From Fragility to Flexibility: How do Firms Respond to Upstream Technology Vulnerability?*

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Abstract

We examine how upstream technology vulnerability affects downstream firms' reliance on supply-chain relationships and the associated economic consequences. Using patent litigation as a plausible exogenous shock to upstream technology vulnerability, we find that upstream lawsuits reduce downstream supply-chain reliance by 8.2% in the following year. Our results are robust to quasi-natural experiments exploiting staggered anti-troll legislation and litigation outcome reversals. We identify two plausible underlying mechanisms: heightened legal risk surrounding upstream technologies and disruptions to the supply of affected inputs. Moreover, we find that downstream firms respond to disrupted upstream technology supply by shifting toward in-house development. By increasing R&D investments and recruiting external inventors, affected customer firms enhance their innovation capabilities, particularly in the disrupted technological domains. Collectively, these responses expand firm boundaries and provide new evidence on how technology-related supply shocks shape firms' make-or-buy decisions.

Keywords: Supply chain, Patent litigation, Technology risk, Innovation

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"The supplier shall manage technology and know-how in a manner that protects intellectual property rights, ensuring that products and technologies are neither copied nor misused."

— from Apple Supplier Code of Conduct [1]

1 Introduction

In the modern economy, deep specialization across sectors fosters complex and interdependent supply-chain networks. This structure, however, has intensified supply-chain fragility, as disruptions at any point in the network can propagate throughout the entire economy.[2] Previous research has shown that disruptions to production processes—stemming from natural disasters, climate risks, financial shocks, or geopolitical tensions—trigger cascading damage to many downstream firms (Barrot and Sauvagnat 2016; Snyder et al. 2016; Costello 2020; Elliott, Golub, and Leduc 2022; Han, Jiang, and Mei 2024; Pankratz and Schiller 2024; Acharya et al. 2025). However, input-output linkages encompass not only the transfer of materials and goods but also the delivery of technology and knowledge (Chu, Tian, and Wang 2019). Unlike physical goods, technology often involves intellectual property (IP) rights, which are inherently complex and difficult to define. This ambiguity within the patent system, often described as "too broad, too loose, and too expensive", enables patent holders to initiate costly infringement lawsuits against other companies (Jaffe and Lerner 2011; Cohen, Gurun, and Kominers 2019)[3]. According to the U.S. Patent Litigation Report (Lex Machina 2024; Lex Machina 2025), federal courts handled more than 44,000 patent cases over the past decade, with filings rising by over 20% in 2024 and annual damages exceeding $4.3 billion. Despite of the increasing prevalence and financial costs of patent litigation, little is known about how these technology vulnerabilities disrupt the broader supply chain, especially for downstream firms reliant on upstream technologies.

[1] In Apple's Supplier Code of Conduct, it explicitly emphasizes intellectual property protection in selecting suppliers. See details: Apple Supplier Code of Conduct.

[2] An industry study by Resilinc documented 1,069 supply-chain disruption events worldwide over a six-month period in 2018 (Supply Chain Quarterly, 2018).

[3] Recently, a growing body of literature on patent litigation has identified the drivers and consequences of patent infringement, intellectual property defense strategies against competitors, actions initiated by non-practicing entities (NPEs), and the efficiency of patent litigation system (Cohen, Gurun, and Kominers 2019; Mezzanotti 2021; Acikalin et al. 2025; Michaely, Xie, and Zhang 2025; Antill et al. 2025).

In this paper, we study how upstream technology vulnerability affects downstream firms through supply-chain relationships by reshaping their sourcing strategies and innovation decisions. Our empirical setting exploits patent infringement lawsuits in which upstream suppliers are named as defendants, capturing instances where firms are involuntarily exposed to technology-related legal shocks. These events are typically not anticipated by downstream customers and are plausibly orthogonal to their own economic conditions, providing a clean setting to examine the supply-chain effects of patent litigation. Consistent with this intuition, high-profile cases illustrate how such upstream disputes can propagate along the supply chain. A prominent example is the prolonged litigation between NTP Inc. and RIM, which disrupted not only the focal firm but also its downstream ecosystem.[4]

Theories of supplier sourcing and firm boundaries imply that when patent litigation renders upstream technologies more vulnerable, firms must trade off the risks of continued reliance on external suppliers against the costs of supplier switching or vertical integration (Williamson 1985; Grossman and Hart 1986). When upstream suppliers are drawn into patent litigation, downstream firms face two distinct sources of risk. First, patent litigation raises technology-related legal risk by casting doubt on the legality of continued use of supplied technologies and by exposing downstream firms to indirect liability arising from plaintiffs' litigation strategies that target parties connected to the allegedly infringing technology. Such risks are amplified in supply chains with strong technological interdependencies (Acemoglu, Akcigit, and Kerr 2016b; Tian and Zhang 2025). Second, the prolonged and unpredictable nature of patent litigation[5] introduces substantial operational uncertainty by impairing suppliers' production, planning, and innovation activities, which weakens their ability to meet delivery and quality commitments.

On the other hand, despite these incentives to reduce reliance on litigated suppliers, such adjustments are far from costless. First, search costs can be substantial, as upstream technologies are often highly customized and embedded in customers' production systems, which limits the availability of compatible alternatives (Williamson 1981; Dyer and Singh 1998). Identifying alternative

[4] See details:WSJ Articles. Further details of the case study are presented in Appendix IA2.1.

[5] According to U.S. Patent Litigation Report by Lex Machina (2024), among cases resolved on substantive grounds, the likelihood of success for claimants was more than double that of defendants. The median duration of patent lawsuits to reach summary judgment is 814 days.

suppliers with comparable technical capabilities and low exposure to intellectual property disputes requires significant time and resources.Second, transaction costs arise from the need to negotiate and establish new contractual relationships under incomplete information and time constraints. In the presence of relationship-specific investments and rigid production schedules, downstream firms may face ex post bargaining frictions and potential hold-up problems when contracting with new suppliers (Hart and Moore 1990), which increases contracting costs and weakens their bargaining position. Third, switching costs are considerable. Beyond the direct costs of terminating existing relationships and reconfiguring production processes, substituting upstream technologies—particularly through in-house development—requires undertaking risky and resource-intensive R&D investments. Such efforts involve hiring specialized human capital, acquiring new equipment, and bearing substantial technological uncertainty and failure risk (Hall and Lerner 2010).

This trade-off between heightened risks and substantial adjustment costs creates opposing forces that shape firms' reliance on litigated suppliers, leaving the overall effect of upstream technology vulnerability on supply-chain relationships theoretically ambiguous. Taking these considerations together, we propose the following hypothesis: Upstream technology vulnerability reduces downstream reliance on existing suppliers and weakens supply-chain relationships.

To empirically test our hypothesis, we collect patent litigation cases from the United States Patent and Trademark Office (USPTO) Patent Litigation Docket Reports and manually identify cases in which firms are defendants at the initiation of the case. We supplement with RPX database to identify case outcomes and non-practicing entities. We then use the Compustat Customer Segment data to identify major customers and merge this information with litigation records and supplier-customer characteristics. Restricting the sample to publicly listed suppliers and customers yields a panel of 25,040 supplier-customer-year observations, covering 759 unique suppliers and 672 unique customers from 2000 to 2022.

Our baseline tests examine how upstream patent litigation affects downstream firms' reliance on supply-chain relationships, measured by an indicator for relationship termination in the subsequent year (Fee, Hadlock, and Thomas 2006; Dasgupta, Zhang, and Zhu 2021).[6] To construct a

[6]Because U.S. public firms disclose only major customers accounting for more than 10% of sales, smaller transactions are unobserved. As a result, some observed relationship terminations may reflect sales falling below the

credible counterfactual, we employ a matching strategy that pairs each sued supplier with comparable non-sued suppliers within the same litigation year. Our identification compares a customer's reliance on a sued supplier with its reliance on matched non-sued suppliers in the same period. This design exploits within-customer, within-year variation, helping isolate the effect of litigation from time-invariant customer characteristics and common temporal shocks.[7] Our baseline results show that when a supplier is involved in patent litigation as a defendant, downstream reliance declines markedly. In economic terms, upstream litigation increases the probability of relationship termination in the subsequent year by 8.2%. These findings suggest that major customers perceive the risks of sourcing from litigated suppliers as outweighing the costs of severing existing supplier relationships.

An important concern is that patent litigation is not randomly assigned.Our results could be biased by unobserved technological shocks that simultaneously affect upstream and downstream industries (Acemoglu, Akcigit, and Kerr 2016a), or by reverse causality if more fragile supply chains are themselves more likely to attract patent disputes. To address these concerns, we implement a set of identification strategies. First, we use a difference-in-differences design with a restricted event window of [-4,+4] years around litigation, aggregating the data at the supplier level. The results confirm a significant decline in downstream reliance and satisfy parallel-trends tests. We further strengthen causal inference using two quasi-natural experiments that exploit plausibly exogenous variation in litigation risk: (i) the staggered adoption of state anti-troll laws, following Appel, Farre-Mensa, and Simintzi (2019), which lowers the ex ante probability that suppliers are sued; and (ii) voluntary plaintiff dismissals—a novel reversal setting we introduce—which attenuate litigation shocks by exogenously removing ongoing case pressure. Although no empirical design can fully eliminate endogeneity concerns, the evidence collectively suggests that our results are likely causal.

Next, we explore two plausible economic mechanisms underlying our baseline results. First, we examine technology legal risk as a primary channel. We expect the adverse effects of litigation to be stronger when downstream firms face greater legal exposure. Consistent with this conjecture,

reporting threshold rather than actual termination. To address this concern, we complement our analysis with an intensive-margin measure based on trading volumes.

[7]The specification includes year fixed effects, supplier industry × year fixed effects (capturing time-varying industry-level shocks), supplier state × year fixed effects (capturing time-varying state-level shocks), and event year × customer fixed effects (capturing time-varying customer-specific demand conditions).

we find stronger effects when lawsuits involve a supplier's core technologies or patents of greater economic value. The effects are also more pronounced when customers are more closely tied to upstream technologies. Moreover, downstream firms become directly exposed to patent legal disputes: the probability that a customer is subsequently litigated rises significantly after its supplier is sued. Taken together, these results provide evidence that technology legal risk propagates through supply chains. The second mechanism is delivery uncertainty related to production risk. We capture this uncertainty using two observable case characteristics—litigation duration and complexity—which reflect the prolonged and uncertain nature of legal proceedings. We show that the adverse effects of upstream litigation are stronger in longer and more complex cases, consistent with greater uncertainty about suppliers' ability to deliver timely and reliable inputs. In addition, suppliers are 2 percentage points more likely to experience product recalls following litigation, relative to a baseline recall rate of 2.6%. This evidence suggests that upstream litigation undermines delivery quality and stability, increasing the likelihood that downstream firms terminate relationships with affected suppliers.

We have shown that upstream technology vulnerabilities increase fragility in supply chains. A natural follow-up question is how downstream firms respond when upstream suppliers can no longer provide reliable technologies and how such responses affect their economic outcomes. In general, downstream firms have two options: pursuing in-house development or sourcing from alternative suppliers (Cassiman and Veugelers 2006). The literature offers mixed conclusions. In-house development provides greater control over technological inputs, reduces reliance on external partners, and can generate competitive advantages in emerging technological domains (Teece 1986; Cohen, Levinthal et al. 1990), but requires substantial time and resources, with potentially high R&D costs. By contrast, external sourcing allows firms to resume production more quickly, but exposes them to supplier-related risks, including compatibility constraints and uncertainty in delivery (Williamson 1981; Dyer and Singh 1998).

To analyze the effect of upstream patent litigation on downstream innovation, we construct a sample of treated customers with at least one supplier exposed to litigation and control customers whose suppliers are never exposed during the sample period. We examine three dimensions—

innovation inputs, outputs, and new product introductions—capturing both the intensity and direction of firms' responses. Relative to the control group, treated customers increase R&D investment by 27.1% and expand their inventor base by 32.3%. These increases in inputs translate into significantly greater innovation output: treated customers raise patent applications in litigation-exposed technology classes by 43.3%. Moreover, the composition of patenting shifts, with treated firms applying for 2.3 times more patents in litigation-exposed technology classes. These new patents also exhibit higher average value, indicating that the increase in R&D generates economically meaningful innovations.

We next examine whether in-house development enables firms to integrate supply chains and expand into new product markets. Using Compustat Historical Segment data, we find that treated customers are more likely to introduce new product lines following upstream litigation. By contrast, we find no significant evidence that affected customers form new supplier relationships, suggesting that in-house development, rather than switching to alternative suppliers, is the primary response to disrupted technology supply. Taken together, these findings indicate that upstream technology disruptions shift downstream firms toward in-house development and provide greater flexibility.

Our paper makes contributions to two key strands of the literature. First, it contributes to the emerging literature on the transmission of risks along input-output linkages and their effects on downstream performance. Prior studies focus on operational risks, including natural disasters (Barrot and Sauvagnat 2016; Carvalho et al. 2021), climate risks (Pankratz and Schiller 2024), financial risks (Costello 2020), macroeconomic and inflation risks (Acharya et al. 2025), and political risks (Qian and Qiu 2023; Han, Jiang, and Mei 2024), and document how such shocks propagate through supply chains and affect downstream firms. However, this literature pays limited attention to technological vulnerabilities that arise within supply chains through the transmission of knowledge and technologies (Chu, Tian, and Wang 2019; Tian and Zhang 2025). We address this gap by using upstream patent litigation as a proxy for technology risk and examining its effects on downstream dependence and innovation. To our knowledge, this paper is the first to highlight technological vulnerability as a key driver of supply-chain fragility, offering a new perspective on how firms strengthen resilience. [8]

[8] A related research, Han, Jiang, and Mei (2024), investigates the effect of the China-U.S. trade conflict, showing

Second, our paper contributes to the growing literature at the intersection of intellectual property protection, finance, and economics. The U.S. patent system relies on courts to protect intellectual property and enforce patent holders' rights through infringement litigation. Practitioners, policymakers, and scholars hold differing views on how such litigation system should be structured to promote innovation. For example, Antill et al. (2025) assess the efficiency of the patent litigation system using a dynamic model and find that defendant-friendly reforms can improve welfare by 3.29%. Existing studies primarily examine the determinants of patent litigation and its economic consequences for litigating firms, including effects on defendants' innovation (Cohen, Gurun, and Kominers 2019; Mezzanotti 2021), entrepreneurship (Appel, Farre-Mensa, and Simintzi 2019), mergers and acquisitions (Caskurlu 2019; Emery and Woeppel 2025; Michaely, Xie, and Zhang 2025), and competition (Acikalin et al. 2025). Our study introduces a supply-chain perspective, showing that upstream litigation increases downstream firms' exposure to technology-related risks and disrupts the supply-chain stability, while also inducing downstream adaptive responses such as increased in-house innovation. This dual effect along supply chains provides a more complete view of how the patent system shapes broader economic outcomes.

2 Data and Sample

2.1 Patent Litigation Data

Our patent litigation data mainly comes from USPTO *Patent Litigation Docket Reports Data*, which is updated through March 2024 and contains detailed patent litigation information during the period 1963-2020. It provides six files, including case details (*cases file*), the patents involved in litigation cases (*patents file*), information on the parties and their attorneys (*names file*; *attorneys file*), descriptions of all documents submitted in each case (*documents file*), and PACER case-level metadata (*Pacer cases file*). We also supplement these data with the RPX database to identify case outcomes and non-practicing entities(NPEs).

We identify litigating parties that can be matched to CRSP–Compustat firms by combining

that downstream firms in sanctioned sectors suffered while upstream firms enhanced productivity through innovation. Distinct from their focus on a specific geopolitical context, we provide a more generalizable perspective by studying technology risks arising from patent litigation across industries.

patent-level linkages with fuzzy name-matching procedures. Using the USPTO *names* file, we further restrict the sample to firms named as defendants at the initiation of each case. Details of the matching procedure are provided in Appendix IA3.2. This procedure enables us to accurately identify publicly listed firms that are named as defendants in patent litigation. Such disputes generate substantial uncertainty over firms' ability to use, commercialize, and appropriate returns from the underlying technologies, because an adverse resolution may expose them to injunction risk, damages, or costly settlement.

To accurately capture the technologies under dispute, we link each identified defendant firm to all patents involved in the corresponding litigation cases using the *patents* file. Because the *patents* file begins in 2003, we limit our sample of defendant firms to the period from 2003 to 2020. In the Internet Appendix, Figure IA1.1 presents the distribution of patent litigation across Fama-French 12 industries. The figure shows that *Hlth* (Healthcare, Medical Equipment, and Drugs) exhibits substantially greater patent-litigation intensity than *Shops* (Wholesale, Retail, and Some Services) and *Utils* (Utilities). Figure IA1.2 presents the corresponding distribution across CPC (Cooperative Patent Classification) technology classes and indicates that health-, drug-, and high-technology-related classes are associated with greater exposure to patent litigation.

As a robustness check, we also construct an alternative sample that includes firms appearing in broader defendant-related roles. Specifically, these roles include not only original defendants, but also counter-defendants in countersuits and third-party defendants.

2.2 Supply-Chain Data

To examine how patent litigation risk propagates through supply-chain networks, we construct a supply-chain sample based on major customer relationships from the Compustat Customer Segment database, a standard source in the supply-chain literature. Companies are required to report all major customers in their 10-K filings, defined as those that account for more than 10% of their total sales. Following Fee, Hadlock, and Thomas (2006) and Barrot and Sauvagnat (2016), we treat firm S as a supplier to firm C in all years between the first and last year in which S reports C as a customer. We also require that both suppliers and customers be included in the CRSP–Compustat sample. Consequently, we consider only cases involving major listed customers of listed suppliers.

We ultimately obtain a supply-chain sample with a total of 86,692 pair-year observations from 1976 to 2022.

One caveat of our study is that our data do not allow us to identify the full set of a supplier's customers, but only major customers that contribute more than 10% of the supplier's total sales. However, this focus on major customers aligns well with the purpose of our research, as substantial technology transfer and utilization are more likely to occur between suppliers and their major customers. Evidence suggests that suppliers are more likely to develop relationship-specific innovations for their major customers, customized to the latter's products or production processes (Dasgupta, Zhang, and Zhu 2021; Tian and Zhang 2025). Smaller customers, by contrast, may engage in more standardized transactions that rely less on technological interactions. By focusing on these key supplier-customer relationships, our analysis is well positioned to uncover the critical role of technology in vertical production networks and supply-chain dynamics. As a robustness check, we supplement the Compustat Customer Segment data with the FactSet Revere Supply Chain data, which covers a broader set of supplier-customer links

2.3 Accounting and Innovation Data

We obtain firm financial data from Compustat and construct financial control variables, including size ($Ln(Asset)$), operating income (ROA), sales growth ($SaleGRW$), cash liquidity ($Cash$), book-to-market ratio (B/M), leverage (LEV), asset tangibility (PPE) and innovation input ($R\&D$). We obtain innovation data from USPTO and build key variables at the firm level or pair level, including the age of patent portfolio ($InnovAge$), number of patents granted ($IssueNum$), technology dependence ($Tech_Dependence$) and technology proximity ($Tech_Proximity$), following literature convention (e.g., Jaffe 1986; Bena and Li 2014). Firm industries are defined based on the Fama–French 49 industry classifications. Detailed descriptions of all variables used in the analysis can be found in Appendix IA3.1.

2.4 Sample Construction

We begin with the supply-chain sample and merge it with our sample of defendant firms, as well as firm-level financial data from Compustat and patent-based innovation data from the USPTO.We

require that litigation occur during the active period of the supply-chain relationship, restrict the sample to post-2000, and exclude suppliers or customers in the finance or utility industries.We exclude cases in which downstream customers initiate patent litigation against their suppliers, because these cases likely reflect endogenous breakdowns in transaction relationships rather than exogenous shocks to technology risk.

Since patent litigation may affect a supplier's fundamentals—such as sales growth, cash holdings, and the book-to-market ratio—which are also potential control variables in our regression specification, directly controlling for these time-varying characteristics can introduce bias in estimating the coefficient of interest (Angrist and Pischke 2009; Roberts and Whited 2013). To mitigate this "bad control" problem, we first implement a propensity score matching (PSM) procedure for each sued supplier by identifying comparable non-sued suppliers in the same litigation year. Matching is based on a logit model and uses the nearest-neighbor method, with each treated supplier paired with its three closest neighbors in terms of the estimated propensity score. Details on the selection of covariates and the implementation of the matching procedure are provided in Appendix IA3.3.

Matching covariates are measured one year before the litigation event so that counterfactual suppliers are selected based on pre-treatment characteristics that are not yet affected by the litigation shock. Using lagged covariates helps ensure that the matching procedure relies on predetermined firm fundamentals rather than endogenous post-treatment adjustments. In the subsequent regressions, we therefore hold supplier characteristics fixed at their pre-litigation, one-year-lagged values. This approach follows Angrist and Pischke (2009) and Roberts and Whited (2013), who caution that conditioning on post-treatment variables introduces "bad control" bias and can distort the estimated effect of interest. By fixing covariates at their pre-litigation levels, we exploit only ex ante variation and avoid contaminating the estimates with firms' endogenous responses to litigation.

2.5 Summary Statistics

Table 1 Panel B reports summary statistics for supplier, customer, and pair characteristics at the pair-year level. After winsorizing all continuous variables at the 1% and 99% levels, average total assets are $3.1 billion for suppliers and $84.7 billion for customers. The large size of customers is consistent with our sample construction: customers are major downstream firms that are publicly

listed and have observable innovation activity, and thus tend to be large, mature firms. The average cash ratio and leverage ratio are 16% and 45% for suppliers, compared with 10% and 64% for customers. Consistent with prior studies (e.g., Banerjee, Dasgupta, and Kim 2008; Pankratz and Schiller 2024), we observe systematic asymmetries between upstream and downstream firms across accounting characteristics. In particular, customers tend to be larger and exhibit slower sales growth, whereas suppliers are smaller and grow faster. At the pair level, the average duration of supply-chain relationships is 14.0 years, longer than that reported in the existing literature. This difference arises because we focus on listed suppliers matched to their major listed customers and further require suppliers to have patenting activity during the sample period, which selects for more stable and long-term relationships. All other summary statistics are broadly consistent with existing studies.

Table 2 Panel A presents the distribution of patent litigation involving upstream suppliers in our sample. Panel B reports summary statistics for litigation-related characteristics of defendant suppliers, including litigation duration and legal complexity. In Panel A, the average litigation rate is 12.4% at the pair level and 13.8% at the supplier level. The number of sued suppliers declines after 2013, coinciding with the passage of the first U.S. state-level anti-troll law in Vermont. These laws aim to curb "bad faith assertions of patent infringement" through demand letters (Vermont Act 44) and were subsequently adopted by other states in a staggered manner. The overall trend in patent litigation is illustrated in Figure 1. Consistent with the evidence in Panel A, both the number and the percentage of litigated suppliers decline after 2013. In addition, patent litigation imposes a substantial burden on affected suppliers in our sample. As shown in Panel B, defendant suppliers experience litigation lasting 545 days on average and face approximately 460 legal filings, reflecting the prolonged and resource-intensive nature of these disputes.

3 Patent Litigation and Supply-Chain Fragility

In this section, we examine whether upstream technology vulnerability affects supply-chain stability, using exposure to upstream patent litigation as a specific proxy for such vulnerability. Our central hypothesis is that downstream customers reduce their reliance on suppliers that are named

as defendants in ongoing patent disputes. Supplier–customer relationships constitute an important channel for technology transmission, as downstream firms incorporate and build upon upstream innovations embodied in intermediate inputs (Acemoglu et al. 2012). A large literature documents that knowledge spillovers across firms contribute to productivity growth (e.g., Bloom, Schankerman, and Van Reenen 2013), while production networks provide a natural channel through which such spillovers extend across firm boundaries. Patent litigation, however, introduces substantial uncertainty regarding the use and availability of the contested technologies. From a supply-chain perspective, this uncertainty arises both from the potential disruption of critical inputs and from downstream firms' indirect exposure to legal risks, such as vicarious infringement (Meurer 2017).

3.1 Empirical Design

We use the matched supplier × customer × year sample constructed in Section 2.4. Following the standard approach in the literature (e.g., Fee, Hadlock, and Thomas 2006; Dasgupta, Zhang, and Zhu 2021), we construct $1(Last\ Rel.Year)$ as a proxy for the strength of a customer's reliance on its supplier. This variable equals one if a given supplier–customer relationship terminates in the subsequent year, and zero otherwise, and is multiplied by 100 for ease of interpretation. [9] We then estimate the following model using the matched sample at the annual frequency.

$$1(Last\ Rel.Year)_{c,s,t} = \beta_0 + \beta_1 \times 1(Litigation_s) \times Post_t + \beta_2 \times 1(Litigation_s) + Controls_{s,T-1} + \gamma_{n(s)} + \eta_{d(s)} + \lambda_t + \zeta_{c,T} + \varepsilon_{c,s,t} \quad (1)$$

where the dependent variable $1(Last\ Rel.Year)_{c,s,t}$, captures the likelihood that customer c ceases its relationship with supplier s following year t. The key independent variable, $1(Litigations)$, is an indicator equal to one for suppliers s that are ever involved in patent litigation as defendants during the sample period (treatment group), and zero otherwise (control group). $Post_t$ is an indicator equal to one for years following the litigation event, and zero otherwise. Accordingly, the interaction term $1(Litigation_s) \times Post_t$ equals one for treated supplier in years after becoming involved in patent

[9] One caveat is that $1(Last\ Rel.Year) = 100$ does not necessarily imply a complete termination of the relationship; it may also reflect that sales to this customer fall below the disclosure threshold, leading to the disappearance of the relationship from the data.

litigation, and zero otherwise. For treated suppliers, the litigation event is defined as the first year since 2003 in which the supplier is named as a defendant in a patent litigation case. For matched control suppliers, the event year is assigned based on the corresponding matched treated supplier. Controls include supplier characteristics ($Ln(Asset)$, ROA, $SaleGrw$, $Cash$, B/M, LEV, PPE, $R\&D$, $InnovAge$, $IssueNum$) (see all definitions in Appendix IA3.1) following prior studies (e.g., Cohen, Gurun, and Kominers 2019; Caskurlu 2019; Dasgupta, Zhang, and Zhu 2021; Emery and Woeppel 2025). All supplier characteristics are measured in the fiscal year prior to the litigation event. We further include supplier industry fixed effects ($\gamma_{n(s)}$) and supplier state fixed effects ($\gamma_{d(s)}$) to absorb time-invariant heterogeneity across industries and geographic locations that may jointly affect litigation exposure and supply chain relationships. In addition, we include year fixed effects (λ_t) to control for aggregate shocks over time, as well as event-year $\times$ customer fixed effects ($\zeta_{c,T}$), which capture customer-specific time-varying factors around the event window. Standard errors are clustered at the pair level, consistent with common practice in the supply-chain literature (Chu, Tian, and Wang 2019; Dasgupta, Zhang, and Zhu 2021; Agca et al. 2022; Chen et al. 2023).

Under this specification, β_1 captures the differential change in the probability of relationship termination for treated suppliers after the litigation event, relative to control suppliers linked to the same customer and observed in the same event year. This design differences out time-varying downstream demand shocks and isolates variation stemming from supplier-side litigation exposure.

3.2 Main Results

We first assess the quality of our propensity score matching (PSM) procedure following Caliendo and Kopeinig (2008). The validation results are reported in Appendix IA3.3. After matching, standardized biases are substantially reduced and covariates between sued and non-sued suppliers become statistically indistinguishable, indicating that the matching procedure effectively mitigates observable differences.

Table 3 reports the baseline estimates from equation (1). Columns (1) to (3) present results based on the baseline matched sample. Across all specifications, the coefficient on $1(Litigation) \times Post$ is positive and statistically significant, indicating that supplier involvement in patent litigation as defendants increases the likelihood of relationship termination, as captured by $1(Last\ Rel.Year)$.

This suggests that downstream firms are more likely to discontinue relationships with suppliers following litigation events. In Column (2), adding supplier-level controls leaves the coefficient largely unchanged, suggesting that the estimated effect is not driven by observable supplier characteristics. In Column (3), we further include event $\times$ customer fixed effects, which absorb customer-specific time-varying shocks around the event window. While the coefficient attenuates, it remains both statistically and economically significant, indicating that the effect is not solely attributable to demand-side fluctuations at the customer level. In terms of economic magnitude, patent litigation increases the probability of relationship termination by 8.2%. This effect corresponds to 62.1% of the sample mean of $1(Last\ Rel.Year)$ (13.2%), indicating a substantial disruption to supplier–customer relationships. These findings support our central hypothesis that litigation-induced technological risks at the supplier level reduces downstream firms' willingness to maintain existing relationships.

A potential concern is that our sample consists of customer firms in retail or wholesale sectors. Such firms are less likely to engage in relationship-specific investments or rely on upstream technological inputs, and they typically exhibit low patenting activity. Consequently, including them could attenuate the estimated effects and obscure the underlying mechanism centered on the spillover of technology risks. To address this concern, we re-estimate our baseline specification after excluding observations where customers operate in retail or wholesale industries. This restriction focuses the analysis on customers—primarily in manufacturing sectors—that are more likely to rely on supplier-specific knowledge inputs and engage in relationship-specific investments. Results are reported in Columns (4)–(6). We find that the estimated effects become stronger, alleviating concerns that our baseline results are driven by customer firms for whom supplier relationships are relatively arm's-length and less sensitive to technological shocks.

Overall, the evidence suggests that litigation-induced uncertainty is not confined to the focal firm but propagates through the production network. These findings underscore the fragility of supply chains to upstream innovation shocks and highlight patent disputes as an important source of systemic disruption in interfirm networks.

3.3 Identification Strategies

In this section, we address potential endogeneity concerns in our baseline specification. Litigation exposure is unlikely to be randomly assigned, and unobserved factors may still jointly affect both the likelihood of being sued and the stability of supplier–customer relationships. For example, adverse technological shocks may both increase the risk of litigation (e.g., through weakened patent positions or increased disputes) and reduce downstream reliance. In addition, strategic litigation targeting by external entities and reverse causality—where suppliers embedded in more fragile or declining relationships may be more vulnerable to litigation—represent potential threats to identification. These considerations motivate a set of additional empirical strategies.

3.3.1 Event Study at the Supplier Level

We first implement a difference-in-differences (DiD) analysis at the supplier × year level by aggregating supply-chain outcomes to the supplier level. For each supplier–year observation, we construct two measures of downstream reliance. The first measure follows our baseline definition in Section 3.1: $1(\textit{Last Rel. Year})$ equals one if any of the supplier's major customer relationships terminate in the subsequent year, and zero otherwise, multiplied by 100 for ease of interpretation. The second measure, $CustomerNum$, captures the number of major disclosed customers of a supplier in the following year. As an additional robustness check, we construct $SalesRatio$, defined as the ratio of next year's total sales to major customers to total assets.

We construct a matched sample of sued and non-sued suppliers for each litigation event year using the same propensity score matching procedure described in Section 2.4. We then estimate a DiD model within an event window of $[-4, +4]$ years around the litigation event. Specifically, we estimate the following regression.

$$Reliance_{i,t} = \lambda_1 \times 1(Litigation_i) \times Post_t + Controls_{i,t} + \eta_{n(i),t} + \zeta_{d(i),t} + \xi_i + \varepsilon_{i,t} \tag{2}$$

$Reliance_{i,t}$ denotes supplier i's downstream reliance measure. The treatment indicator $1(Litigation_i)$ and the post-event indicator $Post_t$ are defined consistently with the baseline specification in (1). $Controls_{i,t}$ includes $Ln(Asset)$, ROA, $SaleGrw$, $Cash$, B/M, LEV, PPE, $R\&D$, $InnovAge$, and

$IssueNum$ (see definitions in Appendix IA3.1). We include supplier industry × year fixed effects ($\eta_{n(i)t}$) and supplier state × year fixed effects ($\zeta_{d(i)t}$) to absorb time-varying industry- and region-specific shocks. In our most stringent specification, we further include supplier fixed effects (ξ_i) to control for time-invariant firm characteristics. Standard errors are clustered at the supplier level.

To assess the validity of the parallel-trends assumption, we estimate an event-study specification following Baker, Larcker, and Wang (2022) and Roth et al. (2023). Specifically, we estimate:

$$Reliance_{i,t} = \sum_{s \neq -1} \lambda_s \times 1(\text{Litigation in } t-s \text{ Year}_{i,t,s}) + Controls_{i,t} + \eta_{n(i),t} + \zeta_{d(i),t} + \varepsilon_{i,t} \quad (3)$$

The indicator variable 1(Litigation in $t-s$ $\text{Year}_{i,t,s}$) equals one if supplier i is first involved in patent litigation as a defendant in year $t-s$, and zero otherwise. The coefficients λ_s trace the dynamic effects relative to the year immediately preceding the event ($s=-1$), which is omitted as the reference period. The specification includes industry × year and state × year fixed effects.

Table 4 reports the PSM-DiD results over 2000–2022. In Column (1), without supplier fixed effects, the coefficient on $1(Litigation) \times Post$ implies that litigation increases the probability of at least one relationship termination by 18.3% relative to matched controls. Including supplier fixed effects reduces the estimate to 14.7%, though it remains statistically significant. It suggests that part of the baseline estimate reflects time-invariant firm differences, while a sizable within-firm effect persists. Using $CustomerNum$ as the dependent variable, we find a contraction in suppliers' customer base: treated suppliers lose 0.42 major customers on average relative to controls in Column (4). Results for $SalesRatio$ are reported in Appendix IA4.3. In the most stringent specification with supplier fixed effects, litigation leads to a decline of approximately 4 percentage points in the ratio of major-customer sales to total assets, relative to matched control suppliers. Overall, these findings reinforce our baseline results and support a causal interpretation.

The event-study results, reported in Figure 2, further support the identification strategy. The estimated coefficients in the pre-event period are small in magnitude and statistically indistinguishable from zero, indicating no evidence of differential pre-trends between treated and control suppliers. Following the litigation event, the coefficients become positive and statistically significant, with effects emerging shortly after the event and persisting over subsequent years.

3.3.2 The First Quasi-Natural Experiment: State Anti-Troll Litigation Law

We further exploit the staggered adoption of U.S. state-level anti-troll legislation as a quasi-natural experiment to generate plausibly exogenous variation in firms' exposure to patent litigation. This law, enacted across states between 2013 and 2017, is designed to curb bad-faith patent assertion by imposing stricter pleading standards, disclosure requirements, and penalties for abusive litigation practices. By increasing the cost of opportunistic lawsuits, it reduces the likelihood that firms are targeted by patent litigation (Appel, Farre-Mensa, and Simintzi 2019). Such laws provide variation in litigation exposure across states and over time due to staggered adoption that is plausibly unrelated to firm-level supply-chain dynamics, in order to help mitigate endogeneity concerns in our baseline specification.

We leverage this institutional setting in an instrumental DiD framework (Duflo 2001; De Chaisemartin and d'Haultfoeuille 2018; Agarwal et al. 2024). Specifically, we define treated suppliers as those located in states that adopt anti-troll legislation from 2013 to 2017. For each treated supplier, we construct a matched control group using the same propensity score matching procedure as in Section 2.4, matching on the year of law adoption (i.e., the event year). Given that this policy shock affects a broad set of firms simultaneously, resulting in a larger treated group than in our baseline setting, we match each treated supplier to its two nearest neighbors to preserve balance. We then estimate the model within an event window of $[-4, +4]$ years around the law adoption year, consistent with Section 3.3.1.

In the first stage, the instrument is $1(Litigation\ Law)$, an indicator equal to one if the supplier's state has enacted anti-troll legislation by year t, and zero otherwise. The endogenous variable is $1(Litigation) \times Post$, defined as in the baseline specification (1). We include supplier state fixed effects to control for time-invariant differences across states, as well as industry $\times$ year fixed effects to absorb time-varying industry-wide shocks. In the second stage, we use the fitted value $\widehat{1(Litigation)} \times Post$ from the first stage to estimate the causal effect of litigation on supply-chain fragility. The dependent variable is $1(Last\ Rel.Year)$, defined as in specification (2). We include state $\times$ year and industry $\times$ year fixed effects to control for time-varying regional and industry conditions. We also include the same control variables as in specification (2). Standard errors

are clustered at the state level to allow for correlation in the error terms within states, given that treatment varies at the state level.

Table 5 Panel A reports the results. In Column (1), the first-stage estimates show that the adoption of anti-troll legislation significantly reduces the litigation exposure by 7%. The corresponding F-statistic is 221.9, well above conventional thresholds, confirming the relevance of the instrument. In Column (2), the second-stage results show that the coefficient on $1(\widehat{Litigation}) \times Post$ is positive and statistically significant. The estimate implies that an exogenous increase in patent litigation exposure raises the probability of relationship termination by 27.7%. This magnitude is economically large and consistent with our baseline findings. The exclusion restriction is plausible in this setting, as these laws primarily target the legal environment governing patent enforcement and are unlikely to directly affect supplier–customer relationships except through their effects on upstream patent litigation. Taken together, these results provide additional causal evidence that exogenous increases in upstream litigation risk weaken supply-chain stability.

3.3.3 The Second Quasi-Natural Experiment: Litigation Case Reversal

We further exploit a quasi-natural experiment based on patent litigation cases that end in plaintiff-initiated voluntary dismissal. A voluntary dismissal refers to a procedural outcome in which the plaintiff withdraws the lawsuit before the court reaches a final judgment, typically under Rule 41(a) of the Federal Rules of Civil Procedure. Unlike the state anti-troll laws, which affects the ex ante probability of being sued, voluntary dismissal occurs after litigation is initiated and can be interpreted as an unexpected resolution that eliminates litigation risk faced by the defendant supplier ex post without imposing legal penalties or requiring a court ruling on liability. To strengthen identification, we focus on voluntary dismissals that are plausibly unrelated to the supplier's underlying innovation activities or supply-chain conditions. Such decision to dismiss a case is made unilaterally by the plaintiff and often reflects factors such as litigation strategy, cost considerations, or evidentiary constraints that are outside the control of the defendant supplier. As a result, conditional on having been sued, the timing of voluntary dismissal provides a plausibly exogenous shock to litigation exposure.

We restrict the baseline sample to suppliers that have been involved in patent litigation as de-

fendants and identify a subsample of treated suppliers whose cases are resolved through voluntary dismissal. This subsample consists of 58 suppliers, accounting for 15.8% of all treated suppliers. To construct an appropriate control group, we match each litigated supplier with voluntary dismissal to non-dismissed litigated suppliers in the same filing year and Fama–French 12 industry. This matching ensures that treated and control firms in this subsample face comparable litigation environments and industry conditions at the time of case initiation. We further exclude cases in which filing and resolution occur within the same year to ensure a clear temporal separation between the litigation shock and its resolution. We then estimate a DiD model over an event window of $[-4, 4]$ years around the case resolution year. The indicator $1(Reversal) \times Post$ equals one for supplier–year observations after a voluntary dismissal and zero otherwise. The dependent variable $1(Last\ Rel.Year)$ is defined as in the baseline specification. We include the same set of control variables, as well as state $\times$ year, industry $\times$ year, and firm fixed effects, consistent with specification 2. In addition, we include case filing-year fixed effects to absorb cohort-specific litigation shocks associated with the timing of case initiation.

The results are reported in Table 5 Panel B. We find that the coefficient on $1(Reversal) \times Post$ is negative and statistically significant, indicating that the probability of relationship termination declines following voluntary dismissal. Economically, the estimates imply an 18.9% reduction in termination likelihood relative to suppliers whose litigation cases are not dismissed. Given the inclusion of firm fixed effects, this estimate reflects a within-supplier change in supply-chain stability following the removal of litigation risk.

Taken together, these findings provide complementary evidence to our baseline results. While patent litigation increases supply-chain fragility, the resolution of litigation through voluntary dismissal reverses this effect, reinforcing the interpretation that litigation-induced technology uncertainty is a key driver of downstream relationship adjustments. In the next section, we explore the underlying mechanisms that give rise to this pattern.

3.4 Underlying Mechanisms

We focus on two distinct economic mechanisms underlying the negative effects of upstream patent litigation on supply-chain stability. The first channel operates through intellectual property risk

and is specific to patent litigation. The second channel reflects production-related uncertainty, which captures disruptions to input supply and is common to a broad range of external shocks.

3.4.1 Technology Legal Risk

Supplier–customer relationships serve as an important channel for technology transmission, as downstream firms incorporate upstream innovations embodied in intermediate inputs into their own production and innovation processes (Acemoglu et al. 2012). When a supplier becomes involved in patent litigation, this channel is exposed to heightened technology legal risk.

On the one hand, downstream firms that directly use inputs supplied by the litigated firm may face potential legal exposure if those inputs are found to infringe existing patent rights. Even before a final court ruling, uncertainty arises regarding the legality of continued use of the supplied technology, increasing the expected costs of maintaining the relationship. On the other hand, patent litigation risk may extend to downstream firms when plaintiffs expand litigation to parties connected to the allegedly infringing technology. Prior research suggests that plaintiffs have incentives to target stakeholders connected to the disputed technology, including downstream customers ((Meurer 2017; Bessen and Meurer 2012). Such strategies can strengthen plaintiffs' position in litigation. As a result, downstream firms may face indirect litigation exposure even if they are not initially named as defendants. This spillover risk amplifies the uncertainty associated with maintaining relationships with litigated suppliers. We next provide empirical evidence to support the technology legal risk channel discussed above.

The Importance of Litigated Patents. We argue that litigation involving more important technology should have a stronger effect on supply-chain stability. The intuition is that core or high-value technologies are more likely to be embedded in upstream products and transmitted to downstream customers. As a result, when such technologies become subject to legal dispute, downstream firms face greater uncertainty regarding the legality of continued use of these inputs. In addition, litigation involving technologically or economically important patents is likely to be more complex and prolonged, increasing both the magnitude and duration of uncertainty faced by downstream firms. Consequently, customers may have stronger incentives to reduce exposure to suppliers whose important technologies are involved in patent disputes.

To capture the importance of litigated patents, we adopt two complementary measures that proxy for technological importance and economic importance, respectively. We identify whether a litigated patent belongs to the supplier's core technology class. We define the core technology class as the three-digit CPC classification with the largest number of patent grants for the supplier over the preceding three years. We then split the sample based on whether the litigated patent falls within this core class. Second, we measure the economic value of each litigated patent using the approach of Kogan et al. (2017), and partition the sample into high- and low-value groups based on the sample median.

Table 6 Panel A reports the results. Columns (1) and (2) report subsample regressions estimated separately for observations in which the litigated patent falls within versus outside the supplier's core technology class. The negative effect of patent litigation on supply-chain stability is significantly stronger when the disputed patent belongs to the supplier's core technology domain. Columns (3) and (4) report subsample regressions based on patent value. We find that the negative effect of patent litigation on supply-chain stability is significantly stronger for patents with higher economic value, consistent with the technology legal risk channel.

Technological Linkages Between Suppliers and Customers. We next directly examine the role of technology transmission within supplier–customer relationships, focusing on how the extent of technological linkage between suppliers and customers shapes the propagation of litigation-induced risk. The underlying idea is that if downstream firms are more technologically connected to their suppliers, upstream technology shocks are more likely to transmit along the supply chain, amplifying the effect of litigation on downstream supply-chain adjustment.

We begin by measuring the extent to which customers depend on their suppliers' technologies. Following Bena and Li (2014), we construct a measure of technology dependence as the fraction of a customer's patents that cite the supplier's patents over the past three years. This measure captures the extent to which the customer builds on the supplier's innovations, and thus reflects a directional dependence of the customer on the supplier's technology base. We also measure technological proximity between each supplier–customer pair. Following Jaffe (1986) and Bena and Li (2014), we represent each firm's patent portfolio as a vector of patent counts across CPC

technology classes in three digits over the past three years, and define technological proximity as the correlation between the supplier's and the customer's patent vectors. This measure captures the overall technological overlap between the two firms.

Table 6 Panel B reports the results. Columns (1) and (2) present subsample regressions based on technology dependence. The estimated effect of patent litigation on supply-chain fragility is substantially stronger when customers exhibit positive technological dependence on their suppliers, indicating that downstream firms that rely on upstream knowledge are more sensitive to litigation-induced uncertainty. Columns (3) and (4) report subsample regressions based on technological proximity. We find that the effect is similarly amplified for supplier–customer pairs with positive technological proximity, suggesting that closer alignment in technological activities increases the transmission of litigation risk.

Taken together, these results provide direct evidence that the propagation of patent litigation shocks operates through technological linkages within the supply chain. When downstream firms are more closely tied to upstream technologies—either through direct knowledge dependence or broader technological overlap—they are more exposed to upstream legal uncertainty and respond by reducing reliance on affected suppliers.

Effects on Customers' Future Litigation Risk. According to prior studies and legal practices, patent plaintiffs often pursue a strategic litigation approach that extends beyond the focal defendant by naming economically connected stakeholders—such as customers—as co-defendants. This practice effectively links upstream and downstream firms within the same liability chain, exposing customer firms to litigation risk when their suppliers are sued.

To empirically examine this mechanism, we construct a sample of treated customer firms that have at least one supplier exposed to patent litigation during our sample period. The control group consists of customer firms whose suppliers are never involved in patent litigation. We identify the treated and control customers using the full pre-matching sample rather than the baseline PSM sample, in order to retain a broader set of customer observations. We define the independent variable, $1(Litigation\ from\ supplier)$, as an indicator equal to one if any supplier of a given customer firm is involved in patent litigation in the current year. The dependent variable, $1(Litigation)$, equals one

if the customer firm becomes subject to patent litigation following the upstream litigation event. Customer-level controls include firm size, return on assets, sales growth, cash holdings, book-to-market ratio, leverage, property, plant, and equipment (PPE), and R&D intensity. We further include customer industry × year fixed effects to absorb time-varying downstream industry-wide shocks. Standard errors are clustered at the customer firm level.

Table 6 Panel C reports the results. We find that exposure to upstream patent litigation significantly increases the likelihood that downstream customer firms are subsequently involved in litigation. The effect is strongest contemporaneously and gradually attenuates over time, with economically meaningful increases in litigation probability of 17% in the current year. These findings support the notion that patent litigation risk exhibits dynamic spillover effects along supply chains, consistent with a mechanism in which strategic legal enforcement and joint liability considerations expand the effective boundary of legal exposure beyond the initially targeted firm.

3.4.2 Delivery Uncertainty

Patent litigation is typically prolonged and highly unpredictable in its resolution. According to the U.S. Patent Litigation Report by Lex Machina (2024), the median time to reach summary judgment is 814 days, and plaintiffs are more than twice as likely to prevail as defendants. Such prolonged and uncertain legal processes introduce high delivery uncertainty. When a supplier is drawn into litigation as a defendant, downstream firms face uncertainty about the supplier's ability to ensure timely and consistent delivery of intermediate inputs. Even in the absence of an immediate adverse ruling, ongoing litigation can delay decision-making, constrain production planning, and weaken supply reliability.

Prior studies show that, in addition to legal exposure, patent litigation can also disrupts production, reduces sales, delays product launches, and may even trigger product withdrawals (Cohen, Gurun, and Kominers 2019; Acikalin et al. 2025; Lemley and Melamed 2013; Tucker 2014). These effects reflect deterioration in firms' internal operations. As a result, litigated suppliers may become less reliable and lower-quality partners from the perspective of downstream firms. This channel is distinct from technology-related legal risk: it operates through operational instability, which undermines suppliers' ability to consistently meet delivery and quality requirements, and weakens

their suitability as long-term supply-chain partners.

To empirically capture this mechanism, we examine litigation characteristics that proxy for the intensity of operational disruption. Specifically, we collect information on filing dates, case resolution dates, and the number of docket filings, and construct two measures: case duration (*Case Length*) and litigation complexity (*Case Complexity*). Longer and more complex cases are more likely to absorb managerial attention, increase resource diversion, and prolong operational disruptions. These features directly map into greater delivery uncertainty and less stable input supply for downstream customers. Table 7, Panels A presents the results. The negative effects of patent litigation are significantly stronger for cases with longer duration and higher complexity, suggesting that the intensity of litigation drives downstream consequences heterogeneously.

We further directly examine whether litigation-induced shocks affect suppliers' operational outcomes by focusing on product quality. Product recalls typically arise when firms fail to maintain production standards, making them a direct indicator of delivery reliability. Following Chen et al. (2025), we estimate the same DiD specification in Equation 2 at the supplier-year level using product recalls as an outcome. We define two dependent variables: $1(Product\ Recalls)$ equals one if a supplier issues any product recall in a given year, and $\#\ of\ Product\ Recalls$ measures the total number of recalls. We estimate count specifications using a Poisson model. All regressions include the same supplier-level controls as in Section 3.3.1, along with supplier-state $\times$ year and supplier-industry $\times$ year fixed effects. As reported in Table 7, Panel B, Column (1), suppliers exposed to patent litigation are 2 percentage points more likely to issue product recalls relative to control firms, compared to a sample mean of 2.6 percentage points. Column (2) shows a 5.1% increase in the number of recalls following litigation exposure. These results indicate that patent litigation is associated with a deterioration in production quality and delivery reliability.

4 Economic Consequences for Downstream Firms

In this section, we turn to our second research focus: the economic consequences of upstream patent litigation for downstream firms. Building on the evidence in Section 3 that downstream firms reduce reliance on suppliers exposed to litigation—leading to more fragile supply chain relationships—we

examine how downstream firms further respond to such disruptions and the resulting economic outcomes. Our focus is on how upstream legal shocks propagate downstream and affect firm value and real decisions, and how these outcomes may ultimately relate to firm boundaries.

4.1 Capital Market Reactions

We begin by examining whether capital markets incorporate upstream litigation risk into downstream customer valuations. This test serves two purposes: First, it provides a market-based assessment of whether investors recognize the transmission of technology risks along supply chains. Second, it establishes whether downstream firms face stockholder pressure following upstream litigation, which may in turn shape their subsequent real decisions examined in the following subsections.

Prior studies document negative stock market reactions for firms directly named as defendants in litigation. However, evidence on economically linked firms—such as major customers of litigated suppliers—remains limited. We hypothesize that the stock market reacts negatively to downstream firms whose suppliers become involved in patent litigation. Prior studies document that adverse events affecting suppliers can spill over to their customers. For example, RepRisk reports that supplier-related controversies often trigger negative market reactions for downstream partners.[10] Similarly, Dai, Liang, and Ng (2021) shows that supplier misconduct propagates through supply chains, amplifying reputational and market risks.

We conduct an event study of cumulative abnormal returns (CARs) for affected customers around the filing dates of upstream patent litigation. For each event, we estimate the Fama-French three-factor model over the estimation window [-169,-20] and compute CARs over the event window [-5, +5]. Results in Appendix IA4.4 show that affected customers experience a significant median equity decline of 0.5%, compared with 0.8% for direct litigated suppliers in our baseline sample, corresponding to a median market value loss of 97.5 million USD. Figure IA1.3 reports consistent evidence, illustrating pronounced stock price declines for major downstream customers around supplier litigation events. These findings indicate that capital markets respond to upstream litigation shocks and incorporate the associated risks faced by downstream firms into equity valuations.

[10] See RepRisk publications.

Such heightened market pressure provides a natural motivation for the adjustments in innovation, product market behavior, and supply chain structure that we examine in the subsequent sections.

4.2 Innovation Strategies

Upstream patent litigation may disrupt the supply of external technologies to downstream firms. We therefore examine how affected customers adjust their innovation strategies in response to potential gaps in technology supply, focusing on both innovation inputs and outputs.

4.2.1 Empirical Design

Our customer sample is identical to that used in Section 3.4.1 when we examine effects on customer's future litigation risk. Specifically, the treatment group consists of customers with at least one supplier exposed to patent litigation, while the control group includes customers whose suppliers are never exposed during the sample period. We adopt a difference-in-differences framework to identify the causal effect of upstream litigation shocks on downstream innovations. This approach allows us to compare changes in innovation outcomes before and after the initial exposure to supplier litigation between treated and control customers.

$$\begin{aligned} Y_{i,t} = \lambda_1 \times 1(\textit{Exposed to Supplier Litigation})_i \times Post_t + \\ \lambda_2 \times 1(\textit{Exposed to Supplier Litigation}) + Controls_{i,t} + \eta_{n(i),t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

$Y_{i,t}$ denotes the dependent variable in year t, capturing different measures of innovations. $1(\textit{Exposed to Supplier Litigation})$ equals one if a customer is in the treatment group that are ever exposed to supplier litigation, and zero otherwise. $1(\textit{Exposed to Supplier Litigation}) \times Post$ equals one for treated customers in years after the initial exposure to upstream patent litigation, and zero otherwise. Control variables include customer firm characteristics ($Ln(Asset)$, ROA, $SaleGrw$, $Cash$, B/M, LEV, PPE, $R\&D$), as well as an indicator for whether the customer itself is involved in patent litigation (see definitions in Appendix IA3.1). We include customer industry $\times$ year fixed effects, $\eta_{n(i),t}$, to account for time-varying industry shocks. Standard errors are clustered at the customer firm level to allow for serial correlation within firms.

4.2.2 Innovation Inputs

R&D Investment. We measure innovation input as the natural logarithm of R&D expenditure. Table 8 Panel A Column (1) shows that downstream customers increase R&D investment by approximately 27.1% following upstream patent litigation. The effect remains significant in Column (2) when we restrict the sample to customers with greater reliance on supplier-specific knowledge and higher innovative intensity by excluding firms in retail and wholesale industries.

Human Capital Investment. We measure human capital investment using inventor mobility. Following Marx, Strumsky, and Fleming (2009) and Li and Wang (2023), we identify an inventor's employer based on patent assignee information and construct inventor-level measures using disambiguated USPTO data. We then aggregate at the firm-level. The main dependent variable is the total number of inventors in a given year ($\#\ of\ Total\ Inventors$), estimated using a Poisson model (Cohn, Liu, and Wardlaw 2022; Chen and Roth 2024). Table 8 Panel B shows that treated customers increase their inventor base by approximately 32.3% relative to control firms after exposure to upstream litigation. The effect remains robust when excluding firms in retail and wholesale industries (Column (2)). To further examine hiring patterns, we focus on gross inventor inflows. $\#\ of\ New$ measures the number of newly hired inventors in a given year. We further distinguish between inventors without prior patenting experience at other public firms ($\#\ of\ NewFirst$) and those with prior patenting experience ($\#\ of\ NewMove$). Results reported in Appendix IA5.1 show that treated customers increase inventor recruitment following upstream litigation shocks. Overall, upstream technology shocks are associated with increases in both R&D investment and inventor hiring, indicating that downstream firms expand innovation inputs when facing disruptions in external technology supply.

4.2.3 Innovation Outputs

We next examine innovation outputs based on patent applications. As upstream patent litigation disrupts the supply of external technologies, downstream firms may respond by increasing in-house innovation, especially in affected technology domains to fill the resulting gaps.

Litigation-Exposed Technology Fields. We refer *litigation-exposed CPC classes* as the set of

CPC classes associated with patents challenged in upstream litigation.[11] For control customers, we construct a comparable benchmark using the core CPC classes of their suppliers, defined as the classes with the largest number of granted patents over the prior three years. We then measure patenting activity as the number of applications in these respective technology classes for both treated and control firms, ensuring a consistent definition of the dependent variable across groups. Using a Poisson specification, Table 9 Panel A shows that treated customers increase patent applications in litigation-exposed technology classes by 43.3% relative to control firms. The effect is stronger when excluding customers in retail and wholesale industries.

To further examine within-firm adjustments, we exploit within-firm variation across technology classes by using a firm $\times$ CPC class $\times$ year panel. Unlike the previous analysis, which compares treated and control firms, this specification allows us to compare patenting changes across technology classes within the treated customers. The key independent variables are defined as follows. $1(Litigation\ CPC) \times 1(Not\ Core\ CPC) \times Post$ equals one when the technology class is exposed to upstream litigation but is not the firm's core CPC class in years after exposure. $1(Litigation\ CPC) \times 1(Core\ CPC) \times Post$ and $1(Not\ Litigation\ CPC) \times 1(Core\ CPC) \times Post$ are defined similarly. We include industry fixed effects, CPC three-digit class fixed effects, and year fixed effects to control for industry heterogeneity, technology-class factors, and common time shocks. Results in Table 9, Panel B reveal a clear reallocation of innovative activity across technology classes. After upstream litigation, patenting in litigation-exposed non-core technology fields is approximately 2.3 times higher than in non-exposed non-core fields. This increase is more pronounced when exposed classes overlap with core technologies, where the effect is about 77% larger than in exposed non-core fields.

Beyond patent counts, we examine the economic value of new patent applications in litigation-exposed CPC classes using the measure of Kogan et al. (2017). We compare the distribution of patent values for applications filed in litigation-exposed classes after upstream litigation to the corresponding pre-litigation distribution (averaged over the prior three years). Figure 3 shows that the distribution shifts to the right, indicating that these new patents are of higher economic value

[11] Each litigated patent may belong to multiple CPC classes under the USPTO Cooperative Patent Classification scheme, and we therefore include all relevant classes.

relative to the historical benchmark.

Original Core Technology Fields. A natural question is whether increased innovation in litigation-exposed fields crowds out investment in firms' original core technologies. To examine this, we measure patenting activity in each firm's core CPC class, defined as the class with the largest number of granted patents over the prior three years, as well as its share of total patent applications. Appendix IA5.2 Panel A reports no significant changes in either patent counts or shares, suggesting no evidence of crowding out. We further examine dynamic effects by tracking these measures over the litigation year and the subsequent two years (Panel B), and find no significant effects throughout.

Taken together, these results indicate that downstream firms respond to upstream technology disruptions by increasing in-house innovation, particularly in affected technology domains. Importantly, this expansion does not come at the expense of core technological activities, but instead reflects a broadening of innovative efforts in response to supply-side shocks.

4.3 Product Market Performance

Patent applications not only protect a firm's intellectual property in specific technological domains, but also expand its capacity to develop differentiated and innovative products. However, patents are intermediate outputs of the innovation process, and a substantial share of their economic value is realized when they are translated into commercially viable products and services.

In this section, we examine the product-market implications for downstream customer firms. Using data from Compustat Historical Segment, we identify newly introduced product lines (segments) in a given year relative to the firm's reported segments over the preceding five years. We define $1(New\ Products)$ as an indicator equal to one if the customer introduces at least one new product line. We also construct the total number of product lines ($\#\ of\ Total\ Products$) to capture the extensive margin of product scope. We employ the same sample and empirical specification as in Section 4.2.1. Given the count nature of the dependent variable, we estimate Poisson models when using $\#\ of\ Total\ Products$. Table 10 Panel A reports the baseline results. We find that treated customers are 3% more likely to introduce new product lines and exhibit a 13.9% increase

in the total number of product lines following upstream patent litigation, relative to control customers. These results remain positive and statistically significant when excluding firms in the retail and wholesale industries, as shown in Panel B.

Overall, the evidence indicates that exposure to upstream technological shocks not only induces greater innovation efforts among downstream firms, but also accelerates the conversion of such innovation into product-market outcomes. This process expands firms' product scope and enhances their operational flexibility, with potential implications for firm boundaries and long-term growth.

4.4 Robustness Checks

Matched Customer Sample. To mitigate concerns that treated and control customers in Section 4.2.1 differ systematically in observable characteristics, we implement a PSM procedure to construct a matched sample. We then re-estimate equation (4) to examine the effect of upstream patent litigation on downstream R&D investment and product outcomes. As reported in Appendix IA5.3, treated customers increase R&D investment by 29.7% and expand the number of product lines by 20.9% relative to matched controls following upstream litigation, consistent with our main results in Sections 4.2 and 4.3.

An Event Study. To assess the validity of the parallel-trends assumption, we estimate an event-study specification following Baker, Larcker, and Wang (2022) and Roth et al. (2023).

$$Y_{i,t} = \sum_{s \neq -1} \lambda_s \times 1(\text{Exposed to Supplier Litigation in } t-s \text{ Year}_{i,t,s}) + Controls_{i,t} + \eta_{n(i),t} + \varepsilon_{i,t} \tag{5}$$

The indicator 1(Exposed to Supplier Litigation in $t-s$ Year$_{i,t,s}$) equals one when customer i is first exposed to upstream litigation in year $t-s$, and zero otherwise. The coefficients λ_s trace dynamic responses of customer outcomes relative to the year prior to the event ($s=-1$), which is the omitted benchmark. The specification includes customer industry $\times$ year fixed effects. Figure 4 presents the results. We find no differential pre-trends prior to the event, supporting the parallel-trends assumption. Following the shock, R&D investment increases immediately and remains positive in subsequent periods. In contrast, the effect on product outcomes emerges with a lag and

becomes statistically significant starting in the fourth year after the event. This delay is consistent with the time required to translate innovation inputs into marketable outputs. The innovation process typically involves multi-stage delays from R&D investment to patenting and to product introduction, often spanning several years.

4.5 Supply Chain Restructuring

Our analysis so far yields two main insights. First, major customers reduce reliance on suppliers involved in patent litigation, increasing supply-chain fragility. Second, affected firms respond by intensifying independent innovation, expanding firm boundaries. We next examine whether customers adjust supply-chain relationships following disruptions to existing supplier relationships, in addition to increased in-house innovation. Using the same sample and DiD specification in Section 4.2.1, we test whether customers expand their supplier base after severing ties with litigated suppliers. Appendix IA6.1 Panel A shows no significant change in the number of new suppliers. As our data capture only publicly listed suppliers, this result should be interpreted cautiously, as adjustments involving private suppliers are unobserved.

We then examine how customers select new supplier partners after litigation exposure, which directly relates to supply-chain restructuring along the intensive margin. Specifically, we focus on whether customers replace disrupted suppliers with partners that differ in litigation risk and technological characteristics. We identify customer firms whose suppliers are exposed to patent litigation in year t and whose relationships terminate in year $t+1$. We then track the formation of new vertical relationships over the subsequent three years.

To assess whether partner selection reflects new potential suppliers' litigation exposure and innovation capabilities—particularly within the litigation-exposed technology space—we follow Bena and Li (2014) and Emery and Woeppel (2025). For each new relationship, we identify the chosen supplier (target) and construct an opportunity set of twenty control firms using nearest-neighbor matching on technology proximity ($Tech_Proximity$), patent count ($PatNum$), and patent age ($InnovAge$). Each set consisting of the target supplier and its matched controls defines a new-

relationship group. We estimate the following specification:

$$1(Target\ Pair)_{s,c,t+1} = \beta \times X_{s,t} + Controls + \xi_g + \varepsilon_{cst} \tag{6}$$

where $1(Target\ Pair)_{s,c,t+1}$ equals one if supplier s is selected by customer c in a new relationship in year $t+1$, and zero otherwise. $X_{s,t}$ is the independent variable. $Controls$ include supplier-level variables including $Ln(Asset)$, ROA, $SaleGrw$, $Cash$, B/M, LEV, PPE, $R\&D$, $InnovAge$, and $IssueNum$ (see definitions in Appendix IA3.1). We include new-relationship-group fixed effects ξ_g, and cluster standard errors at the group level.

Appendix IA6.1 Panel B shows that affected customers are 3% less likely to select suppliers involved in patent litigation within the litigation-exposed technology classes during the four years prior to the new relationship. Panel C reports statistically insignificant results on patenting activity in litigation-exposed technology classes when selecting new suppliers. Together with the evidence presented in Section 4.2, these results suggest that, rather than actively seeking new upstream partnerships, customers tend to focus more on conducting in-house research to mitigate supply-chain fragility and address the disrupted "missing" technology gaps.

5 Robustness & Extensions

Alternative Specifications and Samples. First, we address potential biases from district-court selection, which may confound litigation outcomes and jurisdiction-specific characteristics. In Appendix IA4.1 Panel A, we exclude cases filed in the Eastern District of Texas and the District of Delaware. These two venues account for a disproportionately large share of U.S. patent litigation and are widely viewed as having systematic differences in adjudication, including relatively plaintiff-friendly environments, as documented by Lex Machina's litigation statistics.[12] Second, in Panel B, we restrict sample to suppliers who has filed at least one patent application by the current year, focusing on firms that are actively engaged in innovation and plausibly exposed to patent litigation risk. Third, in Panel C, we implement two-way clustering of standard errors at the supplier–customer pair and year levels, following Petersen (2008) and Pankratz and Schiller

[12]See details:Lex Machina Details

(2024). Fourth, in Panel D, we estimate a Cox proportional hazards model to examine the effect of upstream litigation on the timing of relationship termination, which accounts for the duration of supplier–customer relationships and accommodates right-censoring. The results show that upstream patent litigation is associated with a 54% increase in the hazard of relationship termination. Fifth, in Panel E, we consider an alternative proxy for supply-chain reliance. To capture adjustments along the intensive margin, we examine changes in disclosed sales conditional on the relationship remaining observable. The dependent variable is defined as the percentage change in pair-level sales from year t to $t+1$. The results are significantly negative, indicating that upstream patent litigation is associated with an approximately 10.95% decline in transaction intensity.

Exclude Non-Practicing Entity (NPE) Effects. Prior studies show that NPEs account for a large share of patent litigation, with NPE-initiated lawsuits rising sharply since 2005 (Appel, Farre-Mensa, and Simintzi 2019; Cohen, Gurun, and Kominers 2019). Because such lawsuits are often viewed as more opportunistic and less tied to firms' core technologies, they may be less likely to generate the technology risks emphasized in our analysis. We exclude NPE cases identified from the RPX database, whose classification is based on detailed analyst review and used in prior studies (e.g., Cohen, Gurun, and Kominers 2019). Re-estimating the baseline model after excluding these observations yields similar results (see Appendix IA4.2), indicating that our findings are not driven by NPE litigation.

Consider the Claim Outcome. We examine whether litigation outcomes affect the relationship between upstream patent litigation and supply-chain fragility. We first manually verify the outcome of each litigation case in our sample using the RPX database. We classify litigation outcomes based on whether the case results in a ruling unfavorable to the supplier, which can take two forms. First, the supplier may be found to have infringed another party's patent. Second, the litigation may result in a ruling that invalidates the supplier's asserted patent rights, because patent litigations frequently involve counterclaims or validity challenges. Both infringement and invalidity rulings can represent adverse resolutions. Based on this classification, we define $AdverseOutcome$ as an indicator equal to one if the treated supplier is subject to an unfavorable litigation outcome, and zero otherwise. The complementary indicator $NonAdverseOutcome$ is defined analogously.

We then partition the sample by litigation outcome and re-estimate the baseline specification. The results reported in Appendix IA4.5 show that the effect of patent litigation on supply-chain fragility remains present under both adverse and non-adverse outcomes. This suggests that once a supplier is sued, downstream customers may already perceive heightened uncertainty regarding the supplier's ability to continue providing technology-related inputs or maintaining stable transactions. More broadly, the evidence supports the view that litigation risk, rather than only realized litigation outcomes, has first-order effects on firm behavior (Meurer 2017).

Include all Patent Litigation. In Appendix IA4.6, we extend the baseline analysis by including all upstream litigation events for a given supplier spaced at least five years apart. We re-estimate the effects on supply-chain fragility using this expanded sample. The negative effect of upstream litigation on downstream supply-chain stability still persists.

An Alternative Supply-Chain Sample. In Appendix IA4.7, we augment the Compustat Customer Segment data with FactSet Revere Supply Chain data to broaden coverage of supplier–customer links. Using this expanded sample, we re-estimate the effects of upstream litigation shocks on supply-chain fragility. The results are robust.

Broaden the Definition of Treatment. We expand the definition of treated suppliers to include not only original defendants, but also counter-defendants, third-party defendants, and other defendant-related roles. In addition, we use an alternative approach that links patent litigation to public firms based solely on patent-number linkage. Specifically, we start from the USPTO *patents* file and match all litigation-involved patents to CRSP-Compustat firms using the patent database of Kogan et al. (2017). We further merge it with the *names* file to retain only firms in defendant-related roles. This procedure yields a more precise sample of litigated firms with patents directly under dispute. We then re-estimate the effects of upstream litigation shocks on supply-chain fragility. The results in Appendix IA4.8 and Appendix IA4.9 remain robust.

Unmatched Sample Estimates. In Appendix IA4.10, we use the raw sample prior to PSM to re-estimate the effects of upstream litigation shocks at the pair-year level. This exercise assesses the sensitivity of our results to the matching procedure. Supplier-level controls are the same as in Section 3.1. We additionally include customer-level controls as well as a pair-level control for the

duration of the customer–supplier relationship. All regressions include supplier-industry × year fixed effects, supplier-state × year fixed effects, and customer firm fixed effects. The results remain robust.

Alternative Difference-in-Differences Specifications. We implement a staggered difference-in-differences design in Section 3.3.1. Recent studies show that conventional two-way fixed effects DiD estimators may be biased in the presence of treatment effect heterogeneity across cohorts or over time. To address this concern, we re-estimate our main specification using a stacked DiD approach following Cengiz et al. (2019). The results, reported in Figure IA1.4, remain robust.

Consider all Types of Litigation. In Appendix IA4.12, we examine the effects of all types of upstream litigation on supply-chain stability, distinguishing patent from non-patent litigation. This test ensures that the baseline results are driven by patent-related technological disruptions rather than general legal shocks. Non-patent litigation is identified using the *Legal and Regulatory Litigation Data* and matched to public firms via CUSIP identifiers and fuzzy name matching. We re-apply the PSM procedure in Section 2.4 to construct a comparable matched sample. Panel A reports estimates following Section 3.1, where $1(Litigation) \times Post$ equals one if a supplier experiences any type of litigation by year t since 2003. Panel B distinguishes patent from non-patent litigation: $1(Litigation) \times Post \times 1(Patent)$ equals one if the supplier is exposed to patent litigation by year t, while $1(Litigation) \times Post \times 1(NotPatent)$ equals one if the supplier is exposed only to non-patent litigation. Panels C and D report analogous supplier-year results following Section 3.3.1. Overall, the results confirm that the observed adjustments in customer reliance are driven by upstream patent litigation.

6 Conclusions

The input–output linkages in vertical supply chains encompass not only the transfer of raw materials and intermediate goods, but also the diffusion of technology and knowledge. However, there is limited micro-level evidence on how technology risks affect supply-chain stability and propagate along supply chains. In this paper, we study the effects of external technology vulnerabilities on the fragility and flexibility of downstream supply chains. Specifically, we use upstream patent

litigation as an idiosyncratic shock that captures a source of technology vulnerability.

We find that upstream technology vulnerability reduces downstream reliance on affected suppliers. This fragility arises from legal risks associated with contested technologies and heightened delivery uncertainty. While such shocks weaken supply-chain relationships, they also induce greater independent innovation by downstream firms. In response to disruptions in upstream technology supply, customer firms increase investment in in-house R&D and innovative human capital, file more patent applications in litigation-exposed technology domains, and accelerate new product introductions. These responses are consistent with an expansion of firm scope, suggesting that firms substitute internal innovation for external sourcing when faced with technology-related supply disruptions, with implications for theories of firm boundaries and vertical integration.

Amid the ongoing debate over the reform of the U.S. patent system, this paper highlights the economic consequences of patent litigation along the supply chain. Our results demonstrate that upstream patent litigation can significantly disrupt vertical production networks, while subsequently fostering downstream innovations. These insights contribute to the broader discourse on patent litigation reform by providing policymakers with a nuanced understanding of the negative and positive spillover effects such reforms may have on supply chains. In addition, Antill et al. (2025) finds that defendant-friendly reforms enhance both innovation and social welfare in model calibration. Our empirical results complement Antill et al. (2025)'s theoretical predictions by providing additional empirical micro-level evidence from a different perspective, suggesting that a defendant-friendly patent system can also play a pivotal role in preserving supply-chain stability.

References

Acemoglu, D., U. Akcigit, and W. Kerr. 2016a. Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual* 30:273–335.

Acemoglu, D., U. Akcigit, and W. R. Kerr. 2016b. Innovation network. *Proceedings of the National Academy of Sciences* 113:11483–8.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi. 2012. The network origins of aggregate fluctuations. *Econometrica* 80:1977–2016.

Acharya, V. V., M. Crosignani, T. Eisert, and C. Eufinger. 2025. How do supply shocks to inflation generalize? evidence from the pandemic era in europe. Working Paper, National Bureau of Economic Research.

Acikalin, U., T. Caskurlu, G. Hoberg, and G. M. Phillips. 2025. Intellectual property protection lost and competition: An examination using large language models. *Available at SSRN 4023622* .

Agarwal, S., P. Ghosh, J. Li, and T. Ruan. 2024. Digital payments and consumption: Evidence from the 2016 demonetization in india. *Review of Financial Studies* 37:2550–85.

Agca, S., V. Babich, J. R. Birge, and J. Wu. 2022. Credit shock propagation along supply chains: Evidence from the cds market. *Management Science* 68:6506–38.

Angrist, J. D., and J.-S. Pischke. 2009. *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Antill, S., M. A. Celik, X. Tian, and T. M. Whited. 2025. The efficiency of patent litigation. *Available at SSRN 4842424* .

Appel, I., J. Farre-Mensa, and E. Simintzi. 2019. Patent trolls and startup employment. *Journal of Financial Economics* 133:708–25.

Baker, A. C., D. F. Larcker, and C. C. Wang. 2022. How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144:370–95.

Banerjee, S., S. Dasgupta, and Y. Kim. 2008. Buyer–supplier relationships and the stakeholder theory of capital structure. *The Journal of Finance* 63:2507–52.

Barrot, J.-N., and J. Sauvagnat. 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics* 131:1543–92.

Bena, J., and K. Li. 2014. Corporate innovations and mergers and acquisitions. *The Journal of Finance* 69:1923–60.

Bessen, J., and M. J. Meurer. 2012. The private costs of patent litigation. *JL Econ. & Pol'y* 9:59–.

Bloom, N., M. Schankerman, and J. Van Reenen. 2013. Identifying technology spillovers and product market rivalry. *Econometrica* 81:1347–93.

Caliendo, M., and S. Kopeinig. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22:31–72.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi. 2021. Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics* 136:1255–321.

Caskurlu, T. 2019. Effects of patent rights on acquisitions and small firm r&d. *Available at SSRN 2427191* .

Cassiman, B., and R. Veugelers. 2006. In search of complementarity in innovation strategy: Internal r&d and external knowledge acquisition. *Management Science* 52:68–82.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer. 2019. The effect of minimum wages on low-wage jobs. *Quarterly Journal of Economics* 134:1405–54.

Chen, C., S. Dasgupta, T. D. Huynh, and Y. Xia. 2023. Product market competition and corporate relocations: Evidence from the supply chain. *Management Science* 69:5147–73.

Chen, J., and J. Roth. 2024. Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics* 139:891–936.

Chen, Y., L. Ma, J. Pittman, and X. Yang. 2025. Penny wise and pound foolish: Does striving to meet earnings expectations by manipulating real activities trigger product recalls? *Management Science* 71:3405–27.

Chu, Y., X. Tian, and W. Wang. 2019. Corporate innovation along the supply chain. *Management Science* 65:2445–66.

Cohen, L., U. G. Gurun, and S. D. Kominers. 2019. Patent trolls: Evidence from targeted firms. *Management Science* 65:5461–86.

Cohen, W. M., D. A. Levinthal, et al. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative science quarterly* 35:128–52.

Cohn, J. B., Z. Liu, and M. I. Wardlaw. 2022. Count (and count-like) data in finance. *Journal of Financial Economics* 146:529–51.

Costello, A. M. 2020. Credit market disruptions and liquidity spillover effects in the supply chain. *Journal of Political Economy* 128:3434–68.

Dai, R., H. Liang, and L. Ng. 2021. Socially responsible corporate customers. *Journal of Financial Economics* 142:598–626.

Dasgupta, S., K. Zhang, and C. Zhu. 2021. Do social connections mitigate hold-up and facilitate cooperation? evidence from supply chain relationships. *Journal of Financial and Quantitative Analysis* 56:1679–712.

De Chaisemartin, C., and X. d'Haultfoeuille. 2018. Fuzzy differences-in-differences. *The Review of Economic Studies* 85:999–1028.

Duflo, E. 2001. Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American Economic Review* 91:795–813.

Dyer, J. H., and H. Singh. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *Academy of Management Review* 23:660–79.

Elliott, M., B. Golub, and M. V. Leduc. 2022. Supply network formation and fragility. *American Economic Review* 112:2701–47.

Emery, L. P., and M. Woeppel. 2025. Patent thickets and mergers and acquisitions. *Available at SSRN 4249384* .

Fee, C. E., C. J. Hadlock, and S. Thomas. 2006. Corporate equity ownership and the governance of product market relationships. *The Journal of Finance* 61:1217–51.

Grossman, S. J., and O. D. Hart. 1986. The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of Political Economy* 94:691–719.

Hall, B. H., and J. Lerner. 2010. The financing of r&d and innovation. In B. H. Hall and N. Rosenberg, eds., *Handbook of the Economics of Innovation*, vol. 1, 609–39. Elsevier.

Han, P., W. Jiang, and D. Mei. 2024. Mapping us–china technology decoupling: policies, innovation, and firm performance. *Management Science* 70:8386–413.

Hart, O., and J. Moore. 1990. Property rights and the nature of the firm. *Journal of Political Economy* 98:1119–58.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting anomalies: An investment approach. *The Review of Financial Studies* 28:650–705.

Jaffe, A. B. 1986. Technological opportunity and spillovers of r&d: Evidence from firms' patents, profits, and market value. *American Economic Review* 76:984–1001.

Jaffe, A. B., and J. Lerner. 2011. *Innovation and its discontents: How our broken patent system is endangering innovation and progress, and what to do about it.* Princeton University Press.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* 132:665–712.

Lemley, M. A., and A. D. Melamed. 2013. Missing the forest for the trolls. *Colum. L. Rev.* 113:2117–.

Lex Machina. 2024. Patent litigation report of 2024.

———. 2025. Patent litigation report of 2025.

Li, K., and J. Wang. 2023. Inter-firm inventor collaboration and path-breaking innovation: Evidence from inventor teams post-merger. *Journal of Financial and Quantitative Analysis* 58:1144–71.

Marx, M., D. Strumsky, and L. Fleming. 2009. Mobility, skills, and the michigan non-compete experiment. *Management Science* 55:875–89.

Meurer, M. J. 2017. Allocating patent litigation risk across the supply chain. *Tex. Intell. Prop. LJ* 25:251–76.

Mezzanotti, F. 2021. Roadblock to innovation: The role of patent litigation in corporate r&d. *Management Science* 67:7362–90.

Michaely, R., Y. Xie, and B. Zhang. 2025. Sue and acquire: Evidence from patent lawsuits. *Available at SSRN 4381547* .

Pankratz, N. M., and C. M. Schiller. 2024. Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies* 37:1729–77.

Petersen, M. A. 2008. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of financial studies* 22:435–80.

Qian, X., and S. Qiu. 2023. Political risk and corporate international supply chain. *Journal of International Money and Finance* 137:102899–.

Roberts, M. R., and T. M. Whited. 2013. Endogeneity in empirical corporate finance1. In *Handbook of the Economics of Finance*, vol. 2, 493–572. Elsevier.

Roth, J., P. H. Sant'Anna, A. Bilinski, and J. Poe. 2023. What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics* 235:2218–44.

Snyder, L. V., Z. Atan, P. Peng, Y. Rong, A. J. Schmitt, and B. Sinsoysal. 2016. Or/ms models for supply chain disruptions: A review. *IIE Transactions* 48:89–109.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research policy* 15:285–305.

Tian, X., and C. Zhang. 2025. Diffusion of technological innovation along the supply chain. *Available at SSRN 5198889* .

Tucker, C. E. 2014. Patent trolls and technology diffusion: The case of medical imaging. *Available at SSRN 1976593* .

Williamson, O. E. 1981. The economics of organization: The transaction cost approach. *American Journal of Sociology* 87:548–77.

———. 1985. Assessing contract. *The Journal of Law, Economics, and Organization* 1:177–208.

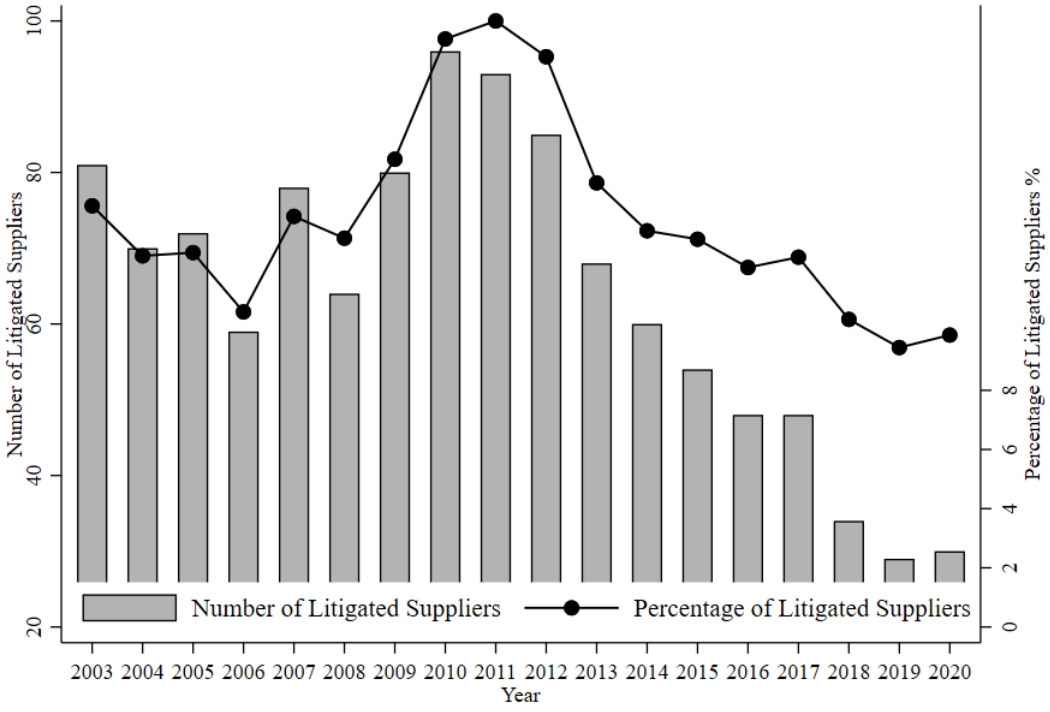
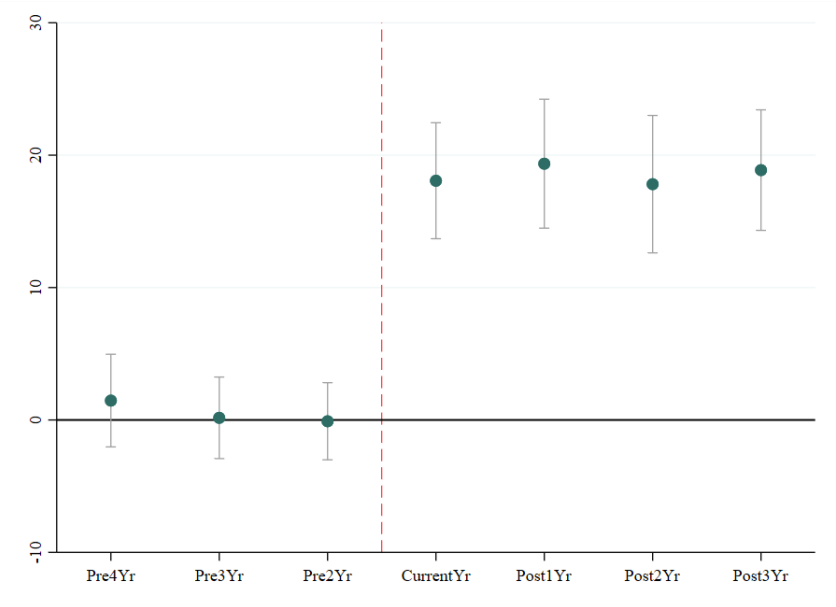
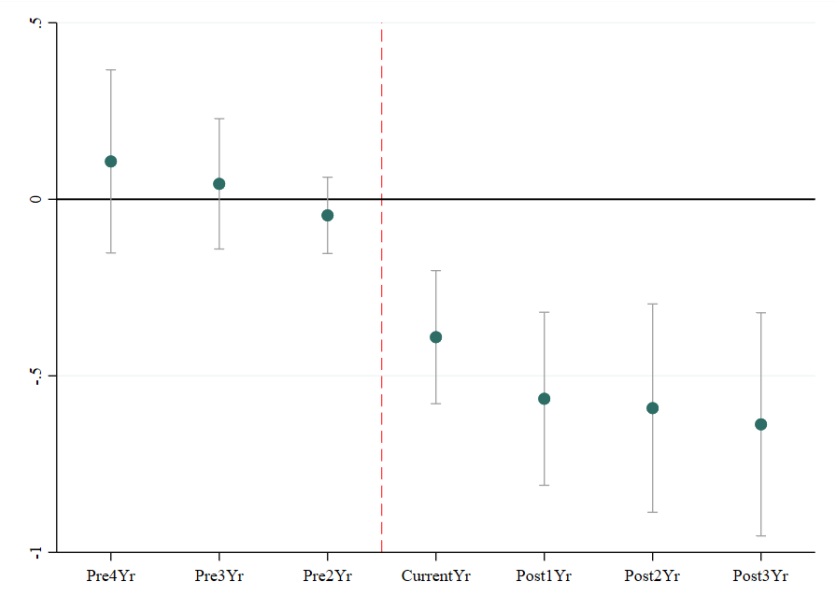


Figure 1. Distribution of Litigated Suppliers over Time. This figure plots the annual number of suppliers involved in patent litigation as defendants and their share among all suppliers. The litigation share (*Percentage of Sued Suppliers*) is defined as the fraction of unique suppliers named as defendants in patent lawsuits relative to the total number of unique suppliers in a given year.



Panel A. 1(Last Rel.Year)



Panel B. CustomerNum

Figure 2. Event-Study Evidence on Supply-Chain Outcomes. This figure presents the dynamic effects of upstream patent litigation on supply-chain outcomes based on the event-study specification in Equation 3. Panel A reports estimates for $1(Last\ Rel.Year)$, an indicator equal to 100 if any downstream customer relationship terminates in the following year, and zero otherwise. Panel B reports estimates for $CustomerNum$, defined as the number of a supplier's major listed customers in the subsequent year. The regressions use the same sample and supplier-level controls as in Table 4, and include supplier state × year and supplier industry × year fixed effects. Coefficients are plotted with 10% confidence intervals.

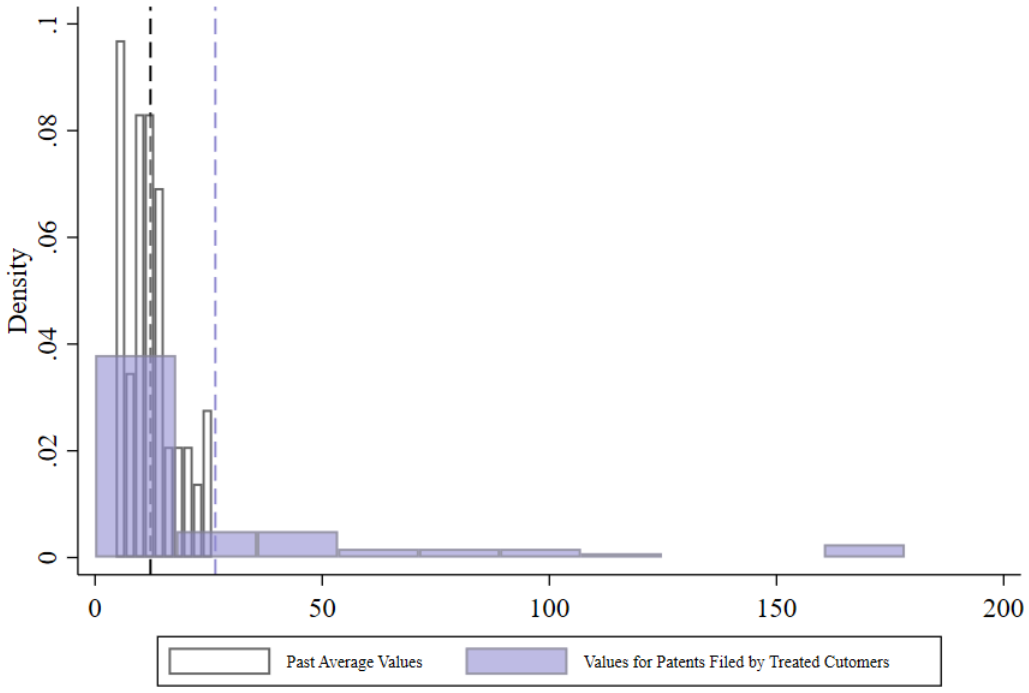
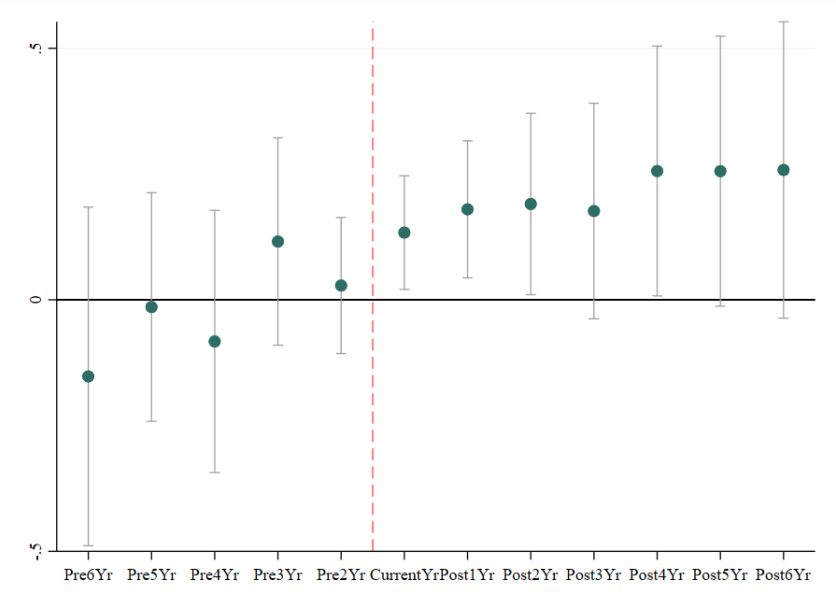
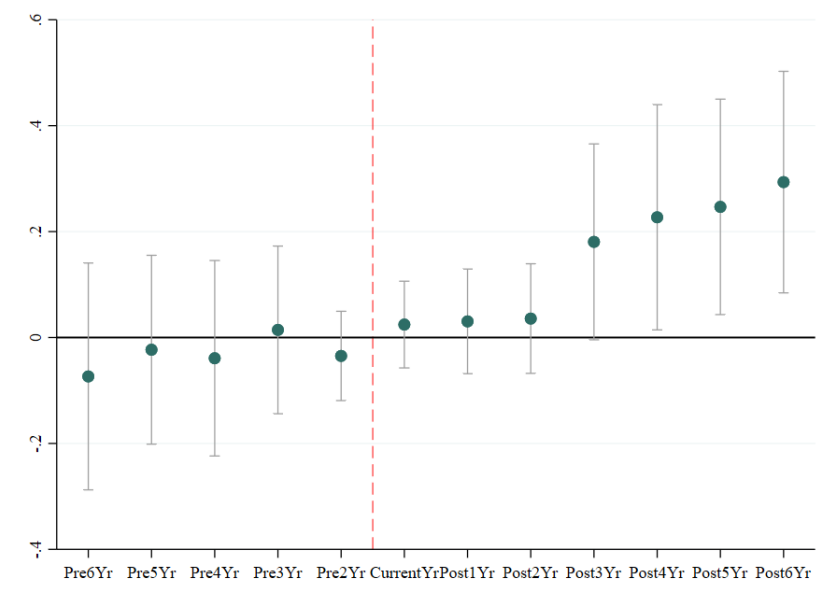


Figure 3. Distribution of Patent Values in Litigation-Exposed CPC Classes. This figure compares the distribution of real economic values of patent applications filed by treated customers in litigation-exposed CPC classes in the year following upstream patent litigation (purple) to the baseline distribution computed as the three-year average prior to the litigation year (white). The economic values of patents are measured following Kogan et al. (2017) and expressed in millions of U.S. dollars. Dashed lines indicate the mean of each distribution. Litigation-exposed CPC classes refer to technology classes directly affected by upstream patent disputes. Treated customers are defined as downstream firms with at least one supplier involved in patent litigation as defendants.



Panel A. Ln(1 + R&D)



Panel B. # of Total Products

Figure 4. Event-Study Evidence on Downstream Innovation Outcomes. This figure presents the dynamic effects of upstream patent litigation on downstream firm innovation using the event-study specification in Equation 5. Panel A reports estimates for $Ln(1 + R\&D)$, the logarithm of one plus R&D investment. Panel B reports estimates for $\#\ of\ Total\ Products$, the total number of products. The regressions use the PSM-matched customer sample described in Section 4.4 and customer-level controls as in Table 8, and include customer industry × year fixed effects. Coefficients are plotted with 10% confidence intervals.

Table 1. Sample Formation and Summary Statistics

Table 1 reports the formation of the baseline sample and summary statistics. Panel A describes the sample formation procedure. We exclude supplier–customer pairs in which the supplier's patent litigation falls outside the duration of the relationship, as well as pairs involving firms in the financial or utility industries. Panel B presents summary statistics for supplier, customer, and pair-level characteristics. $1(Last\ Rel.Year)$ equals one if the relationship terminates in the following year and zero otherwise, and is multiplied by 100 for ease of interpretation. $Tech_Dependence$ measures the customer's reliance on the supplier's technology, and $Tech_Proximity$ captures the technological similarity between the pair. Variable definitions are provided in Appendix IA3.1.

Panel A. Sample Formation

Procedures	# of observations	# of firms
All pairs in *Compustat Segments Customer* from 1976 to 2022	86,692 pair-year	
(1) Matching with *USPTO-Patent Litigation Docket Reports*	86,692 pair-year	
(2) Matching with Financial Information in *Compustat*	86,692 pair-year	
(3) Excluding pairs in which the supplier's litigation occurs outside the tenure of the supply chain relationship	78,295 pair-year	
(4) After restricting the sample after 2000	53,900 pair-year	
(5) After removing firms in Finance or Utility industry	39,397 pair-year	
(6) After the Propensity Score Matching (PSM)	29,490 pair-year	
Final sample after requiring that the necessary data be available for all test variables	25,040 pair-year	759 Suppliers; 672 Customers

(Continued on next page)

Panel B. Summary Statistics

Variable	N	Mean	Std	P25	Median	P75
Supplier Characteristics						
Asset($billions)	25,040	3.05	7.60	0.20	0.65	2.10
ROA	25,040	-0.02	0.18	-0.05	0.04	0.07
SaleGRW	25,040	0.11	0.35	-0.06	0.07	0.21
Cash	25,040	0.16	0.16	0.05	0.12	0.23
B/M	25,040	0.59	0.42	0.29	0.50	0.76
LEV	25,040	0.45	0.23	0.25	0.43	0.62
PPE	25,040	0.36	0.28	0.16	0.29	0.47
R&D	25,040	0.08	0.11	0.01	0.04	0.11
InnovAge	25,040	8.46	8.14	2.96	5.25	11.37
IssueNum	25,040	59.50	115.68	1.00	8.00	44.00
Customer Characteristics						
Asset($billions)	23,995	84.74	108.98	12.45	42.55	120.22
ROA	23,989	0.05	0.09	0.02	0.05	0.09
SaleGRW	23,839	0.06	0.16	-0.01	0.05	0.12
Cash	23,171	0.10	0.08	0.04	0.08	0.13
B/M	22,484	0.47	0.35	0.24	0.37	0.61
LEV	23,991	0.64	0.24	0.48	0.62	0.78
PPE	23,957	0.52	0.37	0.23	0.41	0.77
Pair Characteristics						
1(Last Rel.Year)	25,040	13.11	33.75	0.00	0.00	0.00
Length	25,040	14.01	9.39	7.00	12.00	20.00
Sales	14,474	0.59	1.48	0.02	0.07	0.37
Tech_Dependence	25,040	0.32	0.34	0.00	0.19	0.61
Tech_Proximity	25,040	0.00	0.02	0.00	0.00	0.00

Table 2. Summary Statistics for Litigation Sample

Table 2 reports summary statistics on patent litigation. Panel A presents the annual distribution of suppliers involved in litigation as defendants, including the number of litigated supplier–customer pairs (suppliers), the total number of pairs (suppliers), and the corresponding share each year. Panel B summarizes litigation-related variables. We focus on the first litigation event in which a supplier is named as a defendant. *LitPatNum* (*LitPatRatio*) measures the number (fraction) of a supplier's patents involved in litigation in a given year. *LitDuration* captures the average case length, and *LitDocument* measures the average number of case filings; both are constructed at the supplier–year level.

Panel A. Litigation Distribution Across Years

Year	# of litigated pairs	# of pairs	% of litigated pairs	# of litigated suppliers	# of suppliers	% of litigated suppliers
2003	147	892	16.48%	81	569	14.24%
2004	108	879	12.29%	70	558	12.54%
2005	122	917	13.30%	72	569	12.65%
2006	84	902	9.31%	59	554	10.65%
2007	111	925	12.00%	78	562	13.88%
2008	98	810	12.10%	64	487	13.14%
2009	118	876	13.47%	80	506	15.81%
2010	156	873	17.87%	96	483	19.88%
2011	151	854	17.68%	93	454	20.48%
2012	152	851	17.86%	85	441	19.27%
2013	120	859	13.97%	68	453	15.01%
2014	85	857	9.92%	60	448	13.39%
2015	79	771	10.25%	54	412	13.11%
2016	64	716	8.94%	48	395	12.15%
2017	69	718	9.61%	48	384	12.50%
2018	58	605	9.59%	34	327	10.40%
2019	52	552	9.42%	29	307	9.45%
2020	50	546	9.16%	30	304	9.87%
Total	**1,824**	**14,403**	**12.40%**	**1,149**	**8,213**	**13.80%**

Panel B. Summary Statistics for Litigation-Related Variables

Variable	N	Mean	Std	P25	Median	P75
LitDuration	1,149	545.45	540.02	186.00	389.00	735.00
LitDocument	1,149	459.62	935.57	44.00	136.00	423.00

Table 3. Patent Litigation and Relationship Reliance

Table 3 reports estimates of the effects of patent litigation on supply chain outcomes. The unit of observation is supplier–customer pair × year. The dependent variable, 1(*Last Rel.Year*), equals 100 if the relationship terminates in the following year and zero otherwise. 1(*Litigation*) equals one for firms that are involved in patent litigation as defendants during the sample period (treatment group), and zero otherwise. The interaction term 1(*Litigation*) × *Post* equals one for treated suppliers in years after becoming involved in patent litigation. Columns (4)–(6) exclude observations in which customers operate in the retail or wholesale sectors. All specifications include supplier-level controls fixed at the year prior to the litigation as described in Section 3.1. To mitigate concerns about bad controls and selection, we implement propensity score matching by pairing each sued supplier with observationally similar non-sued suppliers in the same litigation year (see Section 2.4). The event year is defined as the first year in which a treated supplier is sued; matched control firms are assigned the same event year as their treated counterparts. The sample period is 2000–2022. All regressions include supplier industry, supplier state and year fixed effects. We further include event year and customer fixed effects in Columns (1)-(2), (4)-(5), and include event year × customer fixed effects in Columns (3) and (6). Standard errors are clustered at the pair level.Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Dep.Var	1(Last Rel.Year)					
	All Sample			Exclude Customers in the Retail or Wholesale Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Litigation) × Post	9.38***	9.37***	8.16***	10.08***	9.81***	8.26***
	(0.96)	(0.94)	(1.22)	(1.23)	(1.23)	(1.63)
1(Litigation)	-13.99***	-13.71***	-13.35***	-16.06***	-15.77***	-15.53***
	(0.87)	(0.89)	(1.35)	(1.21)	(1.24)	(2.24)
Ln(Asset)		-0.03	-0.02		0.66	1.10
		(0.32)	(0.46)		(0.44)	(0.71)
ROA		0.47	4.80		0.21	2.88
		(2.22)	(3.38)		(3.06)	(5.43)
SaleGrw		-1.95**	-0.40		-1.61	0.69
		(0.80)	(1.48)		(1.02)	(2.28)
Cash		4.75**	7.90*		2.04	7.04
		(2.33)	(4.51)		(2.72)	(6.14)
B/M		0.83	2.67*		1.42	3.26*
		(0.81)	(1.47)		(0.87)	(1.90)
LEV		-1.61	1.95		-3.49	-3.40
		(1.72)	(2.66)		(2.16)	(3.95)
PPE		1.87	-1.47		2.74	1.35
		(1.53)	(2.46)		(1.95)	(3.29)
R&D		6.01	11.23		9.86*	13.44
		(4.37)	(6.87)		(5.79)	(11.96)
InnovAge		-0.05	0.04		-0.09	-0.03
		(0.05)	(0.08)		(0.07)	(0.12)
IssueNum		-0.02***	-0.02***		-0.02***	-0.02**
		(0.00)	(0.01)		(0.00)	(0.01)
Year FE	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y
Supplier State FE	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	N	Y	Y	N
Customer FE	Y	Y	N	Y	Y	N
Event × Customer FE	N	N	Y	N	N	Y
Observations	25,040	25,040	25,040	18,588	18,588	18,588
Adjusted R^2	0.16	0.17	0.20	0.18	0.19	0.23

Table 4. Identification Strategy: Event Study

Table 4 reports estimates of the effects of patent litigation on supply chain outcomes from the supplier perspective, where we aggregate outcomes to the supplier level and the unit of observation is supplier × year. In Columns (1) and (2), the dependent variable, $1(Last\ Rel.Year)$, equals 100 if any of the supplier's downstream relationships terminate in the following year, and zero otherwise. In Columns (3) and (4), the dependent variable, $CustomerNum$, measures the number of a supplier's major listed customers in the subsequent year. As a robustness check, we construct $SalesRatio$ as the ratio of next year's total sales from major customers to total assets in Appendix IA4.3. $1(Litigation)$ and $1(Litigation) \times Post$ are as defined in Table 3. All regressions include the same set of control variables as in Table 3. The sample period is 2000–2022. We estimate a staggered difference-in-differences specification using the matched sample described in Section 2.4. All regressions include supplier state × year and supplier industry × year fixed effects. Columns (2) and (4) further include supplier firm fixed effects. Standard errors are clustered at the supplier firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Dep.Var:	1(Last Rel.Year)		CustomerNum	
	(1)	(2)	(3)	(4)
1(Litigation) × Post	18.31***	14.74***	-0.55***	-0.42***
	(1.84)	(2.58)	(0.18)	(0.16)
1(Litigation)	-22.16***		0.24	
	(1.47)		(0.17)	
Ln(Asset)	-0.95	-3.55	0.06	0.16
	(0.68)	(3.11)	(0.06)	(0.11)
ROA	-1.66	0.32	0.25	-0.04
	(5.26)	(6.74)	(0.30)	(0.18)
SaleGRW	1.82	1.00	0.05	0.03
	(2.23)	(2.41)	(0.06)	(0.04)
Cash	2.98	8.24	0.40	0.42*
	(5.86)	(8.72)	(0.38)	(0.24)
B/M	5.45***	7.55***	0.11	-0.15*
	(1.95)	(2.75)	(0.12)	(0.08)
LEV	2.45	4.49	0.91**	0.10
	(4.47)	(7.41)	(0.37)	(0.31)
PPE	0.66	-7.11	0.07	-0.49
	(3.40)	(10.48)	(0.37)	(0.35)
R&D	4.75	-0.16	-0.01	-0.32
	(10.35)	(20.62)	(0.64)	(0.51)
InnovAge	-0.09	3.02***	0.02	-0.01
	(0.12)	(0.86)	(0.02)	(0.04)
IssueNum	-0.02*	0.00	-0.00**	-0.00*
	(0.01)	(0.02)	(0.00)	(0.00)
State × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
Firm FE	N	Y	N	Y
Observations	6,328	6,284	6,328	6,284
Adjusted R^2	0.21	0.34	0.18	0.77

Table 5. Identification Strategy: Quasi-Natural Experiments

Table 5 reports the identification results based on the staggered adoption of state-level anti-troll litigation laws and supplier-level case reversals. In Panel A, we estimate the instrumental difference-in-differences specification using the introduction of state anti-troll laws based on a matched sample. $1(Litigation)$ and $1(Litigation) \times Post$ are as defined in Table 3. The independent variable in the first stage is $1(Litigation\ Law)$, an indicator equal to one if the state in which the firm is located has enacted the law by the current year. The second-stage independent variable is $\widehat{1(Litigation)} \times Post$, the fitted value from the first stage. The dependent variable in the second stage is $1(Last\ Rel.Year)$ that equals 100 if any of the supplier's downstream relationships terminate in the following year, and zero otherwise. We include state and industry × year fixed effects in the first stage, and include supplier state × year and supplier industry × year fixed effects in the second stage. Standard errors are clustered at the state level. Panel B exploits within-supplier variation in litigation outcomes within the treatment group. The treated sample consists of suppliers whose cases are resolved through voluntary dismissals by plaintiffs for reasons plausibly unrelated to downstream dependence, thereby mitigating litigation-induced technological risk. Each treated supplier is matched to control suppliers in the same filing year and Fama–French 12 industry, excluding cases with filing and resolution in the same year. We estimate difference-in-differences models over an event window of $[-4, 4]$ around the resolution year. The indicator $1(Reversal) \times Post$ equals one for treated suppliers after a voluntary dismissal, and zero otherwise. We include supplier state × year, supplier industry × year, supplier, and case-filing-year fixed effects. Standard errors are clustered at the supplier level. All regressions include the same control variables as in Table 3. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. State Anti-Troll Litigation Law		
Dep.Var:	1(Litigation) × Post	1(Last Rel.Year)
	(1)	(2)
1(Litigation Law)	-0.07**	
	(0.03)	
$\widehat{1(Litigation)} \times Post$		27.70*
		(14.54)
Supplier Controls	Y	Y
State FE	Y	N
Industry × Year FE	Y	N
Supplier State × Year FE	N	Y
Supplier Industry × Year FE	N	Y
F-statistic	221.92	
Observations	1,333	1,245
Adjusted R^2	0.41	0.13
Panel B. Litigation Case Reversal		
Dep.Var:	1(Last Rel.Year)	
	(1)	
1(Reversal) × Post	-18.89**	
	(8.25)	
Supplier Controls	Y	
State × Year FE	Y	
Industry × Year FE	Y	
Firm FE	Y	
Case Filing Year FE	Y	
Observations	1,051	
Adjusted R^2	0.42	

Table 6. Mechanism of Technology Legal Risk

Table 6 reports estimates of the effects of patent litigation on supply chain outcomes by focusing on the propagation of technology-related risk. The dependent variable, $1(Last\ Rel.Year)$, equals 100 if the relationship terminates in the following year and zero otherwise. $1(Litigation)$ and $1(Litigation) \times Post$ are as defined in Table 3. In Panel A, Columns (1) and (2) report subsample regressions based on whether the litigated patent falls within the supplier's core technology class. Columns (3) and (4) report subsample regressions based on patent economic value following Kogan et al. (2017), where the sample is split into high- and low-value groups based on the sample median. In Panel B, Columns (1) and (2) report results for customer firms with and without technological dependence on their suppliers, proxied by the customer's cross-citation ratio following Bena and Li (2014). Columns (3) and (4) report results for supply-chain pairs with and without positive technology proximity, constructed following Jaffe (1986) and Bena and Li (2014). We use the same matched baseline sample and include the same control variables as in Table 3. We include supplier industry, supplier state, year, and event year × customer fixed effects. Standard errors are clustered at the pair level. Statistical significance is evaluated using Fisher's combined probability test. In Panel C, we examine the patent litigation risk faced by customers following upstream litigation shock. The independent variable, $1(Litigation\ from\ supplier)$, equals one if any supplier of a customer firm is exposed to patent litigation in the current year. The dependent variable, $1(Litigation)$, equals one if the customer faces any patent litigation within four distinct time periods following the upstream litigation event. All regressions include customer firm controls and customer industry × year fixed effects. Standard errors are clustered at the customer firm level. The sample period is 2000–2022. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. The Importance of Litigated Patents

Dep. Var:	1(Last Rel.Year)			
	If Core Class		Economic Value	
	Yes	No	High	Low
	(1)	(2)	(3)	(4)
1(Litigation) × Post	7.13**	5.98**	12.79***	1.64
	(3.02)	(2.75)	(3.03)	(2.66)
Supplier Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Supplier State FE	Y	Y	Y	Y
Event × Customer FE	Y	Y	Y	Y
Diff		1.15		11.15***
P-value		=0.46		<0.01
Observations	4,361	3,228	4,377	4,281
Adjusted R^2	0.12	0.13	0.11	0.14

(Continued on next page)

Panel B. Technological Linkages Between Suppliers and Customers

Dep. Var:	1(Last Rel.Year)			
	Customer Cross-Citation Ratio (> 0)		Technology Proximity (> 0)	
	Yes	No	Yes	No
	(1)	(2)	(3)	(4)
1(Litigation) × Post	10.02***	5.47***	8.94***	5.02***
	(2.57)	(1.18)	(1.57)	(1.71)
Supplier Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Supplier State FE	Y	Y	Y	Y
Event × Customer FE	Y	Y	Y	Y
Diff		4.56***		3.93*
P-value		<0.01		=0.06
Observations	5,752	20,341	14,947	11,050
Adjusted R^2	0.20	0.14	0.15	0.17

Panel C. Effects on Customers' Future Litigation Risk

Dep. Var:	1(Litigation)			
	T	T - T+1	T - T+2	T - T+3
	(1)	(2)	(3)	(4)
1(Litigation from supplier)	0.17***	0.15***	0.13***	0.10**
	(0.03)	(0.03)	(0.03)	(0.03)
Customer Firm Controls	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y
Observations	8,732	8,482	8,239	7,977
Adjusted R^2	0.24	0.27	0.28	0.28

Table 7. Mechanism of Delivery Uncertainty

Table 7 reports estimates of the effects of patent litigation on supply chain outcomes, focusing on delivery uncertainty. In Panel A, we report results by litigation case characteristics. The dependent variable, $1(Last\ Rel.Year)$, equals 100 if the relationship terminates in the following year and zero otherwise. $1(Litigation)$ and $1(Litigation) \times Post$ are as defined in Table 3. Columns (1) and (2) report results separately for observations with above- and below-median average litigation duration (in days). Columns (3) and (4) report results separately for observations with above- and below-median numbers of document filings in litigation events. We use the same matched baseline sample and include the same control variables as in Table 3. All regressions include supplier industry, supplier state, year, and event year × customer fixed effects. Standard errors are clustered at the pair level. Statistical significance is evaluated using Fisher's combined probability test. In Panel B, we examine the effect of patent litigation on suppliers' product recalls using a difference-in-differences specification at the supplier-year level. $1(Litigation)$ and $1(Litigation) \times Post$ are defined as in Table 3. In Column (1), the dependent variable is $1(Product\ Recalls)$, which equals one if a supplier experiences any product recall in a given year and zero otherwise. In Column (2), the dependent variable is $\#\ of\ Product\ Recalls$, the number of product recalls by a supplier. We use the same matched sample and include the same control variables as in Table 4, along with supplier-state × year and supplier-industry × year fixed effects. The sample period is 2000–2022. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Case Characteristics

Dep. Var:	1(Last Rel.Year)			
	Case Duration		Case Complexity	
	Long	Short	High	Low
	(1)	(2)	(3)	(4)
1(Litigation) × Post	7.86***	6.24***	9.00***	5.85***
	(1.78)	(1.68)	(1.71)	(1.65)
Supplier Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Supplier State FE	Y	Y	Y	Y
Event × Customer FE	Y	Y	Y	Y
Diff		1.62		3.14**
P-value		=0.21		=0.04
Observations	12,616	11,898	12,202	12,380
Adjusted R^2	0.14	0.13	0.13	0.12

Panel B: Supplier's Product Recalls

Dep. Var:	1(Product Recalls)	# of Product Recalls
	(1)	(2)
1(Litigation) × Post	0.02**	0.05*
	(0.01)	(0.03)
1(Litigation)	0.01	0.02
	(0.01)	(0.01)
Supplier Firm Controls	Y	Y
State × Year FE	Y	Y
Industry × Year FE	Y	Y
Observations	9,796	9,796
Adjusted/Pseudo R^2	0.17	0.14

Table 8. Subsequent Customer's Innovation Inputs

Table 8 reports estimates of the effects of upstream patent litigation on customers' innovation investments. The independent variable, 1(*Exposed to Supplier Litigation*), equals one if a customer has at least one supplier that is subject to patent litigation and zero otherwise. 1(*Exposed to Supplier Litigation*) × *Post* equals one for treated customers in years after the exposure to upstream patent litigation. In Panel A, the dependent variable is $Ln(1+R\&D)$, the logarithm of one plus R&D investment. In Panel B, the dependent variable is *# of Total Inventors*, the total number of inventors. Customer controls include firm size, return on assets, sales growth, cash holdings, book-to-market ratio, leverage, property, plant, and equipment (PPE), R&D intensity, and an indicator for whether the firm is involved in patent litigation. Column (2) excludes observations in which customers operate in the retail or wholesale sectors. We estimate the difference-in-differences specification as in Equation 4. Panel B is estimated using a Poisson model. The sample period is 2000-2022. We include customer industry × year fixed effects. Standard errors are clustered at the customer level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. R&D Investment

Dep. Var:	Ln(1 + R&D)	
	All Sample	Exclude Customers in the Retail or Wholesale Industries
	(1)	(2)
1(Exposed to Supplier Litigation) × Post	0.24**	0.22*
	(0.12)	(0.12)
1(Exposed to Supplier Litigation)	0.03	0.07
	(0.18)	(0.17)
Customer Controls	Y	Y
Industry × Year FE	Y	N
Observations	5,262	5,027
Adjusted R^2	0.71	0.75

Panel B. Inventor Recruitment

Dep. Var:	# of Total Inventors	
	All Sample	Exclude Customers in the Retail or Wholesale Industries
	(1)	(2)
1(Exposed to Supplier Litigation) × Post	0.28**	0.29**
	(0.12)	(0.13)
1(Exposed to Supplier Litigation)	0.33**	0.32**
	(0.15)	(0.16)
Customer Controls	Y	Y
Industry × Year FE	Y	N
Observations	8,642	8,148
Pseudo R^2	0.81	0.82

Table 9. Subsequent Customer's Innovation Outputs

Table 9 reports estimates of the effects of upstream patent litigation on customers' innovation outcomes in CPC (Cooperative Patent Classification) technology classes (three-digit) directly affected by upstream litigation (hereafter, litigation-exposed CPC classes). In Panel A, the unit of observation is firm × year. $1(Exposed\ to\ Supplier\ Litigation)$ and $1(Exposed\ to\ Supplier\ Litigation) \times Post$ are as defined in Table 8. The dependent variable is the number of patent applications in litigation-exposed CPC classes. We estimate the difference-in-differences specification as in Equation 4 and use Poisson models for count outcomes. We use the same customer sample as in Table 8 and include customer industry × year fixed effects. In Panel B, the unit of observation is firm × technology-class × year. The sample includes treated customers only. $1(Litigation\ CPC) \times 1(Not\ Core\ CPC) \times Post$ equals one for observations in which the technology class corresponds to a litigation-exposed CPC class but is not the firm's core CPC class, in years after exposure to upstream patent litigation. $1(Litigation\ CPC) \times 1(Core\ CPC) \times Post$ and $1(Not\ Litigation\ CPC) \times 1(Core\ CPC) \times Post$ are defined analogously. A firm's core CPC class is defined as the class with the largest number of granted patents over the prior three years. We include customer industry, CPC three-digit class, and year fixed effects. We include customer controls as in Table 8. The sample period is 2000-2022. Standard errors are clustered at the customer level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Regression at the Firm × Year Level

Dep. Var:	# of Patent Application in Litigation-Exposed CPC	
	All Sample	Exclude Customers in the Retail or Wholesale Industries
	(1)	(2)
1(Exposed to Supplier Litigation) × Post	0.36*	0.36*
	(0.18)	(0.20)
1(Exposed to Supplier Litigation)	0.24	0.24
	(0.25)	(0.25)
Customer Controls	Y	Y
Industry × Year FE	Y	N
Observations	3,803	3,587
Pseudo R^2	0.67	0.68

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Panel B. Regression at the Firm × Technology Class × Year Level

Dep. Var:	# of Patent Applications	
	All Sample	Exclude Customers in the Retail or Wholesale Industries
	(1)	(2)
1(Litigation CPC) × 1(Not Core CPC) × Post	0.83***	0.81***
	(0.16)	(0.16)
1(Litigation CPC) × 1(Core CPC) × Post	1.40***	1.19***
	(0.19)	(0.20)
1(Not Litigation CPC) × 1(Core CPC) × Post	-1.14***	-1.14***
	(0.13)	(0.13)
Customer Controls	Y	Y
Industry FE	Y	Y
CPC Class FE	Y	Y
Year FE	Y	Y
Observations	11,5748	11,0678
Pseudo R^2	0.20	0.20

Table 10. Subsequent Customer's Product Market Performance

Table 10 reports estimates of the effects of upstream patent litigation on customers' product market outcomes. 1(*Exposed to Supplier Litigation*) and 1(*Exposed to Supplier Litigation*) × *Post* are as defined in Table 8. In Column (1), the dependent variable is 1(*New Products*), an indicator equal to one if the customer introduces a new product. In Column (2), the dependent variable is *# of Total Products*, the total number of products. In Panel B, we exclude observations in which customers operate in the retail or wholesale sectors. We estimate the difference-in-differences specification as in Equation 4. Column (2) is estimated using a Poisson model. We use the same customer sample and include the same control variables as in Table 8. We also include customer industry × year fixed effects. The sample period is 2000-2022. Standard errors are clustered at the customer firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All Sample

Dep. Var:	1(New Products)	# of Total Products
	(1)	(2)
1(Exposed to Supplier Litigation) × Post	0.03*	0.13**
	(0.02)	(0.06)
1(Exposed to Supplier Litigation)	-0.01	-0.04
	(0.01)	(0.07)
Customer Firm Controls	Y	Y
Industry × Year FE	Y	Y
Observations	8,732	6,829
Adjusted/Pseudo R^2	0.11	0.31

Panel B. Exclude Customers in the Retail or Wholesale Industries

Dep. Var:	1(New Products)	# of Total Products
	(1)	(2)
1(Exposed to Supplier Litigation) × Post	0.03*	0.15**
	(0.02)	(0.07)
1(Exposed to Supplier Litigation)	-0.01	-0.05
	(0.01)	(0.08)
Customer Firm Controls	Y	Y
Industry × Year FE	Y	Y
Observations	8,238	6,380
Adjusted/Pseudo R^2	0.10	0.33

Internet Appendix for

"From Fragility to Flexibility: How do Firms Respond to Upstream Technology Vulnerability?"

(Not to be published)

Table of Contents

IA1 Descriptive Evidence on Patent Litigation

IA1.1 Litigation Distribution across Industries A-2
IA1.2 Litigation Distribution across CPC Technology Classes A-3
IA1.3 Stock Price Dynamics of Treated Customers around Upstream Patent Litigation . A-4

IA2 Anecdotal Evidence

IA2.1 A Case Study of Patent Litigation A-6

IA3 Sample Construction and Variable Definition

IA3.1 Variable Definition A-7
IA3.2 Data Source and Sample Construction A-8
IA3.3 PSM Procedure and Validation A-10

IA4 Supplementary Analyses of Patent Litigation and Supply-Chain Fragility

IA4.1 Robustness Tests on Alternative Specifications and Samples A-11
IA4.2 Exclude Non-Practicing Entity (NPE) Effects A-13
IA4.3 Identification Strategy: Event Study A-14
IA4.4 Economic Consequences on Downstream Capital Market Pressure A-15
IA4.5 Consider the Claim Outcome A-16
IA4.6 All Litigation Events Sample A-17
IA4.7 Alternative Supply-Chain Data and Sample Construction A-18
IA4.8 Expand Definition of Treated Suppliers A-19
IA4.9 Alternative Litigation–Firm Linking Procedure A-20
IA4.10 Unmatched Sample Estimates A-21
IA4.11 Event-Study Evidence on Supply-Chain Outcomes Using Stacked DiD A-5
IA4.12 Analysis of All Types of Litigation A-22

IA5 Supplementary Analyses of Patent Litigation and Downstream Economic Outcomes

IA5.1 Customer Investments in Innovative Human Capital A-24
IA5.2 Customer Innovation Outcomes A-25
IA5.3 Robustness Tests Using a Matched Customer Sample A-26

IA6 Supplementary Analyses of Downstream Supply-Chain Adjustments

IA6.1 Downstream Supply-Chain Adjustments A-27

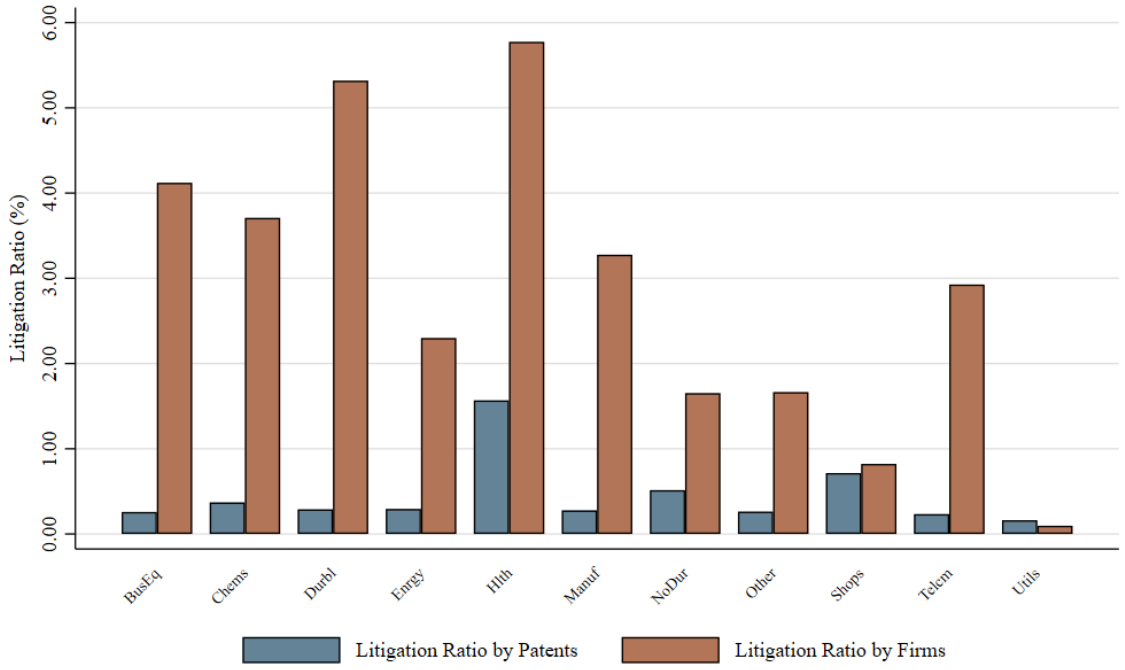
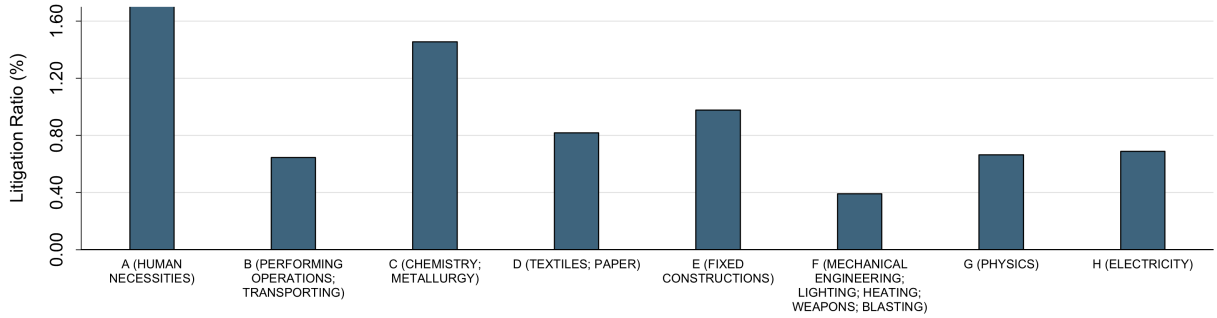
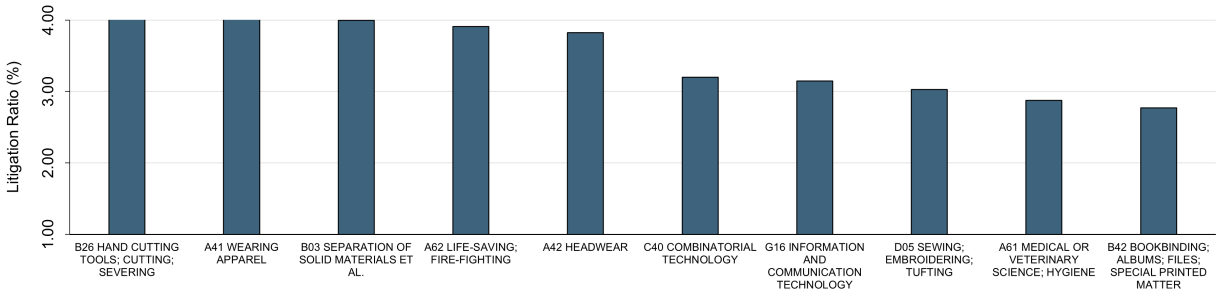


Figure IA1.1 Distribution of Patent Litigation across Industries from 2003 to 2020. *Litigation Ratio by Patents* is defined as the average annual fraction of granted patents that are involved in litigation within each industry over the period 2003–2020. *Litigation Ratio by Firms* is defined as the average annual fraction of firms named as defendants in patent litigation within each industry over the same period.



Panel A. CPC Section



Panel B. Top 10 CPC Class

Figure IA1.2 Distribution of Patent Litigation across CPC Classifications from 2003 to 2020. This figure reports the average annual litigation intensity across CPC classifications. It measures the fraction of litigated patents relative to total granted patents within each 2-digit CPC Section in Panel A and within each 3-digit CPC Class in Panel B over the period 2003–2020. Panel B reports the top ten CPC Classes ranked by litigation intensity.

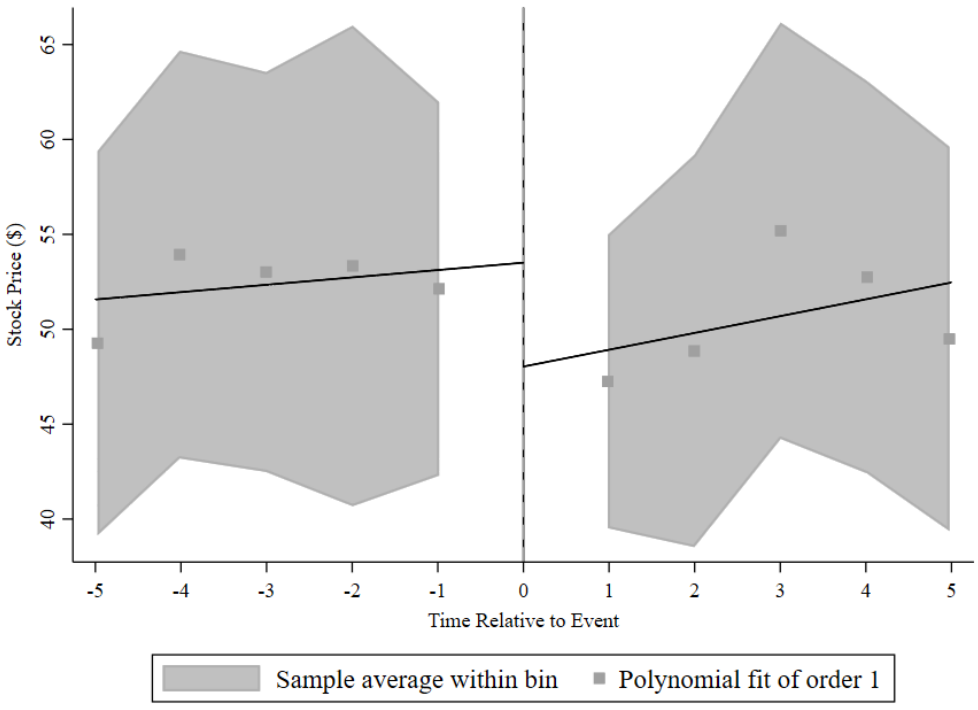
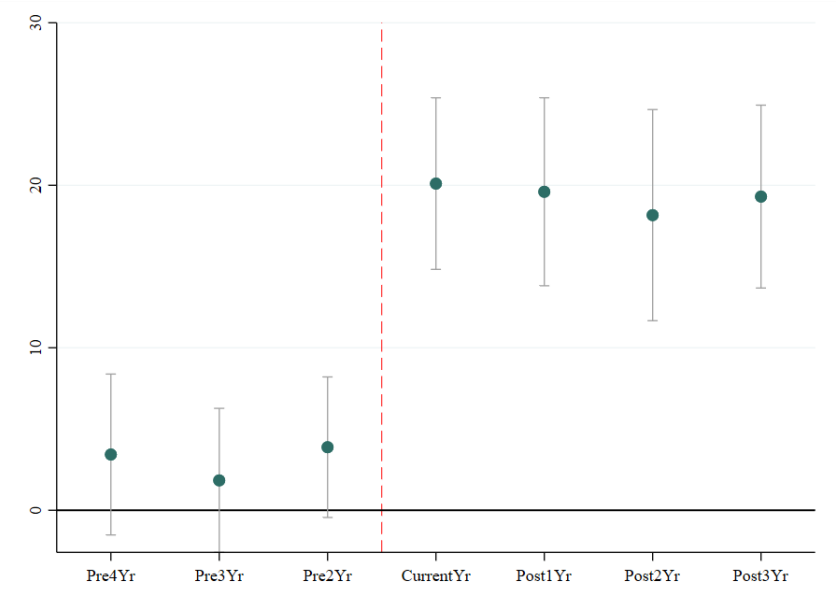
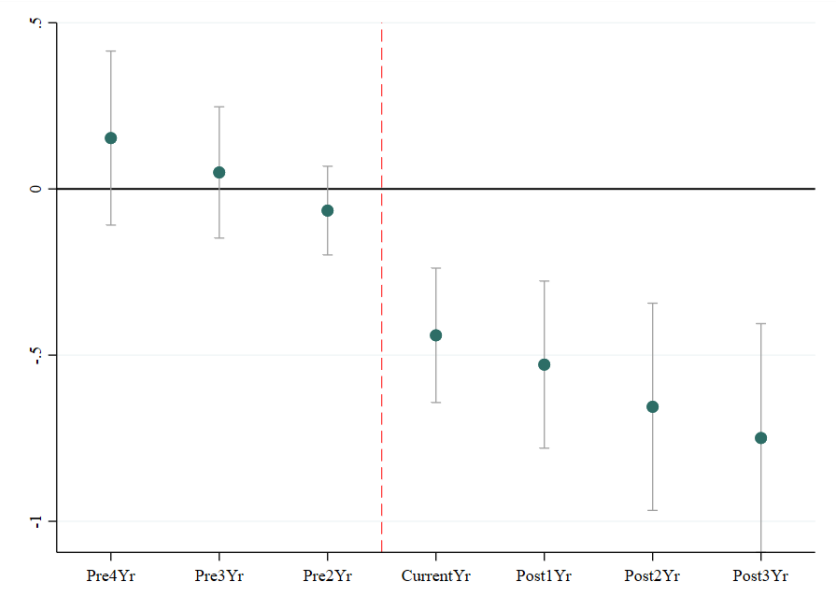


Figure IA1.3 Stock Price Dynamics of Treated Customers around Upstream Patent Litigation. This figure plots the average daily stock price of treated customer firms over the event window surrounding upstream patent litigation. Treated customers are defined as downstream firms connected to at least one supplier involved in patent litigation as defendants during the sample period. The x-axis denotes trading days relative to the litigation event, from -5 to $+5$, and the y-axis reports stock prices in U.S. dollars.



Panel A. 1(Last Rel.Year)



Panel B. CustomerNum

Figure IA1.4 Event-Study Evidence on Supply-Chain Outcomes Using Stacked DiD. This figure presents the dynamic effects of upstream patent litigation on supply-chain outcomes based on a stacked difference-in-differences specification. Panel A reports estimates for $1(Last\ Rel.Year)$, an indicator equal to 100 if any downstream customer relationship terminates in the following year, and zero otherwise. Panel B reports estimates for $CustomerNum$, defined as the number of major listed customers of a supplier in the following year. The regressions use the same supplier-level controls as in Table 4, and include supplier state × year, supplier industry × year, and cohort × year fixed effects. Coefficients are plotted with 10% confidence intervals.

Appendix IA2.1: A Case Study of the Patent Litigation

A prominent case that illustrates how upstream technology vulnerability can reshape downstream supply-chain relationships is the prolonged patent litigation between NTP Inc. and Research In Motion (RIM), the manufacturer of the BlackBerry device. Beginning in 2001, NTP accused RIM of infringing on its wireless email patents, triggering a legal battle that lasted nearly five years and threatened the operational continuity of RIM's flagship product line. The uncertainty was so severe that it culminated in a $612.5 million settlement paid by RIM to NTP in March 2006.

During the litigation, RIM's downstream customers that relied heavily on BlackBerry devices for real-time mobile communication faced significant uncertainty about the continued availability of the technology. This upstream vulnerability directly translated into downstream fragility in supplier-customer relationships. For example, Eugene Stein, Chief Knowledge and Technology Officer at White & Case LLP, noted after the dispute was settled: "I don't have to worry about whether there will be an interruption in BlackBerry technology." His remarks underscored the relief among customers who had been forced to account for the possibility of technology service disruption. Similarly, Sachin Mehta, CIO of Mercer Management Consulting, revealed that during the extended litigation period his firm considered switching to alternative suppliers such as Palm Inc., Good Technology Inc., and Nokia Corp. This illustrates how downstream firms exercised strategic flexibility, preparing contingency plans and evaluating substitutes to mitigate potential risks arising from supplier instability.

This case demonstrates the two-sided effect of upstream technology vulnerability emphasized in our study. On one hand, the uncertainty surrounding RIM's patent dispute weakened downstream customers' reliance on the supplier, amplifying fragility in the supply chain. On the other hand, it prompted customers to adopt more flexible strategic responses, including evaluating alternative suppliers and technologies. In line with our paper's broader argument, the NTP–RIM litigation case shows how patent disputes—an archetype of upstream technology vulnerability—do not remain confined to the defendant but cascade through the supply chain, shaping the behaviors and risk management strategies of downstream firms.

Appendix IA3.1: Variable Definition

This table defines the variables used in the empirical analysis. It includes measures of key independent and dependent variables, supplier and customer firm characteristics, pair-level variables, and patent-based metrics.

Variable	Definition
Dependent Variables at the Pair Level	
1(Last Rel.Year)	It equals one if a given supplier-customer relationship ends in the next year, and zero otherwise, multiplied by 100 for ease of interpretation.
Dependent Variables at the Supplier Level	
1(Last Rel.Year)	It equals one if any of the supplier's downstream relationships terminate in the following year, and zero otherwise, multiplied by 100.
CustomerNum	The number of a supplier's major customers in the next year.
SalesRatio	The ratio of next year's total sales from all major customers to total assets.
Firm Characteristics	
Ln(Asset)	The natural logarithm of a firm's total assets (in millions of U.S. dollars).
ROA	Income before extraordinary items divided by total assets.
SaleGRW	The annual growth rate of total sales.
Cash	Cash and cash equivalents divided by total assets.
B/M	Book equity divided by market equity, following Hou, Xue, and Zhang (2015).
LEV	Total liabilities divided by total assets.
PPE	Property, plant, and equipment divided by total assets.
R&D	Research and development expenditures divided by total assets.
InnovAge	The average age (in years) of a firm's patents, based on application years (restricted to post-1960 patents).
IssueNum	The number of patents granted to a firm over the past three years.
PatNum	The cumulative number of patents granted to a firm up to a given year.
Pair Characteristics	
Length	The duration (in years) of a supplier–customer relationship.
Sales	The annual transaction value between the supplier and the customer (in millions of U.S. dollars).
Tech_Dependence	The fraction of a customer's patents that cite the supplier's patents over the past three years, following Bena and Li (2014).
Tech_Proximity	The correlation of patent portfolios between the supplier and the customer, based on patent applications over the past three years, following Jaffe (1986) and Bena and Li (2014).
Litigation-Related Variables	
LitDuration	The average duration of litigation cases for a treated supplier in the event year.
LitDocument	The average number of case-related documents for a treated supplier in the event year.

Appendix IA3.2: Data Source and Sample Construction

1. Overview

Our sample construction relies on multiple data sources, each described in detail in the Internet Appendix together with the procedures used to construct the sample and key variables. Patent litigation data is obtained from the USPTO Patent Litigation Docket Reports Data, supplemented by the RPX database. Patent information comes from USPTO and the Kogan et al. dataset. Supply-chain data are drawn from the Compustat Customer Segment database and are further supplemented by FactSet Revere Supply Chain to provide a robustness sample. We first match the litigation data and the supply-chain data to CRSP–Compustat public firms separately, and then merge the two datasets using the firm identifier *GVKEY*.

2. Link UPSTO Litigation Docket Reports Data to CRSP-Compustat

The USPTO Patent Litigation Dataset, updated through March 2024, contains detailed information on 96,966 unique district court cases filed during 1963–2020. The dataset is developed and updated against the backdrop of intensive debates over patent litigation reform and the broader patent system. The dataset records all parties involved in each case, including U.S. public firms, private firms, universities, and individuals. For this study, we focus exclusively on U.S. public firms.
To identify litigation records of public firms from 2003 to 2020, we combine a patent-number-based linkage with a fuzzy name–matching procedure. The process consists of three main steps:

(a) **Name Standardization.** We first standardize the names of litigants and CRSP–Compustat firms to improve matching accuracy. This includes removing punctuation, corporate designations (e.g., "Inc." and "Corp."), and special characters.

(b) **Linkage through Patent Numbers.** Since the USPTO provides patent-level identifiers for litigation only from 2003 onward, we link litigated patents to the Kogan et al. dataset (updated through 2023), which covers all granted patents applied by U.S. public firms and uses CRSP *PERMNO* as the firm identifier. We then map *PERMNO* to *GVKEY* using the standard CRSP–Compustat link table. This approach ensures high precision but has two limitations. First, patents may have been reassigned to other entities after issuance, complicating the identification of the true litigant. To address this concern, we review the matches using fuzzy name–matching as an additional verification step. Second, because most patent holders are plaintiffs, relying solely on patent numbers tends to omit many defendants.

(c) **Name Fuzzy Matching.** For remaining litigants not linked through patent numbers, we perform fuzzy string matching on firm names. We retain only matches with a similarity score above 0.85 and manually verify them to ensure accuracy.

3. RPX Database

RPX Corporation has compiled a comprehensive dataset dating back to 1977, capturing from Public Access to Court Electronic Records (PACER) every lawsuit filed by more than 4,000 non-practicing entities (NPEs). The RPX data are systematic and professionally curated, and we use them to identify both case outcomes and NPE status. Case outcomes provide detailed information on the validity and enforceability of challenged patents, as well as the infringement determinations for the parties involved. RPX further reports district court resolutions, including *Plaintiff's Voluntary Dismissal*, *Jury Verdict*, *Likely Settlement*, *Summary Judgment*, *Transfer*, and related categories. NPE identification relies on a manual review conducted by experienced analysts with deep knowledge of the patent industry. This process involves Internet searches for evidence of operating activities or patent monetization, review

of complaints, assessment of outside counsel appearances, and examination of other public filings. The RPX NPE classifications have been used in prior research (e.g., Cohen, Gurun, and Kominers 2019). We link the RPX database to the USPTO Litigation Docket Reports via case numbers.

4. Supply-Chain Data

U.S. public firms are required to disclose all major customers—defined as those purchasing more than 10% of the firm's total sales—in their 10-K filings. These disclosures are compiled in the Compustat Customer Segment database, which is widely used in the literature to identify supply-chain networks. Each supply-chain record reports the supplier and customer names, the start and end dates of the relationship, and associated sales. We standardize firm names and apply a fuzzy-matching procedure to link suppliers and customers to U.S. public firms, following a methodology similar to that used to match USPTO Litigation Docket Reports to CRSP-Compustat. Following Fee, Hadlock, and Thomas (2006) and Barrot and Sauvagnat (2016), we treat firm S as a supplier to firm C in all years between the first and last year in which S reports C as a customer.

As a robustness check, we supplement the analysis with the FactSet Revere Supply Chain database, which covers global supply-chain relationships. We match supplier and customer firms in FactSet to CRSP-Compustat using *CUSIP* identifiers and the same fuzzy-matching procedure.

Appendix IA3.3: PSM Procedure and Validation

In the main causal analysis, we examine whether patent litigation faced by a supplier affects the ex-post supply-chain relationship between the supplier and its customers. To mitigate concerns about endogeneity, we construct a matched sample of litigated and non-litigated suppliers using the Propensity Score Matching model.

$$P(L_{i,t} = 1|X_{i,t}) = \Phi(X^k_{i,t} * \beta_k) + \varepsilon_{i,t}, \tag{7}$$

where i and t denote the supplier firm and year respectively, and L is an indicator equal to 1 if the supplier is involved in a patent lawsuit in year t. X is a vector of explanatory variables, $\Phi(\bullet)$ denotes the cumulative normal distribution function and ε is an i.i.d error term.

We use the filing date of the patent lawsuit as the treatment indicator and match the sample within each treatment year. Control firms are those that never experience patent litigation during the sample period. For the explanatory variables, we choose a series of supplier's firm characteristics which may endogenously affect the probability of litigation in the year before the lawsuit. They include *Ln(Asset)*, *ROA*, *SaleGRW*, *Cash*, *B/M*, *LEV*, *PPE*, *R&D*, *InnovAge*, and *IssueNum* of the supplier (detailed variables definitions are provided in Appendix IA3.1).

The PSM model is estimated for all sued and non-sued suppliers during the period from 2003 to 2020. We estimate the propensity score using a logit model. For each sued firm, we identify its three nearest neighbors in terms of the propensity score, stratifying the matches by treatment year. Balancing tests are conducted to assess match quality, as shown in Table IA3.3. After getting the PSM matching sample at the supplier-year level, we merge it with the original full pair-year sample to construct the PSM-matched sample at the pair-year level.

Table IA3.3. PSM Validation

	%bias		T-Value	
	Before	After	Before	After
Ln(Asset)	69.70	-7.30	42.73	-1.11
ROA	13.80	-1.50	7.10	-0.24
SaleGRW	-2.60	-2.00	-1.30	-0.29
Cash	-0.80	5.40	-0.49	0.82
B/M	-1.50	0.90	-0.73	0.14
LEV	-4.90	-5.20	-2.49	-0.79
PPE	-32.50	0.90	-17.89	0.15
R&D	-3.70	5.50	-1.99	0.84
InnovAge	3.80	-0.40	1.99	-0.06
IssueNum	30.10	2.60	17.93	0.42

Appendix IA4.1: Robustness Tests on Alternative Specifications and Samples

This table reports robustness tests for the estimates of the effects of patent litigation on supply-chain outcomes in Table 3. Panel A excludes litigation cases filed in the Eastern District of Texas and the District of Delaware. Panel B restricts the sample to supplier-year observations after the supplier's first patent application. Panel C reports estimates with two-way clustering at the pair and year levels. Panel D reports estimates using the Cox proportional hazards model. Panel E examines the effects on the share of sales between the supplier–customer pair relative to the supplier's total revenues in the subsequent year. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Exclude litigation in Texas and Delaware District Courts	
Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	6.88***
	(1.31)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	24,677
Adjusted R^2	0.13
Panel B. Suppliers Required to Have Applied for Patents	
Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	8.36***
	(1.23)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	24,238
Adjusted R^2	0.13

(Continued on next page)

Panel C. Double Std. Cluster at the Pair and Year Levels

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	8.16***
	(1.49)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	24,677
Adjusted R^2	0.13

Panel D. COX Proportional Hazards Model

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	0.43***
	(0.12)
Supplier Firm Controls	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	14,665

Panel E. Pair-Year Level Sales Growth

	(1)	(2)
1(Litigation) × Post	-11.43***	-10.95***
	(2.71)	(3.07)
Supplier Firm Controls	Y	Y
Year FE	Y	Y
Supplier Industry FE	Y	Y
Supplier State FE	Y	Y
Event FE	Y	N
Customer FE	Y	N
Event × Customer FE	N	Y
Observations	11,457	11,457
Adjusted R^2	0.13	0.14

Appendix IA4.2: Exclude Non-Practicing Entity (NPE) Effects

This table excludes observations involving non-practicing entities (NPEs) and re-estimates the effects of litigation shocks on supply-chain fragility, following Tables 3 and 4. NPEs are identified using the RPX database, which classifies entities based on manual review by industry experts. The RPX database is widely used in the literature (e.g., Cohen, Gurun, and Kominers (2019)). Panel A reports results at the pair-year level, and Panel B reports results at the supplier-year level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Examination at the Pair-Year Level

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	6.68***
	(1.44)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	16,128
Adjusted R^2	0.12

Panel B. Examination at the Supplier-Year Level

Dep. Var:	1(Last Rel.Year)	CustomerNum	SalesRatio
	(1)	(2)	(3)
1(Litigation) × Post	12.80***	-0.28***	-0.04**
	(3.10)	(0.08)	(0.02)
Firm Controls	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	3,984	3,984	2,693
Adjusted R^2	0.32	0.83	0.86

Appendix IA4.3: Identification Strategy: Event Study

This table extends the event study at the supplier-year level in Table 4 by incorporating one additional outcome variable *SalesRatio*, the ratio of next year's total sales from all major customers to total assets. All regressions include the same set of supplier controls as in Table 4. We include supplier state × year and supplier industry × year fixed effects in Column (1) and further add supplier firm fixed effects in Column (2). Standard errors are clustered at the supplier firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var:	SalesRatio	
	(1)	(2)
1(Litigation) × Post	0.01	-0.04***
	(0.02)	(0.01)
1(Litigation)	-0.03	
	(0.02)	
Ln(Asset)	-0.04***	-0.05***
	(0.01)	(0.02)
ROA	0.08**	0.01
	(0.04)	(0.03)
SaleGRW	0.01	0.02
	(0.01)	(0.01)
Cash	-0.06	-0.08**
	(0.05)	(0.03)
B/M	0.03	-0.01
	(0.02)	(0.02)
LEV	0.22***	0.05
	(0.05)	(0.03)
PPE	0.05	0.13**
	(0.04)	(0.06)
R&D	-0.02	-0.12
	(0.10)	(0.08)
InnovAge	0.00	0.00
	(0.00)	(0.00)
IssueNum	-0.00	0.00
	(0.00)	(0.00)
State × Year FE	Y	Y
Industry × Year FE	Y	Y
Firm FE	N	Y
Observations	4,170	4,219
Adjusted R^2	0.87	0.42

Appendix IA4.4: Economic Consequences on Downstream Capital Market Pressure

This table reports estimates of capital market responses of downstream customers to upstream patent litigation. We report cumulative abnormal returns (CARs) for treated customers around upstream litigation filing dates. Treated customers are defined as firms with at least one supplier that becomes subject to patent litigation during the sample period. For each event, we estimate the Fama-French three-factor model over the estimation window [-169, -20] and compute CARs over the event window [-5, +5]. Statistical significance is assessed using the Fisher sign test and the Wilcoxon signed-rank test. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

	Treated Customers Sample
Median cumulative abnormal return (in %)	-0.54
Median market loss (million USD)	97.52
Sample size	1,067
Number of negative	566**
Fisher Sign Test : p_value	=0.03
Wilcoxon Signed-Rank Test: p_value	=0.02

Appendix IA4.5: Consider the Claim Outcome

This table examines heterogeneity by litigation outcomes. We classify district court cases based on whether they result in a finding of product infringement or patent invalidity, which represent the two primary adjudicated outcomes in patent litigation. Case outcomes are obtained from the RPX database and manually verified. Both infringement and invalidity rulings resolve legal uncertainty and are expected to impose adverse consequences on defendants. We partition the treated sample based on litigation outcomes and re-estimate the effects of litigation shocks on supply-chain fragility as in Table 3. The indicator variable *AdverseOutcome* equals one if the treated supplier is subject to an adverse ruling (i.e., either infringement is found or the patent is invalidated), and zero otherwise. The complementary indicator *NonAdverseOutcome* is defined analogously. We then re-estimate the supply-chain fragility following litigation shocks as in Table 3. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × AdverseOutcome × Post	3.95*
	(2.35)
1(Litigation) × NonAdverseOutcome × Post	8.38***
	(1.24)
1(Litigation) × AdverseOutcome	-11.00***
	(2.78)
1(Litigation) × NonAdverseOutcome	-13.29***
	(1.39)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	24,677
Adjusted R^2	0.13

Appendix IA4.6: All Litigation Events Sample

This table extends the baseline specification, which focuses on the first litigation event for each supplier, by including all upstream patent litigation events that are at least five years apart. We then re-estimate the effects of litigation shocks on supply-chain fragility, following Tables 3 and 4. Panel A reports results at the pair-year level, and Panel B reports results at the supplier-year level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Examination at the Pair-Year Level

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	4.48***
	(1.09)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	39,679
Adjusted R^2	0.14

Panel B. Examination at the Supplier-Year Level

Dep. Var:	1(Last Rel.Year)	CustomerNum	SalesRatio
	(1)	(2)	(3)
1(Litigation) × Post	8.38***	-0.24***	-0.00
	(1.29)	(0.08)	(0.01)
Firm Controls	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	9,806	9,806	6,400
Adjusted R^2	0.33	0.73	0.83

Appendix IA4.7: Alternative Supply-Chain Data and Sample Construction

This table augments the baseline supply-chain sample from Compustat Customer Segment with the FactSet Revere Supply Chain dataset to broaden coverage of supplier–customer links. We merge the two datasets to construct the robustness sample and restrict both suppliers and customers to firms in the CRSP–Compustat universe. Then, we re-estimate the effects of litigation shocks on supply-chain fragility, following Tables 3 and 4. Panel A reports results at the pair-year level, and Panel B reports results at the supplier-year level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Examination at the Pair-Year Level

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	16.01***
	(0.99)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	101,112
Adjusted R^2	0.34

Panel B. Examination at the Supplier-Year Level

Dep. Var:	1(Last Rel.Year)	CustomerNum	SalesRatio
	(1)	(2)	(3)
1(Litigation) × Post	36.68***	-0.14**	-0.02*
	(1.96)	(0.07)	(0.01)
Firm Controls	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	12,297	12,297	4,882
Adjusted R^2	0.44	0.57	0.87

Appendix IA4.8: Expand Definition of Treated Suppliers

This table broadens the definition of treated suppliers to include all firms involved in defendant-related roles in patent litigation. Defendants include both initially named parties and counter-defendants added through counterclaims. Under this definition, all defendants are exposed to technology-related legal risk, as counterclaims frequently challenge patent validity and create potential invalidation risk. Then, we re-estimate the effects of litigation shocks on supply-chain fragility, following Tables 3 and 4. Panel A reports results at the pair-year level, and Panel B reports results at the supplier-year level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Examination at the Pair-Year Level

Dep.Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	9.92***
	(1.25)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	22,837
Adjusted R^2	0.14

Panel B. Examination at the Supplier-Year Level

Dep.Var:	1(Last Rel.Year)	CustomerNum	SalesRatio
	(1)	(2)	(3)
1(Litigation) × Post	11.37***	-0.33**	-0.01
	(2.47)	(0.15)	(0.01)
Firm Controls	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	6,035	6,035	4,130
Adjusted R^2	0.32	0.71	0.88

Appendix IA4.9: Alternative Litigation–Firm Linking Procedure

This table employs an alternative linking approach that starts from the USPTO *patents* file and maps litigation-involved patents to CRSP–Compustat firms using the patent database of Kogan et al. (2017). Because the *patents* file contains all patents asserted or challenged in a case, we further merge it with the *names* file to retain firms in defendant-related roles. This procedure yields a precisely defined sample of sued firms and allows identification of the specific patents under litigation. Then, we re-estimate the effects of litigation shocks on supply-chain fragility, following Tables 3 and 4. Panel A reports results at the pair-year level, and Panel B reports results at the supplier-year level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Examination at the Pair-Year Level

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	3.90**
	(1.85)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	5,807
Adjusted R^2	0.11

Panel B. Examination at the Supplier-Year Level

Dep. Var:	1(Last Rel.Year)	CustomerNum	SalesRatio
	(1)	(2)	(3)
1(Litigation) × Post	13.81***	-0.22	-0.05**
	(4.98)	(0.15)	(0.02)
Firm Controls	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	1,283	1,283	856
Adjusted R^2	0.20	0.64	0.73

Appendix IA4.10: Unmatched Sample Estimates

This table uses the unmatched sample to re-estimate the effects of litigation shocks on supply-chain fragility at the pair × year level. Supplier-level controls include firm size, return on assets, sales growth, cash holdings, book-to-market ratio, leverage, property, plant, and equipment (PPE), R&D intensity, innovation age, and the number of granted patents. Customer-level controls include firm size, return on assets, sales growth, cash holdings, book-to-market ratio, leverage, and PPE. Pair-level controls include relationship duration. All specifications include supplier industry × year fixed effects, supplier state × year fixed effects, and customer fixed effects. Column (2) additionally includes supplier fixed effects. Standard errors are clustered at the pair level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var	1(Last Rel.Year)	
	(1)	(2)
1(Litigation) × Post	6.08***	4.73***
	(1.32)	(0.64)
1(Litigation)	-7.85	
	(7.48)	
Supplier Firm Controls	Y	Y
Customer Firm Controls	Y	Y
Pair Control	Y	Y
Supplier Industry × Year FE	Y	Y
Supplier State × Year FE	Y	Y
Supplier Firm FE	N	Y
Customer Firm FE	Y	Y
Observations	14,998	17,731
Adjusted R^2	0.25	0.13

Appendix IA4.12: Analysis of All Types of Litigation

This table examines the effects of supplier litigation on downstream customers' reliance on supply-chain relationships and distinguishes between patent and non-patent litigation. We use the *Legal and Regulatory Litigation Data* to identify non-patent litigation and match cases to public firms using CUSIP identifiers supplemented with fuzzy name matching. We re-apply the propensity score matching procedure described in Section 2.4 to construct a comparable sample. Panel A reports estimates from Equation (1) at the pair × year level. The indicator $1(Litigation)$ equals one for firms that are involved in any type of litigation as defendants during the sample period (treatment group), and zero otherwise. The interaction term $1(Litigation) \times Post$ equals one for treated suppliers in years after becoming involved in litigation. Panel B distinguishes between patent and non-patent litigation. The variable $1(Litigation) \times Post \times 1(Patent)$ equals one for treated suppliers in years following patent litigation, and $1(Litigation) \times Post \times 1(NonPatent)$ is defined analogously for non-patent litigation. The dependent variables and supplier controls are the same as in Table 3. We include year fixed effects, supplier industry fixed effects, supplier state fixed effects, and event year × customer fixed effects. Standard errors are clustered at the pair level. Panels C and D report results at the supplier × year level using the same specification as in Table 4. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Effects of All Types of Litigation at the Pair–Year Level

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post	6.67***
	(1.23)
1(Litigation)	-15.14***
	(1.34)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	30,725
Adjusted R^2	0.18

(Continued on next page)

Panel B. Decomposition of Effects at the Pair-Year Level

Dep. Var:	1(Last Rel.Year)
	(1)
1(Litigation) × Post × Patent	8.05***
	(2.04)
1(Litigation) × Post × NotPatent	6.37***
	(1.29)
1(Litigation) × Patent	-13.50***
	(2.12)
1(Litigation) × NotPatent	-15.36***
	(1.40)
Supplier Firm Controls	Y
Year FE	Y
Supplier Industry FE	Y
Supplier State FE	Y
Event × Customer FE	Y
Observations	30,725
Adjusted R^2	0.18

Panel C. Effects of All Types of Litigation at the Supplier–Year Level

Dep. Var:	1(Last Rel.Year)	CustomerNum	SalesRatio
	(1)	(2)	(3)
1(Litigation) × Post	11.48***	-0.23***	-0.02*
	(1.60)	(0.06)	(0.01)
Firm Controls	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	8,537	8,537	6,070
Adjusted R^2	0.44	0.77	0.83

Panel D. Decomposition of Effects at the Supplier-Year Level

Dep. Var:	1(Last Rel.Year)	CustomerNum	SalesRatio
	(1)	(2)	(3)
1(Litigation) × Post × Patent	22.94***	-0.34**	-0.02
	(4.46)	(0.14)	(0.02)
1(Litigation) × Post × NotPatent	9.48***	-0.21***	-0.01
	(1.63)	(0.06)	(0.01)
Firm Controls	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	8,537	8,537	6,070
Adjusted R^2	0.44	0.77	0.83

Appendix IA5.1: Customer Investments in Innovative Human Capital

This table examines customer firms' investment in innovative human capital following upstream patent litigation, complementing Panel B of Table 8. We consider three measures of inventor hiring. $\#\ of\ New$ denotes the number of new inventors hired in the current year. We further distinguish between two types of new inventors: $\#\ of\ NewFirst$, which counts first-time inventors with no prior patenting history at other firms, and $\#\ of\ NewMove$, which captures inventors who previously patented at other firms. The former reflects the entry of entirely new inventors, while the latter captures inter-firm inventor mobility. Panel B excludes observations in which customers operate in the retail or wholesale sectors. All regressions include customer firm controls as in Table 8 and customer-industry × year fixed effects. Standard errors are clustered at the customer firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All Sample

Dep. Var:	# of New	# of NewFirst	# of NewMove
	(1)	(2)	(3)
1(Exposed to Supplier Litigation) × Post	40.92**	34.69**	6.23**
	(16.12)	(13.72)	(2.84)
1(Exposed to Supplier Litigation)	18.11	16.86*	1.25
	(11.14)	(9.57)	(2.01)
Customer Controls	Y	Y	Y
Industry × Year FE	Y	Y	Y
Observations	8,732	8,732	8,732
Adjusted R^2	0.28	0.27	0.26

Panel B. Exclude Customers in the Retail or Wholesale Industries

Dep. Var:	# of New	# of NewFirst	# of NewMove
	(1)	(2)	(3)
1(Exposed to Supplier Litigation) × Post	42.01**	35.70**	6.31**
	(17.05)	(14.49)	(3.03)
1(Exposed to Supplier Litigation)	19.37	17.99*	1.38
	(12.09)	(10.38)	(2.17)
Customer Controls	Y	Y	Y
Industry × Year FE	Y	Y	Y
Observations	8,238	8,238	8,238
Adjusted R^2	0.28	0.27	0.26

Appendix IA5.2: Customer Innovation Outcomes

This table reports customer firms' innovation outputs within their core technology classes following upstream litigation shocks. A firm's core CPC class is defined as the technology class with the largest number of granted patents over the prior three years. Using the same sample as in Table 8, Panel A presents difference-in-differences estimates based on the specification above. 1(*Exposed to Supplier Litigation*) and 1(*Exposed to Supplier Litigation*) × *Post* are as defined in Table 8. Panel B examines patenting outcomes in the litigation year and the subsequent two years (T to T+2) to capture dynamic innovation outcomes. The independent variable 1(*Litigation from Supplier*) equals one if any supplier of the customer is involved in patent litigation as defendants in the current year. Columns (1), (3), and (5) report the number of patent applications in years T, T+1, and T+2, respectively, while columns (2), (4), and (6) report the corresponding application ratios. Poisson regressions are used for count outcomes. All regressions include customer firm controls as in Table 8 and customer-industry × year fixed effects. Standard errors are clustered at the customer firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Patent Applications in Core CPC Classes: Difference-in-Differences

	Number	Ratio
	(1)	(2)
1(Exposed to Supplier Litigation) × Post	0.10	-0.01
	(0.17)	(0.02)
1(Exposed to Supplier Litigation)	0.22	0.01
	(0.22)	(0.03)
Customer Controls	Y	Y
Industry × Year FE	Y	Y
Observations	4,150	4,465
Adjusted/Pseudo R^2	0.67	0.21

Panel B. Patent Applications in Core CPC Classes: Effects at Different Horizons

	T		T+1		T+2	
	Number	Ratio	Number	Ratio	Number	Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
1(Litigation from Supplier)	0.07	0.01	0.07	0.02	0.09	0.02
	(0.12)	(0.02)	(0.12)	(0.02)	(0.12)	(0.02)
Customer Firm	Y	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y	Y
Observations	4,150	4,465	4,140	4,465	4,139	4,465
Adjusted/Pseudo R^2	0.67	0.21	0.67	0.19	0.66	0.19

Appendix IA5.3: Robustness Tests Using a Matched Customer Sample

This table uses propensity score matching to construct a matched customer sample and mitigate endogeneity concerns. Using this sample, we re-examine the effects of upstream patent litigation on downstream outcomes. Panels A and B report results for R&D investment and product performance, respectively. The dependent variables follow the definitions in Tables 8 and 10. All regressions include customer firm controls as in Table 8 and customer-industry × year fixed effects. Standard errors are clustered at the customer firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. R&D Investment	
Dep. Var:	Ln(1 + R&D)
	(1)
1(Exposed to Supplier Litigation) × Post	0.26*
	(0.13)
1(Exposed to Supplier Litigation)	0.09
	(0.20)
Customer Controls	Y
Industry × Year FE	Y
Observations	6,503
Adjusted R^2	0.61
Panel B. Product Outcome	
Dep. Var:	# of Total Products
	(1)
1(Exposed to Supplier Litigation) × Post	0.19***
	(0.07)
1(Exposed to Supplier Litigation)	-0.05
	(0.08)
Customer Controls	Y
Industry × Year FE	Y
Observations	7,036
Pseudo R^2	0.39

Appendix IA6.1: Downstream Supply-Chain Adjustments

This table examines how downstream customers adjust their supplier base following upstream patent litigation. Panel A analyzes changes in the customer's supplier network. The dependent variables are the number of suppliers (*# of Supplier*) and the number of newly added suppliers (*# of New Supplier*) in the post-litigation period. The independent variable 1(*Exposed to Supplier Litigation*) × *Post* is as defined in Table 8. All specifications include customer-level controls as in Table 8, as well as year and customer fixed effects. Standard errors are clustered at the customer level. We estimate Poisson models to account for the count nature of the dependent variables. Panels B and C examine supplier selection following litigation shocks and restrict the sample to treated customers. The dependent variable 1(*Target Pair*) equals one if a potential supplier is chosen as a new relationship in the year following upstream patent litigation, and zero otherwise. Following Bena and Li (2014) and Emery and Woeppel (2025), each new-relationship group consists of one target supplier and a set of twenty matched firms selected based on technology proximity (*Tech_Proximity*), patent count (*PatNum*), and patent age (*InnovAge*), as defined in Appendix IA3.1, using nearest-neighbor matching. In Panel B, the independent variable is an indicator equal to one if a potential supplier has prior litigation exposure within the CPC classes of the customer's litigated suppliers before the new relationship is formed. In Panel C, the independent variable measures the number of granted (applied) patents held by a potential supplier in litigation-exposed CPC classes over the three years preceding the new relationship in Column (1) ((2)). All specifications include customer-level controls as in Table 8 and new-relationship-group fixed effects. Standard errors are clustered at the group level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Customer's Supplier Base

Dep. Var:	# of Supplier	# of New Supplier
	(1)	(2)
1(Exposed to Supplier Litigation) × Post	-0.06	0.09
	(0.04)	(0.06)
Customer Controls	Y	Y
Year FE	Y	Y
Customer Firm FE	Y	Y
Observations	8,460	8,373
Pseudo R^2	0.74	0.33

(Continued on next page)

Panel B. Litigation History of New Suppliers

Dep. Var:	1(Target Pair)			
	Prior 1Y	Prior 2Ys	Prior 3Ys	Prior 4Ys
	(1)	(2)	(3)	(4)
1(Litigation)	-0.01	-0.01	-0.03	-0.03*
	(0.03)	(0.02)	(0.02)	(0.02)
Customer Controls	Y	Y	Y	Y
Group FE	Y	Y	Y	Y
Observations	1,129	1,129	1,129	1,129
Adjusted R^2	0.02	0.02	0.02	0.02

Panel C. Patent Applications in the Litigation-Exposed CPC from New Suppliers

Dep. Var:	1(Target Pair)	
	Granted Patents	Applied Patents
	(1)	(2)
# of Patents	0.00	-0.00
	(0.01)	(0.00)
Customer Controls	Y	Y
Group FE	Y	Y
Observations	1,027	1,027
Pseudo R^2	0.03	0.03