Trade Credit and Markups*

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Abstract

Trade credit is the most important form of short-term finance in international trade. 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. 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

JEL Classification:

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*The views expressed are the authors' and do not necessarily represent the views of the Federal Open Market Committee, its principals, or the Board of Governors of the Federal Reserve System.

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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. 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.[1] 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.[2] 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 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.

[1] 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".

[2] 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 (2017) 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.

We test the model with Chilean data. First, we construct markup estimates at the firm-product level using detailed data on inputs and outputs of Chilean plants using the methodology developed by De Loecker and Warzynski (2012). We then use transaction-level trade data with information on the payment choice to test the predictions of the model. We find that trade credit use increases in the markup and that this effects is larger the bigger the difference between the buyer's borrowing rate and the seller's deposit rate.[3] In line with the model's prediction, the effect of the markup also increases in the destination country's rule of law. The results are robust to the inclusions of a large set of fixed effects and other controls.

The model also has predictions on the pricing of transactions between importers and exporters.[4] In general, buyers have 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 for trade credit falls in the destination country's rule of law. We do not find a significant effect for the interest rate interaction, which may in parts be due to the limited variation in that variable.

The paper contributes to the large and growing literature on trade credit.[5] 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.[6] Smith (1987) and Biais and Gollier (1997) show that firms may extend trade credit

[3]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.

[4]Schmidt-Eisenlohr (2013) and Antràs and Foley (2015) also derived price predictions in a payment terms model. We extend the analysis and test it with comprehensive transaction-level trade data.

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

[6]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

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.

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".[7] 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

and trade credit use. On price discrimination through trade credit, see also Schwartz and Whitcomb (1979) and Mian and Smith (1992).

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

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 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 or the relative markup between the buyer and the seller.

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. More recently, Giannetti et al. (2011) and Klapper et al. (2012) further tested theories of trade credit with contract data.[8] Most 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 studying 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.[9] Demir and Javorcik (2018) study Turkish export data and show that an

[8]See also Barrot (2016), Murfin and Njoroge (2014).

[9]See among others Schmidt-Eisenlohr (2013), Antràs and Foley (2015), Hoefele et al. (2016), Ahn (2010) and Niepmann and Schmidt-Eisenlohr (2017).

increase in competition by sellers from other countries leads to more trade credit provision by Turkish exporters. Interestingly, the effect of competition in Demir and Javorcik (2018) goes in the opposite direction than what our model predicts on markups. More competition typically implies lower markups. In our model, lower markups translate into less trade credit provision by the seller.

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.

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 specification, and presents the methodology for deriving firm-product markups. 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.[10] 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.[11]

2.1 Model setup

One buyer is matched with one seller. Both firms are risk neutral. A fraction η (η^*) of buyers (sellers) is reliable, that is these firms always fulfill their contracts.[12] 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 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. Assume that the seller has all bargaining power. 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^*).

[10] 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.

[11] 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.

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

Open Account Under open account (trade credit), the seller solves the following problem:

$$\begin{aligned} \max_{P^{OA}} \mathrm{E}\left[\Pi_s^{OA}\right] &= \tilde{\lambda}^* P^{OA} - (1+r_b)C \\ \text{s.t. } \mathrm{E}\left[\Pi_b^{OA}\right] &= R - P^{OA} \geq 0, \end{aligned} \tag{1}$$

where P^{OA} is the total payment from the buyer to the seller. The first equation 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 equation represents the participation constraint of the buyer. The buyer has to generate revenues that are at least equal to the price paid to the seller. As the seller has all bargaining power, it sets $P^{OA} = R$. Expected profits under open account are thus:

$$\mathrm{E}\left[\Pi_s^{OA}\right] = \tilde{\lambda}^* R - (1+r_b)C \tag{2}$$

Cash-in-Advance Under cash-in-advance, the seller solves the following problem:

$$\begin{aligned} \max_{P^{CIA}} \mathrm{E}\left[\Pi_s^{CIA}\right] &= (1+r_d)(P^{CIA} - C) \\ \text{s.t. } \mathrm{E}\left[\Pi_b^{CIA}\right] &= \tilde{\lambda} R - (1+r_b^*)P^{CIA} \geq 0, \end{aligned} \tag{3}$$

The first equation 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.[13] 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 equation is the participation constraint 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

[13] The reliable sellers are the ones that determine contracts in equilibrium. See Schmidt-Eisenlohr (2013) and the appendix for details.

r_b^*. The seller now chooses $P^{CIA} = \frac{\tilde{\lambda}}{1+r_b^*}R$ which implies expected profits of:

$$\mathrm{E}\left[\Pi_s^{CIA}\right] = (1+r_d)\left(\frac{\tilde{\lambda}R}{(1+r_b^*)} - C\right) \tag{4}$$

Combining equations (2) and (4) implies that a seller prefers open account (trade credit) if:

$$\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right] > 0 \Leftrightarrow R\left[\tilde{\lambda}^* - \tilde{\lambda}\frac{1+r_d}{1+r_b^*}\right] - C\left(r_b - r_d\right) > 0 \tag{5}$$

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

$$\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right] > 0 \Leftrightarrow cq\left[\mu\left(\tilde{\lambda}^* - \tilde{\lambda}\frac{1+r_d}{1+r_b^*}\right) - (r_b - r_d)\right] > 0 \tag{6}$$

2.2 Trade Credit and Markups

Proposition 1 (Trade Credit and the Cost of Financial Intermediation) *Consider two firms facing the same level of contract enforcement λ and interest rates r_b and r_d. All else equal, open account (trade credit) implies lower total financing costs than cash-in-advance if firms charge positive markups ($\mu > 1$) and if there are financial intermediation costs leading to an interest spread on borrowing $r_b > r_d$.*

Proof. See equation (9). ■

Proposition 1 provides a clear rationale for the dominance of trade credit in firm-to-firm relationships, namely saving on costly intermediation by the financial sector. When there is a positive markup and a spread between the borrowing and deposit rate, then trade credit implies lower financing costs than cash-in-advance. Why is this so? Under cash-in-advance, the buyer has to prepay the whole revenues that will be generated from the transaction R. Assuming that the buyer has no extra liquidity available, it has to borrow the amount R from its bank at rate r_b. The seller receives the funds in advance and can deposit them at a rate r_d. The total net financing costs for both firms together are hence:

$$(1+r_b)R - (1+r_d)(R-C) = (r_b - r_d)R + (1+r_d)C. \tag{7}$$

Now consider the alternative of open account (trade credit). The seller pre-finances its production cost C at borrowing rate r_b while the buyer does not have to do any financing. Total financing costs are then:

$$(1+r_b)C. \tag{8}$$

Financing costs under cash-in-advance minus financing costs under open account are then:

$$(r_b - r_d)R + (1+r_d)C - (1+r_b)C = (r_b - r_d)(R-C) = (r_b - r_d)(\mu - 1)cq \tag{9}$$

Hence, financing costs under cash-in-advance are strictly larger than financing costs under open account if there is a positive interest rate spread $r_b > r_d$ and if firms charge a positive markup $\mu > 1$. The interest rate spread $r_b - r_d$ caused by financial intermediation costs generates an advantage for open account over cash-in-advance. As the seller only needs to pre-finance production costs while the buyer needs to pre-finance the full purchase price, both parties can save on their joint financing costs by trading on open account whenever there is a positive markup.

Proposition 2 (Trade Credit and Markups) *Suppose* $\tilde{\lambda}^*(1+r_b^*) > \tilde{\lambda}(1+r_d)$. *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. Define $\Delta \mathrm{E}\Pi = \mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right]$; i) $\frac{\partial \Delta \mathrm{E}\Pi}{\partial \mu} = \left(\tilde{\lambda}^* - \tilde{\lambda}\frac{1+r_d}{1+r_b^*}\right) cq > 0$; ii.a) $\frac{\partial \Delta \mathrm{E}\Pi^2}{\partial \mu\, \partial r_b^*} = \tilde{\lambda}\frac{1+r_d}{\left(1+r_b^*\right)^2} cq > 0$; ii.b) $\frac{\partial \Delta \mathrm{E}\Pi^2}{\partial \mu\, \partial r_d} = -\frac{\tilde{\lambda}}{1+r_b^*} cq < 0$; ii.c) $\frac{\partial \Delta \mathrm{E}\Pi^2}{\partial \mu\, \partial \lambda} = -(1-\eta)\frac{1+r_d}{1+r_b^*} cq < 0$; ii.d) $\frac{\partial \Delta \mathrm{E}\Pi^2}{\partial \mu\, \partial \lambda^*} = (1-\eta^*)cq > 0$. ■

Proposition 2 derives additional predictions to test the mechanism explaining trade credit use. In particular, trade credit use should increase in the markup. And 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

Consider now the case where an importer and an exporter interact repeatedly. Assume that the two trading partners learn over time about the type / 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. Consider the trade-off between trade credit and cash-in-advance within the same country. Equation (6) then simplifies to:

$$\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right] > 0 \Leftrightarrow cq\left[\mu\tilde{\lambda}_k\left(1 - \frac{1+r_d}{1+r_b}\right) - (r_b - r_d)\right] > 0,$$

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.[14] Taking the derivative with respect to λ delivers:

$$\frac{\partial\left(\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right]\right)}{\partial\lambda_k} = \mu\left(1 - \frac{1+r_d}{1+r_b}\right)(1-\eta) > 0 \Leftrightarrow r_b > r_d.$$

That is, as long as the borrowing rate exceeds the deposit rate, open account becomes more attractive the more often the two firms interacted with each other.

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

[14] 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.

becomes:

$$\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right] > 0 \Leftrightarrow cq\left[\mu\tilde{\lambda}_k(\gamma)\left(1 - \frac{1+r_d}{1+r_b}\right) - (r_b - r_d)\right] > 0,$$

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

$$\frac{\partial\left(\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right]\right)}{\partial\lambda_k} = \mu\left(1 - \frac{1+r_d}{1+r_b}\right)(1-\eta)\gamma\left(\lambda_k\right)^{\gamma-1} > 0 \Leftrightarrow r_b > r_d.$$

Taking the derivative with respect to γ delivers:

$$\frac{\partial^2\left(\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{CIA}\right]\right)}{\partial\lambda_k\partial\gamma} = \mu\left(1 - \frac{1+r_d}{1+r_b}\right)(1-\eta)\left(\lambda_k\right)^{\gamma-1}\left(1 + \ln(\lambda_k)\right) > 0.$$

This derivative is positive if $r_b > r_d$ and if $\lambda_k > e^{-\gamma}$. As $\gamma \in [0,1]$, a sufficient condition is: $\lambda_k > 1/e$, which following Hoefele et al. (2016) we assume to hold always.

Proposition 3 (Trade Credit and Learning) *Suppose two firms in the same country trade with each other and learning is symmetric. Then:*

1. *Payment is more likely on open account (trade credit) terms, the longer the two firms have traded.*

2. *This effect is stronger for more complex products.*

[Add theory argument from antras and foley on bank learning about buyer]

The proposition is quite intuitive. The longer two firms trade with each other, the more likely they will fulfill their contracts. As trade credit is the preferred payment choice when only financing costs matter, it becomes more attractive for longer-lasting relationships, as the countervailing force of enforcement frictions becomes weaker. The second part of the proposition states that the effect of repeated interactions is stronger for complex products. This is the case as complex products have stronger enforcement frictions to begin with, so that learning has a disproportionate effect on the payment choice for these products.

2.4 Price Predictions

We now develop additional predictions on the relationship between the payment terms and prices. From now on, let revenues and final sales prices be endogenous to the payment form. Then, under open account, the seller sets the payment by the buyer to $P^{OA} = R^{OA}$. The intermediate price paid by the buyer per unit, p_i^{OA}, is hence equal to the final sales price which we denote as p_f^{OA}. Under cash-in-advance, the optimal payment by the buyer is set to $P^{CIA} = \frac{\tilde{\lambda}}{1+r_b^*} R^{CIA}$. The intermediate price paid by the buyer per unit is then $p_i^{OA} = \frac{\tilde{\lambda}}{1+r_b^*} p_f^{CIA}$. The relative price between open account and cash-in-advance is hence given by:

$$\frac{p_i^{OA}}{p_i^{CIA}} = \frac{(1+r_b^*)}{\tilde{\lambda}} \frac{p_f^{OA}}{p_f^{CIA}}. \tag{10}$$

Now, assume that firms operate under monopolistic competition and that consumers have standard CES preferences of the form $q = p^{-\sigma} A$.[15] We can then solve for the optimal final sales prices as:

$$p_f^{OA} = \frac{1+r_b}{\tilde{\lambda}^*} \frac{\sigma}{\sigma-1} c \quad p_f^{CIA} = \frac{1+r_b^*}{\tilde{\lambda}} \frac{\sigma}{\sigma-1} c. \tag{11}$$

Plugging this into equation (10) delivers:

$$\frac{p_i^{OA}}{p_i^{CIA}} = \frac{(1+r_b)}{\tilde{\lambda}^*} > 1. \tag{12}$$

Proposition 4 *The price charged by the seller to the buyer is always 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 abroad λ^*.*

Proof. *See equation* (12). ■

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.

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

The seller hence needs to be compensated for these two factors implying a higher unit price paid by the buyer. Interestingly, under CES preferences, this price ratio is independent of who has the bargaining power.

3 Estimating Firm-Product Level Markups

A key variable in our empirical analysis are firm-product markups. While there exist many different methodologies for deriving markups, in this paper we follow the methodology proposed by De Loecker and Warzynski (2012). The main advantage of this methodology is that it allows to compute markups without relying on 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 to derive De Loecker and Warzynski's 2012 markup formula, 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; $s^V_{ipt} \equiv P^V_{ipt} V_{ipt} / P_{ipt} Q_{ipt}$):[16]

$$\underbrace{\mu_{it}}_{\text{Markup}} \equiv \frac{P_{it}}{MC_{it}} = \frac{\theta^V_{ipt}}{s^V_{it}} , \tag{13}$$

where P (P^V) denotes the price of output Q (input V), and MC is marginal cost. While the numerator of equation (13) – 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.

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

[16]Note that under perfect competition, the output elasticity equals the expenditure share, so that the markup is equal to one.

inputs:

$$Q_{ipt} = \Omega_{it} F(K_{ipt}, L_{ipt}, M_{ipt}) \tag{14}$$

where Q is physical output, and Ω denotes firm's productivity. There are three important assumptions on equation (14). 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 (14) follows De Loecker et al. (2016) in using the subset of single-product firms to identify the coefficients of the production function.[17] 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).[18]

Our baseline specification assumes a Cobb-Douglas production function, and allows for the presence of a log-additive non-anticipated shock (ε).[19] Taking logs to (14), we obtain

$$q_{ipt} = \alpha_k^j k_{ipt} + \alpha_l^j l_{ipt} + \alpha_m^j m_{ipt} + \omega_{it} + \varepsilon_{ipt} \tag{15}$$

The estimation of (15) 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.[20] To identify the coefficients of the production function, we build moments based on the productivity innovation ξ. We specify the following process for the law of

[17]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.

[18]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 for a detailed explanation on the construction of the price index we use in our sample of Chilean firms.

[19]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.

[20]ACF show that the labor elasticity is in most cases unidentified by the two-stage method of Olley and Pakes (1996) and Levinsohn and Petrin (2003).

motion of productivity:

$$\omega_{it} \;\; = \;\; g(\omega_{it-1}, d^x_{it-1}, d^i_{it-1}, d^x_{it-1} \times d^i_{it-1}, \hat{s}_{it-1}) + \xi_{it} \tag{16}$$

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 (16) 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 (15).[21] 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 (16) 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:

$$\mathbb{E}(\xi_{it}(\boldsymbol{\alpha}) \cdot \mathbf{Z}_{it}) \;\; = \;\; 0 \tag{17}$$

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.[22]

[21] 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.

[22] 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.

Expenditure share. The computation of the expenditure share for multi-product firms require to assign inputs to each output 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} is computed as

$$M_{ipt} \;=\; \rho_{ipt} \cdot M_{it}, \quad \text{where} \quad \rho_{ipt} \;=\; \frac{TVC_{ipt}}{\sum_j TVC_{ipt}}. \tag{18}$$

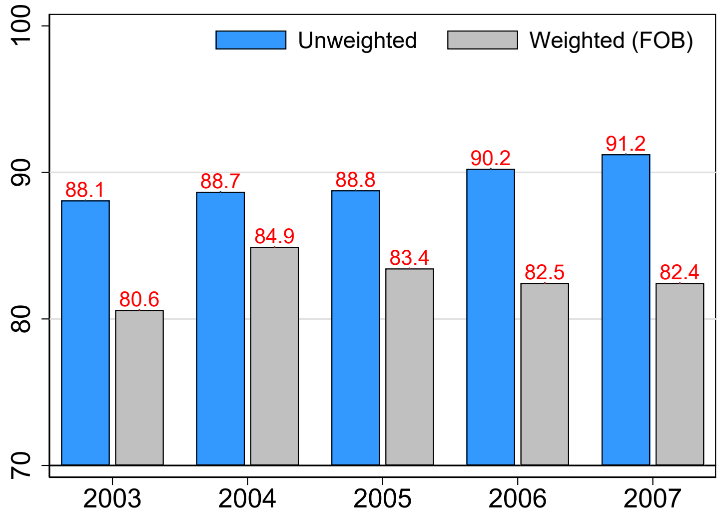
Implementation. To compute markups, we use materials as the relevant flexible input for deriving markups. While in principle, labor could also be used to compute markups, the existence of long-term contracts and firing costs make firms less likely to adjust labor after the occurrence of shocks.

4 Data

We use two main datasets to study the role of markups on the choice of trade credit. 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. 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, and the FOB value and volume of the merchandise, and the financing mode of the export transaction. 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. 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).

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.

There is, however, a large variation in the use of open account across firms and destinations that we exploit to test the theory. To illustrate this, we show in Table 1 the R-squared, adjusted R-squared and standard deviation of the residuals from running a simple regression of an open account dummy on different sets of fixed effects. When controlling for destination-year fixed effects (second row), the standard deviation of the residual variable falls less than one-tenth, from .30 to .28. The firm-destination margin seems quantitatively more relevant. When controlling for firm-product-year fixed effects (third row), the residual standard deviation falls about 30 percent, from .30 to .23. As it can be seen in the fourth row, the overall picture does not change much when both margins are considered at the same time. In this case, the residual standard deviation falls to 0.22.

We complement the transaction-level data from customs with production-level data from the *Encuesta Nacional Industrial Anual* (Annual National Industrial Survey – ENIA). ENIA

Table 1. Open Account Variation within firm-product and destinations

	Explanatory Power		Std. Dev.
Fixed Effects	R^2	Adj. R^2	Residual
None	.0000	.0000	.3007
Country-year (dt)	.1336	.1333	.2799
Firm-HS8-year (ijt)	.3854	.3724	.2336
Country-year + Firm-HS8-year (dt,ijt)	.4474	.4355	.2216

Notes: The table show the R-squared, adjusted R-squared and standard deviation of the residuals from a simple regression of open account dummy at the transaction-level against different sets of fixed effects to illustrate relevance of different margins.

is collected by the Chilean National Statistical Agency (INE), and it 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 a firm identifier, allowing to consolidate plants at the firm-level, and to merge the resulting dataset to customs.

In addition to plants' information, ENIA contains detailed information for each good produced (sales value, production 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.[23]

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 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

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

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 determine the list of HS products that could potentially be matched to each CPC product in ENIA.[24] 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.

Our baseline analysis exploit information at the annual level for each firm-product-destination. This requires us to collapse data from customs at the annual level (adding the FOB value and volume at the firm-HS8-destination-year level) and then merge the resulting dataset to ENIA following the steps described above. To ensure a consistent dataset, we follow three steps. First, we exclude plant-product-year observations that have zero values for raw materials expenditure, sales, or product quantities. Second, we trimmed the top and bottom 2 percentiles of the markup distribution. Third, a similar adjustment is applied to real borrowing rates, to avoid the influence of extreme values resulting from inflationary or deflationary episodes.[25] Our final dataset comprises 125,315 firm-product-destination-year observations. Table 1 provides summary statistics for the final dataset.[26]

[24]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.

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

[26]Appendix A provides more detailed summary statistics for markups, aggregated at the 2-digit level.

Table 2. Summary Statistics

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Transaction Characteristics						
Open Account Dummy	0.8995	0.3007	1	1	1	1,077,159
Export Value (US$)	1.3938	1.6095	0.4662	1.1780	1.8998	1,077,154
Unit Value (in logs)	85,948.4	610,749.4	3,708.0	13,438.3	35,567.9	1,077,159
# Transactions by firm-product-year	30.1	135.8	1	4	16	29,678
# Destinations by firm-product-year	3.1	4.5	1	1	3	29,678
Firm Characteristics						
Employment	235.8	477.1	42	95	238	4,637
Markups (at the firm-CPC level)	1.260	0.595	0.858	1.095	1.468	6,790
Country Characteristics						
Rule of Law Index	0.36265	1.01136	-0.56812	0.38070	1.26599	350
Foreign borrowing rate	0.05447	0.04482	0.02722	0.04513	0.06924	350
Chilean deposit rate	0.00923	0.00588	0.00879	0.00883	0.01202	350
Chilean borrowing rate	0.03993	0.00445	0.03625	0.04072	0.04263	350

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.

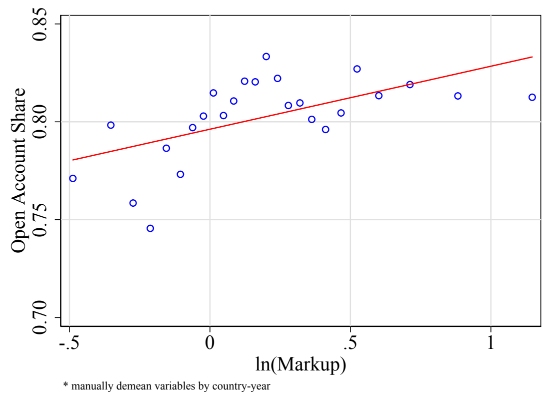
5 Empirical Results

This section presents results on the relationship between trade credit use, markups and interest rates. We begin by presenting descriptive evidence, and then we then turn into the econometric regressions, where we control for a richer set of fixed effects as well as for other variables potentially affecting trade credit choice. Finally, we discuss several robustness checks, as well as additional results for trade credit and prices.

5.1 Descriptive Evidence

Before presenting 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 control for 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 2.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.

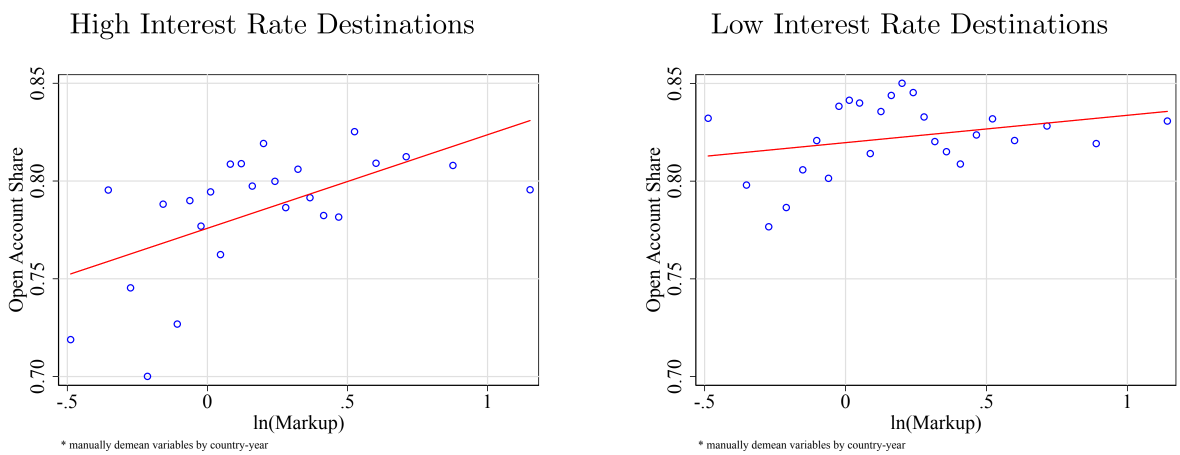
Figure 2. Open Account Share and Markups



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 in the full sample is stronger for exports to high interest rate countries.

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.

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.[27] However, this does not completely dissipate questioning regarding identification. In the next subsection, 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.

[27] 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.

5.2 Determinants of trade credit use

In this section we turn to the main econometric analysis. 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:

$$\rho_{ijpt} = \beta_1 \ \ln(\mu_{ipt}) + \gamma_1 \ \ln(L_{it}) + \delta_i + \delta_p + \delta_{jt} + \epsilon_{ijpt}, \tag{19}$$

where ρ_{ijpt} is the share of open account in all exports of firm i to country j of product p at time t. μ_{ipt} is the firm-product markup estimated from the firm-product level data. Our baseline regression includes a rich set of fixed-effects and control variables. We include firm fixed-effects (δ_i) to control for time-invariant factors affecting firms' trade credit choice, 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.

Table 3 presents our results from estimating (19). 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. In line with the model, the estimated coefficient on markup has a positive sign and is highly significant. That is, firms that have a higher markup sell more on trade credit. Columns 1-2 identify the effect of firm-product markups on trade credit exploiting temporal variation within firm-destinations. The positive and significant coefficients on markups suggest that firms extend relatively more trade credit when they have a higher markup. Next, in columns 3-4 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.

In quantitative terms, the estimated effect of markups on trade credit is moderate. An increase of one standard deviation in firm-product markup (39 percent), increases the likelihood of using trade credit in 43-47 basis points. This is not too surprising 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.[28]

Table 3. Open Account Share and Firm-Product Markup: Baseline Regressions

	(1)	(2)	(3)	(4)
ln(markup)	.0117***	.0113***	.0109***	.0120***
	(.00378)	(.00386)	(.00408)	(.00417)
ln(employment)	.00713**	.00439	.00616	.0057
	(.00359)	(.00372)	(.00418)	(.00435)
Firm-Destination FE	✓	✓	—	—
Year FE	—	✓	—	—
HS8 FE	—	✓	✓	—
Firm FE	—	—	✓	—
Destination-Year FE	—	—	✓	✓
Firm-HS8 FE	—	—	—	✓
Observations	104,783	104,783	104,783	104,783
R^2	.669	.698	.387	.425

Notes: The table reports the coefficient estimates from equation (19). 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). Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

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 test for the mechanism, as testing the interaction terms allows for the inclusion of more fixed effects, thereby reducing concerns of omitted variable bias. To test these predictions, we modify the baseline specification (19) including interaction terms

[28]In section 5.3, 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.

between firm-product markups, interest rates and contract enforcement:

$$\rho_{ijpt} = \beta_1 \ln(\mu_{ipt}) + \beta_2 \ln(\mu_{ipt})\, r^*_{b,jt} + \beta_3 \ln(\mu_{ipt})\, r_{d,jt} + \beta_4 \ln(\mu_{ipt})\, \lambda^*_{jt} + \delta_{it} + \delta_{jt} + \delta_p + \epsilon_{ijpt}, \quad (20)$$

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^*.

Table 4 present the results from estimating equation (20); we report standard errors clustered at the firm-destination level. Results largely confirm the main predictions of the model. Columns (1) through (4) show results on short-term (less than 30 days) interest rates. 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 0.92) and 75th percentile (markup 1.52) of the markup distribution. A one standard deviation higher borrowing rate (4.5 percent) in the destination country makes trade credit use 56 basis points more likely. Columns (5) present results on contract enforcement using the destination country's rule of law index. As predicted by the theory, a stronger enforcement abroad strengthens the relationship between the markup and trade credit provision. Finally, Column (6) shows that results also hold when including all interaction terms simultaneously.

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

	(1)	(2)	(3)	(4)	(5)	(6)
ln(markup)	-.0159	-.0175	.0170	.00158	-.00656	-.00749
	(.0156)	(.0160)	(.0215)	(.0227)	(.0146)	(.0234)
ln(markup)×(r_b^*-r_d)	.209**	—	—	—	—	—
	(.105)					
ln(markup)×r_b^*	—	.208**	—	.208**	—	.244**
		(.105)		(.105)		(.109)
ln(markup)×r_d	—	—	-2.376	-2.292	—	-2.183
			(1.957)	(1.966)		(1.966)
ln(markup)×$\mathbb{I}_{law}$	—	—	—	—	.0158	.0228*
					(0.0132)	(0.0138)
Firm-year FE	✓	✓	✓	✓	✓	✓
HS8 FE	✓	✓	✓	✓	✓	✓
Destination-Year FE	✓	✓	✓	✓	✓	✓
Observations	104,783	104,783	104,783	104,783	104,783	104,783
R^2	.444	.444	.444	.444	.444	.444

Notes: The table reports the coefficient estimates from equation (20). 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%.

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.

5.3 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 13).

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.[29] 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 shows a strong positive relationship with markups. The coefficients in Table 5 are slightly smaller, but not statistically different than the baseline case (compare them with the corresponding coefficients in Table 3). This suggests that input elasticities does not systematically vary with trade credit across firm-products.[30]

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)	.00965**	.00793**	.00885**	.0397**	.0384**	.0410
	(.00406)	(.00404)	(.00443)	(.0181)	(.0181)	(.0304)
ln(employment)	.00691*	.00262	.00599	.00575	.00156	.00504
	(.00387)	(.00402)	(.00451)	(.00400)	(.00415)	(.00466)
Firm-Destination FE	✓	✓	—	✓	✓	—
Year FE	—	✓	—	—	✓	—
HS8 FE	—	✓	✓	—	✓	✓
Firm FE	—	—	✓	—	—	✓
Destination-Year FE	—	—	✓	—	—	✓
Observations	101,908	101,908	101,908	96,707	96,707	96,707
R^2	.673	.674	.389	.673	.673	.390

Notes: The table reports the coefficient estimates from equation (19). 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%.

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

[30] In Table A.2 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.

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 for as an alternative measure of markups. Columns (4) through (6) of Table 5 estimate our baseline level regression using average price-cost margins. As it can be seen, using margins as a proxy for markups does not affect qualitatively our results. 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).[31]

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:

$$\ln\left(\frac{\rho_{ijpt}}{1-\rho_{ijpt}}\right) = \beta_1 \ \ln(\mu_{ipt}) + \gamma_1 \ \ln(L_{it}) + \delta_i + \delta_p + \delta_{jt} + \epsilon_{ijpt}, \tag{21}$$

[31] Table A.2 in the appendix replicates Table 4 using the interaction between the average price-cost margin, interest rates and rule of law. Coefficients are in line with the predictions of the model. In quantitative terms, the interest rate coefficients are similar than in the baseline, while the rule of law coefficient is slightly higher. However, only the latter interaction is statistically significant.

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 proved 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 0.031-0.039 for firm-products with open account share equal to the mean (82.5 percent in our sample). This is almost three time the baseline coefficient estimated in Table 3.

Table 6. Logistic Open Account Share Transformation

	(1)	(2)	(3)
log(Markup)	.269***	.237***	.214**
	(.0905)	(.0886)	(.0961)
ln(employment)	.140	.0382	.124
	(.0883)	(.0907)	(.100)
Implied Avg. Markup Semi-elasticity	.0388	.0342	.0309
Firm-Destination FE	✓	✓	—
Year FE	—	✓	—
HS8 FE	—	✓	✓
Firm FE	—	—	✓
Destination-Year FE	—	—	✓
Observations	104,586	104,586	104,586
R^2	.655	.655	.383

Notes: The table reports the coefficient estimates from equation (19) 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%.

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 (19). 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 0.013.

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)	.00106	.0139**	.0130**	.0142***	.0127***	.00981*
	(.00574)	(.00568)	(.00615)	(.00482)	(.00484)	(.00518)
ln(employment)	-.0118*	-.0219***	-.0105	.00683*	.00283	.00625
	(.00605)	(.00618)	(.00673)	(.00383)	(.00397)	(.00442)
Firm-Destination FE	✓	✓	—	✓	✓	—
Year FE	—	✓	—	—	✓	—
HS8 FE	—	✓	✓	—	✓	✓
Firm FE	—	—	✓	—	—	✓
Destination-Year FE	—	—	✓	—	—	✓
Observations	70,263	70,263	70,263	102,962	102,962	102,962
R^2	.656	.661	.410	.669	.669	.390

Notes: The table reports the coefficient estimates from equation (19). 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%.

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. However, it limits the variation that can be exploited to identify the coefficients, providing less precise estimates. Results in columns (4) through (6) in Table 7 show that coefficients remain quantitatively similar and stay statistically significant at the 10% 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 5.1 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.[32] We also tested whether adding further control affected the main relation between markups and trade credit. First, we added the 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.

5.4 Trade Credit and Export Prices

We now turn to the price predictions of the model. We start with 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:

$$UV_{ijpt} = \beta_1 \; I_{OA} + BX_{ijpt} + \epsilon_{ijpt}, \tag{22}$$

where UV_{ijpt} is the unit values of sales by firm i to destination j of product p at time t and X_{ijpt} 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:

$$\begin{aligned} UV_{ijpt} = \beta_1 \; I_{OA} + \beta_2 \; law^* + \beta_3 \; r \\ + \beta_4 \; law^* \times I_{OA} + \beta_5 \; r \times I_{OA} + BX_{ijpt} + \epsilon_{ijpt} \end{aligned} \tag{23}$$

Based on the theory, we expect $\beta_4 < 0$ and $\beta_5 > 0$.

In all regressions, we include the FOB value of the transaction to control for the existence

[32] 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.

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). Results are shown in Table 8. We first estimate equation (22). As Column (1) shows, 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.

Table 8. Trade Credit and Export Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Open Account Dummy	.0390***	.109	.0841	.0388***	.108	.00312
	(.0127)	(.0882)	(.0925)	(.0127)	(.0886)	(.0979)
$\mathbb{I}_{LAW}$	-.0397	.00629	.00844	-.0408	.00753	-.0265
	(.0276)	(.0357)	(.0355)	(.0274)	(.0354)	(.0335)
r_b	15.11***	16.36***	16.57***	14.91***	16.88***	16.32***
	(1.041)	(2.102)	(2.084)	(.949)	(2.093)	(2.136)
log(FOB sales)	.0348***	.0349***	.0349***	.0349***	.0349***	.0348***
	(.00308)	(.00308)	(.00308)	(.00307)	(.00307)	(.00306)
log(Cum. FOB sales)	.0108***	.0108***	.00861***	.0108***	.00874***	.00713***
	(.00067)	(.00067)	(.00153)	(.00067)	(.00151)	(.00158)
r_b^*	—	—	—	.590**	.600**	-.151
				(.253)	(.250)	(.306)
Open Account Interactions:						
$\times$ $\mathbb{I}_{LAW}$	—	-.0496**	-.0520**	—	-.0525**	-.0163
		(.0251)	(.0247)		(.0248)	(.0224)
$\times$ r_b	—	-1.371	-1.613	—	-2.179	-1.653
		(2.229)	(2.206)		(2.124)	(2.172)
$\times$ log(Cum. FOB sales)	—	—	.00259	—	.00245	.00428**
			(.00162)		(.00159)	(.00167)
$\times$ r_b^*	—	—	—	—	—	.841***
						(.244)
Firm-HS8-Destination FE	✓	✓	✓	✓	✓	✓
Observations	1,101,816	1,101,816	1,101,816	1,101,816	1,101,816	1,101,816
R^2	.954	.954	.954	.954	.954	.954

Notes: The table reports the coefficient estimates from equation (22) (column 1) and (23) columns 2-6). 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. 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-destination level. Key: *** significant at 1%; ** 5%; * 10%.

We next present results in columns (2)-(6) on interactions between trade credit use and the destination country rule of law and the seller's borrowing rate (equation 23). In line with the model, the open account price decreases with the destination country's rule of law: sellers demand a lower price in destinations with better contract enforcement (columns 2-3). We do not find a significant effect on the seller's interest rate interaction. Note, however, that the seller's interest rate has only limited time variation which may explain the non-finding. Finally, in columns (4)-(6) we explore whether the buyer's interest rate affect the price of the export transaction. Interestingly, we find that the trade credit price premium is higher in destinations with higher borrowing rates (column 4-6). This last finding calls for further research as it does not correspond to a direct prediction of our model.

The effect of trade credit on prices is quantitatively important. According to column (1), prices are 3.9% higher when transactions are financed with trade credit. Results in columns (2)-(3) suggest that there is substantial heterogeneity in the average effect reported in column 1. The baseline effect of trade credit is tripled once the interactions are included (from 3.9 to 10.9 percent). Regarding interactions, we find a quantitatively meaningful effect of the rule of law interaction. Consider two destinations in the 25th and 75th percentiles of the rule of law distribution. Results in column (2)-(3) suggest that export prices are between 9.1–9.5 percent lower in the former than in the latter destination country. This is equivalent to one-third of the standard deviation of prices within product-destination-year.

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. Chilean firm-level data supports the model. The model is consistent with recent development in aggregate U.S. data that show rising markups and more reliance on trade credit over time. Based on our model, the rise in markups identified by De Loecker and Eeckhout (2017) may have important consequences for 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.

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A Additional Tables

Table A.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 for details on the computation). Columns 1 displays the unweighted average markup.

Table A.2. Markups and Open Account Share: Alternative Markup Proxies

Markup Proxy:	Translog Markup			Average Price-Cost margin		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(markup)	-.00341	.0189	.00705	.00915	.0254	-.00504
	(.0162)	(.0232)	(.0240)	(.0168)	(.0332)	(.0344)
ln(markup)×r_b^*	.182*	.181*	.230**	.140	.211	.0405
	(.0995)	(.0995)	(.104)	(.155)	(.152)	(.250)
ln(markup)×r_d	—	-2.735	-2.587	—	-2.015	-1.220
		(1.975)	(1.976)		(2.933)	(2.624)
ln(markup)×$\mathbb{I}_{LAW}$	—	—	.0307**	—	—	.109***
			(.0151)			(.0319)
Firm-year FE	✓	✓	✓	✓	✓	✓
HS8 FE	✓	✓	✓	✓	✓	✓
Destination-year FE	✓	✓	✓	✓	✓	✓
N	100,458	100,458	100,458	100,458	100,458	100,458
R-sq	.447	.447	.447	.447	.447	.448

Notes: The table reports the coefficient estimates from equation (22) (column 1) and (23) columns 2-6). 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. 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-destination level. Key: *** significant at 1%; ** 5%; * 10%.

B Theory Appendix

B.1 Letters of Credit

Letters of credit are a third option available in international trade but typically not used for domestic transactions. For completeness, we briefly extend the model by adding the option of a letter of credit to the payment choices. A letter of credit is a promise of payment by the bank that is conditional on fulfilling specific requirements. For example, the seller may have to provide documents confirming shipment of goods to the issuing bank to get paid. This greatly reduces the risk of the transaction. For the purpose of this paper, we will follow Schmidt-Eisenlohr (2013) and assume that the bank perfectly resolves the enforcement problem. In addition, with a letter of credit payment takes place earlier than under open account, as open account terms typically ask for payment within 90-180 days after delivery.

$$\begin{aligned} \max_{P^{LC}} \mathrm{E}\left[\Pi_s^{LC}\right] &= P^{LC} - (1+r_b)\left(1 - T^{OA}\right) C \\ \text{s.t. } \mathrm{E}\left[\Pi_b^{LC}\right] &= R - (1+r_b^*)(P^{LC} + F^{LC}) \geq 0, \end{aligned} \tag{A.1}$$

where F^{LC} is the fixed cost of issuing a letter of credit and T^{OA} is the additional time it takes for payment to take place under open account relative to a letter of credit. The seller chooses $P^{LC} = \frac{R}{1+r_b^*} - F^{LC}$ which implies expected profits of:

$$\mathrm{E}\left[\Pi_s^{LC}\right] = \frac{R}{1+r_b^*} - F^{LC} - (1+r_b)\left(1 - T^{OA}\right) C \tag{A.2}$$

Combining equations (2) and (A.2) implies that a seller prefers open account (trade credit) over a letter of credit if:

$$\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{LC}\right] > 0 \Leftrightarrow R\left[\tilde{\lambda}^* - \frac{1}{1+r_b^*}\right] - (1+r_b)T^{OA}C + F^{LC} > 0 \tag{A.3}$$

Assuming again a constant markup as before, we obtain:

$$\mathrm{E}\left[\Pi_s^{OA}\right] - \mathrm{E}\left[\Pi_s^{LC}\right] > 0 \Leftrightarrow cq\left[\mu\left(\tilde{\lambda}^* - \frac{1}{1+r_b^*}\right) - (1+r_b)T^{OA}\right] + F^{LC} > 0 \qquad \text{(A.4)}$$