Access to Debt and the Provision of Trade Credit

Abstract

We examine how access to debt markets affects firms' provision of trade credit. Using hand-collected data on trade credit between customer-supplier pairs, we show that increased access to debt strengthens firms' bargaining power relative to major customers and reduces the trade credit they provide to those customers. We establish causality using the staggered passage of anti-recharacterization laws that increased firms' debt capacity. Affected firms expand their customer base, reduce customer concentration, and decrease trade credit to powerful customers. The decline in trade credit leads customers to cut investment, increase leverage, and scale back trade credit provision to firms further downstream.

Keywords: Trade Credit, Access to Debt, Creditor Rights, Supply-Chain, Bargaining Power

1 Introduction

Trade credit represents one of the most important sources of funding for U.S. firms, with a total volume exceeding 20% of total GDP (Garcia-Marin et al. 2020). In many segments of the supply chain, small suppliers compete for orders from large, powerful customers. Such power dynamics lead to the surprising phenomenon of "small lending big." In other words, suppliers face pressure to offer generous trade credit terms to retain major clients, even though doing so amplifies financial constraints and prevents them from conducting valuable investments (Klapper et al. 2012; Murfin and Njoroge 2015; Barrot 2016; Giannetti et al. 2021).

How does access to debt financing affect (supplier) firms' incentives to provide trade credit? The answer is not obvious. On the one hand, better access to debt improves corporate liquidity, thus enabling firms to provide more trade credit (i.e., a liquidity pass-through channel). An extensive literature in Finance and Economics documents this effect, focusing on situations where powerful suppliers support weak customers lacking access to bank credit (Schwartz 1974; Petersen and Rajan 1997; Biais and Gollier 1997; Emery 1987; Jain 2001; Meltzer 1960). This effect becomes particularly pronounced when customers are hit by banking crises or economic recessions (Love et al. 2007; Fabbri and Menichini 2016; Garcia-Appendini and Montoriol-Garriga 2013; Costello 2020; Amberg et al., 2021; Cuñat 2007). On the other hand, access to external debt markets could reduce trade credit provision if enriched financial resources allow firms to pursue growth options, reduce their reliance on powerful customers, and enhance their bargaining power over downstream firms. These effects help alleviate the pressure for firms to provide trade financing (a bargaining power channel). This hypothesis, while plausible, has not been empirically tested.

Using a novel dataset, we revisit the relation between access to credit and firms' decision to extend trade credit. We find that better access to debt markets reduces firms' provision of trade credit to downstream firms. Our evidence supports the bargaining power channel. Our study features two empirical design choices. First, we compile a dataset on trade credit balances between U.S. public firms, which allows us to make detailed inferences regarding firms' decision to extend trade credit to individual customers. Our data originate from firms' 10-K filings. The Financial Accounting Standards Board (FASB) No. 105 requires firms to report material information regarding credit concentration, which includes trade credit offered to major customers. Such information is often embedded in footnotes and does not follow a standardized format. We manually collect trade credit data from textual descriptions and compile a granular dataset that contains the identities of both the buyer and the seller, the value of their annual transactions, and the trade credit being extended.

Our dataset covers 623 unique buyers and 969 unique sellers. Given that all of our buyers and sellers are public firms, we are able to observe detailed information regarding firms' financial and operational conditions, industry classification, and sales to individual customers. This sample provides complementary evidence relative to studies using proprietary contract-level datasets, which either cover a limited set of firms, or lack granular information regarding trade counterparties (i.e., customer firms).[1] While we do not observe an exhaustive list of customer-supplier relations in the U.S., we can track the trade credit for the near universe of major customers (who each account for 10% or more of firm's sales) for every supplier in our sample. Another advantage of this granular data is that we can fix the demand for trade credit on the customer side, comparing the changes in trade credit from a supplier with improved access to finance to those from other suppliers of the same customer at the same time.

Second, we exploit the staggered state-level passage of anti-recharacterization laws (ARLs) as exogenous shocks to firms' debt capacity. Seven U.S. states have passed ARLs during the period spanning from 1997 to 2005. These laws eventually affected nearly 60% of all U.S. publicly traded firms. ARLs are designed to protect creditors from the automatic stay provision during bankruptcy proceedings. Consequently, they improve firms' access to credit by increasing the option value for them to create Special Purpose Vehicles (SPVs) and tap additional debt markets. Section 2 provides a detailed descrip-

[1] For example, Costello (2020) utilizes data from Credit2B, which provides more extensive detail on receivables, such as aging reports, but lacks detailed information on buyers. Klapper et al. (2012) focus on a dataset from PrimeRevenue with only 56 buyers.

tion of anti-recharacterization laws. Prior research suggests that firms affected by the laws are able to borrow more, invest in new technology and innovation, and become more productive (Li et al. 2016; Mann 2018; Ersahin 2020; Favara et al. 2021). Yet, the effect of anti-recharacterization laws on product market dynamics remains under-explored.

We first show that, after the passage of anti-recharacterization laws, affected firms experience higher sales growth by around 5% compared to control firms, while simultaneously diversifying their customer base. Affected firms invest more in intangible assets and innovation and build relationships with new customers. Ultimately, this leads to an increase in the total number of customers and a decline in customer concentration. The firms also earn higher gross margins. Collectively, these results are consistent with the argument that access to debt markets enhances firms' bargaining power relative to major customers.

In our main analysis, we document that treated firms significantly reduce trade credit to major customers following the passage of the laws. Our estimation controls for a stringent set of fixed effects. We include customer-supplier-pair fixed effects to track how trade credit between the same customer-supplier pair changes over time. Moreover, we implement the Khwaja and Mian (2008) within-firm estimator by imposing customer-year fixed effects. This allows us to hold constant customer-side conditions, including the demand for trade credit, and compare trade credit extended by a treated supplier and a control supplier to the same customer at the same time. With the most rigorous specification, our estimates suggest that treated suppliers reduce trade credit per dollar of sales by 4 percentage points following the passage of anti-recharacterization laws. This is an economically meaningful magnitude, accounting for around 16% of the average trade credit (over sales) for suppliers in our sample. We document a similar reduction in the dollar amount of trade credit for affected firms. In additional robustness tests, we verify that our findings hold for all Compustat firms and are not driven by the firms' discontinued reporting of customers, or by the FASB disclosure threshold regarding customer sales.

We address recent concerns related to heterogeneous treatment timing in the generalized difference-in-difference (DID) framework in two ways (Goodman-Bacon 2021;

Callaway and Sant'Anna 2020). First, we repeat our analysis on stacked event-study samples. To construct these samples, we match each treated firm with control firms who are never treated (those in states that never passed an ARL). Second, we focus on a single event in Delaware and compare Delaware firms to never-treated firms. Our finding persists in both analyses. Importantly, we test the parallel trend assumption using both the stacked-event sample and the generalized DID sample. We show that the sales and trade credit extension of treated firms do not diverge from control firms prior to the enactment of the laws. Following the enactment, treated firms exhibit a significant increase in sales and a reduction in trade credit.

We provide additional support to the bargaining power channel, i.e., trade credit declines because better access to debt markets improves firms' bargaining power relative to buyers. If this bargaining power channel leads to reduced trade credit provision, our results should be more pronounced in cases where the supplier was in a *weaker* bargaining position relative to the customer prior to the shock. We gauge the relative bargaining position between customers and suppliers in several ways.

First, we expect the reduction in trade credit after the anti-recharacterization laws to be stronger for major customers, who possess stronger bargaining power relative to the supplier than minor customers. We follow the same classification as SEC's SFAS 14, defining major (minor) customers as those that account for at least (less than) 10% of sales from a supplier. Separately examining the changes in trade credit provided to major and minor customers, we indeed find that the reduction in trade credit only occurs for major customers, but not for minor ones.

Our second approach follows the methodology in Ahern (2012) and Ahern and Harford (2014), who measure downstream bargaining power using the sales dependence of a supplier's industry on a customer's industry. Specifically, for each supplier-customer pair, we calculate the percentage of sales from a supplier's industry that goes to a customer's industry, using data from the Input-Output (IO) matrices compiled by the Bureau of Economic Analysis (BEA). A high sales dependence indicates that the supplier relies heavily on the orders from the customer due to the nature of their production technologies. We find that the law-induced reduction in trade credit is concentrated in cases where the supplier is highly dependent on the customer, but is absent in cases of low supply-chain dependence.

Third, we consider customers' financial health as a proxy for bargaining power.[2] Similar to our previous findings, the passage of anti-recharacterization laws leads firms to cut trade credit significantly to financially strong customers, but not to weak ones. We also find consistent changes in sales: firms affected by the laws increase sales to financially weak customers but not strong ones.

Together, these results suggest that better access to debt markets helps suppliers reduce their reliance on powerful customers and face less pressure to extend trade credit to those customers. Moreover, the heterogeneous changes of trade credit across high- and low-power customers help address concerns related to contemporaneous changes in firm fundamentals arising from the law adoption (such as firm size and leasing policies). While other firm characteristics could also change following anti-recharacterization laws, if they do not shape firms' bargaining dynamics with major customers, they are unlikely to explain the differential changes in trade credit across high- and low-power customers.

We explore how the law-induced reduction of trade credit affects downstream (customer) firms. To the extent that U.S. firms are closely connected in a business network (Acemoglu et al. 2012; Barrot and Sauvagnat 2016; Carvalho et al. 2021), deregulations affecting a subset of firms could generate percolating effects downstream. We conjecture that, as treated firms extend less trade credit to major customers, those customers may be forced to borrow from alternative sources at a higher cost and cut back investment. Note that this prediction is not trivial. Customers in our sample are generally large and financially healthy. They may easily find alternative, cheap sources of capital and stay unaffected by the decline in trade financing. Our evidence lends support to the contagion effect. To start, we verify that downstream firms who have more suppliers incorporated in ARL states (higher "Upstream Law Exposure") indeed report lower payables after the laws, indicating that they receive less liquidity from affected suppliers. Those cus-

[2] This approach is motivated by the findings in prior studies. For example, Lang and Stulz (1992) document that financial distress diminishes a firm's product market strength. Klapper et al. (2012) show that financially healthy customers exercise market power and obtain more favorable trade credit terms from suppliers.

tomer firms then increase leverage and reduce investment. Our estimates suggest that a one-standard-deviation increase in a firm's *Upstream Law Exposure* is associated with a 6.8% reduction in investment and 3.9% increase in leverage. These effects become more pronounced as we focus on a set of customers for whom we can track a greater proportion of their purchases and suppliers in the Compustat Segment data.[3]

Importantly, customers of ARL-affected firms further reduce the provision of trade credit to their own customers, creating a cascading effect of liquidity tightening downstream. A back-of-the-envelope calculation suggests that a $1 reduction in trade credit leads to a $0.80 reduction in downstream firms' trade credit provision. These results indicate that the protection of creditor rights generates negative spillover effects for downstream firms.

We assess the external validity of our conclusion using an alternative shock to debt capacity. Specifically, we follow Chaney et al. (2012) and look at changes in firms' real estate asset values. As real estate assets can be used as collateral in credit arrangements, higher values of those assets should improve firms' ability to borrow. In this alternative setting, we again document that increased debt capacity lead to lower trade credit provision. Our estimates suggest that a one-standard-deviation increase in a firm's real estate asset value reduces trade credit by around 7%. This analysis is helpful as it shows that our results are not limited to the setting of anti-recharacterization laws, and are thus unlikely to be explained by confounding changes associated with those laws.

A potential concern with our baseline result is that it may be driven by increased securitization of receivables following the passage of ARLs. Given that the laws enhanced the attractiveness of SPVs and the securitization of assets, it is possible that treated firms do not reduce the provision of receivables, but instead sell more receivables to SPVs. Note that this concern is alleviated by our finding that customers' payables also decline after the laws. We design two additional analyses to further address this concern. First, we show that our results are not only driven by firms that have SPV outstanding. Firms without

[3] Given that the SEC only requires firms to disclose major customers, we are not able to track down all of a firm's major suppliers. We can only gather a firm's known suppliers based on those who report the firm as a major customer. We measure "traceable suppliers" using the percentage of COGS that can be assigned to purchases from known suppliers.

SPVs are still affected by the laws because they now face a higher option value of setting up an SPV. Second, our results are virtually unchanged when we exclude the events in Texas and Louisiana, which had an emphasis on the securitization of accounts receivable. Taken together, our results are unlikely to be explained by receivable securitization.

This study contributes to three streams of research. First, we add to the important topic of how financial frictions affect firms' decision to extend trade credit. Much of this research focuses on the provision of trade credit by larger suppliers to smaller, constrained customers (Schwartz 1974; Petersen and Rajan 1997; Bias and Gollier 1997; Emery 1987; Jain 2001; Meltzer 1960). Recent studies examining the role of financial constraints on trade credit provision utilize crisis-period settings (Calomiris et al. 1995; Love et al. 2007; Fabbri and Menichini 2010; Garcia-Appendini and Montoriol-Garriga 2013; Costello 2020). These studies suggest that firms with access to bank credit extend more trade credit during crises to help buyers survive and continue their business relations. We add to this line of research by showing that outside of crisis periods, when buyer survival is less of a concern, access to debt markets enhances a firm's bargaining position with powerful buyers and reduces the need to provide trade credit to these customers. In particular, we complement Costello (2019), who studies a law change allowing trade creditors (suppliers) to reclaim their sold products in bankruptcy. While she finds that suppliers' ability to *collect* collateral from customers affects trade credit, our results show that suppliers' ability to *pledge* collateral to their own lenders also affects their incentives to extend trade credit, especially to financially healthy, powerful customers.

In addition, our results add to studies that analyze a unique sample of supply-chain contracts, or contracts from other countries (see, e.g., Demirguc-Kunt and Maksimovic 2001; Ng, Smith, and Smith 1999; Klapper et al. 2012; Fabbri and Klapper 2016; Costello 2020). We contribute to this line of research by showing that better access to financing alters supply chain bargaining dynamics, which in turn determine trade credit provision.

Our results also relate to the literature discussing trade credit as a type of "moveable" collateral asset. Existing studies often rely on cross-country comparisons or focus on smaller economies. Their findings suggest that in many non-U.S. countries, creditor rights to "moveable" assets, such as accounts receivable, are not as protected as immovable assets, such as land. This difference in creditor protection makes movable assets a less desirable type of collateral (e.g., Calomiris et al. 2017; Campello and Larrain 2015). Giannetti et al. (2021) use the approval of laws against recharacterization in Italy as a positive shock to the pledgeability of firm receivables, showing that trade credit increases after the law adoption. Our study provides new insights for this literature, suggesting that stronger creditor rights protection does not increase, but instead decreases trade credit in the U.S. We note that the U.S. bankruptcy code is unique in that, even without anti-recharacterization laws, it offers superior protection over trade credit collateral, which qualifies as "cash collateral."[4] Our study also highlights a novel mechanism, i.e., debt capacity increases firms' bargaining power relative to major customers. Better access to debt reduces firms' aversion to bad states of the world, allowing them to establish and strengthen relationships to new, riskier customers.[5] This reduces the pressure they face to provide trade credit to existing, powerful clients. In our setting, the effects from increased bargaining power due to anti-recharacterization laws seem to dominate the effects from increased collateral pledgeability, leading to a reduction in trade credit provision.

Finally, our study adds to the growing literature documenting the effects of anti-recharacterization laws (Vig 2013; Li et al. 2016; Chu 2020; Ersahin 2020; Favara et al. 2021). Our finding that credit rights protection affects supply-chain dynamics is novel to the literature.

[4] Cash collateral receives special protection inside the U.S. Chapter 11 bankruptcy court. Cash collateral includes cash and cash equivalents, a subset of assets that are "as good as cash" because they can be converted to cash easily without much loss of value, including receivables. Secured creditors have a relatively strong control over whether debtors can access proceeds from cash collateral. In cases where such proceeds are vital to a firm's continuing operations, the firm files for an emergency motion to request access from secured creditors. Secured creditors may allow the firm to use cash proceeds and in exchange, obtain concessions from the firm (Ayer et al. 2004). Such concessions commonly include items such as restrictions on the use of cash collateral, roll-ups of pre-petition debt, and creditor control of bankruptcy deadlines (Bussell and Klee 2009).

[5] This mechanism deviates from the theoretical framework outlined in Giannetti et al. (2021), who posit that entry of new customers depends primarily on the pricing of existing customers in downstream markets.

2 Institutional Background

Under the U.S. Chapter 11 bankruptcy code, secured creditors face automatic stay, which is an injunction halting creditors' ability to collect debt payments from a firm who has declared bankruptcy (11 U.S. Code §362). Importantly, automatic stay limits creditors' ability to seize collateral assets, creating uncertainty regarding whether and when secured creditors can obtain collateral and regarding how assets will be divided among various stakeholders. Moreover, the value of collateral assets may diminish during the stay, given the severity of agency conflicts during the bankruptcy proceedings (e.g., under-investment in asset maintenance, asset diversion, risk-shifting, etc.).

While the automatic stay applies to all assets of the debtor, it generally does not apply to assets owned by a firm's special purpose vehicles (SPVs). A firm can raise capital by selling assets to an SPV, which then issues debt backed by those assets. Many types of assets can be transferred to an SPV, including equipment and patents, as well as receivables. If the sponsor firm files for Chapter 11 bankruptcy, the SPV remains "bankruptcy remote," so that secured creditors can seize their collateral without having to face the automatic stay (Gorton and Souleles, 2007). Put simply, SPV financing benefits creditors by facilitating their access to collateral during bankruptcy. In some cases, a bankruptcy court judge may recharacterize the asset sale to the SPV as a loan rather than a true sale. In this case, the collateralized assets are again subject to automatic stay. Thus, recharacterization revokes the creditor benefits of SPV financing.

Since the 1990s, several states have enacted anti-recharacterization laws (ARLs), which prevent judges from recharacterizing assets when adjudicating bankruptcy cases filed by locally incorporated firms. The passage of the ARLs was, to a large degree, driven by the lobbying efforts of financial firms, and not by local industrial firms (Janger 2004; Kettering 2008 and 2011). ARLs were enacted in seven states: Louisiana and Texas in 1997, Alabama in 2001, Delaware in 2002, South Dakota in 2003, Virginia in 2004, and Nevada in 2005. Recent research shows that those laws increase firms' debt capacity because affected firms have the option to borrow through a "better protected" SPV in the future (Li et al. 2016; Favara et al. 2021). Consequently, the passage of ARLs promotes investments in intangible assets that can be used as collateral, such as innovation and technology adoption (Mann 2018; Ersahin 2020).

In 2003, federal judges ignored the anti-recharacterization statute in Texas in the case *Reaves Brokerage Co. Inc. v. Sunbelt Fruit & Vegetable Co. Inc.* In this case, Sunbelt sold accounts receivable to Fidelity Factors through a factoring agreement but the judge recharacterized the transaction as a secured loan rather than a sale. This created uncertainty regarding whether anti-recharacterization laws at the state level will be upheld in future bankruptcy cases. Yet, the case may not be applicable to most cases involving anti-recharacterization laws, as its applicability was specific to the nature of the involved parties' business, namely, fresh produce subject to the *Perishable Agricultural Commodities Act*, or PACA. As explained by Warren and Westbrook (2004): "We also stress that our decision is guided by the policies behind PACA, which mandate protection of suppliers of fresh fruit and other perishable commodities. We express no opinion on the proper construction of factoring agreements in non-PACA contexts."[6] We also explain later in Section 7.1 that our results are not dependent on the sale of receivables or the anti-recharacterization law passed in Texas.

Given that the anti-recharacterization laws improve firms' access to credit and allow firms to explore new growth opportunities, it is plausible that these laws also could influence product market dynamics. Firms affected by the laws could restructure their customer base by reducing reliance on powerful customers, deepening relationships with less powerful ones, and establishing new customer relationships. This ultimately improves the firm's bargaining position with buyers and reduces the need to provide trade credit to "sweeten the deal" with customers. This logic suggests that the passage of ARLs should reduce trade credit provided by affected firms. On the other hand, if better access to

[6] We expect the passage of anti-recharacterization laws should generate similar effects on factoring as on the securitization of trade credit through SPVs. Similar to SPV financing, factoring is an off-balance sheet financing arrangement where firms sell trade credit to a financial intermediary in exchange for cash. This practice is common among small businesses that are cash constrained, or have limited access to bank financing. In contrast to factoring, SPVs are used more by larger companies. In the 2003 case, Sunbelt argues that its factoring arrangement should be protected by Texas' anti-recharacterization laws.Warren and Westbrook (2004) concludes that "*Will this mean the end of asset securitization? Betting money would go with the influence that a trillion-dollar industry* [factoring industry] *can exercise on the legal system.*"

debt markets does not alter supply-chain dynamics in the predicted direction, firms in law states are likely to continue providing the same level of trade credit to customers. They may also "pass on" the liquidity obtained from new debt to downstream firms. In that case, we may observe an increase or no change in firms' trade credit.

3 Empirical Framework

3.1 Data and Sample

Our analysis relies on several samples that originate from firms' reporting of customer relations and trade credit to major customers in their 10-K financial statements.

We start from the Compustat Segment database, which gathers major customer information reported by firms. This reporting is mandated by the SEC's Statement of Financial Accounting Standards (SFAS) No.14 and No.131, which require publicly listed firms to disclose customers comprising 10% or more of their sales. Among all the reporting firms and their customers, we exclude those in the finance and utility industries (SIC codes 6000-6999 and 4900-4999, respectively), and maintain this restriction throughout our analysis. Supplier-years appearing in this dataset form a firm-year panel which we use to examine firm-level changes in sales, new customers, and customer concentration. We label this the "Segment sample." For some analyses, we also construct a customer-supplier pair dataset to examine the changes in sales between a supplier to each of its major customers.

Our primary sample comes from manually collected data on the amount of trade credit extended by each firm to its individual customers based on 10K disclosures. FASB No.105, applicable to fiscal years after June 15, 1990, requires firms to disclose concentrations of credit risk. Under this stipulation, many firms disclose information about receivable balances with major customers. Following the procedures outlined in Freeman (2020), we start with firms disclosing at least one major customer in the Segment sample, and read each firm's annual financial statements, recording the amount of trade credit the firm extends to individual major customers for each fiscal year. This results in a customer-supplier pair-by-year panel that contains the trade credit used between each pair of customer and supplier in a given year.[7] We label this sample the "SEC sample."

Additionally, we identify firms reported as a major customer by at least one supplier in the Compustat Segment database. We use these customer-years to construct a firm-year panel that allows us to examine downstream effects of changes in trade credit provision (i.e., "Segment customer sample").

In later analysis, we verify our results from the SEC and Segment samples using a broader firm-year panel of all industrial firms from the Compustat universe (i.e., the "Compustat sample"). We require sample firms to have available information on receivables, sales, and total assets, and continue to exclude finance and utility firms.

Our identification strategy is based on the staggered passage of anti-recharacterization laws across states during the years 1997 to 2005. We limit our sample period to 1992–2010 to allow five years prior to the passage of the first law and five years after the passage of the last. Also note that our trade credit data is only well-populated after 1995, when the SEC's digital reporting requirements became widely adopted. For the SEC sample, this leaves us with 5,405 observations with 1,775 customer-supplier pairs. Our primary variable of interest is *Trade Credit*, the amount of receivables extended by a supplier to a customer scaled by the sales that the supplier makes to the customer. The value of transaction between a customer and a supplier is obtained from Compustat Segment database.

In the broader Segment and Compustat samples, we have 24,950 and 105,745 firm-year observations, respectively. We compute *Receivables* as the ratio of the total value of accounts receivable of a firm over the firm's total sales in a given year.

3.2 Empirical Strategy

Our main analysis focuses on how firms' provision of trade credit changes around the adoption of the anti-recharacterization laws. We adopt a generalized difference-in-

[7]Ersahin et al. (2021) follow a similar data collection procedure and study the effect of natural disasters on trade credit provision.

difference (DID) design and estimate the following regression model:

$$Trade\ Credit_{i,j,t} = \mu_{i,j} + \tau_t + \beta Supplier\ Law_{i,t} \\ + \gamma Customer\ Law_{j,t} + Controls_{i,j,t} + \epsilon_{i,j,t}, \quad (1)$$

where i indicates a (supplier) firm, j indicates a customer of firm i, and t indicates a year. $Trade\ Credit_{i,j,t}$ represents the ratio of trade credit over sales from supplier i to customer j observed in year t. $Supplier\ Law_{i,t}$ indicates whether supplier i's state of incorporation has implemented an anti-recharacterization law as of year t. We also control for whether customers are affected by the law passed in their state of incorporation in a parallel fashion ($Customer\ Law_{j,t}$). We control for customer-supplier-pair fixed effects ($\mu_{i,j}$) and year fixed effects (τ_t). The pair fixed effects help remove unobservable traits that may affect supply-chain matching, focusing the comparison on how trade credit varies over time within a fixed pair of customer and supplier. In stricter specifications, we impose customer-year fixed effects to hold fixed customer conditions and compare the trade credit provided by a treated and a control supplier to the same customer at the same time. This is akin to the Khwaja and Mian (2008) within-firm estimator. *Controls* include the firm characteristics of both the supplier and the customer, as well as some characteristics of the customer-supplier relationship described in the next section. Standard errors are clustered by the state of incorporation of firm i.

We also test whether the adoption of the laws helps firms expand sales and customer bases. For this analysis, we construct a firm-year panel and compute the log of total sales generated in a firm-year and count the number of new customer relationships formed that year. We perform the following analysis on the Compustat sample or the Segment sample:

$$Y_{i,t} = \alpha_i + \eta_{m,t} + \beta Law_{i,t} + Controls_{i,t} + \epsilon_{i,t}, \quad (2)$$

where i indicates a firm, m indicates the industry of the firm, and t indicates a year. Y includes *Log(Sales)*, the log of total sales, *New Customers*, the number of new customers gained in a year, *Customer Concentration*, the HHI of sales to major customers, and

Sales/COGS, representing gross margin. These variables are all measured at the (supplier) firm-year level. *Law* is an indicator that equals to one if firm i is incorporated in a state that has passed an anti-recharacterization law by year t. In this firm-year panel, we control for firm fixed effects (α_i) and 2-digit SIC industry-year fixed effects ($\eta_{m,t}$).

3.3 Control Variables

In the trade credit analysis using the customer-supplier pair panel, we include control variables that prior literature suggests may affect trade credit usage (e.g., Petersen and Rajan 1997, Giannetti et al. 2011, and Klapper et al. 2012): *Size*, the logarithm of firm assets; *Age*, measured as the log number of years since a firm's first appearance in Compustat; *Q*, the firm's market-to-book ratio; *Leverage*, the book leverage ratio of the firm; *Profitability*, operating income scaled by total assets; and *R&D Intensity*, the ratio of R&D expenditure over total assets. We control for these characteristics both for the customer and supplier. In analysis using a firm-level panel, we include these variables only for the firm of interest.

Given that our main analysis on trade credit usage tracks pairs of customers and suppliers over time, we include additional characteristics in our regression to control for heterogeneity across the pairs, as well as variables describing firms' supply-chain features. To start, we control for relationship-specific characteristics between a pair of customer and supplier. This includes *Relationship Length*, the logarithm of the number of years since the supplier first reported sales to the customer, and *Sales Dependence*, the percentage of sales that a firm makes to a customer. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles.

3.4 Descriptive Analyses

Table 1 reports the summary statistics for the key variables in this study. Panel A reports the statistics related to our main sample (i.e., the SEC sample); while Panel B reports the statistics from the Compustat and Segment samples. In our main sample, 45% of supplier-year observations and 36% of customer-year observations are subject to anti-recharacterization laws. The average (median) supplier offers 17 (13) cents of trade credit outstanding per dollar of sales. Comparing the suppliers to the customers in this sample, the supplier firms are smaller in asset size, younger, have lower leverage, and are less profitable. This suggests that the trade credit agreements in our sample capture the dynamics of "small lending big" (Murfin and Njoroge 2015). While the SEC sample represents a small portion (5%) of the Compustat universe, firms in both samples provide similar levels of trade credit, around 17% of sales.

Table 1 About Here

Figure 1 (below) depicts cross-sectional and time-series patterns of trade credit observed in our main sample (the SEC sample) and compares such statistics with receivables observed in standardized databases, including a sample of all Compustat firms excluding financial and utility industries (i.e., the Compustat sample) as well as the set of all suppliers in the Compustat Segment database (i.e., the Segment sample). Panel A provides the average level of trade credit across industry sectors of the supplier across the three samples. For the Compustat and Segment samples, we present the industry-average level of accounts receivable scaled by sales (i.e, *Receivables*) and for the SEC sample, we plot the industry-average of trade credit over sales between each pair of customer and supplier. In most industries, the three data sources document similar levels of trade credit, although the trade credit-sales ratio in the SEC sample tends to be slightly lower than those in the Compustat and Segment samples.

Panel B reports the time series variation of *Trade Credit* in the SEC sample and compares it with the time series patterns of *Receivables* in the Compustat sample and the Segment sample. Trade credit observed in our sample is similar to the average level of receivables recorded in the Segment database, and both are lower than the receivables reported from Compustat. All three series exhibit similar aggregate movement over time.

Figure 2 reports the distribution of industry sectors for all three samples. Manufacturing firms have a bigger presence in our SEC sample as well as the Segment sample, compared to the Compustat sample. This is not surprising because manufacturers are

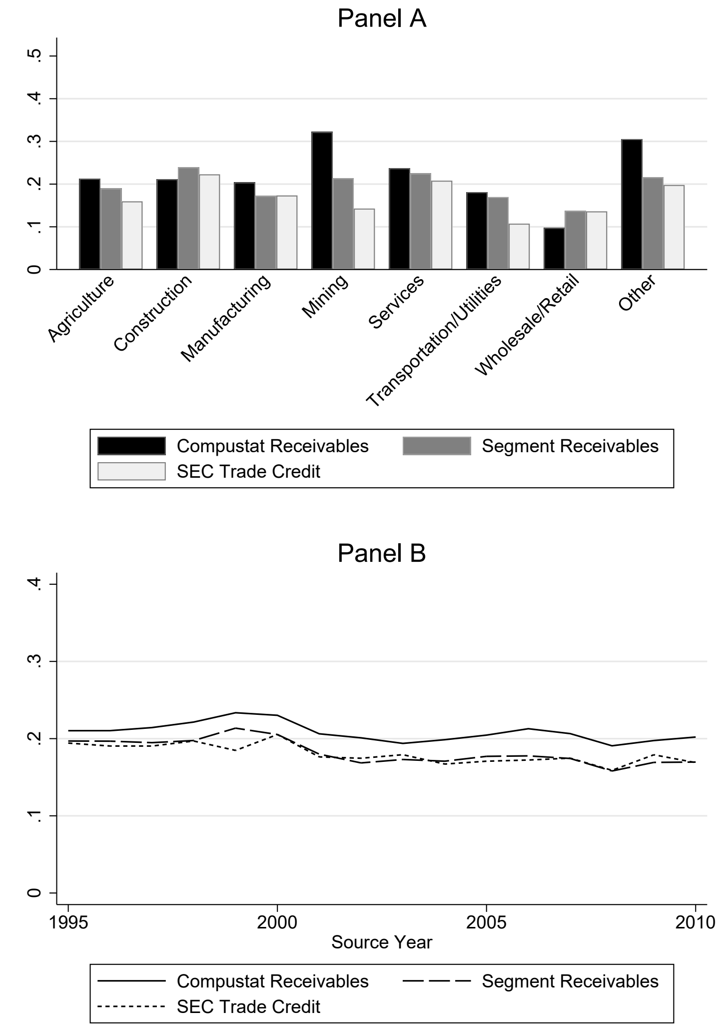

Figure 1. Trade Credit Across Samples. This figure describes cross-industry and time-series patterns of trade credit data in our manually collected sample (i.e., the SEC sample). We then compare such patterns with the accounts receivables of firms in the Compustat sample and the Segment sample. Panel A plots the average level of accounts receivable and trade credit across industry sectors for the three samples. The black columns represent the average accounts receivables (receivables/sales) for all firms in the Compustat universe excluding financial and utility industries (i.e., the Compustat sample). The dark grey columns represent the average receivables for suppliers that appear in Compustat Segment database (i.e., the Segment sample). The light grey columns indicate the average *Trade credit* between pairs of customers and suppliers in our manually collected sample (SEC sample). Panel B plots the average level of trade credit over time for the three samples. The solid (dashed) line represents the time series average of receivables in the Compustat (Segment) sample. The dotted line represents the time series patterns of pairwise trade credit in the SEC sample.

more likely to have major customers and extending trade credit is common industry practice. All three samples contain similar percentages of firms in service and wholesale industries. The wholesale and retail sector accounts for a smaller proportion of firms in the Segment and SEC data than in the Compustat universe, likely because retail firms largely sell to consumers and have few major business customers.

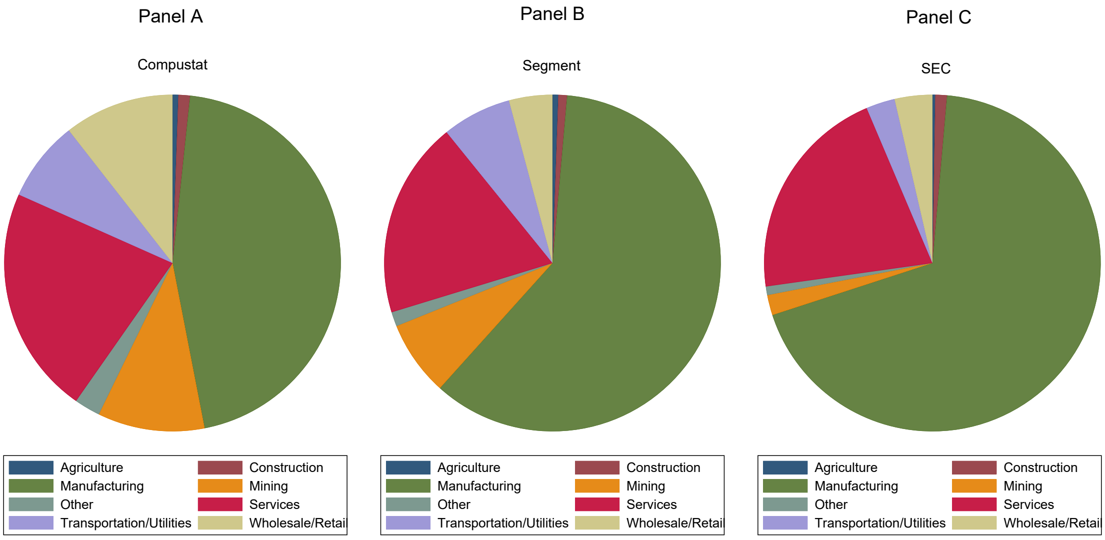

Figure 2. Industry Distribution of Firms Across Samples. This figure depicts the industry distribution in the three samples. Industries are defined at the one-digit SIC level. Panel A shows the distribution across all firms in the Compustat sample. Panels B and C report the distribution across all suppliers in the Segment and SEC samples, respectively.

Figure 3 describes how trade credit varies with simple proxies for supplier power in the our main sample. In Panel A, we look at suppliers' market share, and in Panel B, we examine the relative size ratio, defined as the ratio of the supplier's asset value over the customer's asset value. In each panel, we divide all supplier-customer pairs into quintiles based on suppliers' bargaining power over customers, and plot the average value of *Trade Credit* in each quintile. The patterns suggest that suppliers with higher market shares and larger asset sizes relative to customers offer lower levels of trade credit. These patterns are consistent with the argument that trade credit declines with suppliers' bargaining power.

4 Baseline Results

4.1 Sales and Anti-Recharacterization Laws

We first validate the argument that anti-recharacterization laws improve firms' bargaining position with major customers. We conjecture that a supplier's bargaining power depends on its product market presence and its option to switch to other customers. Thus, we look at the log of total sales that the firm makes to all customers and track various

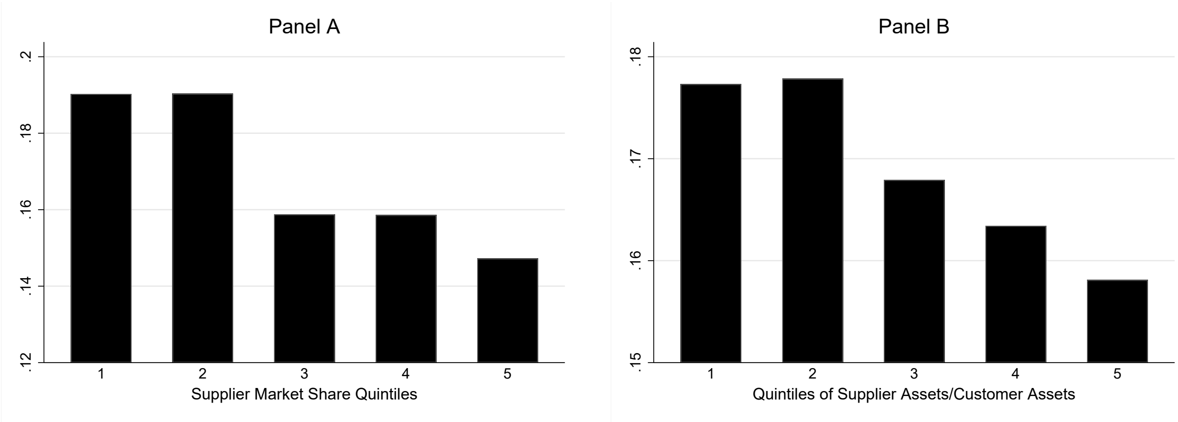

Figure 3. Trade Credit and Supplier Bargaining Power. This figure depicts the relation between trade credit and the market share and sizes of suppliers. Panel A shows the average value of *Trade Credit* across quintiles of supplier market share, measured as the supplier's sales as a percentage of annual industry sales. Panel B shows the average trade credit across quintiles of supplier-customer size ratio. The size ratio is defined as the ratio of supplier asset values to customer asset values.

characteristics of its customer base, including the number of new customer relationships, total customer counts, and customer concentration. The number of new customers and total customer counts proxy for firms' outside options. Customer concentration suggests customer-related risk and is a well-established measure of customer power. If expanded debt capacity relaxes firms' dependence on existing powerful customers, we expect them to expand sales and their client base, and reduce their customer concentration. We estimate Equation 2 using the Segment sample and the full Compustat sample. Table 2 reports the results.

TABLE 2 ABOUT HERE

Panel A presents results from the Segment sample, and Panel B reports results from the Compustat sample. Coefficients from the strictest specification (Column (3)) suggest that the passage of ARLs leads to a significant increase in firm sales. Estimates yield larger economic magnitudes for the Segment sample (a 5% increase) than for the full Compustat sample (around 2%).

While increases in sales generally suggest that firms are becoming more prominent in the product market, how their bargaining power relative to customers changes also depends on the structure of their customer base. If firm sales are still concentrated on a small group of customers, this indicates a high reliance on those customers and a weak bargaining power. In this case, firms may continue to face a strong pressure to provide trade credit. On the contrary, if firms start to establish new customer relations, increase exchanges with minor customers, and ultimately reduce customer concentration, they should achieve a stronger bargaining position and be less pressed to provide trade credit. We examine these channels in Table 3.

In Panel A, we examine whether the laws enable firms to establish more relationships with new customers. We define a new customer as one who is reported by a firm as a major customer for the first time. For this analysis, we adopt a Poisson regression approach given that the dependent variable is an integer count of new customers (Cohn et al. 2022). Consistent with an increased product market presence, we observe that firms establish more new customer relationships after the law. In Table OA.1 of the Online Appendix, we provide a robustness analysis, examining the total number of major customers reported by a firm. We find that the number of customers increases for treated firms after the law passage.

TABLE 3 ABOUT HERE

In Panel B, we investigate changes in customer concentration around law adoption. Customer concentration is measured as the Herfindahl index (HHI) of the percentage sales of a firm attributed to all major customers. This index is commonly used in the literature to gauge the bargaining power of a firm's major customers (see, e.g., Patatoukas 2012; Dhaliwal et al. 2016; Campello and Gao 2017). Higher concentration suggests that a firm's performance and sales are tied up with a small group of customers, and thus the firm likely has lower bargaining power. We find that after an anti-recharacterization law is passed, firms in adoption states experience a significant decline in customer concentration, by around 3% relative to the sample mean ($= -0.022/0.738$).

How does access to debt markets help firms diversify its customer base and reduce customer concentration? As anti-recharacterization laws provide firms with the option to raise additional funding through SPVs, they enhance firms' financial flexibility and alleviate their aversion to bad states of the world. This allows firms to adopt new technology and invest in more intangible assets (Favara et al. 2021). In Section OA.2 of the Online

Appendix, we show that firms affected by anti-recharacterization laws accumulate more knowledge capital and intangible capital, which comes from computerized capital, SG&A spending, and R&D expenditures. Such investment potentially helps firms differentiate themselves in the product market and attract orders from additional clients.

In Panel C, we further gauge whether affected firms are able to extract more profit from customers following the anti-recharacterization laws. While we do not directly observe product prices, we observe the total revenue and costs associated with firms' transactions with customers and can compute the profit margin from those sales (defined as *Sales/COGS*). Our results show that profit margin increases with the passage of the anti-recharacterization laws.

Taken together, results from this analysis suggest that firms affected by ARLs are able to reduce their reliance on powerful customers, and achieve higher profits from sales to customers. These patterns consistently suggest that better access to debt markets allows firms to expand their product market presence and gain greater bargaining power relative to customers.

4.2 Trade Credit and Anti-Recharacterization Laws

We next examine the effect of anti-recharacterization laws on firms' incentives to extend trade credit. Table 4 reports the main results. Panel A presents the results where controls and fixed effects are added in stages. Panel B reports results where we further layer on customer-year fixed effects.

TABLE 4 ABOUT HERE

In Column (1) of Panel A, we start with relatively sparse controls, including only *Customer Law* as well as supplier, customer, and year fixed effects. In Column (2), we control for time-varying characteristics of the customer and the supplier firms. In Column (3), we augment the model by adding both supplier industry-year fixed effects and customer industry-year fixed effects. Finally, we show in Column (4) the results from imposing customer-supplier-pair fixed effects. Across all specifications, *Supplier*

Law generates a negative and statistically significant coefficient with highly consistent magnitudes. From the strictest specification (Column (4)), the estimates suggest that treated supplier firms reduce trade credit to the average customer by around 16% relative to the sample mean (= −0.027/0.169).

One concern with the above result is that changes in a firm's receivables can be driven by its customers' time-varying demand for trade credit. We address this concern using the Khwaja and Mian (2008) within-firm estimator and controlling for customer-year fixed effects to purge out determinants at the customer side. This fixed effect structure allows us to compare the changes in receivables of two different suppliers of the same customer, where one supplier is incorporated in a state that has enacted the laws and the other is in a state that has not. Panel B shows the results from this analysis. *Supplier Law* continues to generate a negative and significant coefficient with similar magnitudes as shown in the baseline test (Panel A). This result suggests that the passage of anti-recharacterization laws generates variation in trade credit provision across suppliers of the same firm at the same time.

Another concern with our finding is that the decline in trade credit-to-sales ratio may be driven by an increase in sales (i.e., a denominator effect) and not a decline in the quantity of trade credit. We address this concern by directly investigating the change in the volume of trade credit offered by a firm to each customer. In Panel C of Table 4, we repeat the within-firm analysis where we impose customer-year fixed effects, but switch the dependent variable to be the log of trade credit (in dollars) attributed to a given customer (*Log(Trade Credit)*). Changes in this outcome variable should not be confounded by the denominator effect. Results from this panel show that access to debt significantly decreases a firm's extension of trade credit. The estimates suggest that following the passage of anti-recharacterization laws, firms reduce trade credit by 14–17%. This magnitude is close to the one estimated from our baseline result in Panel A.

Finally, we discuss the possibility that firms may offer price concessions to customers to compensate for the reduction in trade credit. We cannot directly test this hypothesis given that we do not observe product prices. However, we note that this explanation seems inconsistent with our previous results that firms obtain a stronger bargaining position relative to customers, as indicated by lower customer concentration and higher gross margins (Table 3).

In Online Appendix Table OA.3, we estimate the effect of anti-recharacterization laws on receivables for supplier firms in the Compustat and Segment samples, and find the same negative effect. The estimates suggest that treated firms decrease trade credit by 2.7% after the laws. This magnitude is meaningful, but smaller than the one implied from our baseline (Table 4, Panel A, Column (4)). One explanation for this difference is that, as firms become more powerful, they may reduce trade credit more for major customers and less so for minor ones. Note that our SEC sample only captures trade credit to major customers while the total accounts receivable in Compustat includes trade credit to all customers. We thus observe a lower effect in total receivables in the latter sample. We explore this explanation more in Section 5.

Taken together, our results show that firms increase sales and gain new customers following the adoption of anti-recharacterization laws. At the same time, treated firms reduce trade credit provision to existing customers. These findings are consistent with the argument that better access to debt markets enhances firms' bargaining power, resulting in less short-term financing to their customers.

4.3 Testing Parallel Trends Assumptions

Fundamental to our DID analysis around the passage of ARLs is the assumption that, in the absence of these laws, trends in the outcome variables would be similar for treated and control firms. We validate the parallel-trend assumption by examining whether firms in treated states experienced greater sales or changed their provision of trade credit prior to the passage of anti-recharacterization laws compared to firms in control states. To test this assumption, we code separate indicator variables for whether a firm's state of incorporation passes the law 3 years after the observation year, 2 years after, ... 2 years before, 3 years before, or more than 3 years before the observation year. We include all 8 indicators into the baseline regression, keeping the same set of controls. Specifically, we estimate the following models to gauge the dynamic effects of the laws on firms' sales and trade credit provision. For sales, we estimate:

$$Log(Sales)_{i,t} = \alpha_i + \tau_t + \Sigma_{k>=-3}\beta_k Treated_i \times 1_{i,t+k} + Controls_{i,t} + \epsilon_{i,t}, \tag{3}$$

where k indicates years after an event; $1_{i,t+k}$ equals one if firm i's state of incorporation passes an ARL during year $t+k, k = -3, -2, ..., 3, 3+$), and zero otherwise. $Treated_i$ equals one if a firm is incorporated in a state that eventually passed an ARL, and zero otherwise. In this estimation, we continue to control for firm and year fixed effects, along with the same set of control variables used in Panel A of Table 2. We estimate this equation using the Segment sample.

For trade credit, we estimate the following model using the SEC sample:

$$\begin{aligned} Trade\ Credit_{i,j,t} = \mu_{i,j} + \tau_t + \Sigma_{k>=-3}\beta_k Treated_i \times 1_{i,t+k} \\ + \gamma Customer\ Law_{j,t} + Controls_{i,j,t} + \epsilon_{i,j,t}. \end{aligned} \tag{4}$$

In both equations, our coefficients of interest are β_k, which represent the changes in sales and trade credit of the treated firms relative to control firms during year k after the law adoption. When $k < 0$, the coefficients represent changes in sales and trade credit prior to the event, i.e., "pre-trend."

Figure 4 presents results from this analysis. Panel A reports the results for sales and Panel B shows the results for trade credit. In each panel, the solid dots represent point estimates of the coefficients, while the vertical lines indicate 90% confidence intervals. The difference in dependent variables between treated and control firms in years prior to -3 is absorbed as the benchmark, so the coefficients reflect the changes in the sales and trade credit relative to the benchmark years.

We do not find a significant change in sales or receivables prior to the passage of the laws, but observe an increase in sales and decrease in trade credit after ARL passage. This evidence is important in validating the baseline findings and suggests that our results are unlikely to be driven by persistent firm or local characteristics that affected trade credit

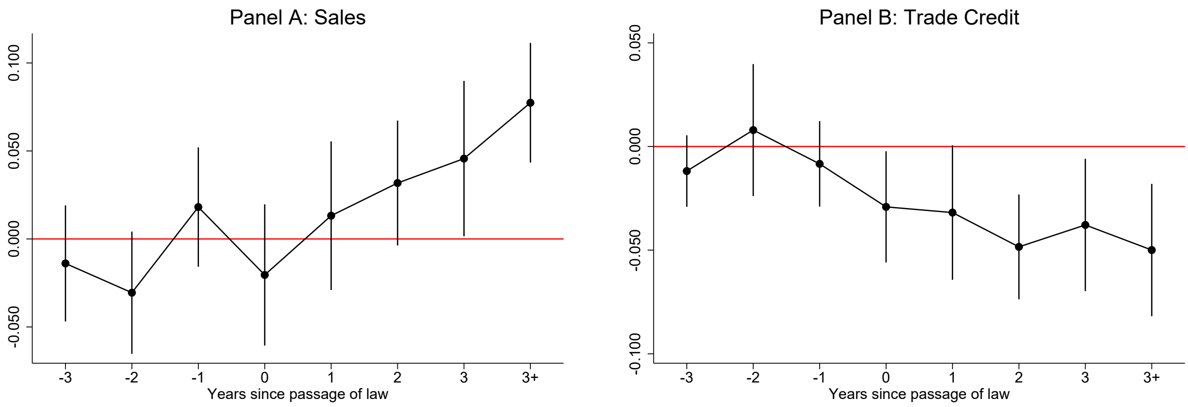

Figure 4. Testing Parallel Trends. This figure plots coefficient estimates from dynamic difference-in-difference regressions around the passage of an anti-recharacterization law. Panel A plots coefficients for *Log(Sales)* from estimating Equation 3, where the sample contains all suppliers in the Segment sample. Sales is measured at the firm level. Panel B plots coefficient estimates for *Trade Credit* from Equation 4 using the SEC sample. Trade credit is measured at the customer-supplier pair level. Point estimates are marked by solid dots, with 90% confidence intervals.

usage prior to the inception of the laws.

4.4 Addressing Heterogeneous Timing Concerns

We now consider the possibility that our findings might be biased due to heterogeneous timing of treatment in a generalized difference-in-difference design (Goodman-Bacon 2021; Callaway and Sant'Anna 2020). The concern arises because the generalized DID framework uses post-treatment units as control observations in later events. We address this concern in two ways.

First, we construct a stacked matched event sample. For each event, a treated firm is paired with a group of control firms that are incorporated in states that never passed the law (i.e., never-treated firms). The matched group is then tracked from three years prior to the event until three years after the event. We then stack all such matched group observations together (Gormley and Matsa 2011; Baker et al. 2022), and repeat our analysis of sales and trade credit provision on the stacked sample. Given that sales regressions are performed on a firm-year panel while trade credit regressions are on a customer-supplier-pair-year panel, we employ different matching methodologies for these analyses. For the sales analysis, we match each treated firm with never-treated firms in the same industry (2-digit SIC code) and belonging to the same size and sales growth quintiles prior to the event. After the matching, the average treated firm is paired with about 3 control firms. For the trade credit analysis, we follow the within-customer design, where we match each treated supplier observation with other suppliers sharing the same customer in the same year, but incorporated in states that never passed ARLs in our sample.

Using the matched sample, we estimate the following equation for sales:

$$Log(Sales)_{e,i,t} = \alpha_{i,e} + \gamma_{g,t} + \Sigma_{t=-3}^{t=3}\beta_t Treated_{e,i} \times 1_{e,t} + Controls_{e,i,t} + \nu_{e,i,t}, \quad (5)$$

where e indexes one of the seven events, i indicates a firm that appears in the matched sample for event e, g represents the matched group, including the treated firm and all its matched control units. t is a year during the 7-year window centering around the event year. $Treated_{e,i}$ equals one if firm i is incorporated in the state that passed the law in event e. $1_{e,t}$ indicates whether the observation time is t years past the event year. In this specification, we control for firm-by-event fixed effects ($\alpha_{i,e}$), so we can track the changes in firm sales over the event window. We also control for matched group-by-year fixed effects ($\gamma_{g,t}$) so as to narrow down the comparison to the group of matched firms. *Controls* indicates the same set of variables used in Panel A of Table 2.

Similarly, we test the effect of the laws on trade credit using the matched sample as follows:

$$Trade\ Credit_{e,i,j,t} = \mu_{i,j,e} + \xi_{j,e,t} + \Sigma_{t=-3}^{t=3}\beta_t Treated_{e,i} \times 1_{e,t} + Controls_{e,i,t} + \xi_{e,i,t}, \quad (6)$$

where i represents a supplier firm i and j represents a customer of firm i. Given that the sample is constructed by matching each treated firm to other, never treated suppliers of customer j, the matched group can be identified by a customer-year-by-event set (j, e, t). We control for customer-supplier-pair-by-event fixed effects ($\mu_{i,j,e}$), which help track the trade credit provided from i to j during the 7-year window around event e. We also control for matched group-by-year fixed effects ($\xi_{j,e,t}$). *Controls* represent the same set of control variables used in Panel C of Table 4.

In both tests, we use year -1 as the benchmark, so the coefficient estimate for β_t

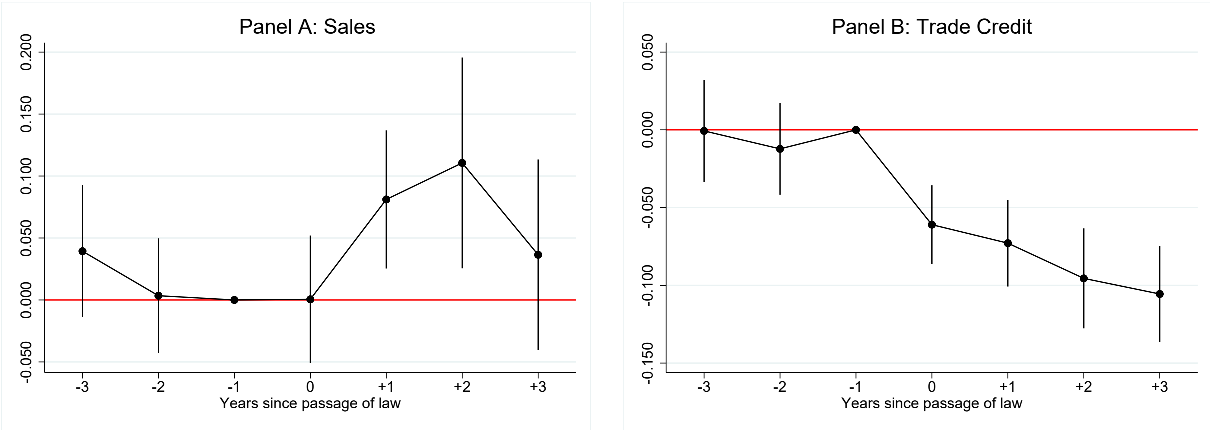

Figure 5. Testing Parallel Trends with a Stacked Sample. This figure plots coefficient estimates from regressions using stacked matched-event samples. These samples are constructed by matching each treated supplier with never-treated control firms and tracing the matched group for a 7-year period centered on the year of the event. Panel A plots coefficient estimates for sales, based on Equation 5. The matching is based on industry, size quintile, and sales growth quintile prior to the event year. The estimation includes firm-event fixed effects, matched group-year fixed effects, and the same set of controls as in Table 2, Panel A Column (2). Panel B plots coefficient estimates for *Trade Credit*, based on Equation 6. In this sample, each treated supplier is matched to other, never-treated suppliers of the same customer-year. Trade credit is measured at the customer-supplier pair level. The estimation includes customer-event year fixed effects and customer-supplier pair-by-event fixed effects. It also includes the same set of controls as in Table 4, Panel C Column (4). In each panel, the dots represent point estimates, and the vertical lines represent 90% confidence intervals.

indicates the changes in sales and trade credit relative to the year prior to the events. Figure 5 reports the results from this analysis. Consistent with the previous results from a generalized DID design, we do not see significant differences between treated and control groups for either sales or receivables prior to the passage of the laws. Effects set in after the laws are enacted. Treated firms increase sales in the year after the enactment, but trade credit declines immediately when the law takes into effect.

Our second approach to address the heterogeneous event timing concern is to validate our results in a single-event setting, where there is no difference in treatment timing. The event influencing the highest number of firms occurs in Delaware in 2002. We thus compare the changes in trade credit and sales of Delaware firms to those of never treated firms around 2002. Online Appendix Table OA.4 shows that our findings continue to hold in this analysis.

Taken together, results from this section suggest that our main findings are unlikely to be purely driven by the heterogeneous treatment timing related to the generalized difference-in-difference design.

5 The Bargaining Power Channel

Our baseline results are consistent with the view that better access to debt markets improves firms' bargaining power relative to downstream firms. If firms face pressure to provide trade credit to powerful customers, and if improved debt capacity helps alleviate such pressure, our results should be stronger in cases where the supplier firm has an *ex ante weaker* bargaining position relative to the customer firm, and likely has faced greater pressure to provide trade credit prior to the law change.

In this section, we provide evidence to support the bargaining power channel by comparing the effects of anti-recharacterization laws on customers who previously had stronger or weaker power relative to the firm. The heterogeneous effects across customers not only shed light on the bargaining power channel, but also helps rule out alternative mechanisms that could arise from other contemporaneous changes in firm characteristics from the ARLs, which are not directly related to supply-chain bargaining dynamics. We design three tests. To start, we track changes in trade credit extended to major and minor customers. Second, we examine the differential responses across firms that have higher and lower dependence on downstream industries. Finally, we compare the changes in trade credit towards financially strong and weak customers.

5.1 Major and Minor Customers

We speculate that the reduction in trade credit extended by treated firms should be more pronounced for major customers than for minor ones. According to FASB No. 14, major customers are defined as ones that contribute at least 10% of sales for a given firm. We follow this convention and classify customers into major and minor ones.

While we do not directly observe trade credit provided to individual minor customers, we can compute the total trade credit and total sales attributed to these customers as a whole. Specifically, trade credit to minor customers equals the difference between total accounts receivable and the receivables attributed to major customers; sales to minor customers equals the difference between total sales and the sales to major customers.

With this information, we can compute the average trade credit per dollar of sales to all minor customers as a group for each supplier-year. Accordingly, we define *Trade Credit (Major Cust)* and *Trade Credit (Minor Cust)* as follows:

$$Trade\,Credit\ (Major\,Cust)_{i,t} = \frac{\sum_{j\in J} Receivables\,(Major\,Cust)_{i,j,t}}{\sum_{j\in J} Sales\,(Major\,Cust)_{i,j,t}}$$

$$Trade\,Credit\ (Minor\,Cust)_{i,t} = \frac{Total\ Receivables_{i,t} - \sum_{j\in J} Receivables\,(Major\,Cust)_{i,j,t}}{Total\ Sales_{i,t} - \sum_{j\in J} Sales\,(Major\,Cust)_{i,j,t}},$$

where i represents a supplier, j represents a customer, J is the set of all customers of supplier i, and t indicates a year. *Receivables (Major Cust)* represents the total trade credit provided to major customers, as reported by the firm in its 10-K footnotes.[8] *Sales (Major Cust)* comes from the Compustat Segment database, indicating the total sales to this same group of major customers. *Total Sales* and *Total TC* represent the total sales and trade credit to all customers, respectively. The data come from Compustat. These variables capture the trade credit-sales ratio for major customers as a group, and for minor customers as a group. They are defined at the supplier level, with one observation per supplier-year.

We regress *Trade Credit (Major Cust)* and *Trade Credit (Minor Cust)* on *Supplier Law*, following a similar method as outlined in Equation 2. Because the test relies on information on the trade credit provided to major customers, it is performed on the set of suppliers identified in the SEC sample. Table 5 reports the results.

We find that treated firms significantly reduce trade credit to major customers, by roughly 4.3 percentage points. This result is consistent with our baseline findings presented in Table 4. However, we do not observe a significant reduction in the trade credit for minor customers. For each dependent variable, we use specifications alternately excluding and including a control for the percentage of sales attributed to major customers. This control accounts for the possibility that changes in the denominator might drive the changes in trade credit-sale ratio. Yet, our results are not sensitive to this control. In

[8]Recall that we capture the near universe of major customers for the supplier firms in the SEC sample.

Column (5), we document an overall decline in receivables-to-sales ratio at the firm level. This decline has a smaller magnitude, 1.1 percentage points, representing around a 6% change relative to the sample mean, and is driven primarily by changes in trade financing for major customers.

<u>Table 5 About Here</u>

5.2 Industry Sales Dependence

We next measure a customer's bargaining power over a supplier using the extent to which the supplier's industry depends on the inputs from the customer's industry. We label this measure "downstream dependence." Following Ahern (2012) and Ahern and Harford (2014), we compute the percentage of the total dollar value of output from a supplier industry that is purchased by a customer's industry. Data come from the Input-Output (IO) matrices that are maintained by the Bureau of Economic Analysis (BEA). A higher value of this ratio represents a greater reliance of the supplier industry on the customer industry, indicating low bargaining power of the supplier over the customer. Given that industry-level input-output flow is largely determined by technologies and the nature of products, this dependence is unlikely to be driven by omitted variables that also influence an individual firm's response to the enactment of anti-recharacterization laws.

We link this ratio to each customer-supplier pair based on the IO-NAICS (or IO-SIC) crosswalk and classify firms based on their industries' dependence on their customers' industries. We then examine the differential effect of anti-recharacterization laws on the trade credit provision of high-dependence firms (above-median) and low-dependence firms (below-median). Following Fan and Lang (2000) and Acemoglu et al. (2009), we exclude firms in retail or wholesale industries from these tests.[9]

Table 6 reports the results from this analysis. In Panel A, we construct the customer-dependence measure using IO matrices updated every five years. For example, we use the IO matrices from 1997 to compute the customer-dependence of industries for years

[9] Acemoglu et al. (2009) note that the input-output classification system is not sufficiently refined for retail codes to reveal meaningful vertical flow patterns, reporting that nearly all SIC codes between 5000-5999 map into two single IO codes.

1997—2001, and IO matrices from 2002 to compute the measure for years 2002—2006. In Panel B, we use only the 2002 matrices, which are computed around the midpoint of our sample period, to calculate a fixed dependence measure for all sample years. This helps alleviate the concern that industry classification was coarse for earlier years. Another advantage of this approach is that it eliminates variation in downstream dependence over time, which could be correlated with broader industry dynamics such as technological shocks as well as trade credit provision. In both panels, we consistently find that the reduction in trade credit after ARLs is more pronounced for suppliers that depend heavily on (or have low bargaining power with) their customers. The estimated reduction is about 4 to 5 percentage points. In contrast, suppliers that have low dependence on (high bargaining power with) downstream industries do not reduce trade credit. These results provide further credence for the argument that better access to credit markets allows firms to extend less trade credit because it enhances their bargaining position relative to buyers.

Table 6 About Here

5.3 Customer Financial Strength

Our third measure of customer bargaining power is financial strength. We follow Klapper et al. (2012) to characterize customer strength based on their credit ratings in the previous year. With low debt capacity, firms are likely to be constrained to supplying products and services to a small group of financially strong customers who have high credit quality and thus a higher likelihood to repay. However, these customers are generally larger and more powerful, and may demand superior trade terms.[10] With the passage of ARLs, firms can better access outside credit markets, and we should observe treated firms reduce trade credit provision to high-rated customers, but less so for low-rated ones.

We partition customers into groups of "high" and "low" ratings group, based on whether their S&P long-term issuer credit ratings are above or below the sample median.

[10] In our SEC sample, the median customer in the above-median credit rating subsample has an asset value 3.7 times as large as the median for the subsample with below-median credit ratings. Similarly, the median market share of highly rated customers is about twice as large as the market share of lowly rated customers.

Given that this sample partition does not rely on sales, we use the pair-level Segment sample to examine the growth in sales from a supplier to financially strong and weak customers, respectively. We also examine changes in the supplier's trade credit extension to those customers using the SEC sample. Table 7 reports the results from this analysis. Panel A shows results for sales and Panel B reports results for trade credit. We find that treated firms only increase sales significantly to financially weaker customers. Coefficients from the most rigorous specification suggest that treated firms increase sales to low-rated customers by about 1–2%, but do not increase sales to high-rated customers. At the same time, treated firms reduce trade credit to high-rated customers by 5% after the adoption of the laws. There is no change in the trade credit to low-rated customers.

TABLE 7 ABOUT HERE

In Online Appendix Table OA.5, we provide a robustness test where we partition customers based on their Z-scores instead of credit ratings. In that analysis, strong (weak) customers are ones with a Z-score above (below) the "safe" level of 3. Our results are robust to the alternative partition.

The evidence from our cross-sectional analysis suggests that, as firms gain better access to credit, they deepen relationships with weaker customers, but not powerful ones. Thus, better creditor protection makes firms less "held-up" by powerful customers, and allows them to scale back costly liquidity transfer to those customers. Importantly, these results help address the concern that our results might be driven by other changes in firm characteristics caused by anti-recharacterization laws, which are not related to supplier bargaining power. Those alternative explanations should generally predict a reduction in trade credit across all customers, and not only the major ones.

6 Implications for Downstream Firms

We examine the implications of reduced trade credit provision for downstream firms. Specifically, we examine changes experienced by downstream firms around the implementation of ARLs in their suppliers' state of incorporation. In this analysis, we take the perspective of a customer firm and gauge the extent to which the firm's suppliers are exposed to the law (i.e., "Upstream Law Exposure"). We then compare the changes in the leverage, investment, and trade credit usage between firms with more or less upstream law exposure. This analysis utilizes a customer firm-year panel, which includes all firms identified as major customers in the Segment data (the "Segment customer sample").[11]

We measure a customer firm's exposure to upstream anti-recharacterization laws using *Upstream Law Exposure*, which is defined as the firm's purchases from suppliers in ARL states divided by the firm's total cost of goods sold. Formally, this measure is defined as:

$$Upstream\, Law\, Exposure_{j,t} = \frac{\Sigma_{i \in I} P_{i,j,t} \times SupplierLaw_{i,t}}{COGS_{j,t}},$$

where i is a supplier, j is a customer firm, and t is a year. I represents the set of all suppliers of firm j. $P_{i,j,t}$ is the dollar amount of purchases made by firm j from supplier i. As previously defined, $SupplierLaw_{i,t}$ is an indicator for whether supplier i is affected by the law as of year t. This measure is similar to the weighted average of law adoption in suppliers' states, with the exception that COGS includes purchases from all suppliers, and not just the ones identified in the Segment database. This potentially leads to noise in the measurement of upstream exposure. We thus refine the sample to firms for whom we are able to identify a minimum percentage (e.g., 10%, 15%, 20%, etc.) of purchases from the Segment data.

To further account for the possibility that variation in *Upstream Law Exposure* may arise from changes in the percentage of reporting suppliers (*Traceable Suppliers*), we also control for this measure our regressions. *Traceable Suppliers* is defined as:

$$Traceable\, Suppliers_{j,t} = \frac{\Sigma_{i \in I} P_{i,j,t}}{COGS_{j,t}}.$$

We analyze how laws imposed on upstream firms influence the customer firm of interest

[11] We do not limit the sample to customer firms in the SEC dataset because we do not need to track trade credit received from individual suppliers.

by estimating the following equation:

$$Y_{j,t} = \phi_j + \tau_t + \beta Upstream\, Law\, Exposure_{j,t} + \psi Traceable\, Suppliers_{j,t} + Controls_{j,t} + u_{j,t}, \tag{7}$$

where *Controls* include customers' *Size*, *Age*, *Q*, *Profitability*, and *R&D Intensity*. We control for firm fixed effects (ϕ_j) and year fixed effects (τ_t). $Y_{j,t}$ is the outcome of interest, which includes customers' accounts payable, leverage, investment, and accounts receivables.

6.1 Customers' Payables

We first validate our baseline finding by examining customer firms' accounts payable, scaled by cost of goods sold. If some suppliers face ARLs and reduce the amount of trade credit they grant to the firm, the customer firm should report lower payables. Critically, our prediction relies on the assumption that the firm cannot costlessly switch to alternative suppliers. We argue that switching costs are likely higher when the treated supplier accounts for a larger percentage of inputs purchased by the firm. As such, we expect that upstream ARLs should only have a meaningful effect on the customer firm's payables when the affected suppliers provide a substantial portion of the firm's inputs. We thus repeat this analysis for multiple samples of firms for which we can identify increasing fractions of input purchases. We expect the effect to be stronger for firms for whom higher fractions of inputs are traceable.

Figure 6 presents the results from this analysis. Consistent with our conjecture, a firm's exposure to upstream ARL is associated with a reduction in payables. As discussed above, we expect the effect to be more precisely estimated when we focus on firms for whom we can trace a greater portion of input purchases. We thus narrow down the sample in stages. We first consider all customers with at least one reported supplier. Next, we gradually increase this threshold to requiring that observed suppliers account for at least 5%, 10%, 15%, and 20% of firms' cost of goods sold. In this figure, the markers represent coefficient estimates of *Upstream Law Exposure*, and the corresponding intervals suggest

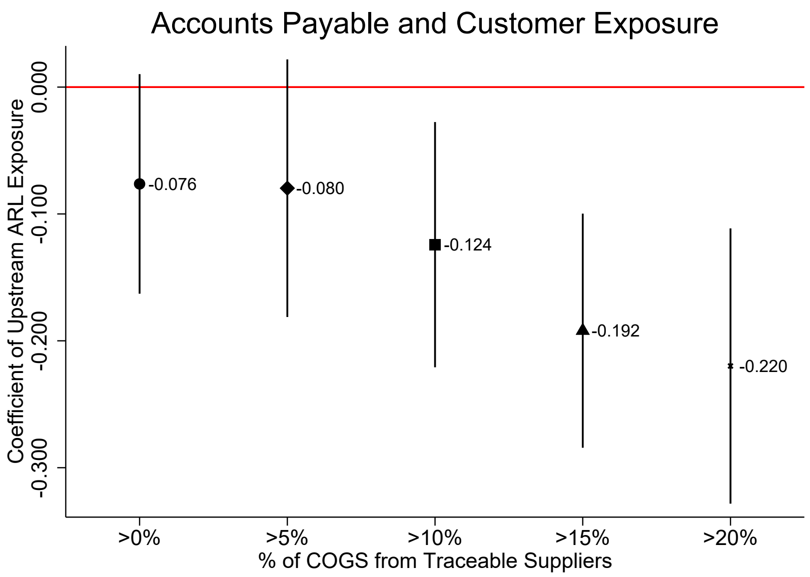

Figure 6. Effects on Customer Payables. This figure plots the coefficient estimates from Equation 7 for customer payables (customer payables scaled by customer cost of goods sold). The coefficients represent the effects of *Upstream Law Exposure*, the percentage of customer cost of goods sold that can be traced to suppliers in ARL states. The x-axis reflects thresholds from sequentially limiting customer-years to those with a specified level of traceable suppliers. Point estimates are marked, with 90% confidence intervals.

90% confidence intervals for each estimate. The horizontal axis indicates the sampling criteria. The figure shows that coefficients of *Upstream Law Exposure* are negative across all tests. As we focus on firms with at least 10% traceable suppliers, effects become more significant both economically and statistically.

Importantly, the upstream law exposure generates a progressively stronger impact on customer payables as more suppliers can be identified. For firms with 10% (15%) traceable inputs, a one-standard deviation increase in supplier exposure is associated with a 3.55% (5.50%) reduction in firm payables, relative to subsample means.[12] This effect becomes 6.3% for the sample with 20% traceable input. The increasing magnitude potentially suggests that, in the narrower samples, we are capturing customer firms who rely on a select number of major suppliers. For those firms, it is likely very costly to switch suppliers, and thus they face a fuller impact of laws imposed on their suppliers. Overall, results from this analysis confirm our baseline finding that the passage of anti-recharacterization laws leads firms to provide less trade credit to their customers.

[12]For the $\geq$ 10% sample, the effect is -3.55% relative to the sample average level (=-0.124 $\times$ 0.051/0.178). For the $\geq$ 15% sample, the effect is computed as -5.50% (=-0.192 $\times$ 0.051/0.178).

6.2 Customers' Investment, Leverage, and Trade Credit

If the enactment of ARLs reduces the amount of liquidity firms provide to their customers, it may also shape customers' financial and investment policies. Further, facing less funding from upstream firms, customers may cut back trade credit provided to their own customers. We test these conjectures by tracing customer firms' investment, debt levels, and trade credit provision further downstream around the implementation of ARLs.

Table 8 provides the results. Following the passage of anti-recharacterization laws in a state, customers of affected firms experience a significant decline in investment activities and an increase in external debt. A one-standard-deviation increase in *Upstream Law Exposure* corresponds to approximately a 3.9% increase in leverage and a 6.8% reduction in investment relative to the sample means.[13] This suggests that the reduction in trade financing forces downstream firms to scale back their operations and substitute external financing for supply-chain financing. Interestingly, the customer firms in our analysis also significantly reduce their own trade credit provision to their own respective customers. This result indicates that the contraction in trade financing is passed through input-output linkages and potentially influences firms indirectly connected through the supply-chain.

TABLE 8 ABOUT HERE

We perform a back-of-the-envelope calculation regarding the pass-through effect along the supply chain based on the customers' receivable analyses. According to estimates from the sample of customers with at least 20% traceable suppliers, a one-standard-deviation increase (0.05) in *Upstream Law Exposure* is associated with around a 1.1 percentage point reduction in payables relative to COGS ($= 0.05 \times 0.22$). Effects on customers' receivables suggest that the same increase in *Upstream Law Exposure* is associated with around a 0.6 percentage point reduction in the customer's receivables-to-sales ratio ($= 0.05 \times 0.128$). Given that the average customer firm in this sample has a sales-to-COGS ratio of 1.38, this suggests a pass-through effect of around 80% ($= 0.128/0.22 \times 1.38$). In other words,

[13]For leverage, the effect is 3.86% relative to the sample average ($0.193 \times 0.051/0.255$). For investment, the effect is -6.78% relative to the sample average ($-0.109 \times 0.051/0.082$).

when firms receive $1 less in trade credit from their suppliers due to the bankruptcy law reform, they will extend $0.80 less trade credit to their own customers.

Lastly, we provide the caveat that accounts payable and debt capacity have different effects on trade credit provision. While both are liability items and provide firms with liquidity, they have different implications on firms' bargaining power relative to customers. As ARLs increase the option value for firms to borrow via SPVs in times of need, they reduce firms' aversion to downside risk and incentivize firms to invest in intangible assets and attract new customers. In contrast, trade credit provides short-term financing (normally 2 or 3 months in maturity) and does not directly alter the structure of downstream markets (Giannetti et al. 2021). This helps explain why customers of ARL-affected firms cut their own provision of trade credit when facing a reduction in accounts payable.

7 Additional Analyses and Discussions

In this section, we discuss various concerns related to our interpretation and results. For example, we address the concern that our results could be driven by firms selling off receivables to an SPV. We also show that our results hold in an alternative empirical setting, and thus our inferences can be extended to other shocks related to debt capacity. Lastly, we demonstrate that firms' reporting choices are unlikely to explain our results.

7.1 Could Results be Driven by Securitization?

We address the concern that our baseline results could be driven by firms securitizing their receivables to an unconsolidated SPV following the passage of anti-recharacterization laws. If the anti-recharacterization laws make it more desirable for firms to sell receivables off-balance sheet to an unconsolidated SPV, the observed decline in receivables could reflect a mechanical effect of receivable securitization. We note that this concern should be alleviated by our earlier results on the decline of customers' payables, which would be unaffected by suppliers' consolidation choices (Section 6.1). We still conduct two analyses to alleviate this concern. First, we exclude from our sample the implementation of two early anti-recharacterization laws, passed in Texas and Louisiana, which focused on the securitization of accounts receivable. If our findings are mechanically driven by the securitization of trade credit, effects should weaken once we exclude these two events. Panel A of Table 9 shows that our results persist in the restricted sample and the coefficients of *Law* generate similar magnitudes as those from Table 4 (Column (4) of Panels A and B).

TABLE 9 ABOUT HERE

Next, we directly estimate the effects of ARLs on trade credit for firms with higher and lower likelihood of SPV usage. While the laws directly affect firms with existing SPVs, it also increases the option value of setting up an SPV in the future. So we expect the ARLs to affect both firms with experiences of setting up SPVs as well as firms without SPVs. We gauge firms' SPV usage by parsing through their disclosure of subsidiaries from 10-K filings, following Feng et al. (2009). We consider a firm to have a high likelihood of using SPVs if it has disclosed having at least one SPV in the past. We then regress *Trade Credit* on separate indicators of treated firms based on its SPV usage, i.e., *Supplier Law, Has SPV*, and *Supplier Law, No SPV*. Panel B of Table 9 presents results from this analysis. We find effects to be similar from firms with and without SPV usage.

Taken together, our collective evidence suggests that our results are unlikely to solely be driven by increased securitization of receivables.

7.2 External Validity: Evidence from Shocks to Firms' Real Estate Values

So far, our evidence suggests that debt capacity reduces firms' incentive to provide trade credit. We illustrate the external validity of this result by showing similar patterns from an alternative shock to debt capacity. In this experiment, we follow Chaney et al. (2012), who document that positive shocks to the value of firms' real estate assets expand firms' debt capacity and increase investment. To the extent that debt capacity increases firms' bargaining power relative to major customers, we should observe a reduction in trade credit following the shocks.

We measure firms' real estate values based on the initial values of firm real estate holdings, multiplied by real estate growth (starting in 1975) or the consumer price index (for years before 1975) at the MSA level. Initial real estate values are measured by the market values of firms' real estate holdings. As the computation of initial real estate values requires accumulated depreciation (which was no longer reported in Compustat after 1993), these tests include only firms with financial data available on Compustat in 1993.

We compute this measure for both the supplier and customer firms in our sample, and regress trade credit extended between the supplier-customer pair on the real estate values of each party. In addition, we control for the real estate pricing index in both the headquarter locations of the supplier and the customer. This helps address the concern that changes in local economic conditions could drive our findings.

Table 10 reports the results from this test. In Column (1), we do not impose any controls aside from year and customer-supplier pair fixed effects. In Column (2), we add firm characteristics controls for both the customer and supplier. In Column (3), following Chaney et al. (2012) we replace contemporary controls with the 1993 firm characteristics (for both firms), interacted with the real estate pricing index for each respective firm's MSA. In Columns (4) and (5), we further impose customer-year fixed effects, with interacted control variables in Column (5). In these specifications with customer-year fixed effects, we use observations from all customers of a firm as we do not require the real estate information from those customers. Across all specifications, suppliers' real estate value generates a negative, significant coefficient, suggesting that greater debt capacity leads to a reduction in trade credit provision. The estimates from Column (3) indicate that a one-standard-deviation increase in the supplier's real estate appreciation reduces trade credit by 6.89% relative to the sample mean.

TABLE 10 ABOUT HERE

7.3 Additional Robustness

We design robustness checks to address two concerns related to firms' reporting choices. The first is that suppliers may stop transacting with customers who demand high levels of trade credit after the laws are enacted. This could contribute to the reduction in the average trade credit observed after the laws. While such an effect should be limited by the inclusion of customer-supplier pair effects, we evaluate the importance of this selection effect by restricting the sample to a set of "stable" supply-chain relations that are observed both before and after the passage of the laws. For each treated supplier, we look at a matched control supplier that shares the same customer during the event horizon. Importantly, we require that both suppliers report trade credit data to the common customer for at least N years ($N = 1, 2, 3$) *both* before and after the passage of the laws. This matched sample method ensures that we can trace the change in trade credit provision to a "surviving" customer around the laws. Table OA.6 of the Online Appendix shows that our results remain unchanged in the restricted sample.

The second concern is related to the requirement regarding firms' 10-K disclosures. Specifically, given that firms only need to disclose customers that account for at least 10% of total sales, firms may stop reporting some major customers after the law if those customers' sales fall under 10%. If these hypothetically "disappearing" customers also command a high level of trade financing, the trade credit we observe will decline mechanically. We note that all our regressions include customer fixed effects, customer-supplier-pair fixed effects, or customer-year fixed effects. These fixed effects make it unlikely that changes in sample composition could influence our results. To further address such concerns, we provide additional analyses in which we artificially increase the customer sales threshold to 11% and 12%. This exercise allows us to gauge the extent to which the 10% threshold could have influenced our results. If it is a major driver of our results, we expect effects to strengthen as we increase the threshold. Table OA.7 of the Online Appendix reports results from this analyses. We note that, not only are our results robust to these alternative sampling restrictions, the estimates remain very close to those in Panel A of Table 4. This suggests that the reporting threshold is unlikely to unduly drive our results.

8 Conclusion

This study examines the effect of credit market frictions on firms' incentives to provide trade credit. We hand collect a dataset on trade credit usage between pairs of customers and suppliers in the U.S. Our analysis generates unique insight on the interaction between financial strength and bargaining power in shaping firms' trade credit policies. Contrary to the conventional wisdom that better credit access increases trade credit extension, we show that better access to debt markets improves firms' bargaining position with powerful customers. Specifically, firms expand sales, invest more in intangible assets, and decrease the concentration of their customer base. This ultimately allows them to cut back on trade credit provided to major customers. The affected customers in turn cut back investment, increase leverage, and reduce trade credit provided to firms further downstream. Our findings highlight the role of product market power on trade credit provision during normal (non-crisis) times, when the option to expand is more valuable.

Our findings also highlight a novel implications of creditor rights protection on supply-chain dynamics. In particular, we show that better creditor rights protection allows firms to achieve greater bargaining power in supply-chain relationships and reduce costly trade credit provision.

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Table 1
Summary Statistics
This table reports the summary statistics of the key variables in the study, spanning 1992 to 2010. Panel A reports summary statistics for the SEC sample, which consists of all firms that appear in the Compustat Segment database with available information regarding customer-supplier level trade credit. Panel B reports summary statistics in the broader samples, including the Compustat universe, supplier-years represented in the Segment sample, and customer-years represented in the Segment database. *Law* is an indicator for the firm being incorporated in a state that has adopted an anti-recharacterization law. *Trade Credit* is the amount of trade credit offered by a supplier to an individual customer, scaled by the value of the transaction between the two. The unit of observation is a customer-supplier-pair-year. *Receivables* is the ratio of accounts receivable over sales, measured at the firm-year level. Other variable definitions are available in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles.

Panel A: SEC Sample

Variable	N	Mean	Std. Dev	25th Pctl.	Median	75th Pctl.
Pair-level characteristics:						
Trade Credit	5,405	0.169	0.153	0.081	0.133	0.207
Sales Dependence	5,402	0.254	0.201	0.122	0.183	0.310
Relationship Length	5,405	1.365	0.867	0.693	1.386	2.079
Supplier characteristics:						
Law	5,405	0.445	0.497	0.000	0.000	1.000
Size	5,405	4.937	1.819	3.717	4.869	6.110
Age	5,405	2.488	0.705	1.946	2.485	2.996
Q	5,405	2.262	1.930	1.143	1.622	2.607
Leverage	5,405	0.189	0.243	0.001	0.103	0.290
Profitability	5,403	0.017	0.262	-0.035	0.085	0.152
R&D Intensity	5,405	0.107	0.188	0.000	0.050	0.138
Customer characteristics:						
Law	5,405	0.360	0.480	0.000	0.000	1.000
Size	5,404	9.778	1.824	8.796	10.059	11.014
Age	5,405	3.231	0.742	2.708	3.401	3.871
Q	5,404	1.957	1.142	1.208	1.599	2.284
Leverage	5,404	0.236	0.161	0.115	0.223	0.316
Profitability	5,398	0.131	0.078	0.082	0.131	0.171
R&D Intensity	5,404	0.035	0.051	0.000	0.012	0.056

Panel B: Broader Samples

Variable	N	Mean	Std. Dev	25th Pctl.	Median	75th Pctl.
Compustat:						
Law	105,745	0.251				
Receivables	105,745	0.186	0.203	0.091	0.151	0.217
Log(Sales)	105,745	4.405	2.625	2.792	4.558	6.227
Segment Suppliers:						
Law	24,983	0.274				
Receivables	24,872	0.179	0.116	0.114	0.159	0.214
Log(Sales)	24,950	4.562	2.178	3.119	4.544	6.034
New Customers	24,985	0.533	0.921	0.000	0.000	1.000
Customer Concentration	24,985	0.738	0.326	0.502	1.000	1.000
Sales/COGS	24,938	2.006	1.738	1.255	1.525	2.064
Segment Customers:						
Payables	12,164	0.178	0.182	0.088	0.130	0.194
Receivables	12,085	0.163	0.119	0.092	0.147	0.207
Upstream Law Exposure	12,175	0.014	0.051	0.000	0.000	0.001
Traceable Suppliers	12,175	0.079	0.176	0.004	0.017	0.065
Leverage	12,175	0.255	0.197	0.107	0.232	0.359
Investment	11,742	0.082	0.089	0.031	0.057	0.099

Table 2
Access to Debt Markets and Sales
This table shows the effect of the anti-recharacterization laws on firms' sales. *Law* is an indicator for the firm being incorporated in a state that has passed the anti-recharacterization law. Panel A examines the effect of the laws on firm sales for supplier-years represented in the Compustat Segment database ("Segment Sample"). Panel B reports results for the Compustat sample. The dependent variable in Panels A and B is the log of total sales. Controls include *Age, Size, Q, Leverage, Profitability*, and *R&D Intensity*. Variable definitions are available in Appendix A. Industry is defined by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Total Sales, Segment Sample

Dep. Var.: *Log(Sales)*	(1)	(2)	(3)
Law	0.200***	0.056***	0.047***
	(5.07)	(4.08)	(3.30)
Controls		Yes	Yes
Year FEs	Yes	Yes	
Firm FEs	Yes	Yes	Yes
Industry×Year FEs			Yes
R^2	0.925	0.970	0.971
Observations	24,044	20,839	20,647

Panel B: Total Sales, Compustat Sample

Dep. Var.: *Log(Sales)*	(1)	(2)	(3)
Law	0.192***	0.025***	0.019**
	(14.99)	(2.67)	(2.05)
Controls		Yes	Yes
Year FEs	Yes	Yes	
Firm FEs	Yes	Yes	Yes
Industry×Year FEs			Yes
R^2	0.904	0.954	0.954
Observations	105,056	90,629	90,599

Table 3
Access to Debt Markets Customer Concentration
This table shows the effect of the anti-recharacterization laws on firms' customer base characteristics. *Law* is an indicator for the firm being incorporated in a state that has passed the anti-recharacterization law. Panel A reports results from a Poisson regression, testing the effect of the laws on the count of suppliers' newly reported major customers for supplier-years represented in the Compustat Segment database ("Segment Sample"). Panel B shows the effect of the laws on customer concentration, measured as the Herfindahl index across major customer sales. Panel C shows the laws' effect on supplier margins, with *Sales/COGS* as the dependent variable. Controls include *Age, Size, Q, Leverage, Profitability*, and *R&D Intensity*. Variable definitions are available in Appendix A. Industry is defined by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier firm's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: New Customers

Dep. Var.: *New Customers*	(1)	(2)	(3)
Law	0.015	0.178*	0.205**
	(0.18)	(1.90)	(2.16)
Controls		Yes	Yes
Year FEs	Yes	Yes	
Firm FEs	Yes	Yes	Yes
Industry×Year FEs			Yes
Observations	22,447	18,625	17,979

Panel B: Customer Concentration

Dep. Var.: *Customer HHI*	(1)	(2)	(3)
Law	-0.024**	-0.026**	-0.022*
	(-2.10)	(-2.29)	(-1.69)
Controls		Yes	Yes
Year FEs	Yes	Yes	
Firm FEs	Yes	Yes	Yes
Industry×Year FEs			Yes
R^2	0.450	0.457	0.460
Observations	24,080	20,847	20,655

Panel C: Sales/COGS

Dep. Var.: *Sales/COGS*	(1)	(2)	(3)
Law	0.111*	0.098*	0.090*
	(1.80)	(1.71)	(1.96)
Controls		Yes	Yes
Supplier FE	Yes	Yes	Yes
Year FE	Yes	Yes	
Industry x Year FE			Yes
R^2	0.695	0.708	0.707
Observations	24,030	20,829	20,637

Table 4
Access to Debt Markets and Trade Credit
This table examines how the passage of anti-recharacterization laws affects suppliers' extension of trade credit. We use the SEC sample, which consists of all firms for which we could identify trade credit data to major customers during the period of 1992–2010. The dependent variable in Panels A and B is *Trade Credit*, defined as the trade credit extended by a supplier to a customer scaled by the total transaction value between the two firms in the same year. In Panel C, the dependent variable is *Log(Trade Credit)*, the natural logarithm of the dollar amount (in millions) of customer-specific receivables. *Law* is an indicator for the firm being incorporated in a state that has passed the anti-recharacterization law. Panel A presents our baseline results. Panel B further includes customer-year fixed effects. Panel C repeats the analysis with customer-year fixed effects, but examines the total amount of trade credit extended between a customer-supplier pair, *Log(Trade Credit)*. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. *t*-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline Results

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)
Supplier Law	-0.024**	-0.024***	-0.036***	-0.027***
	(-2.70)	(-2.77)	(-3.73)	(-2.80)
Customer Law	0.023**	0.021**	0.023**	0.047***
	(2.64)	(2.45)	(2.59)	(4.98)
Sales Dependence		-0.163***	-0.172***	-0.201***
		(-10.71)	(-12.04)	(-10.62)
Relationship Length		-0.015***	-0.015***	-0.028***
		(-3.81)	(-3.53)	(-5.07)
Supplier Age		-0.031**	-0.037*	-0.035**
		(-2.59)	(-1.81)	(-2.27)
Customer Age		-0.027**	-0.007	-0.018
		(-2.42)	(-0.32)	(-1.15)
Supplier Size		0.019***	0.019***	0.021***
		(5.28)	(4.43)	(10.88)
Customer Size		0.007	0.012*	0.003
		(1.25)	(1.84)	(0.66)
Supplier Q		0.004***	0.004**	0.006***
		(4.02)	(2.36)	(5.91)
Customer Q		-0.002	-0.002	-0.002
		(-0.58)	(-0.49)	(-1.13)
Supplier Leverage		0.029***	0.011	0.029***
		(3.17)	(0.73)	(2.95)
Customer Leverage		-0.004	-0.024*	0.000
		(-0.24)	(-1.89)	(0.01)
Supplier Profit		-0.006	-0.013	-0.001
		(-0.63)	(-1.43)	(-0.16)
Customer Profit		0.021	0.015	0.032
		(1.01)	(0.26)	(1.63)
Supplier R&D Intensity		-0.030***	-0.023*	-0.025***
		(-3.54)	(-1.77)	(-3.65)
Customer R&D Intensity		0.076	0.163	0.071
		(0.94)	(1.50)	(0.96)
Year FE	Yes	Yes		Yes
Supplier FE	Yes	Yes	Yes	
Customer FE	Yes	Yes	Yes	
Supplier Industry x Year FE			Yes	
Customer Industry x Year FE			Yes	
Pair FE				Yes
R^2	0.423	0.449	0.430	0.497
Observations	5,100	5,086	4,740	4,820

Panel B: Controlling for Customer-Year FE

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)
Supplier Law	-0.026*	-0.032**	-0.034**	-0.043***
	(-1.96)	(-2.28)	(-2.48)	(-2.74)
Supplier Characteristics		Yes	Yes	Yes
Pair Characteristics		Yes	Yes	Yes
Supplier FEs	Yes	Yes	Yes	
Customer×Year FEs	Yes	Yes	Yes	Yes
Supplier Industry×Year FE			Yes	
Pair FE				Yes
R^2	0.490	0.503	0.509	0.503
Observations	3,212	3,210	3,018	2,979

Panel C: Pair-specific Trade Credit, with Customer-Year FE

Dep. Var.: *Log(Trade Credit)*	(1)	(2)	(3)	(4)
Supplier Law	-0.144***	-0.159***	-0.139**	-0.166**
	(-3.04)	(-2.95)	(-2.11)	(-2.57)
Supplier Characteristics		Yes	Yes	Yes
Pair Characteristics		Yes	Yes	Yes
Supplier FEs	Yes	Yes	Yes	
Customer×Year FEs	Yes	Yes	Yes	Yes
Supplier Industry×Year FE			Yes	
Pair FE				Yes
R^2	0.876	0.907	0.906	0.916
Observations	3,212	3,210	3,018	2,979

Table 5
Major and Minor Customers

This table examines the effect of the adoption of the anti-recharacterization laws on suppliers' extension of trade credit for major and minor customers. The sample is a supplier-year panel, including all supplier firms observed in the SEC sample. In Columns (1) and (3), the dependent variable is *Trade Credit (Major Cust)*, the ratio of the total amount of trade credit to all reported major customers over total sales to these major customers. In Columns (2) and (4), the dependent variable is *Trade Credit (Minor Cust)*, the ratio of suppliers' receivables not designated as major customer receivables over suppliers' sales not assigned to major customers. In Column (5), the dependent variable is *Receivables*, the ratio of total receivables over total sales, to all customers. Columns (3) and (4) control for the percentage of supplier sales attributed to major customers. Other controls are included but suppressed for presentation. Control variables are the same as in Table 2. Variable definitions are available in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are shown in parentheses, calculated from standard errors clustered by supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.:	*Trade Credit, Major Cust*	*Trade Credit, Minor Cust*	Difference	*Trade Credit, Major Cust*	*Trade Credit, Minor Cust*	Difference	*Receivables*
	(1)	(2)	(Major−Minor)	(3)	(4)	(Major−Minor)	(5)
Supplier Law	-0.040***	-0.005	-0.035**	-0.043**	-0.001	-0.041**	-0.011**
	(-3.24)	(-0.48)	(-2.12)	(-3.36)	(-0.14)	(-2.49)	(-2.12)
%Sales to Major Customers				Yes	Yes		
Controls	Yes	Yes		Yes	Yes		Yes
Year FEs	Yes	Yes		Yes	Yes		Yes
Firm FEs	Yes	Yes		Yes	Yes		Yes
R^2	0.461	0.447		0.474	0.461		0.521
Observations	3,652	3,650		3,648	3,646		3,648

Table 6
Supply-Chain Dependence

This table shows the differential effect of the anti-recharacterization laws on firms' extension of trade credit between suppliers in industries with high and low dependence on customers' industries. The dependent variable is *Trade Credit*, the amount of trade credit provided by a supplier to a customer scaled by their transaction value in a year. *Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. In Panels A and B, we partition the sample by whether a supplier's industry has above- or below-median downstream dependence, which is measured as the percent of the supplier's industry output purchased by the customer's industry using the BEA's input-output (IO) matrices. In Panel A, customer dependence is measured by all BEA matrices, while in Panel B, this measure is constructed using only the 2002 table. In each panel, *High Customer Dependence* refer to suppliers whose industries have a dependence on the customer industry that is above the sample median. Both panels use the SEC sample. In both panels, Columns (1) and (2) control for supplier fixed effects and customer fixed effects separately. Columns (3) and (4) control for supplier-customer pair fixed effects. Controls include all the controls in Table 4. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Supplier Dependence Above and Below Median (Time-Varying IO)

Sample: Downstream Dependence	High	Low	Difference	High	Low	Difference
Dep. Var.: *Trade Credit*	(1)	(2)	(High−Low)	(3)	(4)	(High−Low)
Supplier Law	-0.043*	0.027	-0.069**	-0.053**	0.027	-0.080**
	(-2.04)	(1.06)	(-2.28)	(-2.51)	(1.05)	(-2.50)
Controls	Yes	Yes		Yes	Yes	
Year FEs	Yes	Yes		Yes	Yes	
Supplier FEs	Yes	Yes				
Customer FEs	Yes	Yes				
Pair FE				Yes	Yes	
R^2	0.486	0.418		0.537	0.483	
Observations	1,086	1,088		1,027	1,036	

Panel B: Supplier Dependence Above and Below Median (2002 IO)

Sample: Downstream Dependence	High	Low	Difference	High	Low	Difference
Dep. Var.: *Trade Credit*	(1)	(2)	(High−Low)	(3)	(4)	(High−Low)
Supplier Law	-0.074***	0.040	-0.110***	-0.077***	0.047**	-0.118***
	(-3.96)	(1.69)	(-3.22)	(-3.22)	(2.12)	(-3.24)
Controls	Yes	Yes		Yes	Yes	
Year FEs	Yes	Yes		Yes	Yes	
Supplier FEs	Yes	Yes				
Customer FEs	Yes	Yes				
Pair FE				Yes	Yes	
R^2	0.484	0.393		0.538	0.460	
Observations	1,204	1,214		1,147	1,168	

Table 7
Sales and Trade Credit to Strong and Weak Customers
This table shows the effect of the anti-recharacterization laws on firms' customer sales and trade credit to customers with high and low credit ratings. High (Low) ratings refer to credit ratings that are above (below) sample median. In Panel A, we report results for *Log(Sales)*, the log of transaction volume between a firm and a customer, using the pair-level Segment sample. In Panel B, we examine *Trade Credit*, the amount of trade credit provided by a supplier to a customer scaled by their transaction value in a year, using the SEC sample. *Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. In both panels, we report results from separate subsamples of customers whose credit rating lies above and below the sample median. Strong (Weak) customers refer to customers with above (below)-median credit ratings. Columns (1) and (2) control for supplier fixed effects and customer fixed effects separately. Columns (3) and (4) control for supplier-customer pair fixed effects. Controls include all the control variables in Table 4. In Panel A, we exclude *Sales Dependence* from the list of controls. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. *t*-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Sales to Customers with High and Low Credit Ratings

Sample: Customer Credit Rating	High	Low	Difference	High	Low	Difference
Dep. Var.: *Ln(Customer Sales)*	(1)	(2)	(High−Low)	(3)	(4)	(High−Low)
Supplier Law	-0.028	0.214***	-0.242***	-0.029	0.162***	-0.191***
	(-0.74)	(4.72)	(-4.55)	(-0.54)	(4.41)	(-3.36)
Controls	Yes	Yes		Yes	Yes	
Year FEs	Yes	Yes		Yes	Yes	
Supplier FEs	Yes	Yes				
Customer FEs	Yes	Yes				
Pair FE				Yes	Yes	
R^2	0.893	0.910		0.923	0.931	
Observations	12,236	11,695		11,245	10,618	

Panel B. Trade Credit to Customers with High and Low Credit Ratings

Sample: Customer Credit Rating	High	Low	Difference	High	Low	Difference
Dep. Var.: *Trade Credit*	(1)	(2)	(High−Low)	(3)	(4)	(High−Low)
Supplier Law	-0.047***	-0.004	-0.044**	-0.046***	0.002	-0.047**
	(-3.29)	(-0.28)	(-2.34)	(-2.92)	(0.13)	(-2.28)
Controls	Yes	Yes		Yes	Yes	
Year FEs	Yes	Yes		Yes	Yes	
Supplier FEs	Yes	Yes				
Customer FEs	Yes	Yes				
Pair FE				Yes	Yes	
R^2	0.500	0.424		0.528	0.490	
Observations	1,946	2,296		1,859	2,194	

Table 8
Effects on Downstream Firms
This table shows the effect of the adoption of the anti-recharacterization laws on downstream firms' investment and leverage. Panel A shows the effect for customer investment (capital expenditures scaled by beginning-of-year assets), Panel B shows the effect for customer leverage, and Panel C for customer receivables. The sample is a customer-year panel, including observations in which a firm is reported as a major customer by at least one supplier from the Compustat Segment database. *Upstream Law Exposure* is defined as the percentage of a firm's cost of goods sold that can be traced to suppliers in ARL states. *Traceable Suppliers* is the percentage of a firm's cost of goods sold that can be traced to any supplier in the Segment database. Other controls are included but suppressed for presentation. Control variables are the same as in Table 2. Variable definitions are available in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *t*-statistics are shown in parentheses, calculated from standard errors clustered at the customer firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Customer Investment

Dep. Var.: *Customer Investment* Sample: Traceable Purchase/COGS	(1) All	(2) ≥5%	(3) ≥10%	(4) ≥15%	(5) ≥20%
Upstream Law Exposure	-0.049**	-0.047	-0.043	-0.075*	-0.109**
	(-1.99)	(-1.49)	(-0.99)	(-1.80)	(-2.25)
Traceable Suppliers	0.027**	0.026*	0.007	0.023	0.003
	(2.26)	(1.88)	(0.32)	(1.26)	(0.14)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.632	0.662	0.668	0.662	0.645
Observations	10,305	2,821	1,654	1,083	800

Panel B: Customer Leverage

Dep. Var.: *Customer Leverage* Sample: Traceable Purchase/COGS	(1) All	(2) ≥5%	(3) ≥10%	(4) ≥15%	(5) ≥20%
Upstream Law Exposure	0.101	0.145*	0.189*	0.234**	0.193
	(1.53)	(1.71)	(1.89)	(2.14)	(1.54)
Traceable Suppliers	-0.041*	-0.026	-0.030	-0.019	-0.011
	(-1.74)	(-1.04)	(-0.95)	(-0.49)	(-0.24)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.722	0.762	0.772	0.773	0.811
Observations	9,373	2,861	1,679	1,097	808

Panel C: Customer Trade Credit Provision

Dep. Var.: *Customer Receivables* Sample: Traceable Purchase/COGS	(1) All	(2) ≥5%	(3) ≥10%	(4) ≥15%	(5) ≥20%
Upstream Law Exposure	-0.077***	-0.062*	-0.080*	-0.132***	-0.128**
	(-2.83)	(-1.82)	(-1.86)	(-2.98)	(-2.17)
Traceable Suppliers	0.046***	0.030	0.019	0.033	0.036
	(2.59)	(1.59)	(0.71)	(1.35)	(1.36)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.794	0.776	0.778	0.787	0.787
Observations	10,404	2,854	1,674	1,092	803

Table 9
Robustness: Addressing Effects of Securitization
This table examines whether the baseline results could be driven by increases in the securitization of receivables following anti-recharacterization laws. The dependent variable is *Trade Credit*, the amount of trade credit provided by a supplier to a customer scaled by transaction value in a year. *Supplier Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. Panel A reports results when we exclude firms incorporated in Texas or Louisiana. In Panel B, we separately test the effects for firms with and without known SPV usage. SPV usage is defined as one if a firm has disclosed having subsidiaries before, following the approach used in Feng et al. (2009). Control variables are the same as Panel B of Table 4. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Excluding Observations from TX and LA Laws

Dep. Var.: *Trade Credit*	(1)	(2)
Supplier Law	-0.033**	-0.042**
	(-2.40)	(-2.68)
Supplier Characteristics	Yes	Yes
Pair Characteristics	Yes	Yes
Supplier FEs	Yes	
Customer×Year FEs	Yes	Yes
Pair FE		Yes
R^2	0.502	0.500
Observations	3,112	2,890

Panel B: Effects for Firms With and Without SPV Usage

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)	(4)
Supplier Law, Has SPV	-0.029**	-0.026**	-0.029**	-0.035*	-0.049**
	(-2.53)	(-2.54)	(-2.54)	(-1.84)	(-2.47)
Supplier Law, No SPV	-0.029**	-0.024**	-0.028**	-0.027	-0.037*
	(-2.73)	(-2.29)	(-2.59)	(-1.50)	(-1.92)
Supplier Characteristics		Yes	Yes	Yes	Yes
Customer Characteristics		Yes	Yes		
Pair Characteristics		Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes		
Supplier FEs	Yes	Yes		Yes	
Customer FEs	Yes	Yes			
Customer×Year FEs				Yes	Yes
Pair FE			Yes		Yes
R^2	0.425	0.460	0.515	0.516	0.511
Observations	4,001	3,992	3,768	2,534	2,336

Table 10
Effects from An Alternative Financing Shock: Real Estate Collateral Values
This table presents additional evidence of how enhanced access to credit affects firms' extension of trade credit, using changes to the firm's collateral values induced by changes in local real estate values. *Supplier RE Value* measures the market value of real estate assets for the supplier, based on local real estate inflation and historical cost information computed from accumulated depreciation, following Chaney et al. (2012). The sample period is 1993-2007. When included, controls are either contemporary characteristics as in Panel A of Table 4 (Columns (2) and (4)) or are based on 1993 characteristics inflated by local real estate inflation, following Chaney et al. (2012) (Columns (3) and (5)). Supplier HPI and Customer HPI indicate controls for local real estate inflation at the MSA of corporate headquarters for the supplier and customer, respectively, with HPI normalized to 1 in 1993. Variable definitions are available in Appendix A. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of headquarters. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)	(5)
Supplier RE Value	-0.006**	-0.006**	-0.011**	-0.009*	-0.017***
	(-2.21)	(-2.22)	(-2.47)	(-1.85)	(-3.56)
Controls	None	Yes	Interacted	Yes	Interacted
Supplier HPI	Yes	Yes	Yes	Yes	Yes
Customer HPI	Yes	Yes	Yes		
Customer RE Value	Yes	Yes	Yes		
Year FE	Yes	Yes	Yes		
Pair FE	Yes	Yes	Yes	Yes	Yes
Customer×Year FE				Yes	Yes
R^2	0.558	0.584	0.579	0.555	0.540
Observations	618	617	533	631	554

Appendix A Variable Definitions

Variable	Definition
Law	Indicator for firm being incorporated in state with ARL
Trade Credit	Pair-level receivables scaled by pair-level sales
Log(Trade Credit)	Logarithm of pair-level (in dollars)
Receivables	Firm-level receivables scaled by sales
Trade Credit (Major Cust)	Aggregate receivables owed by major customers, scaled by aggregate sales to the same group of major customers
Trade Credit (Minor Cust)	Firm-level receivables - aggregate receivables owed by major customers, scaled by firm-level sales - aggregate sales to major customers
Size	Logarithm of total assets
Age	Logarithm of number of years firm has appeared in Compustat
Q	Tobin's Q, defined as (market cap + total book assets – book equity)/ (total book assets)
Leverage	Short-term debt + long-term debt, scaled by total assets
Profitability	Operating income before depreciation scaled by total assets
R&D Intensity	R&D expense scaled by total assets
Sales Dependence	Sales to customer as proportion of total supplier sales
Relationship Length	Logarithm of the number of years since the supplier first reported the customer as a major client
New Customers	Count of the number of customers reported as a major client for the first time
Customer Concentration	HHI index of the percentage sales of a firm attributed to all major customers
Sales/COGS	Ratio of firm sales to firm COGS
Payables	Accounts payable scaled by COGS
Upstream Law Exposure	Percentage of customer COGS that can be traced to suppliers in ARL states
Traceable Suppliers	Percentage of customer COGS that can be traced to any supplier
Investment	Capital expenditures scaled by beginning-of-year assets

Online Appendix

OA.1 Total Customer Counts

We conduct a robustness analysis, examining changes in the firm's total customer count around the passage of anti-recharacterization laws in Table OA.1. The dependent variable is the log number of major customers reported by a firm in a year. The sample is a firm-year panel, including all firms that report customers in the Segment database (i.e., Segment sample). Results show that treated firms experience an increase in the number of total customers following the passage of anti-recharacterization laws. The results are consistent with those in Table 3, suggesting that better access to debt markets allow firms to expand its customer base.

OA.2 Effects of Anti-recharacterization Laws on Intangible Investment

We examine whether firms affected by anti-recharacterization laws increase their investment in innovation and intangible assets. We follow Falato et al. (2022) in defining the stock of knowledge capital and intangible capital. The stock of knowledge capital is computed from firms' past R&D expenses using the perpetual inventory method with a 15% depreciation rate. Intangible capital is the sum of knowledge capital, SG&A stock, and the stock of computerized information. The stock of computerized information is calculated as the cumulative level of fixed reproducible tangible wealth divided by total assets in an industry (source: BEA) using a depreciation rate of 31%. The SG&A stock is the accumulated SG&A expenditure over total assets, calculated using a perpetual inventory method with a depreciation rate of 20%. SG&A expenditures are deflated to the 2000 level.

Table OA.2 shows that firms affected by ARLs significantly increase their investment in knowledge and intangible capital. This effect holds for both the full Compustat sample as well as the sample of suppliers in the Compustat Segment database. These results help validate a mechanism through which better access to debt enables firms to expand and diversify their customer base. Specifically, as firms invest in more knowledge and intangible capital, they can potentially provide new and differentiated products and service. This helps them establish and strengthen relations to less powerful customers.

OA.3 Effects of the Laws in Broader Samples

In Table OA.3, we examine the effect of anti-recharacterization laws on trade credit extension in broader samples. Columns (1) and (2) present results for the Compustat universe excluding financial and utility industries. Columns (3) and (4) report results for the Segment sample, which includes all firms reporting at least one major customer. For each sample, we first examine the effect from regressions including firm and year fixed effects, and then impose industry-by-year interactive fixed effects. Across both samples, *Law* generates a negative coefficient, significant in three out of the four specifications, suggesting that firms extend less trade credit following the passage of anti-recharacterization laws. The economic magnitude is meaningful: the coefficient in Column (2) suggests that after the passage of the laws, treated firms decrease trade credit by 2.7% relative to the sample average ($= -0.005/0.186$). Note that the estimates from the SEC sample (Table 4, Panel A, Column (4)) imply higher economic magnitudes than those from the Compustat sample. One explanation is that the SEC sample allows us to track granular, within-trade-pair variation in trade credit. Our stringent fixed effect structure allows us to better remove noise generated by other determinants of trade credit policies and identify changes in trade credit attributable to the enactment of the anti-recharacterization laws. The second explanation is that trade credit reductions are concentrated in relationships with more powerful customers, and thus effects are more significant among the major customers which can be identified in the SEC sample (Table 4, Panel A). Similarly, the firm-level result in Column (5) of Table 5, using firm-years for suppliers appearing in the SEC sample, is greater in magnitude than estimates below, because it samples across firms with greater customer sales dependence.

OA.4 Single-Event Analysis

In Table OA.4 we present results from specifications corresponding to our baseline analyses in Table 2 and Table 4. In Panel A, Column (1) includes firm (supplier) and year fixed effects; Column (2) augments the regression with controls as in Panel A Column (2) of Table 2; and Column (3) adds supplier industry-by-year fixed effects. In Panel B, Column (1) includes supplier, customer, and year fixed effects, along with a full set of controls; Column (2) augments the regression with supplier industry-by-year fixed effects as well as customer industry-by-year fixed effects; Column (3) imposes customer-by-year fixed effects to absorb variation related to customers' demand for trade credit; and, finally, Column (4) includes both customer-year and customer-supplier-pair fixed effects. Our results are robust across all specifications.

OA.5 Customer Strength Measured by Z-Score

Table OA.5 reports the results related to sales and trade credit extension by firms affected by anti-recharacterization laws to strong and weak customers. In this analysis, strong (weak) customers are defined as ones with a Z-score above (below) 2.99. The sample median of Z-scores is around 3. We observe a consistent pattern as in Table 7: firms affected by the anti-recharacterization laws increase sales to weak customers but not to strong ones. They also reduce trade credit only to safe customers but not to risky customers. Customers with high Z-scores face a reduction in trade credit by 4% after the adoption of the laws, but there is no change in the trade credit to low-Z-score customers.

OA.6 Addressing Concerns Related to Sample Selection Bias

This section present results to address two concerns related to firms' reporting choices.

The first concern is about "survivorship bias", i.e., suppliers may stop transacting with customers who demand high levels of trade credit after the laws are enacted. To address this concern, we design a novel matching approach to focus our comparison to "stable pairs" around the law passage.

For each treated supplier, we look at a matched control supplier that shares the same customer during the event horizon. We require that both suppliers report trade credit data to the common customer for at least N years ($N = 1, 2, 3$) *both* before and after the passage of the laws. For example, Steelcloud is incorporated in Virginia, where the anti-recharacterization law passed in 2004. Steelcloud reports trade credit to its major customer, Lockheed Martin, during two years before 2004 and two years after 2004. Over the same time period, Moog Inc., incorporated in New York (a control state), also reports trade credit to Lockheed Martin. In this example, we compare the change in trade credit extended by Steelcloud (treated) to Lockheed Martin around 2004 to the change in trade credit extended by Moog (matched control) to Lockheed Martin over the same time period. This matched sample method ensures that we can trace the change in trade credit provision to a "surviving" customer around the laws.

Table OA.6 reports the results from this analysis. In the first two columns, we require the treated and control relations to report at least one year of trade credit data both before and after the laws. In Columns (3) and (4), we raise this requirement to two years, and for the last two columns, we require three years. Customer-year fixed effects are included in all regressions, which help narrow down the comparison between matched pairs. Across all sample restrictions, our baseline findings persist. Importantly, the magnitude of this effect gradually increases as we raise the stringency of sample requirements. Column (6) suggests that suppliers affected by the laws cut trade credit to customers by 11 percentage points more compared to unaffected suppliers. The higher magnitude could arise from us focusing on a set of customers that have limited outside options, who are more likely to accept worse trade terms.

The second concern is related to firms' 10-K reporting threshold. Given that firms only report customers that contribute at least 10% of total sales, if some customers that demand a high level of trade credit fall under the 10% threshold, this will lead to a mechanical decline in the trade credit we observe. To address this concern, we refine the sample where we only include customers who account for 11% or 12% of a firm's total sales. This exercise allows us to gauge the extent to which the 10% threshold could have influenced our results. If it is a major driver of our results, we expect effects to strengthen as we increase the threshold. Table OA.7 reports the results. In Panel A, we replicate the baseline tests using a sample that includes only customers that contribute over 11% of a firm's sales. In Panel B, we lift the threshold to 12%. We note that our results are robust to these alternative sampling restrictions. Importantly, the estimates remain very close to those in Panel A of Table 4. This finding suggests that the reporting threshold is unlikely to unduly drive our key results.

Table OA.1
ARLs and The Number of Customers

This table shows the effect of the anti-recharacterization laws on the firms' number of customers. *Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. The dependent variable is the natural logarithm of the number of reported customers within a reporting year, using the Compustat Segment database ("Segment Sample"). Controls include *Age, Size, Q, Leverage, Profitability*, and *R&D Intensity*. Variable definitions are available in Appendix A. Industry is defined by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: *Log(Number of Customers)*	(1)	(2)	(3)
Law	0.028	0.046**	0.042*
	(1.53)	(2.32)	(1.88)
Controls		Yes	Yes
Year FEs	Yes	Yes	
Firm FEs	Yes	Yes	Yes
Industry×Year FEs			Yes
R^2	0.512	0.525	0.524
Observations	24,080	20,847	20,655

Table OA.2

Effects of ARLs on Firm Investment in Knowledge and Intangible Capital

This table shows the effect of the anti-recharacterization laws on the firms' investment in intangible capital and R&D. In both panels, Columns (1) and (2) report results for the Compustat sample. Column (3) and (4) report results for suppliers in the Segment sample, i.e., firm-years wherein the firm reports at least one major customer. The dependent variable is *Knowledge Capital*, the firm's stock of research and development investment in Panel A, and *Intangible Capital*, the firm's stock of intangible capital investment in Panel B. The definition of these variables follow the ones in Falato et al. (2022). All regressions include the same set of controls as Table 2, except R&D intensity. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel B: Knowledge Capital

Sample:	Compustat		Segment	
Dep. Var.: *R&D Stock*	(1)	(2)	(3)	(4)
Law	0.040**	0.041**	0.074***	0.060***
	(8.89)	(8.05)	(5.04)	(4.98)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes		Yes	
Industry×Year FEs		Yes		Yes
R^2	0.807	0.815	0.841	0.847
Observations	75,810	66,083	18,575	18,365

Panel B: Intangible Capital

Sample:	Compustat		Segment	
Dep. Var.: *Intangible Captial*	(1)	(2)	(3)	(4)
Law	0.031**	0.042**	0.070*	0.029
	(2.47)	(2.96)	(1.98)	(0.96)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes		Yes	
Industry×Year FEs		Yes		Yes
R^2	0.822	0.825	0.841	0.846
Observations	75,416	65,690	18,521	18,312

Table OA.3
Effects of ARLs on Accounts Receivable in Alternative Samples
This table reports results for broader samples. Columns 1 and 2 report results for the Compustat sample. Column 3 and 4 report results for suppliers in the Segment sample, i.e., firm-years wherein the firm reports at least one major customer. The dependent variable is *Receivables*, the accounts receivable of a firm divided by total sales. All regressions include the same set of controls as Table 2. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Compustat		Segment	
Dep. Var.: *Receivables*	(1)	(2)	(3)	(4)
Law	-0.005**	-0.005**	-0.003	-0.004*
	(-2.03)	(-2.16)	(-1.32)	(-1.71)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes		Yes	
Year FEs	Yes	Yes	Yes	Yes
Industry×Year FEs		Yes		Yes
R^2	0.453	0.454	0.527	0.527
Observations	90,629	90,599	20,770	20,575

Table OA.4
Single-Event Difference-in-Difference: Delaware

This table presents results from a single-event setting, where we focus only on the law passed in Delaware. Panel A reports results for *Log(Sales)* and Panel B reports results for *Trade Credit*. *Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. Panel A uses suppliers in the Segment data. Control variables are the same as Panel A of Table 2. In Panel B we use the SEC sample. Control variables are the same as Panel A of Table 4. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. *t*-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Total Sales, Segment Sample

Dep. Var.: *Log(Sales)*	(1)	(2)	(3)
Law	0.234***	0.059***	0.049***
	(5.38)	(3.71)	(2.78)
Controls		Yes	Yes
Year FEs	Yes	Yes	
Firm FEs	Yes	Yes	Yes
Industry×Year FEs			Yes
R^2	0.924	0.970	0.970
Observations	22,723	19,651	19,446

Panel B: Trade Credit, SEC Sample

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)
Supplier Law	-0.021**	-0.033***	-0.024*	-0.040**
	(-2.39)	(-3.57)	(-1.76)	(-2.52)
Customer Characteristics	Yes	Yes		
Supplier Characteristics	Yes	Yes	Yes	Yes
Pair Characteristics	Yes	Yes	Yes	Yes
Year FEs	Yes			
Supplier FEs	Yes	Yes	Yes	
Customer FEs	Yes	Yes		
Supplier Industry×Year FE		Yes		
Customer Industry×Year FE		Yes		
Customer×Year FEs			Yes	Yes
Pair FE				Yes
R^2	0.448	0.430	0.505	0.503
Observations	4,792	4,461	2,999	2,781

Table OA.5

Sales and Trade Credit, Subsamples of Strong and Weak Customers (Z-score)

This table shows the effect of the anti-recharacterization laws on firms' customer sales and trade credit to strong and weak customers. Strong (Weak) customers are defined as customers with above (below)-median Z-scores. Panel A reports results for *Log(Sales)* using the pair-level Segment sample, and Panel B examines *Trade Credit* using the SEC sample. *Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. Controls include all the control variables in Table 4. In Panel A, we exclude *Sales Dependence* from the list of controls. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Sale to Strong and Weak Customers, Z-score

Sample:	Strong Customer	Weak Customer	Difference	Strong Customer	Weak Customer	Difference
Dep. Var.: *Log(Sales)*	(1)	(2)	(Strong−Weak)	(3)	(4)	(Strong−Weak)
Supplier Law	0.073	0.101*	-0.028	0.014	0.120**	-0.106
	(1.63)	(1.73)	(-0.40)	(0.25)	(2.55)	(-1.37)
Controls	Yes	Yes		Yes	Yes	
Year FEs	Yes	Yes		Yes	Yes	
Supplier FEs	Yes	Yes				
Customer FEs	Yes	Yes				
Pair FE				Yes	Yes	
R^2	0.894	0.906		0.923	0.932	
Observations	15,052	12,498		13,618	11,136	

Panel B: Trade Credit For Strong and Weak Customers

Sample:	Strong Customer	Weak Customer	Difference	Strong Customer	Weak Customer	Difference
Dep. Var.: *Trade Credit*	(1)	(2)	(Strong−Weak)	(3)	(4)	(Strong−Weak)
Supplier Law	-0.043***	-0.003	-0.040*	-0.047***	-0.005	-0.041*
	(-3.39)	(-0.17)	(-1.90)	(-3.79)	(-0.33)	(-1.90)
Controls	Yes	Yes		Yes	Yes	
Year FEs	Yes	Yes		Yes	Yes	
Supplier FEs	Yes	Yes				
Customer FEs	Yes	Yes				
Pair FE				Yes	Yes	
R^2	0.460	0.448		0.510	0.493	
Observations	2,806	1,956		2,649	1,863	

Table OA.6
Robustness: Checking Survivorship Bias
This table shows the robustness of our results for several sample restrictions. We require the customer-supplier relations in our sample to appear both before and after the law passage for at least 1 year (Columns (1) and (2)), 2 years (Columns (3) and (4)), and 3 years (columns (5) and (6)), respectively. The dependent variable is *Trade Credit*, defined as the trade credit extended between a supplier to a customer, scaled by the total transaction value between the two firms in the same year. *Law* is an indicator for the firm being incorporated in a state that has passed the anti-recharacterization law. All columns use the SEC sample. Controls include *Sales Dependence* and *Relationship Length*, and *Age, Size, Q, Leverage, Profitability, and R&D Intensity* for the supplier. Customer controls are subsumed by customer-year fixed effects. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Sample:	≥1 pre- and post-		≥2 pre- and post-		≥3 pre- and post	
Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)	(5)	(6)
Supplier Law	-0.045**	-0.048**	-0.054**	-0.060**	-0.103***	-0.111***
	(-2.58)	(-2.76)	(-2.36)	(-2.57)	(-3.75)	(-4.20)
Supplier Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Pair Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FEs	Yes		Yes		Yes	
Customer×Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Pair FE		Yes		Yes		Yes
R^2	0.564	0.552	0.384	0.394	0.408	0.428
Observations	1,087	1,087	630	630	384	384

Table OA.7
Robustness: Effects of SEC Reporting Threshold
This table shows the robustness of our results to the SEC reporting threshold for what qualifies as a major customer. In Panel A (B), we artificially raise the reporting threshold to 11% (12%) of sales. The dependent variable is *Trade Credit*, defined as the trade credit extended between a supplier to a customer, scaled by the total transaction value between the two firms in the same year. *Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. All columns use the SEC sample. Controls include *Age, Size, Q, Leverage, Profitability, R&D Intensity*, for both the customer and the supplier. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics are shown in parentheses, calculated from standard errors clustered by the supplier's state of incorporation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Above 11%

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)
Supplier Law	-0.020**	-0.021**	-0.030***	-0.024***
	(-2.46)	(-2.69)	(-3.53)	(-2.89)
Customer Law	0.019***	0.017***	0.025***	0.030***
	(3.12)	(3.50)	(3.44)	(3.83)
Controls		Yes	Yes	Yes
Year FE	Yes	Yes		Yes
Supplier FE	Yes	Yes	Yes	
Customer FE	Yes	Yes	Yes	
Supplier Industry×Year FE			Yes	
Customer Industry×Year FE			Yes	
Pair FE				Yes
R^2	0.481	0.500	0.499	0.541
Observations	4,124	4,113	3,788	3,875

Panel B: Above 12%

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)
Supplier Law	-0.022***	-0.024***	-0.030***	-0.026***
	(-2.84)	(-3.34)	(-3.53)	(-3.35)
Customer Law	0.023***	0.021***	0.031***	0.033***
	(3.86)	(4.30)	(4.27)	(5.01)
Controls		Yes	Yes	Yes
Year FE	Yes	Yes		Yes
Supplier FE	Yes	Yes	Yes	
Customer FE	Yes	Yes	Yes	
Supplier Industry×Year FE			Yes	
Customer Industry×Year FE			Yes	
Pair FE				Yes
R^2	0.484	0.502	0.507	0.539
Observations	3,856	3,845	3,522	3,620