Proprietary Costs and Supply Chain Collaboration*

Wenzhi Ding† **Xiong Li**‡ **Guoman She**§ **Guochang Zhang**¶

First draft: November 20, 2022
This version: November 4, 2023

Abstract

Suppliers and customers inevitably share proprietary information to collaborate, but concerns of information misappropriation limit their relationship-based transactions. To understand how proprietary cost concerns shape supply chain collaboration, we exploit three quasi-natural experiments that alter the risk of information misappropriation by customer firms and their employees. We find that when information misappropriation risk is alleviated, suppliers expand sales to their major customers, especially in situations in which the prior risk of information misappropriation is high and suppliers' operations are more unique. Along with increased sales, suppliers' R&D investments respond more closely to customers' growth opportunities and suppliers' patents become more integrated with their customers' innovation. Suppliers' financial performance improves, mainly driven by increased cost efficiency (as opposed to operational scale). Our evidence suggests that proprietary costs play a significant role in hindering relationship-based transactions along supply chains.

Keywords: Proprietary Costs, Product-Market Transactions, Supply Chain, Inevitable Disclosure Doctrine, Uniform Trade Secrets Act

---

*The authors acknowledge the helpful comments and suggestions of Matthias Breuer, Omri Even-Tov, Shiyang Huang, Jinhwan Kim, Tse-Chun Lin, Lynn Linghuan Wang, and the workshop participants at the University of Hong Kong and the Hong Kong Polytechnic University.

† Hong Kong Polytechnic University wenzhi.ding@polyu.edu.hk
‡ University of Hong Kong, xliev@connect.hku.hk
§ University of Hong Kong, gshe@hku.hk
¶ University of Hong Kong, acgezhang@hku.hk

1. Introduction

Relationships between suppliers and (major) customers are built on the premise that the two sides share intimate knowledge about each other's operations, but this gives rise to the possibility of information leakage to third parties via the partners (Baiman and Rajan 2002). Despite the various measures taken by firms and regulators to bolster information security, supply chains remain a primary source of proprietary information losses (PricewaterhouseCoopers, U.S. Chamber of Commerce, and American Society for Industrial Security 2002; CREATe.org 2012). Thus far, there is little systematic evidence regarding how proprietary costs are at work in shaping supply chain collaboration—in particular, to what extent do such concerns shift firms away from relationship-based transactions in favor of arm's length dealings? These questions speak to the real effect of proprietary costs manifested through supply chain transactions, which are a prevalent form of business practices and are a major force propelling business growth (e.g., Cohen and Frazzini 2008; Patatoukas 2012; Costello 2013).[1] In this study, we explore how proprietary costs impact supply chain relationships through both sales activities (outcome) and relationship-specific investments (input).

To develop testable predictions, we construct a simple model depicting a supplier firm's decision to collaborate with a customer, which determines the extent of information sharing. The model follows prior theoretical work that establishes that information exchange is pivotal to efficient supply chain collaboration (e.g., Baiman and Rajan 2002) and that information transfer carries proprietary costs (e.g., Verrecchia 1983). While collaboration leads to increased transaction volume and profit, the supplier, in engaging in collaboration, has to share with the customer various types of information such as industrial techniques, manufacturing processes, sources of upstream raw materials, product designs, and formulas. With a nonnegative probability (p), the shared information will subsequently be misappropriated or leaked to other

[1] Supply chain relationships constitute a continuum of intermediate scenarios between markets and hierarchies (Williamson 1975, 1986). Firms choose between in-depth collaboration with a small number of partners versus dealing with many partners (more) at arm's length; whereby, the amount of information exchange and the depth of production coordination vary (Baiman and Rajan 2002).

parties, causing the supplier economic harm.[2] The supplier's decision thus trades off the gains from collaboration against the expected proprietary costs (which reflects *p*). An immediate prediction is that an exogenous decrease in *p* (as in our empirical settings described below) reduces the expected proprietary cost and therefore increases the supplier's willingness to share information and collaborate with the customer. The model further predicts that a given change in probability *p* has a greater impact on the level of collaboration when the customer is more likely to break up the relationship and when the supplier relies on more proprietary resources (such as intangibles).

The testing of these predictions is confronted with an identification challenge because proprietary costs are inseparable from transaction volume (i.e., the extent of collaboration). To demonstrate this, note that proprietary costs depend on the amount of information flow along supply chains, which increases with transaction levels. Further, proprietary costs are not directly observable. Prior studies often use industry concentration, a proxy for product-market competition, to capture variation in proprietary costs (Li 2010; Ali, Klasa, and Yeung 2014; Huang, Jennings, and Yu 2016). However, this measure likely depends on the fundamental factors of an industry that also drive product supply and demand, so it does not allow us to get away from the endogeneity issue as explained.

In our primary analyses, we overcome the empirical challenge by exploiting the staggered adoption of the Inevitable Disclosure Doctrine (IDD) in the United States, which grants employers substantial power to stop former employees from leaking trade secrets (Klasa, Ortiz-Molina, Serfling, and Srinivasan 2018). In the supply chain context, it is inevitable that supply chain counterparty's employees (e.g., C-suites and procurement officers) possess intimate knowledge of the focal firm (including the identity, formulas, know-how, and capacity),[3] and employee departure from supply chain partners is one of main sources of information leakage (e.g., CREATe.org 2012). For example, in *Merck & Co. Inc. v. Lyon*, the

[2] For instance, in the case of *Trinity Graphic v. Tervis Tumbler* and the case of *Berry Metal v. Smith*, the customers were alleged to have misappropriated and leaked the suppliers' proprietary information, leading to significant losses for the suppliers.

[3] Although counterparty firms may enter into nondisclosure agreements with employees, there remains a significant risk of information misappropriation due to both the incomplete nature of such agreements and their weak enforceability (Garmaise 2011).

customer firm's employee was accused of leaking the supplier's pricing and capacity information. Therefore, we expect IDD enactment in a counterparty's state to reduce the focal firm's expected proprietary costs, because it would allow the two sides to better coordinate and safeguard proprietary information within the IDD framework. Even without explicit coordination, the counterparty's incentive to safeguard its own trade secrets would indirectly benefit the focal firm.

Our empirical design is aimed at exploring the effect of IDD enactment in a *customer*'s state that is transmitted to supplier firms. In the United States, firms are required to disclose their major customers but not their suppliers. As a result, there is richer and more systematic information about a firm's transactions with its customers (than with its suppliers), and these customers are of material importance to the focal firm. In contrast, the suppliers covered in publicly available databases are less material to focal firms. In fact, the total purchases from all these suppliers contribute to less than 3% of firms' costs of goods sold (Patatoukas 2012). For the reasons of data availability and economic relevance, our study focuses on the setting of customer-state IDD enactment (rather than supplier-state IDD).

We retrieve supply-chain transaction data from the Compustat Segment Customer database to construct a customer-supplier relationship year panel for the period 1977–2019. To examine the impact of customer-state IDD enactment on transaction levels, we adopt both staggered difference-in-differences (DID) and "stacked" DID approaches (Baker et al. 2022). Specifically, for each IDD event, we create a separate cohort that includes both (i) the relationships of suppliers with affected customers (treatment group) and (ii) the relationships of suppliers with customers that have yet to undergo IDD (control group), covering a 10-year window around the event.

We find that following IDD enactment in customer states, suppliers increase sales dependence to IDD-affected customers by 1.6 percentage points, which amounts to an increase of 9.4% from the sample mean point. These results hold after controlling for supplier-year fixed effects, which addresses unobservable supplier-level factors. The results also hold in our further tests designed to address (i) potential violations of the SUTVA (Stable Unit Treatment Value Assumption) condition due to the spillover effects of IDD and (ii) repeated uses of IDD as an experiment to study corporate decisions (Heath, Ringgenberg, Samadi, and Werner 2023). Overall, our evidence indicates that when proprietary cost concerns are eased, suppliers engage in deeper collaboration with customers and put greater emphasis on relationship-based transactions versus arm's length sales.

We conduct two cross-sectional analyses to explore the varying effect of proprietary cost concerns. The first analysis exploits variation in employee mobility. If the documented effect is attributed to customer states' IDD alleviating the risk of information leakage by the departing employees of customer firms, we expect that suppliers will react more strongly to customer-state IDD events when customer firms' employees have greater mobility. Supporting this prediction, we find that customer-state IDD enactment has a stronger effect on suppliers when (i) customer states have weaker enforcement of pre-existing noncompete covenants (CNC) and (ii) customer employees have more external employment opportunities.

Our second cross-sectional analysis investigates how the IDD effect depends on the nature (uniqueness) of proprietary information. Our model predicts that for a given change in information leakage probability p, the effect is greater when the supplier's operation is more unique (in terms of either input or output) and so the supplier has more secrets to safeguard. Consistent with this prediction, we find that the effect of customer-state IDD enactment is more pronounced for suppliers with a higher degree of asset intangibility and for suppliers manufacturing more-differentiated products.

In complementing the aforementioned analyses that focus on the output of collaboration (sales), we also explore suppliers' relationship-specific investments (inputs). We find that, following the enactment of IDD in a customer's state, suppliers' R&D expenditures respond more closely to IDD-affected customers' growth opportunities and, at the same time, their patents (innovation outputs) are more likely to cite their customers' patents. Given that the innovation process is intensely knowledge based, the intensified collaboration through R&D suggests that supply chain partners engage in more extensive communication and knowledge sharing. These results suggest that suppliers dedicate more resources to their relationships with customers when proprietary cost concerns are mitigated.

To complement the tests involving customer-state IDD adoption, we next exploit the *rejection* of previously enacted IDD in a customer state, a reverse experiment. If the aforementioned result is indeed caused by customer-state IDD enactment rather than concurrent events, we expect to see a reversal of the effect (i.e., decreased collaboration) following IDD rejection (i.e., an *increase* in probability *p*). Consistent with our expectation, we find that, on average, sales dependence on (reversely) affected customers decreases by an amount equal to 6.4% of the sample mean post IDD rejection. The magnitude of this (reverse) effect is somewhat smaller than that of IDD adoption, possibly because of the irreversibility of relationship-specific investment (Williamson 1979; Dixit and Pindyck 1994). Together, our findings support the prediction that proprietary cost concerns arising from potential information leakage impede supply chain collaboration.

A third quasi-natural experiment we employ is the adoption of Uniform Trade Secrets Act (UTSA) in customer states, which serves another identification strategy. From a supplier's perspective, UTSA adoption in customer states alleviates proprietary cost concerns because UTSA adoption provides an additional mechanism through which suppliers are able to file misappropriation (infringement) lawsuits against customers (Glaeser 2018).[4] Using a stacked IDD design, we find that customer-state UTSA adoption leads to an increase in suppliers' sales dependence on treatment customers. This result reaffirms the idea that supply chain partners deepen their collaborations as proprietary cost concerns are eased.

The final part of our study examines supplier firms' financial performance. With the enactment of IDD in customer states, transaction costs (in the form of information frictions) along supply chains decrease (Williamson 1979, 1981; Grossman and Hart 1986). Consequently, suppliers may dedicate more resources geared to (affected) customers and embark on deeper collaborations with them (Jap 1999). For this analysis, we create a supplier-year sample whereby we measure a supplier's exposure to IDD enactment through its relationships with affected customers weighed by sales to individual customers, which follows

[4] We primarily investigate the effect of IDD reform instead of UTSA reform in this study for two reasons. First, the majority of U.S. states (49) have adopted UTSA and 40 of these states adopted UTSA in 1980s. The clustering of UTSA events creates a threat to the identification assumption that there are not enough time variations. In this sense, the effects found could be affected by confounding events in the 1980s. Second, the reversal of IDD provides us an opportunity to make stronger causal inference, while UTSA has seen no reversal up until now.

the idea of Bartik instruments (Goldsmith-Pinkham, Sorkin, and Swift 2020; Bourveau, She, and Žaldokas 2020; Breuer 2022).[5] We find that supplier firms' Tobin's *q* and returns on assets (ROA) are positively related to their exposure to customer-state IDD enactment. Further analysis shows that the source of improved performance and value gains is enhanced cost efficiency rather than increased operational scale, suggesting that supplier chain partners are able to utilize relationship-specific investments more efficiently.

Our study contributes to the literature in the following ways. First, it is among the first to investigate the role of proprietary cost concerns in shaping supply chain relationships. Prior studies have shown that potential information leakage discourages rival firms from sharing a common provider of capital or services such as lenders (Breuer, Hombach, and Müller 2018), investment banks (Asker and Ljungqvist 2010), and auditors (Aobdia 2015; Kang, Lennox, and Pandey 2022). We find that proprietary cost concerns engender significant consequences for supply chains both in terms of transaction outcomes and relationship-specific investments. Supply chain relationships, which constitute firms' core business activities, are distinct from those examined in prior papers. These relationships make up a substantial portion of ongoing business transactions and are of great importance for business growth (e.g., Cohen and Frazzini 2008; Patatoukas 2012; Costello 2013). Prior studies have also found that suppliers use two measures—reducing public disclosure and avoiding M&A activities—to alleviate customers' concerns about information leakage (Afrin, Kim, and Roychowdhury 2022; Chen, Tian, and Yu 2022), but there is little direct evidence on how proprietary costs affect supply chain collaboration. By exploiting various quasi-natural experiments that introduce exogenous variations in information misappropriation risk, we show that, despite the protective measures business partners often take, information leakage remains an important concern that significantly constrains supply chain collaboration.

Second, our study contributes to the broader literature on the consequences of proprietary costs. A well-known result is that firms make less public disclosure to capital

[5] Note that the unit of analysis for this test is different from our main analysis because we are interested in firm-level instead of relationship-level performance. In our main analysis, we do not use the Bartik instrument because we use a firm-customer-year panel and we are interested in how IDD shapes interfirm transactions between suppliers and customers.

markets when their disclosures can be used by product market rivals (e.g., Harris 1998; Botosan and Harris 2000; Ellis et al. 2012; Glaeser 2018; Li et al. 2018). A growing line of research examines the real effects of mandatory public disclosures about firms' innovative investments (Breuer, Leuz, and Vanhaverbeke 2021; Kim and Valentine 2022). In our study, however, information exchange takes place voluntarily and privately in the course of interfirm business transactions. In this context, how much information the supplier shares is endogenous to the extent of its collaboration with customers. Our study contributes to understanding how proprietary costs affect real decisions (Leuz and Wysocki 2016; Roychowdhury, Shroff, and Verdi 2019).

Third, we contribute to research on the role of information asymmetry in supply chains. Existing literature documents that firms use financial covenants and financial reports to overcome information asymmetry problems (Raman and Shahrur 2008; Hui, Klasa, and Yeung 2012; Costello 2013; Dou, Hope, and Thomas 2013; Samuels 2020; Bourveau, Kepler, She, and Wang 2022) and that public disclosure of supply chain information affects firms' incentives to monitor counterparties (She 2022; Baik, Even-Tov, Han, and Park 2021; Christensen, Macciocchi, Morris, and Nikolaev 2022). We show that information protection facilitates firms' relationships with customers, ultimately improving their firm performance. Thus, our paper sheds light on firms' value creation from major customer relationships (e.g., Patatoukas 2012; Irvine et al. 2015; Hui et al. 2019).

Lastly, we extend the literature on how employee mobility affects corporate outcomes. It has been shown that employee-mobility frictions hinder firm investment and innovation and affect disclosure policies (Garmaise 2011; Samila and Sorenson 2011; Chen, Zhang, and Zhou 2018; Contigiani, Hsu, and Barankay 2018; Li et al. 2018; Ali, Li, and Zhang 2018; Gu, Huang, Mao, and Tian 2022). Our study shows an unintended bright side—namely, mobility restrictions enhance interfirm transactions by alleviating the concern of information leakage via departing employees.

2. Institutional Background

2.1. Risk of Information Leakage by Supply Chain Partners

Supply chain transactions require the transfer of extensive proprietary information covering such operational aspects as industrial techniques, manufacturing processes, sources of upstream raw materials, product designs, and formulas (e.g., Dyer and Singh 1998; Martin et al. 1998; Kotabe et al. 2003; Klein and Rai 2009; Li et al. 2010). Information sharing is necessary for deep interfirm collaboration, but the risk is obvious that proprietary information can be leaked or misappropriated by partners, which would erode a firm's competitiveness. For example, in 2018 Qualcomm filed a lawsuit against its major customer, Apple, which allegedly revealed Qualcomm's proprietary software and data files to Intel. Qualcomm claimed that the information leakage enabled Intel to upgrade its products and replace Qualcomm as Apple's supplier. In another example, Sinovel, a wind-turbine manufacturer, was convicted of stealing trade secrets from its long-term supplier AMSC, a world-leading power-system software provider.

Employee departure at supply chain partner firms is frequently a source of information leakage (e.g., CREATe.org 2012). For instance, in the case of *Merck & Co.* v. *Lyon*, a former employee of Merck & Co., Gary Lyon, who had left for its major competitor, Glaxo, was alleged to have disclosed Merck's supply agreement, which contained information on the supplier's raw materials, pricing, and capacity. In another case, *Berry Metal* v. *Smith*, Todd Smith acquired a large amount of information about Berry Metal's customers during the time he worked for Berry Metal and then used this information to earn consulting fees after leaving the company. These examples demonstrate that employee departure from supply chain partners poses a serious threat to information security (e.g., CREATe.org 2012).

2.2. IDD and Proprietary Information Protections

The adoption of the Inevitable Disclosure Doctrine (IDD) represents one of the most important initiatives for safeguarding proprietary information in the United States (Klasa et al. 2018). The IDD prevents key employees from working at any place where the employees may unavoidably use or divulge former employers' trade secrets.

Unlike nondisclosure agreements or noncompete agreements between an employer and its employees, the IDD provides ex ante protection without requiring concrete evidence of trade-secret leakage from the former employer. The IDD also provides broader protection across jurisdictions, while noncompete covenants typically become less effective when former employees leave a job to take a job in a different state (Garmaise 2011). Further, the IDD is in effect even if an employee does not sign a nondisclosure or noncompete agreement (e.g., *Merck & Co. v. Lyon*). Therefore, the IDD can be a powerful tool for safeguarding firms' proprietary information (Klasa et al. 2018).

In the context of supply chains, we expect that IDD enactment in a customer's state reduces the risk of information leakage by the partner for two reasons. First, because supplier information (including the identity, formulas, and capacity) constitutes an important portion of trade secrets covered by IDD, the supplier would coordinate with the customer within the IDD framework to protect the supplier's information from being leaked by the customer's departing employees. Second, even without explicit coordination, the customer's incentive to safeguard its own trade secrets is likely to benefit suppliers indirectly. In fact, in the two cases mentioned above—*Merck & Co. v. Lyon* and *Berry Metal v. Smith*—the courts ruled in favor of the former employers on the basis of the inevitable disclosure theory. For example, Gary Lyon's new employment at Glaxo was suspended because he would inevitably disclose the supplier's proprietary information to Glaxo.

Based on the above discussion, we posit that IDD adoption in customer states eases suppliers' concerns over information leakage via customers' employees, which should enhance collaboration in supply chains. Further, the effect of customer-state IDD on supplier firms is expected to vary in the cross-section, depending on whether customer firms have a strong incentive to maintain their relationships with the existing suppliers and how much they could benefit from leaking information to suppliers' rivals.

3. Predictions

To develop testable predictions, we construct a simple model depicting the supplier firm's decisions involving collaboration with a customer. In the model, a supplier firm (S) engages with a given customer firm (C). S needs to decide the extent of business collaboration with C, denoted as x. Collaboration leads to increased sales and thus enables S to earn more benefits, $B(x)$. However, in order to engage in collaboration, S has to share proprietary information with C (e.g., Baiman and Rajan 2002). For simplicity, we assume a monotonic relation between the amount of information shared and the transaction level x. With probability p, this information will subsequently be leaked to other parties, which harms S's ability to compete with rival firms (e.g., Verrecchia, 1983). Thus, S suffers a cost of information leakage, $C(x)$. For technical convenience, we assume that the benefit function is increasing and concave: $B'(\cdot) > 0$, $B''(\cdot) < 0$; whereas, the cost function is increasing and convex: $C'(\cdot) > 0$, $C''(\cdot) \geq 0$. Further, we assume $C(0) = 0$ and $C'(0) = 0$; no cost is incurred when no information is shared, and the marginal cost at this initial position is 0 when other parties learn virtually nothing about S's proprietary information.

In a representative period, S chooses the extent of collaboration (information sharing) to maximize the expected net benefit:

$$\text{Max } \pi = B(x) - p\, C(x). \tag{1}$$

The first-order condition below determines the optimal x, denoted as x_0:

$$B'(x) - p\, C'(x) = 0. \tag{2}$$

Now consider an exogenous event shifting the probability of information leakage by Δp. To see how the level of collaboration changes, we calculate the following derivative from Eq. (2):

$$\frac{dx}{dp} = -\frac{C'(\cdot)}{pC''(\cdot) - B''(\cdot)}. \tag{3}$$

In the context of the IDD event, the probability of information leakage is expected to decrease—that is, $\Delta p < 0$. Thus, we predict that the level of collaboration will increase:

$$\Delta x \approx \frac{dx}{dp}(\Delta p) = \frac{C'(\cdot)}{pC''(\cdot) - B''(\cdot)}[-\Delta p] > 0. \tag{4}$$

Prediction 1. *An exogenous reduction in the probability of information leakage increases S's collaboration with C.*

Next, we explore the role of supply chain characteristics in affecting the impact of IDD on business collaboration. These characteristics are relevant factors for S's decisions because they determine the cost of leaking proprietary information. At this stage of our analysis, we need to impose greater structure on the above generic setup. In the empirical setting, there can be a variety of such factors, each of which may affect supplier decisions in its own ways. Therefore, it is challenging to incorporate such factors together into one unified model. Below, we separately consider two types of supply chain characteristics.

Type (i). Customer C's incentive to deviate. S faces the risk of C deviating from the terms of their relationship. C's incentives to deviate from the established relationship are a function of its dependence on S for supplying products as well as of the external opportunities available to C's managers. To explore cross-sectional variation induced by the parties' misaligned incentives, we now decompose the probability of information leakage (p) into (i) C's (or its manager's) incentive to deviate, denoted as γ, and (ii) his or her ability to leak information conditional on his or her deviation from the relation with S, denoted as q. For technical convenience, we assume $p = \gamma\ q$; that is, as the customer firm has a greater incentive to deviate from the relationship with S, the probability of information leakage increases. Assuming that IDD reduces the ability of C's managers to leak information by a given amount $\Delta q < 0$, then, from Eq. (4), we have

$$\Delta x \approx \frac{dx}{dp}(\Delta p) = \frac{\gamma\ C'(\cdot)}{\gamma\ q\ C''(\cdot) - B''(\cdot)}[-\Delta q]. \tag{5}$$

Eq. (5) implies that S's adjustment to the extent of collaboration is greater where C has stronger incentives to deviate; that is, $d(\Delta x)/d\gamma > 0$.

Prediction 2. *The incremental level of collaboration (Δx) triggered by a given Δq ($<$ 0) is greater when C has a stronger incentive to deviate from its relationship with S.*

Type (ii). Supplier characteristics affecting the cost function (but not the benefit function). This section will examine supplier characteristics that affect the cost, but not the benefit, function. An example of this is the asset intangibility of the supplier. Intangibility captures the uniqueness of the supplier's business and the number of secrets it possesses, increasing the supplier's need to be safeguarded against competitors (e.g., Hand and Lev 2003; Glaeser 2018) . To capture this feature in our model, we transform the cost function to $C(x) = \theta\ c(x)$, where $\theta > 0$ reflects the degree of asset tangibility (or some other feature with similar effects); a greater value of θ indicates a higher cost of information leakage. From Eq. (4), S's adjustment to the level of collaboration can be expressed as

$$\Delta x \approx \frac{dx}{dp}(\Delta p) = \frac{C'(\cdot)}{pC''(\cdot) - \frac{B''(\cdot)}{\theta}}[-\Delta p] > 0 \tag{6}$$

From Eq. (5), we conclude that $d(\Delta x)/d\theta > 0$.

Prediction 3. *The incremental level of collaboration* (Δx) *triggered by a given* Δp (< 0) *is greater when S has a higher level of asset intangibility.*

4. Data and Empirical Methodology

4.1. Sample Selection

We start with customer-supplier relationship data from the Compustat Segment Customer database from the period 1977 to 2019.[6] The database collects annual transactions between suppliers and customers from annual reports. We consider the first (last) year that a supplier reports transactions made to the customer as the start (end) year of a relationship. Following Intintoli et al. (2017), we set the missing sales volume between the first and last year of the relationship to 0. Our results are robust to alternative ways of treating missing transaction volumes (see the Internet Appendix Table IA1).

To assemble financial data, we then merge Segment Customer data with Center for Research in Security Price (CRSP) data and Compustat data. For the historical headquarters states of both suppliers and customers, we rely on Bai et al. (2020) and Bill McDonald's Augmented 10-X Header Data.[7] Following prior literature (Coles, Daniel, and Naveen 2006), we exclude firms in the financial (SIC codes between 6000 and 6999) and utility industries (SIC codes between 4900 and 4999). We also require firms to have nonnegative sales and total assets. We exclude observations with missing data on control variables.

4.2. Identifying IDD Enactments

[6] Under SFAS No. 14, suppliers are required to report all customers that account for 10% or more of the supplier's sales. In practice, many firms choose to report significant customers even below the threshold, which are also included in our analysis.
[7] The corporate 10-K header information from the EDGAR system is available at https://sraf.nd.edu/data/.

We merge the two lists of IDD enactments compiled by Klasa et al. (2018) and Qiu and Wang (2018). The Internet Appendix Table IA2, displays the complete list with enactment years. There are five states for which Klasa et al. (2018) and Qiu and Wang (2018) disagree on the enactment year. For these five states, we use the earlier IDD cases to identify the enactment year for our primary analyses. For example, Iowa has two IDD enactment cases, *Uncle B's Bakery v. O'Rourke (N.D. Iowa 1996)* and *Barilla Am., Inc. v. Wright (S.D. Iowa 2002)* that are identified by Klasa et al. (2018) and Qiu and Wang (2018), respectively. We code the enactment year for Iowa as 1996. Based on the consolidated IDD list, 19 states adopted IDD during our sample period (1977–2019). In robustness tests, we confirm that our results (reported in the Internet Appendix, Table IA3) are qualitatively and quantitatively similar if we use the two lists separately or if we use only the intersection of the two lists.

4.3. Empirical Methodology

4.3.1. Staggered DID approach

We exploit the staggered adoption of IDD in customer states to establish the causal effect of proprietary costs on supply-chain transactions. We follow prior studies (e.g., Klasa et al. 2018) and start with the staggered difference-in-differences (DID) designs as follows:

$$Sales\ Dependence_{s,c,t} = \beta_0 + \beta_1 IDD_{c,t} + \gamma_s X_{s,t} + \gamma_c X_{c,t} + \delta_{s,c} + \delta_t + \varepsilon_{s,c,t} \qquad (7)$$

where *s*, *c*, and *t* denote supplier *s*, customer *c*, and year *t*, respectively. The dependent variable, *Sales Dependence*, is sales to a customer scaled by the total sales of a supplier in a year (Freeman 2023; Oliveira, Kadapakkam, and Beyhaghi 2017; Intintoli et al. 2017). $IDD_{c,t}$ is the indicator that equals 1 if IDD is effective in the customer *c*'s headquarters state in year *t*.[8] $X_{s,c,t}$ stands for a series of supplier and customer-firm control variables. Following prior literature (Intintoli et al. 2017; Cen, Maydew, Zhang, and Zuo 2017), we control for returns on assets (*ROA*), firm size (*Size*), capital expenditure intensity (*CAPEX*), leverage ratio (*Leverage*), and cash holdings (*Cash*) of each of supplier *s* and customer *c*. We use subscription *Cus* to denote

[8] For example, Massachusetts adopted IDD in 1994 but overturned it in 2012. Then $IDD_{c,t}$ for relationships with customer firms headquartered in Massachusetts equals 0 for the years 1979–1993 and 2013–2019 and equals 1 for the years 1994–2012.

customer-firm characteristics and subscription *Sup* to denote supplier-firm characteristics. We also include the length of the relationship as of year *t* (*Relation_Length*) to control for the stage of the relationship life cycle (Irvine et al. 2015). The supplier-customer fixed effect that controls for time-invariant, unobservable supplier, customer, and relationship characteristics is represented by $\delta_{s,c}$, and δ_t is the year fixed effect that controls for economy-wide factors that could affect product demand and the state's adoption of the IDD. We cluster the standard errors at the supplier-customer relation level. The sample for staggered DID analyses includes 45,434 customer-supplier-year observations with nonmissing control variables.

4.3.2. Stacked DID approach

In light of the recent development in econometric studies concerning the staggered DID approach (Sun and Abraham 2021; Callaway and Sant'Anna 2020; de Chaisemartin and D'Haultfœuille 2020; Baker et al. 2022), we employ a stacked DID design to mitigate concerns of treatment effect heterogeneity.

First, for each IDD event, we create a separate cohort that includes the treatment state and focuses on a 10-year window surrounding the event year. For example, the sample period for Washington's IDD adoption (1997) is from 1993 to 2002. In the cases in which IDD was rejected within 5 years following its enactment, we remove observations after the rejection year. For example, Indiana adopted IDD in 1995 and overturned it in 1998, so the sample period for this cohort is 1991–1998. Next, we create a control group for the cohort using states that have yet to enact IDD before the end of the event window. Last, we collect all supplier-customer relationship-years with customers headquartered in either a treatment state or a control state over the 10-year window around the event year, which constitutes an event sample (i.e., a cohort). We then stacked all 19 IDD event samples (i.e., "stacked" sample), which produces a cohort-customer-supplier-year sample with 66,382 observations. We then estimate the following stacked DID model (8):

$$Sales\ Dependence_{s,c,t} = \beta_0 + \beta_1 Treat_{e,c} \times Post_{e,t} + \gamma_s X_{s,t} + \gamma_c X_{c,t} + \delta_{e,s,c} + \delta_{e,t} + \varepsilon_{s,c,t} \quad (8)$$

where e, s, c, and t denote IDD event (cohort), supplier, customer, and year, respectively. *Sales Dependence* and X are the same as in Eq. (7). $Treat_{e,c}$ is a dummy variable that equals 1 if the customer c is headquartered in a state that adopted IDD for event e and 0 otherwise. $Post_{e,t}$ is a dummy variable equal to 1 for the period after the event year and 0 otherwise for event e. β_1 captures the effect of customer-state IDD enactment on suppliers' transaction volume. The cohort-supplier-customer fixed effect is represented by $\delta_{e,s,c}$, and $\delta_{e,t}$ represents the cohort-year fixed effects. Standard errors are clustered at the cohort-supplier-customer relation level. All subsequent tables are based on Eq. (8), except for those indicated otherwise.

4.4. Descriptive Statistics

Table 1 shows the summary statistics for the variables used in our staggered DID regressions (Panel A) and stacked DID regressions (Panel B). All continuous variables are winsorized at the top and bottom 1%. The mean values of *Sales Dependence* are 0.166 in Panel A, 0.171 in Panel B, 0.171 in Panel C, and 0.169 in Panel D; that is, on average, a major customer accounts for around 17% of the supplier's total sales. With this magnitude of transactions, it is highly plausible that a considerable amount of proprietary information is transferred along supply chains.

In Panel A, the mean value of *IDD* is 0.54, meaning that for 54% of the customer-supplier years in the staggered DID sample, IDD is recognized by the state court. Thus, it is quite common for U.S. firms to be protected by IDD. The mean values of customer-firm asset size (in natural logarithm) are 9.55, 8.70, 9.94, and 8.77 for the samples reported in Panels A, B, C, and D, respectively; whereas, the mean values of supply-firm size in the corresponding samples are 4.94, 4.31, 5.28, and 3.99, respectively. These statistics are generally in line with those in prior studies (Patatoukas 2012; Intintoli et al. 2017; Freeman 2021).

5. Empirical Results

5.1. Main Analysis

Table 2 presents the results of our main analysis to examine the effect of customer IDD on suppliers' transaction volume. Columns (1) to (3) report the baseline results of staggered DID estimation of Eq. (7). We control for the supplier-customer and year fixed effects in column (1) and add customer, supplier, and relationship characteristics in column (2). In both columns, we find that the coefficients on *IDD* are positive and significant at the 1% level. The estimate in column (2) suggests that the supplier increases its sales to a customer by 1.7 percentage points after the customer undergoes IDD. Column (3) includes supplier-year fixed effects to control for time-varying supplier characteristics (e.g., production capacity). We continue to find a positive and significant coefficient on *IDD*, suggesting that suppliers deepen collaboration with customers when concerns about proprietary costs are eased.

We next turn to the stacked DID sample and estimate Eq. (8). Columns (4) and (5) show that *Treat* × *Post* is positive and significant at the 1% level, both with and without controlling for firm characteristics. Our results are robust to including supplier-year fixed effects, as shown in column (6). The coefficient on *Treat* × *Post* in column (5) suggests that suppliers' sales dependence on affected customers increases by 1.6 percentage points following the shock, amounting to 9.4% (= 0.016 / 0.171) of the sample mean. The results are consistent with Prediction 1.

In the Internet Appendix (Table IA4), we show that our results remain qualitatively and quantitatively similar after we include an additional list of time-varying proxies for customer fundamentals (which address demand changes triggered by IDD adoption), including size and sales growth for customers and suppliers. Overall, the results support the hypothesis that suppliers expand collaboration with customers when concerns over information leakage via customers are mitigated.

5.2. Dynamic Effects of IDD Enactment

We evaluate the dynamic effects of IDD enactment to validate the parallel trends assumption. Following Cengiz et al. (2019) and Deshpande and Li (2019), we use the stacked sample and estimate the dynamic effects of IDD reform using the following model (9):

$$Sales\ Dependence_{s,c,t} = \beta_0 + \sum_{i=-4;i\neq-1}^{5} \beta_i\, Treat_{e,c} \times D_{e,i} + \gamma_{\mathrm{s}} X_{s,t} + \gamma_c X_{c,t} + \delta_{e,s,c} + \delta_{e,t} + \varepsilon_{e,s,c,t} \qquad (9)$$

where $D_{e,i}$ is a vector of dummies equal to 1 if the difference between this year and the treatment year of event e is i and 0 otherwise. We set the benchmark year to the year before treatment (i.e., $i = -1$). Other features resemble Eq. (8).

Figure 1 shows a plot of the estimates of β_i. Consistent with the parallel trends assumption, the effect of customer-state IDD enactment is muted before enactment years. It also shows that IDD enactment in a customer state persistently increases suppliers' sales to and their dependence on affected customers after the shock, suggesting that customer IDD enactment's impact on supply chain transactions is causal and long-lasting.

5.3. Cross-Sectional Analyses

Our model predicts a greater impact of customer IDD enactment when suppliers have greater proprietary cost concerns, which can be attributed to employee departure risks (Prediction 2) and the nature of proprietary information (Prediction 3). In this section, we will provide evidence for these predictions.

5.3.1. Employee Departure Risk

To corroborate our argument that IDD reduce concerns about information leakage associated with customer-firm employee departure, we explore the cross-sectional variations in ex ante employee departure risk. Specifically, we consider the strength of noncompete covenant (CNC) enforcement, a variable that is plausibly exogenous to the customer-state IDD adoption. CNCs help to deter information leakage by limiting (customer firm) employees' outside opportunities and, thus, if well enforced, provide another layer of protection for supplier firms. We conjecture that suppliers would be more concerned where CNC enforceability is low in their customer states. We follow Garmaise (2011) and use the CNC enforceability index (*CNC Strength*) of a customer state in the event year of its IDD enactment. As shown in column (1) of Table 5, the coefficient on *Treat* × *Post* × *CNC Strength* is significantly negative, indicating that customer-state IDD enactment has a greater (incremental) role in affecting supply-chain collaboration when, ex ante, the state provides weaker enforcement of CNCs (and hence suppliers have greater concerns about information leakage).

It is of interest to note that the sum of *Treat* × *Post* × *CNC Strength* and *Treat* × *Post* is significantly positive, consistent with our earlier argument that CNCs (as an alternative mechanism) do not fully mitigate proprietary cost concerns, allowing IDD to have an incremental effect. The exogeneity of CNC strength confirms the impact of IDD on trade secrets channels through restricting employee mobility, and reveals that IDD plays a greater role where substitute mechanisms are less effective.

At the customer-employee level, we use the employees outside job-market opportunities to proxy for the risk to supplier firms. Following prior studies (e.g., Cremers and Grinstein 2014), we assume that key employees' outside job opportunities mostly come from the same industry as the current employment and use the number of peer firms in a firm's product market to gauge its employees' outside opportunities. Specifically, we construct a binary variable, *Low Outside Opportunities*, whose value is set to 1 if the customer's average number of peer firms in the same TNIC-3 industry over the 5-year window preceding the IDD event is below the median of the event sample and 0 otherwise. Column (2) of Table 5 shows that the coefficient on *Treat* × *Post* × *Low Outside Opportunities* is significantly negative, suggesting that customer IDD enactment has a stronger effect when suppliers have greater concerns about information leakage via departing customer employees.

Taken together, our evidence shows that in reducing proprietary concerns, customer-state IDD has a greater effect on supply-chain collaboration where customer firms or their employees are more prone to deviate from relationships with suppliers.

5.3.2. Nature of Proprietary Information

We use two proxies for the uniqueness of supplier operations (nature of proprietary information), which determines the extent of the loss that suppliers would suffer if information were leaked. The first proxy is the degree of asset intangibility (which concerns the input aspect of operation), defined as the amount of intangible assets other than goodwill divided by total assets.[9] Intangibles such as recipes or blueprints enable firms to gain a competitive edge vis-à-

[9] We remove goodwill from total intangible assets since goodwill is generated by mergers and acquisitions and has a weaker link to proprietary information.

vis rivals and, thus, are highly valuable information that firms want to protect. Imparting such information to other parties can quickly erode the firm's advantage. We measure a supplier's ex ante asset intangibility using its average intangibility in a 5-year window preceding an IDD event and create a binary variable, *Low Intangibility*, to indicate suppliers with a below-the-median value of intangibility. Column (1) of Table 4 reports the results. The coefficient estimates on control variables are omitted for brevity. Consistent with Prediction 3, we find that the coefficient on *Treat* × *Post* × *Low Intangibility* is significantly negative, suggesting that customer-state IDD enactment has a greater impact when suppliers have greater information-protection needs.

Our second proxy pertains to the uniqueness of supplier products (the output aspect). Suppliers producing unique products are more likely to safeguard related information against their rivals (Lindman 2000). We create a dummy variable, *Low Uniqueness*, whose value is set to 1 if the sector does not provide differentiated goods and 0 otherwise, which follows the classification by Giannetti et al. (2011). As shown in column (2) of Table 4, the coefficient on *Treat* × *Post* × *Low Uniqueness* is significantly negative, suggesting that customer-state IDD enactment has a greater impact when suppliers produce unique products and, thereby, have more proprietary information to protect.

6. Additional Analyses

6.1. Proprietary Costs and Relationship Investment

Our analysis thus far has focused on sales activities, which pertain to the outcome of supply chain collaboration. We now seek evidence from the perspective of input resources that suppliers dedicate to their specific relationships with customers.

When information security is enhanced in a business relationship, counterparty opportunism is mitigated (Williamson 1979, 1981) and, consequently, suppliers would be more willing to share information with customers and develop relationship-specific assets (Arrow 1975). We conduct two tests to confirm this idea.

First, we examine how closely the supplier's R&D investment responds to its customer firm's growth opportunities—that is, sensitivity, using the following regression model:

$$\begin{aligned} Supplier\ R\&D_{s,t} &= \beta_1 Treat_{e,c} \times Post_{e,t} \times CustGrowth_{c,t} + \beta_2 Treat_{e,c} \times Post_{e,t} \\ &+ \beta_3 Treat_{e,c} \times CustGrowth_{c,t} + \beta_4 Post_{e,t} \times CustGrowth_{c,t} \\ &+ \beta_5 CustGrowth_{c,t} + \gamma_s X_{s,t} + \gamma_c X_{c,t} + \delta_{e,s,c} + \delta_{e,t} \\ &+ \varepsilon_{e,s,c,t}, \qquad (10) \end{aligned}$$

where subscripts e, s, c, and t denote IDD enactment event, supplier, customer, and year, respectively. $Supplier\ R\&D_{s,t}$ is the ratio of R&D expense to assets of the supplier s. $CustGrowth_{c,t}$ represents customer growth opportunities, including Tobin's q and sales growth. Panel A of Table 6 reports the results. The coefficients on *Treat* × *Post* × *CustGrowth* are positive and statistically significant for both growth opportunity proxies, suggesting that the supplier's R&D investment becomes more responsive to the customer's growth opportunity after IDD enactment in the customer state.

Second, we examine whether suppliers' innovation is more deeply integrated with their customers' technologies. We retrieve patent-filing and citation data from the NBER patent database (Hall, Jaffe, and Trajtenberg 2001) and construct three measures of suppliers' innovation specificity to customers. *Cite Customer Dummy* is a binary variable that equals 1 if the supplier has at least one patent citing the customer's patents in a year. *Cite Customer Ratio* is the fraction of supplier's patents that cite customer's patents in a year.

We rerun Eq. (8) to explain these two measures of innovation outcome, with the results in Panel B of Table 6. In all columns, the coefficients on *Treat* × *Post* are positive and statistically significant, indicating that suppliers are more likely to cite customer patents following the customer-state IDD enactment. The coefficient estimates on *Treat* × *Post* in column (2) suggest that the number of supplier patents citing customers' patents increases by 1.6%. In sum, our results suggest that IDD enactment in a customer state increases the supplier's investment sensitivity and specificity to the customer, which again suggests a deeper level of supply chain collaboration.

6.2. Evidence from a Reverse Experiment

In complementing the above tests using IDD enactment in customer states as an exogenous shock, we now exploit the reverse shock of IDD rejection, which helps to further validate our inference. During our sample period, nine states rejected previously enacted IDD (reported in the Internet Appendix, Table IA2). If it is IDD enactment in customer states that leads to increased transactions with major customers, as shown above, rather than some confounding factors, we expect to observe decreased transactions—an opposite effect—when IDD is rejected in customer states.

To test this prediction, we follow the same procedure as described in Section 4.3.2. to create a sample for stacked DID regressions. In this case, each IDD rejection-event cohort includes treatment relationships (i.e., customer state with IDD rejection) and control relationships (i.e., customer state with IDD in place throughout the period) over a 10-year window surrounding the event year. We then estimate a stacked DID regression by (i) replacing *Treat* in Eq. (8) with *IDD_Abortion*, a binary variable indicating treatment relationships of the IDD rejection, and (ii) replacing $Post_{Cus}$ with *Post_Abortion*, a binary variable indicating the years after IDD rejection.

Table 6 reports the results. We find a significantly negative coefficient on *IDD_Abortion* × *Post_Abortion* across all specifications. This indicates that IDD rejection in customer states has the effect of weakening firms' collaboration with customers, which reverses the effect of previous IDD adoption. However, we note that the magnitude of the IDD abortion effect is somewhat smaller than that of IDD enactment. The coefficient in column (2) suggests that, on average, suppliers reduce sales to their affected customers by 6.4% (= −0.011/0.171) relative to the sample mean following customer-state IDD rejection (compared with a 9.4% increase at IDD adoption). The lack of a complete reversal of the IDD effect can be justified given that relationship-specific investments are not fully reversable. Thus, the evidence here strengthens our inference that proprietary cost concerns are a significant force that hinders relationship-based transactions along supply chains, as opposed to arm's length sales in market-based settings.

6.3. Evidence from Customer UTSA Adoption

To further validate our inference, we now exploit another trade secret protection reform—namely, the Uniform Trade Secrets Act (UTSA) for separate evidence. The UTSA provides a clear definition of misappropriation of trade secrets, extends the timeframe for pursuing litigations regarding trade secret infringement, and reduces uncertainties on the legal safeguards of trade secrets (Samuels and Johnson 1990). For example, in the state of Texas, which adopted the UTSA in 2013, the act explicitly includes financial data and the list of customers and suppliers within the realm of "trade secrets."[10] Notably, under Section 2 of the UTSA, the owner has a legal claim for trade secret misappropriation to obtain injunctive relief (Li, Lin, and Zhang 2018). Consequently, the passage of the UTSA in customer states establishes an additional mechanism that enables suppliers to pursue legal protection against customers' unlawful appropriation of their proprietary information (Glaeser 2018). This should significantly diminish the risk of proprietary information leakage.

During our sample period from 1979 to 2019, all 50 states except one passed the UTSA. We use a stacked DID method to assess the effect of UTSA adoption in customer states on suppliers' sales. Following the same procedure as for the stacked IDD design described above, we construct 49 UTSA-event cohort samples to generate a cohort-customer-supplier-year panel that comprises 15,594 distinct observations. We then run Eq. (8) whereby we define *Treat* and *Post* based on customer-state UTSA reform. We include cohort-supplier-customer and cohort-year fixed effects to account for unobserved time-invariant supplier-customer characteristics and time-varying factors influencing sales dependence.

Table 7 reports the results. In column (1), we use a basic specification that excludes the control variables. The coefficient on *Treat_UTSA* × *Post_UTSA* is positive and statistically significant, confirming our expectation that customer UTSA increases suppliers' sales dependence. In column (2), we control for supplier and customer characteristics that may influence suppliers' sales dependence. Again, the coefficient on *Treat_UTSA* × *Post_UTSA* is positive and significant (0.021, t = 2.06). On average, suppliers increase sales to their (treated) customers by 2.1 percentage points after the event, amounting to 12.4% of the sample mean.

[10] "Texas Adopts Version of Uniform Trade Secrets Act": https://www.crowell.com/en/insights/client-alerts/texas-adopts-version-of-uniform-trade-secrets-act

The results here lend further support to our hypothesis that enhanced protection against trade secrets leakage facilitates supply chain transactions.

6.4. Consequences for Supplier Firm Performance

With the easing of proprietary cost concerns through customer-state legislations, supplier firms engage in more extensive collaborations with customers. We now examine how the effect is transmitted to supplier firms' performance. Since customer firms in our sample are all of material importance to suppliers, we expect to observe a significant impact on supplier firms' financial performance. For this test, we construct a supplier-year panel of data and run the following regression:

$$Performance_{s,t} = \beta_1 IDD\ Exposure_{s,t} + \gamma X_{s,t} + \delta_s + \delta_t + \varepsilon_{s,t}. \quad (11)$$

The dependent variable, $Performance_{s,t}$, is the performance of supplier firm *s* in year *t*, in terms of Tobin's *q* or return on assets (*ROA*). *IDD Exposure* captures the extent to which a supplier firm is exposed to customer-state IDD, calculated as the weighted average IDD exposure across all major customers of the supplier, with the weights determined by individual customers' purchases from the supplier in a year. The construction of this measure follows the idea of Bartik instruments (Goldsmith-Pinkham et al. 2020; Bourveau et al. 2020; Breuer 2022). We control for supplier-firm characteristics including *Size*, *Leverage*, *Cash*, *CAPEX*, and *Firm Age*. We include supplier firm and year fixed effects and cluster standard errors at the supplier-firm level. We expect a positive coefficient on *IDD Exposure* if suppliers experience improved performance following an increase in exposure to customer-state IDD.

The results are reported in Table 8. Columns (1) and (2) show that both supplier Tobin's *q* and *ROA* are significantly positively associated with *IDD Exposure*; that is, supplier firms experience increased valuation and improved profitability as their exposure to customer IDD increases. We then decompose *ROA* into *Turnover* (sales scaled by total assets) and *Operating Expenses* (operating expenses scaled by sales) to trace the source of economic gains. Columns (3) and (4) show that *IDD Exposure* is positively (but insignificantly; *t-stat* = 1.52) related to *Turnover* and is significantly negatively related to *Operating Expenses.* Thus, performance improvement is driven mainly by enhanced operational efficiency, consistent with the view that reduced informational frictions enable partners to make use of relationship-specific investments more efficiently and, hence, to enhance cost efficiency.

6.5. Stable Unit Treatment Value Assumption

A key assumption of DID tests is the Stable Unit Treatment Value Assumption (SUTVA), which requires that the treatment status of one firm does not affect the outcomes of other firms (Armstrong and Kepler 2018). If suppliers reallocate transactions from control customers to treatment customers while keeping a consistent level of overall transaction volume, our estimates may overstate the positive effect of trade secrets protection on supplier sales dependency. We adopt two approaches to alleviate this concern.

First, because our primary dependent variable, *Sales Dependence*, is scaled by the supplier's total sales, it may be affected by changes in the supplier firm's sales to control customers (through the denominator). To address this possibility, we alternatively use the raw value of sales to customers (*Sales to Customer*) as the outcome variable and employ Poisson regressions for estimation. Column (1) of Table IA5 presents the result, and here we continue to find a significantly positive association between customer IDD and suppliers' overall sales to customers.

Second, we use two alternative control groups for our stacked DID regressions (which avoids potential spillovers to untreated customer firms). In column (2) of the Internet Appendix Table IA5, we have removed the control customers of treatment suppliers; whereas, in column (3) we remove all customers that are in the same SIC 2-digit industries as treatment customers. We continue to find that customer IDD adoption is positively related to transaction volume. To the extent that customers in these control groups are unlikely affected by treatment suppliers' potential resource allocation, these analyses alleviate the concern of SUTVA violation (Bisetti, She, and Zaldokas 2023).

6.6. Concerns About Repeated Uses of IDD

Prior studies have shown that IDD has an impact on capital structure (Klasa et al. 2018), knowledge asset investment (Qiu and Wang 2018), innovation outcomes (Contigiani et al. 2018), and earnings management (Callen, Fang, and Zhang 2020; Gao, Zhang, and Zhang 2018). Because of the repeated uses of IDD as a quasi-natural experiment, one might be concerned about possible false discovery in our study (Heath et al. 2023).

As a way to mitigate this concern, we developed a theoretical framework to predict the IDD effects in our context. Both our baseline and cross-sectional findings are consistent with the theoretical predictions. With a theory-guided analysis, our empirical results are less prone to being false discoveries (Armstrong, Kepler, Samuels, and Taylor 2022; Leuz 2022). The concern should be further eased by noting that (i) our baseline results have high statistical significance (the *t* statistics from the staggered DID analyses range from 3.34 to 4.01); (ii) our results are robust to including supplier-year fixed effects, which control for changes in the corporate-level policies of suppliers; and (iii) we reach consistent conclusions not only from IDD adoption and its subsequent reversal but also from the separate setting of UTSA.

Lastly, we conduct further analyses to confirm that our results still hold after controlling for changes in customer firms' characteristics that have been examined in prior studies. In particular, in the Internet Appendix Table IA6, we show that our results are robust to controlling for customer innovation (*Patent Number*, *R&D*), investment (*CAPX*), customer earnings management (*Earnings Management*), customer SGA expense (*SG&A Expense*), and capital structure (*Leverage*).[11] Based on the collective evidence, we thus conclude that our findings are unlikely to be false discoveries.

7. Conclusion

We examine how proprietary information costs affect supply chain transactions. Information sharing facilitates business collaboration, but concerns with information leakage via partners arise. We develop a simple model wherein a supplier trades off collaboration gains against proprietary costs, and predict how shocks to information protection affect supply chain

[11] Prior studies also show that IDD enactment affects management earnings forecast (Ali, Li, and Zhang 2018). Our results are robust when we control for the frequency of management earnings forecast. However, due to the data availability, adding this measure would substantially reduce our sample size.

collaboration in terms of both transaction outcomes and input resources dedicated to specific customers.

To test our predictions, we use three natural experiments in major customers' states as exogenous shocks that change the risk of information leakage. We find robust evidence indicating that suppliers increase sales dependence to affected major customers when proprietary cost concerns are eased. The documented effect is more pronounced when suppliers face higher prior risk of information misappropriation. At the same time, suppliers dedicate more resources to customers in the affected states, as evidenced by their innovations becoming more responsive to customers' growth opportunities and their patents more integrated with customers' patents. Supplier firms also display improved performance and greater market valuation, which are traced to cost efficiency gains (as opposed to increased scale). Overall, our study demonstrates that proprietary cost concerns are a significant factor that constrains supplier firms' ability to engage in relationship-based dealings with major customers as opposed to arm's length transactions.

References

Afrin, F., J. Kim, and S. Roychowdhury. 2022. Internalizing Peer Firm Proprietary Costs: Evidence from Supply Chain Relations. SSRN Scholarly Paper. Rochester, NY: Unpublished Working Paper.

Ali, A., S. Klasa, and E. Yeung. 2014. Industry concentration and corporate disclosure policy. *Journal of Accounting and Economics* 58 (2). 2013 Conference Issue: 240–264.

Ali, A., N. Li, and W. Zhang. 2018. Restrictions on Managers' Outside Employment Opportunities and Asymmetric Disclosure of Bad versus Good News. *The Accounting Review* 94 (5): 1–25.

Aobdia, D. 2015. Proprietary information spillovers and supplier choice: evidence from auditors. *Review of Accounting Studies* 20 (4): 1504–1539.

Armstrong, C., J. D. Kepler, D. Samuels, and D. Taylor. 2022. Causality redux: The evolution of empirical methods in accounting research and the growth of quasi-experiments. *Journal of Accounting and Economics* 74 (2): 101521.

Armstrong, C. S., and J. D. Kepler. 2018. Theory, research design assumptions, and causal inferences. *Journal of Accounting and Economics* 66 (2): 366–373.

Arrow, K. J. 1975. Vertical Integration and Communication. *The Bell Journal of Economics* 6 (1): 173–183.

Asker, J., and A. Ljungqvist. 2010. Competition and the Structure of Vertical Relationships in Capital Markets. *Journal of Political Economy* 118 (3): 599–647.

Bai, J. (Jianqiu), D. Fairhurst, and M. Serfling. 2020. Employment Protection, Investment, and Firm Growth. *The Review of Financial Studies* 33 (2): 644–688.

Baik, B., O. Even-Tov, R. Han, and D. Park. 2021. The Real Effects of Conflict Minerals Disclosures. SSRN Scholarly Paper. Rochester, NY.

Baiman, S., and M. V. Rajan. 2002. The Role of Information and Opportunism in the Choice of Buyer-Supplier Relationships. *Journal of Accounting Research* 40 (2): 247–278.

Baker, A. C., D. F. Larcker, and C. C. Y. Wang. 2022. How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144 (2): 370–395.

Bisetti, E., G. She, and A. Zaldokas. 2023. ESG Shocks in Global Supply Chains. Unpublished Working Paper.

Botosan, C. A., and M. S. Harris. 2000. Motivations for a Change in Disclosure Frequency and Its Consequences: An Examination of Voluntary Quarterly Segment Disclosures. *Journal of Accounting Research* 38 (2): 329–353.

Bourveau, T., J. D. Kepler, G. She, and L. L. Wang. 2022. Firm Boundaries and Voluntary Disclosure. SSRN Scholarly Paper. Rochester, NY: Unpublished Working Paper.

Bourveau, T., G. She, and A. Žaldokas. 2020. Corporate Disclosure as a Tacit Coordination Mechanism: Evidence from Cartel Enforcement Regulations. *Journal of Accounting Research* 58 (2): 295–332.

Breuer, M. 2022. Bartik Instruments: An Applied Introduction. *Journal of Financial Reporting* 7 (1): 49–67.

Breuer, M., K. Hombach, and M. A. Müller. 2018. How Does Financial Reporting Regulation Affect Firms' Banking? *The Review of Financial Studies* 31 (4): 1265–1297.

Breuer, M., C. Leuz, and S. Vanhaverbeke. 2021. Reporting Regulation and Corporate Innovation. SSRN Scholarly Paper. Rochester, NY: Unpublished Working Paper.

Callaway, B., and P. H. C. Sant'Anna. 2020. Difference-in-Differences with multiple time periods. *Journal of Econometrics*.

Callen, J. L., X. Fang, and W. Zhang. 2020. Protection of proprietary information and financial reporting opacity: Evidence from a natural experiment. *Journal of Corporate Finance* 64: 101641.

Cen, L., E. L. Maydew, L. Zhang, and L. Zuo. 2017. Customer–supplier relationships and corporate tax avoidance. *Journal of Financial Economics* 123 (2): 377–394.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer. 2019. The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics* 134 (3): 1405–1454.

de Chaisemartin, C., and X. D'Haultfœuille. 2020. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review* 110 (9): 2964–2996.

Chen, G., X. (Shaolee) Tian, and M. Yu. 2022. Redact to protect? Customers' incentive to protect information and suppliers' disclosure strategies. *Journal of Accounting and Economics* 74 (1): 101490.

Chen, T.-Y., G. Zhang, and Y. Zhou. 2018. Enforceability of non-compete covenants, discretionary investments, and financial reporting practices: Evidence from a natural experiment. *Journal of Accounting and Economics* 65 (1): 41–60.

Christensen, H. B., D. Macciocchi, A. Morris, and V. V. Nikolaev. 2022. Financial shocks to lenders and the composition of financial covenants. *Journal of Accounting and Economics* 73 (1): 101426.

Cohen, L., and A. Frazzini. 2008. Economic Links and Predictable Returns. *The Journal of Finance* 63 (4): 1977–2011.

Coles, J. L., N. D. Daniel, and L. Naveen. 2006. Managerial incentives and risk-taking. *Journal of Financial Economics* 79 (2): 431–468.

Contigiani, A., D. H. Hsu, and I. Barankay. 2018. Trade secrets and innovation: Evidence from the "inevitable disclosure" doctrine. *Strategic Management Journal* 39 (11): 2921–2942.

Costello, A. M. 2013. Mitigating incentive conflicts in inter-firm relationships: Evidence from long-term supply contracts. *Journal of Accounting and Economics* 56 (1): 19–39.

CREATe.org. 2012. *Trade Secret Theft: Managing the Growing Threat in Supply Chain*.

Cremers, K. J. M., and Y. Grinstein. 2014. Does the Market for CEO Talent Explain Controversial CEO Pay Practices? *Review of Finance* 18 (3): 921–960.

Dechow, P. M., and I. D. Dichev. 2002. The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *The Accounting Review* 77: 35-59,61-69.

Deshpande, M., and Y. Li. 2019. Who Is Screened Out? Application Costs and the Targeting of Disability Programs. *American Economic Journal: Economic Policy* 11 (4): 213–248.

Dixit, A.K., and R.S. Pindyck. 1994. Investment under uncertainty: Princeton university press.

Dou, Y., O.-K. Hope, and W. B. Thomas. 2013. Relationship-Specificity, Contract Enforceability, and Income Smoothing. *The Accounting Review* 88 (5): 1629–1656.

Dyer, J. H., and H. Singh. 1998. The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage. *Academy of Management Review* 23 (4): 660–679.

Ellis, J. A., C. E. Fee, and S. E. Thomas. 2012. Proprietary Costs and the Disclosure of Information About Customers. *Journal of Accounting Research* 50 (3): 685–727.

Freeman, K. 2023. Overlapping Ownership Along the Supply Chain. SSRN Scholarly Paper. Rochester, NY.

Gao, H., H. Zhang, and J. Zhang. 2018. Employee turnover likelihood and earnings management: evidence from the inevitable disclosure doctrine. *Review of Accounting Studies* 23 (4): 1424–1470.

Garmaise, M. J. 2011. Ties that Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment. *The Journal of Law, Economics, and Organization* 27 (2): 376–425.

Giannetti, M., M. Burkart, and T. Ellingsen. 2011. What You Sell Is What You Lend? Explaining Trade Credit Contracts. *The Review of Financial Studies* 24 (4): 1261–1298.

Glaeser, S. 2018. The effects of proprietary information on corporate disclosure and transparency: Evidence from trade secrets. *Journal of Accounting and Economics* 66 (1): 163–193.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift. 2020. Bartik Instruments: What, When, Why, and How. *American Economic Review* 110 (8): 2586–2624.

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 (4): 691–719.

Gu, L., R. Huang, Y. Mao, and X. Tian. 2022. How Does Human Capital Matter? Evidence from Venture Capital. *Journal of Financial and Quantitative Analysis* 57 (6): 2063–2094.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg. 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. Working Paper. Working Paper Series. National Bureau of Economic Research.

Hand, John, and Baruch Lev, eds. 2003. *Intangible Assets: Values, Measures, and Risks*. 1st edition. Oxford ; New York: Oxford University Press.

Harris, M. S. 1998. The Association between Competition and Managers' Business Segment Reporting Decisions. *Journal of Accounting Research* 36 (1): 111–128.

Heath, D., M. C. Ringgenberg, M. Samadi, and I. M. Werner. 2023. Reusing Natural Experiments. *The Journal of Finance* n/a (n/a).

Hoberg, G., and G. Phillips. 2016. Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy* 124 (5): 1423–1465.

Huang, Y., R. Jennings, and Y. Yu. 2016. Product Market Competition and Managerial Disclosure of Earnings Forecasts: Evidence from Import Tariff Rate Reductions. *The Accounting Review* 92 (3): 185–207.

Hui, K. W., S. Klasa, and P. E. Yeung. 2012. Corporate suppliers and customers and accounting conservatism. *Journal of Accounting and Economics* 53 (1): 115–135.

Hui, K. W., C. Liang, and P. E. Yeung. 2019. The effect of major customer concentration on firm profitability: competitive or collaborative? *Review of Accounting Studies* 24 (1): 189–229.

Intintoli, V. J., M. Serfling, and S. Shaikh. 2017. CEO Turnovers and Disruptions in Customer–Supplier Relationships. *Journal of Financial and Quantitative Analysis* 52 (6): 2565–2610.

Irvine, P. J., S. S. Park, and Ç. Yıldızhan. 2015. Customer-Base Concentration, Profitability, and the Relationship Life Cycle. *The Accounting Review* 91 (3): 883–906.

Jap, S. D. 1999. Pie-Expansion Efforts: Collaboration Processes in Buyer–Supplier Relationships. *Journal of Marketing Research* 36 (4): 461–475.

Kang, J. K., C. Lennox, and V. Pandey. 2022. Client concerns about information spillovers from sharing audit partners. *Journal of Accounting and Economics* 73 (1): 101434.

Kim, J., and K. Valentine. 2022. Public Firm Disclosures and the Market for Innovation. SSRN Scholarly Paper. Rochester, NY: Unpublished Working Paper.

Klasa, S., H. Ortiz-Molina, M. Serfling, and S. Srinivasan. 2018. Protection of trade secrets and capital structure decisions. *Journal of Financial Economics* 128 (2): 266–286.

Klein, R., and A. Rai. 2009. Interfirm Strategic Information Flows in Logistics Supply Chain Relationships. *MIS Quarterly* 33 (4): 735–762.

Kotabe, M., X. Martin, and H. Domoto. 2003. Gaining from vertical partnerships: knowledge transfer, relationship duration, and supplier performance improvement in the U.S. and Japanese automotive industries. *Strategic Management Journal* 24 (4): 293–316.

Leuz, C. 2022. Towards a design-based approach to accounting research. *Journal of Accounting and Economics* 74 (2): 101550.

Leuz, C., and P. D. Wysocki. 2016. The Economics of Disclosure and Financial Reporting Regulation: Evidence and Suggestions for Future Research. *Journal of Accounting Research* 54 (2): 525–622.

Li, J. J., L. Poppo, and K. Z. Zhou. 2010. Relational mechanisms, formal contracts, and local knowledge acquisition by international subsidiaries. *Strategic Management Journal* 31 (4): 349–370.

Li, X. 2010. The impacts of product market competition on the quantity and quality of voluntary disclosures. *Review of Accounting Studies* 15 (3): 663–711.

Li, Y., Y. Lin, and L. Zhang. 2018. Trade Secrets Law and Corporate Disclosure: Causal Evidence on the Proprietary Cost Hypothesis. *Journal of Accounting Research* 56 (1): 265–308.

Lindman, M. 2000. New Product Uniqueness In The Context Of Industrial Product Development. *Journal of Marketing Management* 16 (1–3): 247–271.

Martin, X., A. Swaminathan, and W. Mitchell. 1998. Organizational evolution in the interorganizational environment: Incentives and constraints on international expansion strategy. *Administrative Science Quarterly* 43 (3): 566–601.

Oliveira, M., P.-R. Kadapakkam, and M. Beyhaghi. 2017. Effects of customer financial distress on supplier capital structure. *Journal of Corporate Finance* 42: 131–149.

Patatoukas, P. N. 2012. Customer-Base Concentration: Implications for Firm Performance and Capital Markets: 2011 American Accounting Association Competitive Manuscript Award Winner. *The Accounting Review* 87 (2): 363–392.

PricewaterhouseCoopers, U.S. Chamber of Commerce, and American Society for Industrial Security. 2002. *Trends in Proprietary Information Loss*.

Qiu, B., and T. Wang. 2018. Does Knowledge Protection Benefit Shareholders? Evidence from Stock Market Reaction and Firm Investment in Knowledge Assets. *Journal of Financial and Quantitative Analysis* 53 (3): 1341–1370.

Raman, K., and H. Shahrur. 2008. Relationship-Specific Investments and Earnings Management: Evidence on Corporate Suppliers and Customers. *The Accounting Review* 83 (4): 1041–1081.

Roychowdhury, S., N. Shroff, and R. S. Verdi. 2019. The effects of financial reporting and disclosure on corporate investment: A review. *Journal of Accounting and Economics* 68 (2): 101246.

Samila, S., and O. Sorenson. 2011. Noncompete Covenants: Incentives to Innovate or Impediments to Growth. *Management Science* 57 (3): 425–438.

Samuels, D. 2020. Government Procurement and Changes in Firm Transparency. *The Accounting Review* 96 (1): 401–430.

Samuels, L. B., and B. K. Johnson. 1990. The Uniform Trade Secrets Act: The States' Response. *Creighton Law Review* 24: 49.

She, G. 2022. The Real Effects of Mandatory Nonfinancial Disclosure: Evidence from Supply Chain Transparency. *The Accounting Review* 97 (5): 399–425.

Sun, L., and S. Abraham. 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* 225 (2). Themed Issue: Treatment Effect 1: 175–199.

Verrecchia, R. E. 1983. Discretionary disclosure. *Journal of Accounting and Economics* 5: 179–194.

Williamson, O. E. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications, A Study in the Economics of Internal Organization*. New York: The Free Press.

Williamson, O. E. 1979. Transaction-Cost Economics: The Governance of Contractual Relations. *The Journal of Law and Economics* 22 (2): 233–261.

Williamson, O. E. 1981. The Economics of Organization: The Transaction Cost Approach. *American Journal of Sociology* 87 (3): 548–577.

Williamson, O. E. 1986. Vertical Integration and Related Variations on a Transaction-Cost Economics Theme. In *New Developments in the Analysis of Market Structure: Proceedings of a conference held by the International Economic Association in Ottawa, Canada*, edited by J. E. Stiglitz and G. F. Mathewson, 149–176. International Economic Association Series. London: Palgrave Macmillan UK.

Appendix I. Variable Definitions

This table shows the definition of all variables used in our analyses. Klasa et al. (2018), Qiu and Wang (2018), Glaeser (2018), Hoberg and Phillips (2016), Hall et al. (2001), and Giannetti et al. (2011) are denoted as KOSS, QW, GLA, HP, HJT, and GBE, respectively, in the table.

Variable	Definition	Source
Sales Dependence	Sales to customer divided by the total sales of a supplier.	Compustat
IDD	Equals 1 if the customer headquarters state has an inevitable disclosure doctrine and 0 otherwise.	KOSS, QW
Weighted_IDD	Average customer headquarters *IDD* weighted by customer share in a year.	Compustat, KOSS, QW
Treat	For each Inevitable Disclosure Doctrine enactment, equals 1 if the customer headquarters is in the treatment state and 0 otherwise.	KOSS, QW
Post	For each Inevitable Disclosure Doctrine enactment, equals 1 if this year is after the enactment of treatment state and 0 otherwise.	KOSS, QW
IDD_Abortion	Equals 1 if the customer headquarters is the treatment state for an IDD abortion event and 0 otherwise.	KOSS, QW
Post_Abortion	For each Inevitable Disclosure Doctrine abortion, equals 1 if this year is after the abortion of treatment state and 0 otherwise.	KOSS, QW
Treat_UTSA	For each Uniform Trade Secrets Act enactment, equals 1 if the customer headquarters is in the treatment state and 0 otherwise.	GLA
Post_UTSA	For each Uniform Trade Secrets Act enactment, equals 1 if this year is after the enactment of treatment state and 0 otherwise.	GLA
Relation_Length	Natural logarithm of the number of years since this supply-chain relationship was disclosed.	Compustat
Firm_Age	Natural logarithm of the number of years since the firm has been listed.	Compustat
ROA	EBITDA scaled by total assets.	Compustat
Size	Natural logarithm of total assets.	Compustat
Sales_Growth	Sales growth rate compared with last fiscal year.	Compustat
Ln(Sales)	Natural logarithm of sales.	Compustat
CAPEX	Capital expenditure scaled by total assets.	Compustat
Leverage	Total debt scaled by total assets.	Compustat
Cash	Cash and cash equivalent scaled by total assets.	Compustat
Turnover	Sales scaled by total assets.	Compustat
Operating Expenses	Operating expense scaled by sales.	Compustat
Tobin's q	Market value of equity plus book value of debt divided by total assets.	Compustat
Low Outside Opportunity	Average number of rivals in TNIC3 peers in the previous 5 years is below the median before the event.	HP
CNC Strength	Value of index of the enforceability of covenants not-to-compete (CNC) in customer state before the event year. The	Garmaise (2011)

Variable	Definition	Source
	index takes a value from 0 to 12, where larger values represent a higher level of CNC enforcement in the customer state.	
Low Intangibility	Average intangibility in the previous 5 years is below the median before the event. Intangibility equals total intangible assets (less goodwill) divided by total assets.	Compustat
Low Uniqueness	Equals 1 if the sector does not provide differentiated goods and 0 otherwise. SIC two-digit sectors that provide differentiated goods are coded by Giannetti et al. (2011).	GBE, Compustat
Low Profitability	Average gross margin in the previous 5 years is below the sample median before the event.	Compustat
R&D Expense	R&D expense scaled by the total assets.	Compustat
Cite Customer Dummy	Equals 1 if supplier has at least one patent filed this year that cites customer's patents and 0 otherwise.	HJT, Compustat
Cite Customer Ratio	Number of patents that cite customer's patents divided by the total number of patents filed by the supplier this year.	HJT, Compustat
Public Information Acquisition	Natural logarithm of 1 plus the number of the supplier's SEC filings acquired by the customer and the customer's SEC filings acquired by the supplier in a year following Bernard et al. (2020).	SEC Log File
Earnings Management	Accruals quality calculated using the method of Dechow and Dichev (2002).	Compustat
SGA Expense	Selling and general administration expenses divided by total sales.	Compustat
Patent Number	Total number of patents filed in a year.	HJT

Figure 1. Dynamic Effects of IDD Adoption

This figure presents the change in supplier-customer transaction volume around the customer's headquarters state IDD adoption. We estimate the β_i relative to the year before IDD adoption from the following model:

$$Sales\ Dependence_{s,c,t} = \beta_0 + \sum_{i=-4;i\neq-1}^{5} \beta_i\, Treat_{e,c} \times D_{e,i} + \gamma_s X_{s,t} + \gamma_c X_{c,t} + \delta_{e,s,c} + \delta_{e,t} + \varepsilon_{e,s,c,t},$$

where $D_{e,i}$ represents a vector of dummies equal 1 if the difference between this year and the treatment year of IDD adoption event e is i and 0 otherwise. $Treat_{e,c}$ is a dummy that equals 1 if the customer is in the treatment state for a given event e and 0 otherwise. $X_{s,t}$ and $X_{c,t}$ are vector of time-varying supplier and customer controls. We include event-supplier-customer fixed effects $\delta_{e,s,c}$ and event-year fixed effects $\delta_{e,t}$. The solid line represents the coefficients estimated. The shadow area represents the 90% confidence interval of the coefficients with standard errors clustered at the event-supplier-customer level.

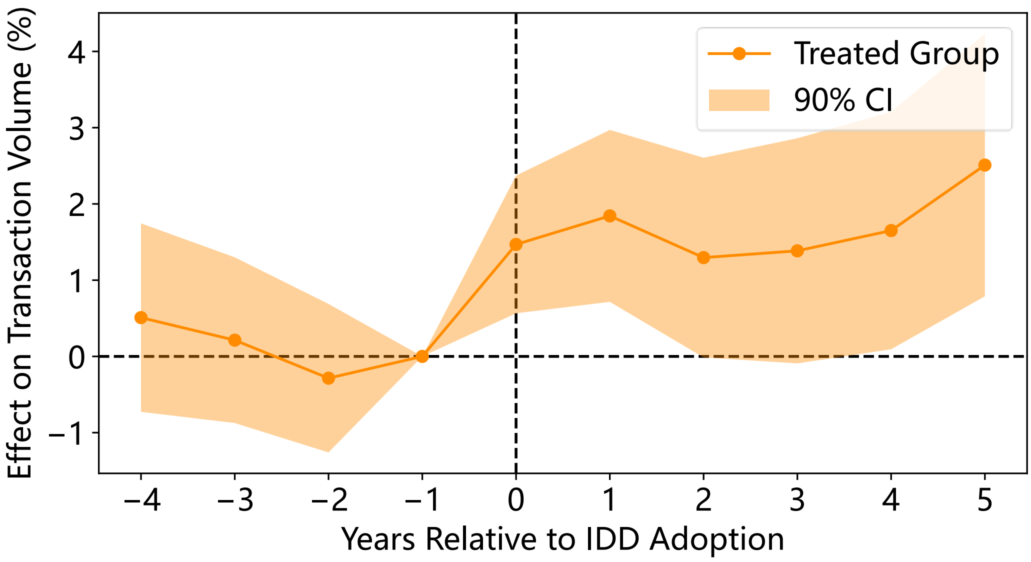

Table 1. Summary Statistics

This table presents the summary statistics of the variables we use in our main analyses. Panels A and B report the statistics for staggered sample and stacked DID sample, respectively. Column (1) is the number of nonmissing observations. Column (2) is the mean. Column (3) is the standard deviation. Column (4) is the 25th percentile. Column (5) is the median. Column (6) is the 75th percentile. All variables are defined in the Appendix.

Panel A. Staggered DID Sample

	N	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
Sales Dependence	45,434	0.166	0.175	0.048	0.129	0.210
IDD	45,434	0.540	0.498	0.000	1.000	1.000
Relation Length	45,434	1.229	0.875	0.693	1.099	1.946
ROA_{Cus}	45,434	0.144	0.075	0.097	0.146	0.182
$Size_{Cus}$	45,434	9.552	1.919	8.484	9.827	10.814
$CAPEX_{Cus}$	45,434	0.067	0.047	0.031	0.059	0.093
$Leverage_{Cus}$	45,434	0.258	0.159	0.144	0.244	0.342
$Cash_{Cus}$	45,434	0.092	0.104	0.025	0.057	0.118
ROA_{Sup}	45,434	0.057	0.241	0.028	0.112	0.173
$Size_{Sup}$	45,434	4.937	2.179	3.316	4.809	6.479
$CAPEX_{Sup}$	45,434	0.062	0.071	0.018	0.038	0.077
$Leverage_{Sup}$	45,434	0.270	0.275	0.046	0.218	0.396
$Cash_{Sup}$	45,434	0.181	0.215	0.023	0.088	0.263

Panel B. Stacked DID Sample—IDD Adoption

	N	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
Sales Dependence	66,382	0.171	0.175	0.062	0.130	0.214
Treat	66,382	0.096	0.294	0.000	0.000	0.000
Post	66,382	0.582	0.493	0.000	1.000	1.000
Relation Length	66,382	1.020	0.771	0.693	1.099	1.609
ROA_{Cus}	66,382	0.146	0.081	0.099	0.149	0.191
$Size_{Cus}$	66,382	8.703	1.970	7.477	9.004	10.157
$CAPEX_{Cus}$	66,382	0.076	0.052	0.034	0.068	0.106
$Leverage_{Cus}$	66,382	0.248	0.163	0.135	0.231	0.343
$Cash_{Cus}$	66,382	0.087	0.110	0.014	0.042	0.118
ROA_{Sup}	66,382	0.050	0.251	0.014	0.109	0.176
$Size_{Sup}$	66,382	4.307	1.919	2.942	4.131	5.591
$CAPEX_{Sup}$	66,382	0.068	0.075	0.020	0.043	0.086
$Leverage_{Sup}$	66,382	0.271	0.284	0.032	0.209	0.405
$Cash_{Sup}$	66,382	0.178	0.212	0.019	0.085	0.270

Table 2. Baseline Results

This table presents the relationship between IDD enactment in customer headquarters state and the supplier's share of sales to this customer. The dependent variable, *Sales Dependence*, is the sales to customer divided by the supplier's total sales. Columns (1) to (3) are estimated using the staggered difference-in-difference model. The explanatory variable is *IDD*, which equals 1 if the customer headquarters state has IDD in place and 0 otherwise. Columns (4) to (6) are estimated using the stacked difference-in-difference model. *Treat* is a binary variable that equals 1 if customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the relationship level in columns (1) to (3) and the cohort-relationship level in columns (4) to (6); *t* statistics are reported in parentheses; and ***, ** , and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**					
	Staggered DID			Stacked DID		
	(1)	(2)	(3)	(4)	(5)	(6)
IDD	0.022***	0.017***	0.022***			
	(4.01)	(3.34)	(3.69)			
Treat × Post				0.016***	0.016***	0.023**
				(2.63)	(2.61)	(2.07)
Relation_Length		-0.000	0.027***		0.010***	0.026***
		(-0.16)	(6.45)		(4.49)	(5.05)
ROA_{Cus}		0.056***	0.041		0.032**	-0.001
		(2.94)	(1.34)		(2.35)	(-0.03)
$Size_{Cus}$		0.033***	0.027***		0.020***	0.017**
		(8.49)	(4.61)		(7.49)	(2.53)
$CAPEX_{Cus}$		0.038	0.071		0.137***	0.094**
		(1.20)	(1.53)		(6.74)	(2.49)
$Leverage_{Cus}$		-0.003	-0.036*		0.005	-0.033**
		(-0.27)	(-1.94)		(0.68)	(-2.31)
$Cash_{Cus}$		-0.001	0.026		-0.015	-0.084***
		(-0.08)	(1.29)		(-1.55)	(-4.43)
ROA_{Sup}		0.023***			0.029***	
		(3.61)			(5.69)	
$Size_{Sup}$		-0.028***			-0.031***	
		(-11.08)			(-16.12)	
$CAPEX_{Sup}$		0.047***			0.062***	
		(2.58)			(5.75)	
$Leverage_{Sup}$		-0.010*			-0.000	
		(-1.77)			(-0.06)	
$Cash_{Sup}$		0.065***			0.075***	
		(7.36)			(11.38)	
Relationship FE	Y	Y	Y	N	N	N
Cohort-Relationship FE	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	N	N	N
Cohort-Year FE	N	N	N	Y	Y	Y
Supplier-Year FE	N	N	Y	N	N	Y
Observations	46,566	45,434	23,062	69,206	66,382	60,823
# Singletons	5,463	5,393	27,765	19,691	19,267	24,826
Adjusted R^2	0.695	0.707	0.687	0.737	0.746	0.971

Table 3. Cross-Sectional Tests: Employee Departure Risk

This table presents the relationship between IDD enactment in customer headquarters state and the supplier's share of sales to this customer, differentiated by the customer's incentives to deviate from the contractual commitment. The dependent variable, *Sales Dependence*, is the sales to the customer divided by the supplier's total sales. *Treat* is a binary variable that equals 1 if customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. The term **X** represents a series of variables that proxy for concerns of customer opportunism of the supplier, as indicated at the top of the table. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the cohort-relationship level; *t* statistics are reported in parentheses; and ***, **, and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**	
X =	CNC Strength	Low Outside Opportunity
	(1)	(2)
Treat × Post × **X**	-0.014**	-0.091**
	(-2.27)	(-2.01)
Post × **X**	0.000	0.002
	(0.90)	(1.32)
Treat × Post	0.104***	0.101**
	(2.85)	(2.39)
Controls	Y	Y
Cohort-Relationship FE	Y	Y
Cohort-Year FE	Y	Y
Supplier-Year FE	Y	Y
Observations	33,260	40,289
# Singletons	15,933	17,719
Adjusted R^2	0.979	0.975

Table 4. Cross-Sectional Tests: Proprietary Costs Concern

This table presents the relationship between IDD enactment in customer headquarters state and the supplier's share of sales to this customer, differentiated by the supplier's proprietary-information risk. The dependent variable, *Sales Dependence*, is the sales to customer divided by the supplier's total sales. *Treat* is a binary variable that equals 1 if customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. The term **X** represents a series of variables that proxy for the proprietary-information risk of the supplier as indicated at the top of the table. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the cohort-relationship level; *t* statistics are reported in parentheses; and ***, **, and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**	
X =	Low Intangibility	Low Uniqueness
	(1)	(2)
Treat × Post × **X**	-0.123***	-0.050*
	(-7.07)	(-1.86)
Post × **X**	0.001	-0.000
	(0.39)	(-0.10)
Treat × Post	0.030*	0.057**
	(1.83)	(2.45)
Controls	Y	Y
Cohort-Relationship FE	Y	Y
Cohort-Year FE	Y	Y
Supplier-Year FE	Y	Y
Observations	36,854	48,974
# Singletons	13,924	20,081
Adjusted R^2	0.969	0.970

Table 5. Relationship-Specific Investment

This table presents the relationship between IDD enactment in customer headquarters state and the supplier's relation-specific investment to the customer. In Panel A, the dependent variable, *Supplier R&D*, is the supplier's R&D expense divided by total assets. *CustGrowth* is customer Tobin's *q* in column (1) and customer sales growth in column (2). In Panel B, the dependent variables are three measures of the extent to which the supplier's innovation is specific to the customer. *Cite Customer Dummy* equals 1 if the supplier has at least one patent filed this year that cites customer's patents and 0 otherwise. *Cite Customer Ratio* is the number of patents that cite customer's patents divided by the total number of patents filed by the supplier in this year. *Treat* equals 1 if the customer headquarters is in the treatment state for an IDD enactment event and 0 otherwise. *Post* equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the cohort-relationship level; *t* statistics are reported in parentheses; and ***, ** , and * denote significance levels at 1%, 5%, and 10%.

Panel A. Supplier R&D Sensitivity

Dep. Var. =	Supplier R&D	
CustGrowth =	Customer Tobin's *q*	Customer Sales Growth
	(1)	(2)
Treat × Post × CustGrowth	0.006**	0.019*
	(2.02)	(1.77)
Treat × Post	-0.009*	-0.001
	(-1.66)	(-0.32)
Treat × CustGrowth	-0.002	0.005
	(-0.84)	(0.68)
Post × CustGrowth	-0.003**	-0.009**
	(-2.48)	(-2.28)
CustGrowth	0.001	-0.002
	(1.23)	(-0.50)
Relation_Length	0.021***	0.022***
	(17.28)	(17.89)
ROA_{Cus}	0.000	0.005
	(0.03)	(0.49)
$Size_{Cus}$	-0.003*	-0.002
	(-1.71)	(-1.07)
$CAPEX_{Cus}$	0.021	0.020
	(1.33)	(1.27)
$Leverage_{Cus}$	0.019***	0.020***
	(3.46)	(3.80)
$Cash_{Cus}$	0.005	0.008
	(0.73)	(1.04)
ROA_{Sup}	0.011***	0.012***
	(2.93)	(3.35)
$Size_{Sup}$	0.003**	0.004***
	(2.44)	(2.98)
$CAPEX_{Sup}$	-0.037***	-0.039***
	(-4.52)	(-4.91)
$Leverage_{Sup}$	-0.010***	-0.013***
	(-2.59)	(-3.41)
$Cash_{Sup}$	0.067***	0.070***
	(10.94)	(11.69)
Cohort-Relationship FE	Y	Y
Cohort-Year FE	Y	Y
Observations	62,345	64,515
# Singletons	17,889	18,601
Adjusted R^2	0.687	0.686

Table 5 (continued)

Panel B. Supplier R&D Specificity

Dep. Var. =	**Cite Customer**	
	Dummy	Ratio
	(1)	(2)
Treat × Post	0.020**	0.037**
	(2.37)	(1.99)
Relation_Length	0.001	-0.005
	(0.45)	(-0.69)
ROA_{Cus}	-0.010	-0.046
	(-0.66)	(-1.09)
$Size_{Cus}$	0.015***	0.023***
	(5.10)	(2.98)
$CAPEX_{Cus}$	-0.014	0.015
	(-0.57)	(0.24)
$Leverage_{Cus}$	-0.004	-0.007
	(-0.42)	(-0.27)
$Cash_{Cus}$	0.005	-0.017
	(0.33)	(-0.44)
ROA_{Sup}	-0.001	-0.007
	(-0.56)	(-1.17)
$Size_{Sup}$	0.007***	0.019***
	(4.47)	(4.72)
$CAPEX_{Sup}$	-0.016*	-0.049**
	(-1.77)	(-2.41)
$Leverage_{Sup}$	-0.000	0.006
	(-0.00)	(0.88)
$Cash_{Sup}$	-0.019***	-0.044***
	(-3.55)	(-3.16)
Cohort-Supplier-Customer FE	Y	Y
Cohort-Year FE	Y	Y
Observations	66,382	66,382
# Singletons	19,267	19,267
Adjusted R^2	0.475	0.345

Table 6. Evidence from IDD Abortion

This table presents the relationship between IDD abortion in customer headquarters state and the supplier's share of sales to this customer. The dependent variable, *Sales Dependence*, is the sales to customer divided by the supplier's total sales. The explanatory variable is *IDD_Abortion* × *Post_Abortion*. *IDD_Abortion* equals 1 if customer headquarters is the treatment state for an IDD abortion event and 0 otherwise. *Post_Abortion* equals 1 if the year is after the treatment for an IDD abortion event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the cohort-relationship level; *t* statistics are reported in parentheses; and ***, **, and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**	
	(1)	(2)
IDD_Abortion × Post_Abortion	-0.013**	-0.011*
	(-2.16)	(-1.81)
Relation_Length		0.005**
		(2.49)
ROA_{Cus}		0.083***
		(4.63)
$Size_{Cus}$		0.032***
		(8.82)
$CAPEX_{Cus}$		0.116***
		(3.00)
$Leverage_{Cus}$		-0.003
		(-0.27)
$Cash_{Cus}$		0.004
		(0.26)
ROA_{Sup}		0.032***
		(5.75)
$Size_{Sup}$		-0.023***
		(-10.75)
$CAPEX_{Sup}$		0.042*
		(1.89)
$Leverage_{Sup}$		-0.012***
		(-2.60)
$Cash_{Sup}$		0.060***
		(8.31)
Cohort-Relationship FE	Y	Y
Cohort-Year FE	Y	Y
Observations	57,161	55,946
# Singletons	11,062	10,899
Adjusted R^2	0.728	0.735

Table 7. Evidence from Customer UTSA Adoption

This table presents the relationship between UTSA enactment in the customer headquarters state and the supplier's share of sales to this customer. The dependent variable, *Sales Dependence*, is the sales to customer divided by the supplier's total sales. Columns (1) to (2) are estimated using the stacked difference-in-difference model. *Treat_UTSA* is a binary variable that equals 1 if customer headquarters is the treatment state for a UTSA enactment event and 0 otherwise. *Post_UTSA* is a binary variable that equals 1 if the year is after the treatment for an UTSA enactment event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the cohort-relationship level; *t* statistics are reported in parentheses; and ***, **, and * denote significant levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**	
	(1)	(2)
Treat_UTSA × Post_UTSA	0.022**	0.021**
	(2.27)	(2.06)
Relation_Length		-0.003
		(-0.54)
ROA_{Cus}		0.034
		(1.06)
$Size_{Cus}$		0.012
		(1.36)
$CAPEX_{Cus}$		-0.081**
		(-2.34)
$Leverage_{Cus}$		-0.022
		(-1.10)
$Cash_{Cus}$		0.011
		(0.44)
ROA_{Sup}		0.041***
		(3.11)
$Size_{Sup}$		-0.043***
		(-6.23)
$CAPEX_{Sup}$		0.033
		(1.50)
$Leverage_{Sup}$		-0.021
		(-1.58)
$Cash_{Sup}$		0.036**
		(2.08)
Cohort-Relationship FE	Y	Y
Cohort-Year FE	Y	Y
Observations	16,090	15,594
# Singletons	0.752	0.762
Adjusted R^2	4,473	4,363

Table 8. Ex Post Supplier Performance

This table presents the relationship between the supplier's IDD exposure via the customer and the supplier's firm-level outcomes. The dependent variables are Tobin's *q*, *ROA*, *Turnover*, and *Operating_Expense* in columns (1) to (4), respectively. *IDD Exposure* is the average customer headquarters IDD weighted by customer share in a year. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level; *t* statistics are reported in parentheses; and ***, ** , and * denote significant levels at 1%, 5%, and 10%.

Dep. Var. =	**Tobin's *q***	**ROA**	**Turnover**	**Operating Expenses**
	(1)	(2)	(3)	(4)
IDD Exposure	0.325**	0.035**	0.056	-0.050***
	(2.44)	(2.39)	(1.52)	(-3.65)
Size	-0.401***	0.064***	-0.262***	-0.024***
	(-12.37)	(15.02)	(-24.10)	(-6.59)
Leverage	0.536***	-0.189***	0.043	0.028***
	(4.39)	(-12.71)	(1.42)	(2.70)
Cash	1.030***	-0.019	-0.671***	0.045***
	(6.92)	(-1.11)	(-16.44)	(2.65)
CAPEX	2.008***	-0.136***	0.098	0.089***
	(8.23)	(-3.75)	(1.39)	(3.19)
Firm_Age	-0.401***	-0.034***	0.105***	0.012***
	(-9.77)	(-7.51)	(7.96)	(3.00)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	27,150	27,996	28,025	27,996
# Singletons	1,629	1,621	1,624	1,621
Adjusted R^2	0.579	0.632	0.813	0.763

Internet Appendix

Table IA1. Alternative Approaches to Filling the Missing Transaction Volume

This table presents the relationship between IDD enactment in the customer headquarters state and the supplier's share of sales to the customer, using different versions of IDD events compiled by prior studies. The dependent variable, *Sales Dependence*, is the sales to customer divided by the supplier's total sales. We drop the observation in column (1) with a missing transaction volume. In columns (2) and (3), we fill the missing transaction volume with 0.05 and 0.10, respectively. *Treat* is a binary variable that equals 1 if the customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the cohort-relationship level; *t* statistics are reported in parentheses; and ***, **, and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**		
	Drop Missing	Filled by 0.05	Filled by 0.10
	(1)	(2)	(3)
Treat × Post	0.016**	0.015***	0.015***
	(2.39)	(2.60)	(2.58)
Controls	Y	Y	Y
Cohort-Relationship FE	Y	Y	Y
Cohort-Year FE	Y	Y	Y
Observations	55,216	66,382	66,382
# Singletons	15,402	19,267	19,267
Adjusted R^2	0.749	0.741	0.735

Internet Appendix

Table IA2. IDD Adoption and Rejection

This table shows the IDD adoption and rejection events compiled by Klasa et al. (2018) and Qiu and Wang (2018). Klasa et al. and Qiu and Wang are denoted KOSS and QW in the table, respectively. States not listed in this table do not have IDD adoption/rejection events until 2019. We indicate whether a specific event is included in the IDD adoption sample or IDD rejection sample in the last two columns, respectively.

State	Year	Decision	Case	Source	Adoption Sample	Rejection Sample
Arkansas	1997	Adopt	*Southwestern Energy v. Eickenhorst, 955 F. Supp. 1078 (1997)*	KOSS, QW	Y	
California	1999	Adopt	*Electro Optical Indus., Inc. v. Stephen White, 90 Cal. Rptr. 2d 680 (1999), 76 Cal. App. 4th 653*	QW	Y	
	2000	Reject	Supreme Court Overrule	QW		Y
	2002	Reject	*Whyte v. Schlage Lock Co., No. G028382 (Ct. of App. of California 2002)*	QW		A rejection exists before
Connecticut	1996	Adopt	*Branson Ultrasonics Corp. v. Stratman, 921 F. Supp. 909 (D. Conn. 1996)*	KOSS, QW	Y	
Delaware	1964	Adopt	*E. I. DuPont de Nemours & Co. v. American Potash and Chemical Corp., 200 A. 2d 428 (Del. Ch. 1964)*	KOSS, QW	Out of sample period	
Florida	1960	Adopt	*Fountain v. Hudson Cush-N-Foam Corp., 122 So. 2d 232, 234 (Fla. Dist. Ct. App. 1960)*	KOSS, QW	Out of sample period	
	2001	Reject	*Del Monte Fresh Produce Co. v. Dole Food Co., 148 F. Supp. 2d 1326 (S.D. Fla. 2001)*	KOSS, QW		Y
Georgia	1998	Adopt	*Essex Group Inc. v. Southwire Co., 501 S.E. 2d 501 (Ga. 1998)*	KOSS	Y	
Illinois	1989	Adopt	*Teradyne Inc. v. Clear Communications Corp., 707 F. Supp. 353 (N.D. 111. 1989)*	KOSS	Y	
	1995	Adopt	*PepsiCo, Inc. v. Redmond, 54 F.3d 1262, 1272 (7th Cir. 1995)*	QW	An adoption exists before	

State	Year	Decision	Case	Source	Adoption Sample	Rejection Sample
Indiana	1995	Adopt	*Ackerman v. Kimball Int'l, Inc., 652 N.E. 2d 507, 510-11 (Ind. 1995)*	KOSS, QW	Y	
	1998	Reject	*Bridgestone/Firestone, Inc. v. Lockhart, 5 F. Supp. 2d 667 (S.D. Ind. 1998)*	QW		Y
Iowa	1996	Adopt	*Uncle B's Bakery v. O'Rourke, 920 F. Supp. 1405 (N.D. Iowa 1996)*	KOSS	Y	
	2002	Adopt	*Barilla Am., Inc. v. Wright, No. 4-02-CV-90267, 2002 U.S. Dist. Lexis 12773 (S.D. Iowa 2002)*	QW	An adoption exists before	
Kansas	2006	Adopt	*Bradbury Co. v. Teissier-Ducros, 413 F. Supp. 2d 1203, 1209 (D. Kan. 2006)*	KOSS, QW	Y	
Massachusetts	1994	Adopt	*Bard v. Intoccia, 1994 U.S. Dist. LEXIS 15,368 (D. Mass. 1994)*	KOSS	Y	
	1995	Adopt	*Marcam Corp. v. Orchard, 885 F. Supp. 294, 298-300 (D. Mass. 1995)*	QW	An adoption exists before	
	2012	Reject	*U.S. Elec. Servs. v. Schmidt, Civil Action No. 12-10845-DJC (U.S. Dist. Ct. for the Dist. of Mass. 2012)*	QW		Y
Michigan	1966	Adopt	*Allis-Chalmers Manufacturing Co. v. Continental Aviation & Engineering Corp., 255 F. Supp. 645, 654 (E.D. Mich. 1966)*	KOSS, QW	Out of sample period	
	2002	Reject	*CMI International Inc. v. Intermet Inter. Corp., 649 N.W. 2d 808 (Mich. Ct. App. 2002)*	KOSS, QW		Y
Minnesota	1986	Adopt	*Surgidev Corp. v. Eye Tech., Inc., 648 F. Supp. 661 (D. Minn. 1986)*	KOSS, QW	Y	
	1992	Reject	*IBM Corp. v. Seagate Tech., Inc., 941 F. Supp. 98 (D. Minn. 1992)*	QW		Y
	1996	Adopt	*La Calhene, Inc. v. Spolyar, 938 F. Supp. 523 (W.D. Wis. 1996)*	QW	Y	
Missouri	2000	Adopt	*H&R Block Eastern Tax Services, Inc. v. Enchura, 122 F. Supp. 2d 1067 (W.D. Mo. 2000)*	KOSS, QW	Y	

State	Year	Decision	Case	Source	Adoption Sample	Rejection Sample
New Jersey	1987	Adopt	*National Starch and Chem. Corp. v. Parker Chemical Corp., 530 A. 2d 31 (N.J. Super. Ct. App. Div. 1987)*	KOSS, QW	Y	
New York	1919	Adopt	*Eastman Kodak Co. v. Powers Film Prod., 189 A.D. 556 (N.Y.A.D. 1919)*	KOSS	Out of sample period	
	1997	Adopt	*DoubleClick, Inc. v. Henderson, No. 116914/97, 1997 N.Y. Misc. Lexis 577 (Sup. Ct. N.Y. Co. Nov. 7, 1997)*	QW	An adoption exists before	
	1999	Reject	*EarthWeb, Inc. v. Schlack, 71 F. Supp. 2d 299 (S.D. N.Y. 1999)*	QW		Y
North Carolina	1976	Adopt	*Travenol Labs., Inc. v. Turner, 228 S.E. 2d 478, 483 (N.C. Ct. App. 1976)*	KOSS, QW	Out of sample period	
	1996	Adopt	*Merck & Co. v. Lyon, 941 F. Supp. 1443 (M.D. N.C. 1996)*	QW	An adoption exists before	
	2014	Reject	*RCR Enters., LLC v. McCall, 14 CVS 3342 (N.C. Sup. Ct. 2014)*	QW		Y
Ohio	2000	Adopt	*Procter & Gamble Co., v. Stoneham, 747 N.E. 2d 268 (Ohio Ct. App. 2000)*	KOSS, QW	Y	
Pennsylvania	1982	Adopt	*Air Products & Chemical, Inc. v. Johnson, 442 A. 2d 1114 (Pennsylvania Superior Ct. 1982)*	KOSS, QW	Y	
South Carolina	2008	Adopt	*Nucor Corp. v. Bell, C/A No. 2: 06-CV-02972-DCN (U.S. Dist. Ct. for the Dist. of South Carolina 2008)*	QW	Y	
Texas	1993	Adopt	*Rugen v. Interactive Bus. Sys., Inc., 864 S.W. 2d 548, 551 (Tex. App. 1993)*	KOSS, QW	Y	
	2003	Reject	*Cardinal Health Staffing Network Inc. v. Bowen, 106 S.W. 3d 230 (Tex. App. 2003)*	KOSS, QW		Y
Utah	1998	Adopt	*Novell, Inc. v. Timpanogos Research Group, Inc., 46 U.S.P.Q. 2d 1197 (Utah Dist. Ct. 1998)*	KOSS, QW	Y	
Washington	1997	Adopt	*Solutec Corp., Inc. v. Agnew, 1997 WL 794496, 8 (Wash. Ct. App.)*	KOSS, QW	Y	

Internet Appendix

Table IA3. Alternative Definition of IDD Event

This table presents the relationship between IDD enactment in the customer headquarters state and the supplier's share of sales to this customer, using different versions of IDD events complied by prior studies. The dependent variable, *Sales Dependence*, is sales to customer divided by the supplier's total sales. The explanatory variable is *IDD*, which equals 1 if the customer headquarters state has IDD in place and 0 otherwise. *Treat* is a binary variable that equals 1 if customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. In columns (1) and (2), we report the results using IDD events compiled by Klasa et al. (2018). In columns (3) and (4), we report the results using IDD events compiled by Qiu and Wang (2018). In columns (5) to (6), we report the results using the intersected IDD events compiled by both groups of scholars. The equation is estimated by either the staggered difference-in-difference model or stacked difference-in-difference model, as indicated at the top of the table. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the cohort-relationship level; *t* statistics are reported in parentheses; and ***, **, and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**					
IDD version:	KOSS		QW		Both	
	Staggered DID	Stacked DID	Staggered DID	Stacked DID	Staggered DID	Stacked DID
	(1)	(2)	(3)	(4)	(5)	(6)
IDD	0.021***		0.013**		0.014**	
	(3.14)		(2.43)		(2.52)	
Treat × Post		0.013**		0.015**		0.019**
		(2.02)		(2.39)		(2.54)
Controls	Y	Y	Y	Y	Y	Y
Cohort-Relationship FE	Y	Y	Y	Y	Y	Y
Cohort-Year FE	Y	Y	Y	Y	Y	Y
Observations	45,434	58,107	45,434	58,876	45,434	43,649
# Singletons	5,393	17,551	5,393	17,166	5,393	12,973
Adjusted R^2	0.707	0.745	0.706	0.740	0.706	0.740

Internet Appendix

Table IA4. Additional Controls

This table presents the relationship between IDD enactment in the customer headquarters state and the supplier's share of sales to this customer. The dependent variable, *Sales Dependence*, is sales to customer divided by the supplier's total sales. Columns (1) to (2) are estimated by a staggered difference-in-difference model. The explanatory variable is *IDD*, which equals 1 if the customer headquarters state has IDD in place and 0 otherwise. Columns (3) to (4) are estimated using a stacked difference-in-difference model. *Treat* is a binary variable that equals 1 if customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the relationship level in columns (1) to (2) and the cohort-relationship level in columns (3) to (4); *t* statistics are reported in parentheses; and ***, **, and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**			
	Staggered DID		Stacked DID	
	(1)	(2)	(3)	(4)
IDD	0.013**	0.020***		
	(2.50)	(3.00)		
Treat × Post			0.013**	0.024**
			(2.05)	(2.02)
Ln(Sales)$_{Cus}$	0.038***	0.024**	0.030***	0.022***
	(5.27)	(2.04)	(6.46)	(2.62)
Ln(Sales)$_{Sup}$	-0.022***		-0.023***	
	(-4.39)		(-5.36)	
Sales Growth$_{Cus}$	-0.008*	-0.001	-0.007***	-0.011*
	(-1.78)	(-0.19)	(-2.59)	(-1.94)
Sales Growth$_{Sup}$	0.005***		0.007***	
	(2.68)		(5.93)	
Controls	Y	Y	Y	Y
Relationship FE	Y	Y	N	N
Cohort-Relationship FE	N	N	Y	Y
Year FE	Y	Y	N	N
Cohort-Year FE	N	N	Y	Y
Supplier-Year FE	N	Y	N	Y
Observations	49,232	30,890	68,053	63,419
# Singletons	4,512	22,854	16,116	20,750
Adjusted R^2	0.724	0.837	0.767	0.974

Internet Appendix

Table IA5. Concerns About Denominator Effect and Violating SUTVA

This table presents the relationship between IDD enactment in the customer headquarters state and the supplier's sales to this customer, using the Poisson model with fixed effects to estimate the treatment effect. The dependent variable, *Sales to Customer*, is the total amount of sales to customers. In column (2), we remove control customers of treatment suppliers. In column (3), we remove customers in the same SIC 2-digit industry with treatment suppliers. *Treat* is a binary variable that equals 1 if the customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are heteroskedasticity robust; *t* statistics are reported in parentheses; and ***, **, and * denote significance levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales to Customer**		
Estimation	Poisson	Poisson	Poisson
Sub-sample		Remove control customers of treatment suppliers	Remove customers in the same SIC 2-digit industry with treatment suppliers
	(1)	(2)	(3)
Treat × Post	0.098**	0.079*	0.100**
	(2.45)	(1.89)	(2.50)
Controls	Y	Y	Y
Cohort-Relationship FE	Y	Y	Y
Cohort-Year FE	Y	Y	Y
Observations	55,216	31,883	44,813
# Singletons	15,402	9,315	12,317

Internet Appendix

Table IA6. Concerns About Repeated Uses of IDD

This table presents the relationship between IDD enactment in the customer headquarters state and the supplier's share of sales to this customer. The dependent variable, *Sales Dependence*, is sales to customer divided by the supplier's total sales. Columns (1) and (2) are estimated using a staggered difference-in-difference model. The explanatory variable is *IDD*, which equals 1 if the customer headquarters state has IDD in place and 0 otherwise. Columns (3) and (4) are estimated using a stacked difference-in-difference model. *Treat* is a binary variable that equals 1 if customer headquarters is the treatment state for an IDD enactment event and 0 otherwise. *Post* is a binary variable that equals 1 if the year is after the treatment for an IDD enactment event and 0 otherwise. Variable definitions are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the relationship level in columns (1) and (2) and the cohort-relationship level in columns (3) and (4); *t* statistics are reported in parentheses; and ***, **, and * denote significant levels at 1%, 5%, and 10%.

Dep. Var. =	**Sales Dependence**			
	Staggered DID		Stacked DID	
	(1)	(2)	(3)	(4)
IDD	0.018***	0.015**		
	(3.40)	(2.02)		
Treat × Post			0.015**	0.027***
			(2.32)	(2.60)
Earnings Management$_{Cus}$	0.007	0.012	0.002	0.015
	(0.36)	(0.47)	(0.14)	(0.55)
SGA Expense$_{Cus}$	-0.012	0.051	-0.022	0.092**
	(-0.38)	(1.27)	(-0.95)	(2.06)
Patent Number$_{Cus}$	0.000	0.000	0.000	0.000*
	(0.40)	(1.03)	(0.00)	(1.85)
Relation_Length	-0.001	0.026***	0.008***	0.027***
	(-0.25)	(5.99)	(3.38)	(5.24)
ROA$_{Cus}$	0.047**	0.073**	0.030*	0.059**
	(2.15)	(2.29)	(1.87)	(2.12)
Size$_{Cus}$	0.035***	0.029***	0.021***	0.032***
	(7.70)	(4.98)	(6.69)	(3.90)
CAPEX$_{Cus}$	0.042	0.069	0.180***	0.158***
	(1.19)	(1.40)	(8.15)	(4.19)
Leverage$_{Cus}$	-0.005	-0.030	0.007	-0.026
	(-0.37)	(-1.58)	(0.74)	(-1.55)
Cash$_{Cus}$	0.010	0.022	0.003	-0.068***
	(0.54)	(0.99)	(0.25)	(-3.25)
ROA$_{Sup}$	0.017**		0.026***	
	(2.58)		(4.46)	
Size$_{Sup}$	-0.026***		-0.028***	
	(-9.71)		(-13.42)	
CAPEX$_{Sup}$	0.043**		0.058***	
	(2.17)		(4.84)	
Leverage$_{Sup}$	-0.011*		0.004	
	(-1.67)		(0.74)	
Cash$_{Sup}$	0.069***		0.065***	
	(7.23)		(8.45)	
Relationship FE	Y	Y	N	N
Cohort-Relationship FE	N	N	Y	Y
Year FE	Y	Y	N	N
Cohort-Year FE	N	N	Y	Y
Supplier-Year FE	N	Y	N	Y
Observations	44,439	26,261	63,321	58,811
# Singletons	4,462	22,640	15,560	20,070
Adjusted R^2	0.722	0.848	0.759	0.977