was least represented in terms of the total number of observations. Table 4 displays the correlations among the variables used in the specifications.

TABLE 3 Descriptive statistics

Variable	Mean	*SD*	Min	Max
Licensing per patent	.001	.037	0	8
Licensing per patent (log)	.000467	.016	0	2.197
Operating revenue	59,399.021	1,086,989.8	−1,165,885	88,523,208
Number of employees	152.895	2,215.349	0	135,000
Profit margin	.322	2.949	−96.4	75.95
Firm age category	5.741	2.831	1	10
United States	.496	.5	0	1
Germany	.411	.492	0	1
Switzerland	.093	.29	0	1
Small	.711	.453	0	1
Discrete	.119	.324	0	1
Machinery	.463	.499	0	1
Computer	.252	.434	0	1
Chemical	.119	.324	0	1
Electric	.109	.311	0	1
Medical	.057	.232	0	1

TABLE 4 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Licensing per patent	1.000							
(2) Licensing per patent (logged)	0.936	1.000						
(3) Operating revenue	0.004	0.008	1.000					
(4) Number of employees	0.004	0.008	0.851	1.000				
(5) Profit margin	0.001	0.002	0.141	0.125	1.000			
(6) Firm age category	−0.011	−0.014	0.037	0.048	0.035	1.000		
(7) United States	0.005	0.005	−0.002	−0.011	−0.015	−0.018	1.000	
(8) Small firm	−0.005	−0.010	−0.081	−0.096	−0.114	−0.156	0.006	1.000
(9) Discrete	0.023	0.034	0.065	0.055	0.036	0.006	−0.008	−0.069

3.6 | Empirical results on incentives to license

In Table 5, we present the fixed effects estimates of Equation (2), with robust *SE*s clustered at the firm level. The dependent variable across all columns is the log-transformed licensing propensity—*Licensing per patent*. This operationalization enables the estimation of a simple linear model with fixed effects rather than more complex count models, which generates

TABLE 5 Results of fixed-effects estimations for firms' propensity to license

DV: Licensing per patent (logged) (coefficients and errors × 10^3)	Main sample (1) b/se/p	Main sample (2) b/se/p	Excluding 2005 (3) b/se/p	Fully-flexible models (4) b/se/p	Fully-flexible models (5) b/se/p
POST-EBAY × US	−.385 (0.186) (.039)	−.344 (0.187) (.065)	−.376 (0.203) (.064)		
2002 × US				−.352 (0.311) (.259)	−.352 (0.312) (.258)
2003 × US				.130 (0.401) (.745)	.131 (0.402) (.744)
2004 × US				−.544 (0.461) (.237)	−.543 (0.462) (.240)
2005 × US				−.365 (0.392) (.351)	−.365 (0.392) (.351)
2007 × US				−.369 (0.349) (.290)	
2008 × US				−.536 (0.476) (.260)	
2009 × US				−.593 (0.320) (.064)	
2010 × US				−.834 (0.400) (.037)	
AFTER 2006 × US					−.584 (0.352) (.097)
CONTROLS	No	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes	Yes
NUMBER OF OBSERVATIONS	128,111	127,482	112,279	127,482	127,482
NUMBER OF CLUSTERS	22,652	22,492	21,948	22,492	22,492
R-SQUARED (OVERALL)	.388	.389	.410	.389	.389
ADJUSTED *R*-SQUARED	.257	.258	.266	.258	.258

Note: Robust *SE*s are clustered around firms and reported in parentheses below the coefficient. *p*-Values are reported in parentheses, below robust *SE*s. The dependent variable is *log*(*1 + # licensing*/*patent*). Estimated coefficients and *SE*s are multiplied by 10^3 for clarity. Controls include OPERATING REVENUE, NUMBER OF EMPLOYEES, PROFIT MARGIN, dummy variables indicating missing values for these controls, and Firm-age category controls. An estimated constant is excluded from the table.

more conservative estimates with smaller coefficients and larger *SE*s (Hausman, Hall, & Griliches, 1984). All models include year and firm fixed effects. In Models 2–5, we control for firms' operating revenue, number of employees, profit margin, and firm-age category.[12] Table 5 presents the estimated coefficients for the variables of interest, while a full version of this table, including the coefficients for control variables, can be found in the online appendix (Table A1). In the baseline model (Model 1), we analyzed the impact of the Supreme Court's decision on firms' propensity to license using the main sample (2001–2010, excluding 2006), in the absence of controls. The coefficient of interest (i.e., the DiD coefficient) showed a negative and significant effect (p-value = .039). This result is robust to the inclusion of the controls in Model 2 (p-value = .065). The estimated average treatment effect on the treated (ATT) in Models 1–3 is a drop around 0.04%, on average—the effect becomes stronger in the years 2009 and 2010 (Model 4), with an increase up to more than twice the average magnitude.[13] This implies that a shift from property rules toward liability rules decreased US firms' licensing propensities compared to those of matched European firms. This result is in line with our theoretical arguments. We performed several robustness checks (in Models 3–5) to alleviate concerns about potential pretreatment trends. In Model 3, we excluded 2005 from the analysis because the court proceedings began during that year. The analyses in this model, therefore, compared the periods before (2001–2004) and after the Supreme Court process (2007–2010). The results were very similar to those in Model 2. Next, to check the robustness of our results regarding the potential failure of the parallel trends assumption, we used the *fully flexible group-specific dynamics* specification proposed by Mora and Reggio (2017) in Models 4 and 5. We used this specification in two ways. In Model 4, we controlled for yearly pretreatment trends and estimated the yearly posttreatment effects. The results showed that accounting for potential pre-trends, the effect was negative right after the court decision, with its significance starting with a lag (p-values are .064 and .037 for the years 2009 and 2010, respectively). The effect sizes for the years toward the end of our sample are larger than the ATT in Models 1–3 and show a drop of more than twice the average magnitude in Models 1–3 in licensing propensity. Model 5 estimated a very similar model to account for the pretreatment effect, yet it bundled the posttreatment years (as AFTER2006) to estimate the ATT. While the effect size was comparable to the estimates in Models 1–3, the p-value was relatively higher (p-value = .097). In the online appendix, we present further tests to check the robustness of our results. First, we reestimated the DiD coefficient by excluding the firm and year fixed effects (Table A2). Second, we reestimated the main model using lagged control variables (Table A3, Model 1). The results remain robust. These results lend support to our theoretical argument regarding the effect of the Supreme Court's decision on firms' licensing propensity. Thus, our analyses highlight the adverse effect of the shift from property rules toward liability rules on US firms' propensity to license.

In Section 2.4, we predicted that the effect of the Supreme Court's ruling would mainly be driven by small firms. To assess this prediction and perform a finer-grained analysis of the data, we conducted several split-sample analyses. First, following the argument that the licensing propensity of small firms may depend significantly on the strength of IP protection (Arora & Gambardella, 2010), we split our sample according to the firm size in Table 6. This table shows the main coefficients of interest; however, a version with the coefficients of controls is available in the online appendix—Table A4. The analyses showed noisy and insignificant results for the

[12]These models also include dummy variables indicating missing values for these controls.

[13]When the dependent variable is not logged, the DiD estimation of the treatment's impact on licensing propensity produces an effect size that is almost equivalent to the mean of the dependent variable.

TABLE 6 Results of fixed-effects estimations for the licensing propensity of small and large firms

	Large firms			Small firms		
	Main sample		Excluding 2005	Main sample		Excluding 2005
***DV*: Licensing per patent (logged) (coefficients and errors × 10^3)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	b*/*SE*/*p	***b*/*SE*/*p***	***b*/*SE*/*p***	***b*/*SE*/*p***	***b*/*SE*/*p***	***b*/*SE*/*p***
POST-EBAY × US	−.275 (0.457) (.547)	−.209 (0.455) (.646)	−.290 (0.445) (.515)	−0.431 (0.185) (.020)	−0.378 (0.188) (.044)	−0.383 (0.225) (.089)
CONTROLS	No	Yes	Yes	No	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
NUMBER OF OBSERVATIONS	36,953	36,868	32,406	91,158	90,614	79,873
NUMBER OF CLUSTERS	6,789	6,766	6,545	15,863	15,726	15,403
R-SQUARED (OVERALL)	.316	.316	.308	.433	.436	.458
ADJUSTED *R*-SQUARED	.161	.162	.132	.313	.317	.329

Note: Robust *SE*s are clustered around firms and reported in parentheses below the coefficient. *p*-Values are reported in parentheses, below robust *SE*s. The dependent variable is *log*(*1 + # licensing/patent*). Estimated coefficients and *SE*s are multiplied by 10^3 for clarity. Controls include OPERATING REVENUE, NUMBER OF EMPLOYEES, PROFIT MARGIN, dummy variables indicating missing values for these controls, and Firm-age category controls. An estimated constant is excluded from the table.

licensing propensity of large US firms in the post-eBay period (Model 1, no controls: *p*-value = .547). In contrast, the estimates for the small firms exhibited a strong and significant pattern (Model 4, no controls: *p*-value = .020). The effect size was comparable to the ATT effect in Table 5, but it carried more significance. When controls were included, the distinction between small and large firms' licensing propensity remained robust (Model 2: *p*-value = .646 and Model 5: *p*-value = .044). These results imply that the ATT effect shown in Table 5 is mainly driven by the effect on small firms.

To test the robustness of these findings, we excluded the year 2005 from the analyses and presented the results in Models 3, and 6. The results are in line with the view that the Supreme Court's decision generated a sharp and uniformly negative impact on small firms, while the effect on large firms remained insignificant. The analyses in Table 6 are not intended to statistically compare the effect sizes between small and large firms, but to further explore and conclude that the main driver of ATT is small firms. Further robustness checks are presented in the online appendix (Table A3, Model 2 and Table A5).

3.7 | Empirical results on industry characteristics

Based on the arguments in Section 2.5, we expect that the Supreme Court's decision will have a greater impact on small firms in discrete technology industries compared to small firms in complex technology industries. Table 7 presents the results of the fixed-effect estimations for the licensing propensity of small firms in discrete versus complex technology industries (a version that presents the coefficients of controls is available in the online appendix—Table A6). Models 1 and 2 estimated the coefficients for the full sample, excluding and including the controls respectively. The variable of interest in these models is the three-way interaction term (Post-eBay × US × Discrete), which shows a negative, but insignificant effect in the full sample (*p*-values = .201 and .251). In line with our expectations, the three-way interaction term for small firms (Models 5 and 6) is negative and highly significant (*p*-values = .027 and .041). According to the estimate, the impact of the treatment on small firms is amplified by approximately 0.25%. This result shows that for small firms, the effect of the Supreme Court's ruling on licensing propensity is stronger when they operate in discrete technology industries. We did not find a similar trend for large firms, such that the coefficient is positive and insignificant (Models 3 and 4: *p*-values = .946 and .917). Our analyses show that the shift from property rules toward liability rules, on average, has a negative effect on firms' propensity to license and this effect is mainly driven by small firms, and magnified in discrete technology industries. Further robustness checks are presented in the online appendix (Table A3, Model 3 and Table A7).

3.8 | Additional robustness checks

3.8.1 | Alternative operationalization of the dependent variable

Our dependent variable consisted of many zeros, while the majority of licensing firms in our sample have only one license agreement. In the main specifications, we used a log transformation of the dependent variable to estimate the treatment effect. Alternatively, as a robustness test, we operationalized the dependent variable as a license agreement dummy (i.e., whether a firm engages in licensing). Estimations with this dependent variable can be interpreted as the

TABLE 7 Results of fixed-effects estimations for the licensing propensity of small and large firms across discrete versus complex industries

	Main sample		Large firms		Small firms	
***DV*: Licensing per patent (logged) (coefficients and errors × 10^3)**	**(1)** *b/SE/p*	**(2)** *b/SE/p*	**(3)** *b/SE/p*	**(4)** *b/SE/p*	**(5)** *b/SE/p*	**(6)** *b/SE/p*
POST-EBAY × US	−.220	−.197	−.367	−.311	−.165	−.135
	(0.129)	(0.135)	(0.225)	(0.253)	(0.156)	(0.165)
	(.089)	(.144)	(.103)	(.218)	(.293)	(.413)
POST-EBAY × DISCRETE	−.900	−.894	−2.517	−2.474	.066	.041
	(0.862)	(0.854)	(2.237)	(2.207)	(0.279)	(0.278)
	(.296)	(.295)	(.261)	(.262)	(.814)	(.881)
POST-EBAY × US × DISCRETE	−1.633	−1.465	.183	.282	−2.687	−2.469
	(1.277)	(1.275)	(2.720)	(2.700)	(1.216)	(1.210)
	(.201)	(.251)	(.946)	(.917)	(.027)	(.041)
CONTROLS	No	Yes	No	Yes	No	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes
NUMBER OF OBSERVATIONS	128,111	127,482	36,953	36,868	91,158	90,614
NUMBER OF CLUSTERS	22,652	22,492	6,789	6,766	15,863	15,726
R-SQUARED (OVERALL)	.388	.389	.316	.317	.433	.436
ADJUSTED *R*-SQUARED	.257	.258	.162	.162	.314	.317

Note: Robust *SE*s are clustered around firms and reported in parentheses below the coefficient. *p*-Values are reported in parentheses, below robust *SE*s. The dependent variable is *log*(*1* + *# licensing*/*patent*). Estimated coefficients and *SE*s are multiplied by 10^3 for clarity. Controls include OPERATING REVENUE, NUMBER OF EMPLOYEES, PROFIT MARGIN, dummy variables indicating missing values for these controls, and Firm-age category controls. An estimated constant is excluded from the table.

extensive margin of licensing propensity. This operationalization does not require the estimation of a count model. Also, given the relatively large sample size, it can simply be estimated with a linear probability model, with coefficients qualitatively similar to Logit. As reported in Table A8 (in the online Appendix), our results are fully robust to this alternative operationalization of the dependent variable.

3.8.2 | Global economic downturn

An alternative explanation for the decline in the licensing propensity of US firms could be the economic downturn of 2008. If the economic crisis affected US firms earlier or more severely than European firms, this would generate the observed decrease in licensing propensity via an alternative mechanism. The academic literature on the global crisis, however, does not support this conjecture. Macro data on US and European countries show that these economies experienced a comparable impact from the global downturn (e.g., Baldwin, 2009). For instance, the drop in imports and exports—as a direct proxy for the effect on companies—seems "synchronized" between the United States and Europe (Baldwin, 2009, p. 3), and the global crisis hit all countries in question simultaneously. In addition, quarter-on-quarter real GDP growth, compared to the Organization for Economic Co-operation and Development database, shows a very similar drop for both the US and EU15 countries, with the latter being affected slightly more significantly (Baldwin, 2009). Thus, we could not justify this alternative explanation. However, to account for the possible confounding effect of the global crisis in all analyses, we controlled for firms' operating revenue and profit margins. Thus, the potential impact of the economic downturn on firms' financial performance was controlled in the analyses.

3.8.3 | Global operations and the treatment effect

One could argue that for firms operating globally and patents being applied for international use, the shift from property rules toward liability rules may have a smaller impact compared to firms solely operating within the United States. However, this potential bias would be operating against our theorized results such that if this effect were strong, it would be harder to find significant results due to the underestimation of the impact of the shift. However, the current study shows a significant decline in the licensing propensity of US firms compared to that of European firms. To eliminate any potential impact of the US Supreme Court's decision on our control group, we retested the arguments advanced in this study on a subset of the control group without any heavy patenting activities in the United States, and we found very similar results.

3.8.4 | Placebo test

Finally, to determine whether the DiD estimation applied in the analyses was specifically capturing the impact of the US Supreme Court's decision or a trend that had begun before the decision, we applied a placebo DiD test. We retested the arguments for a placebo shock in 2002, with 2-year intervals before and after. The analysis generated an insignificant and positive estimate (p-value = .690) and showed no potential preexisting trends before the Supreme Court's decision in 2006.

4 | DISCUSSION AND CONCLUSION

Profiting from innovation via licensing is an important value capture strategy that has enduring relevance for the strategic management field (Teece, 2018). The appropriability regime is among the three pillars of profiting from innovation framework (Teece, 1986) that determine potential value capture mechanisms for innovative firms. In this study, we argue that patent remedies underlie the strength of an appropriability regime and have several implications for innovative firms' licensing strategies. To the best of our knowledge, our study is the first attempt to examine the impact of patent remedies on firms' propensity to license.

It is well established in the management literature that the strength of an appropriability regime influences firms' ability to capture value and plays a central role in business strategy formulation (Gans et al., 2002; Teece, 2006). However, some researchers have suggested that, at times, the appropriability regime can be endogenously shaped by a firm's actions, such as strategic disclosure (Peters, Thiel, & Tucci, 2013) or open-source software development (Pisano, 2006).

Recently, this framework has been expanded and applied to general purpose technologies and enabling technologies (Gambardella et al., 2021; Teece, 2018). We inform this body of research by looking closely at the remedies in patent law, distinguishing between injunctions and ongoing royalties, and studying how these patent remedies differentially affect potential licensors' value capture opportunities in licensing negotiations. Our results indicate that injunctions pose a credible threat to potential licensees' product market activities and enhance the bargaining power of licensors in deals. Thus, an appropriability regime that predominantly favors the issuance of injunctions as a remedy protects innovators from imitation and increases the incentives of potential licensors and licensees to engage in technology trade. In contrast, ongoing royalties provide innovators with little protection against imitation. In an appropriability regime where ongoing royalties are granted as a remedy, potential licensors' and licensees' incentives to license diminish, and capturing value from innovation via licensing becomes challenging.

In the original framework of profiting from innovation, licensing is the recommended value capture strategy when the appropriability regime is strong (Teece, 1986). In a weak appropriability regime, an innovator's potential to earn private returns on R&D is enhanced by acquiring specialized or co-specialized complementary assets for downstream production. If complementary assets are not easily accessible, the innovator is suggested to either build them or form partnerships with the incumbent firms that control these key assets (Teece, 1986). Our findings imply a more nuanced approach to strategy formulation regarding the appropriability environment. Based on our results, licensing works best in appropriability regimes where injunctions are granted as a remedy. Akin to weak appropriability, when ongoing royalties are the prevalent patent remedies, innovators may capture value by acquiring or building the complementary assets necessary for product commercialization or forming partnerships with industry incumbents.

Our study also informs the extant literature on licensing and markets for technology (Arora et al., 2001b; Fosfuri, 2006; Gans & Stern, 2003; Rivette & Kline, 2000). This literature highlights the benefits of strong patent protection in facilitating market transactions (Arora & Ceccagnoli, 2006; Gans et al., 2002, 2008). We contribute to this line of research by providing large-scale evidence on the interplay between patent remedies and potential licensors' and licensees' incentives to license. Our results suggest that issuing injunctions, as opposed to ongoing royalties, as a patent remedy enhances market safety by alleviating expropriation risk. Indeed, strong and enforceable IP rights are argued to ensure market safety and facilitate bilateral and multilateral market transactions (Gans & Stern, 2010). Similarly, research on the sources of deal failure points to the lack of market safety as an impediment to reaching an agreement (Agrawal, Cockburn, & Zhang, 2015). In addition, our split-sample analyses indicate that small firms are more reliant on the excludability provided by injunctions for their licensing activities. This finding is in line with prior research that suggests small firms are more dependent on patent protection (Galasso & Schankerman, 2018), especially for their licensing strategies, due to higher exposure to expropriation risk and a lack of alternative mechanisms of protection (Arora & Gambardella, 2010). Likewise, our analyses of industry characteristics corroborate the existing innovation literature such that, similar to the variations in patent protection across industries (Cohen et al., 2000), the impact of patent remedies on licensing varies by industry. Our findings are consistent with research showing that firms in discrete technology industries are more adversely impacted by a lack of market safety in licensing negotiations than firms in complex technology industries (Agrawal et al., 2015).

Finally, this study contributes to research on the US Supreme Court's landmark decision. The scholarly debate on the consequences of this ruling has been largely theoretical and centered around the law and patent policy literature (e.g., Chao, 2008; Davis, 2008; Diessel, 2007).

A few empirical studies that have investigated post-eBay injunction rates have found that they range between 72 and 75%, down from an estimated 95% pre-eBay rate (Chien & Lemley, 2012; Seaman, 2016). Firms are also observed to be less likely to file for an injunction after the Supreme Court's decision (Gupta & Kesan, 2016). Some recent research that focuses on patenting, R&D spending, and venture capital investment outcomes has found no evidence of a change in the post-eBay period (Mezzanotti & Simcoe, 2019). Research comparing firms' innovative output based on their exposure to litigation has shown an increase in litigating firms' patenting activities (Mezzanotti, 2021). Others have shown a decline in the number of technology-based firm acquisitions, small firms' access to venture capital funds, and their propensity to patent (Caskurlu, 2019). We extend this line of research by examining the implications for firms' propensity to license. Our study draws attention to how this ruling has impacted firms' propensity to license and provides evidence that this effect varies by firm size and industry. These findings are particularly useful in incentivizing technology trade. Overall, this research points to the need for more comprehensive theorizing on patent remedies and their diverse impacts on firms' propensity to license.

Our study, similar to any other research, is not free of limitations. To build our dependent variable, we relied on a dataset composed of public announcements of license agreements. To our knowledge, this is the best available dataset for our study. However, firms are not compelled to publicly report such agreements, which precludes covering the entire universe of license agreements. This may create bias, especially if there are systematic differences in firms' disclosure strategies. Nevertheless, it is unlikely that the factors that drive firms' tendency to disclose license agreements are influenced by the Supreme Court's decision. Thus, DiD estimations largely handle this potential concern. Additionally, our DiD estimations rely on the comparability assumption between the treatment and control groups. We did our best to confirm this assumption in our study context. Nevertheless, the matching procedure was inevitably based on observable factors. Thus, time-variant unobservable factors could introduce bias to our estimates. Our analyses exploited a rich dataset of firm–patent matching per year. However, studying the impact of patent remedies on royalty rates in license agreements would certainly be a fruitful area for future research. Likewise, research has argued that strong patent protection facilitates vertical specialization and the division of innovative labor (Hall & Ziedonis, 2001). Future work could extend our knowledge of how patent remedies impact industry structure.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Orbis, Amadeus, ktMINE, and Factiva databases.

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SUPPORTING INFORMATION

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

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