Trade Credit and Markups*

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Abstract

Trade credit is the most important form of short-term finance for U.S. firms. In 2017, non-financial firms had about $3 trillion in trade credit outstanding equaling 20 percent of U.S. GDP. Why do sellers lend to their buyers in the presence of a well-developed financial sector? This paper proposes an explanation for the puzzling dominance of trade credit: When sellers charge markups over production costs and financial intermediation is costly, then buyer-seller pairs can save on their overall financing costs by utilizing trade credit. We derive a model of trade credit and markups that captures this mechanism. In the model, the larger is the markup and the larger is the difference between the borrowing and the deposit rate, the more attractive is trade credit. The model also implies that trade credit use increases with repeated interactions and that this effect is stronger for complex products. Using Chilean data at the firm-level to estimate markups and at the trade-transaction level to analyze payment choices, we find strong support for the model.

Keywords: trade credit, markups, financial intermediation, learning

JEL Classification: F12, F14, G21, G32

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1 Introduction

Trade credit is the most important form of short-term finance for U.S. firms. In 2017, non-financial firms had about $3 trillion in trade credit outstanding equaling 20 percent of U.S. GDP.[1] Why do sellers lend to their buyers in the presence of a well-developed financial sector? While several theories about trade credit have been proposed, the popularity of trade credit remains a puzzle.[2] This paper proposes an explanation for why trade credit is so popular: When sellers charge markups over production costs and financial intermediation is costly, then buyer-seller pairs can save on their overall financing costs by utilizing trade credit.

A buyer can pay for a purchase in two ways: through cash-in-advance, where the buyer pays the full price of the goods before delivery, and on an open account where the buyer has some time after delivery to pay for the goods and thus implicitly receives a trade credit from the seller.[3] Under cash-in-advance, the buyer needs to pre-pay the full amount to the seller which requires liquidity equal to the full invoice. In contrast, extending trade credit is cheaper in liquidity terms, as the seller only needs to cover its production costs in advance which may be substantially lower than the sales price if there is a markup. If financial intermediation is costly and a firm pays more to a bank for borrowing funds than it receives for depositing them, then this difference in liquidity needs between cash-in-advance and trade credit affects profits.

The larger is the markup and the larger the difference between the borrowing and the deposit rate, the more attractive is trade credit. All else equal, trade credit is preferred over

[1]See also Figure A.1 in Appendix A that shows the development of trade credit and markups over time in the United States.

[2]See in particular Ellingsen et al. (2016) who argue that based on their evidence there is a need for a "new theory of short term finance".

[3]In international trade, additional financing options are available that are called letter of credit and documentary collections. For these alternatives, banks act as intermediaries to reduce the risk involved in a transaction. See Niepmann and Schmidt-Eisenlohr (2017a) for details. They find that letters of credit cover about 13 percent and documentary collections about 2 percent of world trade. Both payment forms do not play a role for domestic transactions. There may also be a partial advance-payment, on which data is even more limited. In our data from Chile two-part contracts (partial cash-in-advance) represent only 0.2% of transactions. Similarly, Antràs and Foley (2015) report that the firm they study does not rely on two-part contracts.

cash-in-advance if there is a positive markup and a positive interest rate spread. As the world typically features positive markups and positive interest rate spreads, the theory thus provides a clear rationale for the dominance of trade credit in firm-to-firm transactions.

We test the model using two rich panel datasets of Chilean firms. First, we construct markup estimates at the firm-product level using detailed production data on inputs and outputs of Chilean plants following the method developed by De Loecker et al. (2016). We then combine these markup estimates with transaction-level trade data, which contains detailed information on the payment choice to test the predictions of the model. We find that trade credit use increases with markups and that this effects is larger the bigger the difference between the buyer's borrowing rate and the seller's deposit rate.[4] In line with the model's prediction, the effect of the markup also increases in the destination country's rule of law. In addition, the results are robust to alternative measures of markups, and to the inclusions of a large set of fixed effect and control variables. Taken together, these results provide strong support for the main mechanism of the model.

Our results are very similar when we focus on the subset of firms with low participation in export markets. For these firms, markups mostly reflects the firm's pricing decisions in the domestic market. Hence, any endogenous response of the markup to the trade credit choice in a particular destination gets mitigated when fixing markups at their initial value for each seller-product or computing markups at the firm-level. Jointly, these results suggest that, even though firms charge higher markups on transactions involving trade credit, the resulting bias should be relatively modest.

We also develop a dynamic version of the model, showing that when firms learn about their trading partners, trade credit becomes more attractive over time. The key intuition is that learning reduces the relevance of enforcement frictions. As trade credit has a financing cost advantage over cash-in-advance, learning thus tilts the payment choice towards trade credit as enforcement frictions becomes less central. We show that this rationale also implies that the effects of learning are stronger for more complex products.[5] In the empirical section,

[4]Petersen and Rajan (1997) provided evidence that firms with larger gross profit margins over costs extend more trade credit. As gross profit margins can arguably be seen as a rough proxy for markups, their findings are thus consistent with the model presented here.

[5]Giannetti et al. (2011) also look at the relationship between product type and trade credit and find that for the case of domestic firm-to-firm transactions, trade credit is higher in differentiated products.

we provide evidence that strongly supports these dynamic predictions.

The model also has implications for the pricing of transactions between importers and exporters. Schmidt-Eisenlohr (2013) and Antràs and Foley (2015) also derived price predictions in a payment terms model. We extend the analysis, showing that there is an unambiguous ordering of prices that is independent of the distribution of bargaining power. Specifically, a buyer has to pay a higher price to the seller when buying with trade credit than when paying in advance. This difference should increase in the borrowing rate of the seller and decrease in the level of contract enforcement in the buyer's country. We find that buyers pay a higher price when receiving trade credit and that the price difference decreases in the destination country's rule of law and increases in source country's borrowing rate.

The paper contributes to the large and growing literature on trade credit.[6] Several theoretical reasons have been given for the importance of trade credit. Schwartz (1974) and Ferris (1981) develop models where trade credit arises from a transaction motive, by separating the exchange of goods from the exchange of money, which may simplify cash management and allow for risk-sharing. Brennan et al. (1988) show that trade credit can be used to price discriminate when cash buyers have higher reservation values than credit buyers.[7] Smith (1987) and Biais and Gollier (1997) show that firms may extend trade credit because they have an informational advantage relative to banks. In Burkart and Ellingsen (2004) sellers extend trade credit because this type of credit is "in-kind" and is thus harder to divert than cash. Our model is closely related to these earlier papers in that parts of the spreads between borrowing rates and deposit rates that banks charge are likely attributable to the monitoring and enforcement frictions emphasized there. However, bank spreads are also due to factors like regulation, capital requirements and general overhead costs. The key message of our model is that firm pairs should for this reason minimize their reliance on the financial sector for financing their transactions, and are able to do so through trade credit if sellers charge positive markups over marginal costs.

[6] Petersen and Rajan (1997) provide an early overview of the main theories for the existence and prevalence of trade credit and present empirical evidence.

[7] Petersen and Rajan (1997) argue that this channel should be stronger when gross profit margins are higher as sellers have a stronger incentive to sell one more unit at a discount when their marginal profit is higher. For this reason, price discrimination may also give rise to a positive correlation between markups and trade credit use. On price discrimination through trade credit, see also Schwartz and Whitcomb (1979) and Mian and Smith (1992).

Wilner (2000) builds a model that studies the interaction of trade credit provision and long-term relationships, where firms are willing to give more concessions when there is a dependency. In a related paper, Cunat (2007) shows that trade credit may work better in buyer-supplier relationships as the supplier can threaten to cut supplies if trade credit is not repaid. Emery (1984) argues for "a pure financial explanation of trade credit".[8] In his model, sellers have to hold liquidity for a precautionary motive in a world characterized by imperfect financial markets. As trade credit can be factored, lending to a buyer only marginally reduces liquidity while it raises profits by exploiting the difference between the buyer's borrowing rate and the sellers deposit rate. While his explanation of trade credit is also based on the difference between the borrowing and the lending rate, the underlying mechanism is quite different. In his paper, sellers need to have a liquidity holding motive to extend trade credit. In the model presented here, in contrast, trade credit is desirable even in the absence of any liquidity holdings. With positive markups, a seller can be willing to borrow from a bank to extend trade credit to the buyer as this saves on overall financing costs.

Closest to our paper, Daripa and Nilsen (2011) develop a model of inventory holding, demand uncertainty and trade credit. In their model, an upstream firm supplies trade credit to a downstream buyer to alleviate an externality that arises from inventory holding costs. If the upstream seller's markup over production costs is larger than the downstream buyer's markup over the intermediate good's price, then the upstream seller wants to subsidize the downstream buyer's inventory holdings. It does so through a lower price when it has higher financing costs than the buyer and through trade credit when it has lower financing costs than the buyer. In the model, trade credit is thus preferable if the upstream margin is larger than the downstream margin and if, at the same time, the upstream firm faces lower financing costs. While our model is also based on markups and financing costs, there are important differences that give rise to a much more general preference for trade credit. Most importantly, we introduce the realistic feature of a margin between the borrowing rate that banks charge and the deposit rate that savers receive. As we show below, in the presence of a positive financing friction, trade credit dominates cash-in-advance as long as

[8] See also Ahn (2014), who also studies this mechanism and tests it with Chilean and Colombian data.

the seller charges a positive markup. In contrast to the model in Daripa and Nilsen (2011), the preference for trade credit does not depend on the buyer's markup, the relative markup between the buyer and the seller or a difference in financing costs between the two firms.

Our paper also relates to a recent literature that studies the role of trade credit as a form of limiting competition. Peura et al. (2017) develop a model with Bertrand competition, and potential liquidity shocks, and show that trade credit exposes firms to higher financing costs, reducing their incentives to undercut prices. Giannetti et al. (2018) argue that suppliers extend trade credit to financially-unconstrained large firms as a form to transfer surplus to these firms without cannibalizing sales to small buyers. Chod et al. (2019) develop a model where trade credit allows buyers to use the additional liquidity to increase their purchases of inputs. Thus, in this model sellers are more willing to offer trade credit when competition is lower, because then they internalize more of the benefits related to trade credit provision. Assuming that lower competition is reflected in a higher markup, these papers would also generate a positive correlation between trade credit and markups as our paper. However, notice that our mechanism is quite different. In our model, trade credit arises as a way of reducing financing costs, while in their case trade credit is chosen strategically either, as a form of limiting competition or for reaping benefits from the supply chains.

Our paper also adds to the empirical evidence on trade credit. Most papers have focused on domestic data. Ng et al. (1999), for example, exploit detailed data to analyze the terms of trade credit contracts. Giannetti et al. (2011) and Klapper et al. (2012) further tested theories of trade credit with contract data.[9] Recently, Ellingsen et al. (2016) study detailed trade credit data from Sweden. Consistent with earlier papers, they find that when a firm's financial position improves, it has less accounts payable (that is trade credit that needs to be repaid) on its balance sheet. The correlation between trade credit volume and financial health is, however, not due to shorter trade credit terms but instead due to less purchases by the firm from its suppliers. This finding is inconsistent with the standard view in the literature that trade credit is less desirable to firms than bank credit.

There is a small and growing literature on international trade finance, typically study-

[9] See also Barrot (2016) on trade credit and entry in the trucking industry and Murfin and Njoroge (2014) on the opportunity cost of extending trade credit to large firms.

ing three payment forms, open account, cash-in-advance and letters of credit. While open account corresponds to providing trade credit, letters of credit are a financing form that is almost exclusively used international transactions due to the larger risks involved in cross-border trade. Schmidt-Eisenlohr (2013), Antràs and Foley (2015) and Niepmann and Schmidt-Eisenlohr (2017a) study how payment choices depend on financing cost and limited contract enforcement. Hoefele et al. (2016) extend that analysis and look at the role of product complexity. Demir and Javorcik (2018) employ Turkish export data, showing that the removal of the Multi-Fiber Arrangement led to more trade credit provision by Turkish exporters.[10]

There is substantial evidence on the macro-economic importance of trade credit. Fisman and Love (2003) show that trade credit can alleviate concerns of limited contract enforcement and thereby increase growth, while Nilsen (2002) explores the relationship between the bank lending channel and trade credit. Love et al. (2007) study trade credit use in emerging economies in the wake of financial crises. Jacobson and von Schedvin (2015) look at trade credit propagation and its effects on corporate failure.

To summarize, this paper contributes to the literature by proposing an explanation for the dominance of trade credit based on markups and the costs of financial intermediation and by providing evidence for this theory exploiting Chilean international trade data and domestic production data. It also generalizes the standard trade finance model, allowing for arbitrary bargaining weights between buyers and sellers and providing unambiguous predictions on relative prices between trade credit and cash in advance. Finally, it shows that the use of trade credit increases in the number of interactions between buyers and sellers and that this effect is stronger for more complex products, rationalizing this finding with a simple model of learning.

The remainder of the paper is organized as follows. Section 2 presents a theoretical framework for trade credit use and derives the main testable predictions. Section 3 discusses the empirical specifications, and presents the methodology for deriving firm-product markups.

[10]See also Ahn (2010), Olsen (2010) and Niepmann and Schmidt-Eisenlohr (2017a). For papers studying the broader relationship of financial constraints and trade, see among others Amiti and Weinstein (2011), Chor and Manova (2012), Manova (2013), Paravisini et al. (2014) and Niepmann and Schmidt-Eisenlohr (2017b).

Section 4 describes our dataset. Section 5 presents the empirical results, and quantifies the general importance of trade credit. Finally, section 6 discusses implications of our study and routes for future research.

2 A model of trade credit and markups

In this section, we extend the model in Schmidt-Eisenlohr (2013) and show how a positive markup and a financial intermediation cost lead to a natural preference for trade credit. In the model there are three key elements. First, there is a time delay between the production of the goods by the seller and the sale of the goods by the buyer. Second, financing is costly. To pay for goods or production costs, firms have to borrow funds from the financial sector. Firms can also deposit surplus liquidity as deposits with the banking sector. Importantly, because of regulation, monitoring and general overhead costs, banks charge a higher interest rate when lending funds to firms than the interest rates they pay to depositors.[11] Third, there is imperfect contract enforcement. When a buyer or seller do not fulfill their contractual obligations, firms can sue them in court. This is, however, only successful with a certain probability.[12]

2.1 Model setup

One buyer is matched with one seller. Both firms are risk neutral. A fraction η (η^*) of sellers (buyers) is reliable, that is these firms always fulfill their contracts.[13] If a firm is unreliable and thus does not fulfill its contract voluntarily, the other firm can try to enforce the contract in court which is successful with probability λ (λ^*). When facing an opportunity to cheat, a random firm thus fulfills the contract with probability $\tilde{\lambda} = \eta + (1 - \eta)\lambda$.

There are two periods. In period 0 the seller produces the goods and sends them to the buyer. In period 1, the buyer sells the goods to a final consumer. Because of this time gap

[11] This interest rate difference may be further increased by borrower risk. The point here is that abstracting from the pricing of risk, financial intermediation by banks is costly.

[12] An alternative interpretation would be that all contracts get enforced in court eventually but this generates a legal cost as well as a time delay in settlement.

[13] For the remainder of the paper, all variables related to the buyer are denoted with an asterisk.

between production and final sale, firms have to agree on payment terms. They have two options. First, buyers can pay in advance (cash-in-advance), that is the buyer pays before receiving the goods. Second, they can trade on an open-account, where the buyer pays after delivery, that is the seller extends trade credit to the buyer. A seller produces output for total cost C and sells it to the buyer. The buyer can then sell the goods to final consumers and generate revenues R. For now, we assume that R and C are given exogenously. To finance their transactions, firms can borrow from banks at an interest rate r_b (r_b^*). Firms can deposit surplus funds at banks for a deposit rate of r_d (r_d^*).

The seller and the buyer bargain over the surplus with weights θ and $1-\theta$, that is they maximize the objective function (Nash product): $NP = \Pi_s^\theta \Pi_b^{1-\theta}$.[14] Bargaining takes place under the assumption that the sharing rule has to be acceptable to a reliable trading partner, while payoffs account for the fact that a firm may be matched with an unreliable firm.[15]

Open Account Under open account (trade credit), the two firms solve the following problem:

$$NP^{OA} = \mathrm{E}[\Pi_S^{OA}]^\theta [\Pi_B^{OA}]^{1-\theta} = (\underbrace{\tilde{\lambda}^* P^{OA} - (1+r_b)C}_{\text{Seller Profit}})^\theta (\underbrace{R - P^{OA}}_{\text{Buyer Profit}})^{1-\theta} \tag{1}$$

where P^{OA} is the total payment from the buyer to the seller. The first part of the Nash product represents the expected profits of the seller. Under open account, the seller gets paid P^{OA} with probability $\tilde{\lambda}^*$, while incurring the production costs C with certainty. Because production takes place in period 0 while sales only take place in period 1, the seller has to borrow the production costs C from a bank and pay the interest rate r_b. The second part of the Nash product represents the expected profits of the buyer. Solving for the optimal P^{OA} that maximizes NP^{OA} delivers:

$$P^{OA} = \frac{\theta \tilde{\lambda}^* R + (1-\theta)(1+r_b)C}{\tilde{\lambda}^*} \tag{2}$$

[14]This generalizes the model presented in Schmidt-Eisenlohr (2013) that focused on the case of full bargaining power of the seller, while deriving the case of full bargaining power of the buyer in an appendix. It is easily verified that results derived for the more general model nest these two special cases.

[15]That is, we focus on contracts that are determined by reliable firms, with unreliable firms imitating the contract choice of reliable firms.

The expected Nash product under open account is thus:

$$NP^{OA} = \theta^{\theta}(1-\theta)^{1-\theta}(\tilde{\lambda}^{*})^{\theta-1}\left(\tilde{\lambda}^{*}R-(1+r_b)C\right) \tag{3}$$

Cash-in-Advance Under cash-in-advance, the two firms solve the following problem:

$$NP^{CIA} = \mathrm{E}[\Pi_S^{CIA}]^{\theta}[\Pi_B^{CIA}]^{1-\theta} = (\underbrace{(1+r_d)(P^{CIA}-C)}_{\text{Seller Profit}})^{\theta}(\underbrace{\tilde{\lambda}R-(1+r_b^{*})P^{CIA}}_{\text{Buyer Profit}})^{1-\theta} \tag{4}$$

The first part of the Nash product again shows the expected profits of a reliable seller. Under cash-in-advance, the seller gets paid P^{CIA} with certainty. At the same time, a reliable seller incurs production costs C with certainty as well. If the price charged to the buyer exceeds production costs, the seller deposits the surplus funds at a bank for interest rate r_d. The second part of the Nash product captures the expected profits of the buyer. Now, the buyer generates revenues R with probability $\tilde{\lambda}$. The buyer pays P^{CIA} with certainty in period 0, borrowing from a bank at interest rate r_b^{*}. Solving for the optimal P^{CIA} that maximizes NP^{CIA} delivers:

$$P^{CIA} = \frac{\theta\tilde{\lambda}R+(1-\theta)(1+r_b^{*})C}{1+r_b^{*}} \tag{5}$$

With an expected Nash product of:

$$NP^{CIA} = \theta^{\theta}(1-\theta)^{1-\theta}(1+r_d)^{\theta}(1+r_b^{*})^{-\theta}\left(\tilde{\lambda}R-(1+r_b^{*})C\right) \tag{6}$$

Optimal Contract Combining equations (3) and (6) implies that a buyer-seller pair chooses open account (trade credit) if:

$$\theta^{\theta}(1-\theta)^{1-\theta}\left[(\tilde{\lambda}^{*})^{\theta-1}\left(\tilde{\lambda}^{*}R-(1+r_b)C\right)-(1+r_d)^{\theta}(1+r_b^{*})^{-\theta}\left(\tilde{\lambda}R-(1+r_b^{*})C\right)\right]>0 \tag{7}$$

Now, assume that firms charge a constant markup to final consumers given by μ so that $R = \mu C$.[16] Open account (trade credit) is then preferred over cash-in-advance if:

$$(\tilde{\lambda}^*)^{\theta-1}\left(\tilde{\lambda}^*\mu - (1+r_b)\right) - (1+r_d)^{\theta}(1+r_b^*)^{-\theta}\left(\tilde{\lambda}\mu - (1+r_b^*)\right) > 0 \tag{8}$$

2.2 Trade Credit and Markups

Taking the derivative of equation (8) with respect to μ and rearranging delivers:

$$(1+r_b^*)^{\theta}\left(\tilde{\lambda}^*\right)^{\theta} - (1+r_d)^{\theta}\,\tilde{\lambda} > 0 \tag{9}$$

The condition is quite weak. As long as the buyer's borrowing rate is above the seller's deposit rate and enforcement is not too different between buyers and sellers, trade credit becomes more attractive when the markup goes up. Consider the symmetric case to build intuition, where the buyer and the seller face the same interest rates and enforcement frictions. The condition then simplifies to:

$$(1+r_b)^{\theta} > (\tilde{\lambda})^{1-\theta}(1+r_d)^{\theta}. \tag{10}$$

It is easy to see that a sufficient condition for (10) to hold is that the borrowing rate exceeds the deposit rate. The following Proposition summarizes our results on trade credit and markups:

Proposition 1 (Trade Credit and Markups) *Suppose* $(1+r_b^*)^{\theta}\left(\tilde{\lambda}^*\right)^{\theta} > (1+r_d)^{\theta}\,\tilde{\lambda}$. *Then:*

i) The use of open account increases in the markup μ

ii) This effect increases in r_b^* *and* λ^* *and decreases in* r_d *and* λ

Proof. Follows from equation (9) ■

Part ii) of Proposition 1 presents additional predictions to test the mechanism explaining

[16] We only assume this to simplify the exposition of the main mechanism. In section Appendix B.2, we show that the main results hold with endogenous revenues and costs, R and C, for the special case of CES preferences. We discuss these results below in section 2.5.

trade credit use: the effect of the markup should be stronger when the destination country borrowing rate and the destination country enforcement are higher and when the source country deposit rate and source country enforcement are lower.

2.3 Trade Credit and Repeated Interactions

Trade Credit and Learning Consider now the case where an importer and an exporter interact repeatedly. Assume that the two trading partners learn over time about the reliability of their trading partner, so that $\partial\eta_k/\partial k > 0$, where k is the number of previous interactions and η_k is the probability that a firm is reliable after k interactions.[17]

For tractability, consider the trade-off between trade credit and cash-in-advance in the symmetric case where the buyer and the seller face the same interest rates and enforcement frictions (e.g. because they reside in the same country). Equation (8) then simplifies to:

$$(\tilde{\lambda}_k)^{\theta-1}\left(\tilde{\lambda}_k\mu-(1+r_b)\right)-(1+r_d)^{\theta}(1+r_b)^{-\theta}\left(\tilde{\lambda}_k\mu-(1+r_b)\right)>0 \tag{11}$$

where $\tilde{\lambda}_k$ is increasing in the number of previous interactions k. Assume further that learning is symmetric, that is with each interaction, independent of the payment form used - the two trading partners learn about each other.[18] Taking the derivative with respect to η_k delivers:

$$\frac{\partial\left(NP^{OA}-NP^{CIA}\right)}{\partial\eta_k}=\left(\mu\left[\theta\tilde{\lambda}_k^{\theta-1}-\left(\frac{1+r_d}{1+r_b}\right)^{\theta}\right]+(1-\theta)(1+r_b)\left(\tilde{\lambda}_k\right)^{\theta-2}\right)(1-\lambda) \tag{12}$$

First, consider the special case $\theta=1$ where the seller has all bargaining power. Then, the condition simplifies to:

$$\frac{\partial\left(NP^{OA}-NP^{CIA}\right)}{\partial\eta_k}|_{\theta=1}=\mu\left[1-\frac{1+r_d}{1+r_b}\right](1-\lambda) \tag{13}$$

This derivative is positive as long as the borrowing rate exceeds the deposit rate. Then, open

[17] This learning can take multiple forms. One example would be Bayesian updating as in Araujo and Ornelas (2007), Antràs and Foley (2015), Macchiavello and Morjaria (2015) and Monarch and Schmidt-Eisenlohr (2016).

[18] In principle, the speed of learning could be a function of the payment terms. That is there could be more learning about the seller under cash-in-advance and vice versa. As the general case becomes intractable quite quickly, we restrict the analysis to the symmetric case here to show the general intuition.

account becomes more attractive the more often the two firms interacted with each other. As the bargaining power of the seller, θ, declines, this effect becomes less clear-cut. For the other extreme case where the buyer has all bargaining power, the derivative changes to:

$$\frac{\partial \left(NP^{OA} - NP^{CIA}\right)}{\partial \eta_k}|_{\theta=0} = \left(\frac{1+r_b}{(\tilde{\lambda})^2} - \mu\right)(1-\lambda), \tag{14}$$

which does not have a clear sign.

Product Complexity In addition, now assume that products differ by their complexity. Following, Hoefele et al. (2016), assume that product complexity is captured by parameter $\gamma \in [0, 1]$, where a higher γ represents a more complex product. Assume further that contract enforcement is harder for more complex products. More specifically, assume that a contract now gets enforced exogenously with probability λ^γ. The optimal decision in the symmetric case now becomes:

$$(\tilde{\lambda}_k(\gamma))^{\theta-1}\left(\tilde{\lambda}_k(\gamma)\mu - (1+r_b)\right) - (1+r_d)^\theta(1+r_b)^{-\theta}\left(\tilde{\lambda}_k(\gamma)\mu - (1+r_b)\right) > 0 \tag{15}$$

with $\tilde{\lambda}_k(\gamma) = \eta_k + (1-\eta_k)\lambda^\gamma$. Taking the derivative with respect to η_k delivers:

$$\frac{\partial \left(NP^{OA} - NP^{CIA}\right)}{\partial \eta_k} = \left(\mu\left[\theta\tilde{\lambda}_k(\gamma)^{\theta-1} - \left(\frac{1+r_d}{1+r_b}\right)^\theta\right] + (1-\theta)(1+r_b)\left(\tilde{\lambda}_k(\gamma)\right)^{\theta-2}\right)(1-\lambda^\gamma) \tag{16}$$

Taking the derivative with respect to γ and rearranging delivers:

$$\begin{aligned}\frac{\partial \left(NP^{OA} - NP^{CIA}\right)}{\partial \eta_k \partial \gamma} &= -\left((1-\lambda^\gamma)\left(\mu\theta + (2-\theta)\frac{(1+r_b)}{\tilde{\lambda}_k(\gamma)}\right)(1-\eta_k) + (1+r_b)\right) \\ &\quad \left(\tilde{\lambda}_k(\gamma)\right)^{\theta-2}(1-\theta)\lambda^\gamma \ln\lambda,\end{aligned}$$

which is greater equal zero as $\ln\lambda < 0$. That is, the effect of learning on the difference between trade credit and cash-in-advance is stronger for more complex products (higher γ). This is quite intuitive: contracts for more complex products are harder to enforce and hence learning has a stronger effect on a firm's decision problem for these products. The preceding insights are summarized in Proposition 2.

Proposition 2 (Trade Credit and Learning) *Suppose two firms in the same country trade with each other, learning is symmetric and the borrowing rate is above the deposit rate, $r_b > r_d$. Then:*

1. *If the seller has all bargaining power ($\theta = 1$), payment is more likely on open account (trade credit) terms, the longer the two firms have traded.*

2. *If the seller does not have all bargaining power ($\theta < 1$), learning increases the attractiveness of trade credit the more, the more complex the product that is traded.*

The proposition is quite intuitive. The longer two firms trade with each other, the more likely they will fulfill their contracts. The key advantage of trade credit is that it saves on financing costs as compared to cash-in-advance. Through learning, contract enforcement becomes less of an issue and financing costs differences matter for the contract choice. Therefore, as firms learn that their trading partners are reliable they tend to favor trade credit over cash-in-advance. The effect of repeated interactions is stronger for complex products. With complex products enforcement frictions are more severe to begin with but this also creates a stronger effect from learning, leading to a sharper rise in trade credit within relationships over time.

2.4 Price Predictions

We now look at the relationship between the payment terms and prices. To fully assess the price effects, let revenues and final sales prices be endogenous to the payment form. Let p_f^{OA} and p_f^{CIA} denote the prices charged to final consumers and c denote constant marginal costs. Assume that firms operate under monopolistic competition and that consumers have standard CES preferences of the form $q = p^{-\sigma}A$.[19] Then, the relative (per unit) price between open account and cash-in-advance is given by:

$$\frac{P^{OA}/Q^{OA}}{P^{CIA}/Q^{CIA}} = \frac{1+r_b^*}{\tilde{\lambda}^*}\left[\frac{\theta\tilde{\lambda}^* p_f^{OA} + (1-\theta)(1+r_b)c}{\theta\tilde{\lambda} p_f^{CIA} + (1-\theta)(1+r_b^*)c}\right] \tag{17}$$

[19]More specifically, assume the following demand: $Q = \left(\int q\left(z\right)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}}$, with the ideal price index $P = \left(\int p\left(z\right)^{1-\sigma} dz\right)^{\frac{1}{1-\sigma}}$. In this context, aggregate demand $A = P^{\sigma}Q$.

Optimal final sales prices are:[20]

$$p_f^{OA} = \frac{1 + r_b}{\tilde{\lambda}^*} \frac{\sigma}{\sigma - 1} c; \quad p_f^{CIA} = \frac{1 + r_b^*}{\tilde{\lambda}} \frac{\sigma}{\sigma - 1} c. \tag{18}$$

Combining the equations delivers:

$$\frac{P^{OA}/Q^{OA}}{P^{CIA}/Q^{CIA}} = \frac{1 + r_b}{\tilde{\lambda}^*} \tag{19}$$

Proposition 3 *All else equal, the price charged by the seller to the buyer is higher under open account than under cash in advance. This price difference increases in the interest rate of the seller* r_b *and decreases in the enforcement in the country of the buyer* λ^**.*

Proof. *See equation* (17). ■

The proposition is quite intuitive. By providing trade credit (offering open account), the seller takes on the financing cost and the risk that the buyer does not pay after delivery. The seller hence needs to be compensated for these two factors implying a higher unit price paid by the buyer. Interestingly, with a constant markup, this price ratio is independent of the distribution of bargaining power.

2.5 CES Demand and Wholesale Markup

In this section we discuss the main predictions of the model for the cases of (i) endogenous revenues and costs, and (ii) wholesale markups. This last extension is important, because the wholesale markup is the object we use for testing the predictions of our theory.

CES Preferences We begin reviewing the case of CES preferences. To simplify the discussion, we only present the main results here. Details can be found in Appendix B.3. Assume again standard CES preferences with implied aggregate demand $A = P^\sigma Q$. The

[20] Details on the derivation of prices are provided in Appendix B.1.

Nash Products given optimal price decisions can be derived as:

$$NP^{OA} = B\left(\tilde{\lambda}^*\right)^{\theta-1+\sigma}(1+r_b)^{1-\sigma}, \tag{20}$$

$$NP^{CIA} = B(1+r_d)^{\theta}(1+r_b^*)^{-\theta+1-\sigma}\left(\tilde{\lambda}\right)^{\sigma}. \tag{21}$$

with $B = \theta^{\theta}(1-\theta)^{1-\theta}\frac{c^{1-\sigma}}{\sigma-1}A\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}$. From this, it follows that open account is preferred over cash in advance if:

$$\left(\tilde{\lambda}^*\right)^{\theta-1+\sigma}(1+r_b)^{1-\sigma} - (1+r_d)^{\theta}(1+r_b^*)^{-\theta+1-\sigma}\left(\tilde{\lambda}\right)^{\sigma} > 0. \tag{22}$$

In the symmetric case, this condition simplifies to:

$$(1+r_b)^{\theta} > \left(\tilde{\lambda}\right)^{1-\theta}(1+r_d)^{\theta}, \tag{23}$$

the same condition we derived earlier in equation (10). To study the role of the markup under CES preferences, we can take the derivative of condition (22) with respect to the elasticity of substitution σ which delivers:

$$\left(\tilde{\lambda}^*\right)^{\theta-1+\sigma}(1+r_b)^{1-\sigma}\ln\left(\frac{\tilde{\lambda}^*}{1+r_b}\right) - (1+r_d)^{\theta}(1+r_b^*)^{-\theta+1-\sigma}\left(\tilde{\lambda}\right)^{\sigma}\ln\left(\frac{\tilde{\lambda}}{1+r_b^*}\right) \tag{24}$$

In the symmetric case, as $\ln\left(\frac{\tilde{\lambda}}{1+r_b}\right) < 0$, this derivative is negative if:

$$(1+r_b)^{\theta} > \left(\tilde{\lambda}\right)^{1-\theta}(1+r_d)^{\theta}, \tag{25}$$

which is the case when $r_b > r_d$. More generally, the derivative (24) is negative when $r_b^* > r_d$ and interest rates and enforcement are not too different across countries. A negative derivative implies that trade credit becomes more attractive when markups go up (lower σ), in line with Proposition 1. Moreover, as in Proposition 1, equation (24) implies that the effect of the markup is stronger when the destination country borrowing rate and the destination country enforcement are higher, and when the source country deposit rate and source country enforcement are lower.

Wholesale Markup So far, we have solved the model for the full markup between final consumer prices and marginal production costs, captured by $\mu = R/C$. In the following we derive results as a function of the intermediate (or wholesale) markups, that is the prices charged to the buyer by the seller over marginal costs, $\mu_W^{OA} = P^{OA}/C^{OA}$ and $\mu_W^{CIA} = P^{CIA}/C^{CIA}$.

With endogenous revenues and costs, wholesale markups differ between open account and cash-in-advance. In appendix B.3 we show that the wholesale markups are given by:

$$\mu_W^{OA} = \frac{1+r_b}{\tilde{\lambda}^*}\left((1-\theta)+\theta\frac{\sigma}{\sigma-1}\right) \tag{26}$$

$$\mu_W^{CIA} = \left((1-\theta)+\theta\frac{\sigma}{\sigma-1}\right) \tag{27}$$

Equations (26) and (27) are quite intuitive. They show that the markup obtained by the seller is a fraction of the full markup. This fraction depends on the degree of bargaining power the seller has. In particular, when the seller has all the bargaining power ($\theta = 1$), she captures the full markup between final price and marginal cost. In the other extreme, when the buyer has all the bargaining power ($\theta = 0$), the seller only receives the production costs (adjusted for the financing cost and enforcement friction in the open account case).

In Appendix B.3, we show that in the CES case, open account is preferred over cash in advance if:

$$\left[(\tilde{\lambda}^*)^{\theta-1+\sigma}(1+r_b)^{1-\sigma} - (1+r_d)^{\theta}(1+r_b^*)^{-\theta+1-\sigma}(\tilde{\lambda})^{\sigma}\right]\left(\mu_W^{CIA}-1\right) > 0. \tag{28}$$

Or expressed as a function of the open account wholesale markup:

$$\left[(\tilde{\lambda}^*)^{\theta-1+\sigma}(1+r_b)^{1-\sigma} - (1+r_d)^{\theta}(1+r_b^*)^{-\theta+1-\sigma}(\tilde{\lambda})^{\sigma}\right]\left(\mu_W^{OA}-\frac{1+r_b}{\tilde{\lambda}^*}\right) > 0. \tag{29}$$

This conditions imply the same predictions as those derived for the full markups. The preference for trade credit increases in the markup and this effect becomes stronger when r_b^* and λ^* are larger and when r_b and λ are smaller.

3 Empirical Framework

3.1 Estimating Markups

In the model, markups for each seller and product vary at the level of buyers located in different destinations. In practice, however, the computation of markups at this level of disaggregation is unfeasible, because it imposes severe data requirements that cannot be satisfied when using information for multiple industries and markets.[21] Hence, to test the predictions of the theory we shut down the seller's dimension, and compute markups at the seller-product level using the methodology proposed by De Loecker et al. (2016). The main advantage of this methodology is that it allows to compute markups abstracting from market-level demand information. It only requires to assume that firms minimize cost for each product, and that at least one input is fully flexible.

The starting point in De Loecker et al. (2016), is to consider the firm's cost minimization problem. After rearranging the first-order condition of problem for any flexible input V, the markup of product p produced by firm i at time t (μ_{ipt}) can be computed as the ratio between the output elasticity of product j with respect to the flexible input V (θ^V_{ipt}) and expenditure share of the flexible input V (relative to the sales of product p; $s^V_{ipt} \equiv P^V_{ipt} V_{ipt} / P_{ipt} Q_{ipt}$):[22]

$$\underbrace{\mu_{ipt}}_{\text{Markup}} \equiv \frac{P_{ipt}}{MC_{ipt}} = \frac{\theta^V_{ipt}}{s^V_{ipt}} , \tag{30}$$

where P (P^V) denotes the price of output Q (input V), and MC is marginal cost. While the numerator of equation (30) – the input-output elasticity of product j – needs to be estimated, the denominator is directly observable in our data. We next explain the procedure we follow for deriving each of these elements.

[21] Deriving markups at the buyer-seller-product level requires either detailed market or production information at the level of buyers and products. These data requirements are rarely fulfilled. A notable exception is Cajal-Grossi et al. (2019), who uses detailed information for the Bangladeshi garment industry to derive markups at the buyer-seller-product level.

[22] The derivation of (30) assumes that multi-product firms are equivalent to a collection of single-product firms; thus, this setup does not allow for economies of scope in production. Below, we show that our results also hold for single-product firms.

Input-output elasticity. To estimate the input-output elasticities, we specify production functions for each product p using labor (L), capital(K) and materials (M) as production inputs:

$$Q_{ipt} \quad = \quad \Omega_{it} F(K_{ipt}, L_{ipt}, M_{ipt}) \tag{31}$$

where Q is physical output, and Ω denotes firm's productivity. There are three important assumptions on equation (31). First, the production function is product-specific, which implies that single and multi-product firms use the same technology to produce a given product. However, second, productivity is firm-specific. Finally, as is standard in the estimation of production functions, we assume Hicks-Neutrality, so that Ω is log-additive.

The estimation of (31) follows De Loecker et al. (2016) in using the subset of single-product firms to identify the coefficients of the production function.[23] Different from them, we deflate inputs expenditure with firm-specific input price indexes to avoid that the so-called input price bias affect the estimated coefficients (see De Loecker and Goldberg, 2014).[24]

Our baseline specification assumes a Cobb-Douglas production function, and allows for the presence of a log-additive non-anticipated shock (ε).[25] Taking logs to (31), we obtain

$$q_{ipt} \quad = \quad \alpha_k^j k_{ipt} + \alpha_l^j l_{ipt} + \alpha_m^j m_{ipt} + \omega_{it} + \varepsilon_{ipt} \tag{32}$$

The estimation of (32) follows Ackerberg et al. (2015) (henceforth, ACF), who extend the methodology proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) to control for the endogeneity of firms' inputs choice –which is based on the actual level of firms' productivity.[26] To identify the coefficients of the production function, we build moments

[23]The reason for using only single-product firms, is that for this set of firms there is no need of specifying how inputs are distributed across individual outputs.

[24]In De Loecker et al. (2016), input prices are not available in their sample of Indian firms, so they implement a correction to control for input price variation. See the Appendix C.1 for a detailed explanation on the construction of the price index we use in our sample of Chilean firms.

[25]A shortcoming of the Cobb-Douglas specification is that it assumes that input-output elasticities are constant across firms, and over time. On the other hand, the Cobb-Douglas specification is widely used, allowing for a more direct comparison of our results with other estimates in the literature. In the robustness checks section we present results with derived using a more flexible Translog production function, which allows for different types of complementarities among production inputs. Results are quantitatively similar, although coefficients are slightly less precisely estimated than with the Cobb-Douglas baseline.

[26]ACF show that the labor elasticity is in most cases unidentified by the two-stage method of Olley and

based on the productivity innovation ξ. We specify the following process for the law of motion of productivity:

$$\omega_{it} \quad = \quad g(\omega_{it-1}, d^x_{it-1}, d^i_{it-1}, d^x_{it-1} \times d^i_{it-1}, \hat{s}_{it-1}) + \xi_{it} \tag{33}$$

where d^x is an export dummy, d^i is a categorical variable for periods with positive investment, and $\hat{s}$ is the probability that the firm remains single-product. The endogenous productivity process (33) follows the corrections suggested by De Loecker (2013), allowing firms' productivity path to be affected by past exporting and investment decisions. In addition, it follows De Loecker et al. (2016) in including the probability of remaining single-product to correct for the bias that results from firm switching non-randomly from single to multi-product.

The first step of the ACF procedure involves expressing productivity in terms of observables. To do so, we use inverse material demand $h_t(\cdot)$ as in Levinsohn and Petrin (2003) to proxy for unobserved productivity, and estimate expected output $\phi_t(k_{it}, l_{it}, m_{it}; \mathbf{x}_{it})$ to remove the unanticipated shock component ε_{it} from (32).[27] Then, the ACF procedure exploits this representation to express productivity as a function of data and parameters: $\omega_{it}(\boldsymbol{\alpha}) = \hat{\phi}_t(\cdot) - \alpha_k k_{it} - \alpha_l l_{it} - \alpha_m m_{it}$, and form the productivity innovation ξ_{it} from (33) as a function of the parameters $\boldsymbol{\alpha}$. The second step of ACF routine forms moment conditions on ξ_{it} to identify all parameters $\boldsymbol{\alpha}$ through GMM:

$$\mathbb{E}(\xi_{it}(\boldsymbol{\alpha}) \cdot \mathbf{Z}_{it}) \quad = \quad 0 \tag{34}$$

where $\mathbf{Z}_{it}$ contains lagged materials, labor, and capital, and current capital. Once the parameters are estimated, the input-output elasticities are recovered for each product as $\theta^V_{ipt} \equiv \partial \log Q_{ipt} / \partial \log V_{ipt}$. For the Cobb-Douglas case, $\theta^V_{ipt} = \alpha^j_V$, so that the input-output elasticity is constant for all plants producing a given product p.[28]

Pakes (1996) and Levinsohn and Petrin (2003).

[27]The vector $\mathbf{x}_{it}$ includes other variables affecting material demand, such as time and product dummies. We approximate $\phi_t(\cdot)$ with a full second-degree polynomial in capital, labor and materials.

[28]In the Translog case, the input elasticities θ^V_{ipt} depends on firms' input use. This information is directly observed in single-product firms. For multi-product firms, we derive inputs' use by each output following the same procedure we apply for computing the expenditure share of the inputs s^V_{ipt} explained next.

Implementation. To derive markups, we use materials as the relevant flexible input to compute the output elasticity. While in principle, labor could also be used to compute markups, the existence of long-term contracts and firing costs make firms less likely to adjust labor after the occurrence of shocks. The second component needed in (30) to compute markups is the expenditure share, which requires to identify the assignment of firms' inputs across outputs produced by the firm. To implement this, we follow Garcia-Marin and Voigtländer (2018) and exploit a unique feature of our data: ENIA provide information on total variable costs (labor cost and materials) for each product produced by the firms. We use this information to proxy for product-specific input use assuming that inputs are used approximately in proportion to the variable cost shares, so that the value of materials' expenditure $M_{ipt} = P^V_{ipt} V_{ipt}$ is computed as

$$\tilde{M}_{ipt} \;=\; \rho_{ipt} \cdot \tilde{M}_{it}, \quad \text{where} \quad \rho_{ipt} \;=\; \frac{TVC_{ipt}}{\sum_j TVC_{ipt}}. \tag{35}$$

Finally, we compute the expenditure share dividing the value of material inputs by product-specific revenues, which are observed in the data.

Note that the markup measure we compute corresponds to wholesale markups, because our data only provide information for wholesale revenues. Nevertheless, as we discuss in section 2.5, all the main predictions of the baseline model hold both when markups are in terms of final consumer and for wholesale price.

3.2 Empirical Specifications

Trade Credit and Markups We first test the theoretical predictions on the choice between open account (trade credit) and cash-in-advance. We start with the following baseline regression:

$$\rho_{ipjt} = \beta_1 \;\ln(\mu_{ipt}) + \gamma_1 \;\ln(L_{it}) + \delta_i + \delta_p + \delta_{jt} + \epsilon_{ipjt}, \tag{36}$$

where ρ_{ipjt} denotes the share of open account value exported by firm i shipping product p to country j at time t, and μ_{ipt} corresponds to firm-product level markups. The main prediction of the model is that $\beta_1 > 0$, that is, all else equal, firms with larger markups should sell more on open account. The baseline specification include firm fixed-effects (δ_i) to control for time-invariant factors affecting firms' open account share, and product-fixed effects (δ_j) to account for differences in product characteristics leading to dispersion in trade credit use. In addition, we include destination-year fixed effects (δ_{jt}) to account for country-level characteristics directly affecting trade credit choice for all firms, such as the strength of contract enforcement in the destination country (Antràs and Foley, 2015). Finally, we include firm employment (L_{it}) to control for the effect of differences in firm size on trade credit use.

Next, we test the second main prediction of the model. According to our theory, the effect of markups on trade credit decreases in the seller's deposit rate and increases in the buyer's borrowing rate and the destination country's contract enforcement. To test these predictions, we modify the baseline specification (36) including interaction terms between firm-product markups, interest rates and contract enforcement:

$$\begin{aligned} \rho_{ijpt} \;=\; & \beta_1 \; \ln(\mu_{ipt}) + \beta_2 \; \ln(\mu_{ipt}) \; r^*_{b,jt} + \beta_3 \; \ln(\mu_{ipt}) \; r_{d,jt} \\ & + \beta_4 \; \ln(\mu_{ipt}) \; \lambda^*_{jt} + \delta_{it} + \delta_{jt} + \delta_p + \epsilon_{ijpt}, \end{aligned} \tag{37}$$

From the theory we expect $\beta_2 > 0$, $\beta_3 < 0$, and $\beta_4 > 0$: the positive effect of markups increases with the destination-country borrowing rate, r^*_b, decreases with the source-country deposit rate, r_d, and increases with the destination-country enforcement, λ^*.

One potential concern with respect to our baseline specification is that it relies on the exogeneity of markups, which may not hold if exporters charge higher markups in transactions involving trade credit. Our discussion in 2.5 reveals that this is indeed the case in the case of CES demand. This concern is, however, mitigated to a large extent when we compute markups at the seller-product level, because the endogenous response of markup to trade credit choice is mitigated when averaging across destinations. Thus, even if firms charge higher markups on transactions involving trade credit, the resulting bias should be relatively modest, especially for firm-products with sales well diversified across markets, or with low participation in export markets. Later in the next section we build on this insight and show that our results largely hold for the subset of firms with low exposure to export markets.

We note, however, that the endogeneity of markups to trade credit choice does not disappear when averaging markups across destinations. To address this concern, we apply a battery of additional tests to evaluate if the bias is substantial, including fixing markups at their initial value for each seller-product, and computing markups at the firm-level (diluting even more the markups' endogeneity). In all cases, results hold to a great extent, suggesting that the potential endogeneity of markups does not drive the correlation between markups and trade credit choice. Finally, note that when testing predictions involving interactions between markups and importing country characteristics, we apply an even more strict test for our theory including firm-year, and firm-product-year fixed effects. The fact that the results are in line with the main theory in this case as well is reassuring and suggests that the overall mechanism holds in the data.

Prices and Trade Credit To test the price predictions of the model, we specify a simple baseline regression testing for a price difference between open account and cash-in-advance by estimating the following regression at the transaction level:

$$\ln UV_{ipjt} \;=\; \beta_1 \, \mathbb{I}^{OA}_{ipjt} + \mathbf{\Gamma}'\mathbf{X}_{ijpt} + \delta_{ipj} + \delta_{it} + \delta_{jt} + \varepsilon_{ipjt}, \tag{38}$$

where UV_{ipjt} is the unit values of sales by firm i of product p to destination j at time t and X_{ipjt} is a vector of controls including the value of the shipment and the total value of all previous shipments for the same firm-product-destination. The model predicts a higher price for open-account transactions, that is $\beta_1 > 0$. Next, we check the model prediction that the seller interest rate and the buyer enforcement should affect the price difference between open account and cash-in-advance transactions. We thus estimate:

$$\ln UV_{ipjt} = \beta_1 \, \mathbb{I}^{OA}_{ipjt} + \beta_2 \, \mathbb{I}^{LAW*}_{jt} \cdot \mathbb{I}_{OA} + \beta_3 \, r^b_{jt} \cdot \mathbb{I}_{OA} + \mathbf{\Gamma}'\mathbf{X}_{ijpt} + \delta_{ipj} + \delta_{it} + \delta_{jt} + \varepsilon_{ipjt} \tag{39}$$

Based on the theory, we expect $\beta_2 < 0$ and $\beta_3 > 0$. We include as controls the FOB value of the transaction to control for the existence of volume discounts, and the cumulative firm-product sales within each destination (excluding the value of the current transaction), to account for the effect of buyer-seller relationships (see Monarch and Schmidt-Eisenlohr, 2018).

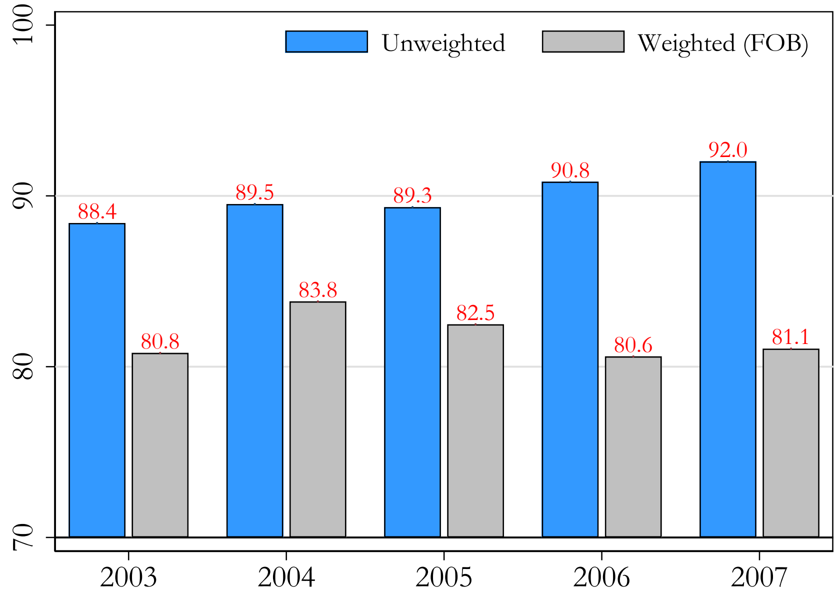
4 Data

We use two main datasets to test the main predictions of the model. Both datasets cover different pieces of information for the universe of Chilean manufacturing exporters over the period 2003-2007. This section reviews the main features of these data sources, describes the sample of our analysis, and provides descriptive evidence on the nature of the data.

The first data source is the Chilean National Customs Service, and provides transaction-level data for the universe of Chilean exports. The data is available for the 90 main destinations of Chilean exports, which account for over 99.7% of the value of overall national exports in our sample period. For each export transaction, the dataset details the identity of the exporter, the importing country, a product description and the 8-digit HS code to which the product belongs, the date of the transaction, the FOB value and volume of the merchandise, and the financing mode of the export transaction. While the data allows to identify if each transactions was paid in advance (cash-in-advance – CIA), post-shipment (open account – OA), or with other modes (such as letters of credit, or other two-part contract), we focus on open account transactions to test the trade credit theory. Open account transactions represent about 90 percent of the transactions, and 83 percent of the export value of manufacturing exporters in our sample (see figure 1).

We complement the transaction-level data from customs with production-level data from the *Encuesta Nacional Industrial Anual* (Annual National Industrial Survey – ENIA). ENIA is collected by the Chilean National Statistical Agency (INE), and provides annual production information for the universe of Chilean manufacturing plants with 10 or more employees, according to the International Standard Industrial Classification (ISIC), revision 3. It surveys approximately 4,900 manufacturing plants per year, out of which 20% are exporters. ENIA provides standard micro-level information (e.g., sales, inputs expenditures, employment, investment), and detailed information for each good produced (sales value, production

Figure 1. Open Account Transactions in the Chilean Data



Notes: The figure shows the aggregate share of open account transactions among Chilean manufacturing exporters, for the period 2003-2007. The blue bars show the share of open account transactions by year; the gray bars weight transactions by their FOB value.

cost, number of unit produced and sold), and inputs purchased by the firm (value and volume for each input purchased by the plant). Outputs and inputs products are defined according to Central Product Classification (CPC) at the 8-digit level, identifying 1,190 products over 2003-2007.[29]

We use two additional data sources to obtain information on the destination countries' characteristics. First, we obtain information for the importing countries' deposit and lending rate, as well as for domestic inflation from the International Monetary Fund's *International Financial Statistics*. We use this data to construct real (ex-post) interest rates as the difference between the nominal rates and the realized inflation in the respective year. Second, we use the Rule of Law index constructed by the World Bank's *World Government Indicator* to proxy for the likelihood of contract enforcement in each country.

The main issue in combining data from Customs and ENIA at the firm-product level is that product are classified using different nomenclatures in both datasets. To deal with this issue, we follow several steps. First, we use United Nations' correspondence tables to

[29]For example, the wine industry (ISIC 3132) is disaggregated by CPC into 4 different categories: "Sparkling wine", "Wine of fresh grapes", "Cider", and "Mosto".

determine the list of HS products that could potentially be matched to each CPC product in ENIA.[30] We then merge the resulting dataset with customs data at the firm-HS-year level. This procedure results in two cases: (i) All exported HS products in customs within a firm-year pair are merged to ENIA, and (ii) Only a fraction (or none) of the exported products are matched to ENIA within a firm-year pair. For the latter cases, whenever there is concordance within 4-digit HS categories, we manually merge observations based on HS and CPC product's descriptions. Borderline cases (no clear connection between product descriptions), as well as cases with no concordance at the 4-digit HS level are dropped. In addition, to ensure a consistent dataset, we exclude: (i) plant-product-year observations that have zero values for raw materials expenditure, sales, or product quantities, with extreme values for markups (above the 98th or below the 2nd percentiles), and (ii) destination-year pairs with extreme values of the real borrowing rates to avoid the influence of extreme values resulting from inflationary or deflationary episodes.[31] Table 1 provides summary statistics for the final dataset.[32]

[30] The correspondence table establishes matches between 5-digit CPC and 6-digit HS products. This level of disaggregation corresponds to 783 5-digit CPC products.

[31] In practice, this correction drops country-years with real borrowing rates above 35%, and below -4%.

[32] Table D.1 in appendix D provides more detailed summary statistics for markups, aggregated at the 2-digit level.

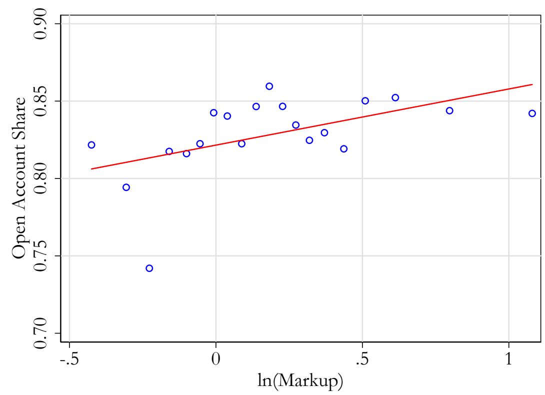
Table 1. Summary Statistics

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Transaction Characteristics						
Open Account Dummy	0.9006	0.2992	1	1	1	1,016,523
Export Value (US$)	82,258.1	601,595.4	3,777.2	13,638.5	35,806.8	1,016,523
Unit Value (in logs; demeaned)	0	0.4711	-0.1752	-0.0096	0.1522	1,014,147
Firm-product Characteristics						
Employment (at the firm level)	273.1	522.3	51	119	283	3,546
Markups	1.255	0.538	0.882	1.111	1.466	26,584
# Transactions by firm-product-year	38.2	165.7	1	5	21	26,584
# Destinations by firm-product-year	3.5	5.3	1	1	4	26,584
Country Characteristics						
Rule of Law Index	0.36189	1.00966	-0.56894	0.38070	1.26830	362
Foreign borrowing rate	0.05466	0.04521	0.02717	0.04505	0.06924	362
Chilean deposit rate	0.00929	0.00579	0.00879	0.00883	0.01202	362
Chilean borrowing rate	0.03989	0.00442	0.03625	0.04072	0.04263	362

Notes: The table lists the summary statistics for the variables used in the paper's baseline analysis sample. It comprises transaction-level data for the universe of Chilean manufacturing exporters that can be matched to the Chilean Annual Manufacturing Survey (ENIA), over the period 2003-2007.

Descriptive Evidence. Before turning to the main econometric results, we explore the raw data seeking to determine whether the main mechanism holds unconditionally. Figure 2 shows our main result – trade credit use increases with firm-product level markups. The figure plots a binscatter diagram for the open account share – defined as the percent of export value financed through open account – against firm-product markup (in logarithms). Both variables represent residuals after taking out country-year fixed effects. As it is evident in the figure, there is a positive relationship between the open account share and markups in the data. This provides support to proposition 1.i): trade credit use increases with markups. The association is relatively stronger for the bottom half of the markup distribution, and it fades out for high markup values. This suggests that the markup mechanism as a reason for firm-to-firm lending is more prominent in firms with low markups. In the econometric specifications, we study if this non-linear relation holds when controlling for other variables affecting trade credit choice and a richer set of fixed-effects.

Figure 2. Open Account Share and Markups

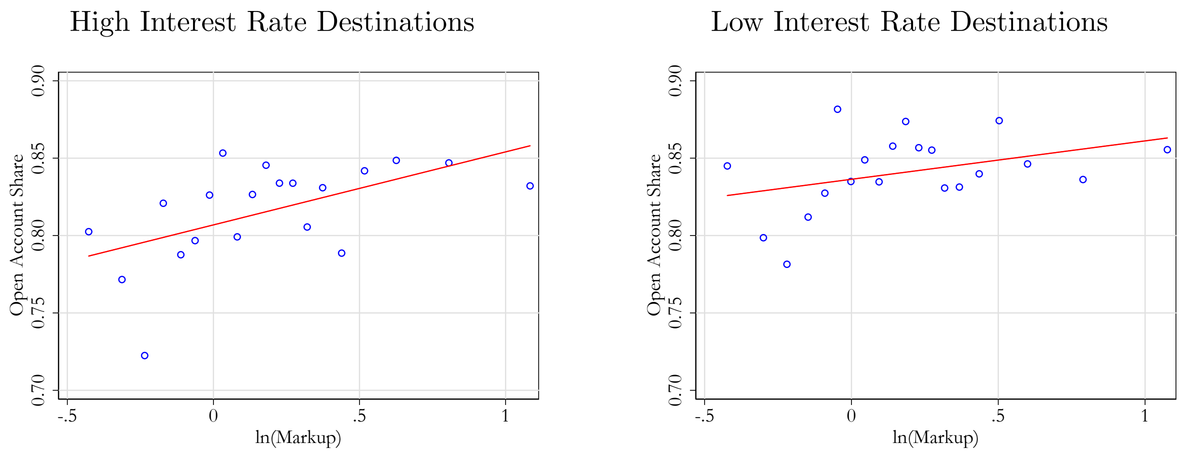


Notes: The figure shows a binscatter diagram for the open account share against markups for a sample of 1,642 Chilean exporters over 2003-2007. Markups are computed at the firm-product level following the methodology by De Loecker et al (2016). Open account share is competed at the firm-product-destination level. Both variables control for country-year fixed effects.

The theoretical framework in section 2 predicts that the markup and foreign borrowing rate are complementary in their effect on trade credit choice. To study if this prediction holds in the data, we split the data in terms of trade credit extended to high interest rate and low interest rate destinations, depending on whether the foreign borrowing rate is above or below the median rate across years and destinations, respectively. The resulting binscatter diagrams are plotted in Figure 3. The left panel shows trade credit in high interest rate countries, while the right panel focuses on low interest rate countries. Consistent with the theory, the figure shows that the positive correlation between trade credit and markups is stronger for exports to high interest rate countries.

Several other observations based on Figure 3 are noteworthy. First, trade credit differences in high- and low-interest rate destinations mostly come from firm-products with low markups. In contrast, firm-products charging high markups extend similar high levels of trade credit, regardless on whether destination has high or low borrowing rates. Second, one may argue that the relatively stronger relation between trade credit and markups in high interest rate destinations is due to other confounding factors, such as low financial development and contract enforcement. The fact that both panels control for destination-year fixed-effects mitigates this possibility, accounting for third factors affecting both high and low markup firm-products.[33] However, this does not completely dissipate questioning regarding identification. In the next section, we present a richer analysis based on regression analysis, allowing us to include additional controls and a richer set of fixed effect to control for alternative mechanisms.

Figure 3. Open Account Share, Markups and Interest Rates



Notes: The figures show the open account share and markups of Chilean firms. Markups are computed at the firm-product level following the methodology by De Loecker et al (2016). Open account share is computed at the firm-product-destination level. Panel A considers export destinations with borrowing rate above the median rate across destinations. Panel B considers export destinations with borrowing rate below the median rate across destinations.

5 Econometric Results

In this section, we test the theoretical predictions of the model we developed in section 2 using the Chilean customs-level data introduced in the previous section. We begin studying the predictions on the relationship between firm-product level markups and trade credit choice. Next, we explore how the length of trade relationships affects the choice of contract payment. Finally, we show results for trade credit and product prices.

[33] In a complementary exercise – available upon request – we split the sample further using using destination countries' rule of law and financial development. This exercise reveals that most of the effect in high interest rate destinations comes from the fact that low markup firms extend less trade credit to buyers in countries with low contract enforcement and financial development.

5.1 Trade Credit, Markups and Interest Rates

5.1.1 Baseline Results

We first test the theoretical predictions on the choice between open account (trade credit) and cash-in-advance. Table 2 presents results from the estimation of equation (36). In line with the model, the estimated coefficient for the markup has a positive sign and is highly significant across all specifications, suggesting that that firms that have a higher markup sell more on trade credit. Column 1 identifies the effect of firm-product markups on trade credit exploiting temporal variation within firm-destinations. Next, in columns 2-3 we study whether the inclusion of destination-year fixed effects changes the quantitative effect of markups on trade credit. As it can be seen, the coefficient on markups is largely unaffected by the inclusion of destination-year fixed-effects. Across specifications, the coefficient on markups is very stable and fluctuates between 0.019 and 0.021. In quantitative terms, the estimated effect suggests that an increase of one standard deviation in firm-product markup (37.3 percent), increases the likelihood of using trade credit by 70–78 basis points.[34]

[34]The moderate magnitude of the markups effect should not be surprising after considering the pervasiveness of trade credit use: in our sample, about 90% of the transactions involve trade credit (see Figure 1). Consequently, firm-products with already high open account share have a smaller margin to increase with markups, attenuating the effect of markups on trade credit. Below we revisit the question on the magnitude of the markup mechanism using a logit transformation on the open account share and show that the average response increases substantially using this alternative specification.

Table 2. Open Account Share and Firm-Product Markup: Baseline Regressions

Markup Proxy:	— Baseline —			Initial	Average
	(1)	(2)	(3)	(4)	(5)
log(markup)	.0202***	.0211***	.0185***	.0379***	.0731***
	(.00443)	(.00467)	(.00474)	(.0133)	(.0206)
ln(employment)	.00109	.00152	.00248	.000792	.000893
	(.00424)	(.00474)	(.00488)	(.00469)	(.00469)
Firm-Destination FE	✓	—	—	—	—
Year FE	✓	—	—	—	—
HS8 FE	✓	✓	—	✓	✓
Firm FE	—	✓	—	✓	✓
Destination-Year FE	—	✓	✓	✓	✓
Firm-HS8 FE	—	—	✓	—	—
Observations	93,507	93,507	93,507	93,507	93,507
R^2	.691	.368	.408	.368	.368

Notes: The table reports the coefficient estimates from equation (36). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Markups are computed at the firm-product level. Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

Next, we move to study whether reverse causality from trade credit choice to markups could explain the positive correlation reported in above. For this, we construct two alternative markup measures, first fixing markups at their value when firm-products are first observed in the sample (column 4, Table 2), and then, computing the average markup within firm-product across all years (column 5, Table 2). Note that by construction, both specifications shut-down all temporal variation within firm-products, and since we include firm and product fixed effects, the possibility of open account choice leading to higher markups is reduced to a great extent. Nevertheless, in both cases the coefficient on markups is positive and highly significant – despite the limited variation we exploit by imposing firm and product fixed effects.

Table 3 provides further evidence on the positive effect of markups on trade credit choice, restricting the sample to the set of firms with relatively low export participation. The aim of this exercise is to check the robustness of the baseline estimates when focusing on a sample where average markups mostly reflect firms' pricing decision in the domestic market. We report results for three different subsamples of firms, according to their overall export share. We begin with the sample of exporters with at most 50% export share, and then move to plants with less than 25%, and 10% export share. As can be seen, when using the baseline markup measure, coefficients lie between .021 and .036 – although the coefficient is less precisely estimated as we increasingly restrict the sample. Results in columns (4) through (6) replicate the exercise using markups fixed at their initial value within firm-products, while columns (7) through (9) use the average markup within firm-products. In all these cases, coefficient are positive, and highly significant, strengthening the evidence on the positive effect of markups on trade credit choice.

Table 3. Open Account Share and Markup – Sample of Firms with Low Export Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Markup measure	—— Baseline ——			—— Initial Markup ——			—— Average Markup ——		
Export share	< 50%	< 25%	< 10%	< 50%	< 25%	< 10%	< 50%	< 25%	< 10%
ln(markup)	.0357***	.0213*	.0251	.0723***	.1010***	.0952***	.1132***	.1298***	.0629*
	(.00903)	(.0122)	(.0194)	(.0181)	(.0208)	(.0289)	(.0255)	(.0287)	(.0357)
ln(employment)	-.0287***	-.0132	-.0189	-.0291***	-.0132	-.0184	-.0287***	-.0126	-.0189
	(.00759)	(.0122)	(.0206)	(.00761)	(.0122)	(.0205)	(.00761)	(.0122)	(.0205)
HS8 FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	40,011	26,655	14,762	40,011	26,655	14,762	40,011	26,655	14,762
R^2	.441	.493	.540	.441	.494	.541	.441	.494	.540

Notes: The table reports the coefficient estimates from equation (36). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Markups are computed at the firm-product level. Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

5.1.2 Interactions.

We now analyze the second main prediction of the model. According to our theory, the effect of markups on trade credit decreases in the seller's deposit rate and increases in the buyer's borrowing rate and the destination country's contract enforcement. This is an important check for the mechanism, as testing the interaction terms allows for the inclusion of a more complete set of fixed effects, thereby reducing concerns of omitted variable bias.

Table 4 present the results from estimating (37); we report standard errors clustered at the firm-destination level. Columns (1) through (4) show results using separate firm-year and product (defined at the 8-digit HS level) fixed-effects, while columns (5) through (8) use firm-product-year fixed effects. Consequently, in the latter set of regressions, the level of markups, and its interaction with the domestic lending rate is not identified.

Table 4. Open Account Share and Firm-Product Markup: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(markup)	-.0215	-.0182	-.0264	-.0373	—	—	—	—
	(.0199)	(.0310)	(.0316)	(.0328)				
ln(markup)×(r_b^*-r_d)	.291**	—	—	—	.308**	—	—	—
	(.121)				(.136)			
ln(markup)×r_b^*	—	.291**	.325***	.343***	—	.308**	.342**	.364**
		(.121)	(.126)	(.128)		(.136)	(.141)	(.143)
ln(markup)×r_d	—	-.661	-.612	-.682	—	—	—	—
		(2.487)	(2.489)	(2.492)				
ln(markup)× Law	—	—	.0211	—	—	—	.0212	—
			(.0151)				(.0164)	
ln(markup)× DomCred	—	—	—	.0234*	—	—	—	.0252*
				(.0123)				(.0134)
Firm-Year FE	✓	✓	✓	✓	—	—	—	—
HS8 FE	✓	✓	✓	✓	—	—	—	—
Destination-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm-HS8-Year FE	—	—	—	—	✓	✓	✓	✓
Observations	93,507	93,507	93,507	93,507	93,507	93,507	93,507	93,507
R^2	.420	.420	.420	.420	.437	.437	.438	.438

Notes: The table reports the coefficient estimates from equation (37). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Markups are computed at the firm-product level (product are defined at the 5-digit CPC level). All regressions control for the logarithm of firm employment. Standard errors (in parentheses) are clustered at the firm-destination level. Key: *** significant at 1%; ** 5%; * 10%.

Results in Table 4 confirm the main predictions of the model. In Column (1) the coefficient on the interaction between markups and the difference between the buyer's borrowing rate and the seller's deposit rate is positive and significant. Splitting the effects of the interest rate difference into the effects of the two individual interest rates in Columns (2) through (4) further confirms the theory. The coefficient on the seller's deposit rate, r_d, is negative and the coefficient on the buyer's borrowing rate, r_b^* is positive, although only the latter is statistically significant. The interaction interest rate terms have a similar quantitative effect as the baseline markup effect. Consider two firms at the 25th (markup 0.88) and 75th percentile (markup 1.47) of the markup distribution. A one standard deviation higher borrowing rate (4.5 percentage points) in the destination country makes trade credit use in about 77 basis points more likely. Columns (3) and (4) present results on contract enforcement using the destination country's rule of law index, and domestic credit in the destination countries as proxies for contract enforcement. As predicted by the theory, a stronger enforcement abroad strengthens the relationship between the markup and trade credit provision, although the coefficient on the interaction term is only significant at the 10% level for the latter case. Next, columns (5) through (8) repeat the analysis in the previous columns, but include firm-product-year fixed-effects. Results are largely consistent with estimates in the previous columns and the magnitudes of the coefficients are very stable, suggesting that the coefficients are most likely not subject to omitted variable bias occurring at the firm-product level.

To summarize, we find evidence that firms with larger markups extend more trade credit. Moreover, as predicted by the theory, this effect increases in the buyer's borrowing rate and the destination country's rule of law and decreases in the seller's deposit rate.

5.1.3 Robustness and Additional Results

We performed a number of robustness tests using alternative specifications, and considered a series of extensions. In this subsection we discuss the most important of them (in some cases we summarize the results without providing detailed tables; many of these, however, are provided in the Appendix and/or are available on request):

Translog Markups. One potential concern with respect to our results is that they rely on the correct estimation of markups. Our baseline markup measures are computed using input-ouput elasticities derived from a Cobb-Douglas production function (see equation 30). One shortcoming of this specification is that it imposes constant elasticities across all firms producing the same product. If firms with higher trade credit use have a lower input-output elasticity, then imposing constant input elasticities would lead us to overestimate the positive relationship between trade credit and markups. To analyze whether the Cobb-Douglas specification drives our results, in Table 5, we present results using markups derived from the more flexible translog production function, which allows for a rich set of interactions between the different inputs.[35] Columns (1) through (3) of Table 5 estimate the baseline level regression using average translog markups. As in the baseline case, the open account share

[35] We use a second order Translog specification. In this case, materials input elasticity varies with the usage of all input, and is computed as $\theta^M_{ipt} = \alpha^p_m + 2\alpha^p_{mm} m_{ipt} + \alpha^p_{km} k_{ipt} + \alpha^p_{lm} l_{ipt}$.

shows a strong positive relationship with markups. The coefficients in Table 5 are very similar and not statistically different than the baseline case (compare them with the corresponding coefficients in Table 2). This suggests that input elasticities do not systematically vary with trade credit across firm-products.[36]

Table 5. Markups and Open Account Share: Alternative Markup Proxies

Markup Proxy:	— Translog Markup —			— Avg. Price-Cost Margin —		
	(1)	(2)	(3)	(4)	(5)	(6)
log(markup)	.0205***	.0187***	.0206***	.0324***	.0324***	.0361*
	(.00452)	(.00447)	(.00493)	(.0116)	(.0116)	(.0187)
ln(employment)	.00645	.00222	.00526	.000602	-.00310	.000267
	(.00429)	(.00445)	(.00497)	(.00407)	(.00416)	(.00474)
Firm-Destination FE	✓	✓	—	✓	✓	—
Year FE	—	✓	—	—	✓	—
HS8 FE	—	✓	✓	—	✓	✓
Firm FE	—	—	✓	—	—	✓
Destination-Year FE	—	—	✓	—	—	✓
Observations	91,291	91,291	91,291	86,746	86,746	86,746
R^2	.664	.665	.368	.668	.669	.361

Notes: The table reports the coefficient estimates from equation (36). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Markups in columns 1–3 are computed at the firm-product-year level; average price-cost margins in columns 4–6 are computed at the firm-product level (products are defined at the 5-digit CPC level). Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

Average product margin. An additional proxy for markups that we can compute in our sample are product-level price-cost margins. ENIA report the variable production cost per product, defined as the sum of raw material and direct labor costs involved in the production of each product. Product margins can be derived dividing prices (unit values) over this reported measure of average variable cost. Note that average variable cost are self-reported by managers, making the application of rules of thumb likely. As we discuss in the Appendix, reported margins tend to align more closely with markups and other measures of profitability over longer time periods. Consequently, we use firm-product average margins computed over all periods as an alternative measure of markups. Columns (4) through (6) of Table 5 estimate our baseline level regression using average price-cost margins. As can

[36]In Table D.3 the appendix we replicate Table 4 using the interaction between translog markups, interest rates and rule of law. Again, results are very similar to the baseline Cobb-Douglas markups.

be seen, using margins as a proxy for markups does not affect our results qualitatively. Coefficients are significantly larger than in the baseline case, but the range of variation of the margins measure is smaller. Standard errors are slightly larger than in our baseline case, which is consistent with the more limited variation of the average margin measure (the unconditional standard deviation of average margins is about one-third smaller than in the Cobb-Douglas benchmark).

Censoring. The dependent variable we use to analyze the effect of markups on trade credit is a proportion with limited variation in the range 0-1. Since average trade credit is relatively high in our sample (around 90% according to Figure 1), using the open account share as the main dependent variable limits the potential response of trade credit use to markups for firm-products with initially high trade credit use. In Table 6 we revisit the question on the magnitude of the markup mechanism using a logit transformation on the open account share, to pull out its variation over all of the real numbers. We run the following specification:

$$\ln\left(\frac{\rho_{ijpt}}{1-\rho_{ijpt}}\right) = \beta_1 \ \ln(\mu_{ipt}) + \gamma_1 \ \ln(L_{it}) + \delta_i + \delta_p + \delta_{jt} + \epsilon_{ijpt}, \tag{40}$$

where ρ denotes the open account share. In this alternative specification, the marginal response of the open account share ρ to markups is non-linear and varies with the amount of trade credit use. In particular, it can be shown that the effect of log-markups over the open account share can be computed as $\beta_1 \times \rho_{ijpt} \times (1-\rho_{ijpt})$. Plugging in the coefficients from Table 6, leads to an estimated implied open account share-markup elasticity of 0.041-0.044 for firm-products with open account share equal to the mean (90 percent in our sample). This is almost twice the baseline coefficients estimated in Table 2.

Single-product firms. In order to estimate product-level and markups, we needed to assign inputs to individual outputs in multi-product plants. This is not needed in single-product plants, where inputs are used in the production of a single final product. Columns (1) through (3) in Table 7 use only the subset of single-product firms to estimate the relationship between markups and trade credit use following equation (36). Despite the fact that the sample is smaller, results for single-product plants remain statistically highly significant and quantitatively similar to the full sample, with a coefficient of 0.036-0.039.

Table 6. Logistic Open Account Share Transformation

	(1)	(2)	(3)
log(Markup)	.491***	.465***	.461***
	(.105)	(.102)	(.110)
ln(employment)	.0447	-.0535	.0250
	(.0999)	(.102)	(.113)
Implied Avg. Markup Semi-elasticity	.0442	.0419	.0415
Firm-Destination FE	✓	✓	—
Year FE	—	✓	—
HS8 FE	—	✓	✓
Firm FE	—	—	✓
Destination-Year FE	—	—	✓
Observations	93,507	93,507	93,507
R^2	.645	.646	.365

Notes: The table reports the coefficient estimates from equation (36) using a logistic transformation on the open account share as dependent variable. All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

Firm-level markups. An alternative strategy to determine the robustness of our results is to compute markups at the firm-level. As in the case of single-product firms, computing markups at the firm-level has the advantage that it avoids assigning inputs to individual outputs. Results in columns (4) through (6) in Table 7 show that coefficients remain quantitatively similar and stay statistically significant at the 1% level.

Further Robustness Checks. We performed a number of additional robustness checks; here we discuss the results shown in more details in the appendix. The descriptive evidence presented in section 4 suggests a nonlinear relationship between markups trade credit use in the raw data. However, when we include a quadratic markup term to the baseline regression, the coefficient – although negative – is typically small and statistically insignificant (t-statistic -0.20). In contrast, the linear markup term stays positive and its magnitude is very similar to the baseline linear specification.[37] We also tested whether adding further control affected the main relation between markups and trade credit. First, we added the

[37]We also tested potential non-linearities using markup quintiles instead of quadratic terms. Results provide no evidence of a non-linear relation between markups and trade credit use.

log FOB value of firm-product level exports to control for the size of the export shipments. The coefficient on the log FOB value is positive and statistically significant, but the markup coefficient stayed unchanged. Next, to test whether the existence of previous export relations could drive our results, we included the cumulative sum of the FOB value of all previous shipments of the same product to each destination. While the cumulative exports coefficient turned positive and statistically significant, the markup coefficient didn't vary significantly, confirming our main finding.

Table 7. Markups and Open Account Share: Alternative Markup Proxies

Sample/Markup Measure:	— Single-Product Firms —			— Firm-Level Markup —		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Markup)	.0359***	.0377***	.0385***	.0275***	.0272***	.0270***
	(.00726)	(.00745)	(.00782)	(.00511)	(.00510)	(.00536)
ln(employment)	-.0141**	-.0158***	-.0122	.00765*	.00365	.00566
	(.00586)	(.00598)	(.00746)	(.00420)	(.00436)	(.00486)
Firm-Destination FE	✓	✓	—	✓	✓	—
Year FE	—	✓	—	—	✓	—
HS8 FE	—	✓	✓	—	✓	✓
Firm FE	—	—	✓	—	—	✓
Destination-Year FE	—	—	✓	—	—	✓
Observations	44,589	44,589	44,589	94,184	94,184	94,184
R^2	.688	.719	.384	.661	.662	.370

Notes: The table reports the coefficient estimates from equation (36). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Markups in columns 1–3 are computed at the firm-product-year level; average price-cost margins in columns 4–6 are computed at the firm-product level (products are defined at the 5-digit CPC level). Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

5.2 Trade Credit and Repeated Interactions

We now turn to evidence on trade credit and seller-buyer relationship length. According to proposition 2, trade credit use tends to increase with the length of the relationships. Moreover, the effect is larger for more complex products. To test these predictions, we exploit the data at the transaction-level, and define relationships as in Antràs and Foley (2015) in terms of customer locations.

We begin exploring the relative use of financing terms in our data. Table 8 shows the share of transactions financed through the main contracts in our data. Two broad patterns emerge from the data. First, consistent with Figure 1, open account is the dominant financing contract in the data. Almost 90 percent of the transactions are paid for this way. In contrast, only 4 percent of the transactions are financed in cash-in-advance terms, and 5 percent in letters of credit terms. Second, when focusing in new customers, the dominance of open account is significantly dampened. Considering only first transactions for new export destinations, 73 percent of them occur on open account terms, 15 percent in cash-in-advance terms, and 8 percent in letter of credits terms. These patterns are strengthened when defining relationships at the location-product level. In this case, open account transactions decrease to 64 percent. Cash-in-advance increases to 20 percent, while the share of letters of credit remains unchanged.

This evidence is broadly consistent with results in Antràs and Foley (2015), and suggests that exporters tend to extend more trade credit to repeat as opposed to new customers. Note however, that this finding is more surprising than may be evident. Antràs and Foley (2015) studied the special case of a large U.S. food exporter. From the perspective of buyers, that firm was very reliable both because it was large and had been around for a long time and because it was located in the Unites States, a country with strong contract enforcement. In that special case, it is natural to start with cash-in-advance (or letters of credit) and then move to open account over time. Our empirical analysis show that this pattern holds for the universe of Chilean exporters: many relationships start on cash-in-advance terms and then move to open account. This general pattern does not follow from the basic trade finance model as developed in Schmidt-Eisenlohr (2013) and Antràs and Foley (2015) but can only be rationalized by the model with costly financial intermediation and positive markups derived in this paper.

Table 8. Relative use of Financing Terms (%)

	Open Account Share	Cash in Advance Share	Letter of Credit Share	Other Payment Forms
All customers	90.0	3.9	5.2	0.9
New Destinations	75.0	13.9	8.7	2.4
New Product and new Destination	67.9	16.6	8.6	6.9

Notes: The Table shows the percentage of transactions financed through open account terms (column 1), cash-in-advance terms (column2), letter of credit terms (column 3) and other forms of payment (column 4). 'New Destinations' and 'New Product and Destinations' only considers the first day of the relationship, defined at the destination and destination-product level, respectively.

Next, we look at the role of relationship length. We define relationship length as the cumulative number of transactions occurring from the beginning of the relationship.[38] A potential problem for computing this metric lies in the identification of the starting point of the relation. We avoid this issue using transaction level-data from 2001 – two year before the start of our sample – to identify the first time the firm exports to a given customer location.[39] In this way, we reduce the possibility of bias in our results coming from censoring on the starting date of the relationship. Note that we do not have a firm identifier in the destination country. So when we observe a firm's second trade transaction with a destination-product, we do not know if the firm sells to the same buyer or a new buyer. While we acknowledge this data limitation, we see our relationship length measure as a good proxy for the actual underlying relationship length at the firm-pair-product level.

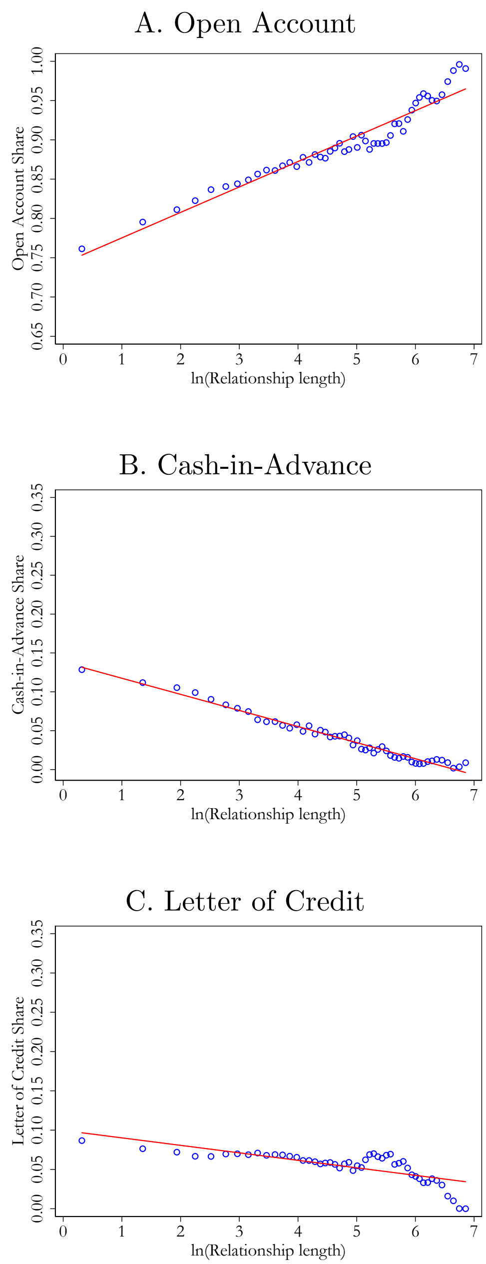
Figure 4 plots a binscatter diagram for the logarithm of relationship length and the average use of three main financing contracts in our data. Panel A shows that the use of open account increases almost monotonically with the length of the relationship. Only 75 percent of first transactions are financed in open account terms, but this percentage increases with the age of the relationship, until that eventually all relationships use open account. Panels B and C shows that the opposite occurs with transactions financed through cash-in advance and letters of credit: these contracts tend to be used at the beginning of a relationship, and cease to be used as a relationship ages. These evidence is consistent with

[38]An alternative definition of relationship length is in terms of cumulative FOB sales within the relationship. Since results are very similar to the main case, we relegate these results to the appendix.

[39]We have access to transaction-level data for the period 2001-2007, but we can only identify the use of trade credit in a reliable way for the period 2003-2007. This explains the shorter time span used in the main analysis involving trade credit use. See data section.

proposition 2.1, and suggests that firms are more likely to use trade credit as they learn about their partner's reliability.

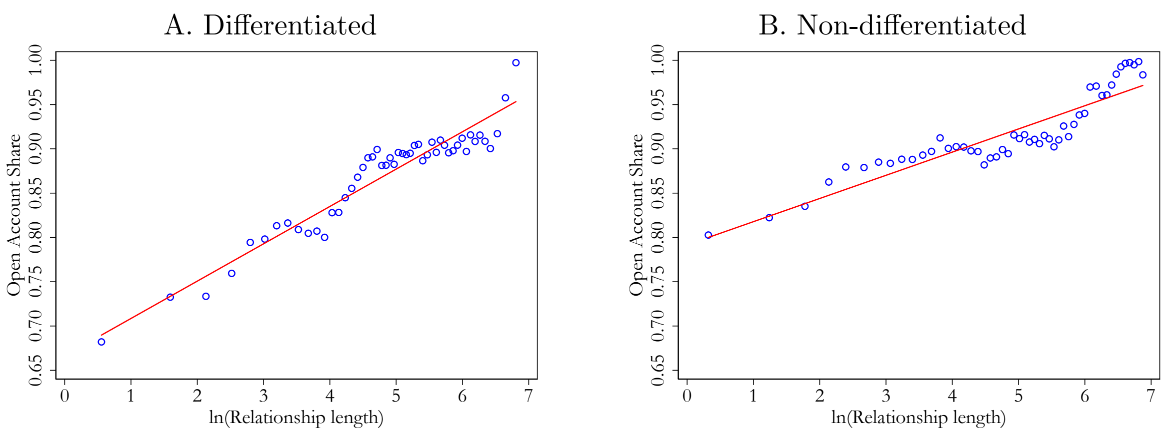
Figure 4. Open Account Share and the the Length of the Relationship



Notes: The figure plots the frequency of use of the three main financial contracts in the Chilean data, and the length of the buyer-seller relationship. Relationship length is defined as the cumulative number of transactions occurring from the beginning of the relation. Relationships are defined as customer locations as in Antràs and Foley (2015).

Finally, we study whether the pattern for open account and relationship length varies with the degree of product complexity. We proxy for product complexity using the degree of product differentiation, as defined by Rauch's (1999). Results are shown in Figure 5. The plots show that the pattern for the open account share and the length of the relationship is stronger for differentiated (left panel) than for non-differentiated products (right panel). This provides support to proposition 2.2: learning has a stronger effect on trade credit choice for differentiated (complex) products. According to our theory, this is due to the fact that contract enforcement is harder in more complex products and thus learning has a disproportionate effect on the payment choice for these products.

Figure 5. Relationships and Open Account Share



Notes: The figure plots the frequency of use of open account contracts and the length of the buyer-seller relationship. Differentiated products are defined (at the 6-digit HS level) according to the liberal product classification of Rauch (1999). Relationship length is defined as the cumulative number of transactions occurring from the beginning of the relation. Relationships are defined as customer locations as in Antràs and Foley (2015).

5.3 Trade Credit and Export Prices

We now turn to the price predictions of the model. Results are shown in Table 9. We first estimate equation (38). As Column (1)-(2) show, the buyer pays a strictly higher price to the seller when trade credit is provided. This is intuitive as the lower price both reflects the fact that the seller bears the financing costs and also faces the risk of non-payment by the buyer. We next present results in columns (3)-(4) on interactions between trade credit use and the destination country rule of law and the seller's borrowing rate (equation 39). In line with the model, the open account price decreases with the destination country's rule of law, and increases with the domestic borrowing rate.

Table 9. Trade Credit and Export Prices

	(1)	(2)	(3)	(4)
Open Account Dummy	.0213***	.0179***	-.0246	-.0302
	(.00679)	(.00685)	(.0269)	(.0266)
log(FOB sales)	—	.0154***	—	.0155***
		(.00243)		(.00243)
log(Cum. FOB sales)	—	.00238***	—	.00239***
		(.000472)		(.000472)
Open Account Interactions:				
$\times\ r_b$	—	—	1.395*	1.464**
			(.734)	(.724)
$\times\ \mathbb{I}_{LAW}$	—	—	-.0284*	-.0302*
			(.0155)	(.0157)
Firm-HS8-Destination FE	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓
Destination Year FE	✓	✓	✓	✓
Observations	1,006,903	1,006,903	1,006,903	1,006,903
R^2	.971	.971	.971	.971

Notes: The table reports the coefficient estimates from equation (38) (column 1-2) and (39) columns 3-4). All regressions are run at the level of individual export transactions for each firm-product-destination (with products defined at the HS8-level). Export prices (in logs) are computed as the ratio of FOB value and volume of the transaction. Standard errors (in parentheses) are clustered at the firm-product-destination level. Key: *** significant at 1%; ** 5%; * 10%.

The quantitative effect of trade credit on prices is moderate. According to columns (1)–(2), prices are 1.8%–2.1% higher when transactions are financed with trade credit. Results in columns (3)–(4) also show moderate effects for the domestic borrowing rate and the rule of law interactions. Consider the increase in the Chilean borrowing rate between 2003 (3.4%) and 2007 (4.6%). The results suggest that the higher rate in 2007 led prices to be 1.7% – 1.8% higher than in 2003. Our estimates show a similar quantitative effect for the rule of law interaction. In effect, in destinations with high contract enforcement, prices are between 2.8% and 3.0% lower.

6 Conclusions

Trade credit is the most important form of short-term finance for U.S. firms. This paper presented a theory that explains the prominence of trade credit for firm-to-firm transactions by the ability of firms to save on financial costs when there are positive markups and when financial intermediation is costly. The theory also predicts that trade credit use should become more prevalent the longer two firms trade with each other, an effect that should be stronger for complex products. Chilean firm-level data supports all predictions of the model.

The model is also qualitatively consistent with recent developments in aggregate U.S. data that show rising markups and more use of trade credit over time. Based on our model, the rise in markups identified by De Loecker and Eeckhout (2017) should affect financial markets. As higher markups make trade credit more attractive, firms may rely more on that financing form and less on the formal financial sector. Future work should shed more light on the macro implications of our findings and on how heterogeneity in the adoption of trade credit may affect the size and the development of the financial sector. The last point may be particularly relevant in the context of developing and emerging economies where financial frictions are larger and hence the potential savings from using trade credit more prominent.

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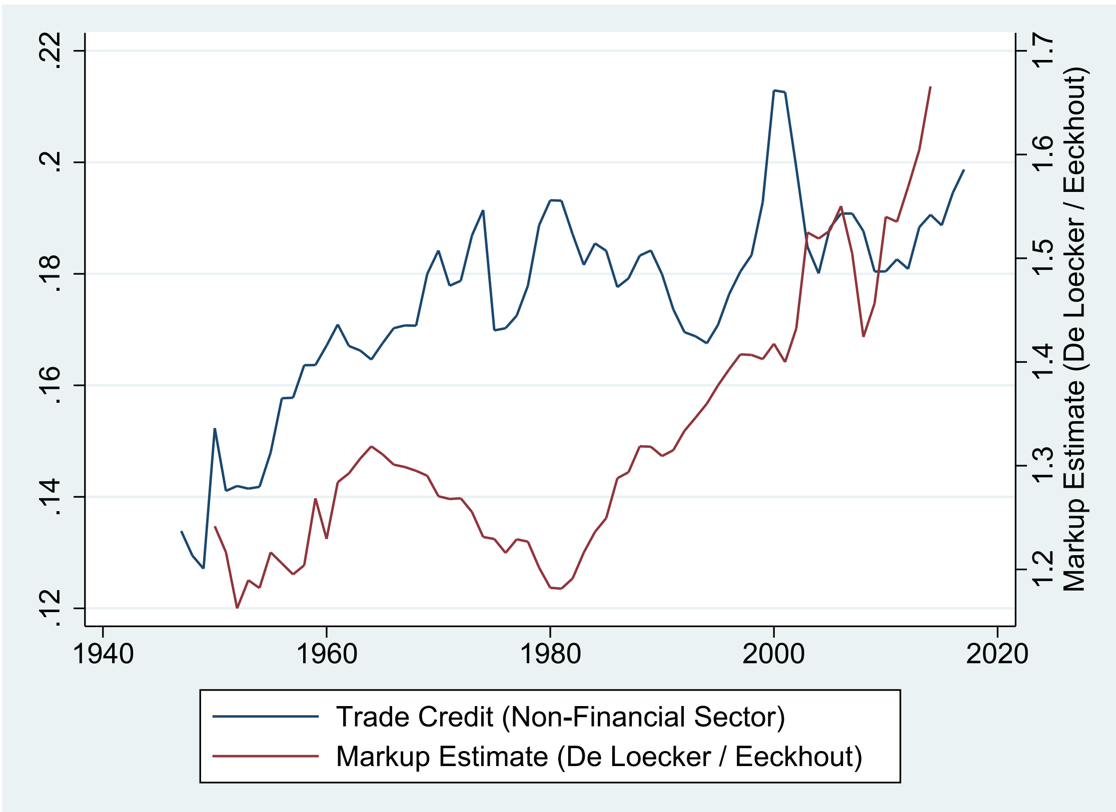
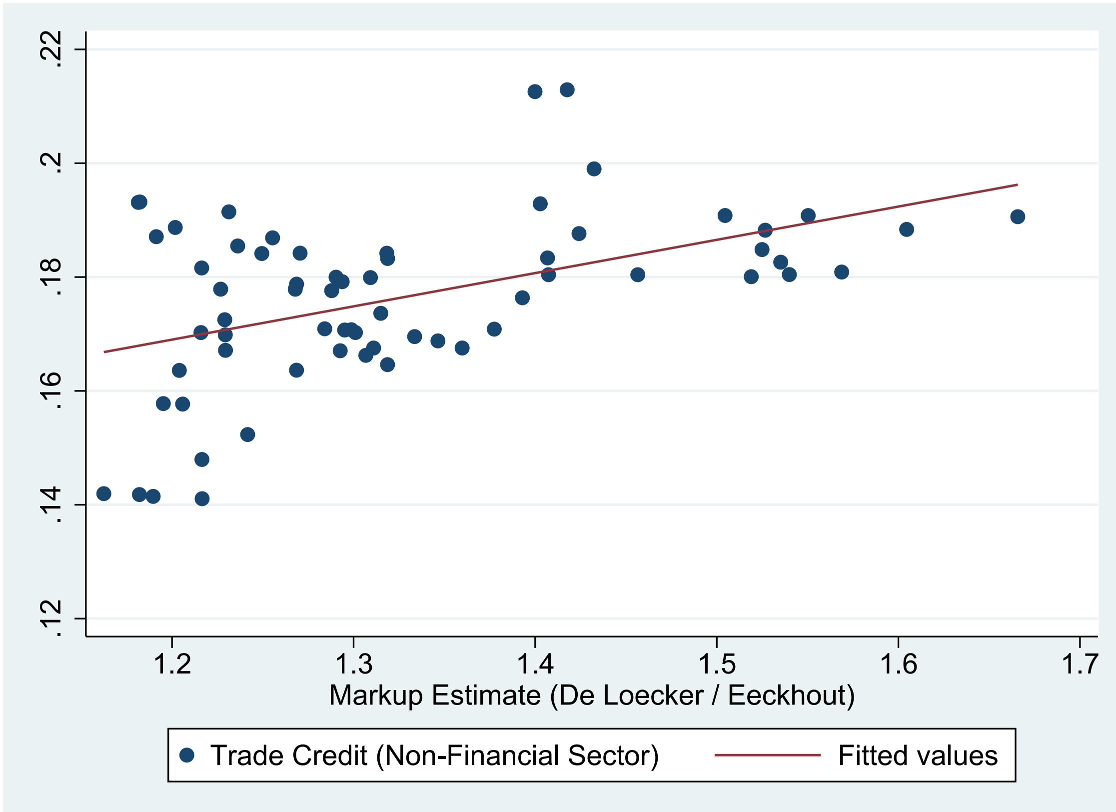
A Trade Credit and Markups in the United States over time

Figure A.1. Trade Credit and Markups in the U.S.



Notes: This figure shows the time series of the total trade credit receivables of the non-financial corporate and non-corporate sectors over GDP on the left Y-axis. On the right Y-axis it shows the markups as estimated by De Loecker and Eeckhout (2017).

Figure A.2. Trade Credit and Markups in the U.S.



Notes: This figure plots the total trade credit receivables of the non-financial corporate and non-corporate sectors against the markups as estimated by De Loecker and Eeckhout (2017).

B Theory Appendix

B.1 Derivation of Final Consumer Prices

In this subsection, we derive the prices charged to final consumers under CES preferences.

Open Account The Nash Product under Open Account is given by:

$$NP^{OA} = B^{OA}\left(\tilde{\lambda}^{*}R - (1+r_b)C\right), \tag{1}$$

with $B^{OA} = \theta^{\theta}(1-\theta)^{1-\theta}(\tilde{\lambda}^{*})^{\theta-1}$. Plugging in the demand $q = p_f^{-\sigma}A$ delivers:

$$NP^{OA} = AB^{OA}\left(\tilde{\lambda}^{*}(p_f^{OA})^{1-\sigma} - (1+r_b)c(p_f^{OA})^{-\sigma}\right), \tag{2}$$

Solving for the optimal price delivers:

$$p_f^{OA} = \frac{1+r_b}{\tilde{\lambda}^{*}}\frac{\sigma}{\sigma-1}c. \tag{3}$$

Cash in Advance The Nash Product under Cash in Advance is given by:

$$NP^{CIA} = B^{CIA}\left(\tilde{\lambda}R - (1+r_b^{*})C\right), \tag{4}$$

with $B^{CIA} = \theta^{\theta}(1-\theta)^{1-\theta}\left(\frac{1+r_d}{1+r_b^{*}}\right)^{\theta}$. Plugging in the demand $q = p_f^{\sigma}A$ delivers:

$$NP^{CIA} = AB^{CIA}\left(\tilde{\lambda}(p_f^{CIA})^{1-\sigma} - (1+r_b^{*})c(p_f^{CIA})^{-\sigma}\right), \tag{5}$$

Solving for the optimal price delivers:

$$p_f^{CIA} = \frac{1+r_b^{*}}{\tilde{\lambda}}\frac{\sigma}{\sigma-1}c. \tag{6}$$

B.2 Solving the model with CES

We can plug in the CES revenues R and total cost C into the Nash Product for Open Account to get:

$$NP^{OA} = \theta^{\theta}(1-\theta)^{1-\theta}\frac{c^{1-\sigma}}{\sigma-1}A\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}\left(\tilde{\lambda}^{*}\right)^{\theta-1+\sigma}(1+r_b)^{1-\sigma} \tag{7}$$

For Cash in Advance, we get:

$$NP^{CIA} = \theta^{\theta}(1-\theta)^{1-\theta}\frac{c^{1-\sigma}}{\sigma-1}A\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}(1+r_d)^{\theta}(1+r_b^{*})^{-\theta+1-\sigma}\left(\tilde{\lambda}\right)^{\sigma} \tag{8}$$

Combining the two conditions, we get that Open Account is preferred over Cash in Advance if:

$$\left(\tilde{\lambda}^{*}\right)^{\theta-1+\sigma}(1+r_b)^{1-\sigma} - (1+r_d)^{\theta}(1+r_b^{*})^{-\theta+1-\sigma}\left(\tilde{\lambda}\right)^{\sigma} > 0 \tag{9}$$

Or, rewriting for interpretation:

$$\left(\tilde{\lambda}^{*}\right)^{\theta-1}\left(\tilde{\lambda}^{*}\right)^{\sigma}(1+r_b)^{1-\sigma} - \left(\frac{1+r_d}{1+r_b^{*}}\right)^{\theta}(1+r_b^{*})^{1-\sigma}\left(\tilde{\lambda}\right)^{\sigma} > 0 \tag{10}$$

Within a country, the equation simplifies to:

$$\left(\tilde{\lambda}\right)^{\theta-1} - \left(\frac{1+r_d}{1+r_b}\right)^{\theta} > 0, \tag{11}$$

which always holds when $r_b > r_d$. We can also take the derivative of equation (22) with respect to σ. This delivers:

$$\left(\tilde{\lambda}^{*}\right)^{\theta-1+\sigma}(1+r_b)^{1-\sigma}\left(\ln\tilde{\lambda}^{*} + \ln\left(\frac{1}{1+r_b}\right)\right) - (1+r_d)^{\theta}(1+r_b^{*})^{-\theta+1-\sigma}\left(\tilde{\lambda}\right)^{\sigma}\left(\ln\tilde{\lambda} + \ln\left(\frac{1}{1+r_b^{*}}\right)\right)$$

B.3 Trade Credit and Wholesale Markup

In this appendix we show that proposition 1 also holds for the markup in terms of the wholesale price that the seller charges to the buyer.

Note that the Nash products for the open account (equation 3) and cash-in-advance cases (equation 6) can be written in terms of the ratio of their respective prices to marginal costs replacing $\tilde{\lambda}R$ and $\tilde{\lambda^*}R$ with the optimal open account and cash-in-advance prices:

$$NP^{OA} = \left(\frac{1-\theta}{\theta}\right)^{1-\theta} (\tilde{\lambda}^*)^{\theta} \left(P^{OA} - \frac{(1+r_b)}{\tilde{\lambda}^*} C^{OA}\right) \tag{12}$$

$$NP^{CIA} = \left(\frac{1-\theta}{\theta}\right)^{1-\theta} (1+r_d)^{\theta}(1+r_b^*)^{1-\theta} \left(P^{CIA} - C^{CIA}\right) \tag{13}$$

Recall from section 2.4 (under the CES assumption) that the buyer-seller open account price can be expressed in terms of the buyer-seller cash-in-advance price as:

$$P^{OA} = \frac{1+r_b}{\tilde{\lambda}^*} \left(\frac{1+r_b}{1+r_b^*}\right)^{-\sigma} \left(\frac{\tilde{\lambda}}{\tilde{\lambda}^*}\right)^{-\sigma} P^{CIA} \tag{14}$$

In addition, assuming CES, we can derive:

$$C^{OA} = C^{CIA} \left(\frac{p_f^{OA}}{p_f^{CIA}}\right)^{-\sigma} = C^{CIA} \left(\frac{1+r_b}{1+r_b^*}\right)^{-\sigma} \left(\frac{\tilde{\lambda}}{\tilde{\lambda}^*}\right)^{-\sigma} \tag{15}$$

Combining equations (12) and (13) implies that a buyer-seller pair chooses open account if:

$$\left(\frac{1-\theta}{\theta}\right)^{1-\theta} \left[\left(\frac{1+r_b}{1+r_b^*}\right)^{-\sigma} \left(\frac{\tilde{\lambda}}{\tilde{\lambda}^*}\right)^{-\sigma} (\tilde{\lambda}^*)^{\theta-1}(1+r_b) - (1+r_d)^{\theta}(1+r_b^*)^{1-\theta}\right] (P^{CIA} - C^{CIA}) > 0$$

Which can be simplified to:

$$\left[(\tilde{\lambda}^*)^{\theta-1+\sigma}(1+r_b)^{1-\sigma} - (1+r_d)^{\theta}(1+r_b^*)^{-\theta+1-\sigma}(\tilde{\lambda})^{\sigma}\right] \left(\frac{P^{CIA}/Q^{CIA}}{c} - 1\right) > 0 \tag{16}$$

Deriving the markups: Open Account Under CES preferences, note that:

$$\frac{R^{OA}}{C^{OA}} = \frac{p_f^{OA}}{c} = \frac{1+r_b}{\tilde{\lambda}^*}\frac{\sigma}{\sigma-1} \tag{17}$$

From this, we can derive that:

$$\mu_W^{OA} \equiv \frac{P^{OA}/Q^{OA}}{c} = \frac{1+r_b}{\tilde{\lambda}^*}\left(1+\frac{\theta}{\sigma-1}\right) \tag{18}$$

Deriving the markups: Cash in Advance For CIA, note that:

$$\frac{R^{CIA}}{C^{CIA}} = \frac{p_f^{CIA}}{c} = \frac{1+r_b^*}{\tilde{\lambda}}\frac{\sigma}{\sigma-1} \tag{19}$$

Which delivers:

$$\mu_W^{CIA} \equiv \frac{P^{CIA}/Q^{CIA}}{c} = 1+\frac{\theta}{\sigma-1} \tag{20}$$

C Additional Details on Markups Estimation

C.1 Input Price Index

In this appendix we explain the construction of the firm-specific price index we construct to deflate materials' expenditure at the firm-level. This is necessary to avoid that the production function parameters we estimate are affected by input price bias (see De Loecker and Goldberg, 2014, for details).

The construction of the firm-specific input price deflator involves five steps. First, we define the unit value of input j puchased by firm i in period t as $P_{ijt} = V_{ijt}/Q_{ijt}$, where V_{ijt} denotes input j value, and Q_{ijt} denotes the corresponding quantity purchased. Next, we calculate the (weighted) average unit value of input j across all firms purchasing the input at time t. Then, for each firm we compute the (log) price deviation from the (weighted) average for all the inputs purchased by the firm at time t. The next step involves averageing the resulting price deviations at the firm level, using inputs' expenditure as weight.[1] Finally, we anchor the resulting average firm-level input price deviation to aggregate (4-digit) input price deflators provided by the Chilean statistical agency. Therefore, the resulting input price index reflects both, changes in the aggregate input price inflation, as well as firm-level heterogeneity in the price paid by firms for their inputs.

C.2 Markups and its relation with self-reported average margins

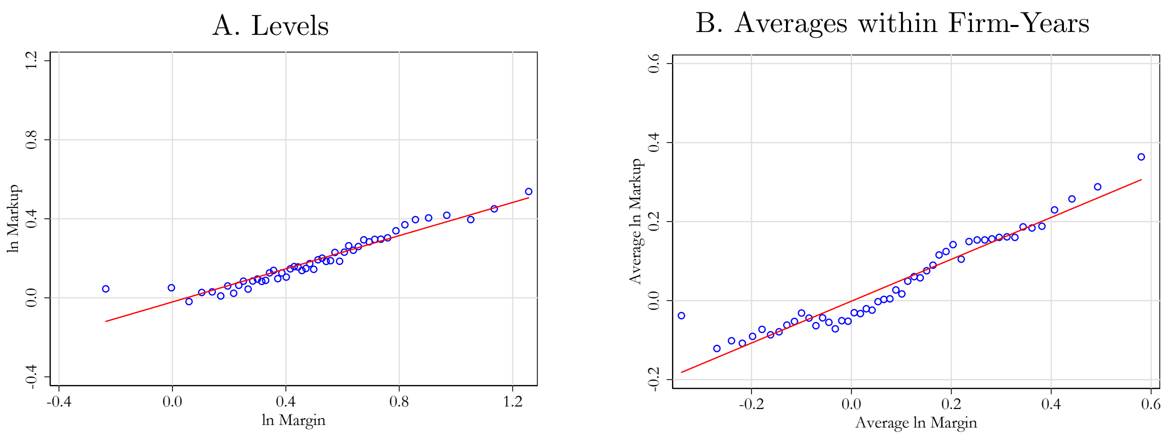
A unique feature of ENIA is that it provides information for the variable production cost per product defined as the product-specific sum of raw material costs and direct labor involved in production). Consequently, dividing sales by the reported total variable cost by the units produced of a given product yields the average product margin that we use as an alternative rough approximation for markups in the main text.

Figure C.1 plots binscatters diagram for firm-product markups and sales-cost margins (with products defined at the HS-8 level), for the raw data (left panel), and averaging across

[1] Note that up to this point we have derived a unit-free input price index, that can be interpreted as the average firm-level input price deviation from the average. However, this price index will fail to detect aggregate changes in input prices.

observations within firm-product pairs (right panel). Both figures control for country-year fixed effects (that is, the figure plots the within plant-product variation that we exploit empirically). There is a remarkable positive relationship between markups and reported margins, suggesting that our markup estimates yield sensible information about the profitability for the products produced by the firm. This lends strong support to the markup-based methodology for backing out marginal costs by De Loecker et al. (2016). In addition, there seems to be a tighter relationship between markups and margins when both variables are averaged within firm-products.[2] Consequently, in the main text we use firm-product average margins computed over all periods for as an alternative measure of markups (see Table 5).

Figure C.1. Firm-Product level Markup and Sales-Cost Margin



Notes: The figure plots a binscatters diagram for firm-product markups and sales-cost margins. Both plots controls for country-year fixed effects.

For completeness, Table D.2 replicates columns (4)-(6) of Table 5 using sales-cost margin in levels. As it can be seen, the positive relationship reported in the main text remains, but the magnitude and statistical significance of the coefficients are smaller than in the baseline analysis.

[2]One reason why both measures could be more correlated over longer periods of time is that the sales-cost margin measure relies on self-reported average variable cost. If managers measure product-level variable costs with error, then sales-cost margin may be a poorer approximation of markups in the short run. However, if managers does not make systematic mistakes when reporting average variable costs, the measurement error cancels out when averaging over longer periods.

D Additional Results

D.1 Average Markups by 2-digit industries

This appendix performs a number of additional robustness checks. Table D.1 presents the estimated markups at the level of 2-digit industries. Note that the average markups are somewhat lower than the average markups estimated for the entire manufacturing industry in Garcia-Marin and Voigtländer (2018).

Table D.1. Estimated Markups

Product	Mean	Median	St. Deviation
Food and Beverages	1.344	1.2189	0.5711
Textiles	1.581	1.4491	0.6420
Apparel	1.267	1.2261	0.4649
Wood and Furniture	1.123	1.0070	0.4455
Paper	1.273	1.1214	0.5687
Basic Chemicals	1.389	1.2236	0.6555
Plastic and Rubber	1.241	1.0924	0.5305
Non-Metallic Manufactures	1.779	1.5555	0.8774
Metallic Manufactures	1.316	1.0241	0.7156
Machinery and Equipment	1.146	1.0102	0.4986
Total	1.318	1.178	0.583

Notes: This table reports the estimated markup by aggregate sector for the sample of exporting firms over the period 2003-2007 (see section 3.1 for details on the computation). Columns 1 displays the unweighted average markup.

Table D.2. Sales-cost Margin (levels) and Open Account Share

	(1)	(2)	(3)
log(markup)	.0102**	.00902*	.00692
	(.00500)	(.00498)	(.00591)
ln(employment)	-.000829	-.00425	-.00141
	(.00418)	(.00428)	(.00494)
Firm-Destination FE	✓	✓	—
Year FE	—	✓	—
HS8 FE	—	✓	✓
Firm FE	—	—	✓
Destination-Year FE	—	—	✓
Observations	87,295	87,295	87,295
R^2	.662	.663	.368

Notes: The table replicates columns (4)-(6) of Table 5 using sales-cost margin in levels. All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

Table D.3. Translog Markups and Open Account Share: Heterogeneity

	(1)	(2)	(3)
log(markup)	-.0150	-.00642	-.0161
	(.0203)	(.0292)	(.0299)
ln(markup)$\times r_b^*$	.205*	.205*	.247**
	(.107)	(.107)	(.112)
ln(markup)$\times r_d$	—-	-.978	-.892
		(2.370)	(2.373)
ln(markup)$\times$ Law	—	—	.0251
			(.0161)
Firm-year FE	✓	✓	✓
HS8 FE	✓	✓	✓
Destination-Year FE	✓	✓	✓
Observations	91,291	91,291	91,291
R^2	.421	.421	.421

Notes: The table reports the coefficient estimates from equation (36). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Open account shares are computed as the ratio of the FOB value of open account transactions to the FOB value of all export transactions over a year. Markups are computed at the firm-product-year level (products are defined at the 8-digit HS level). Standard errors (in parentheses) are clustered at the destination-year level. Key: *** significant at 1%; ** 5%; * 10%.