Litigation Risk and Innovation Portfolio: Analysing Firms' Direction of Innovation

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Abstract

This study examines the impact of litigation risk on corporate innovation, using the 2006 eBay v. MercExchange Supreme Court decision as a natural experiment. By employing a difference-in-differences approach and leveraging firm-level variation in exposure to patent litigation, this dissertation analyses how firms adjust their innovation strategies in response to reduced litigation risk. The ruling, which altered the enforcement of patent rights, serves as the basis for this analysis. The findings of the study reveal that the ruling significantly increased overall patenting activity and the number of patents in existing technological fields. However, firms remained cautious about exploring new fields. The study also highlights variations based on firm size, with larger firms more likely to increase patents filed in familiar domains while smaller firms focused on reinforcing their core technologies without significantly increasing their number of patents. These results provide important insights into the complex relationship between legal environments and innovation strategies, suggesting that changes in patent enforcement may have differential impacts based on firm characteristics.

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1 Introduction

Patent enforcement is crucial for the volume and direction of innovation by protecting inventors and encouraging investment in research and development (R&D) (Arqué-Castells & Fons-Rosen, 2022; Hall & Ziedonis, 2001; Khan, 2005; Khan & Sokoloff, 1993). However, its effects can vary significantly across different sectors and countries (Lerner, 2002; Levin et al., 1987; Mansfield, 1986; Moser, 2005). While patent enforcement can provide substantial benefits such as protecting intellectual property and incentivising innovation by enhancing firms' ability to capture rents from their innovations, it also introduces legal uncertainties and potential litigation costs that can hinder firms by raising costs and slowing innovation (Bessen & Meurer, 2014; Boldrin & Levine, 2013; Galasso & Schankerman, 2015; Lanjouw & Lerner, 2001). Litigation risk is a major concern, as patent infringement lawsuits can result in substantial financial losses. For example, the study by Bessen et al. (2018) finds that publicly traded companies accused of patent infringement faced an average loss of $41.4 million per event between 1986 and 2009. The potential for such high costs compels firms to carefully weigh the risks of pursuing new innovations due to the fear of inadvertently infringing on existing patents. In an era where innovation drives competitive advantage and economic growth, firms must navigate these legal risks, which significantly impact their strategic decision-making.

Patent enforcement involves a range of legal actions and remedies that patent holders can pursue to protect their intellectual property rights. This process primarily includes monetary damages and injunctive relief. Monetary damages can be compensatory, which covers lost profits, or punitive, which may include reasonable royalties.(Arqué-Castells & Fons-Rosen, 2022; Gupta & Kesan, 2016). When monetary damages are inadequate, injunctive relief becomes a key option. The potential for injunctive relief adds a layer of complexity to patent enforcement, as permanent injunction can be a powerful remedy for a patent holder but can also impose significant operational restrictions on the alleged infringer, leading to substantial business disruptions. An injunction can prohibit a company from manufacturing, using, or selling a product that allegedly infringes on a patent, which can have severe consequences for the infringer's business operations (Mezzanotti & Simcoe, 2019). The possibility of being forced to halt production or withdraw a product from the market adds significant pressure on firms. This often leads to a 'hold-up problem,' where patent holders exploit their leverage to demand high royalties (Shapiro, 2010).

A notable example is the 2001 lawsuit between NTP Inc. and Research in Motion (RIM), the company behind BlackBerry. NTP sued RIM for patent infringement and secured both an injunction and significant monetary damages. Although the injunction was temporarily halted while RIM appealed the decision, the threat of potentially having to stop BlackBerry sales pressured RIM into settling for $612.5 million—about half of their annual revenue. Ironically, after extensive reexamination, some of NTP's patent claims were later invalidated, but RIM was unable to recover the settlement funds already paid (Lane, 2006; Mezzanotti & Simcoe, 2019).[1]

In this dissertation, I examine how firms in the United States of America (US) adjust their innovation strategies in response to changes in litigation risk, with a particular focus on the 2006 eBay v. MercExchange US Supreme Court ruling. This decision, which removed automatic permanent injunctions for patent infringements, is a natural experiment to analyse how firms respond to changes in the legal environment. Although the ruling impacted the entire US patent system, I measure firms' exposure to patent litigation to identify those most likely affected by the Supreme Court's decision. The underlying premise is that the ruling significantly impacts firms operating in technological areas with higher patent litigation intensity. Mezzanotti (2021) finds that the ruling led to a general increase in innovation among more exposed firms by mitigating the distortions from patent litigation, which had previously constrained R&D investments.

Using a difference-in-differences (DiD) approach, I examine how the ruling influenced firms' innovation portfolios, particularly focusing on the direction of innovation. The identification strategy relies on comparing changes in innovation activities across firms with varying levels of exposure to patent litigation before the ruling. Specifically, this analysis leverages the variation in firms' exposure to litigation, which is more pronounced in technology classes with higher litigation intensity. This firm-level exposure is measured as a weighted average of litigation activity across the technology classes where a firm operates, with weights based on the share of patents in each technology class. Firms operating in areas with more intense patent litigation are expected to be more affected by the Supreme Court decision, thereby enabling a clearer isolation of the ruling's effect on their innovation strategies.

[1] See *RIM v. NTP, Yet Again: The BlackBerry's ill-fated patent dispute with NTP takes a final turn.* Retrieved from https://spectrum.ieee.org/rim-v-ntp-yet-again.

The key contribution of my research is the focus on the impact of the Supreme Court decision on the direction of innovation, highlighting how firms' innovation strategies evolve in response to reduced litigation risk. By reducing litigation risk, the verdict may have encouraged more exposed firms not only to enhance their innovations in familiar areas but also to engage in imitation and explore new technological domains. This shift could lead to valuable follow-on innovations. The reduced litigation cost associated with removing automatic injunctions makes it more financially viable for firms to take on riskier projects in uncharted areas, leveraging existing patents from rivals and non-rivals as inspiration. However, this decreased litigation risk might also reinforce a strategy of safe, incremental innovation within familiar technological classes, as firms aim to minimise the risk of failure from exploring new technological fields. Firms may balance their approach by innovating in both familiar and new technological areas to gain a competitive edge and maximise their innovation potential. Alternatively, the reduced litigation risk could discourage firms from pursuing entirely new technological domains. With easier imitation due to lower litigation risks, other firms could more readily invent around existing patents, potentially reducing profitability for the original innovator. If the expected returns from innovating in new technological fields are insufficient to cover the costs due to weaker patent enforcement, firms may opt not to innovate in these areas. Thus, does the Supreme Court ruling raise the returns to invest in existing areas of expertise, or does it reduce the risks of innovating in new technology fields? To explore this, I assess its impact on the number of patents in established technology classes (existing tech) versus new areas (new tech), as well as on the proportion of patents in existing technology field relative to total patents (existing tech share) versus the proportion of patents in new technology field relative to total patents (new tech share), technological proximity, and firms' innovative search patterns.

The findings of this study show that reduced litigation risk led to a notable increase in overall patenting, particularly in familiar technological areas. These results remain consistent across various robustness checks, reinforcing the validity of the main findings. However, the effect on new tech was less pronounced, suggesting firms were cautious about exploring unfamiliar fields despite the lower risk. For other innovation measures, such as existing tech share and new tech share, technological proximity, and firms' innovative search patterns, the ruling had no significant impact. Furthermore, the heterogeneity analysis shows that older and larger, established firms with extensive resources benefited

the most, expanding their patenting in established areas following the ruling. Smaller firms, however, concentrated their innovation efforts on strengthening their existing technological domains without significantly increasing the number of patents.

This dissertation contributes to strands of literature on patent enforcement and litigation (e.g Appel et al., 2019; Arqué-Castells & Fons-Rosen, 2022; Boldrin & Levine, 2013; Hall & Ziedonis, 2001; Lerner, 2009; Moser, 2005; Peng et al., 2024; Sakakibara & Branstetter, 2001; Shapiro, 2010) and consequences of the 2006 Supreme Court eBay v. MercExchange ruling (e.g Aydin Ozden & Khashabi, 2023; Bereskin et al., 2023; Gupta & Kesan, 2016; Mezzanotti & Simcoe, 2019; Seaman, 2016). While it shares similarities with the work of Mezzanotti (2021), this dissertation takes a distinct approach in several aspects. Unlike Mezzanotti (2021), which focuses on broad innovation outcomes such as total patents and patent citations, my study provides a more comprehensive set of innovation metrics to capture the impacts of the ruling on firms' direction of innovation. By analysing the impact of the ruling on existing and new technology classes, existing tech share, new tech share, technological proximity, and innovative search patterns, this research offers a more granular view of how firms adjust their innovation strategies in response to changes in litigation risk, shedding light on both incremental innovations and potential breakthroughs. Furthermore, this dissertation employs annual data spanning eleven years (2001-2011), which offers a broader longitudinal perspective compared to Mezzanotti (2021) use of quarterly data over a four-year window (2004Q2-2008Q1). The longer time frame helps capture both long-term trends and any delayed effects of the ruling. Additionally, I incorporate an analysis of heterogeneity based on firm size and age, adding depth to the understanding of how different types of firms respond to changes in litigation risk. These advancements contribute to a more detailed and varied perspective on the implications of the 2006 Supreme Court ruling for innovation strategies.

The subsequent sections of this dissertation are organised as follows. Section 2 presents an overview of the eBay v. MercExchange ruling and reviews the relevant empirical literature. Section 3 details the data and sample selection, variable construction, and the empirical methods employed. Section 4 presents and interprets the findings from the empirical analysis, including robustness checks. The final section presents the conclusion.

2 Literature Review

This section presents an overview of the eBay v. MercExchange case and empirical evidence on patent litigation, enforcement and innovation.

2.1 Overview of the eBay v. MercExchange Case

Before 2006, US patent owners held a strong advantage in court. If they could prove the validity of their patent and infringement, they could routinely obtain an injunction—a court order preventing the infringer from continuing the contested activity. This was mainly due to a general rule by the Court of Appeals for the Federal Circuit (the CAFC), which made securing injunctions relatively straightforward (Clugston & Kim, 2017; Gupta & Kesan, 2016). There was a rarely used exception to this rule where courts could deny an injunction if it harmed the public interest, such as limiting access to essential medical treatments (Chao, 2008).

As the 2000s progressed, concerns grew regarding the fairness of this system. Studies have argued that issuing injunctions might not always serve the best interests of innovation (such as Boldrin & Levine, 2002; Lanjouw & Lerner, 2001; Lemley & Shapiro, 2007). The ease of obtaining injunctions gives patent owners significant leverage in legal disputes, even in cases involving minor inventions, allowing them to halt the operations of infringing firms that had invested heavily in the disputed product. As a result, the threat of an injunction heavily influences negotiation dynamics between parties, even before litigation begins (Shapiro, 2010).

This situation led to what is known as a "hold-up problem." Patent hold-up occurs when patent owners can demand much higher royalties after a product is developed by threatening an injunction (Shapiro, 2010). Having invested heavily in the product, the company that infringed becomes vulnerable to large settlement demands, which would have been lower if a license had been negotiated in advance. The increased litigation costs and uncertainty discourage investment in innovation, as firms become hesitant to invest in R&D due to the potentially crippling nature of these disputes.

A pivotal change to the automatic permanent injunction occurred with the Supreme Court's decision in eBay Inc. v. MercExchange, LLC 2006. This case centred around the "Buy It Now" feature, in which MercExchange owns the

patent with the US Patent No. 5845265. eBay expressed interest in purchasing MercExchange's patent portfolio, which included valuable business method patents related to online sales. However, negotiations fell through, and in September 2001, MercExchange sued eBay for infringing on three of its patents. In 2003, the district court jury found eBay guilty of wilful infringement and awarded MercExchange $29.5 million in damages. Despite this, the district court denied MercExchange's request for a permanent injunction, citing concerns about the growing trend of business method patents and Non-Practicing Entities (NPEs) using patents primarily for licensing revenue. The court reasoned that since MercExchange was not practising the patent itself but was willing to license it, monetary damages would suffice.[2]

MercExchange appealed, and the CAFC reversed the district court's decision in 2005, stating that issuing a permanent injunction is standard practice in the US, except in rare circumstances. The Court of Appeal stressed that injunctions are not exclusively for patentees planning to utilise their patents and that general concerns with business method patents do not warrant denying injunctive relief.[3] This decision prompted eBay to appeal to the Supreme Court. In May 2006, the Supreme Court rejected both the district court's categorical denial and the Federal Circuit's general rule favouring injunctions. The Supreme Court emphasised that injunctions should not be automatic but decided based on a traditional four-factor test. This test assesses whether the plaintiff has suffered irreparable injury, if monetary damages are inadequate, the balance of hardships between the parties, and the public interest.[4]

The Supreme Court's ruling emphasised that patent cases should be treated like other areas of law regarding injunctive relief and that patent holders do not have an automatic right to an injunction. Each case has to be evaluated individually. The Court also noted that NPEs, which hold patents but do not practise them, should not be automatically denied injunctions. However, it acknowledged concerns about the rise of patent trolls who leverage injunction threats to extract high licensing fees.[5] Upon remand, the district court again denied MercExchange's request for a permanent injunction, applying the

[2]See MercExchange, LLC v. eBay, Inc., 275 F. Supp. 2d 695 (E.D. Va. 2003). Available at https://law.justia.com/cases/federal/district-courts/FSupp2/275/695/2463432.

[3]See MercExchange, L.L.C. v. eBay, Inc., 401 F.3d 1323 (Fed. Cir. 2005). Available at https://law.justia.com/cases/federal/appellate-courts/F3/401/1323/551581/.

[4]See eBay Inc. v. MercExchange, L.L.C., 547 U.S. 388 (2006). Available at https://supreme.justia.com/cases/federal/us/547/388.

[5]See the Wikipedia article "eBay Inc. v. MercExchange, L.L.C." accessed August 6, 2024, at https://en.wikipedia.org/wiki/EBay_Inc._v._MercExchange,_L.L.C.

Supreme Court's four-factor test. The court found that MercExchange's licensing activities indicated that monetary damages were adequate. The balance of hardships did not favour either party, and the public interest slightly disfavoured an injunction.

The Supreme Court's ruling marked a pivotal shift in patent law enforcement. Before this ruling, courts typically issued injunctions almost automatically upon finding patent infringement. The eBay decision required courts to consider whether an injunction was appropriate in each case, marking a significant shift from the previous approach where injunctions were the default response to patent infringement. The eBay decision initiated a new, hybrid approach to patent enforcement, where financial compensation could be employed as an alternative to permanent injunctions to address infringements (Shapiro, 2016). Between 2000-2015, eBay v. MercExchange was the second most cited Supreme Court patent decision (Mezzanotti & Simcoe, 2019), and the third most cited Supreme Court patent case between 1952-2021.[6]

Following the eBay v. MercExchange case, Gupta and Kesan (2016) observed a significant decrease in both the frequency of injunction requests and their approval rates, with preliminary injunctions becoming 31% less likely to be granted and permanent injunctions 44.1% less likely. Clugston and Kim (2017) noted a 29.8% injunction denial rate in patent cases, aligning with Chien and Limley's (2012) findings that injunction grants declined from an estimated 95% pre-eBay to 75% post-eBay. These statistics underscore the substantial shift in patent litigation dynamics following the eBay v. MercExchange decision. Seaman (2016) also finds that the decline in injunction rates is particularly prominent among cases involving non-NPEs or firms that are not direct competitors.

2.2 Empirical Evidence on Patent Litigation and Innovation

2.2.1 Evidence on the Effect of Patent Litigation

Several studies provide empirical evidence on the effects of patent litigation and enforcement, with some explicitly focusing on changes to automatic permanent injunctions.

[6]See Patently-O blog posts from March 11, 2015, and December 20, 2021, available at https://patentlyo.com/patent/2015/03/supreme-court-cases.html and https://patentlyo.com/patent/2021/12/cited-supreme-patent.html.

Aydin Ozden and Khashabi (2023) examine the impact of the Supreme Court decision in the eBay v. MercExchange case using a quasi-experimental design on technology licensing. They compare how US firms and their European counterparts handle patent licensing, and their findings reveal a significant decline in US firms' likelihood of licensing patents after the Supreme Court's ruling. This change is linked to the shift from automatic injunctions to a four-factor test, which reduces the chances of obtaining injunctions. This legislative shift mainly affects small firms and those in specialised technology sectors, where market stability is essential.

Bereskin et al. (2023) investigate how the reduced likelihood of injunctions affects the market values of firms after the 2006 Supreme Court ruling in eBay v. MercExchange, mainly focusing on ICT patents. Using a DiD technique, they find that reduced injunction likelihood leads to positive stock price reactions and higher profitability for affected firms. These firms, especially those with limited cash reserves and more significant financial constraints, boost their branding and patenting activities. The study highlights the substantial impact of injunction threats on firm operations and market performance, suggesting that the eBay ruling alleviates the financial burdens of patent litigation.

Broadening the scope, Appel et al. (2019) explore the impact of non-practicing entities, or patent trolls, on startup employment. Using a DiD methodology, the authors analyse the effects of adopting state-level anti-troll legislation and find that such laws result in increased employment within affected startups, especially in the IT sector. They find that frivolous patent infringement claims by NPEs or patent trolls create significant challenges for high-tech startups, often leading to project cancellations and hampered growth.

Caskurlu (2019) uses the eBay Inc. v. MercExchange ruling to study how patent infringement affects the acquisitions of firms. The study finds that cash-rich firms facing infringement claims react differently based on the strength of patent rights. In strong regimes, these firms boost their spending on patent-motivated acquisitions by 6.9% over two years after a lawsuit, targeting companies with substitute patents. This approach allows them to modify products and sustain production. However, in weak regimes where automatic injunctions are not granted, acquisition does not significantly increase, as infringers can negotiate more favourable royalty agreements. The research concludes that stronger patent rights lead to more acquisitions of substitute patents, thereby boosting innovation, attracting venture capital, and enhancing

the prospects for smaller firms.

Michaely et al. (2024) explore how firms use patent litigation as a strategic tactic called "sue and acquire," where lawsuits against competitors help facilitate potential acquisitions. They find that patent lawsuits significantly raise the possibility of future mergers and acquisitions (M&A) attempts by about 13 times. Their research also reveals that sue-and-acquire strategies often involve abstract patents. They are more common in favourable market conditions, such as particular jurisdictions and industries prone to strategic patent use. Additionally, they show that the Supreme Court's ruling in Alice v. CLS Bank, which raises the cost of strategic lawsuit filing, reduces the use of sue-and-acquire tactics. Their findings highlight how incumbent firms strategically manipulate patent litigation, and the study aligns with the findings of Caskurlu (2019), as both studies demonstrate how litigation influences acquisition strategies—whether through defensive acquisitions to sustain production or strategic acquisitions to consolidate the market position.

2.2.2 How Patent Litigation and Enforcement Affects Innovation

Studies have examined how patent litigation and enforcement dynamics impact innovation. Mezzanotti (2021) investigates this relationship by analysing the impact of the Supreme Court's eBay v. MercExchange decision on corporate R&D. Adopting a DiD approach, the study shows that this legal change led to a general increase in innovation among firms that previously faced high litigation risks. The ruling reduces the adverse effects of patent litigation, leading to more patent applications and greater R&D investment while maintaining patent quality. The author also finds that the decrease in litigation risks allows firms to allocate resources to more innovative projects, suggesting that stringent patent enforcement can stifle innovation by raising financial and operational risks. In contrast, a reduction in such risks can encourage more innovative projects.

While Mezzanotti (2021) highlights the positive impacts of reduced litigation risks on innovation, Boldrin and Levine (2013) explore a more complex relationship between patents and productivity growth. They suggest that the positive effect of patents on innovation incentives may be less straightforward than it appears. The authors posit that the many monopolies created by existing patents can actually stifle innovation, as new inventors often face legal challenges and licensing demands from earlier patent holders. This "downstream blocking effect," where existing patent monopolies hinder future

innovation, is made worse because many patents are not actively used. Additionally, the authors note that patent litigation frequently involves struggling firms with extensive patent portfolios. Unable to compete effectively, these firms often turn to suing innovative new businesses instead. This supports the findings of Lerner (1995), who examines the link between firms' patenting behaviour and their litigation costs. The study finds that firms with high litigation costs avoid patenting in the same categories as their competitors. This finding suggests that firms with higher litigation costs are more careful to avoid lawsuits. Essentially, the threat of expensive litigation appears to influence how and where companies choose to patent their innovations.

Hall and Ziedonis (2001) demonstrate that in the semiconductor industry, characterised by cumulative innovation, the strengthening of US patent rights in the 1980s led to a surge in patenting activity. Similarly, Giebel (2023) investigates how patent litigation influences future innovation. By analysing a dataset of U.S. utility patents and related litigated cases using a DiD approach, the study finds that follow-on patent citations tend to rise during ongoing litigation. This increase is due to signals about patent value and improved information flow. However, once the case concludes, this effect weakens. While litigation can boost follow-on innovation, it often leads to patents with lower originality and greater similarity to the disputed patents.

Building on these findings, J. Chen et al. (2023) explore how the Chinese government's campaign against counterfeiting and intellectual property rights (IPR) infringements affects corporate innovation. They use a quasi-natural experiment and a DiD approach to find that companies in the highly litigated and counterfeiting industry see significant increases in patent counts and citations after the crackdown. Similarly, Peng et al. (2024) investigate the impact of IP protection on corporate innovation investment persistence during intellectual property (IP) infringement disputes. Using the system method of moments (SYS-GMM) and data from Chinese A-share listed companies, they find that stronger IP protection significantly reduces the R&D intensity of the infringers while increasing the R&D intensity efforts of the infringed firms. Non-high-tech and non-state-owned firms are especially affected by this. Their findings highlight the importance of stronger patent enforcement in shaping firms' innovation investment strategies.

In a different context, Moser (2005) investigates how patent laws influence the direction of innovation by analysing exhibitions from two nineteenth-century

world fairs. The results suggest that in countries lacking patent protection, inventors concentrate on a limited range of industries where patents hold less significance, whereas innovation in countries with patent laws becomes more diversified. This implies that introducing patent laws in countries previously without them could reshape existing patterns of comparative advantage.

Beyond traditional patent disputes between competing firms, the influence of patent trolling NPEs adds another layer to the litigation-innovation relationship. F. Chen et al. (2023) examine the impact of NPEs litigation on innovation and market dynamics among technologically related firms. They find that NPEs lawsuits significantly reduce R&D activities in defendant firms and cause non-litigated peer firms to shift their innovation strategies. These peer firms that have not been involved in legal disputes enhance their R&D to create alternative technologies, a response driven by the chilling effects of NPEs litigation. However, this increase in R&D often leads to lower-quality innovations and significant adverse stock price reactions for these peer firms. Cohen et al. (2019) support these findings in their study on the effects of NPEs on innovation within targeted firms. They discover that NPEs strategically target financially strong companies, regardless of the actual relevance of the alleged infringement. Their research shows that NPE litigation severely hampers the innovation capacity of the targeted firms, resulting in a notable reduction in R&D expenditures following legal disputes.

Bessen and Meurer (2014) study the rise of patent litigation initiated by NPEs and its impact on innovation incentives within the American patent system. They find that while NPEs historically helped small inventors monetise their patents, the current surge in litigation harms innovation by diverting investments away from R&D. Their findings suggest that NPEs undermine the innovation ecosystem and impose high costs without providing corresponding benefits to genuine inventors.

2.2.3 Contribution of This Study to the Existing Literature

As noted in the introduction, recent literature documents the influence of patent enforcement and litigation (e.g., Aydin Ozden & Khashabi, 2023; Bereskin et al., 2023; J. Chen et al., 2023; Michaely et al., 2024; Peng et al., 2024); this dissertation specifically contributes to the existing literature on the impact of patent litigation on firms' innovation patterns in several key ways.

Building on the work of Mezzanotti (2021) and Mezzanotti and Simcoe

(2019), who explored the impact of the eBay v. MercExchange ruling on corporate innovation, this dissertation further examines how changes in the legal environment resulting from this ruling impact firms' innovation portfolio, particularly in terms of their technological areas they patent in. By doing so, this offers a refined analysis of how litigation risk affects the direction and novelty of innovation. In contrast to Boldrin and Levine (2013) and Lerner (1995), who focuses on how patent litigation costs determine how and where companies patent in relation to their competitors, and Giebel (2023) and Hall and Ziedonis (2001), who explore the impact of patent enforcement and litigation on specific industries and patent value respectively, this dissertation provides a more granular analysis. It focuses on how litigation exposure influences the distribution of a firm's patent portfolio between new and existing technological fields. While Moser (2005) examines how patent laws influence the industries in which firms choose to patent, my approach offers a comprehensive view of the consequences of litigation risk across the innovation ecosystem.

This research broadens the scope of existing studies on litigation involving NPEs (e.g., Bessen & Meurer, 2014; F. Chen et al., 2023; Cohen et al., 2019), offering a broader perspective on how litigation risk affects the entire innovation ecosystem. It also complements the work of J. Chen et al. (2023) and Peng et al. (2024) by providing insights from the US market, in contrast to their focus on China. This enriches the understanding of how the legal environment shapes firms' innovation and patenting decisions across different jurisdictions.

Overall, by leveraging the eBay v. MercExchange Supreme Court decision as a natural experiment, this dissertation provides empirical evidence on how litigation risk influences firms' innovation portfolios. It aims to contribute to the ongoing academic discourse on the complex relationship between patent litigation, enforcement, and innovation. This adds a novel dimension to understanding how firms might pursue innovation either within their established technological domains or in entirely new fields when the legal environment changes.

3 Data, Variables and Methodology

This section describes the data used in the study and outlines the empirical methodology adopted to analyse the data.

3.1 Data and Sample Selection

The dataset for the analysis comes from three sources: the United States Patent and Trademark Office (USPTO) patent data, patent litigation intensity data from Mezzanotti (2021), and firm-level data from Bureau Van Dijk's (BVD) Orbis database.

The USPTO offers comprehensive data on all patents granted in the United States of America (US), including those issued to foreign firms. This patent data, downloaded from PatentsView,[7] spans from 1976 to March 2024 and includes detailed information on US patents such as filing date, grant date, assignee names, and patent technological classifications. PatentsView also has a disambiguation process that assigns unique identifiers to patent inventors and assignees, enabling me to track patents granted to firms over time.[8]

For this study, the sample is restricted to utility patents granted to corporate assignees (i.e., firms) with complete information on filing year, assignee ID, assignee name and United States Patent Classification (USPC) technology class.[9] The innovation measures I construct for this dissertation use this dataset from 2001 to 2011, which spans five years before and after the eBay v. MercExchange 2006 Supreme Court decision. This analysis is conducted based on the year a patent is filed rather than the year it is granted because there is typically a two-year delay between filing and granting. Thus, the filing year more accurately reflects the period of actual innovation and helps avoid problems caused by the time lag between the application and the granting of the patent (Chemmanur & Tian, 2018; Griliches et al., 1987).

Using the USPC patent technology classes, I combine the USPTO patent data with the patent litigation intensity index from Mezzanotti (2021), which I explained in more detail below. As an overview, this index was constructed by Mezzanotti (2021) by assessing the distribution of patent litigation across different technology fields using Westlaw data. The litigation size for each USPC

[7] https://patentsview.org. PatentsView is a patent data visualisation and analysis platform supported by the Office of the Chief Economist at the USPTO. It provides free access to linked US patent data through various tools such as an API, bulk downloads, and a visualisation interface.

[8] The USPTO does not track inventors and assignees. To address this, PatentsView has a disambiguition process which involves a set of algorithms and post-processing methods to track the patenting activities of inventors and assignees across different time periods. For more details, see https://patentsview.org/disambiguation.

[9] Utility patents are patents that cover new, non-obvious, and useful inventions or improvements, including processes, machines, and compositions with practical utility.

technology class is determined by normalising the number of patents involved in litigation in that class relative to the total number of patents litigated. Using this data as a foundation, I integrate it with USPTO patent data to create the exposure variable. The construction of the exposure measure requires firms to have at least one patent within five years before the 2006 Supreme Court decision. This results in the combined firm-year exposure and innovation data for 2001-2011, including 89,935 US and non-US firms with at least one patent filed five years before the decision, where each firm's innovation portfolio is tracked annually.

To obtain the firm-level measures, I use the Orbis database,[10] which provides information on over 527 million companies worldwide.[11] Due to inconsistencies such as name ambiguity, spelling errors, and special characters in the patent dataset, exact name matching with Orbis data is often challenging. To overcome this, I employ fuzzy matching techniques to link firm-year patent data with their corresponding Orbis company records. This process resulted in numerous unmatched firms, reducing the sample to 38,412 firms (see details on name matching algorithm in Appendix A).

The final sample used in the analysis is determined through several screening criteria. First, firms with missing information for all relevant variables and years in the Orbis data are omitted.[12] Also, firms with missing revenue and asset information in all years are excluded. The focus is further narrowed to US-based non-financial and non-regulated entities.[13] Additionally, companies that consistently report negative equity are eliminated to exclude potentially distressed or restructuring entities. After applying these filters, the final sample comprises 13,882 observations spanning an average of 11 panel years from 1,262 US companies, each holding at least one patent in the five years preceding the decision.

[10] A difference of this research with respect to Mezzanotti (2001) is that I use annual company data from Orbis, whereas Mezzanotti (2021) used quarterly data from Compustat.

[11] https://www.moodys.com/web/en/us/capabilities/company-reference-data/orbis.html

[12] A substantial number of firms (20,374 firms) are excluded due to this filtering.

[13] I exclude firms with SIC codes in the following categories: 60, 61, 62, 63, 64, 65, 66, 67, 83, 86, 88, 91, 92, 93,94, 95, 96, 97.

3.2 Variables construction

3.2.1 Innovation Measures

To measure innovation outcomes, I construct several indicators using the patent dataset. First, I determine the annual count of successfully granted patent applications per firm, assigning a value of zero if a firm does not apply for a patent in a given year.

Using the methodology from Balsmeier et al. (2023), I adopt two variables to examine the technological similarity between a firm's current and previous patent portfolios. The technology class of a patent is identified using the three-digit primary USPC technology classification codes defined by the USPTO.[14] The variable, *Existing tech*, represents the number of patents filed in a technology field where the firm has patented in the previous five years. The variable, *New tech*, represents the number of patents filed in a technology field that is new to the firm within the previous five years.[15] These variables are based on the idea that a firm's innovation strategy can be characterised by either exploration (entering new technological fields to the firm) or exploitation (enhancing existing firm knowledge). I also calculate these existing tech and new tech as proportions of total patents to derive *Existing tech share* and *New tech share*, which range between 0 and 1 and take a zero value when no relevant patents exist.[16]

Additionally, I measure the *technological proximity* between current-year patents and the firm's five-year patent portfolio using cosine similarity, (Balsmeier et al., 2017; Jaffe, 1989). The measure of technological proximity compares patents granted from applications in year t (denoted as f) with the firm's existing patent portfolio (denoted as g). This existing portfolio includes all patents granted from applications made in the previous five years $t-1$ to $t-5$. The comparison is based on the distribution of patents across USPC technological classes.

[14] If a patent is assigned to multiple technology classes, I use the first one listed on the patent grant.

[15] In Balsmeier et al. (2023), these variables are referred to as *old tech* and *new tech* respectively

[16] Although *existing tech share* and *new tech share* are related, they do not perfectly mirror each other. If a company does not file any patents in a given year, both ratios will be zero. This means that a zero value for one ratio does not imply the other must be one. This is why both variables are included.

$$Tech\_Prox_{it} = \frac{\sum_{k=1}^{K} f_{i,k,t}\, g_{i,k,t-1\ldots t-5}}{\sqrt{\left(\sum_{k=1}^{K} f_{i,k,t}^2\right)\left(\sum_{k=1}^{K} g_{i,k,t-1\ldots t-5}^2\right)}} \tag{1}$$

where $f_{i,k,t}$ represents the proportion of firm i patents in technology class k in year t and $g_{i,k,t-1\ldots t-5}$ is the proportion in class k over the previous five years. Technological proximity ranges between 0 and 1, with 1 indicating identical technological distribution and 0 otherwise.

The final innovation outcome, named *innovative search*, is then constructed as one minus technological proximity (Manso et al., 2023) and captures the extent to which a firm's current innovation deviates from its previous technological class:

$$Innov\_Search_{it} = 1 - Tech\_Prox \tag{2}$$

3.2.2 Exposure Measure

Following Mezzanotti (2021) approach, a firm's exposure to patent litigation is based on the intensity of legal disputes in its technology classes. Although patent litigation is often more concentrated in particular technological classes, firms typically patent across multiple classes. As a result, even companies primarily operating in less-litigated classes may encounter significant litigation risk due to some of their patents in high-risk classes (Allison et al., 2009; Breschi et al., 2003; Mezzanotti, 2021). As firms broaden their patent portfolios to include various technological classes, their exposure to patent disputes increases (Bessen & Meurer, 2013).

Exposure of firm i to litigation is determined by assigning weights to the litigation risk of each technology class based on the firm's level of activity in those classes (Mezzanotti, 2021).

$$Exposure_i = \sum_{k=1}^{K} \sigma_k^i p_k \tag{3}$$

where σ_k^i represents firm i's proportion of granted patents in technology class k, applied for within five years before the Supreme Court decision. I construct this proportion with the patent data using the USPC 3-digit technology class of patent. p_k is calculated as the percentage of patents in a specific technological

class k involved in litigation case relative to the total number of litigated patents across all classes. This patent litigation intensity index data p_k is provided by Mezzanotti (2021) and was calculated using data on patent lawsuits filed between 2000 and 2006. I then estimate $Exposure_i$ by combining σ_k^i and p_k, as shown in Equation 3.

3.3 Empirical Methodology

To analyse the impact of the 2006 Supreme Court decision eBay v. MercExchange on firms' innovation portfolios, I employ a difference-in-differences model as follows:

$$E[y_{it}] = \exp\left[\alpha Exposure_i \times Post_t + \lambda_i + \lambda_{jt} + [x'_{it}\gamma]\right] \tag{4}$$

where y_{it} is the innovation outcome of a firm i in year t. $Exposure_i$ denotes the time-invariant firm-level exposure to litigation as defined in equation 3. $Post_t$ is a binary variable which equals one from 2006 onwards. λ_i captures firm fixed effects, which account for time-invariant differences across firms. λ_{jt} captures industry-year fixed effects to control for industry-specific time trends. The vector x_{it} includes time-varying firm-level controls, which I add in some specifications to control for possible covariates. This vector includes firm age, measured as the natural logarithm of the number of years since the firm's establishment or the year of its first patent, whichever is earlier, and large firm, a binary variable set to 1 if the firm falls within the top 25% of the total assets distribution. Firm characteristics such as age and size have been shown to significantly influence innovation activities (Balasubramanian & Lee, 2008; Balsmeier et al., 2017; Lin et al., 2021; Wang et al., 2017). Larger firms often benefit from structural advantages, such as economies of scale, easier access to finance, and the capacity to invest in a broader range of R&D projects. These factors help them innovate more effectively, enabling them to enter new technological fields and build upon existing knowledge (Birkholz et al., 2022). For firm age, older firms may adopt a more conservative innovation approach, focusing more on established technological areas and investing less in new technology compared to younger firms, who are more likely to explore new technologies and innovative strategies to gain a competitive edge. As firms age, they often develop routines and processes around their core technologies, which can lead to a focus on refining and improving existing innovations fields rather than the exploration of new technologies (Balasubramanian & Lee, 2008; Balsmeier et al., 2017). Table 1

presents the descriptive statistics for the variables used in the analysis.

Table 1: Descriptive Statistics

	Obs.	Mean	Sd	Min	Max
Total Patents	13,882	10.25	51.70	0	1,480
Existing Tech	13,882	9.41	50.76	0	1,472
New Tech	13,882	0.84	1.96	0	37
Existing Tech Share	13,882	0.42	0.46	0	1
New Tech Share	13,882	0.16	0.31	0	1
Tech Proximity	13,882	0.35	0.41	0	1
Innovative search	13,882	0.19	0.30	0	1
Exposure	13,882	1.03	0.98	0	4.18
Firm Age	13,882	24.06	21.02	0	130
Large Firm	10,950	0.22	0.41	0	1

Note: Table 1 reports the descriptive statistics for the sample of US firms that applied for at least one granted patent in the five years preceding the Supreme Court decision. The table includes the number of observations, mean, standard deviation, minimum, and maximum values. For details on sample construction, see section 3.1, and for information on variable construction, refer to section 3.2.

The primary coefficient of interest is α. A positive (negative) α would suggest that firms with higher exposure to patent litigation experienced a relative increase (decrease) in the innovation outcome following the 2006 Supreme Court eBay v. MercExchange ruling.

Considering that the dependent variables y_{it} are non-negative with many zero values, I use a Poisson Pseudo-Maximum-Likelihood (PPML) estimator, as recommended by Chen and Roth (2023) and Santos Silva and Tenreyro (2011). This approach addresses the substantial bias and inconsistency typically present in Ordinary Least Square (OLS) estimates of log-linear models (Santos Silva & Tenreyro, 2006) and effectively manages high-dimensional fixed effects in large panel datasets (Long & Yi, 2024). Importantly, PPML does not require the data to follow a Poisson distribution and is suitable for continuous data (Santos Silva & Tenreyro, 2011), making it increasingly popular in innovation research (e.g., Guceri & Liu, 2019). To account for over-dispersion, I cluster standard errors at the firm level throughout the analysis.

4 Empirical Results

This section presents the main results of the empirical analysis and several robustness checks to validate these results.

4.1 Baseline Results

Table 2 shows the baseline results from PPML, with no controls and robust standard errors clustered at the firm level. The dependent variables are total patents in column (1), existing tech in column (2) and new tech in column (3). All regressions include firm fixed effects and industry-year fixed effects.

The coefficient of *Exposure* × *Post* in column (1), representing the DiD coefficient of interest, is positive and statistically significant. This suggests that firms more exposed to litigation increased their patent applications following the 2006 eBay v. MercExchange Supreme Court decision. Specifically, a one percentage point increase in a firm's pre-decision litigation exposure is associated with a 26.9% increase in total patent applications post-2006.[17] In terms of economic significance, firms with mean exposure (1.03) increased their patent applications by 24.5% relative to those with minimal exposure (zero exposure).[18] This positive and significant finding aligns with the findings of Mezzanotti (2021) and could be attributed to the decision's impact on patent holders' rights.[19] By ending automatic permanent injunctions for patent violations, the ruling potentially reduced the high litigation costs and risks associated with patenting, allowing firms to redirect resources towards innovation.

Examining the effect on firms' existing tech, the coefficient in column (2) reveals that the 2006 Supreme Court decision had a positive and significant effect on the number of existing tech. Particularly, the economic magnitude shows that firms with the mean exposure index (1.03) increased their total patent applications by 28.2% relative to those with minimal exposure (zero).[20] This suggests that firms that are more likely to be affected by the Supreme Court decision increased their patenting in familiar technologies. This reduction in litigation barriers allowed firms to strengthen their competitive advantage by continuing to patent in established technology fields without the fear of

[17]The percentage is calculated as: [exp(0.238)-1]*100.

[18]The percentage is calculated as: [(1.03-0)*0.238]*100.

[19]Mezzanotti (2021) finds that firms operating in more litigious areas experienced a 3% relative increase in patent applications for a one-standard deviation increase in exposure to litigation. This result is based on a DiD analysis using collapsed quarterly data from the two years preceding and the two years following the Supreme Court decision, with the logarithm of the total number of patents as the dependent variable. The substantial difference between Mezzanotti's coefficient and mine likely stems from the extended timeframe in my analysis, the use of PPML instead of OLS, and other estimation differences. When I re-estimate using OLS, the coefficient of the total patents aligns more closely with Mezzanotti's result for the effect of the ruling on overall patent count. The OLS results are provided in Table B12 in the Appendix.

[20]The percentage is calculated as: [(1.03-0)*0.274]*100.

costly injunctions. Therefore, the increase in existing tech reflects a strategic response to the more favourable post-2006 litigation environment, enabling firms to confidently pursue innovation in areas where they had prior success and expertise. This could be a way to stay competitive while playing it somewhat safe in the new legal environment.

The effect of the 2006 Supreme Court decision on more exposed firms is positive but statistically insignificant for new tech (column (3)). Despite the reduced litigation risk resulting from the ruling, which removed automatic permanent injunctions and significantly altered the balance of costs and benefits associated with filing a lawsuit, more exposed firms did not substantially increase their patents in new technological areas post-2006. This could suggest that while the litigation risks might be reduced, firms may have remained cautious about venturing into unfamiliar technology classes. This caution could be due to the significant costs, uncertainties and investment associated with entering unfamiliar technology fields, even with reduced litigation risk. Firms might prefer to focus on their established areas of expertise due to the significant risks and investments required for exploring new technologies.

Also, considering other innovative outcomes such as existing tech share and new tech share, technological proximity, and innovative search, the coefficient of interest remains statistically insignificant (see Table B1 in Appendix). This suggests that while more exposed firms increased the number of patents in established technological classes and total patents in response to reduced litigation risk, there was no significant difference in the proportion of familiar and new technological areas relative to the total patents post-2006 ruling. More exposed firms appear to have scaled up their innovation efforts broadly by increasing the volume of their patenting activity post-2006 ruling, but without substantially changing the composition of their innovative efforts.

Table 3 presents the results of the DiD analysis but with firm-level controls that may affect a firm's patenting behaviour, such as firm age and firm size in the baseline specification. The DiD coefficients remain positive and statistically significant for total patents and existing tech (column (1)- (2)), but the magnitudes of the coefficients increase compared to those reported in Table 2. This suggests that the result is robust to the inclusion of these controls. However, with the addition of controls, the DiD coefficient becomes positive and statistically significant for new tech (column (3)). This is a change from Table 2, where the effect on new tech was positive but not statistically

Table 2: Effect on Innovation Measures: Baseline Results

	(1) Total Patents	(2) Existing Tech	(3) New Tech
Exposure × Post	0.238**	0.274**	0.027
	(0.104)	(0.116)	(0.061)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	13,636	11,551	12,738
Pseudo R^2	0.879	0.882	0.384

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using the sample of US firms that applied for at least one patent in the five years before the Supreme Court decision. The dependent variable *Total Patents* is the annual count of successfully granted patent applications by a firm. *Existing Tech* denotes the number of patents filed in a technology class where the firm has patented in the previous five years. *New Tech* represents the number of patents filed in a technology class that is new to the firm within the previous five years. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% significance levels, respectively.

significant. The significance of the DiD coefficient suggests that previously unaccounted firm-specific factors are influencing the relationship between litigation exposure and the number of new tech. Without these controls, the baseline results might have averaged out effects across firms of varying sizes and ages, making the true effects harder to see. By accounting for firm age and size, the analysis better isolates the impact of the Supreme Court ruling, showing that firms with higher litigation exposure before the ruling increased their patenting in new technological areas post-2006.

Along with the baseline results, the analysis reveals that larger firms exhibit higher patenting activity across all measures—total patents, existing and new tech. This suggests that larger firms possess greater resources and capacity for R&D, which enable them to file more patents across various technological categories. On the other hand, while firm age is positive and statistically insignificant for total patents and existing tech, it is negative and significant for new tech. This means that older firms are less likely to pursue patents in new technologies and tend to focus more on their established areas of expertise. This may be due to a more cautious approach or preference for building on existing technology classes. For the other innovation outcomes (see Table B2 in the Appendix), the DiD coefficient of interest remains statistically insignificant,

consistent with the findings in the baseline estimation (see Table B1 in the Appendix).

Table 3: Effect on Innovation Measures: Adding Controls

	(1) Total Patents	(2) Existing Tech	(3) New Tech
Exposure × Post	0.315**	0.337**	0.128**
	(0.125)	(0.141)	(0.062)
Firm Age	0.083	0.209	-0.346***
	(0.211)	(0.241)	(0.126)
Large Firm	0.427***	0.426***	0.347***
	(0.093)	(0.099)	(0.116)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	10,599	8,971	9,942
Pseudo R^2	0.892	0.894	0.383

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 with control variables using the sample of US firms that applied for at least one patent in the five years before the Supreme Court decision. The dependent variable *Total Patents* is the annual count of successfully granted patent applications by a firm. *Existing Tech* denotes the number of patents filed in a technology class where the firm has patented in the previous five years. *New Tech* represents the number of patents filed in a technology class that is new to the firm within the previous five years. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards.*Firm Age* is the natural logarithm of the number of years since the firm's establishment or the year of its first patent, whichever is earlier. *Large Firm* is a binary variable set to one if the firm falls within the top 25% of the total assets distribution. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

4.2 DiD Validity and Robustness Checks

4.2.1 Alternative Sample: Restricted Sample Size

To validate that the difference in the result of the baseline model without control variables (Table 2) and the model with control variables (Table 3) are not driven by variations in sample size, I re-estimate the baseline model without control variables using the same sample size as in the model with control variables.

Table 4 presents the result of this restricted sample. The results of the DiD coefficient for total patents and existing tech (columns (1) and (2)) in this restricted sample remain positive and statistically significant, which is consistent

with the findings from the baseline model without controls in Table 2 (columns (1) and (2)). Similarly, the result of the DiD coefficient of interest for new tech (column (1)), which remains positive but statistically insignificant, aligns with the baseline results in Table 2 (column (3)). This consistency suggests that the observed effects in the baseline results without control variables are robust and not solely attributable to the variation in sample size.

For the other innovation outcomes (see Table B3, the results of the DiD coefficient for new tech share (column (2)) and innovative search (column (4)) remain statistically insignificant, which is consistent with the baseline results without controls in Table B1 (columns (2) and (4)). This suggests that the lack of significant findings in these areas is not influenced by the sample size, reinforcing the validity of these results. However, for existing tech share (column (1)) and technological proximity (column (3)), the coefficient of interest is positive and statistically significant in the restricted sample, although they were previously positive but not significant with the larger sample in Table B1 (columns (2) and (4)). This indicates that these findings are sensitive to sample size, highlighting that the statistical significance may be influenced by sample variation.

Table 4: Effect on Innovation Measures: Restricted Sample Size

	(1) Total Patents	(2) Existing Tech	(3) New Tech
Post=1 × Exposure	0.332***	0.368***	0.096
	(0.113)	(0.126)	(0.062)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	10,599	8,971	9,942
Pseudo R^2	0.891	0.893	0.382

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using a restricted sample of US firms as in the model with control variables (Table 3). The dependent variable *Total Patents* is the annual count of successfully granted patent applications by a firm. *Existing Tech* denotes the number of patents filed in a technology class where the firm has patented in the previous five years. *New Tech* represents the number of patents filed in a technology class that is new to the firm within the previous five years. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

4.2.2 Event Studies: Flexible Estimations

For the observed changes in innovation outcomes to be attributed to the 2006 Supreme Court eBay v. MercExchange ruling, the parallel trends assumption must be satisfied. This assumption is crucial to the difference-in-differences methodology. It suggests that if the verdict had not occurred, firms with varying levels of litigation exposure would have shown similar trends in innovation over time. To examine the validity of this assumption, I employ a flexible event study approach to check for any pre-treatment trends. I modify my baseline equation by substituting the *Exposure* × *Post* indicator in Equation 4 with a series of interactions between the time-invariant 'Exposure' measure and dummies for each year from 2001 to 2011, using 2005 as the base year.

$$E[y_{it}] = \exp\left(\sum_{t=2001}^{2011} \alpha_t Exposure_i \times Year_t + \lambda_i + \lambda_{jt}\right) \tag{5}$$

Figure 1 depicts these results for total patents, existing tech, and new tech. The intuition is that if the parallel trends assumption holds, I should observe no significant differences in innovation outcomes between firms with varying exposure levels in the years leading up to 2006. Any difference should only appear after the ruling takes effect.

For total patents and existing tech, I do not observe any significant differences between firms with different exposure levels before 2006 (see Figure 1 (a) and (b)), lending strong support to the parallel trends assumption. Following the ruling, there is a statistically significant increase in total and existing tech for firms with higher exposure to litigation. This effect not only persists but continues to grow over the subsequent five years, indicating a sustained impact of the ruling on these innovation outcomes. For total patents and existing tech, where I find significant effects in the baseline model, this event study supports the initial findings. The lack of pre-existing trends for these outcomes strengthens the confidence in attributing the observed changes to the ruling. For technological proximity and innovative search, I also do not see any significant pre-2006 ruling differences, and thus, it does not violate the parallel trend assumption (see Figures B1 (c) and (d) in the Appendix).

However, for new tech, there is a statistically significant coefficient associated with the year 2003. This deviation from the parallel trends assumption suggests that firms with different levels of litigation exposure might have been on different

paths regarding new tech even before the ruling. The baseline model did not show significant effects for this type of patent, and the event study reveals significant pre-existing differences in one pre-treatment year. This combination of results suggests that this aspect of innovation was likely not significantly affected by the ruling and that it may be influenced by factors unrelated to the legal change being studied. Similar issues are seen with existing tech share and new tech share (see Figures B1 (a) and (b) in the Appendix). These findings highlight the need for careful interpretation of the causal effects of the changes in automatic permanent injunctions on new tech and the proportion measurements (existing tech share and new tech share).

Detailed regression coefficient values for these event studies are provided in Table B4 in the Appendix.

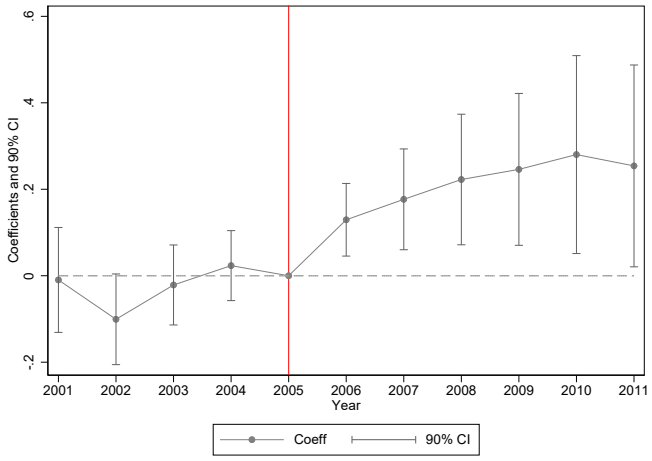
4.2.3 Alternative Sample: Incumbent Firms

To further validate my baseline findings, I check for robustness using a sub-sample of U.S. firms with consistent patenting activity before and after the 2006 Supreme Court decision. Specifically, I focus on firms that filed at least one patent both in the five years preceding and the five years following the ruling. By conditioning the sample on firms that did not completely stop their patenting activity during the years immediately following the shock, this approach ensures that we are examining firms that were actively engaged in innovation around five years post-ruling. This approach provides a clearer picture of the decision's impact on the direction of innovation of firms that were consistently engaged in innovation before and after the ruling.

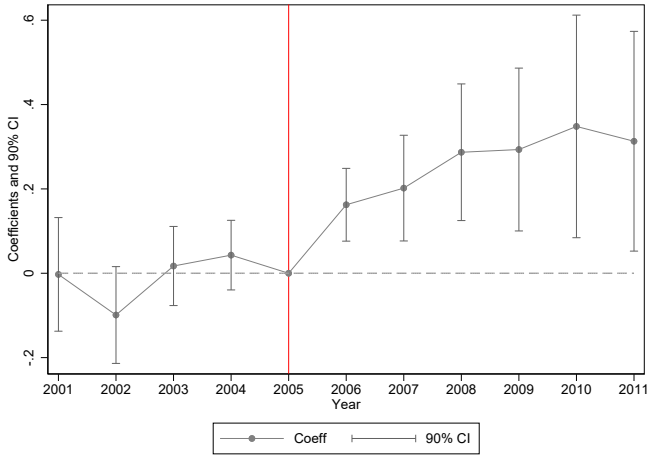
Table 5 presents the estimation results with this sub-sample. The results for total patents, existing tech, and new tech are similar to my baseline results in Table 2. This analysis reinforces that while the 2006 Supreme Court decision reduced litigation barriers and encouraged firms with higher litigation exposure to continue patenting in established technology fields, it did not significantly impact the number of patents filed in new technological areas. Also, the results for additional innovation measures, including existing tech share and new tech share, technological proximity, and innovative search (see columns (1)-(4) in Table B5 in the Appendix), are consistent with the baseline findings (see columns (1)-(4) in Table B1 in the appendix). Specifically, the impact of the 2006 Supreme Court decision on firms more exposed to litigation relative to less exposed firms remains statistically insignificant across these measures.

Figure 1: Event Studies - Baseline Results

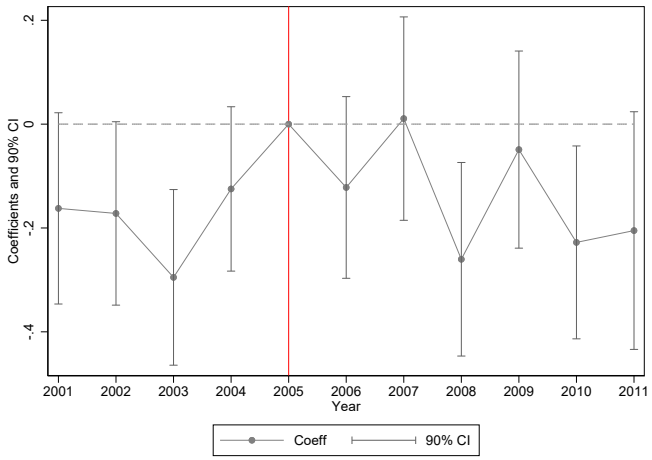
(a) Total Patents



(b) Existing Tech



(c) New Tech



Note: This figure presents the event-study coefficient estimates along with 90% confidence intervals for the interactions between the *Exposure* variable and year dummies for 2001 through 2011, using 2005 as the base year.

This consistency across different US sample specifications reinforces the robustness of the main findings. It suggests that the observed effects in total patents and existing tech are not influenced by changes in the composition of firms within the sample but rather reflect actual changes in patenting behaviour in response to the legal changes.

Table 5: Effect on Innovation Measures: Incumbent Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech
Exposure × Post	0.245**	0.280**	0.016
	(0.105)	(0.117)	(0.061)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	10,328	9,677	10,065
Pseudo R^2	0.873	0.879	0.357

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using the sample of US firms that filed at least one patent in both the five years before and the five years after the 2006 Supreme Court decision. The dependent variable *Total Patents* is the annual count of successfully granted patent applications by a firm. *Existing Tech* denotes the number of patents filed in a technology class where the firm has patented in the previous five years. *New Tech* represents the number of patents filed in a technology class that is new to the firm within the previous five years. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

4.2.4 Alternative Sample: Non-US Firms

For additional robustness checks, I consider a sample of non-US firms. Specifically, I focus on firms located outside the United States that filed at least one patent with the USPTO in the five years before the 2006 eBay v. MercExchange Supreme Court decision. This alternative sample allows me to examine whether the effects observed in the main analysis extend beyond US-based firms and potentially capture broader international implications of the legal change.

Given that the Supreme Court's decision primarily affects US patent laws, it is reasonable to expect that the impact of the eBay v. MercExchange ruling would be limited to domestic firms. If other factors, such as changes in patenting practices or market conditions, were influencing patenting behaviour globally, I would expect to see similar significant effects for more exposed non-US firms

that filed a patent with the USPTO following the 2006 ruling. Interestingly, the results show that, for the non-US sample, the changes in patenting behaviour for firms more exposed to litigation relative to less exposed firms are not statistically different from zero across all measures (see Tables 6 and B6). This lack of significant effects, despite large coefficients, could indicate that the effects are not as strongly identified in non-US firms due to less precision in the estimates. Alternatively, non-US firms might be more influenced by the patent enforcement practices in other countries where they primarily operate.

Table 6: Effect on Innovation Measures: Non-US Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech
Exposure × Post	0.184	0.201	-0.025
	(0.118)	(0.134)	(0.069)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Observations	19,131	13,887	18,516
Pseudo R^2	0.932	0.934	0.461

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using the sample of non-US firms that applied for at least one patent in the five years before the Supreme Court decision. The dependent variable *Total Patents* is the annual count of successfully granted patent applications by a firm. *Existing Tech* denotes the number of patents filed in a technology class where the firm has patented in the previous five years. *New Tech* represents the number of patents filed in a technology class that is new to the firm within the previous five years. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects, industry-year and country-year fixed effects. Robust standard errors clustered at firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

4.2.5 Heterogeneous Effects

To further explore the effect of the Supreme Court ruling, I investigate heterogeneous effects by splitting the sample based on the firm characteristics before the 2006 ruling. This approach provides insight into whether the impact of the ruling varies across different types of firms.

When I split the sample based on firm size before the Supreme Court ruling, using total assets (see Table B7 in Appendix) and total sales (see Table B8 in Appendix) as indicators, interesting patterns emerge. For large firms—those with total assets or sales above the median before the treatment year—the

DiD coefficients for total patents and existing tech are positive and statistically significant. This suggests that larger firms (which typically have more resources) that are more exposed to litigation risk experienced a significant increase in their patenting activities in familiar technological classes following the ruling. The positive impact on total patents and existing tech indicates that these firms, leveraging their greater resources, were able to intensify their focus on areas where they had existing expertise, taking advantage of the reduced litigation risks to expand their patent portfolios in familiar technological domains. However, for small firms—those with total assets or sales below the median before the treatment year—the significant effects are observed in existing tech share and technological proximity. This implies that while smaller firms also responded to the reduced litigation risks, their strategy was more concentrated. Instead of broadly increasing their patent counts, these firms focused on enhancing their efforts in technologies that are closely related to their existing patents. The absence of significant effects on total patents and existing tech among small firms suggests that the ruling had less impact on their overall patent counts and the number of patents in established fields. However, for the patents filed, they strategically concentrated their efforts on strengthening and refining their core technological areas, which are closely aligned with their previous patents.

When examining firms based on their patent counts, I split the sample based on total patents before the ruling into high-patent (above median) and low-patent (below median) firms (see Table B9 in Appendix). Among high-patent firms, the DiD coefficient is significant only for total patents and existing tech, while low-patent firms did not exhibit significant changes across all innovation outcomes. This finding indicates that firms with a high baseline of patenting activity leveraged the more favourable litigation environment to boost their patenting efforts in areas where they were already active and thus saw a notable increase in their patent filings post-2006 ruling. On the other hand, low-patent firms—those with a patent count below the median—did not show significant changes in their patenting activities. This could suggest that firms with fewer patents before the ruling did not substantially adjust their strategies in response to the verdict or that the ruling had a limited impact on their patenting behaviour. Overall, these results suggest that firms that were already more active in patenting before the ruling were more responsive to changes in the legal environment.

The analysis of firm age reveals further distinctions (see Table B10 in Appendix). For older firms—those above the median age—the DiD coefficients

for only total patents and existing tech are positive and significant. This implies that older firms, likely with more established technology portfolios, increased their patenting in familiar areas following the Supreme Court verdict. The positive effect on total patents and existing tech among these firms indicates that they could utilise the reduced litigation risks to strengthen their position in established technology fields. In contrast, younger firms—those below the median age—did not exhibit significant changes in their patenting behaviour. This lack of significant effect might reflect that younger firms, still in the process of developing their technological capabilities, did not substantially alter their patenting strategies in response to the ruling. This implies that more established firms are better positioned to take advantage of the new legal landscape, possibly due to their greater experience and resources.

The analysis of heterogeneous effects highlights that the impact of the 2006 Supreme Court ruling varied depending on firm characteristics. Larger, more established firms with substantial patent portfolios appear to benefit the most in terms of increased patenting activity. Smaller firms, while not showing increases in absolute patent numbers, seem to respond by focusing more on their core technological areas. Older firms leveraged the changes in the legal environment to boost their patenting in established fields, whereas younger firms did not exhibit significant adjustments.

4.2.6 Alternative Exposure Measure

To ensure the robustness of the main results, I recalculated the exposure measure by modifying the timeframe for calculating σ (the firm's proportion of granted patents in each technology class). Specifically, I used data from 2001 to 2004 and excluded 2005 to avoid potential anticipation effects related to the Supreme Court decision. This robustness check verifies that the results are not sensitive to the period used to calculate litigation exposure.

Table B11 in the appendix presents the results of this analysis. Firms that first appeared in the sample in 2005 and thus had missing exposure values were excluded from this analysis. The findings indicate that the results of total patents, existing tech, and new tech (column (1)-(3)) remain consistent with those from the baseline model (see Table 2), showing positive and significant DiD coefficients for total patents and existing tech and a positive but insignificant coefficient for new tech. This consistency suggests that the main results are robust to changes in the exposure calculation period and are not driven by

potential anticipation effects. For the other innovation outcomes (see Table B11 column (4)-(7) in the Appendix), the results also remain largely consistent with the baseline findings (see Table B1 in the appendix). Overall, this robustness check reinforces the validity of my main results and suggests that the findings are not sensitive to the specific time frame used for calculating exposure to litigation.

5 Conclusion

Using the 2006 eBay v. MercExchange US Supreme Court ruling, this study adopts a difference-in-differences empirical setting to examine how litigation risk affects firms' innovation strategies. It contributes to the existing literature on patent enforcement and litigation by focusing specifically on the technological field direction of firm innovation. The empirical analysis was conducted using a combination of data covering a period of 2001 to 2011 from USPTO, Orbis and patent litigation intensity from Mezzanotti (2021).

The results of the analysis reveal that the ruling had a positive effect on the total patent count of US firms, which is similar to the findings of Mezzanotti (2021). In addition, while there was a significant increase in overall patenting activity, specifically within established technological domains, firms exhibited caution in exploring new technology areas. This suggests that companies are reluctant to stray from their core competencies even with reduced litigation risk, indicating a preference for reinforcing existing strengths over pursuing unfamiliar innovations. For non-US firms filing patents with the USPTO, no significant effect was observed, suggesting that the ruling's influence might be confined mainly to the US legal and innovation environment.

The analysis of heterogeneous effects provides further clarity on this behaviour. Larger firms, equipped with more substantial resources, were quick to capitalise on the changed legal environment by intensifying their patenting activities in established areas, thus bolstering their competitive positions. On the other hand, smaller firms did not show a significant increase in their overall patenting but concentrated on enhancing their core technological areas, reflecting a strategic focus rather than broad expansion.

In conclusion, this study highlights the critical role that litigation risk plays in shaping corporate innovation strategies and direction of innovation. The findings suggest that while legal reforms like the 2006 eBay v. MercExchange

ruling can stimulate increased patenting activity, the benefits are not uniformly distributed across firms or technological domains. Future policy efforts should aim to balance the protection of patent rights with the need to minimise the potential chilling effects of excessive litigation risk on innovation. Achieving this balance will help to build a more dynamic and equitable innovation ecosystem that supports technological progress for all firms.

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Appendix

A Matching Patents Data to Orbis

Linking unique assignees from the patent dataset to unique firms in Orbis is a complex process due to name ambiguity, misspellings, and the presence of special characters. Using Python, I implemented a multi-step matching algorithm with exact and fuzzy matching techniques to address these challenges.[21] The following sections detail the preprocessing steps and the various matching stages used to achieve a linkage between the datasets.

Data Preprocessing

The preprocessing phase involves cleaning and standardising the names in both the patent and Orbis datasets to enhance the accuracy of subsequent matching steps.

- **Lowercasing and trimming:** Convert all firm names to lowercase and remove leading and trailing whitespace to ensure uniformity.
- **Cleaning names:** Remove all non-alphanumeric characters (e.g., punctuation, special characters) from the firm names. This step helps in reducing discrepancies caused by variations in name formatting.
- **Standardising names:** Remove common company suffixes (e.g., "Inc.", "Ltd.", "Corp.") using a predefined list of company terms. This is crucial for improving the matching process since patent datasets use different suffixes interchangeably for the same assignee ID.
- **Stemming names:** Generate a stem name for efficient fuzzy matching using the first 15 characters of each standardised name or the full standardised name if it is less than 15 characters.

Matching Steps

The algorithm employs a cascading approach, proceeding to the next step for firms unmatched in previous stages:

- **Exact matching:** Match lowercase firm names precisely, including

[21] Some papers that have used fuzzy matching techniques include Bell et al. (2018), Bernstein et al. (2016), Bowen et al. (2023), Gupta and Stiebale (2024), Kline et al. (2019), Lerner et al. (2024) and Sharoni (2023).

country information, to avoid false positives.

- **Suffix category matching:** For firms that did not match in the exact matching step, categorise them based on their suffixes using a pre-computed suffix category dictionary. Match firms with the same suffix category and country.
- **Cleaned name matching:** For unmatched firms, perform a match based on names stripped of all non-alphanumeric characters.
- **Standardised name matching:** Use names with common suffixes removed for another matching round.
- **Fuzzy matching:** For the remaining unmatched firms, employ the fuzzywuzzy library. Consider names as matches if their similarity score exceeds 75 out of 100 and they share the same country.

Handling Duplicates

Throughout the process, several checks are conducted to handle duplicate entries:

- Delete duplicates within all matches based on unique identifiers.
- For fuzzy matches, retain only the highest-scoring match for each firm.

Final Data Cleaning

After the matching process, additional manual checks are performed to ensure the integrity and uniqueness of the matched dataset. Duplicate entries that could not be resolved through automated steps are manually reviewed and deleted as necessary. This includes deleting all duplicated Orbis BVD IDs and checking and removing duplicates across all match types. A sample of fuzzy matches is also generated for manual checks.

Results

After all matching steps, subsequent manual checks, and duplicate removals, the final dataset comprises 38,412 unique firms, each successfully linked to the patent dataset and Orbis.

B Additional Tables and Figures

Table B1: Effect on Other Innovation Measures: Baseline Results

	(1) Existing Tech Share	(2) New Tech Share	(3) Tech Proximity	(4) Innovative Search
Exposure × Post	0.063	-0.012	0.059	0.070
	(0.043)	(0.055)	(0.045)	(0.058)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	11,551	12,738	11,551	11,929
Pseudo R^2	0.125	0.118	0.141	0.114

This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using the sample of US firms that applied for at least one patent in the five years before the Supreme Court decision. The dependent variable *Existing Tech Share* is the proportion of existing tech to total patents.*New Tech Share* is the proportion of new tech to total patents. *Tech Proximity* represents the degree of overlap between granted patents filed in the current year and the existing patent portfolio in the last five years. *Innovative Search* captures the extent to which a firm's current innovation deviates from its previous five years technological class. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B2: Effect on Other Innovation Measures: Adding Controls

	(1) Existing Tech Share	(2) New Tech Share	(3) Tech Proximity	(4) Innovative Search
Exposure × Post	0.064	0.034	0.062	0.073
	(0.041)	(0.057)	(0.042)	(0.060)
Firm Age	0.212***	-0.600***	0.181**	0.013
	(0.077)	(0.104)	(0.073)	(0.116)
Large Firm	0.083*	0.025	0.090*	0.036
	(0.047)	(0.115)	(0.048)	(0.093)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	8,971	9,942	8,971	9,373
Pseudo R^2	0.109	0.113	0.126	0.108

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 with control variables using the sample of US firms that applied for at least one patent in the five years before the Supreme Court decision. The dependent variable *Existing Tech Share* is the proportion of existing tech to total patents.*New Tech Share* is the proportion of new tech to total patents. *Tech Proximity* represents the degree of overlap between granted patents filed in the current year and the existing patent portfolio in the last five years. *Innovative Search* captures the extent to which a firm's current innovation deviates from its previous five years technological class. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards.*Firm Age* is the natural logarithm of the number of years since the firm's establishment or the year of its first patent, whichever is earlier. *Large Firm* is a binary variable set to one if the firm falls within the top 25% of the total assets distribution. Refer to section 3.2 for details on variable construction.. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% significance levels, respectively.

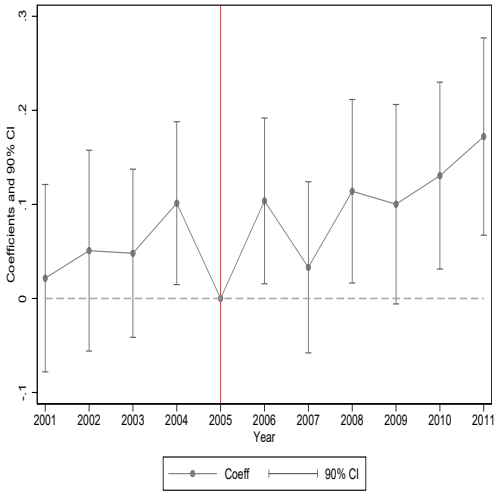
Table B3: Effect on Other Innovation Measures: Restricted Sample Size

	(1) Existing Tech Share	(2) New Tech Share	(3) Tech Proximity	(4) Innovative Search
Exposure × Post	0.077*	-0.006	0.073*	0.073
	(0.041)	(0.057)	(0.042)	(0.061)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	8,971	9,942	8,971	9,373
Pseudo R^2	0.109	0.111	0.126	0.108

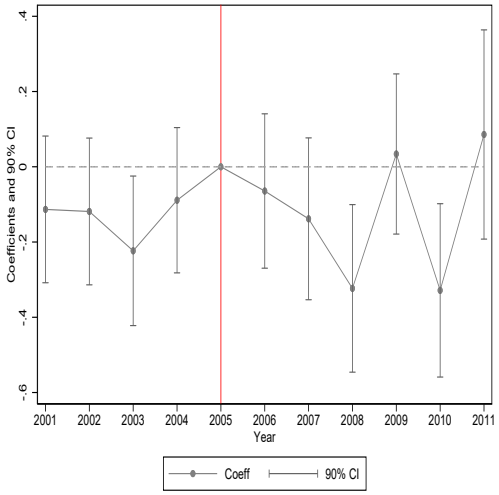
Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using a restricted sample of US firms as in the model with control variables (Table B2). The dependent variable *Existing Tech Share* is the proportion of existing tech to total patents.*New Tech Share* is the proportion of new tech to total patents. *Tech Proximity* represents the degree of overlap between granted patents filed in the current year and the existing patent portfolio in the last five years. *Innovative Search* captures the extent to which a firm's current innovation deviates from its previous five years technological class. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Figure B1: Event Studies for Other Innovation Measures

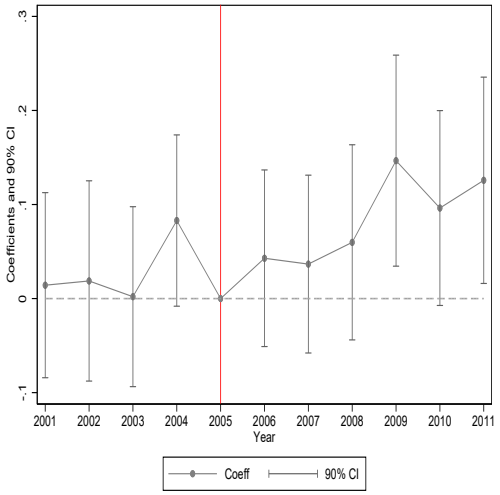
(a) Existing Tech Share



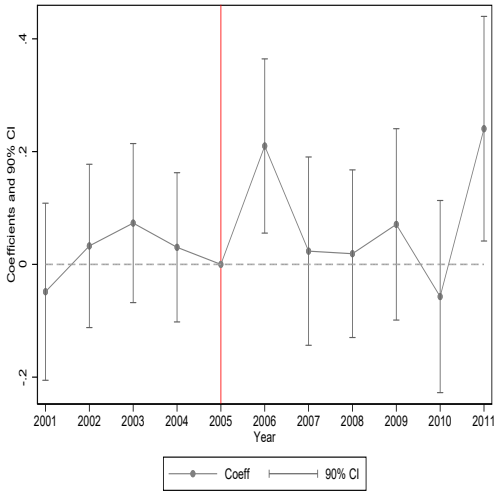
(b) New Tech Share



(c) Tech Proximity



(d) Innovative Search



Note: This figure presents the event-study coefficient estimates along with 90% confidence intervals for the interactions between the *Exposure* variable and year dummies for the years 2001 through 2011, using 2005 as the base year.

Table B4: Effect on Innovation Measures: Event Studies

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Year2001	-0.010	-0.003	-0.162	0.022	-0.113	0.014	-0.049
	(0.074)	(0.082)	(0.112)	(0.061)	(0.119)	(0.060)	(0.095)
Exposure × Year2002	-0.101	-0.099	-0.172	0.051	-0.119	0.019	0.033
	(0.064)	(0.070)	(0.107)	(0.065)	(0.119)	(0.065)	(0.088)
Exposure × Year2003	-0.021	0.017	-0.295***	0.048	-0.223*	0.002	0.073
	(0.056)	(0.057)	(0.103)	(0.054)	(0.121)	(0.058)	(0.086)
Exposure × Year2004	0.023	0.043	-0.125	0.101*	-0.089	0.083	0.030
	(0.049)	(0.050)	(0.096)	(0.053)	(0.117)	(0.055)	(0.080)
Exposure × Year2006	0.129**	0.162***	-0.122	0.104*	-0.064	0.043	0.210**
	(0.051)	(0.052)	(0.106)	(0.054)	(0.125)	(0.057)	(0.094)
Exposure × Year2007	0.177**	0.202***	0.011	0.033	-0.138	0.037	0.023
	(0.071)	(0.076)	(0.119)	(0.055)	(0.131)	(0.057)	(0.102)
Exposure × Year2008	0.223**	0.287***	-0.260**	0.114*	-0.323**	0.060	0.019
	(0.092)	(0.098)	(0.113)	(0.059)	(0.135)	(0.063)	(0.090)
Exposure × Year2009	0.246**	0.293**	-0.049	0.100	0.034	0.147**	0.071
	(0.107)	(0.117)	(0.115)	(0.064)	(0.129)	(0.068)	(0.103)
Exposure × Year2010	0.280**	0.348**	-0.228**	0.131**	-0.328**	0.096	-0.057
	(0.139)	(0.160)	(0.113)	(0.060)	(0.140)	(0.063)	(0.104)
Exposure × Year2011	0.254*	0.313**	-0.205	0.172***	0.086	0.126*	0.241**
	(0.142)	(0.158)	(0.139)	(0.064)	(0.169)	(0.067)	(0.121)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,636	11,551	12,738	11,551	12,738	11,551	11,929
Pseudo R^2	0.879	0.882	0.385	0.125	0.119	0.141	0.114

Notes: This table shows results from the PPML flexible difference-in-differences estimation based on equation 5 using the sample of US firms that filed at least one patent in the five years before the 2006 Supreme Court decision. The dependent variables are *Total Patents*, *Existing Tech*, *New Tech*, *Existing Tech Share*, *New Tech Share*, *Tech Proximity* and *Innovative Search*. The independent variables include *Exposure* and a full set of year dummies from 2001 to 2011 with 2005 as the base year. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B5: Effect on Other Innovation Measures: Incumbent Firms

	(1) Existing Tech Share	(2) New Tech Share	(3) Tech Proximity	(4) Innovative Search
Exposure × Post	0.053	-0.046	0.056	0.040
	(0.041)	(0.050)	(0.042)	(0.055)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	9,677	10,065	9,677	9,832
Pseudo R^2	0.101	0.106	0.117	0.101

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using the sample of US firms that filed for least one patent in both the five years before and the five years after the 2006 Supreme Court decision. The dependent variable *Existing Tech Share* is the proportion of existing tech to total patents.*New Tech Share* is the proportion of new tech to total patents. *Tech Proximity* represents the degree of overlap between granted patents filed in the current year and the existing patent portfolio in the last five years. *Innovative Search* captures the extent to which a firm's current innovation deviates from its previous five years technological class. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B6: Effect on Other Innovation Measures: Non-US Firms

	(1) Existing Tech Share	(2) New Tech Share	(3) Tech Proximity	(4) Innovative Search
Exposure × Post	-0.003	0.017	0.014	0.008
	(0.039)	(0.049)	(0.041)	(0.053)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
Observations	13,887	18,516	13,887	15,418
Pseudo R^2	0.148	0.115	0.162	0.116

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables using the sample of non-US firms that applied for at least one patent in the five years before the Supreme Court decision. The dependent variable *Existing Tech Share* is the proportion of existing tech to total patents.*New Tech Share* is the proportion of new tech to total patents. *Tech Proximity* represents the degree of overlap between granted patents filed in the current year and the existing patent portfolio in the last five years. *Innovative Search* captures the extent to which a firm's current innovation deviates from its previous five years technological class. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects, industry-year and country-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B7: Heterogeneous Effects on Innovation Measures by Total Assets

Panel A: Large Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.294**	0.307**	0.135	-0.050	-0.015	-0.085	-0.024
	(0.143)	(0.154)	(0.090)	(0.052)	(0.086)	(0.055)	(0.079)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,778	5,743	6,323	5,743	6,323	5,743	5,949
Pseudo R^2	0.888	0.887	0.403	0.111	0.140	0.131	0.125

Panel B: Small Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.044	0.077	-0.005	0.148**	0.030	0.162**	0.137
	(0.089)	(0.108)	(0.090)	(0.066)	(0.071)	(0.066)	(0.086)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,668	5,633	6,144	5,633	6,144	5,633	5,870
Pseudo R^2	0.550	0.557	0.229	0.124	0.110	0.135	0.109

Notes: This table presents results from the PPML difference-in-differences estimation of equation 4 without control variables, with the sample split based on total assets. In Panel A, firms with pre-2006 mean total assets at or above the median total assets of the entire sample are classified as large, while in Panel B, those below the median are classified as small firms. The dependent variables are *Total Patents*, *Existing Tech*, *New Tech*, *Existing Tech Share*, *New Tech Share*, *Tech Proximity* and *Innovative Search*. The independent variables include *Exposure* and *Post*, a post-treatment dummy variable that equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects, and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B8: Heterogeneous Effects on Innovation Measures by Sales

Panel A: Large Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.286*	0.310*	0.131	-0.054	0.015	-0.080	0.021
	(0.155)	(0.166)	(0.098)	(0.060)	(0.094)	(0.061)	(0.091)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,795	5,745	6,316	5,745	6,316	5,745	5,957
Pseudo R^2	0.893	0.891	0.405	0.121	0.136	0.141	0.124

Panel B: Small Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.066	0.071	0.033	0.130**	0.043	0.143**	0.104
	(0.089)	(0.105)	(0.087)	(0.062)	(0.072)	(0.062)	(0.085)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,714	5,670	6,187	5,670	6,187	5,670	5,889
Pseudo R^2	0.545	0.546	0.226	0.121	0.109	0.132	0.108

Notes: This table presents results from the PPML difference-in-differences estimation of equation 4 without control variables, with the sample split based on total sales. In Panel A, firms with pre-2006 mean total sales at or above the median total sales of the entire sample are classified as large, while in Panel B, those below the median are classified as small firms. The dependent variables are *Total Patents*, *Existing Tech*, *New Tech*, *Existing Tech Share*, *New Tech Share*, *Tech Proximity* and *Innovative Search*. The independent variables include *Exposure* and *Post*, a post-treatment dummy variable that equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects, and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B9: Heterogeneous Effects on Innovation Measures by Total Patents

Panel A: High-Patent Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.249**	0.268**	0.031	0.004	-0.115	0.002	-0.054
	(0.121)	(0.133)	(0.086)	(0.042)	(0.080)	(0.045)	(0.066)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,026	5,826	6,381	5,826	6,381	5,826	6,202
Pseudo R^2	0.863	0.864	0.356	0.048	0.137	0.064	0.117

Panel B: Low-Patent Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.059	0.083	-0.023	0.116	0.020	0.095	0.118
	(0.078)	(0.102)	(0.081)	(0.079)	(0.070)	(0.081)	(0.082)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,375	5,532	6,050	5,532	6,050	5,532	5,569
Pseudo R^2	0.275	0.290	0.173	0.112	0.111	0.119	0.121

Notes: This table presents results from the PPML difference-in-differences estimation of equation 4 without control variables, with the sample split based on total patents. In Panel A, firms with pre-2006 mean total patents at or above the median total patents of the entire sample are classified as high-patent firms, while in Panel B, those below the median are classified as low-patent firms. The dependent variables are *Total Patents*, *Existing Tech*, *New Tech*, *Existing Tech Share*, *New Tech Share*, *Tech Proximity* and *Innovative Search*. The independent variables include *Exposure* and *Post*, a post-treatment dummy variable that equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects, and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B10: Heterogeneous Effects on Innovation Measures by Firm Age

Panel A: Older Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.286*	0.314*	0.019	0.083	-0.094	0.046	0.043
	(0.158)	(0.171)	(0.093)	(0.061)	(0.082)	(0.062)	(0.080)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,751	5,699	6,332	5,699	6,332	5,699	6,075
Pseudo R^2	0.905	0.907	0.419	0.130	0.131	0.151	0.124

Panel B: Younger Firms

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure × Post	0.174	0.210	0.034	0.034	0.078	0.061	0.057
	(0.124)	(0.145)	(0.081)	(0.061)	(0.074)	(0.064)	(0.085)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,660	5,639	6,109	5,639	6,109	5,639	5,683
Pseudo R^2	0.777	0.778	0.329	0.120	0.119	0.130	0.111

Notes: This table presents results from the PPML difference-in-differences estimation of equation 4 without control variables, with the sample split based on firm age. In Panel A, firms with pre-2006 median firm age at or above the median age of the entire sample are classified as older firms, while in Panel B, those below the median are classified as younger firms. The dependent variables are *Total Patents*, *Existing Tech*, *New Tech*, *Existing Tech Share*, *New Tech Share*, *Tech Proximity* and *Innovative Search*. The independent variables include *Exposure* and *Post*, a post-treatment dummy variable that equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects, and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B11: Effect on Innovation Measures: Alternative Exposure Measure

	(1) Total Patents	(2) Existing Tech	(3) New Tech	(4) Existing Tech Share	(5) New Tech Share	(6) Tech Proximity	(7) Innovative Search
Exposure_Alt × Post	0.260**	0.297**	0.031	0.051	0.001	0.040	0.071
	(0.106)	(0.118)	(0.061)	(0.040)	(0.057)	(0.041)	(0.054)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,977	11,190	12,078	11,190	12,078	11,190	11,512
Pseudo R^2	0.879	0.882	0.387	0.124	0.126	0.140	0.115

Notes: This table shows results from PPML difference-in-differences estimation of equation 4 without control variables, using alternative exposure measure. The sample consists of U.S. firms that applied for at least one patent in the five years before the Supreme Court decision, excluding firms whose first patenting appearance was in 2005, as their exposure values would be missing. The dependent variables are *Total Patents*, *Existing Tech*, *New Tech*, *Existing Tech Share*, *New Tech Share*, *Tech Proximity* and *Innovative Search*. The independent variable *Exposure_Alt* denotes the alternative time-invariant firm-level exposure to litigation, computed using patent application proportions (σ) from 2001 to 2004. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

Table B12: Effect on Innovation Measures: OLS Regression on Log Outcomes

	(1) ln_Total Patents	(2) ln_Existing Tech	(3) ln_New Tech	(4) ln_Existing Tech Share	(5) ln_New Tech Share	(6) ln_Tech Proximity	(7) ln_Innovative Search
Exposure × Post	0.044*	0.040*	0.025**	0.015	0.003	0.012	0.014**
	(0.024)	(0.023)	(0.010)	(0.009)	(0.005)	(0.008)	(0.006)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,761	13,761	13,761	13,761	13,761	13,761	13,761
R-squared	0.806	0.818	0.487	0.544	0.207	0.569	0.330

Notes: This table shows results from the OLS estimation based on equation 4 using the sample of US firms that applied to at least one patent five years before the Supreme Court decision. The dependent variables are *Total Patents*, *Existing Tech*, *New Tech*, *Existing Tech Share*, *New Tech Share*, *Tech Proximity* and *Innovative Search*. All outcome variables are log-transformed versions of the respective dependent variables, with one added before taking the logarithm to avoid dropping a large number of zeros. The independent variable *Exposure* denotes the time-invariant firm-level exposure to litigation. *Post* is a binary variable which equals one from 2006 onwards. Refer to section 3.2 for details on variable construction. All regressions include a constant, firm fixed effects and industry-year fixed effects. Robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.