Access to Debt and the Provision of Trade Credit

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Abstract

We examine how access to debt markets affects firms' incentives to provide trade credit. Using hand-collected trade credit data between customer-supplier pairs and two exogenous shocks to firms' debt capacity, we show that better access to debt reduces firms' provision of trade credit per dollar of sales. The decline in trade credit is concentrated on ex-ante powerful customers, but absent for weak ones, suggesting that better access to debt improves firms' bargaining position relative 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.

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

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1 Introduction

Trade credit represents one of the most important sources of financing for U.S. firms, with a total volume exceeding 20% of total GDP (Garcia-Marin et al., 2019). 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 conventional view is that better access to debt relaxes suppliers' liquidity constraints and allows them to provide more trade credit (i.e., a liquidity pass-through channel). Many studies document this effect in situations where financially strong suppliers can support customers that lack access to bank credit (Meltzer, 1960; Schwartz, 1974; Petersen and Rajan, 1997; Biais and Gollier, 1997; Emery, 1987; Jain, 2001), particularly when the customers are hit by financial or economic crises (Love et al., 2007; Cunat, 2007; Garcia-Appendini and Montoriol-Garriga, 2013; Costello, 2020; Amberg et al., 2021). While prominent, this literature overlooks the possibility that access to credit could alter the bargaining dynamics between suppliers and customers, which in turn affects trade credit provision (a bargaining power channel). Specifically, access to debt allows firms to pursue growth options, reduces their reliance on powerful customers, and enhances their bargaining power over downstream firms. The increased bargaining power alleviates the pressure for firms to provide trade financing. This mechanism may be particularly relevant in normal times when firms may benefit more from growth options, rather than in times of crisis when preserving customer relationships may be paramount for survival.

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, a result that 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 concentrations, which include 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 exogenous shocks to firms' debt capacity. Our main analysis relies on the staggered state-level passage of anti-recharacterization laws (ARLs). We exploit the passage of ARLs in seven U.S. states during the period spanning 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

[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.

them to create Special Purpose Vehicles (SPVs) and tap into additional debt markets.[2] Section 3 provides a detailed description of anti-recharacterization laws. The passage of ARLs is a suitable setting for us because firms affected by the laws are able to increase investment, expand production, and pursue new technology and innovation (Li et al., 2016; Mann, 2018; Ersahin, 2020; Favara et al., 2021), all of which can help firms diversify their customer base and solidify their bargaining position towards downstream firms.

We find that firms affected by the ARLs 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 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 3–4 percentage points more than control suppliers following the passage of anti-recharacterization laws. This is an economically meaningful magnitude, accounting for around 16–24% of the average trade credit (over sales) for suppliers in our sample.[3] We document a similar reduction in the dollar amount of trade credit for affected firms.

While our baseline specification includes customer-year fixed effects to compare suppliers of the same customer, this specification does not ensure that suppliers affected or unaffected by the ARLs had similar characteristics prior to the law adoption. We address this concern in several ways. First, we directly check that the treated and control firms in our testing sample do not differ substantially in their pre-event characteristics. After absorbing customer-year fixed effects, the differences are that treated suppliers are

[2] Note that the ARLs not only affect firms with existing SPVs, but also firms who do not have SPVs but can create SPVs in the future.

[3] To put this magnitude in perspective, the Anti-Recharacterization Laws brought about significant changes in firms' financial and operational decisions. Li et al. (2016) find ARLs increase leverage by 4–7 percentage points, which translates to a $29.2–51.1 million more debt for our sample firms. This is a substantial amount of resource that firms can use to expand their production, make investments, and pursue innovation. The changes in trade credit we document translate to about a $4.3 million reduction, a value that is moderate compared to the total expansion in debt capacity.

slightly younger, have greater asset size, and have a higher Q ratio than control firms. To further address the concern that such differences may contribute to our main effects, we use an entropy-balanced sample, constructing a set of matching weights for control customer-supplier pairs such that their pre-event balanced characteristics are identical to the treated pairs. The matching ensures that the treated and control groups have precisely the same pre-event characteristics, including the same trade credit-to-sales ratio, sales dependence on the customer, age, size, profitability, leverage, and cash flow volatility. We then stack together all matched observations from treated and control firms during a [-3, +3] event window.[4] We verify that our results persist in this entropy-balanced sample, suggesting that the pre-event differences in firm characteristics are not driving our results. We test the parallel trends assumption using this sample and find that the trade credit extension of treated firms does not diverge from control firms prior to the event, but significantly drops relative to control firms after the enactment of ARLs.

To illustrate how laws affecting firms' debt capacity can influence trade credit provision, we re-state our findings in a two-stage-least-squares framework, using the passage of ARLs as an instrument for firms' debt capacity. Specifically, in the first stage, we regress (supplier) firm leverage on an indicator for whether an ARL has passed in the firm's state of incorporation. In the second stage, we regress trade credit on the leverage predicted from the first stage. We find results consistent with our expectations: the passage of ARLs significantly increased supplier firms' leverage by 6–13 percentage points, depending on the specification. In the second stage, we find that the predicted increase in leverage is associated with a 4-percentage-point decline in trade credit provision, a magnitude that is in line with our baseline analysis.

Through what channels does access to debt influence trade credit provision? We conjecture that better access to debt markets improves firms' bargaining power relative to buyers. Given the significant cost associated with trade credit provision, an elevated bargaining position allows firms to curtail the trade credit they provide to major customers.

[4] Given that the entropy-balanced sample is a stacked sample, it helps address the concern related to heterogeneous treatment timing in the generalized difference-in-difference (DID) framework (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Baker et al., 2022).

We substantiate this mechanism in several ways. First, we show that after the passage of anti-recharacterization laws, affected firms expand their production and diversify their customer base. Importantly, we note that treated firms invest more in intangible assets and innovation, which could help them develop relationships with new customers. We find that these firms not only increase the number of customers, but also diversify their customer base by supplying products to more industries. Ultimately, treated firms increase sales and earn higher profits. After the ARL adoption, treated firms also become less likely to cite their major customers' patents, suggesting a reduced technology reliance on those customers. Collectively, these results are consistent with the argument that access to debt markets makes firms less reliant on the largest, most powerful customers. Our findings also highlight that technological innovation and differentiated investment could be a mechanism through which the ARLs improve firms' bargaining power.

We next look into the heterogeneity of our effects to shed light on the bargaining power channel. Specifically, we expect our results to 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 two ways. First, we begin with the notion that, for the same supplier, major customers possess greater bargaining power than minor customers. We examine the aggregate trade credit provided to major customers disclosed under SFAS 14 and FASB No. 105, and compare it to the residual trade credit provided to minor customers. We then examine the changes in trade credit provided to major and minor customers separately and find that the reduction in trade credit only occurs for major customers, but not for minor ones. This result holds even when we control for the total accounts receivables issued by the supplier.

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. 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 industry sales dependence indicates that the supplier relies heavily on the orders from the customer due to the nature of their production linkages. 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.

Together, these results are consistent with the view 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. More importantly, 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). Other firm characteristics could also change following anti-recharacterization laws; however, 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), deregulation 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 either borrow from alternative sources at a higher cost and/or cut back on investment. Note that this prediction is not trivial. On the one hand, customers may easily replace the lost trade credit, by borrowing more from other sources. On the other hand, customers may face financial frictions, making it difficult to replace trade credit, which has close-to-zero cost. This means that the reduction in trade credit can lead to real consequences such as cutbacks in investment. Our evidence support the latter conjecture. 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 customer 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 0.002–0.006 reduction in investment relative to total assets (a 2.9%–6.8% change compared to the sample mean) and 0.005–0.012 higher leverage (an increase of approximately 2%–5% relative to the sample average). 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.[5]

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.[6] These results indicate that the protection of creditor rights generates negative spillover effects for downstream firms.

We conduct a battery of robustness analyses to bolster our inferences. First, we verify that our findings hold for the accounts receivable-to-sales ratio for all Compustat firms. Second, we address a selection concern that firms may not report customer relations or trade credit data consistently before and after the ARL adoption. We show that our results do not change when we restrict the sample to customer-supplier pairs that appear at least 1, 2, or 3 years both before and after the events. In addition, our results remain robust if we use changes in firms' real estate value as an alternative shock to debt capacity (Chaney et al., 2012).

Finally, we address the concern that our results 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 remain robust in a subsample of firms without SPVs. These firms are still affected by the laws because they now face a higher option value of setting up an

[5]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.

[6]We show that these results are not driven by a 2003 SEC regulation regarding the disclosure of purchase agreements, which is studied in Noh (2020).

SPV in the future. But without an SPV, they are unlikely to be currently securitizing trade credit. 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.

2 Relation to Literature

This study builds upon and contributes to the important literature studying the determinants of trade credit usage. Petersen and Rajan (1997) categorize and summarize a number of theories that explain the use of trade credit: (1) "Financing advantage theories" suggest that suppliers have advantages over financial intermediaries in providing funds to customers. These advantages can arise from several channels, including the advantage in acquiring information, in monitoring the buyer and enforcing repayment, and in liquidating/salvaging value from the firm's assets.[7] Biais and Gollier (1997) build on the asymmetric information between banks and firms and generate similar predictions, i.e., customers without banking relationships rely more on trade credit, and suppliers with higher cash holdings provide more trade credit. Numerous empirical studies document findings consistent with this theory (e.g., Demirguc-Kunt and Maksimovic 2001; Love et al. 2007; Cunat 2007; Garcia-Appendini and Montoriol-Garriga 2013 Costello 2020, Amberg et al. 2021). (2) "Price discrimination through trade credit" suggests that, by extending trade credit at favorable terms, the supplier effectively lowers the net price of its goods and expands sales. This way, suppliers could provide different prices to different customers by adjusting trade credit terms without altering the product. Giannetti et al. (2021) provide evidence consistent with the price discrimination role of trade credit. (3) The "transaction costs motive" means that customers can accumulate payments at a monthly or quarterly frequency, instead of paying at each delivery, thus requiring less frequent (aggregated) payments.

Our study explores the effect of access to financing on the provision of trade credit.

[7] Another finance-related motive is discussed by Burkart and Ellingsen (2004) who develop a finance advantage agency-based theory that uses the notion that lending inputs is less risky because they are harder to divert than cash.

It is thus related to the financing advantage theories. The financing advantage theories predict that financially strong suppliers should provide more trade credit to financially vulnerable customers. Yet, in the modern economy, we often observe the opposite pattern, i.e., financially strong customers obtaining trade credit from smaller, financially weaker suppliers (e.g., Murfin and Njoroge 2015; Klapper et al. 2012). To explain this phenomenon, alternative theories are needed, in particular those analyzing the bargaining power between customers and suppliers.

The bargaining power theories of trade credit discuss how the relative power of the customer and supplier (e.g., monopoly and monopsony powers) determines trade credit usage, but generate mixed predictions. For example, Petersen and Rajan (1997) articulate how a supplier's monopoly power relates to extending trade credit. If a supplier has a monopoly, then customer firms have less bargaining power, given no alternative suppliers exist, and will be more likely to repay. This leads to greater trade credit extension as the monopoly power of suppliers increases. However, Fabbri and Menichini (2010) suggest that the opposite may be true, i.e., supplier power can reduce trade credit provision. Consistent with this latter prediction, Fisman and Raturi (2004), Giannetti et al. (2011), Dass et al. (2015), and Fabbri and Klapper (2016) document in various contexts that suppliers of differentiated goods (who are more reliant on their customers) are more likely to provide trade credit, and powerful customers receive more trade credit and more favorable terms.

We document that suppliers with increasing access to financing provide less, not more trade credit to customers. Our findings are consistent with the bargaining power theories that predict seller power reduces trade credit provision. Moreover, we also provide rich evidence to reveal economic mechanisms: When suppliers have greater access to external debt markets, they have greater financial flexibility to broaden their customer base, reduce their dependence on powerful customers, and upgrade technology, all of which enhance their bargaining power over downstream firms. This ultimately leads to decreased trade credit provision to powerful customers.

Our findings stand in contrast with studies showing that firms with access to bank credit extend more trade credit during crises to help buyers survive and continue their business relations (Calomiris et al., 1995; Love et al., 2007; Fabbri and Menichini, 2010; Garcia-Appendini and Montoriol-Garriga, 2013; Costello, 2020). We add to this line of research by showing that effects are reversed outside of crisis periods, when buyer survival is less of a concern.

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 (Calomiris et al., 2017; Campello and Larrain, 2016). 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 it offers superior protection over trade credit collateral, which qualifies as "cash collateral," even without the anti-recharacterization laws.[8] With the strong protection over trade credit collateral in place, limited improvement can be made to the creditor protection of receivables collateral from anti-recharacterization laws. Thus, in the U.S. context, the effect of the laws on firm growth and bargaining power may have dominated their effect on receivables' pledgeability, which could explain the reduction in trade credit after the law adoption. In contrast, the protection of trade credit collateral in European countries is relatively weak, especially in Italy (see, e.g., Garrido (2016) and Day (2007)).[9] Thus, any

[8]Cash collateral receives special protection inside 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 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 (Bussel and Klee, 2009).

[9]According to Garrido (2016), the bankruptcy courts in Italy provide unrestricted scope of automatic

laws that would substantially enhance creditor rights would likely encourage even more trade credit-backed lending.

3 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.

stay, making the recovery of claim extremely long for secured creditors. The article also notes that the bankruptcy protection over secured creditors is particularly weak in Italy, even compared to peer E.U. countries. While there were out-of-court resolution measures introduced in 2016, the Italian insolvency system remains complex and less friendly to creditors. Day (2007) compares the Chapter 11 bankruptcy code in the U.S. and Italy, and shows that the automatic stay in Italy is stricter and more debtor-friendly: "Upon the admission of the company to the procedure of extraordinary administration (bankruptcy) the actions of both secured and unsecured creditors are automatically stayed without exception." In the U.S., there are more exceptions to the automatic stay, and for cash collateral, "the prohibition on using cash collateral without the consent of the lienholder or court approval gives an undersecured creditor with liens on current assets significant leverage in Chapter 11 cases though the negotiation of the 'cash collateral' order."

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, 2003; Kettering, 2008, 2010). 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."[10] We also explain later in Section 8 that our results are not dependent on the sale of receivables or the

[10] 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.*"

anti-recharacterization law passed in Texas.

Our study builds on the literature documenting the effects of anti-recharacterization laws in the U.S. (Li et al., 2016; Chu, 2020; Ersahin, 2020; Favara et al., 2021). Importantly, studies in this literature document that ARLs lead firms to borrow more, invest more, adopt new technology and increase innovation. Given these findings, it is plausible that ARLs 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 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.

4 Empirical Framework

4.1 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 pair-level characteristics.

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 (2024), 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.[11] 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, which we label the "Segment customer sample." We use these customer-years to construct a firm-year panel that allows us to examine downstream effects of changes in trade credit provision.

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/Sales*, the amount of receivables extended by a supplier

[11] Ersahin et al. (2024) follow a similar data collection procedure and study the effect of natural disasters on trade credit provision.

to a customer scaled by the pair-specific 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 21,709 and 105,745 firm-year observations, respectively. We compute *Firm Receivables/Sales* as the ratio of the total value of accounts receivable of a firm over the firm's total sales in a given year.

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

$$
\begin{aligned}
Trade\ Credit/Sales_{i,j,t} = \mu_{i,j} + \tau_t + \beta Supplier\ Law_{i,t} \\
+ \gamma Customer\ Law_{j,t} + Controls_{i,j,t} + \epsilon_{i,j,t}, \quad (1)
\end{aligned}
$$

where i indicates a (supplier) firm, j indicates a customer of firm i, and t indicates a year. $Trade\ Credit/Sales_{i,j,t}$ 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.

In later analysis, we also test whether the adoption of the laws helps firms expand their customer base. For this set of analysis, We compute the characteristics of a firm and its customer base, such as the number of new customers, total customer counts, the number of customer industries covered, etc. We perform the following analysis on the Compustat sample or the Segment sample:

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

where i indicates a firm, m indicates the industry of the firm, and t indicates a year. Y includes *New Customers*, the number of new customers gained in a year, *Total Customers*, the total number of major customers, *Downstream Industry Count*, the number of industries (SIC-4 or SIC-2) the supplier sells to in a reported year, *Gross Margin*, the ratio of firm sales over cost of goods sold, minus one, and *ROA*, the ratio of net income over total assets. These variables are all measured at the (supplier) firm-year level. In addition, we look into firms' intangible assets and knowledge capital, following Falato et al. (2022). *Law* is an indicator that equals 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 ($\eta_{m,t}$).

4.3 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 (Petersen and Rajan, 1997; Giannetti et al., 2011; 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; *R&D Intensity*, the ratio of R&D expenditure over total assets; and *Cash Flow Vol.*, the past 10-year standard deviation of cash flow.[12]

[12]Following Bates et al. (2009), we require at least three years of available cash flows; for observations with fewer than three observations, we use the industry median of that year. Our results are robust if

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. *Leverage* is restricted to between 0 and 1. Detailed definitions are provided in Appendix A. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles.

4.4 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 (14) 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 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

we exclude observations with fewer than three observations.

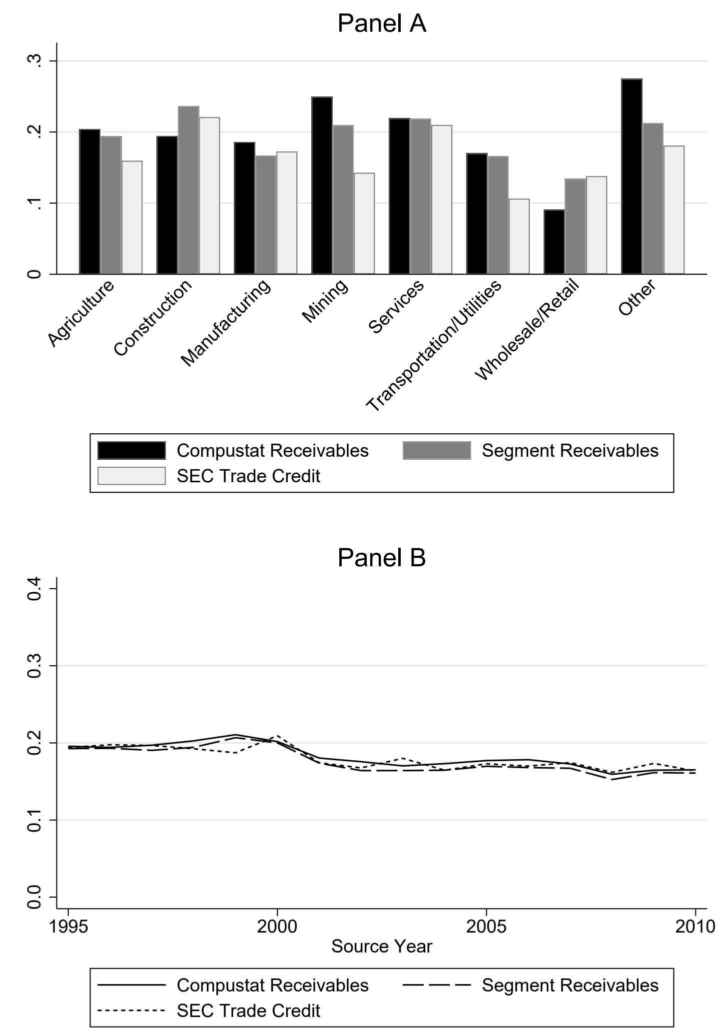

Figure 1. Trade Credit Across Samples. This figure presents cross-industry and time-series patterns of trade credit data in our manually collected sample (i.e., the SEC sample). We then compare such patterns with the accounts receivables of firms in the Compustat sample and the Segment sample. Panel 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 (firm 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/Sales* 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.

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, *Firm Receivables/Sales*) 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/Sales* in the SEC sample and compares it with the time series patterns of *Firm Receivables/Sales* in the Compustat sample and the Segment sample. The level of trade credit observed in our sample is similar to the average level of receivables recorded in the other two broader datasets. 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 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 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 these proxies for suppliers' bargaining power over customers, and plot the average value of *Trade Credit/Sales* 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.

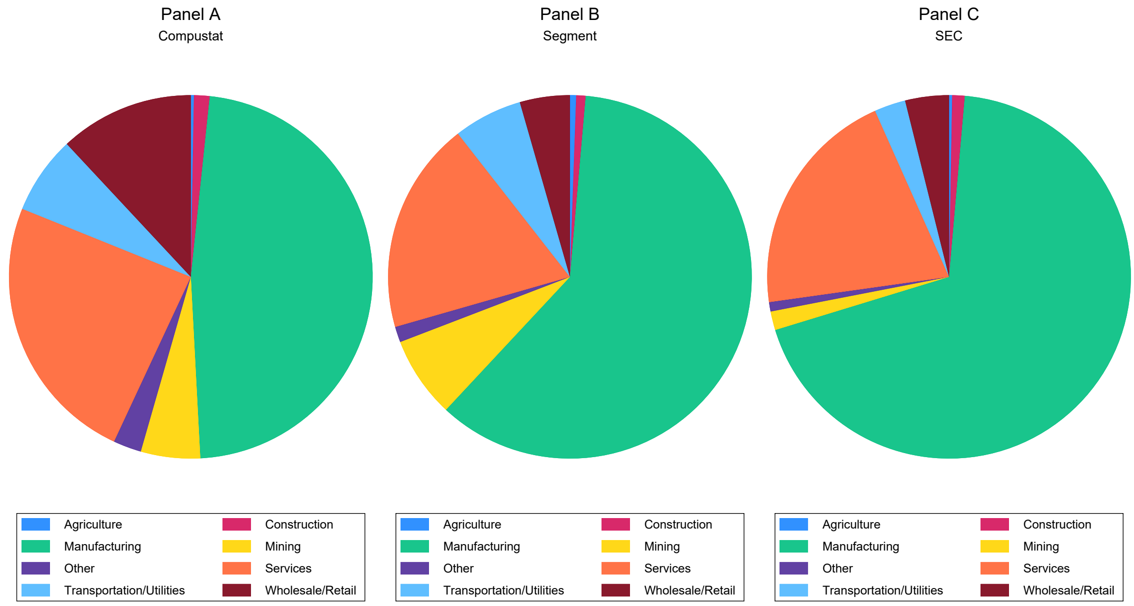

Figure 2. Industry Distribution of Firms Across Samples. This figure depicts the industry distribution in the three samples. Industries are defined at the one-digit SIC level. Panel A shows the distribution across all firms in the Compustat sample. Panels B and C report the distribution across all suppliers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

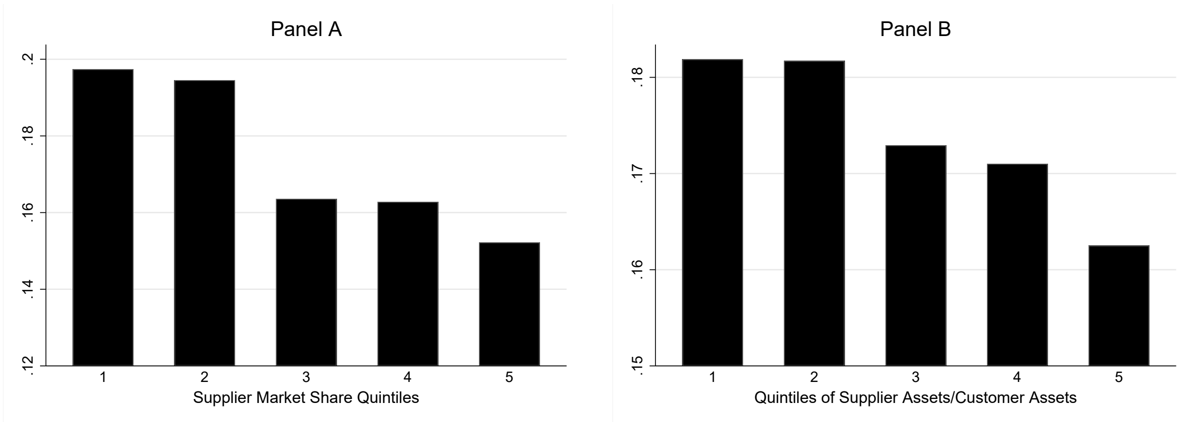

Figure 3. Trade Credit and Supplier Characteristics. This figure depicts the relation between trade credit and the market share and sizes of suppliers. Panel A shows the average value of *Trade Credit/Sales* across quintiles of supplier market share, measured as the supplier's sales as a percentage of 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.

5 Baseline Results

5.1 Trade Credit and Anti-Recharacterization Laws

We next examine the effect of anti-recharacterization laws on firms' incentives to extend trade credit. Table 2 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 2 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 ($= -0.028/0.174$).

To put this magnitude into perspective, the anti-recharacterization laws brought about significant changes in firms' financial and operational decisions. For example, Li et al. (2016) find that ARLs increase firm leverage by 4–7 percentage points, around 14–24% of the mean value in their sample. For an average firm in our sample, a 4–7 percentage point increase in leverage translates to a \$29.2–51.1 million increase in debt capacity. This is a substantial amount of resources that firms can use to expand their production, make investments, and pursue innovation. Our documented effect of a 2.8 percentage points reduction in the trade credit-sales ratio translates to around \$4.3 million, a moderate value compared to the total expansion in debt capacity.

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 from 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. Our estimates from Column (4) suggest that treated suppliers reduce trade credit by 4 percentage points more than other suppliers of the same customer who are not affected by ARLs, accounting for a 24% change relative to the sample average of trade credit-to-sales ratio.

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. Specifically, we repeat the analysis using the dollar value of trade credit between a customer-supplier pair as the dependent variable (*Trade Credit*) and estimate results from a Poisson fixed effects regression. We report results in Panel C of Table 2. 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 to a customer by 16–20%, close to the magnitude from our baseline estimates in Panel A.

Our findings so far suggest that after the adoption of the anti-recharacterization laws, firms reduce the trade credit provided to those customers, both in terms of dollar amount and per-dollar of sales. In Table OA.1 of the Online Appendix, 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 2, 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, which we verify in later analysis. 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 6.

5.2 Entropy Balancing on Covariates

Our baseline specification includes customer-year fixed effects, which restricts the comparison to treated and non-treated suppliers of the same customer. While this approach sharpens the comparison, it does not ensure that treated and control suppliers have similar firm characteristics prior to the event. In Panel A of Table 3, we directly test the differences in firm characteristics between treated and control suppliers of the same customers. We do so by first removing customer-year fixed effects from each characteristic and then computing the sample average residuals for treated and control suppliers separately. We find that treated and control suppliers display very similar characteristics across many dimensions; however, we also find that treated suppliers are younger, have larger asset sizes, and have higher Q than the control group.

TABLE 3 ABOUT HERE

To address the concern that these observable differences may be driving our findings, we construct an entropy-balanced sample, where we compute a set of balancing weights for control (never-treated) suppliers based on an array of pre-event characteristics. We then track both the treated and control units through a seven-year event window centered around the year of the ARL adoption for the treated supplier.

To construct this sample, we require a customer-supplier pair to appear at least once in the three years prior to the event-year and at least once in the three years following the event-year for inclusion in the sample.[13] To facilitate the use of customer-year fixed effects and the comparison of trade credit across suppliers of the same customer in the same year, we require a customer to have at least two suppliers in the same event-year. We balance the sample of customer-supplier pairs based on pre-event characteristics: *Trade*

[13]This ensures that any reporting biases do not affect our findings. In Section 8, we further show that the reporting biases or firms' attrition from the sample are unlikely to drive our main results.

Credit/Sales, *Sales Dependence*, *Size*, *Age*, *Profitability*, *Leverage*, and *Cash Flow Vol.* The matching relies on the most recent firm and pair-level characteristics prior to the event. We balance on the first two moments with a tolerance of 0.001, computing entropy balancing weights for the control pairs to ensure balanced pre-event characteristics. Entropy balancing effectively equalizes the pre-event matching characteristics, as shown in Panel B of Table 3. Notably, we also find that the treated and control groups are similar across characteristics not used in the balancing.

In Panel C, we repeat our baseline analyses (Equation 1) using the entropy-matched sample. We run weighted least squares regressions, wherein the weights equal the balancing weights from the entropy balancing procedure. We present results with and without customer-event-year fixed effects. Importantly, we augment the controls by interacting each fixed effect with an event-cohort fixed effect. These interactive fixed effects help further address potential confounding effects arising from changes in the matching between customer and suppliers across events, or differential impacts coming from changes in customer conditions across events. Across both specifications, we continue to find that the adoption of anti-recharacterization laws leads to a large reduction in trade credit provision, with magnitudes similar to those in Table 2. We note that results from Table 3 come from stacked regressions, which address concerns related to the heterogeneous treatment timing in the generalized difference-in-difference approach (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Baker et al., 2022).

5.3 Testing Parallel Trends Assumption

We test the parallel trends assumption using the entropy-balanced sample. We estimate the following equation:

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

where e indicates an event, i represents a supplier firm i, and j represents a customer of firm i. We control for pair-event fixed effects ($\mu_{i,j,e}$), which help track the trade credit

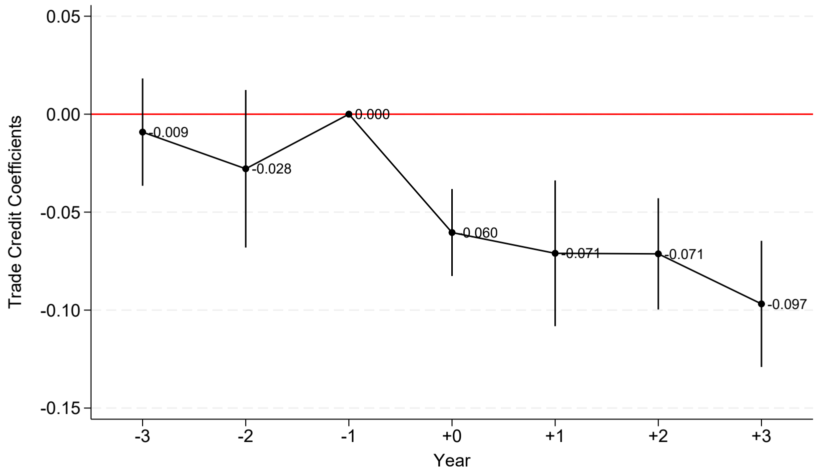

Figure 4. Testing Parallel Trends with a Stacked Sample. This figure plots coefficient estimates from a regression using entropy balancing weights in the entropy-balanced sample, constructed by balancing the pre-event characteristics of control customer-supplier pairs to treated customer-supplier pairs and tracing them for a 7-year period centered on the year of the event. The figure plots coefficient estimates for *Trade Credit/Sales*, based on Equation 3. The estimation includes customer-event-year fixed effects and pair-event fixed effects, as well as the same set of controls as in Table 2, Panel B, Column (4). In each panel, the dots represent point estimates and the vertical lines represent 90% confidence intervals.

provided from supplier firm i to customer j during the 7-year window around event e. We utilize customer-event-year fixed effects ($\xi_{j,e,t}$), so that identification comes from a comparison of treated and control suppliers to the same customer in the same event-year. $Controls$ represent the same set of control variables used in Panel C of Table 3. Standard errors are clustered by suppliers' state of incorporation.

We use year -1 as the benchmark, so the coefficient estimate for β_t indicates the change in trade credit relative to the year prior to the events. Figure 4 reports the results from this analysis. We do not see significant differences between treated and control groups prior to the passage of the laws, but trade credit at treated firms declines substantially when the law takes effect.

There are at least two explanations for why the effect sets in immediately after the law adoption. First, firms may decide to reduce trade credit provision immediately as they anticipate a shift in bargaining power in the future and make plans for downstream expansion. When a state passes the anti-recharacterization law, firms realize that they can raise capital more easily and at a lower cost (Favara et al., 2021). They may anticipate an expansion of production and customer base in the near future, and thus negotiate harsher terms with their existing customers. Second, some of the anti-recharacterization laws are passed at the beginning of the year. For example, Delaware, where the majority (67%) of our treated firms are incorporated, passed the ARL in January of 2002. The effect in year $t = 0$ could account for firms' response during the year 2002.

5.4 The Role of Debt Capacity

We design an analysis to validate the mechanism that the effects of the ARLs originate from increases in firms' debt capacity. Specifically, we run a two-stage-least-squares regression, examining whether the adoption of ARLs leads to increases in firms' financial leverage, which in turn leads to reductions in trade credit. In the first stage, we regress *Leverage* on *Supplier Law*, and in the second stage, we regress the *Trade Credit/Sales* between the customer-supplier pair on the predicted *Leverage* from the first stage. Following recommendations from Atanasov and Black (2021) to ensure covariate balancing, we use the entropy-balanced sample for this analysis, which achieves covariate balance between the treated and control firms.

Table 4 reports the results from the two-stage-least-squares analysis. Panel A reports results from the first stage, and Panel B reports second-stage results. In each panel, we add fixed effects in stages, starting with customer-supplier-pair-by-event fixed effects and event-year fixed effects in Column (1), then imposing customer-event-year fixed effects in Column (2). From the first-stage results, we find that *Supplier Law* generates a significant, positive effect on suppliers' leverage ratios, with the magnitude ranging from 7 to 13 percentage points, depending on the specification. The predicted increase in leverage, in turn, leads to significant reductions in trade credit, by about 4 percentage points.[14] This economic magnitude is consistent with our results from the baseline analysis.

Table 4 About Here

[14]We compute the magnitude on the effect of the laws on trade credit by multiplying the coefficients from the two stages. Specifically, estimates in Column (1) suggest that the adoption of an ARL leads to a 0.067 increase in leverage, which in turns leads to a 3.8 percentage point ($= 0.067 \times 0.560$) decline in trade credit. Similarly, estimates in Column (2) suggest around a 4.6 percentage point reduction ($= 0.129 \times 0.360$). Another way to interpret the magnitude from the second stage is that a one-percentage-point increase in leverage is associated with 3–8 percentage points reduction in trade credit.

Taken together, results from this section suggest that the anti-recharacterization laws improved firms' access to debt market, which allows firms to borrow more and consequently provide less trade credit to their major customers. This finding is unlikely to be driven by the heterogeneous treatment timing related to the generalized difference-in-difference design, or pre-existing differences or diverging trends between treated and control firms before the law adoption.

6 The Bargaining Power Channel

In this section, we investigate the mechanisms through which access to debt affects trade credit provision. Our investigation focuses on a bargaining power channel. To start, we directly examine changes in firms' customer base, focusing on the number of customers, customer concentration, and gross margins. If better access to debt markets improves firms' bargaining position relative to customers, we should observe increases in the number of customers and a more diverse set of customers following the shock.

We next compare the effects of anti-recharacterization laws on trade credit to customers who previously had stronger or weaker power relative to the supplier firm of interest. 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 customer had an *ex ante stronger* bargaining position relative to the supplier firm. We design two tests along this dimension. 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.

For the analyses in this section, we revert to the main sample rather than using the entropy-balanced stacked event approach. Using the full sample allows for a richer exploration of heterogeneity across customers which would not be possible in the narrower matched sample setting. Additionally, some tests in this section examine supplier-level effects employing a panel constructed at the firm-year level, rather than the pair-level used in the stacked sample.

6.1 Expansion and Customer Base Diversification

A firm's bargaining power relative to customers often depends on its outside options and whether it relies on a small set of customers or has a diversified customer base. Thus, we look at characteristics of firms' customer base and examine whether firms start to expand and diversify their customer base after the law adoption. In this investigation, we look at the number of new customer relationships, total customer counts, and the number of industries covered by major customers. The number of new customers and total customer counts proxy for firms' operational scale and thus outside options for selling its products. The number of customer industries represents a firm's operational diversity and the ability to allocate productive resources across different products. If expanded debt capacity leads to customer base expansion and greater customer diversification, such effects would be indicative of greater bargaining power against major customers.

As a primer, we show in Table OA.2 that treated firms increase their total sales after the adoption of ARLs. Combined with evidence from the existing literature that the adoption of ARLs also fosters firm investment, this suggests that expanded debt capacity allows firms to expand production and sales, potentially allowing them to sell their products to more customers. Next, we estimate Equation 2 using the Segment sample to examine the effects of ARLs on the firms' customer diversification. If firms start to establish new customer relations and supply to more industries, they should achieve a stronger bargaining position and be less pressed to provide trade credit. We examine these channels in Table 5.

In Panel A, we examine whether the laws enable firms to expand their customer base. In the first three columns, we examine how many new major customers a firm attains after the adoption of ARLs, where new customers are defined as those reported by a firm as major customers for the first time. In Columns (4) to (6), we examine the total number of major customers reported by a firm. 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).[15] We observe that firms establish more new major customer relationships af-

[15]Note that because the Poisson estimation drops separated observations, the sample size in Panel A

ter the law. This effect could be driven by firms establishing a new customer relationship, or by firms increasing their transactions with previously non-major customers. Treated firms also provide products and services to a greater number of major customers. These results are consistent with firms expanding their customer base after the law adoption.

TABLE 5 ABOUT HERE

In Panel B, we investigate the changes in firms' downstream industry coverage. Downstream industry coverage is measured by the number of industries in which firms' major customers operate. In Columns (1) to (3), customer industries are measured by 4-digit SIC codes, while in the next three columns, customer industries are measured by 2-digit SIC codes. Across both measures, we find a significant increase in the number of customer industries following the ARLs, suggesting that the laws lead firms to broaden the types of customers they serve.

In Panel C, we further gauge changes in firms' bargaining power relative to customers by examining whether treated firms earn higher profits 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. We measure profitability using both gross margins and returns on assets. Our results show that profitability increases with the passage of the anti-recharacterization laws. This finding also helps rule out the concern that treated firms may offer price concessions to customers to compensate for the reduction in trade credit.

How does access to debt markets help firms diversify their customer base? One potential channel is that the enhanced debt capacity allows firms to adopt new technology and invest in more intangible assets (Ersahin, 2020; Favara et al., 2021). With more advanced technology, firms can develop new products and services to cater to a broader group of customers. We test this conjecture by examining changes in firms' knowledge capital and intangible assets. The construction of these dependent variables follows Falato

is smaller than in Panels B and C; see Correia et al. (2020) and Cohn et al. (2022) for details.

et al. (2022).[16]

Results are shown in Panels A and B of Table 6. We find that firms affected by anti-recharacterization laws accumulate more knowledge capital (Panel A) and intangible capital (Panel B). This effect holds for both the full Compustat sample (Columns (1) and (2)) and for suppliers in the Segment sample (Columns (3) and (4)). 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 services. This helps them establish new customers and strengthen relationships with less powerful customers.

TABLE 6 ABOUT HERE

Another channel through which debt capacity influences supply-chain bargaining power is by changing the technological reliance between a firm and its major customers. As suppliers often cater their production process to the specific demand of major customers, their products and technology may be intertwined with those of the customers. An expansion in financial access allows firms to reduce their technological reliance and develop new technology that is independent from their existing customers and allows them to cater to a broader set of clients.

We test this hypothesis by examining the technological overlap between suppliers and their customers. Following Jaffe et al. (1993), we measure technological overlap by the cross-citations of firms' patents to their major customers' patents. For each supplier-customer-year, we collect all the patents filed by the supplier in that year and the portfolio of all patents that are ever filed by the customer as of that year. We create an indicator, *I(Citation)*, that equals one if the supplier's patents cite at least one patent in its customer's patent portfolio, and zero otherwise. We then regress this indicator on *Supplier*

[16]Specifically, 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.

Law. For this analysis, the sample contains only observations where the supplier files at least one patent, and the customer has previously filed at least one patent.

Panel C of Table 6 reports the results. The coefficient on *Supplier Law* indicates the differential probability of a treated supplier filing a patent that cites its customer's existing patents (Chu et al., 2019; Jaffe et al., 1993). Based on the estimate in Column (4), a treated supplier is around 6 percentage points less likely to cite their customers' patents after ARLs. This represents a reduction of around 18% relative to the sample mean $(= -0.056/0.304)$. In untabulated results, we observe no reduction in the probability of the supplier filing a patent nor in the number of patents filed, which helps rule out the concern that the reduction in citations is driven by a reduction in patenting activities. Instead, this result is consistent with the argument that better access to financing allows suppliers to invest in more independent innovation, rather than catering their technology specifically to the existing set of customers.

Taken together, results from this analysis suggest that firms affected by ARLs are able to diversify their customer base and achieve higher profits from sales to customers. They also accumulate more intangible capital and become more independent from their major customers in their knowledge space. These patterns consistently suggest that better access to debt markets allows firms to reduce their reliance on major, powerful customers.

6.2 Major and Minor Customers

In line with the argument that better access to financing reduces the pressure for firms to provide liquidity to powerful customers, we conjecture that the reduction in trade credit extended by treated firms should be more pronounced for major customers than for minor ones. We consider major customers to be all customers disclosed by a firm under FASB No.14.

While we only observe customer-level trade credit with disclosed major customers and do not directly observe trade credit provided to individual minor customers, we can compute the total trade credit and total sales aggregated by customer type (i.e., for major customers and for minor customers). Specifically, receivables to minor customers equals the difference between total accounts receivable and the receivables attributed to major customers; sales to minor customers equal 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/Sales (Major Cust)* and *Trade Credit/Sales (Minor Cust)* as follows:

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

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

where i represents a supplier, j represents a disclosed major customer, J is the set of all major 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.[17] *Sales (Major Cust)* comes from the Compustat Segment database, indicating the total sales to this same group of major customers. *Firm Sales* and *Firm Receivables* 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/Sales (Major Cust)* and *Trade Credit/Sales (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 7 reports the results.

We find that treated firms significantly reduce trade credit to major customers, by roughly 4.2 percentage points. This result is consistent with our baseline findings presented in Table 2. However, we do not observe a significant reduction in trade credit for minor customers. In Columns (3) and (4), we include two more controls, one being the percentage of sales attributed to major customers, which accounts for the possibility that changes in the denominator might drive the changes in trade credit-sale ratio, and the

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

other suppliers' total accounts receivable/sales, which absorbs firms' overall willingness to supply trade credit. The latter control variable helps us gauge the *differential* effect of the laws on suppliers' provision of trade credit towards major customers relative to the average customer. Our results are not sensitive to these controls. We continue to see the difference between the trade credit to major and minor customers to be 4.8 percentage points. Finally, in Column (5), we document an overall decline in receivables-to-sales ratio at the firm level. This decline has a smaller magnitude, 1.2 percentage points, representing around a 7% change relative to the sample mean, and is driven primarily by changes in trade financing for major customers.

TABLE 7 ABOUT HERE

6.3 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.[18] Throughout the table, we also control for the supplier firm's overall provision of trade credit (i.e., accounts receivable/sales) as in Table 7. This control absorbs firms' overall willingness to supply trade credit to the average customer, and allows us to compare the "excess" changes in suppliers' provision of trade credit across high-power and low-power customers relative to the average customer.

Table 8 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 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 6 to 8 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 8 ABOUT HERE

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

[18] 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.

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, rather than just for the major ones.

7 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").[19]

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:

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

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, $Supplier\ Law_{i,t}$ 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

[19]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.

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 by estimating the following equation:

$$Y_{j,t} = \phi_j + \tau_t + \beta Upstream\,Law\,Exposure_{j,t} + \psi Traceable\,Suppliers_{j,t} + Controls_{j,t} + u_{j,t}, \tag{4}$$

where *Controls* include customers' *Size*, *Age*, *Q*, *Leverage*, *Profitability*, *R&D Intensity*, and *Cash Flow Vol.*. 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.

7.1 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

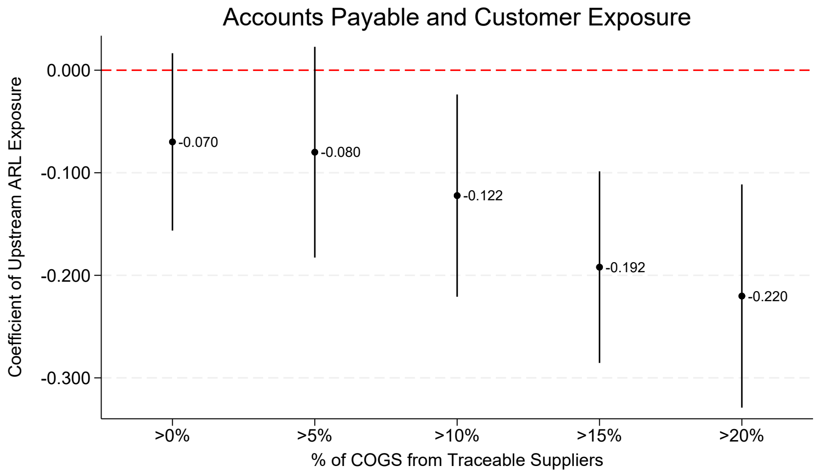

Figure 5. Effects on Customer Payables. This figure plots the coefficient estimates from Equation 4 for customer payables/COGS (customer payables scaled by customer cost of goods sold). The coefficients represent the effects of *Upstream Law Exposure*, the percentage of customer cost of goods sold that 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.

increasing fractions of input purchases. We expect the effect to be stronger for firms with higher fractions of traceable inputs.

Figure 5 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 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 3.50%

(5.50%) reduction in firm payables, relative to subsample means.[20] 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.

7.2 Customers' Investment, Leverage, and Trade Credit

If the enactment of ARLs reduces the amount of liquidity firms provide to their customers, it may also impact customers' financial and investment policies. Further, facing less funding from upstream firms, customers may curtail 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 9 provides the results. Following the passage of anti-recharacterization laws in a state, customers of affected firms experience a significant decline in investment activities (Panel A) and an increase in external debt (Panel B). A one-standard-deviation increase in a firm's *Upstream Law Exposure* corresponds to a 0.005 to 0.01 ($= 0.096 \times 0.051$ and $= 0.234 \times 0.051$) increase in leverage, which is around 2–5% increase relative to the sample average value. It is also associated with a 0.002 to 0.006 ($= -0.047 \times 0.051$ and $= -0.109 \times 0.051$) reduction in investment, measured by capital expenditures relative to total assets, which accounts for a 2.9–6.8% change compared to the sample mean (0.082).

This suggests that the reduction in trade financing forces downstream firms to scale back their operations and substitute external financing for supply-chain financing. To put the magnitude of the investment result in perspective, prior studies examining the effect of negative financing shocks on corporate investments often document larger magnitudes. For example, Almeida (2012) show that firms who faced external financing constraints

[20] For the $\geq$ 10% sample, the effect is -3.50% relative to the sample average level (=-0.122 $\times$ 0.051/0.178). For the $\geq$ 15% sample, the effect is computed as -5.50% (=-0.192 $\times$ 0.051/0.178).

during the financial crisis reduced investment by 0.025 relative to total assets. Gan (2007) uses a natural experiment to explore the impact of a drop in collateral values on firm investment in Japan. She finds that a 10% reduction in collateral causes an 0.8 percentage point reduction in the investment rate, which is one-third of the sample average.[21] In our setting, the reduction in trade credit generates a smaller effects than these above-mentioned studies, likely because the customer firms in our sample face less binding external financing constraints compared to the firms in those studies. Customer firms in our sample can raise costlier debt from other sources to offset the reduction in accounts payable, as evidenced by the increase in leverage (Panel B).

Interestingly, the customer firms in our analysis also significantly reduce their own trade credit provision to their own respective customers (Panel C). 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.[22]

<u>TABLE 9 ABOUT HERE</u>

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 ($= 0.05 \times 0.127$). 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% ($= 0.127/0.22 \times 1.38$). In other words,

[21] It is also meaningful to compare this magnitude with the ones in Murfin and Njoroge (2015), who examine the effect of providing trade credit on suppliers' investment. Murfin and Njoroge document that a one-month extension of trade credit terms corresponds to 1.2 percentage points reduction in investment. This magnitude rises to 2.5 percentage points in an event study using payment delays by HomeDepot. The suppliers in their study are likely smaller firms than the customer firms in our sample, which helps explain why they find a much larger effect than we do.

[22] In Section OA.3 of the Online Appendix, we discuss an SEC regulation in 2003 that changes firms' incentives to report purchase agreements. We show that our results are robust if we focus on the post-2003 period, which suggests that our finding on customer investment changes are unlikely to be driven by this 2003 regulation.

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.

We expect the reduction in trade credit to have a bigger effect on the investment of constrained customers than unconstrained ones. To test this conjecture, we partition customer firms by financial constraint, as indicated by above-/below-median values of the Hadlock-Pierce index (Hadlock and Pierce, 2010). For each subsample, we repeat the investment regression (Equation 4). This analysis utilizes the full set of customers in our SEC sample, as partitioning smaller samples reduces our statistical power. Table 10 shows that the reduction in investment is concentrated among customers that face higher levels of financial constraints.

Table 10 About Here

Finally, we discuss the implication from a 2003 SEC regulation that required more transparent disclosure of purchase obligations. Such disclosure requirements may have affected firms' investment policies (Noh, 2020). We show in Table OA.3 that removing post-2003 years from our testing sample does not affect our results. This suggests that the 2003 SEC disclosure rule does not unduly affect our findings.

8 Additional Analyses and Discussions

In this section, we discuss various concerns related to our interpretation and results. Particularly, we show results are not driven by changes in how firms disclose transactions with customers and 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.

8.1 Influence of Firm Reporting Choices

We design robustness checks to address several 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. A related concern is that firms may stop reporting the trade credit extended to certain customers after the laws. Regarding the second concern, it is important to note that suppliers in our sample tend to consistently disclose the trade credit for a given customer. For example, if supplier i reports trade credit to customer j in year t, it will report trade credit to the same customer in year $t+1$ with 85% likelihood, as long as the trade relationship continues. Moreover, our trade credit data has good coverage of the major customers included in the Compustat Segment database. The average supplier that appeared in our sample discloses the trade credit for around 95% of all of its major customers.

More importantly, both concerns are alleviated by the inclusion of customer-supplier pair effects in our baseline specification. To further evaluate the importance of this selection effect, we restrict the sample to a set of "stable" supply-chain relationships 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. Panel A of Table OA.4 shows that our results remain unchanged in the restricted sample.

The third concern relates 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 "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 our results are driven by changes in sample composition. To further address such concerns, we provide additional analyses in which we artificially increase the customer sales threshold to 11% and 12%. This exercise helps us 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. Panel B of Table OA.4 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 B of Table 2. This suggests that the reporting threshold is unlikely to unduly drive our results.

8.2 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 ARLs. 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 7.1). Still, in the Online Appendix, we 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 OA.5 shows that our results persist in the restricted sample and the coefficients of *Law* generate similar magnitudes as those from Table 2 (Column (4) of Panels A and B).

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, they also increase the option value of setting up an SPV in the future. We show in Panel B of Table OA.5 that our effects are 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.

8.3 External Validity

Lastly, we exploit an alternative shock to debt capacity following Chaney et al. (2012), who document that positive shocks to the value of firms' real estate assets expand firms' debt capacity and increase investment. Using this experiment, we expect a reduction in trade credit following an increase to firms' real estate asset values.

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. 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. Results are reported in Table OA.6 of the Internet Appendix. We find that suppliers' real estate value generates a negative, significant coefficient, suggesting that greater debt capacity leads to a reduction in trade credit provision.

9 Conclusion

This study examines the effect of credit market frictions on firms' incentives to provide trade credit using a hand-collected 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 add new customers, invest more in intangible assets, and decrease their downstream concentration. 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 extend less trade credit themselves, further propagating downstream effects. 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 implication 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/Sales* is the amount of trade credit offered by a supplier to an individual customer, scaled by the value of the transaction between the two. 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/Sales	5,405	0.174	0.157	0.083	0.136	0.214
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	0.185	0.227	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
Cash Flow Vol.	5,405	0.143	0.195	0.043	0.083	0.154
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	0.034	0.051	0.000	0.012	0.056
Cash Flow Vol.	5,405	0.035	0.039	0.015	0.023	0.037

Panel B: Broader Samples

Variable	N	Mean	Std. Dev	25th Pctl.	Median	75th Pctl.
Compustat:						
Law	105,745	0.251	0.434	0.000	0.000	1.000
Firm Receivables/Firm Sales	105,745	0.186	0.203	0.091	0.151	0.217
Segment Suppliers:						
Law	21,704	0.288	0.453	0.000	0.000	1.000
Firm Receivables/Firm Sales	21,627	0.177	0.113	0.114	0.159	0.213
Total Customers	21,704	1.803	1.308	1.000	1.000	2.000
New Customers	21,704	0.461	0.849	0.000	0.000	1.000
Gross Margin	21,687	1.006	1.750	0.255	0.518	1.056
Segment Customers:						
Payables	12,166	0.178	0.182	0.087	0.130	0.194
Firm Receivables/Firm Sales	12,087	0.163	0.119	0.092	0.147	0.207
Upstream Law Exposure	12,177	0.014	0.051	0.000	0.000	0.001
Traceable Suppliers	12,177	0.079	0.176	0.004	0.017	0.065
Leverage	12,177	0.255	0.197	0.107	0.232	0.359
Investment	11,744	0.082	0.089	0.031	0.057	0.099

Table 2
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. Panel A presents our baseline results, with *Trade Credit/Sales*, trade credit extended by a supplier to a customer scaled by the total transaction value between the two firms in the same year, as the dependent variable. Panel B further includes customer-year fixed effects. Panel C repeats the analysis using fixed effect Poisson estimations, with *Trade Credit*, the dollar amount (in millions) of customer-specific receivables, as the dependent variable. *Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law Control variables include the *Sales Dependence*, *Relationship Length* between a supplier and a customer, together with suppliers' and customers' *Age, Size, Q, Leverage, Profitability, R&D Intensity*, and *Cash Flow Volatility*. Variable definitions are available in Appendix A. Industry fixed effects are captured by 2-digit SIC codes. t-statistics (Panels A and B) or z-scores (Panel C) 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/Sales*	(1)	(2)	(3)	(4)
Supplier Law	-0.024***	-0.024**	-0.034***	-0.028***
	(-2.80)	(-2.69)	(-3.38)	(-2.81)
Customer Law	0.023**	0.021**	0.021**	0.049***
	(2.57)	(2.43)	(2.44)	(4.68)
Controls	Yes	Yes		Yes
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	0.417	0.443	0.428	0.488
Observations	5,100	5,086	4,740	4,820

Panel B: Controlling for Customer-Year FE

Dep. Var.: *Trade Credit/Sales*	(1)	(2)	(3)	(4)
Supplier Law	-0.023**	-0.029**	-0.030**	-0.041**
	(-1.76)	(-2.08)	(-2.15)	(-2.53)
Controls		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	0.485	0.498	0.504	0.495
Observations	3,212	3,210	3,018	2,979

Panel C: Trade Credit Dollars, Poisson

Dep. Var.: *Trade Credit*	(1)	(2)	(3)	(4)
Supplier Law	-0.198***	-0.197***	-0.150***	-0.163**
	(-5.14)	(-4.27)	(-2.78)	(-2.52)
Controls	Yes	Yes	Yes	Yes
Supplier FE	Yes		Yes	
Customer FE	Yes			
Year FE		Yes		
Customer × Year FE			Yes	Yes
Supplier Industry × Year FE	Yes		Yes	
Customer Industry × Year FE	Yes			
Pair FE		Yes		Yes
Observations	4,733	4,813	3,012	2,972

Table 3
Results From An Entropy-Balanced Sample.
This table examines the importance of using an entropy balanced sample, and the effects of anti-recharacterization laws on firms' trade credit provision in that sample. Panel A reports the average firm characteristics for treated and control firms after removing customer-year fixed effects. Panel B reports the same statistics in a matched sample using Entropy Balancing. Both sets of statistics are computed using years prior to the ARL passage year for treated firms. Panel C reports results from estimating Equation 1 using the entropy balanced sample. Controls refer to the same set of variables as those used in Table 2. Variable definitions are available in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. In Panel C, *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: Covariate Balance, SEC Sample

Variable	Treated	Control	Difference
Trade Credit	0.002	-0.002	0.004
Sales Dependence	0.003	-0.003	0.006
Relationship Length	-0.009	0.009	-0.018
Age	-0.050	0.046	-0.096***
Size	0.079	-0.073	0.152*
Q	0.142	-0.131	0.273***
Book Leverage	-0.001	0.001	-0.002
Profitability	-0.006	0.006	-0.012
R&D	0.004	-0.004	0.007
Cash Flow Volatility	0.004	-0.004	0.008

Panel B: Covariate Balance, Entropy-Balanced Sample

Variable	Treated	Control	Difference
Matching Characteristics:			
Trade Credit	0.185	0.185	-0.000
Sales Dependence	0.275	0.275	-0.000
Age	2.286	2.286	-0.000
Size	4.857	4.857	0.000
Leverage	0.225	0.225	-0.000
Profitability	-0.081	-0.081	0.000
Cash Flow Volatility	0.143	0.143	-0.000
Non-matching Characteristics			
Relationship Length	1.662	1.555	0.108
R&D	0.115	0.138	-0.023
Q	2.246	2.185	0.061

Panel C: Trade Credit Provision, Entropy-Balanced Sample

Dep. Var.: *Trade Credit*	(1)	(2)
Supplier Law	-0.041**	-0.051**
	(-2.27)	(-2.64)
Controls	Yes	Yes
Pair-Event FE	Yes	Yes
Event-Year FE	Yes	
Customer-Event-Year FE		Yes
R^2	0.640	0.645
Observations	1,309	1,304

Table 4
Leverage Effects: Changes in Trade Credit Instrumented by Leverage
This table reports the results from a 2-stage regression, where we instrument suppliers' financial leverage using the passage of anti-recharacterization laws in their state of incorporation. Panel A reports results from the first stage, while Panel B reports results from the second stage. The dependent variable of the first stage is *Leverage*, measured as the ratio of total debt over total assets, and the dependent variable of the second stage is *Trade Credit/Sales*, the amount of trade credit provided by a supplier to a customer scaled by the transaction value between them in a year. *Supplier Law* is an indicator for the firm being incorporated in a state that has passed an anti-recharacterization law. The sample is the 7-year entropy-balanced stacked sample used in Panel C of Table 3. Control variables are the same as in Table 2. Variable definitions are available in Appendix A. An "Event" is a state's passage of anti-recharacterization laws. *F-Stat (KP)* and *F-Stat (CD)* are the first-stage Kelibergen-Paap and the Cragg-Donald Wald statistics, respectively. 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: First-Stage Results

Dep. Var.: *Leverage*	(1)	(2)
Supplier Law	0.067***	0.129**
	(3.74)	(2.30)
Controls	Yes	Yes
Pair-Event FE	Yes	Yes
Event-Year FE	Yes	Yes
Customer-Event-Year FE		Yes
F-Stat (KP)	13.97	5.29
F-Stat (CD)	11.96	37.27
R^2	0.770	0.772
Observations	1,309	1,304

Panel B: Second-Stage Results

Dep. Var.: *Trade Credit/Sales*	(1)	(2)
$\widehat{Leverage}$	-0.560**	-0.360**
	(-2.08)	(-2.22)
Controls	Yes	Yes
Pair-Event FE	Yes	Yes
Event-Year FE	Yes	Yes
Customer-Event-Year FE		Yes
Observations	1,309	1,304

Table 5
Access to Debt Markets and Customer Base Diversification
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. Panels A and B report results from a Poisson regression. Panel A tests the effect of the laws on the count of suppliers' newly reported major customers (Columns (1)-(3)) and total reported major customers (Columns (4)-(6)) for supplier-years represented in the Compustat Segment database ("Segment Sample"). Panel B shows the effect of the laws on downstream industry concentration, measured as the count of customer industries reported by the supplier, using 4-digit SIC code industries in Columns (1)-(3) and 2-digit SIC codes in Columns (4)-(6). Panel C shows the laws' effect on supplier margins, with gross margin (sales/COGS - 1) as the dependent variable in Columns (1)-(3) and *ROA* (operating income before depreciation, scaled by total assets) in Columns (4)-(6). Controls include *Age, Size, Q, Leverage, Cash Flow Vol., Profitability*, and *R&D Intensity*. *Profitability* is excluded from the set of controls in Panel C. Variable definitions are available in Appendix A. Industry is defined by 2-digit SIC codes. z-scores (Panels A and B) or t-statistics (Panel C) 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 and Total Major Customers (Poisson Regressions)

Dep. Var.:	*New Major Customers*			*Total Major Customers*		
	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.136	0.171*	0.198**	0.061**	0.062**	0.072***
	(1.41)	(1.83)	(2.08)	(1.97)	(2.07)	(2.62)
Controls		Yes	Yes		Yes	Yes
Year FEs	Yes	Yes		Yes	Yes	
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FEs			Yes			Yes
Observations	18,625	18,625	17,982	20,846	20,846	20,657

Panel B: Customer Industry Coverage (Poisson Regressions)

Dep. Var.:	*#Downstream SIC-4 Industries*			*#Downstream SIC-2 Industries*		
	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.047*	0.050**	0.065**	0.042**	0.044**	0.047**
	(1.89)	(2.02)	(2.48)	(2.01)	(2.00)	(2.25)
Controls		Yes	Yes		Yes	Yes
Year FEs	Yes	Yes		Yes	Yes	
Firm FEs	Yes	Yes	Yes	Yes	Yes	
Industry×Year FEs			Yes			Yes
Observations	20,846	20,846	20,657	20,846	20,846	20,657

Panel C: Margins and Profitability

Dep. Var.:	*Gross Margins*			*ROA*		
	(1)	(2)	(3)	(4)	(5)	(6)
Law	0.147**	0.123*	0.114**	0.029***	0.018**	0.019**
	(2.29)	(1.95)	(2.31)	(3.29)	(2.26)	(2.56)
Controls		Yes	Yes		Yes	Yes
Year FEs	Yes	Yes		Yes	Yes	
Firm FEs	Yes	Yes	Yes	Yes	Yes	
Industry×Year FEs			Yes			Yes
R^2	0.689	0.691	0.691	0.631	0.733	0.734
Observations	20,828	20,828	20,639	20,846	20,846	20,657

Table 6
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, and on patent cross-citations. In Panels A and B, Columns (1) and (2) report results for the Compustat sample, while Columns (3) and (4) report results for suppliers in the Segment sample, i.e., firm-years wherein the firm reports at least one major customer. In both samples, the unit of observation is a firm-year. In Panel C the sample is the Segment pairwise data, where the unit of observation is a customer-supplier-year. The sample is limited to observations where the supplier filed at least one patent in the observation year and the customer had filed at least one patent in the past. The dependent variable in Panel A is *Knowledge Capital*, the firm's stock of research and development investment; in Panel B *Intangible Capital*, the firm's stock of intangible capital investment; and in Panel C *I(Citation)*, an indicator equal to one if the supplier cites a patent held by the customer. The definitions of *Knowledge Capital* and *Intangible Capital* follow the ones in Falato et al. (2022). Controls include *Age, Size, Q, Leverage, Cash Flow Vol,Profitability* and *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 A: Knowledge Capital

Sample:	Compustat		Segment	
Dep. Var.: *R&D Stock*	(1)	(2)	(3)	(4)
Law	0.036***	0.031***	0.069***	0.056***
	(9.55)	(8.12)	(4.68)	(4.80)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes		Yes	
Industry×Year FEs		Yes		Yes
R^2	0.860	0.867	0.885	0.890
Observations	75,803	75,762	18,573	18,366

Panel B: Intangible Capital

Sample:	Compustat		Segment	
Dep. Var.: *Intangible Capital*	(1)	(2)	(3)	(4)
Law	0.027**	0.032***	0.059*	0.020
	(2.19)	(2.62)	(1.72)	(0.65)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes		Yes	
Industry×Year FEs		Yes		Yes
R^2	0.834	0.839	0.855	0.859
Observations	75,409	75,368	18,519	18,313

Panel C: Cross-Citations

Dep. Var.: *I(Citation)*	(1)	(2)	(3)	(4)
Supplier Law	-0.062**	-0.071***	-0.068**	-0.056*
	(-2.11)	(-2.60)	(-2.56)	(-2.02)
Controls		Yes	Yes	Yes
Supplier FEs	Yes	Yes		Yes
Customer FEs	Yes	Yes		Yes
Pair FEs			Yes	
Year FEs	Yes	Yes	Yes	
Supplier Industry×Year FEs				Yes
Customer Industry×Year FEs				Yes
R^2	0.485	0.492	0.595	0.489
Observations	10,672	10,546	9,285	10,236

Table 7
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 *Firm Receivables/Firm Sales*, 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, as well as the aggregate *Firm Receivables/Sales* of the firm. Other controls are included but suppressed for presentation. Control variables are the same as in Table 5. 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/Sales*	*Major Cust*	*Minor Cust*	Difference	*Major Cust*	*Minor Cust*	Difference	*Firm Receivables/Sales*
	(1)	(2)	(Major−Minor)	(3)	(4)	(Major−Minor)	(5)
Supplier Law	-0.042***	-0.000	-0.042***	-0.034***	0.013	-0.046***	-0.012**
	(-3.47)	(-0.06)	(-2.79)	(-2.88)	(1.58)	(-3.30)	(-2.19)
Firm Receivables/Sales				Yes	Yes		
%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	0.453	0.424		0.623	0.597		0.521
Observations	3,652	3,652		3,648	3,648		3,648

Table 8
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/Sales*, 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 *Firm Receivables/Sales*, as well as all the controls in 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.

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

Sample: Downstream Dependence	High	Low	Difference	High	Low	Difference
Dep. Var.: *Trade Credit/Sales*	(1)	(2)	(High−Low)	(3)	(4)	(High−Low)
Supplier Law	-0.050**	0.033	-0.083***	-0.060***	0.040	-0.100***
	(-2.54)	(1.34)	(-2.84)	(-2.96)	(1.48)	(-2.86)
Firm Receivables/Sales	Yes	Yes		Yes	Yes	
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	0.552	0.543		0.596	0.592	
Observations	1,119	1,107		1,056	1,052	

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

Sample: Downstream Dependence	High	Low	Difference	High	Low	Difference
Dep. Var.: *Trade Credit/Sales*	(1)	(2)	(High−Low)	(3)	(4)	(High−Low)
Supplier Law	-0.067***	0.044*	-0.111***	-0.074***	0.046**	-0.120***
	(-3.11)	(1.72)	(-2.76)	(-2.64)	(2.14)	(-2.76)
Firm Receivables/Sales	Yes	Yes		Yes	Yes	
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	0.539	0.524		0.585	0.584	
Observations	1,217	1,230		1,160	1,183	

Table 9
Effects on Downstream Firms
This table shows the effect of the adoption of the anti-recharacterization laws on downstream firms' investment, leverage, and customer receivables. 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 include *Size, Age, Q, Profitability, Cash Flow Vol., R&D Intensity,* and *Leverage* (the latter excluded in Panel B). 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	-0.047*	-0.047	-0.043	-0.075*	-0.109**
	(-1.90)	(-1.46)	(-0.97)	(-1.80)	(-2.32)
Traceable Suppliers	0.027**	0.026*	0.005	0.022	0.000
	(2.20)	(1.82)	(0.26)	(1.18)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.631	0.660	0.664	0.657	0.637
Observations	10,306	2,822	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	0.096	0.144*	0.191*	0.234**	0.190
	(1.46)	(1.70)	(1.93)	(2.15)	(1.52)
Traceable Suppliers	-0.039*	-0.024	-0.027	-0.015	-0.007
	(-1.66)	(-0.96)	(-0.85)	(-0.41)	(-0.14)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.715	0.762	0.773	0.774	0.771
Observations	10,464	2,861	1,679	1,097	808

Panel C: Customer Trade Credit Provision

Dep. Var.: *Firm Receivables/Firm Sales* Sample: Traceable Purchase/COGS	(1) All	(2) ≥5%	(3) ≥10%	(4) ≥15%	(5) ≥20%
Upstream Law Exposure	-0.074***	-0.060*	-0.079*	-0.133***	-0.127**
	(-2.74)	(-1.78)	(-1.83)	(-2.99)	(-2.16)
Traceable Suppliers	0.045**	0.030	0.019	0.032	0.036
	(2.57)	(1.57)	(0.70)	(1.34)	(1.33)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.794	0.777	0.778	0.787	0.786
Observations	10,405	2,854	1,674	1,092	803

Table 10
Downstream Investment Effects for Constrained and Unconstrained Customers
This table reproduces the result of Table 9, Panel B, Column (1) split on the Hadlock-Pierce (size-age) index for financial constraints. Column (1) reports the results for firms with above-median HP index, while Column (2) reports results for firms with below-median HP index. 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. Other controls are included but suppressed for presentation, including *Traceable Suppliers, Size, Age, Q, Profitability, Cash Flow Vol., R&D Intensity,* and *Leverage*. 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.

Sample: HP Index Dep. Var.: *Investment*	Above Median (1)	Below Median (2)	Difference (1-2)
Upstream Law Exposure	-0.093**	-0.010	-0.084*
	(-2.12)	(-0.39)	(-1.66)
Controls	Yes	Yes	
Firm FEs	Yes	Yes	
Year Fes	Yes	Yes	
R^2	0.630	0.625	
Observations	4,727	5,469	

Appendix A Variable Definitions

Variable	Definition
Law	Indicator for firm being incorporated in state with ARL
Trade Credit/Sales	Pair-level receivables scaled by pair-level sales
Trade Credit	Pair-level trade credit (in dollars)
Firm Receivables/Firm Sales	Firm-level receivables scaled by sales
Trade Credit/Sales (Major Cust)	Aggregate receivables owed by major customers, scaled by aggregate sales to the same group of major customers
Trade Credit/Sales (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
Cash Flow Vol.	The 10-year standard deviation of cash flow (EBITDA net of taxes, interest expense, and dividends, 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 Major Customers	Count of the number of customers reported as a major client for the first time
Total Customers	Count of the number of customers reported by the supplier
Gross Margin	Ratio of firm sales to firm COGS, minus 1
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 Effects of the Laws in Broader Samples

In Table OA.1, 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 2, 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 2, Panel A). Similarly, the firm-level result in Column (5) of Table 7, 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.2 Sales Effects

Table OA.2 reports results related to sales by firms affected by recharacterization laws. Our results suggest that firms affected by anti-recharacterization laws increase sales significantly, by around 4–5% relative to control firms.

OA.3 Robustness: 2003 SEC Regulation

In Table OA.3, we address the possibility that a 2003 SEC regulation requiring more transparent disclosure of firms' purchase obligations might affect firms' investment policies (Noh, 2020). Table OA.3 repeats the results from Panel B of Table 9, regressing the customers' investment on its *Upstream Law Exposure*, but removing years after 2003. Our results remain robust.

OA.4 Robustness: Firms' Reporting Threshold

We perform two analyses to test whether our results may be influenced by the reporting threshold of 10% major customers. First, we restrict the sample to a set of "stable" supply-chain relationships 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. Panel A of Table OA.4 shows that our results remain unchanged in the restricted sample.

Second, we artificially increase the customer sales threshold to 11% and 12%. This exercise helps us 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. Panel B of Table OA.4 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 B of Table 2. This suggests that the reporting threshold is unlikely to unduly drive our results.

OA.5 Securitization Robustness

Table OA.5 provides two sets of results addressing the concern that baseline results could be driven by securitization of receivables in off-balance sheet SPVs after the passage of ARLs. In Panel A, we exclude the two anti-recharacterization law events in Texas and Louisiana, which focused on the securitization of accounts receivable. We find consistent results (and coefficient magnitudes) when excluding firms in these two states, suggesting suggesting results are not mechanically driven by off-balance sheet receivables securitizations. the securitization of trade credit, effects should weaken once we exclude these two events.

In Panel B, we examine the effect of ARLs for forms based on their likelihood of actually using SPVs. We parse disclosure of subsidiaries from firm 10-K filings, following Feng et al. (2009) to define an indicator for whether the firm has used an SPV in the past. We then regress *Trade Credit/Sales* 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 OA.5 presents results from this analysis, and reports similar effects for both groups of firms.

OA.6 Alternative Experiment: Firm Real Estate Value Shocks

In Table OA.6 we exploit an alternative shock to debt capacity following Chaney et al. (2012), who document that positive shocks to the value of firms' real estate assets expand firms' debt capacity and increase investment. Using this experiment, we expect a reduction in trade credit following an increase to firms' real estate asset values.

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 OA.6 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 8.77% relative to the sample mean. Overall, OA.6 corroborates the main analysis by showing consistent results in a different empirical setting.

Table OA.1
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. Controls include *Size, Age, Q, Leverage, Cash Flow Vol., Profitability*, and *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.

Sample:	Compustat		Segment	
Dep.Var.: *Firm Receivables/Firm Sales*	(1)	(2)	(3)	(4)
Law	-0.005**	-0.005**	-0.003	-0.004*
	(-1.93)	(-2.09)	(-1.32)	(-1.69)
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	0.529	0.528
Observations	90,620	90,597	20,775	20,583

Table OA.2
ARLs and Firm Sales
This table shows the effect of the anti-recharacterization laws on firms' total sales. *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 total revenues, measured at the firm level. The sample includes supplier-years represented in the Compustat Segment database ("Segment Sample"). Controls include *Age, Size, Q, Leverage, Cash Flow Vol., 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.

Dep. Var.: *Log(Sales)*	(1)	(2)	(3)
Law	0.188***	0.054***	0.045***
	(5.76)	(3.89)	(3.17)
Controls		Yes	Yes
Supplier FE	Yes	Yes	Yes
Year FE	Yes	Yes	
Industry × Year FE			Yes
R^2	0.929	0.970	0.971
Observations	20,837	20,837	20,648

Table OA.3

The 2003 SEC Disclosure Rule and Downstream Investment

This table shows the effect of the adoption of the anti-recharacterization laws on downstream firms' investment, replicating. Panel A of Table 9, but excluding years after 2003. 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 include *Size, Age, Q, Profitability, Cash Flow Vol., R&D Intensity,* and *Leverage.* 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.

Customer Investment, through 2003

Dep. Var.: *Customer Investment* Sample: Traceable Purchase/COGS	(1) All	(2) ≥5%	(3) ≥10%	(4) ≥15%	(5) ≥20%
Upstream Law Exposure	-0.122***	-0.123***	-0.144**	-0.175**	-0.178**
	(-3.32)	(-2.62)	(-2.51)	(-2.46)	(-2.01)
Traceable Suppliers	0.034**	0.027	0.011	0.036	-0.001
	(2.15)	(1.47)	(0.40)	(1.64)	(-0.06)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.602	0.624	0.644	0.641	0.649
Observations	6,637	1,718	1,025	641	469

Table OA.4
Robustness: Survivorship Bias and Reporting Threshold
This table shows the robustness of our results for several sample restrictions. In Panel A, we require the customer-supplier relationships 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. In Panel B, we report robustness of our results to the SEC reporting threshold for what qualifies as a major customer, artificialy raising the reporting threshold to 11% (12%) of sales in Columns (1) and (2) (Columns (3) and (4)). The dependent variable is *Trade Credit/Sales*, 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, Cash Flow Vol., 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.

Panel A: Minimum Pre- and Post-Observations

Sample:	≥1 pre- and post-		≥2 pre- and post-		≥3 pre- and post	
Dep. Var.: *Trade Credit/Sales*	(1)	(2)	(3)	(4)	(5)	(6)
Supplier Law	-0.042**	-0.046**	-0.054**	-0.060**	-0.098***	-0.108***
	(-2.35)	(-2.56)	(-2.25)	(-2.51)	(-3.51)	(-4.00)
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	0.551	0.542	0.350	0.365	0.380	0.412
Observations	1,087	1,087	633	633	384	384

Panel B: Raising the Reporting Threshold

Dep. Var.: *Trade Credit*	Above 11%		Above 12%	
	(1)	(2)	(3)	(4)
Supplier Law	-0.026**	-0.040***	-0.020*	-0.039***
	(-2.52)	(-4.19)	(-1.85)	(-4.22)
Supplier Characteristics	Yes	Yes	Yes	Yes
Pair Characteristics	Yes	Yes	Yes	Yes
Supplier FEs	Yes		Yes	
Customer×Year FEs	Yes	Yes	Yes	Yes
Pair FE		Yes		Yes
R^2	0.553	0.557	0.560	0.562
Observations	2,532	2,367	2,323	2,159

Table OA.5
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/Sales*, 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 in Panel A match those in Panel B of Table 2. Controls in Panel B match those in Panel A of 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.

Panel A: Excluding Observations from TX and LA Laws

Dep. Var.: *Trade Credit/Sales*	(1)	(2)
Supplier Law	-0.026*	-0.038**
	(-1.80)	(-2.21)
Supplier Characteristics	Yes	Yes
Pair Characteristics	Yes	Yes
Supplier FEs	Yes	
Customer×Year FEs	Yes	Yes
Pair FE		Yes
R^2	0.500	0.497
Observations	3,138	2,907

Panel B: Effects for Firms With and Without SPV Usage

Dep. Var.: *Trade Credit/Sales*	(1)	(2)	(3)	(4)
Supplier Law, Has SPV	-0.029**	-0.024**	-0.044***	-0.026*
	(-2.21)	(-2.10)	(-3.51)	(-2.00)
Supplier Law, No SPV	-0.024*	-0.020	-0.035***	-0.023*
	(-1.99)	(-1.65)	(-2.56)	(-1.88)
Supplier Characteristics		Yes	Yes	Yes
Customer Characteristics		Yes	Yes	Yes
Pair Characteristics		Yes	Yes	Yes
Year FEs	Yes	Yes		Yes
Supplier FEs	Yes	Yes	Yes	
Customer FEs	Yes	Yes	Yes	
Supplier Industry×Year FEs			Yes	
Customer Industry×Year FEs			Yes	
Pair FE				Yes
R^2	0.420	0.456	0.435	0.507
Observations	4,001	3,992	3,686	3,768

Table OA.6
An Alternative Experiment: Shocks to Real Estate 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 2 (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/Sales*	(1)	(2)	(3)	(4)	(5)
Supplier RE Value	-0.007**	-0.008***	-0.014***	-0.011**	-0.021***
	(-2.07)	(-2.89)	(-2.95)	(-2.08)	(-3.89)
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	0.496	0.576	0.569	0.530	0.505
Observations	627	617	533	631	554