Trade Credit and Markups*

Alvaro Garcia-Marin[†] Santiago Justel[‡] Tim Schmidt-Eisenlohr[§]

December 2020

Abstract

Trade credit is the most important form of short-term finance for firms. In 2019, U.S. non-financial firms had $4.5 trillion in trade credit outstanding, equaling 21 percent of U.S. GDP. This paper documents that firms with higher markups supply more trade credit, an effect that increases with the buyers' borrowing rate. We rationalize this finding in a model with positive markups and costly financial intermediation. In the model, reducing financial intermediation costs provides a strong rationale for the dominance of trade credit in firm-to-firm transactions. Using U.S. Compustat and detailed Chilean export data, we find strong support for the model.

Keywords: Trade credit, markups, financial intermediation

JEL Classification: F12, F14, G21, G32

*We would like to thank JaeBin Ahn, Julia Cajal Grossi, Tore Ellingson, Ryan Kim, Volodymyr Lugovskyy, as well as seminar audiences at the Graduate Institute Geneva, ETH Zurich, University of Bayreuth, George Washington University, Universidad de Chile, Universidad Alberto Hurtado, Universidad de Santiago, University of Mainz, and the IDB Research Seminar, and conference participants at the CESifo Conference on Global Economy, LACEA-LAMES, Mid-Atlantic International Trade Workshop, Midwest Trade Conference, SED Conference, EIIT Conference, and RIDGE Conference, for helpful comments and suggestions. 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. Alvaro García-Marin gratefully acknowledges research support from ANID-Chile through project Fondecyt Regular 1191536.

[†]Universidad de los Andes. Email: agarciam@uandes.cl

[‡]World Bank. Email: sjustel@ucla.edu

[§]Federal Reserve Board of Governors. Email: t.schmidteisenlohr@gmail.com

1 Introduction

Trade credit is the most important form of short-term finance for U.S. firms.[1] In 2019, non-financial U.S. firms had about \$4.5 trillion in trade credit outstanding equaling 21 percent of GDP. Trade credit affects key economic outcomes like economic growth (Fisman and Love, 2003; Demirguc-Kunt and Maksimovic, 2001), corporate default (Jacobson and von Schedvin, 2015; Barrot, 2016; Amberg et al., Forthcoming), and the transmission of monetary policy (Adelino et al., 2020).[2]

While there is a large literature on trade credit, detailed micro evidence on its use is still limited, in particular on the choice between trade credit and its main alternative, cash in advance.[3] This paper provides unique evidence on this choice, using firm-level data for the United States from Compustat and transaction-level data on Chilean exports. Our central finding is that firms with higher markups supply more trade credit, as illustrated in figure 1 for the case of the United States. We find that the positive effect of markups on trade credit is stronger when borrowing costs are higher.

We present a model of trade credit choice that can rationalize these findings on markups, trade credit, and financing costs, and can explain the general dominance of trade credit for firm-to-firm transactions. The main insight from the model is that if there are positive markups and banks charge a higher interest rate on borrowing than they pay on deposits, then trade credit has a financial cost advantage. Earlier work has argued that trade credit is an inferior financing form and should be more expensive than bank credit because banks have access to cheaper refinancing.[4] However, the key point of our model is that in the typical environment where firms have no excess liquidity, for any transaction, either the exporter or the importer has to borrow from a bank. Hence, the question is not if bank finance is cheaper than a firm's internal cost of funds, but rather if financing through the buyer or the seller is cheaper. We show that if there are positive markups, then borrowing by the seller tends to be cheaper because the amount borrowed is smaller, as trade credit only requires borrowing the production costs. In contrast, cash in advance requires borrowing the full invoice.

In the model, a seller produces a good that can be sold at a markup to a final consumer.

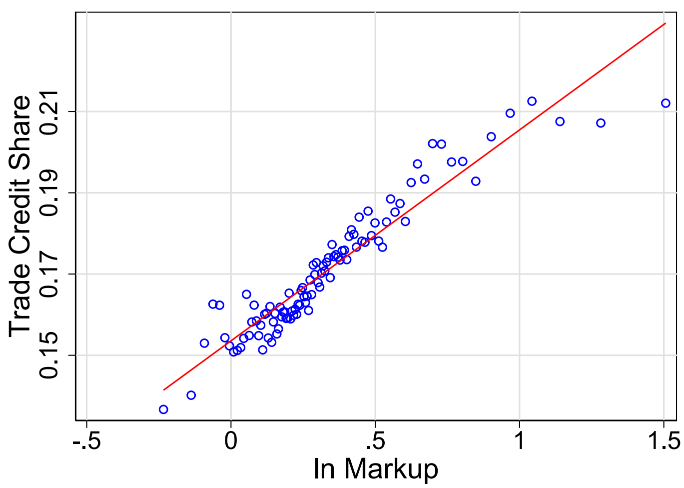
[1] Trade credit is defined as the implicit lending by a seller to a buyer when a buyer is given some time to pay for goods after receiving them.

[2] In addition, see Nilsen (2002) on trade credit and the bank lending channel and Love et al. (2007) on trade credit use in emerging economies in the wake of financial crises.

[3] Some notable exceptions that have used contract-level data are Giannetti et al. (2011), Murfin and Njoroge (2014), Antràs and Foley (2015), Barrot (2016), Amberg et al. (2020), and Giannetti et al. (forthcoming).

[4] See, for example, the discussion in Ellingsen et al. (2016).

Figure 1. Trade Credit Increases with Markups: U.S: Evidence



Notes: The figure shows a binscatter diagrams where the average trade credit share in each bin is plotted against markups. Markups are computed at the firm level as in De Loecker and Eeckhout (2017), using Compustat data for 1965-2016. Markups are in terms of natural logarithms. The figure controls for destination-year fixed effects.

The seller does not sell directly to the final consumer but trades with another firm, settling the transaction either through trade credit or cash in advance.[5] As financial intermediation is costly and the borrowing rate exceeds the deposit rate, the difference in borrowing needs between cash in advance and trade credit affects profits. Under cash in advance, the buyer needs to pre-pay the full amount to the seller which requires borrowing an amount equal to the full invoice. In contrast, extending trade credit requires less borrowing, as the seller only needs to cover her production costs in advance which may be substantially lower than the sales price if there is a markup. Thus, the larger are the markup and 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.

[5]For international transactions, letters of credit provide an additional financing option. However, based on our model, markups should not affect the choice between trade credit and a letter of credit. We corroborate this prediction in the data in section D.1, showing that markups correlate with trade credit and cash in advance shares but not with letter of credit use. There may also be a partial advance payment. However, available data suggest that this is option is not widely used. 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 provide a brief theoretical discussion of partial advance payments in our setup in Appendix A.1. See also Schmidt-Eisenlohr (2013).

We test the model using U.S. firm level data from Compustat and two rich panel datasets of Chilean exporters. While the Compustat data lets us document this relationship for the overall trade credit choice of a large number of U.S. firms, the Chilean export-level export data is key for identification: It allows estimating markups at the firm-product level, instrumenting markups with estimated physical productivity, and controlling, among others, for firm-year fixed effects. We conduct a similar analysis for the United States at a more aggregate level, estimating markups from balance sheet data and relating them to accounts receivable on firms' balance sheets.

With the Chilean data, 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). Importantly, thanks to unique features of the Chilean data, we can obtain quantity-based estimates of markups and productivity following Garcia-Marin and Voigtländer (2019). These quantity-based estimates avoid identification problems that arise when markups are estimated with revenue data (Syverson, 2019). We then combine these markup estimates with customs-level trade data, which contains detailed information on the payment choice to test the predictions of the model.

To address endogeneity concerns regarding the markups, we implement a 2SLS strategy using plant-product physical productivity as an instrument for markups and also include a rich set of fixed effects.[6] Using the physical productivity estimate as the instrument helps addressing concerns about competition and demand-side effects, as the instrument is constructed from technological supply-side factors. To control for other omitted factors that might directly link productivity to trade credit, we control for firm-year fixed effects in our preferred specification. For example, productivity might be correlated with financial constraints or management quality, which in turn may affect trade credit choice. However, these channels should operate at the firm level and should thus be covered by the firm-year fixed effects.

We find that trade credit use increases with markups and that this effect increases with the buyer's borrowing rate. Results are robust to alternative measures of markups, and to the inclusions of a large set of fixed effect and control variables. When instrumenting the markup by plant-product level physical productivity, the markup coefficient becomes substantially larger

[6] We show that introducing variable markups to the baseline model can rationale this instrument. Specifically, we solve the model with a linear demand and show that the predictions on trade credit and markups also hold when modelling variable markups this way. In addition, in the extended model, more efficient firms charge higher markups. These higher markups make trade credit use more attractive, increasing the financing cost advantage of trade credit.

and remains highly significant.[7] Taken together, these results provide strong support for our key prediction that trade credit use increases with markups, and that the effect of markups is stronger when financial intermediation is more costly. In the U.S. data, we uncover the same relationship between markups and trade credit use and show that this relationship is stronger when funding costs are higher, as proxied by the real Effective Fed Funds Rate.

The paper contributes to several strands of the literature, by providing new facts and evidence on trade credit, adding to earlier work that relied on domestic data (see e.g. Petersen and Rajan, 1997; Giannetti et al., 2011; Murfin and Njoroge, 2014; Barrot, 2016; Amberg et al., 2020; Giannetti et al., forthcoming) and international data (see Antràs and Foley, 2015; Ahn, 2014; Demir and Javorcik, 2018), and by extending earlier theories on trade credit and payment choice (in particular, Schmidt-Eisenlohr, 2013; Antràs and Foley, 2015).[8]

First, by showing that trade credit use increases with markups, it speaks to the literature on competition and trade credit (Peura et al., 2017; Giannetti et al., forthcoming; Chod et al., 2019), which links trade credit to market power.[9] In our model, markups affect trade credit choice as they imply lower borrowing needs and hence lower financial costs under trade credit. This mechanism is quite distinct and complementary to the effects that arise from market power and competition. For example, two recent papers, Giannetti et al. (forthcoming) and Demir and Javorcik (2018) develop models that imply a negative correlation between markups and trade credit. Giannetti et al. (forthcoming) provide convincing evidence in support of their model, showing that suppliers provide more trade credit to buyers wither high market power when there is downstream competition. Demir and Javorcik (2018) show that an exogenous shock to downstream competition led sellers to increase their trade credit provision and lower their prices. The implied negative correlation between markups and trade credit due to competition effects should bias our OLS results downwards. We provide additional discussion on this in section 3.2.

[7]The increase in coefficient size indicates a downward bias in the OLS estimates that might be due to competition effects as in Giannetti et al. (forthcoming) and Demir and Javorcik (2018). We discuss this point in more detail below.

[8]For international evidence with more aggregate data see also Hoefele et al. (2016). Additional theoretical work on the payment choice includes Ahn (2014), Olsen (2016), and Fischer (2020). For papers studying the broader relationship of financial constraints and international trade, see among others Amiti and Weinstein (2011), Ahn et al. (2011), Chor and Manova (2012), Manova (2013), Paravisini et al. (2014), Niepmann and Schmidt-Eisenlohr (2017), and Ahn and Sarmiento (2019).

[9]Our evidence on markups is also broadly consistent with predictions from the inventory model in Daripa and Nilsen (2011), and with earlier evidence in Petersen and Rajan (1997) who find 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.

Second, our theory proposes a new mechanism for why trade credit is so dominant: Trade credit minimizes total borrowing from banks, thereby reducing financial costs, when firms charge positive markups and when financial intermediation is costly. Burkart and Ellingsen (2004) propose a prominent and complementary explanation, where sellers extend trade credit because this type of credit is "in-kind" and is thus harder to divert than cash. In recent follow-up work, Amberg et al. (2020) extend this model with a labor-capital choice, showing that trade credit contributes to a capital-bias for financially constrained firms. Schwartz (1974) and Ferris (1981) suggest models where trade credit serves a transaction motive, separating the exchange of goods from the exchange of money. Brennan et al. (1988), Schwartz and Whitcomb (1979), and Mian and Smith (1992) rationalize trade credit use as a way to price discriminate. The idea in our model that trade credit provides a way to save on financial costs is related to earlier work, where trade credit helps channel excess liquidity across firms (Emery, 1984). The assumption in our model that borrowing rates are higher than deposit rates could in part reflect informational asymmetries between banks and borrowers. This point is related to the idea that trade credit is used because of informational advantages of suppliers over banks (see Smith, 1987; Biais and Gollier, 1997). For an early summary of the main theories on trade credit, see also Petersen and Rajan (1997).

Finally, the theory on trade credit developed here generalizes and extends earlier work on payment choice in multiple ways: (i) It shows how introducing markups and a financial intermediation cost generates a financing cost advantage for trade credit; (ii) it shows how the model in Schmidt-Eisenlohr (2013) (and Antràs and Foley, 2015) can be extended to a setting with arbitrary bargaining power based on the *Neutral Bargaining Solution* by Myerson (1984); and (iii) it solves the model for variable markups.

The remainder of the paper is organized as follows. Section 2 presents the model of payment choice and derives the main testable predictions. Section 3 discusses the empirical specifications and presents the methodology for deriving firm-product markups. Section 4 describes our dataset. Section 5 presents the main empirical results with Chilean data. Section 6 presents results with U.S. data. Finally, section 7 discusses the implications of our study and routes for future research.

2 A model of trade credit and markups

In this section, we extend the models in Schmidt-Eisenlohr (2013) and Antràs and Foley (2015), and show how a positive markup and a financial intermediation cost can explain why almost all firm-to-firm interactions rely on trade credit. We start by presenting the most parsimonious model (domestic case) to derive the main result and convey the intuition for financing cost advantage of trade credit. We then expand the model (international case), introducing a two-sided commitment problem and letters of credit.[10]

In the baseline model, there are two key elements. First, there is a time delay between the production of goods by the seller and the sale of goods by the buyer. Second, financing is costly. To pay for goods or production costs, firms need 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]

2.1 Domestic Case

One buyer is matched with one seller. Both firms are risk-neutral. 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 need to agree on payment terms. In the baseline model, firms have two options. First, buyers can pay in advance (cash in advance) before receiving the goods. Second, buyers can pay after delivery (on trade credit). A seller produces output for a total cost of C and sells it to the buyer. The buyer can then sell the goods to final consumers and generate revenues R. Assume that firms charge a constant markup to final consumers given by μ so that $R = \mu C$.[12] In addition, assume that μ is sufficiently large such that $\mu > \frac{1+r_b}{\lambda}$, which will assure that both trade credit and cash in advance always generate positive expected profits. To finance their transactions, firms can borrow from banks at an interest rate r_b. Firms can deposit surplus

[10] Of course, commitment problems may also play a role in domestic transactions. However, as they are not necessary for our main mechanism to work, we only introduce them when moving to the full (international) model.

[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. See, for example, Ho and Saunders (1981) on the determinants of banks' interest rate margins.

[12] For now, we take R and μ as exogenous. In section 2.4.2, we show how our results extend to a model with linear demand and variable markups, and in appendix A.2 we derive results with CES preferences.

funds at banks for a deposit rate of r_d. The seller makes a take-it-or-leave-it offer to the buyer who can choose to accept or reject the offer.[13]

Trade Credit Under trade credit, the seller maximizes:

$$\begin{aligned} \Pi_S^{TC} &= P^{TC} - (1+r_b)C, \\ \text{s.t. } \Pi_B^{TC} &= R - P^{TC} \geq 0, \end{aligned}$$

where P^{TC} is the total payment from the buyer to the seller. Under trade credit, the seller gets paid P^{TC}, while incurring the production costs C. 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 maximization is subject to the participation constraint of the buyer. Solving for the optimal P^{TC} that respects the participation constraint implies $P^{TC} = R$, delivering profits of:

$$\Pi_S^{TC} = R - (1+r_b)C. \tag{1}$$

Cash in Advance Under cash in advance, the seller maximizes:

$$\begin{aligned} \Pi_S^{CIA} &= (1+r_d)(P^{CIA} - C), \\ \text{s.t. } \Pi_B^{CIA} &= R - (1+r_b^*)P^{CIA} \geq 0. \end{aligned}$$

Under cash in advance, in period 0 the seller gets paid P^{CIA} and incurs production costs C. 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 buyer pays P^{CIA} in period 0, borrowing from a bank at interest rate r_b. Solving for the optimal P^{CIA} delivers $P^{CIA} = \frac{1}{1+r_b}R$. With profits of:

$$\Pi_S^{CIA} = (1+r_d)\left(\frac{1}{1+r_b}R - C\right). \tag{2}$$

[13] In section 2.4.1, we extend the model to allow the seller and the buyer to bargain over the surplus with bargaining weights θ and $1-\theta$, respectively. As the full model (international case) features private information about the type of buyer and seller, we follow Myerson (1984) and apply the Neutral Bargaining Solution, which generalizes Nash bargaining to a setting with private information. The domestic case can also be solved based on Nash Bargaining, which delivers identical results to the Neutral Bargaining Solution in the absence of private information. Results on Nash Bargaining are available upon request.

Optimal Payment Choice: Domestic Case When is trade credit preferred over cash in advance? Combining equations (5) and (6) and rewriting shows that trade credit dominates if:

$$\Pi_S^{TC} - \Pi_S^{CIA} = \left[\mu - (1+r_b) - (1+r_d)\left(\frac{1}{1+r_b}\,\mu - 1\right)\right] C > 0. \tag{3}$$

Rearranging terms, we can derive that trade credit dominates cash in advance if:

$$(r_b - r_d)(\mu - (1+r_b)) > 0. \tag{4}$$

We summarize this finding in the following Proposition.

Proposition 1 (Payment Choice: Domestic Case)
Suppose the borrowing rate is above the deposit rate, $r_b > r_d$, and firms charge a positive markup over effective costs ($\mu > 1 + r_b$). Then, firms should always use trade credit.

Proof. Follows directly from equation (4). ■

The financing friction combined with a positive markup provides a clear rationale for the dominance of trade credit in firm-to-firm transactions in the domestic context. Trade credit dominates cash in advance because it minimizes borrowing from financial institutions and thereby financial intermediation costs.

2.2 International Case

We now extend the baseline model in two ways to reflect additional aspects that are particularly relevant for international trade transactions. First, we introduce a two-sided commitment problem between the buyer and the seller with heterogeneous enforcement across countries. Second, we introduce letters of credit, a payment form that is specific to international trade.

Commitment Problem Assume that a fraction η (η^*) of sellers (buyers) is reliable; that is, these firms always fulfill their contracts.[14] If a firm is unreliable it does not fulfill its contract voluntarily, which gives rise to a commitment problem. Under cash in advance, an unreliable seller may not deliver after receiving payment. With trade credit, an unreliable buyer may not pay after receiving the goods. If a firm does not fulfill its contract voluntarily, the other

[14]For the remainder of the paper, all variables related to a foreign buyer are denoted with an asterisk. We will also allow the borrowing rate to differ across buyer and seller countries.

firm can try to enforce the agreement in court, which is successful with probability λ (λ^*).[15] When facing an opportunity to cheat, a random seller thus fulfills the contract with probability $\tilde{\lambda} \equiv \eta + (1-\eta)\lambda$, and a random buyer with probability $\tilde{\lambda}^* \equiv \eta^* + (1-\eta^*)\lambda^*$.

We assume that parameters are such that sellers always offer contracts that are acceptable to both types of buyers, and that unreliable sellers always imitate reliable sellers when choosing the optimal contract. In appendix A.3, we provide the precise conditions under which these assumptions hold. The conditions are relatively weak and either always hold, or require some minimum markup to hold.[16] In the following, the subscripts S and B refer to sellers or buyers of any type, whereas subscripts RS and RB reference reliable sellers and reliable buyers, respectively. Finally, we now need to look at expected profits, as the commitment problem introduces risk.

Trade Credit The seller maximization problem now reads:

$$\begin{aligned} \mathrm{E}[\Pi_S^{TC}] &= \tilde{\lambda}^* P^{TC} - (1+r_b)C \\ \text{s.t. } \mathrm{E}[\Pi_{RB}^{TC}] &= R - P^{TC} \geq 0 \end{aligned}$$

Now, under trade credit, the seller gets paid P^{TC} with probability $\tilde{\lambda}^*$, while still incurring the production costs C with certainty. The optimal payment does not change in the international case and remains $P^{TC} = R$, delivering expected profits of:

$$\mathrm{E}[\Pi_S^{TC}] = \tilde{\lambda}^* R - (1+r_b)C. \tag{5}$$

Cash in Advance Under cash in advance, a reliable seller maximizes:

$$\begin{aligned} \mathrm{E}[\Pi_{RS}^{CIA}] &= (1+r_d)(P^{CIA} - C), \\ \text{s.t. } \mathrm{E}[\Pi_B^{CIA}] &= \tilde{\lambda} R - (1+r_b^*)P^{CIA} \geq 0. \end{aligned}$$

Under cash in advance, there is now a risk that a buyer is matched with an unreliable seller who may not deliver the goods. Thus, the buyer generates revenues R only with probability $\tilde{\lambda}$.

[15] 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.

[16] For example, if η, η^*, λ, and λ are each greater or equal to 0.8, and there is an enforcement cost of 5 percent (not modeled in the baseline to ease the exposition), then revenues have to be at least 1.07 and 1.08 times production costs, respectively.

Solving for the optimal payment delivers $P^{CIA} = \frac{\tilde{\lambda}}{1+r_b^*}R$. With expected profits of:

$$\mathrm{E}[\Pi_{RS}^{CIA}] = (1+r_d)\left(\frac{\tilde{\lambda}}{1+r_b^*}R - C\right). \tag{6}$$

This represents the general solution for all sellers, as we assumed that conditions are such that an unreliable seller always imitates a reliable seller (see appendix A.3 for details).

Letter of Credit Letters of credit are a payment form that is used exclusively in international trade transactions. With a letter of credit, banks serve as intermediaries in the transaction to resolve the two-sided commitment problem between the buyer and the seller. The buyer pays a fee to the bank and commits to paying the seller.[17] Assume that this fee is proportional to the transaction size: $F^{LC} = f^{LC}P^{LC}$. The seller only receives payment from the bank after providing proof of shipment or delivery. Then profits are given by:

$$\Pi_S^{LC} = P^{LC} - (1+r_b)C \tag{7}$$

$$\Pi_B^{LC} = R - P^{LC} - (1+r_b^*)(f^{LC}P^{LC}) \tag{8}$$

With a letter of credit, there is no risk and the seller receives P^{LC} with certainty and the buyer generates revenues R with certainty.[18] Solving for the optimal P^{LC} that makes the buyer indifferent delivers $P^{LC} = \frac{R}{1+f^{LC}(1+r_b^*)}$ And plugging back into seller profits leads to:

$$\Pi_S^{LC} = \frac{R}{1+f^{LC}(1+r_b^*)} - (1+r_b)C. \tag{9}$$

Optimal Payment Choice: International Case We now study when trade credit is preferred over the alternatives cash in advance and letter of credit in the full model. Combining equations (5) and (6) rewriting implies that the seller prefers trade credit over cash in advance if:

$$\mathrm{E}[\Pi_S^{TC}] - \mathrm{E}[\Pi_{RS}^{CIA}] = \left[\tilde{\lambda}^*\mu - (1+r_b) - (1+r_d)\left(\frac{\tilde{\lambda}}{1+r_b^*}\,\mu - 1\right)\right] C > 0. \tag{10}$$

[17]This commitment can either reflect a long-term relationship with the bank or may require a deposit in the bank up to the value of the letter of credit. For tractability, we assume that it is sufficient for the buyer to pay the letter of credit fee in advance.

[18]This is a simplifying assumption, as, in reality, letters of credit are not completely risk-free. Relaxing this assumption should not affect any of our results. For a detailed analysis of letter of credit risk see Niepmann and Schmidt-Eisenlohr (2017).

Rearranging terms, we can derive that trade credit dominates cash in advance if:

$$\mu > \frac{(r_b - r_d)(1 + r_b^*)}{\tilde{\lambda}^*(1 + r_b^*) - \tilde{\lambda}(1 + r_d)} \quad \text{and} \quad \tilde{\lambda}^*(1 + r_b^*) - \tilde{\lambda}(1 + r_d) > 0. \tag{11}$$

Next, compare trade credit with a letter of credit. This delivers:

$$\mathrm{E}[\Pi_S^{TC}] - \mathrm{E}[\Pi_S^{LC}] = \left[\tilde{\lambda}^* - \frac{1}{1 + f^{LC}(1 + r_b^*)}\right] \mu C > 0, \tag{12}$$

Note that the markup, μ, does not affect the choice between trade credit and a letter of credit. These results are summarized in the following Proposition.

Proposition 2 (Payment Choice: International Case)

i) Suppose contract enforcement is not too different across countries and the foreign borrowing rate exceeds the domestic deposit rate ($\tilde{\lambda}^*(1 + r_b^*) - \tilde{\lambda}(1 + r_d) > 0$). Then, there is always a markup, μ, that is large enough to make a firm choose trade credit over cash in advance.

ii) The choice between trade credit and letters of credit is independent of the markup, μ.

Proof. Follows directly from equations (11) and (12). ■

In the international case, trade credit does not always dominate. If the seller is more likely to deliver under cash in advance than the buyer is likely to pay under trade credit ($\tilde{\lambda} > \tilde{\lambda}^*$) or if borrowing costs are very low abroad ($r_b^* < r_d$), then cash in advance may be preferred. The financing cost advantage of trade credit over cash in advance is, however, still present. Therefore, trade credit tends to be preferred if the borrowing rate exceeds the deposit rate and contract enforcement is not too different across countries. Then, for a large enough markup, μ, trade credit always dominates cash in advance. In contrast, the choice between trade credit and a letter of credit is independent of the markup, μ.

2.3 Testable Predictions

To arrive at testable predictions that can be taken to the data, we now take the derivative of the payment choice with respect to the markup and its cross-derivatives with respect to interest rates and enforcement. As we showed above in equation (12), the choice between trade credit and a letter of credit is independent of the markup μ. In the following, we therefore focus on the choice between trade credit and cash in advance.[19]

Start by taking the derivative of (10) with respect to μ. Rearranging the derivative implies that profits with trade credit relative to cash in advance rise in the markup if:

$$\left(1+r_b^*\right)\tilde{\lambda}^* - \left(1+r_d\right)\tilde{\lambda} > 0. \tag{13}$$

That is, as long as the buyer's borrowing rate is above the seller's deposit rate and enforcement is not too different for buyers and sellers, trade credit becomes more attractive relative to cash in advance when the markup goes up. Note that this condition is more likely to hold if the destination country has a higher borrowing rate or better enforcement. The condition is less likely to hold if the source country has a higher deposit rate or better enforcement. The following Proposition summarizes this result:

Proposition 3 (Trade Credit and Markups)
Suppose $\left(1+r_b^*\right)\tilde{\lambda}^* > \left(1+r_d\right)\tilde{\lambda}$*. Then:*

i) The use of trade credit increases with the markup μ*.*

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

Proof. Follows from equation (13) ■

Part ii) of Proposition 3 presents additional predictions to test the mechanism explaining trade credit use: The effect of the markup should be stronger when the destination country's borrowing rate and enforcement are higher, and when the source country's deposit rate and enforcement are lower. The additional results on the interest rates are intuitive. The difference in borrowing needs between trade credit and cash in advance only matters if there is a positive difference between the borrowing rate and the deposit rate. Naturally, this effect is larger, the larger this interest rate difference.

2.4 Model Extensions

In the following we briefly discuss two model extensions: arbitrary bargaining power between the seller and the buyer and variable markups. Further details on the bargaining extension can be found in Appendix A.4.

[19] We validate in robustness exercises in section D.1 that the financing cost advantage channel of trade credit is indeed only present when looking at the choice between trade credit and cash in advance, while the channel does not play a role for the choice between trade credit and a letter of credit.

2.4.1 Introducing Bargaining

So far, we derived results assuming that the seller has all bargaining power. To generalize the results, we now extend the model to allow for different bargaining weights for the buyer and the seller. As there is private information about the type of the buyer and the seller, we use the Neutral Bargaining Solution proposed by Myerson (1984), which generalizes Nash Bargaining to the case of private information. The basic idea is that under the Neutral Bargaining Solution, the two parties play a random dictator game where they must respect constraints from asymmetric information, as the other player can always reject the offer of the dictator. Let θ denote the bargaining weight of the seller. In Appendix A.4, we prove the following corollary:

Corollary 1 (Payment Choice and Bargaining Power)
Suppose the seller has some bargaining power ($\theta \in (0, 1]$). Then all predictions in Proposition 3 hold for the case where both firms have bargaining power. That is:

i) If $(1 + r_b^*)\ \tilde{\lambda}^* > (1 + r_d)\ \tilde{\lambda}$, then the use of trade credit increases with the markup μ.

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

Proof. See Appendix A.4. ■

The corollary states that introducing bargaining power for both sellers and buyers does not affect our main result on trade credit and markups. The financing cost advantage is present as long as the seller has some bargaining power that allows charging a positive markup over marginal costs to the buyer.

2.4.2 Variable Markups

We now introduce variable markups to our model. This is a key extension, as it micro-founds the instrumental-variable approach employed later in the paper, where we instrument markups with productivity estimates. As the main purpose of this exercise is to convey the mechanism, we assume a straightforward linear demand, that would follow, for example, from a demand system as in Melitz and Ottaviano (2008). However, the below results do not depend on this specific modeling choice for variable markups.

Assume that demand takes the form $Q(p) = 1 - p$. Expected profits under the two payment forms can be represented by the general form $\Pi = \alpha p Q(p) - \beta c Q(p) = (\alpha p - \beta c)(1 - p)$. Markups

($\mu = P/Qc$) between the price paid by the buyer and the production cost of the seller are:

$$\mu^{TC} = \frac{1}{2c} + \frac{1+r_b}{\tilde{\lambda}^*}\frac{1}{2}, \tag{14}$$

$$\mu^{CIA} = \frac{\tilde{\lambda}}{1+r_b^*}\left(\frac{1}{2c} + \frac{1+r_b^*}{\tilde{\lambda}}\frac{1}{2}\right) \tag{15}$$

It is easy to see that markups decrease (increase) in the marginal cost (productivity). Assuming linear demand, we can derive the following difference in expected profits between trade credit and cash in advance in the domestic case:

$$\Delta\Pi = \tilde{\lambda}\left[1 - \frac{1+r_d}{1+r_b}\right]\left[\mu^{TC}(c) - \frac{1+r_b}{\tilde{\lambda}}\right]^2 c^2. \tag{16}$$

Note that this difference is positive as long as the borrowing rate exceeds the deposit rate, $r_b > r_d$. Importantly, the marginal cost c enters into equation (16) twice. There is a direct effect, that affects the level of equation (16) but not the sign, and hence does not affect the payment choice. There is also an indirect effect through the markup that we study next. Taking the derivative with respect to c and plugging in for $\frac{\partial \mu^{TC}}{\partial c}$ delivers:

$$\frac{\partial \Delta\Pi}{\partial c} = -(r_b - r_d)\left(\mu^{TC} - \frac{1+r_b}{\tilde{\lambda}}\right)c < 0, \tag{17}$$

which is negative as long as the borrowing rate exceeds the deposit rate, $r_b > r_d$, and the markup exceeds effective costs, $\mu^{TC} > \frac{1+r_b}{\tilde{\lambda}}$. These results are summarized in Proposition 4.

Proposition 4 (Trade Credit and Variable Markups)
Suppose the buyer and the seller face the same financial costs and enforcement frictions, the borrowing rate is above the deposit rate ($r_b > r_d$), the markup exceeds the effective costs ($\mu^{TC} > \frac{1+r_b}{\tilde{\lambda}}$), and firms face a linear demand. Then:

1. *The markup decreases with the marginal cost of production c.*

2. *By decreasing the markup, an increase in the marginal cost of production makes trade credit less attractive relative to cash in advance.*

3. *The marginal cost affects the payment choice only through its effect on the markup.*

Proof. Follows directly from taking the derivatives of equations (14) and (15) with respect to c, and from equations (16) and (17). ■

Proposition 4 is key for the IV strategy we employ in this paper. It states that a decline in marginal costs (increase in productivity) leads to an increase in the markup and thereby to more trade credit provision. Importantly, there is no direct effect of the marginal cost on the payment choice, as marginal costs do not directly affect the sign of the profit difference between trade credit and cash in advance.

3 Empirical Approach

This section presents the main empirical specifications for the Chilean data, discusses threats to identification, and introduces our instrumental variable approach. In addition, it lays out the methodology we use to compute markups at the firm-product level. Section 6 discusses how we adapt the methodology for the U.S. data.

3.1 Empirical Specifications

To test the predictions of the model, we run two main specifications. First, we study how the level of markups relates to trade credit choice. Based on proposition 3, we expect a positive relationship between these variables. We test this prediction estimating the following baseline regression at the firm-product-destination-year level:

$$\rho_{ipjt} = \beta_1 \ \ln(\mu_{ipt}) + \beta_2 \ \ln(L_{it}) + \delta_i + \delta_p + \delta_{jt} + \epsilon_{ipjt}, \tag{18}$$

where ρ_{ipjt} denotes the share of trade credit in total exports by firm i exporting product p to country j in year t. μ_{ipt} is the markup, which is computed at the firm-product-year level according to methodology discussed below in section 3.3. The model predicts that $\beta_1 > 0$. That is, all else equal, firms should sell more on trade credit in products with larger markups. The baseline specification includes firm fixed-effects (δ_i) to control for time-invariant factors affecting firms' trade credit share and product-fixed effects (δ_p) to account for differences in product characteristics leading to dispersion in trade credit use. We also include destination-year fixed effects (δ_{jt}) to account for country-level characteristics directly affecting trade-credit choice for all firms, such as financing costs or 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. While we first present results with firm fixed effects only, our preferred specification includes firm-year fixed effects.

Our second main empirical specification tests for differential effects of markups on trade credit across countries with different interest rates and contract enforcement levels. For this, we modify the baseline specification (18), adding interaction terms between firm-product markups and the domestic deposit rate (r_d), the foreign borrowing rate (r_b^*), and contract enforcement in the destination country (λ^*):

$$\rho_{ijpt} = \beta_1 \ \ln(\mu_{ipt}) + \beta_2 \ \ln(\mu_{ipt}) \ r_{b,jt}^* + \beta_3 \ \ln(\mu_{ipt}) \ r_{d,t} + \beta_4 \ \ln(\mu_{ipt}) \ \lambda_{jt}^* + \delta_{it} + \delta_{jt} + \delta_p + \epsilon_{ijpt}, \tag{19}$$

According to proposition 3, we expect the positive effect of markups to be stronger in destinations with a higher borrowing rate, r_b^*, and enforcement λ^*, and weaker when the deposit rate of the source country, r_d, is lower. That is, we expect $\beta_2 > 0$, $\beta_3 < 0$, and $\beta_4 > 0$:

Specification (19) is a key test for our main mechanism for two reasons. First, a positive coefficient on the interaction term between the markup and the borrowing rate is predicted by the financing cost advantage of trade credit mechanism developed here, but not by any other mechanism that we are aware of. Second, this specification allows us to saturate the regression with a comprehensive set of fixed effects, including firm-year fixed effects (δ_{it}, baseline specification), or even firm-product-year (δ_{ijt}) fixed effects. As we explain below, this allows to relax the exclusion restriction of our instrumental variables approach, and to rule out alternative explanations.

3.2 Identification and IV Estimation

The main threat for identification in specifications (18) and (19) is that markups are endogenous. In particular, there are two concerns that we discuss in the following.

First, changes to competition faced by firms may affect markups and trade credit use simultaneously. Two recent papers, Giannetti et al. (forthcoming) and Demir and Javorcik (2018), imply a negative correlation between markups and trade credit provision. In Giannetti et al. (forthcoming), sellers are more likely to supply trade credit to buyers with higher bargaining power, as this is an efficient way to price discriminate across buyers when there is downstream competition. The key insight from that model is that because of anti-trust concerns, sellers should not only price discriminate through explicit pricing schedules but also through payment terms. To the extent that sellers rely on both margins, this should generate more trade credit and lower prices for firms with stronger bargaining power. In fact, Demir and Javorcik (2018) document that an exogenous increase in downstream competition led to more trade credit provision and a reduction in prices by Turkish exporters to the European Union. If the baseline OLS estimates also capture this competition channel, this will generate a downward bias in the OLS coefficients.

Second, exporters should charge higher prices when using trade credit because they pass financial costs to the buyers and require compensation for the buyer's risk of non-payment. This price effect implies a positive correlation between trade credit choice and markups, biasing the OLS estimates upward. Antràs and Foley (2015) provides suggestive evidence for this mechanism looking at transaction-level data from a U.S. based exporter of frozen and refrigerated food products.[20]

Instrumental Variable Estimation To address the endogeneity of markups, we implement an IV strategy, using firm-product physical total factor productivity (TFPQ) as an instrument for markups. For the baseline specification (18), the IV strategy works as follows. In the first stage, we predict firm-product markups (or the interaction between firm-product markups and country characteristics) based on firm-product TFPQ (and its interactions, whenever it corresponds):

$$\ln(\mu_{ipt}) = \gamma_1 \ln(TFPQ_{ipt}) + \gamma_2 \ln(L_{it}) + \alpha_i + \alpha_p + \alpha_{jt} + \varepsilon_{ipjt} \tag{20}$$

where $TFPQ_{ipt}$ denotes physical productivity of product p produced by firm i in year t, L_{it} is total firm employment, and $\{\alpha_i, \alpha_p, \alpha_{jt}\}$ are firm, product and country-year fixed effects, respectively. We compute TFPQ as the residual between the logarithm of output, and the contribution of the production inputs, using the same production function coefficients we use to compute markups. Importantly, when estimating the production function and computing TFPQ, we specify output and intermediate inputs in terms of physical units to avoid the so-called output and input price biases.[21] As De Loecker and Goldberg (2014) explain, these biases lead to confounding measured productivity with markups. By specifying the production function in physical units, the estimated TFPQ only reflects supply-side production factors

[20] We also estimated the correlation between a trade credit dummy and the unit values in our export data, and found that trade credit transactions, on average, have 3 percent higher unit values.

[21] Appendix B provides technical details on the estimation of the production function at the firm-product level.

and does not reflect any demand conditions, which is crucial for the validity of TFPQ as an instrument.

In the second stage, we regress the share of trade credit value exported by firm i shipping product p to country j in year t, ρ_{ijpt}, on predicted log markups, $\widehat{\ln\mu_{ipt}}$, firm employment, and fixed effects:

$$\rho_{ijpt} = \beta_1 \ \widehat{\ln\mu_{ipt}} + \beta_2 \ \ln(L_{it}) + \delta_i + \delta_p + \delta_{jt} + \epsilon_{ijpt}, \tag{21}$$

Exclusion Restriction and Identification The exclusion restriction for using TFPQ as an instrument for markups requires that it affects trade credit choice only through markups. Our framework is consistent with this restriction, as shown in proposition 4. Nevertheless, there may be factors outside our model that might link productivity directly to trade credit provision. For instance, higher efficiency may reflect better management practices (Bloom and Reenen, 2007) or may imply that firms are less financially constrained (Aghion et al., 2019; Duval et al., 2020). In these cases, efficiency would be linked to an omitted variable that may affect the preference for trade credit. To account for this possibility we run specifications that include firm-year fixed effects. This weakens the exclusion restriction notably, allowing differences in management or access to capital at the firm-year-level. In these specifications, violation of the exclusion restriction would need to operate at the firm-product-year level, as identification of the markup coefficient comes from variation in markups across products within the same firm.

Under the exclusion restriction, instrumenting markups by physical productivity and including detailed fixed effects resolves the two main endogeneity concerns discussed above. First, our IV resolves concerns about changes in competition in destination markets, as we only exploit changes in markups that are due to differences in physical productivity at the firm-product level. Second, the IV also addresses the concern that firms charge higher prices under trade credit, as the physical productivity estimate only reflects differences in technology and efficiency at the firm-product level and does not rely on revenue or price data.

3.3 Markups Estimation

To test the model, we construct markups at the firm-product-year level following the production-based approach by De Loecker et al. (2016).[22] This methodology requires minimal working

[22] For the case of United States, we only have information at the company level. Thus, in this case markups only vary at the firm-year level.

assumptions, is flexible with respect to the underlying demand system, and only requires production data.[23] In this section, we briefly explain the main elements of this methodology, and relegate a more detailed technical discussion to appendix B.

The main insight in De Loecker et al. (2016) is that price-cost markup of a firm-product can be computed as the ratio between two elements: (i) The output elasticity of product p with respect to any flexible input V (θ^V_{ipt}), and (ii) the expenditure share of the flexible input V (relative to the sales of product p; s^V_{ipt}). The former element requires the estimation of the production function at the firm-product level, while the latter component can be directly computed from our data. We briefly explain how we compute each of these elements next.

To estimate the production function coefficients, we specify a Cobb-Douglas production function, with labor, capital, and materials as production inputs for each product p. We consider the widely used Cobb-Douglas production function for our baseline analysis to keep comparability with the U.S. based results, where we use the production function estimates from De Loecker et al. (2020).[24] We measure output in terms of physical units and deflate materials expenditure with a firm-specific input price index.[25] Using output and inputs in terms of physical units is crucial, as it avoids the occurrence of input and output price biases (see De Loecker and Goldberg, 2014, for details). The approach we follow to identify the production function coefficients in multi-product firms follows De Loecker et al. (2016), who assume that products are produced with the same technology in single- and multi-product firms.[26] Hence, we identify the production function coefficients for all firms-products using the subset of single-product firms. To estimate the coefficients, we follow the methodology proposed by Ackerberg et al. (2015) to control for the endogeneity of firms' inputs choice.[27]

The second component needed to compute markups is the expenditure share, which is observed at the firm-level. To estimate this element for products within a firm, we follow Garcia-Marin and Voigtländer (2019) and proxy for product-specific input use assuming that

[23] The main assumptions are that firms minimize costs for each product p, and that at least one input production input is fully flexible.

[24] As we show in the appendix table D.2, our results are not sensitive to using the more flexible Translog production function.

[25] See appendix B for details on the construction of the input price index

[26] The main limitation of this approach is that it restricts economies of scope on the production side. As we discuss in the robustness checks section, our main results also hold when using average product margins (directly observed in our data) or when computing markups at the firm-level, which are not subject to this criticism.

[27] In addition, we implement the correction suggested by De Loecker (2013), to allow past exporting and investment decisions to affect firms' productivity, and include the probability of remaining single-product to correct for the bias that results from firm switching non-randomly from single to multi-product production (see De Loecker et al., 2016, for details).

inputs are used approximately in proportion to overall variable cost shares. For this, we take advantage of the fact that ENIA provides information on total variable costs (labor cost and materials) for each product produced by the firms. Finally, we compute the expenditure share dividing the value of material inputs by product-specific revenues, which are observed in the data.

While the simplicity of the production-based approach to recover markups is compelling, it is subject to some concern raised by recent studies (Bond et al., Forthcoming; Doraszelski and Jaumandreu, 2019; Syverson, 2019). When the production function is estimated with revenue data, the estimated coefficients are subject to the so-called price bias (De Loecker and Goldberg, 2014). As we explain above, our data allow us to directly tackle this issue by using output and inputs in physical units when estimating the production function. Bond et al. (Forthcoming) raise additional concerns related to the identification of the output elasticity under different scenarios. We note that, while the level of log markups will be biased under these concerns, their variation across time and firms within product categories should be unaffected in our Cobb-Douglas baseline specification.

4 Data

The main analysis uses information for the universe of Chilean manufacturing exporters over the period 2003-2007. In addition, we confirm our results with company-level Compustat data from the United States. A key advantage of the Chilean data is that it provides detailed information on physical inputs and outputs, allowing a better identification of the main mechanism. Crucially, the data reports inputs and outputs in terms of physical units, allowing cleaner markup estimates, and the construction of the physical productivity measure we use to instrument for markups. In Compustat, this information is not available.[28] Correspondingly, the Chilean data is our main dataset. In this section, we review the main features of the Chilean data and describe the sample. We describe the U.S. Compustat dataset in section 6.

The Chilean data combines information from two primary datasets. Our first data source is the Chilean National Customs Service and provides information 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. The dataset details

[28]Compustat only provides data on firms' sales and expenditure on a bundle of inputs (cost of goods sold, COGS), leading to important shortcomings (see recent discussions by Traina, 2018; Syverson, 2019)

the identity of the exporter, the importing country, product description, and the 8-digit HS code to which the product belongs, the FOB value and volume of the merchandise, and the financing mode of the export transaction. The data allows to identify if each transaction was paid in advance (cash in advance – CIA), post-shipment (trade credit – TC), or with other modes (such as letters of credit or two-part contracts).

We complement the customs-level data 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 cost, number of units produced and sold), and inputs purchased by the firm (value and volume for each input purchased by the plant). Output and input products are defined according to the 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 collect 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.

To ensure a consistent dataset, we follow several steps, including the deletion of observations that have missing, zero, or implausible variation in the values of any of the main variables. Appendix C provides details on these cleaning procedures, and on the matching procedure we applied to combine the information in the ENIA and Customs datasets. In the empirical analysis, we aggregate the transactions data at the annual frequency, the frequency at which we estimate markups. The final dataset consists of 93,556 firm-product-destinations-year observations. The sample represents 80.5% of the value of Chilean (non-copper) exports over the period 2003-2007.

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

Table 1 provides summary statistics for the main variables. Table C.1 in the appendix provides summary statistics for markups, aggregated at the 2-digit level. The average estimated markup is 1.3, while the median is 1.1.

Table 1. Summary Statistics

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Firm-product-destination Characteristics						
Trade Credit Dummy	0.8317	0.3521	1	1	1	93,556
Cash in advance Dummy	0.0914	0.2730	0	0	0	93,556
Letters of Credit Dummy	0.0633	0.2270	0	0	0	93,556
Export Value (US$)	894,402	15,266,952	3,400	18,131	103,813	93,556
Firm-product Characteristics						
Employment (at the firm level)	273.5	522.4	51	119	284	3,544
Markups (in logs)	0.153	0.373	-0.125	0.105	0.383	26,583
Physical total factor productivity (in logs)	0.381	3.335	-2.582	1.294	2.988	25,521
# Destinations by firm-product-year	3.5	5.3	1	1	4	26,583
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

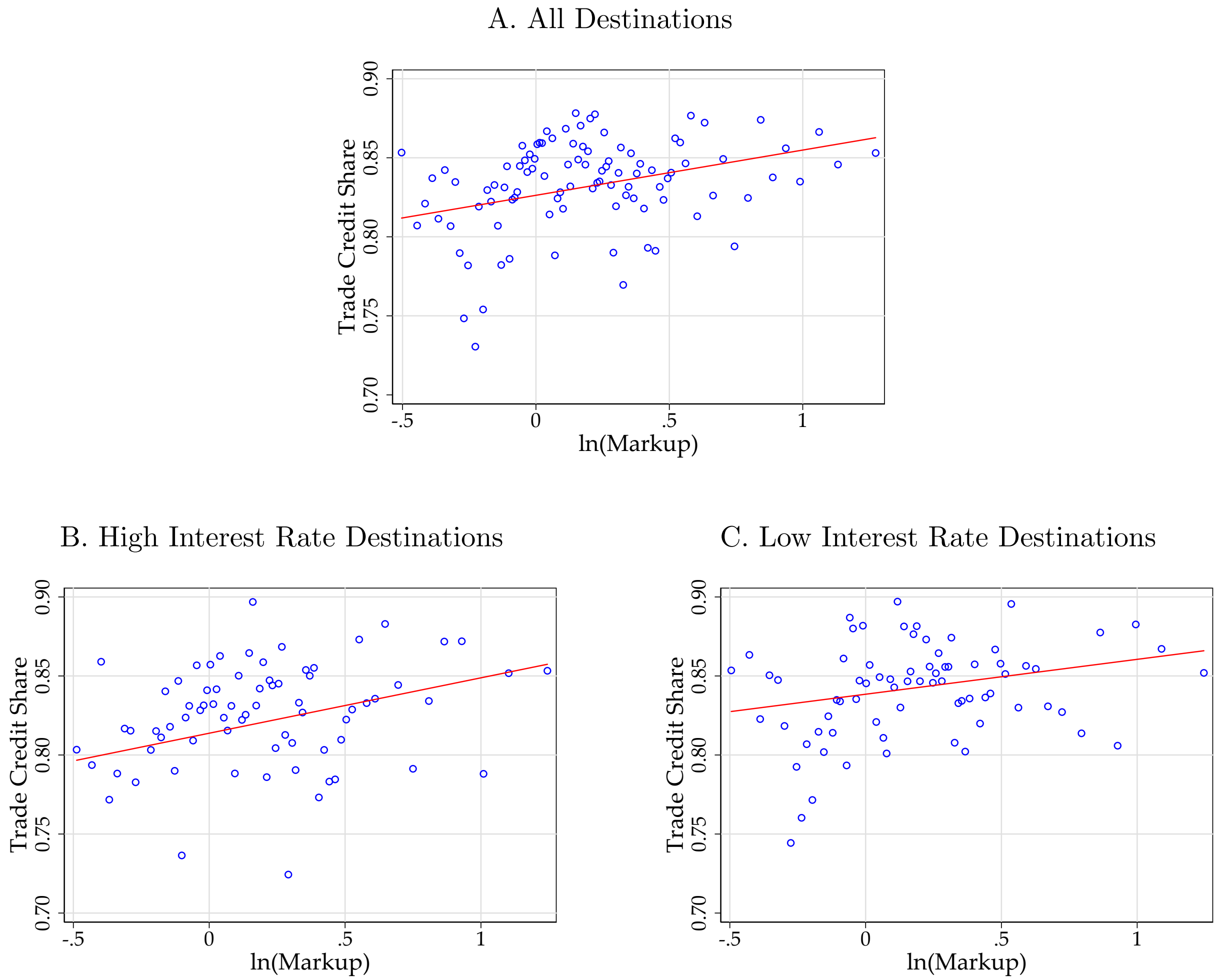
Notes: The table lists the summary statistics for the variables used in the paper's baseline analysis sample. It comprises customs-level data for the universe of Chilean manufacturing exporters that can be matched to the Chilean Annual Manufacturing Survey (ENIA), over the period 2003-2007.

5 Results

Before turning to the econometric evidence, we illustrate our main results in figure 2. The figure shows a binscatter plot, where the average trade credit share in each bin – defined as the percent of export value financed through trade credit – is plotted against the average firm-product markup (in logarithm). For both variables, the plot is based on residuals after taking out country-year fixed effects. Panel A shows a clear positive relationship between the trade credit share and markups. Next, we split the sample for destinations with borrowing rates that are above (panel B) and below (panel C) the median rate across years and destinations. The figure shows that the effect is stronger for destinations with relatively high borrowing rates, as predicted by proposition 3.[30]

[30] Appendix D.1 replicate figure 2 for the share of transactions financed through cash in advance and letters of credit contracts. These figures suggest that firms increase trade credit use with markups at the expense of cash in advance contracts. The use of letters of credit contracts, in contrast, appears unresponsive to markups.

Figure 2. Trade Credit Share, Markups and Interest Rates



Notes: The figures show binscatter plots of the trade credit share against markups (in logs). Panel A shows data for all destinations, while in panels B and C we split the data for export destinations with borrowing rates above and below the median rate across destinations, respectively. The trade credit share is computed at the firm-product-destination level, and markups are computed at the firm-product level, following the methodology by De Loecker et al. (2016). Both figures control for destination-year fixed effects.

5.1 Main Econometric Results.

We now turn to the main econometric analysis. Table 2 presents our baseline results on trade credit use and the level of markups. Column 1 shows OLS results. In line with proposition 3 and the evidence presented in figure 2, we find a positive and highly significant coefficient for markups. Columns 2-4 show the baseline instrumental variable results. First, in column 2, we report results from a reduced form specification, where we directly regress trade credit use on TFPQ. The regression shows a strong positive relationship between the two variables, providing direct support for proposition 4: Firms extend more trade credit in products that they produce more efficiently (at a lower marginal cost).

Table 2. Trade Credit Share and Firm-Product Markup: Baseline Regressions

Specification:	OLS	Reduced Form	First Stage	Second Stage
	(1)	(2)	(3)	(4)
Dependent Variable:	TC Share	TC Share	ln(markup)	TC Share
ln(Markup)	.0204***	—	—	.1050***
	(.0047)			(.0291)
ln(TFPQ)	—	.0054***	.0519***	—
		(.0015)	(.0038)	—
First Stage F-Statistic	—	—	232.2	—
Firm FE	✓	✓	✓	✓
HS8 FE	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓
Observations	93,556	90,727	90,727	90,727
R^2	.368	.371	.692	.368

Notes: All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Trade credit shares are computed as the ratio of the FOB value of trade credit transactions to the FOB value of all export transactions over a year. Markups are computed at the firm-product level. Column 1 reports OLS estimates. Column 2 report the reduced form for the trade credit share against TFPQ. The first stage results of the 2SLS regressions are reported in column 3, together with the (cluster-robust) Kleibergen-Paap rKWald F-statistic. The corresponding Stock-Yogo value for 10% maximal IV bias is 16.4. Second stage results are reported in column 4. Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

Next, in column 3, we report the first stage results, where we instrument markups by TFPQ. The first stage works well, with an F-statistic substantially above the Stock-Yogo critical value of 16.4 for 10% maximal IV bias. Consistent with proposition 4, the coefficient on TFPQ is positive and highly significant, implying that firms charge higher markups in products that they produce more efficiently. The magnitude of the first-stage coefficient implies that a ten percent increase in TFPQ is associated with an increase in markups of 0.52%.

Finally, in column 4, we show the second-stage results. The estimated coefficient on the trade credit share is positive and highly significant at the 1% level. The coefficient is also notably larger than the OLS coefficient in column 1, indicating that without instrumenting for the endogenous markups, results are biased towards zero. In quantitative terms, we find a plausible response of trade credit to changes in markups: based on the IV coefficient in column 4, an increase of one standard deviation in the firm-product markup (37.3 percent) increases the trade credit share by 3.9 percentage points.

One concern with the results in table 2 is that the exclusion restriction may be violated if more efficient firms have better access to capital, are better managed, or have some other time-varying characteristic that might be correlated with the trade credit decision. To address this point, we run additional regressions that include firm-year fixed effects. Adding firm-year fixed effects weakens the exclusion restriction notably, as differences in access to finance or management at the firm level are now permissible. More specifically, when we include firm-year fixed effects, identification comes from variation in markups across products within the same firm. Thus, any violation of the exclusion restriction would need to operate at the firm-product year level.

Table 3 presents these additional regressions that include firm-year fixed effects as well as different sets of other fixed effects. We obtain strong first stages and highly significant markup coefficients across all specifications. Column 1 repeats the baseline analysis, adding firm-year fixed effects. Next, columns 2-4 include additional, more restrictive sets of fixed effects to control for potential omitted variables that may operate at different levels of aggregation. Column 2 adds product-country fixed effects, which address concerns that high-markup products might be systematically exported to countries that receive more trade credit. For instance, this could occur if more complex products were exported to richer countries that tend to have better contract enforcement (Hoefele et al., 2016). Column 3 includes product-year fixed effects to control for factors varying at the product-year level, while column 4 includes all fixed effects simultaneously. Overall, we obtain highly significant and positive coefficients, providing strong evidence for the positive effect of markups on trade credit use.

Interactions. Next, we present results on the interactions between markups, trade credit, and interest rates. Proposition 3 predicts that the effect of markups on trade credit increases with the buyer's borrowing rate and decreases with the seller's deposit rate. Testing these predictions on the interaction terms constitutes an important check of the model for two reasons. First, the interactions between the markup and interest rates directly speak to the key mechanism of the model: Trade credit saves financing costs as it reduces total borrowing needs, and financial cost savings should be proportional to the product of the markup and the interest rate differential. Second, estimating a specification with interaction terms allows for the inclusion of a more complete set of fixed effects, substantially reducing omitted variable bias concerns. Table 4 present the results from estimating equation (19); we report OLS (columns 1 to 4) and 2SLS (columns 5 to 8) estimates. In all specifications, standard errors are clustered at the firm-destination level.

Table 3. Trade Credit Share and Firm-Product Markup: Different Fixed Effects

Specification:	2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
ln(Markup)	.589***	.343**	.526***	.347*
	(.174)	(.146)	(.204)	(.196)
Firm-Year FE	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓
HS8 FE	✓	—	—	—
Country-HS8 FE	—	✓	—	✓
HS8-Year FE	—	—	✓	✓
First Stage F-Statistic	54.3	52.8	40.5	33.9
Observations	90,727	90,727	90,727	90,727

Notes: All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Trade credit shares are computed as the ratio of the FOB value of trade credit transactions to the FOB value of all export transactions over a year. Markups are computed at the firm-product level, and uses TFPQ as an instrument for markups. All regressions report the (cluster-robust) Kleibergen-Paap rKWald F-statistic; the corresponding Stock-Yogo value for 10% maximal IV bias is 16.4. Second stage results are reported in column 6. Standard errors (in parentheses) are clustered at the firm-product level. Key: *** significant at 1%; ** 5%; * 10%.

Results in table 4 confirm the key prediction of proposition 3 that the effect of the markup on the trade credit choice increases with the buyer's borrowing costs. The coefficient on the interaction term between the markup and the buyer's borrowing rate, r_b^*, is positive and highly significant across all specifications. Similar to the baseline estimates in table 2, 2SLS results yield strong first-stages and confirm findings for OLS results, with the 2SLS coefficients again being notably larger. We also test the prediction for the interaction between the markup and the domestic deposit rate, r_d, which has the predicted sign but is not statistically significant. This is not surprising, as there is only one seller country, Chile, in our data. This interaction term drops out in columns 3, 4, 7, and 8, once we include firm-product-year fixed effects. Columns 2 and 6 present results on contract enforcement, using the destination country's rule of law index as a proxy for contract enforcement. As predicted by the theory, stronger enforcement abroad strengthens the relationship between the markup and trade credit provision. However, the interaction term is only significant for the 2SLS specification (column 6), which may be due to limited variation in the rule of law variable.[31] Finally, columns 3, 4, 7, and 8 repeat the previous analysis, adding firm-product-year fixed-effects. Coefficients are very stable, suggesting that omitted variable bias at the firm-product level is not a concern here.

[31] Rule of law estimates by the World Bank are very stable within a country over time, especially at short horizons.

Table 4. Trade Credit Share and Firm-Product Markup: Heterogeneity

Specification	OLS (1)	OLS (2)	OLS (3)	OLS (4)	2SLS (5)	2SLS (6)	2SLS (7)	2SLS (8)
ln(markup)	-.0215	-.0298	—	—	.539**	.459**	—	—
	(.0311)	(.0318)			(.222)	(.226)		
ln(markup)×r_d	-.533	-.485	—	—	-2.130	-1.551	—	—
	(2.510)	(2.512)			(17.34)	(17.64)		
ln(markup)×r_b^*	.293**	.328***	.308**	.315*	.953*	1.232**	1.136**	1.363**
	(.121)	(.126)	(.135)	(.141)	(.545)	(.562)	(.569)	(.587)
ln(markup)× Rule of Law	—	.0212	—	.0212	—	.239*	—	.209
		(.0151)		(.0164)		(.137)		(.147)
First Stage F-Statistic	—	—	—	—	21.1	16.5	51.7	26.9
Firm-Year FE	✓	✓	—	—	✓	✓	—	—
HS8 FE	✓	✓	—	—	✓	✓	—	—
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm-HS8-Year FE	—	—	✓	✓	—	—	✓	✓
Observations	93,556	93,556	93,556	93,556	90,727	90,727	90,727	90,727
R^2	.420	.420	.437	.437	.409	.402	.435	.430

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). Trade credit share corresponds to the ratio of the FOB value of trade credit transactions to the FOB value of all export transactions over a year. Markups are computed at the firm-product level (products are defined at the 5-digit CPC level). Columns 1-4 report OLS, while columns 5-8 report 2SLS results using TFPQ as an instrument for markups. All 2SLS regressions report the (cluster-robust) Kleibergen-Paap rK Wald F-statistic; the corresponding Stock-Yogo value for 10% maximal IV bias is 16.4. 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 gauge the quantitative relevance of these effects, consider two firms at the 25th (markup of 0.88) and 75th percentile (markup of 1.47) of the markup distribution, respectively. Based on the coefficient in column 5, a one-standard-deviation higher borrowing rate (4.5 percentage points) in the destination country increases the share of trade credit by 2.5 percentage points for a firm with a markup at the 75th percentile relative to a firm with a markup at the 25th percentile.

5.2 Further Robustness Checks

We performed several robustness checks using alternative specifications and considered a series of extensions. In this subsection, we discuss the most important robustness checks, relegating a more detailed discussion of these results to appendix D.2.

We begin by studying if our results are dependent on the particular specification used to estimate markups. Our baseline markup measure is based on Cobb-Douglas materials' elasticities. We show that our results are quantitatively very similar when specifying a more flexible Translog production function when estimating markups (table D.2). In the same table, we show that using product-level price-cost margins that are directly reported in the survey as a measure of markups does not affect our results qualitatively. We also examine if our results are dependent on the way inputs are assigned to outputs. In the baseline estimates, inputs are assigned to outputs using the share of variable costs used in each product. When computing markups at the firm-level, we do not need to assume this. Results in table D.2 show similar point estimates as when using the full sample. However, standard errors are larger, because the effective variation is smaller when we do not exploit information across products within a firm.

We then test robustness of the main results to two additional controls. First, we add 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, while the markup coefficient stays unchanged. Second, to test whether the existence of previous export relations could drive our results, we include the cumulative sum of the FOB value of all previous shipments of the same product to each destination. While the cumulative export coefficient turns positive and statistically significant, the markup coefficient does not change substantially, confirming our main finding. These robustness results are available upon request.

To summarize, our baseline results are robust to instrumenting markups by physical productivity at the firm-product level, using alternative markup measures, and to the inclusion of additional controls.

6 Evidence from the United States

In this section, we repeat the main empirical analysis using firm-level data from the United States for the period 1965-2016. For this analysis, we use information on all publicly traded companies included in Compustat. This dataset has been used extensively across different fields (more recently in De Loecker et al., 2020, who document the evolution of market power in the United States). Compustat samples relatively few U.S. companies each year. However, these companies tend to be large and account for a large share of private sector employment and sales.

In the Compustat data, we calculate trade credit use as the ratio of accounts receivables over sales. As before, markups are estimated following the methodology in De Loecker et al. (2016). In the computation of markups, we consider the cost of goods sold (COGS) as the relevant flexible input.[32] We take the elasticity of COGS with respect to output directly from De Loecker et al. (2020), and calculate the share of COGS in sales from the data. As for the case of the Chilean data, we exclude companies with missing or zero NAICS code, sales, or COGS, and firm-years with trade credit share above 100 percent or with extreme values for markups (below the 2nd or above the 98th percentiles of the markups distribution).

One important limitation of Compustat relative to the Chilean export data is that it does not provide information for output in terms of physical units. This prevents us from estimating physical productivity and using the instrumental variable approach that we use in the main analysis. We can thus not resolve endogeneity concerns in the U.S. sample to the same extent as with the Chilean data.

We find very similar results in the U.S. data as in the Chilean data. As shown in figure 1, the U.S. data also exhibit a clear positive relationship between trade credit use and markups, that seems to be even stronger than the one we found for Chile. This is confirmed in columns 1 and 2 of table 5, that show a strong positive correlation between markups and trade credit, controlling for industry-year (at the 2-digit level) and firm fixed-effects.[33] Interestingly, the markup coefficient has a similar magnitude as our OLS estimate for Chile (table 2, column 1). In column 3, we present results on an interaction between the markup and the real (ex-post) effective Fed Funds Rate, our measure of borrowing costs in the U.S. data. Consistent with our theory and the evidence for Chile, the interaction term is positive and highly significant (again, with a similar magnitude as the OLS estimate for Chile). Altogether, the results for the United States indicate that our findings for Chile generalize to the case of large U.S. firms as measured in Compustat: Trade credit use increases with markups, especially when borrowing is more expensive.

[32] COGS is a composite that includes all expenditure incurred by firms in the production of the goods. While its specific composition varies across sectors, it mostly reflect variation in intermediate inputs, labor cost, and energy.

[33] As the data varies at the firm-year level, we only control for firm and industry-year fixed effects, and cluster standard errors at the firm level.

Table 5. Trade Credit Share and Markup in the United States Heterogeneity

	(1)	(2)	(3)
log(markup)	.0457***	.0227***	.0166***
	(.0021)	(.0024)	(.0020)
log(markup) × Real Effective Fed Funds Rate	—	—	.373***
			(.0053)
Industry-year FE	✓	✓	✓
Firm FE	—	✓	✓
Observations	138,680	136,789	129,125

Notes: The table estimates equations (18) and (19) using data for U.S: companies included in Compustat between 1965 and 2016. Trade credit share corresponds to the ratio of account receivables to sales. Markups are computed at the firm-level using cost of goods sold (COGS) as variable input, following De Loecker et al. (2020). All regressions control for the logarithm of firm employment. Standard errors (in parentheses) are clustered at the firm-level. Key: *** significant at 1%; ** 5%; * 10%.

7 Concluding Remarks

Trade credit is the most important form of short-term finance for U.S. firms. This paper studies Chilean firm-product-destination level data and U.S. firm level data, documenting that trade credit use increases in markups, an effect that increases with the buyers' borrowing costs. It proposes a model of trade credit choice with positive markups and a financial intermediation friction to rationalize these facts and the general dominance of trade credit for firm-to-firm transactions.

An important conceptional point of the model is that the choice that firms face is not between trade credit and bank finance, but rather whether the buyer or the seller borrows from a bank. If the seller borrows, she extends trade credit. If the buyer borrows, the seller receives cash in advance, which Mateut (2014) pointedly referred to as "reverse trade credit." The key result of the theory is that in the presence of positive markups and financial frictions, it is almost always better for the seller to borrow, as this minimizes the amount borrowed and hence financial intermediation costs.

As a consequence, the payment choice affects the aggregate level of borrowing, making the size of the financial sector endogenous. This prediction is qualitatively consistent with recent developments in aggregate U.S. data that suggest rising markups (as estimated by De Loecker and Eeckhout, 2017) and more use of trade credit over time. 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 could shed more light on the macro implications of our findings and 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.

References

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Adelino, Manuel, Miguel A Ferreira, Mariassunta Giannetti, and Pedro Pires, "Trade Credit and the Transmission of Unconventional Monetary Policy," Technical Report, National Bureau of Economic Research 2020.

Aghion, Philippe, Antonin Bergeaud, Gilbert Cette, Rémy Lecat, and Hélène Maghin, "Coase Lecture - The Inverted-U Relationship between Credit Access and Productivity Growth," *Economica*, 2019, *86*, 1–31.

Ahn, JaeBin, "Understanding trade finance: theory and evidence from transaction-level data," Technical Report, International Monetary Fund, Washington, DC 2014.

_ **and Miguel Sarmiento**, "Estimating the direct impact of bank liquidity shocks on the real economy: Evidence from letter-of-credit import transactions in Colombia," *Review of International Economics*, 2019, *27* (5), 1510–1536.

_ **, Mary Amiti, and David E Weinstein**, "Trade finance and the great trade collapse," *American Economic Review*, 2011, *101* (3), 298–302.

Amberg, Niklas, Tor Jacobson, Erik Von Schedvin, and Robert Townsend, "Curbing shocks to corporate liquidity: The role of trade credit," *Journal of Political Economy*, Forthcoming.

_ **, Tore Ellingsen, Tor Jacobson, and Erik von Schedvin**, "Trade Credit and Capital Bias," Working Paper, Stockholm School of Economics 2020.

Amiti, Mary and David E. Weinstein, "Exports and Financial Shocks," *The Quarterly Journal of Economics*, 2011, *126* (4), 1841–1877.

Antràs, Pol and C Fritz Foley, "Poultry in Motion: A Study of International Trade Finance Practices," *Journal of Political Economy*, 2015, *123* (4), 853–901.

Balkenborg, Dieter, M Boyer, Y Hiriart, and D Martimort, "Judgment-Proofness and Extended Liability in the Presence of Adverse Selection," in "Frontiers in the Economics of Environmental Regulation and Liability," Vol. 91, Ashgate Aldershot, 2006, pp. 265–290.

Barrot, Jean-Noël, "Trade credit and industry dynamics: Evidence from trucking firms," *The Journal of Finance*, 2016, *71* (5), 1975–2016.

Biais, Bruno and Christian Gollier, "Trade Credit and Credit Rationing," *Review of Financial Studies*, 1997, *10* (4), 903–37.

Bloom, Nicholas and John Van Reenen, "Measuring and Explaining Management Practices Across Firms and Countries," *The Quarterly Journal of Economics*, 2007, *122* (4), 1351–1408.

Bond, Steve, Arshia Hashemi, Greg Kaplan, and Piotr Zoch, "Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Estimation from Production Data," *Journal of Monetary Economics: Carnegie-Rochester-NYU Conference on Public Policy*, Forthcoming.

Brennan, Michael J, Vojislav Maksimovics, and Josef Zechner, "Vendor financing," *The Journal of Finance*, 1988, *43* (5), 1127–1141.

Burkart, Mike and Tore Ellingsen, "In-Kind Finance: A Theory of Trade Credit," *American Economic Review*, June 2004, *94* (3), 569–590.

Chod, Jiri, Evgeny Lyandres, and S Alex Yang, "Trade credit and supplier competition," *Journal of Financial Economics*, 2019, *131* (2), 484–505.

Chor, Davin and Kalina Manova, "Off the cliff and back? Credit conditions and international trade during the global financial crisis," *Journal of International Economics*, 2012, *87* (1), 117 – 133.

Daripa, Arup and Jeffrey Nilsen, "Ensuring sales: A theory of inter-firm credit," *American Economic Journal: Microeconomics*, 2011, *3* (1), 245–79.

De Loecker, Jan, "A Note on Detecting Learning by Exporting," *American Economic Journal: Macroeconomics*, 2013, *5* (3), 1–21.

_ **and Pinelopi Koujianou Goldberg**, "Firm Performance in a Global Market," *Annual Review of Economics*, 2014, *6* (1), 201–227.

_ **, Jan Eeckhout, and Gabriel Unger**, "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

_ **, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik**, "Prices, Markups and Trade Reform," *Econometrica*, 2016, *84* (2), 445–510.

Demir, Banu and Beata Javorcik, "Don't throw in the towel, throw in trade credit!," *Journal of International Economics*, 2018, *111*, 177–189.

Demirguc-Kunt, Asli and Vojislav Maksimovic, "Firms as financial intermediaries - evidence from trade credit data," Policy Research Working Paper Series 2696, The World Bank October 2001.

Doraszelski, Ulrich and Jordi Jaumandreu, "Using Cost Minimization to Estimate Markups," CEPR Discussion Papers 14114, C.E.P.R. Discussion Papers November 2019.

Duval, Romain, Gee Hee Hong, Yannick Timmer, and Philip StrahanEditor, "Financial Frictions and the Great Productivity Slowdown," *Review of Financial Studies*, 2020, *33* (2), 475–503.

Ellingsen, Tore, Tor Jacobson, and Erik L von Schedvin, "Trade credit: Contract-level evidence contradicts current theories," 2016. Stockholm School of Economics.

Emery, Gary W, "A pure financial explanation for trade credit," *Journal of Financial and Quantitative Analysis*, 1984, *19* (3), 271–285.

Ferris, J Stephen, "A transactions theory of trade credit use," *The Quarterly Journal of Economics*, 1981, *96* (2), 243–270.

Fischer, Christian, "Optimal payment contracts in trade relationships," 2020.

Fisman, Raymond and Inessa Love, "Trade credit, financial intermediary development, and industry growth," *The Journal of finance*, 2003, *58* (1), 353–374.

Garcia-Marin, Alvaro and Nico Voigtländer, "Exporting and Plant-Level Efficiency Gains: It's in the Measure," *Journal of Political Economy*, 2019, *127* (4), 1777–1825.

Giannetti, Mariassunta, Mike Burkart, and Tore Ellingsen, "What You Sell Is What You Lend? Explaining Trade Credit Contracts," *Review of Financial Studies*, 2011, *24* (4), 1261–1298.

_ , Nicolas Serrano-Velarde, and Emanuele Tarantino, "Cheap Trade Credit and Competition in Downstream Markets," *Journal of Political Economy*, forthcoming.

Ho, Thomas SY and Anthony Saunders, "The determinants of bank interest margins: theory and empirical evidence," *Journal of Financial and Quantitative analysis*, 1981, pp. 581–600.

Hoefele, Andreas, Tim Schmidt-Eisenlohr, and Zhihong Yu, "Payment Choice in International Trade: Theory and Evidence from Cross-country Firm Level Data," *Canadian Journal of Economics*, 2016, *49* (1), 296–319.

Jacobson, Tor and Erik von Schedvin, "Trade credit and the propagation of corporate failure: an empirical analysis," *Econometrica*, 2015, *83* (4), 1315–1371.

Levinsohn, James and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 2003, *70* (2), 317–341.

Loecker, Jan De and Jan Eeckhout, "The rise of market power and the macroeconomic implications," Technical Report, National Bureau of Economic Research 2017.

Love, Inessa, Lorenzo A Preve, and Virginia Sarria-Allende, "Trade credit and bank credit: Evidence from recent financial crises," *Journal of Financial Economics*, 2007, *83* (2), 453–469.

Manova, Kalina, "Credit constraints, heterogeneous firms, and international trade," *The Review of Economic Studies*, 2013, *80* (2), 711–744.

Mateut, Simona, "Reverse trade credit or default risk? Explaining the use of prepayments by firms," *Journal of Corporate Finance*, 2014, *29*, 303–326.

Melitz, Marc J. and Giancarlo I. P. Ottaviano, "Market Size, Trade, and Productivity," *Review of Economic Studies*, 01 2008, *75* (1), 295–316.

Mian, Shehzad L and Clifford W Smith, "Accounts receivable management policy: theory and evidence," *The Journal of Finance*, 1992, *47* (1), 169–200.

Murfin, Justin and Ken Njoroge, "The implicit costs of trade credit borrowing by large firms," *The Review of Financial Studies*, 2014, *28* (1), 112–145.

Myerson, Roger B, "Two-person bargaining problems with incomplete information," *Econometrica: Journal of the Econometric Society*, 1984, pp. 461–487.

Niepmann, Friederike and Tim Schmidt-Eisenlohr, "No guarantees, no trade: How banks affect export patterns," *Journal of International Economics*, 2017, *108*, 338–350.

Nilsen, Jeffrey H, "Trade credit and the bank lending channel," *Journal of Money, credit and Banking*, 2002, pp. 226–253.

Olley, G. Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–1297.

Olsen, Morten, "How firms overcome weak international contract enforcement: repeated interaction, collective punishment and trade finance," 2016.

Paravisini, Daniel, Veronica Rappoport, Philipp Schnabl, and Daniel Wolfenzon, "Dissecting the effect of credit supply on trade: Evidence from matched credit-export data," *The Review of Economic Studies*, 2014, *82* (1), 333–359.

Petersen, Mitchell A and Raghuram G Rajan, "Trade Credit: Theories and Evidence," *Review of Financial Studies*, 1997, *10* (3), 661–91.

Peura, Heikki, S. Alex Yang, and Guoming Laic, "Trade Credit in Competition: A Horizontal Benefit," *Manufacturing & Service Operations Management*, 2017, *19* (2), 263–289.

Schmidt-Eisenlohr, Tim, "Towards a theory of trade finance," *Journal of International Economics*, 2013, *91* (1), 96 – 112.

Schwartz, Robert A, "An economic model of trade credit," *Journal of financial and quantitative analysis*, 1974, *9* (4), 643–657.

Schwartz, Robert Alan and David K Whitcomb, "The trade credit decision," in J. Bicksler, ed., *Handbook of Financial Ecnomics*, 1979.

Smith, Janet Kiholm, "Trade credit and informational asymmetry," *The journal of finance*, 1987, *42* (4), 863–872.

Syverson, Chad, "Macroeconomics and market power: Context, implications, and open questions," *Journal of Economic Perspectives*, 2019, *33* (3), 23–43.

Traina, James, "Is Aggregate Market Power Increasing? Production Trends Using Financial Statements," Stigler Center New Working Paper Series 17, University of Chicago 2018.

Online Appendix

Trade Credit and Markups

Alvaro Garcia-Marin Santiago Justel Tim Schmidt-Eisenlohr

A Theory Appendix

A.1 Partial Cash in Advance

While contracts with partial advance payment are not empirically relevant in our data or other data that we are aware of (e.g. Antràs and Foley, 2015), they are still interesting to study from a theoretical perspective. In the following we describe a simple extension of our model to study this payment option, building on related analysis in Schmidt-Eisenlohr (2013). In the following, for tractability, consider the case without commitment problem. Suppose the buyer can pre-pay share ϕ of payment P^{IM}. Then, there are two cases.

Case 1 In the first case, the buyer pays at least the production cost C in advance ($P^{IM} \geq C$). This gives us:

$$\begin{aligned}\Pi_S^{IM} &= (1+r_d)(\phi P^{IM} - C) + (1-\phi)P^{IM} \\ \Pi_B^{IM} &= R - (1+r_b^*)\phi P^{IM} - (1-\phi)P^{IM}\end{aligned}$$

Now solve for the maximum payment that satisfies the participation constraint of the buyer to get:

$$P^{IM} = \frac{R}{1+\phi r_b^*}$$

Plugging back into seller profits delivers:

$$\Pi_S^{IM} = (1+r_d)\left(\frac{\phi R}{1+\phi r_b^*} - C\right) + \frac{(1-\phi)R}{1+\phi r_b^*}$$

Taking the derivative of seller profits with respect to ϕ delivers:

$$\frac{\partial \Pi_S^{IM}}{\partial \phi} = (1+r_d)\frac{R}{(1+\phi r_b^*)^2} - (1+r_b^*)\frac{R}{(1+\phi r_b^*)^2},$$

which is negative as long as $r_b^* > r_d$. So we end up in a corner where the buyer exactly pre-pays production costs.

Case 2 In the second case, the buyer pays less than C in advance ($P^{IM} < C$). The problem then reads:

$$\begin{aligned}\Pi_S^{IM} &= (1+r_b)(\phi P^{IM} - C) + (1-\phi)P^{IM} \\ \Pi_B^{IM} &= R - (1+r_b^*)\phi P^{IM} - (1-\phi)P^{IM}\end{aligned}$$

As the buyer profits do not change, the payment remains $P = \frac{R}{1+\phi r_b^*}$. Plugging into seller profits delivers:

$$\Pi_S^{IM} = (1+r_b)\left(\frac{\phi R}{1+\phi r_b^*} - C\right) + \frac{(1-\phi)R}{1+\phi r_b^*}$$

Taking the derivative of seller profits with respect to ϕ delivers:

$$\frac{\partial \Pi_S^{IM}}{\partial \phi} = (1+r_b)\frac{R}{(1+\phi r_b^*)^2} - (1+r_b^*)\frac{R}{(1+\phi r_b^*)^2},$$

Combining the above equations, delivers the following solution: If $r_b^* > r_b$, firms should use trade credit with no pre-payment. If $r_d < r_b^* < r_b$, then the buyer should pay the production cost in advance. Full cash-in-advance is never optimal, as long as $r_d < r_b^*$. To summarize, the financing cost advantage is still active, even when allowing for partial pre-payments. At the same time, the model does not fully rule out the case of a partial pre-payment. To do so would require modelling an additional friction. A good candidate would be a legal enforcement friction. Partial pre-payments are problematic from a legal perspective, as at any point in time the legal ownership has to be assigned to one of the two parties.

A.2 Solving the model with CES and monopolistic competition

Assume that firms operate under monopolistic competition and that final consumers have CES preferences with demand:

$$q = p^{-\sigma} A,$$

where σ is the elasticity of substitution between varieties and A reflects the aggregate level of demand. Expected profits of the seller in the full model are then given by:

$$\begin{aligned}
\mathrm{E}[\Pi_S^{TC}] &= \left(\tilde{\lambda}^* p - (1+r_b)c\right) q \\
\mathrm{E}[\Pi_S^{CIA}] &= \left(\tilde{\lambda}\, \frac{1+r_d}{1+r_b^*}\, p - (1+r_d)c\right) q
\end{aligned}$$

Solving the model delivers the following optimal prices charged to final consumers:

$$\begin{aligned}
p^{TC} &= \frac{1+r_b}{\tilde{\lambda}^*} \frac{\sigma}{\sigma-1} c \\
p^{CIA} &= \frac{1+r_b^*}{\tilde{\lambda}} \frac{\sigma}{\sigma-1} c
\end{aligned}$$

We can plug in the CES quantity q and price p^{TC} into the expected profit for trade credit to get:

$$\mathrm{E}[\Pi_S^{TC}] = \left(\tilde{\lambda}^*\right)^{\sigma} (1+r_b)^{1-\sigma} \frac{c^{1-\sigma}}{\sigma-1} \left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} A$$

For Cash in Advance, we get:

$$\mathrm{E}[\Pi_S^{CIA}] = \left(\tilde{\lambda}\right)^{\sigma} (1+r_d)(1+r_b^*)^{-\sigma} \frac{c^{1-\sigma}}{\sigma-1} \left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} A$$

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

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

Or, rewriting for interpretation:

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

Within a country, the equation simplifies to:

$$1 > \frac{1+r_d}{1+r_b}$$

which always holds when $r_b > r_d$. We can also take the derivative of equation (A.1) with respect to σ. This delivers:

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

This derivative is negative when equation (A.1) is positive. That is, if this condition holds, larger markups (smaller σ) lead to more trade credit use in the CES case.

A.3 Derivations for pooling and separating cases

This section derives conditions under which it is optimal for unreliable firms to imitate reliable firms and for sellers to offer terms that both types of buyers accept. The following exposition builds on and extends the analysis in Schmidt-Eisenlohr (2013). All derivations are for the full model (international case) but subsume the domestic case. In particular, we need to look at four cases:

1. The seller asks for a payment that is only accepted by unreliable buyers under trade credit.
2. The reliable seller chooses cash in advance, but the unreliable seller chooses trade credit.
3. The seller asks for a payment that is only accepted by unreliable buyers under cash in advance.
4. The reliable seller chooses trade credit, but the unreliable seller chooses cash in advance.

Trade Credit - pooling case This is the baseline case discussed in the main text. The seller maximizes:

$$\begin{aligned} \mathrm{E}[\Pi_S^{TC,P}] &= \tilde{\lambda}^* P^{TC,P} - (1+r_b)C, \\ \text{s.t. } \mathrm{E}[\Pi_{RB}^{TC,P}] &= R - P^{TC,P} \geq 0, \end{aligned}$$

and chooses $P^{TC,P} = R$. This implies the following expected profits for both reliable and unreliable sellers under pooling:

$$\mathrm{E}[\Pi_S^{TC,P}] = \tilde{\lambda}^* R - (1+r_b)C \tag{A.2}$$

Trade Credit, Separating Case 1 The seller could ask for a payment that is only acceptable for unreliable buyers. Then, the payment exceeds revenues, $P^{TC,S} > R$. Unreliable buyers still accept this contract, as they know that they can deviate with probability λ^*. Expected profits of an unreliable buyer under separation are:

$$\mathrm{E}[\Pi_{UB}^{TC,S}] \;=\; R - \lambda^* P^{TC,S}.$$

In this case, the seller picks $P^{TC,S} = \frac{R}{\lambda^*}$. Importantly, reliable buyers now reject the contract, so that the exporter only gets the initial contract accepted with probability $1 - \eta^*$, the share of unreliable firms. Expected profits of a seller under a separating contract are hence:

$$\mathrm{E}[\Pi_{S}^{TC,S}] \;=\; (1 - \eta^*)(R - (1 + r_b)C). \tag{A.3}$$

Combining equations (A.2) and (A.3), a seller picks the pooling case as long as:

$$\mathrm{E}[\Pi_{S}^{TC,P}] > \mathrm{E}[\Pi_{S}^{TC,S}] \Leftrightarrow (\eta^* - (1 - \eta^*)(1 - \lambda^*))\, R > \eta^*(1 + r_b)C. \tag{A.4}$$

As long as this condition holds, we can exclude **Case 1**. The condition is relatively weak. For example, suppose $\eta^* = 0.8$, $\lambda^* = 0.8$, and $1 + r_b = 1.025$ (annual rate of 10 percent if trade credit is for 3 months). Then the markup $\mu = R/C$ has to be larger than 1.08. The markup can be smaller if the share of reliable firms η^* is larger, if contract enforcement λ^* is stronger, or if the borrowing rate $1 + r_b$ is lower.

Trade Credit, Separating Case 2 Can it be optimal for the unreliable seller to choose trade credit when the reliable seller chooses cash in advance? No, because under trade credit both types of sellers have the same expected profits, and unreliable sellers have larger expected profits under cash in advance than under trade credit.

Cash in Advance - pooling case Under cash in advance, the reliable seller maximizes:

$$\begin{aligned} \mathrm{E}[\Pi_{RS}^{CIA,P}] &= (1 + r_d)(P^{CIA,P} - C), \\ \text{s.t. } \mathrm{E}[\Pi_{B}^{CIA,P}] &= \tilde{\lambda} R - (1 + r_b^*)P^{CIA,P} \geq 0. \end{aligned}$$

Solving for the optimal $P^{CIA,P}$ delivers $P^{CIA,P} = \frac{\tilde{\lambda}}{1+r_b^*}R$. With expected profits of:

$$\mathrm{E}[\Pi_{RS}^{CIA,P}] \quad = \quad (1+r_d)\left(\frac{\tilde{\lambda}}{1+r_b^*}R - C\right). \tag{A.5}$$

An unreliable seller has expected profits of:

$$\mathrm{E}[\Pi_{US}^{CIA,P}] \quad = \quad (1+r_d)\left(\frac{\tilde{\lambda}}{1+r_b^*}R - \lambda C\right).$$

Cash in Advance, Separating Case 3 Can it be optimal for the seller to ask for a payment that is only acceptable to unreliable firms when using cash in advance? No, because under this payment term, there is no commitment problem on the buyer side. Hence the two types of buyers behave exactly the same way. In particular, they have the same participation constraint.

Cash in Advance, Separating Case 4 Suppose that a reliable seller does not prefer cash in advance. Can it be profitable for an unreliable seller to pick cash in advance anyways, thereby revealing her type? Then, the buyer knows that she is dealing with an unreliable seller and the participation constraint becomes:

$$\mathrm{E}[\Pi_{B}^{CIA,S}] = \lambda R - (1+r_b^*)P^{CIA,S}.$$

The unreliable seller then picks the optimal payment $P^{CIA,S} = \frac{\lambda}{1+r_b^*}R$, delivering expected profits of:

$$\mathrm{E}[\Pi_{US}^{CIA,S}] = (1+r_d)\left(\frac{\lambda}{1+r_b^*}R - \lambda C\right). \tag{A.6}$$

Suppose the reliable seller does not choose cash in advance (our starting point above). Then, a sufficient condition for the unreliable seller not to deviate and choose cash in advance is that expected profits of a reliable seller in the pooling case weakly dominate expected profits of an unreliable seller in the separating case. This is because an unreliable seller always has strictly larger expected profits under pooling than a reliable seller (as long as $\lambda < 1$), as $\mathrm{E}[\Pi_{US}^{CIA,P}] > \mathrm{E}[\Pi_{RS}^{CIA,P}]$. A sufficient condition to exclude the separating case is thus:

$$\mathrm{E}[\Pi_{RS}^{CIA,P}] \geq \mathrm{E}[\Pi_{US}^{CIA,S}].$$

Plugging in from equations (A.5) and (A.6) and rearranging delivers:

$$R > \frac{1 + r_b^*}{\eta} C. \tag{A.7}$$

If this condition holds, we can rule out **Case 4**. The condition is more demanding than condition (A.4). For example, taking correspondent parameters $\eta = 0.8$ and $1 + r_b^* = 1.025$, would require a markup of at least 1.28 to rule out the separating case. It is quite easy though to tighten the condition in a realistic way by introducing an additional contract enforcement cost δ as in Schmidt-Eisenlohr (2013). With the additional enforcement cost, condition (A.7) becomes $R > \frac{1+r_b^*}{\eta} \frac{1-\lambda}{1-\lambda(1-\delta)} C$. Now, assume a small enforcement cost of $\delta = 0.05$. That is, when a contract needs to be enforced in court, the firm that enforces the contract has to pay 5 percent of the amount that it recovers (for cash in advance, this is R). In addition, suppose that $\lambda = 0.8$. Then, the required markup to rule out the separating case falls to 1.07. If $\delta > 0.071$, then the condition always holds, even in the absence of a positive markup over marginal costs ($\mu = 1$).

To summarize, Cases 2 and 3 are never optimal for the seller, while Cases 1 and 4 can be excluded under relatively weak conditions.

A.4 Introducing Bargaining

This section lays out how the model can be extended to the case of bargaining between the buyer and the seller. As there is private information about the type of the buyer and the seller, we use the Neutral Bargaining Solution proposed by Myerson (1984), which generalizes Nash Bargaining to the case of private information. The basic idea is that under the Neutral Bargaining Solution, the two parties play a random dictator game, where they must respect constraints from asymmetric information, as the other player can always reject the offer of the dictator. Specifically, this implies that a buyer or seller cannot propose a solution that violates the participation constraint of the other firm. As shown by Balkenborg et al. (2006), this solution can be generalized to arbitrary bargaining weights be letting the two parties be the dictator in the game with the probability given by the bargaining weight. Let θ denote the bargaining weight of the seller.

A.4.1 Trade Credit Choice under the Neutral Bargaining Solution

Trade Credit Recall that expected profits for reliable buyers and all sellers with trade credit are $\mathrm{E}[\Pi_S^{TC}] = \tilde{\lambda}^* P^{TC} - (1+r_b)C$ and $\mathrm{E}[\Pi_{RB}^{TC}] = R - P^{TC}$, respectively. As shown before, if the seller has all bargaining power, she sets $P_S^{TC} = R$. In contrast, if the buyer has all bargaining power, she sets the payment so that a reliable seller is indifferent, that is $P_B^{TC} = \frac{1+r_b}{\tilde{\lambda}^*}C$. Combining the two solutions of the dictator game, we calculate the payment under trade credit based on the Neutral Bargaining Solution as:

$$P_N^{TC} = \theta P_S^{TC} + (1-\theta)P_B^{TC} = \frac{\theta\tilde{\lambda}^* R + (1-\theta)(1+r_b)C}{\tilde{\lambda}^*}.$$

Expected profits of a seller and reliable buyer are then given by:

$$\mathrm{E}[\Pi_S^{TC}] = \theta\left(\tilde{\lambda}^* R - (1+r_b)C\right), \tag{A.8}$$

$$\mathrm{E}[\Pi_{RB}^{TC}] = \frac{1}{\tilde{\lambda}^*}(1-\theta)\left(\tilde{\lambda}^* R - (1+r_b)C\right). \tag{A.9}$$

Cash in Advance Recall that expected profits for all buyers and reliable sellers under cash in advance are $\mathrm{E}[\Pi_{RS}^{CIA}] = (1+r_d)(P^{CIA} - C)$ and $\mathrm{E}[\Pi_B^{CIA}] = \tilde{\lambda}R - (1+r_b^*)P^{CIA}$, respectively. As shown before, the seller would choose $P_S^{CIA} = \frac{\tilde{\lambda}}{1+r_b^*}R$. If the buyer has all bargaining power, she makes the reliable seller indifferent by setting $P_B^{CIA} = C$. Combining the two solutions of the dictator game, we calculate the payment under cash in advance based on the Neutral Bargaining Solution as:

$$P_N^{CIA} = \theta P_S^{CIA} + (1-\theta)P_B^{CIA} = \frac{\theta\tilde{\lambda}R + (1-\theta)(1+r_b^*)C}{1+r_b^*}.$$

This implies expected profits for a reliable seller and any buyer of:

$$\mathrm{E}[\Pi_{RS}^{CIA}] = \theta\frac{1+r_d}{1+r_b^*}\left(\tilde{\lambda}R - (1+r_b^*)C\right), \tag{A.10}$$

$$\mathrm{E}[\Pi_B^{CIA}] = (1-\theta)\left(\tilde{\lambda}R - (1+r_b^*)C\right). \tag{A.11}$$

Optimal Contract In the following, we derive the optimal contract under the Neutral Bargaining Solution. For this, we assume that the firm that plays the dictator not only chooses the size of the payment but also the contract. The optimal contract is then a mixed strategy between the choice of the buyer and the choice of the seller with weights θ and $1-\theta$, respectively. As in the baseline model, we assume that conditions are such that it is always optimal for unreliable firms to imitate the behavior of reliable firms and for all firms to offer contracts that are acceptable to both types of firms (See Appendices A.3 and A.4.2 for details).

We now need to look separately at the payment choices of both the seller and the buyer. Combining equations (A.8) and (A.10) and replacing $R = \mu C$ delivers the optimal choice of a reliable seller. This condition is, of course, the same condition we derived for the baseline model where the seller had all bargaining power, equation (10). Now, combining equations (A.9) and (A.11) delivers the optimal choice of a reliable buyer:

$$\mathrm{E}[\Pi_{RB}^{TC}] > \mathrm{E}[\Pi_{B}^{CIA}] \Leftrightarrow R - \frac{1+r_b}{\tilde{\lambda}^*}C - (\tilde{\lambda}R - (1+r_b^*)C) > 0. \tag{A.12}$$

Replacing $R = \mu C$ and taking the derivative of equation (A.12) with respect to μ gives:

$$\frac{\partial(\Delta\Pi_B/C)}{\partial\mu} = 1 - \tilde{\lambda}, \tag{A.13}$$

where $\Delta\Pi_B \equiv \mathrm{E}[\Pi_{RB}^{TC}] - \mathrm{E}[\Pi_B^{CIA}]$. For the seller choice, the corresponding derivative ($\frac{\partial(\Delta\Pi_S/C)}{\partial\mu}$) is unchanged from the baseline and given by equation (13), where the preference for trade credit increases with the markup as long as $r_b^* > r_d$ and countries are not too different in their contract enforcement ($(1+r_b^*)\ \tilde{\lambda}^* - (1+r_d)\ \tilde{\lambda} > 0$). Interestingly, equation (A.13) shows that the buyer also prefers trade credit more as the markup increases. This reflects a different mechanism, however. With trade credit, the buyer always obtains the goods, whereas under cash in advance, goods only arrive with probability $\tilde{\lambda}$. The difference $1 - \tilde{\lambda}$ therefore reflects the lost business for the buyer under cash in advance. The buyer cannot offset this loss in business by paying an even lower cash in advance price because that price is bound below by the production cost C, as a payment below production cost would make a reliable seller reject the offer. In the following we summarize our results under the Neutral Bargaining Solution:

Corollary 2 (Payment Choice and Bargaining Power)
Suppose the seller has some bargaining power ($\theta \in (0, 1]$). Then all predictions in Proposition 3 hold for the case where both firms have bargaining power. That is:

i) If $(1+r_b^*)\ \tilde{\lambda}^* > (1+r_d)\ \tilde{\lambda}$, then the use of trade credit increases with the markup μ.

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

Proof. Follows directly from equations (13) and (A.13), and from taking the respective derivatives of these equations with respect to λ, λ^*, r_d, and r_b^*. ■

To summarize, introducing bargaining power for both sellers and buyers does not affect our main result on trade credit and markups. The financial cost advantage of trade credit is active as long as the seller has some bargaining power that allows the seller to charge a positive markup over marginal costs to the buyer.

A.4.2 Pooling and separating cases - Buyer Bargaining Power

For the Neutral Bargaining solution, we also need to understand the optimal payment choice when the buyer makes the decision, that is, when the buyer has all bargaining power. For this reason, we analyze the separating cases again in this alternative setting. Consider the following four cases:

1. The buyer offers a payment that is only accepted by unreliable sellers under trade credit.
2. The reliable buyer chooses cash in advance, but the unreliable buyer chooses trade credit.
3. The buyer offers a payment that is only accepted by unreliable sellers under cash in advance.
4. The reliable buyer chooses trade credit, but the unreliable buyer chooses cash in advance.

Trade Credit - pooling case Under the pooling case, expected profits are given by:

$$\begin{aligned}
\mathrm{E}[\Pi_S^{TC,P}] &= \tilde{\lambda}^* P^{TC,P} - (1+r_b)C, \\
\mathrm{E}[\Pi_{RB}^{TC,P}] &= R - P^{TC,P}, \\
\mathrm{E}[\Pi_{UB}^{TC,P}] &= R - \lambda^* P^{TC,P}.
\end{aligned}$$

The buyer sets the payment to $P_B^{TC,P} = \frac{1+r_b}{\tilde{\lambda}^*}C$, implying expected profits of:

$$\begin{aligned}
\mathrm{E}[\Pi_{RB}^{TC,P}] &= R - \frac{1+r_b}{\tilde{\lambda}^*}C, \\
\mathrm{E}[\Pi_{UB}^{TC,P}] &= R - \frac{\lambda^*(1+r_b)}{\tilde{\lambda}^*}C.
\end{aligned} \tag{A.14}$$

Trade Credit, Separating Case 1 Can it be optimal for the buyer to offer a payment under trade credit that is only acceptable for unreliable sellers? No, because under trade credit expected profits and thus the participation constraint are the same for reliable and unreliable sellers. This is the case because there is no commitment problem on the seller side under trade credit.

Trade Credit, Separating Case 2 Suppose that a reliable buyer does not prefer trade credit. Can it be profitable for an unreliable buyer to pick trade credit anyways, thereby revealing her type? Then, the seller knows that she is dealing with an unreliable buyer and the participation constraint becomes:

$$\mathrm{E}[\Pi_S^{TC,S}] \quad = \quad \lambda^* P^{TC,S} - (1+r_b)C.$$

Now, the buyer needs to pay $P^{TC,S} = \frac{1+r_b}{\lambda^*}C$, and expected profits become:

$$\mathrm{E}[\Pi_{UB}^{TC,S}] \quad = \quad R - (1+r_b)C. \tag{A.15}$$

A sufficient condition to exclude the separating case is $\mathrm{E}[\tilde{\Pi}_{RB}^{TC,P}] \geq \mathrm{E}[\tilde{\Pi}_{UB}^{TC,S}]$, because $\mathrm{E}[\tilde{\Pi}_{UB}^{CIA,P}] = \mathrm{E}[\tilde{\Pi}_{RB}^{CIA,P}] \geq \mathrm{E}[\tilde{\Pi}_{RB}^{TC,P}]$. The expected profits of an unreliable buyer in the separating case under trade credit are smaller than her expected profits in the pooling case. However, they are larger than the expected profits of a reliable firm under trade credit in the pooling case. Hence, it is not straightforward to derive parameter constraints under which the above sufficient condition that rules out this separating case in the baseline model holds.

However, we can derive such parameter constraints in a slightly extended version of the model. Consider again the extension in Schmidt-Eisenlohr (2013), where the firm that enforces the contract has to pay an enforcement cost δ (again proportional to the recovery amount; with trade credit, this is P^{TC}). Then, expected profits change to:

$$\begin{aligned}
\mathrm{E}[\tilde{\Pi}_{RB}^{TC,P}] &= R - \frac{1+r_b}{\eta^* + (1-\eta^*)(1-\delta)\lambda^*}C, \\
\mathrm{E}[\tilde{\Pi}_{UB}^{TC,S}] &= R - \frac{1+r_b}{1-\delta}C.
\end{aligned}$$

This condition holds if:

$$\delta \geq \frac{1-\eta^* - (1-\eta^*)\lambda^*}{1-(1-\eta^*)\lambda^*}.$$

Taking our parameters from before. If $\eta^* = 0.8$ and $\lambda^* = 0.8$, δ has to be greater or equal to 4.8 percent of the recovery value ($\delta \geq 0.048$) to exclude **Case 2**.

Cash in Advance - pooling case Under cash in advance, expected profits are given by:

$$\begin{aligned}
\mathrm{E}[\Pi_B^{CIA,P}] &= \tilde{\lambda}R - (1+r_b^*)P^{CIA,P}, \\
\mathrm{E}[\Pi_{RS}^{CIA,P}] &= P^{CIA,P} - C, \\
\mathrm{E}[\Pi_{US}^{CIA,P}] &= P^{CIA,P} - \lambda C.
\end{aligned}$$

In the pooling case, the buyer makes the reliable seller indifferent by setting $P^{CIA,P} = C$, which implies expected profits of:

$$\begin{aligned}
\mathrm{E}[\Pi_B^{CIA,P}] &= \tilde{\lambda}R - (1+r_b^*)C, \qquad \text{(A.16)} \\
\mathrm{E}[\Pi_{US}^{CIA,P}] &= (1-\lambda)C.
\end{aligned}$$

Cash in Advance, Separating Case 3 The buyer could offer a payment that is only acceptable to unreliable sellers. Then the payment would be less than production costs, C, specifically $P^{CIA,S} = \lambda C$. Only a fraction of contracts that the buyer offers, $1-\eta$, would be accepted, as reliable sellers would reject it. Expected profits of a buyer are then:

$$\mathrm{E}[\Pi_B^{CIA,S}] = (1-\eta)\lambda(R - (1+r_b^*)C) \qquad \text{(A.17)}$$

Combining equations (A.16) and (A.17) implies that pooling dominates if:

$$\eta R > (1-(1-\eta)\lambda)(1+r_b^*)C$$

If this condition holds, we can exclude **Case 3**. The condition is relatively weak. For example, with $\eta = 0.8$, $\lambda = 0.8$, and $r = 1.025$, this condition holds as long as the markup $\mu = \frac{R}{C}$ is greater or equal to 1.08.

Cash in Advance, Separating Case 4 Can it be optimal for the unreliable buyer to choose cash in advance if the reliable buyer chooses trade credit? No, because expected profits under cash in advance are the same across both types of buyers, and unreliable buyer have larger expected profits under trade credit.

To summarize, Cases 1 and 4 are never optimal for the buyer, while Cases 3 can be excluded under relatively weak conditions. Finally, to derive a sufficient condition for Case 2 requires a small and realistic extension of the model that leads to a relatively weak condition.

B Additional Details on Markups Estimation

To test the predictions of the theory, we 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 us 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 the problem for any flexible input V, the markup of product p produced by firm i in year t (μ_{ipt}) can be computed as the ratio between the output elasticity of product p 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; $s^V_{ipt} \equiv P^V_{ipt}V_{ipt}/P_{ipt}Q_{ipt}$):

$$\underbrace{\mu_{ipt}}_{\text{Markup}} \equiv \frac{P_{ipt}}{MC_{ipt}} = \frac{\theta^V_{ipt}}{s^V_{ipt}} \,, \tag{B.1}$$

where P (P^V) denotes the price of output Q (input V), and MC is marginal cost. While the numerator of equation (B.1) – the input-output elasticity of product p – needs to be estimated, the denominator is directly observable in our data. Next, we 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 inputs:

$$Q_{ipt} = \Omega_{ipt}F(K_{ipt}, L_{ipt}, M_{ipt}) \tag{B.2}$$

where Q is physical output, and Ω denotes productivity. There are two important assumptions on equation (B.2). First, the production function is product-specific, which implies that single and multi-product firms use the same technology to produce a given product. Second, as is standard in the estimation of production functions, we assume Hicks-Neutrality, so that Ω is log-additive.

The estimation of (B.2) follows De Loecker et al. (2016) in using the subset of single-product firms to identify the coefficients of the production function.[1] 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. Different from De Loecker et al., 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).[2]

Our baseline specification assumes a Cobb-Douglas production function, and allows for the presence of a log-additive non-anticipated shock (ε). 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 derived with 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. Taking logs to (B.2), we obtain (lower cases denote logarithm of the variables)

$$q_{ipt} \quad = \quad \alpha_k^p k_{ipt} + \alpha_l^p l_{ipt} + \alpha_m^p m_{ipt} + \omega_{ipt} + \varepsilon_{ipt} \tag{B.3}$$

The estimation of (B.3) 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.[3] 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 motion of productivity:

$$\omega_{ipt} \quad = \quad g(\omega_{ipt-1}, d^x_{ipt-1}, d^i_{ipt-1}, d^x_{ipt-1} \times d^i_{ipt-1}, \hat{s}_{ipt-1}) + \xi_{ipt} \tag{B.4}$$

where d^x is an export dummy, d^i is a categorical variable for periods with positive investment,

[1] The methodology implicitly 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. In section D, we show that our results also hold when computing markups at the firm-level.

[2] 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. We discuss below the construction of the input price index we use in our sample of Chilean firms.

[3] 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).

and $\hat{s}$ is the probability that the firm remains single-product. The endogenous productivity process (B.4) 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 $\phi_t(k_{ipt}, l_{ipt}, m_{ipt}; \mathbf{x}_{ipt})$ to remove the unanticipated shock component ε_{ipt} from (B.3).[4] Then, the ACF procedure exploits this representation to express productivity as a function of data and parameters: $\omega_{ipt}(\boldsymbol{\alpha}) = \hat{\phi}_t(\cdot) - \alpha_k k_{ipt} - \alpha_l l_{ipt} - \alpha_m m_{ipt}$, and form the productivity innovation ξ_{ipt} from (B.4) as a function of the parameters $\boldsymbol{\alpha}$. The second step of ACF routine forms moment conditions on ξ_{ipt} to identify all parameters $\boldsymbol{\alpha}$ through GMM:

$$\mathbb{E}(\xi_{ipt}(\boldsymbol{\alpha}) \cdot \mathbf{Z}_{ipt}) \;\; = \;\; 0 \tag{B.5}$$

where $\mathbf{Z}_{ipt}$ contains lagged materials, labor, and capital, and current capital. Once the parameters are estimated, the input-output elasticities are recovered for each product as $\theta^V_{ipt} \equiv \partial \ln Q_{ipt}/\partial \ln V_{ipt}$. For the Cobb-Douglas case, $\theta^V_{ipt} = \alpha^p_V$, so that the input-output elasticity is constant for all plants producing a given product p.[5]

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 (B.1) 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 (2019) and exploit a unique feature of our data: ENIA provides 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

[4]The vector $\mathbf{x}_{ipt}$ 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.

[5]In the Translog case, the input elasticities θ^V_{ipt} depend on the firms' input use. 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.

the variable cost shares, so that the value of materials' expenditure $M_{ipt} = P^V_{ipt} V_{ipt}$ is computed as

$$\tilde{M}_{ipt} = \rho_{ipt} \cdot \tilde{M}_{it}, \quad \text{where} \quad \rho_{ipt} = \frac{TVC_{ipt}}{\sum_j TVC_{ijt}}. \tag{B.6}$$

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

Input Price Index. To avoid input price bias in the estimation of the production function parameters (see De Loecker and Goldberg, 2014, for details), we deflate materials' expenditure using firm-specific price indexes. The construction of the input price deflator involves five steps. First, we define the unit value of input p purchased by firm i in period t as $P_{ipt} = V_{ipt}/Q_{ipt}$, where V_{ipt} denotes input p value, and Q_{ipt} denotes the corresponding quantity purchased. Next, we calculate the (weighted) average unit value of input p across all firms purchasing the input in year t. Then, for each firm, we compute the (log) price deviation from the (weighted) average for all the inputs purchased by the firm in year t. The next step involves averaging the resulting price deviations at the firm level, using inputs' expenditure as weight.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 Data Appendix

In this appendix we provide additional details on the construction of the dataset we use in the main empirical analysis. In the following, we briefly discuss the procedure we follow to combine the production data in ENIA with the customs-level data at the firm-product level. We also explain the data cleaning procedure we apply to avoid inconsistencies.

The main issue in combining data from Customs and ENIA at the firm-product level is that products are classified using different nomenclatures in both datasets: ENIA classifies products according to the Central Product Classification (CPC), while the Chilean Customs Administration classifies products according to the Harmonized System (HS). To deal with this issue, we follow several steps. First, we use the United Nations' correspondence tables to determine the list of HS products that could potentially be matched to each CPC product in ENIA.[6] 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 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 follow several steps. In particular, we exclude: (i) firm-year observations that have zero values for raw materials expenditure or employment, (ii) firm-product-year observations with zero or missing sales, product quantities, or with extreme values for markups (above the 98th or below the 2nd percentiles, or with large unplausible variations in markups within firm-products), and (iii) destination-year pairs with extreme values of the real borrowing rates, to avoid the influence of extreme values resulting from inflationary or deflationary episodes.[7] The final dataset consists of 93,556 firm-product-destinations-year observations. The sample represents 80.5% of the value of Chilean (non-copper) exports over the period 2003-2007. Table C.1 presents the estimated markups at the level of 2-digit industries.

Table C.1. Estimated Markups

Product	Mean	Median	St. Deviation
Food and Beverages	1.268	1.132	0.510
Textiles	1.546	1.435	0.566
Apparel	1.278	1.254	0.469
Wood and Furniture	1.124	1.007	0.433
Paper	1.157	1.042	0.463
Basic Chemicals	1.365	1.162	0.684
Plastic and Rubber	1.215	1.079	0.504
Non-Metallic Manufactures	1.623	1.502	0.786
Metallic Manufactures	1.147	1.979	0.489
Machinery and Equipment	1.131	0.989	0.480
Total	1.255	1.110	0.538

Notes: This table reports the average markup by aggregate sector for the sample Chilean exporters over the period 2003-2007.

[6] 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.

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

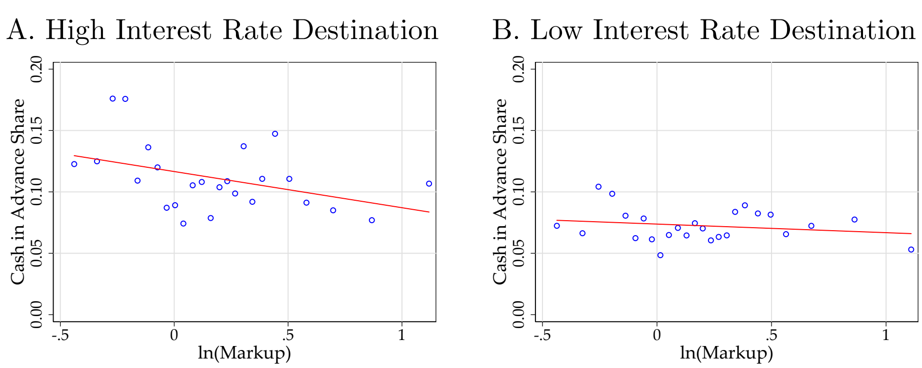
D Additional Results and Robustness Checks

D.1 Markups and the use of Cash in Advance and Letters of Credit Contracts.

The main analysis shows that the use of trade credit increases with markups and that this effect increases in borrowing costs. In this subsection, we provide evidence that the financing cost advantage of trade credit primarily reflects a choice between trade credit and cash in advance. In contrast, the choice between trade credit and a letter of credit is not affected by this mechanism, a finding consistent with the prediction in proposition 2.

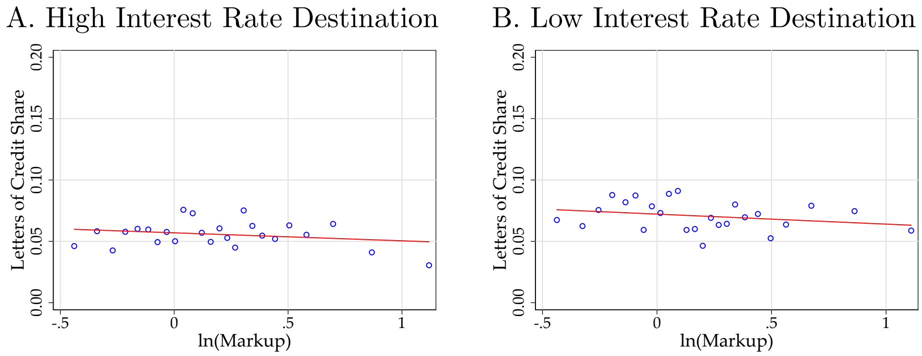
Figure D.1 shows that the use of cash in advance declines in markups, with the effect being stronger for destinations with relatively high borrowing rates (panel A). The figure is almost the exact mirror image of figure 2, suggesting that firms with a higher markup increase their use of trade credit at the expense of cash in advance. Letters of credit, in contrast, appears relatively unresponsive to markups, both in high and low interest rate destinations (panels A and B in figure D.2).

Figure D.1. Cash in Advance Share and Markups



Notes: The figure shows binscatter plots of the cash in advance share against firm-product markups (in logs), computed as in De Loecker et al. (2016). Panels A and B shows results for high and low borrowing rates destination, respectively. All figures control for destination-year fixed-effects.

Figure D.2. Letters of Credit Share and Markups



Notes: The figure shows binscatter plots of the letter of credit share against firm-product markups (in logs), computed as in De Loecker et al. (2016). Panels A and B shows results for high and low borrowing rates destination, respectively. All figures control for destination-year fixed-effects.

Next, we provide additional econometric evidence, focusing on the interaction terms between markups and interest rates and contract enforcement. According to the model, buyer-seller pairs substitute cash in advance with trade credit as the markup increases, and this effect should be stronger in destinations with higher borrowing rates (proposition 3). The choice between trade credit and letters of credit, in contrast, should be independent of the markup (proposition 2). To test these predictions, we estimate versions of equation (19), modifying either the dependent variable or the sample. All regressions use physical productivity as an instrument for markups, and control for firm-product-year fixed effects and country-year fixed effects.

Table D.1 shows the results. Column 1 repeats the baseline using trade credit share as the dependent variable for reference. Then, in columns 2 and 3, we change the dependent variables, using the share of FOB export value financed through cash in advance or letters of credit. As predicted by the theory, the coefficients for the cash in advance share (column 2) closely mirror those for trade credit (column 1), suggesting that firms substitute cash in advance with trade credit in destinations with higher borrowing cost or better contract enforcement. The letter of credit share, in contrast, appears unresponsive to the interaction terms between the markup and the borrowing interest rate and the rule of law in the destination country.

Finally, in columns 4 and 5, we study the source of variation driving the coefficients in column 1, dropping transactions financed exclusively using letters of credit (column 4) or cash in advance (column 5). Results confirm findings in columns 2 and 3, suggesting that most of the variation that explains the financing cost advantage channel comes from firms substituting between cash in advance and trade credit. When dropping the transactions financed with letter of credit, we obtain very similar coefficients to our baseline in column 1. In contrast, when dropping cash in advance transactions, we obtain non-significant coefficients for the interaction between markups, interest rates, and contract enforcement.

Table D.1. Trade Credit Share and Firm-Product Markup: Heterogeneity

Sample:	Full sample			TC vs. CIA	TC vs. LC
Dep. Variable:	TC share	CIA share	LC share	TC share	TC share
	(1)	(2)	(3)	(4)	(5)
log(markup) $\times r_b^*$	1.363**	-1.789***	0.252	1.532***	-0.500
	(0.587)	(0.485)	(0.323)	(0.484)	(0.462)
log(markup) $\times$ ROL	0.209	-0.183**	0.00929	0.232**	0.0293
	(0.147)	(0.0882)	(0.119)	(0.0940)	(0.140)
First stage F-Statistic	26.9	26.9	26.9	30.6	22.7
Firm-HS8-year FE	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Observations	90,727	90,727	90,727	82,394	78,992

Notes: This table replicates table 4 modifying the dependent variable (columns 1-3) and sample (columns 4-5). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Trade credit (TC), cash in advance (CIA) and letters of credit (LC) shares correspond to the ratio of the FOB value of transactions financed through each payment form to the FOB value of all export transactions over a year. Markups are computed at the firm-product level (products are defined at the 5-digit CPC level). Columns 4-5 restrict the sample, dropping transactions financed through letters of credit (column 4) and cash in advance (column 5). All regressions are estimated using TFPQ as an instrument for markups; the (cluster-robust) Kleibergen-Paap rK Wald F-statistic is reported for each of them (the corresponding Stock-Yogo value for 10% maximal IV bias is 16.4). Standard errors (in parentheses) are clustered at the firm-destination level. Key: *** significant at 1%; ** 5%; * 10%.

D.2 Additional Details on Robustness Checks

In this section, we provide details on the robustness checks mentioned in section 5.2:

Translog Markups. Our baseline markup measures are computed using input-output elasticities derived from a Cobb-Douglas production function. 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, columns 1-2 in table D.2 presents results using markups derived from the more flexible translog production function, allowing for a rich set of interactions between the different inputs.[8] As in the baseline case, the trade credit share shows a strong positive relationship with markups. The coefficients in table D.2 are very similar to the baseline case (compare them with the corresponding coefficients in table 2).

Firm-level markups. To estimate product-level and markups, we needed to assign inputs to individual outputs in multi-product plants. This is not needed when computing markups at the firm-level. Results in columns 3-4 in table D.2 show that coefficients remain quantitatively similar and stay statistically significant.

Table D.2. Markups and Trade Credit Share: Alternative Markup Proxies

Specification:	Translog		Firm-level		Margin	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Markup)	.0200***	.102***	.0232***	.172***	.0087†	.8325**
	(.0048)	(.0290)	(.0055)	(.0494)	(.0170)	(.4486)
First Stage F-Statistic	—	193.5	—	112.0	—	5.5
Firm FE	✓	✓	✓	✓	✓	✓
HS8 FE	✓	✓	✓	✓	✓	✓
Destination-Year FE	✓	✓	✓	✓	✓	✓
Observations	92,911	90,187	92,701	89,887	92,267	89,534

Notes: The table reports the coefficient estimates from equation (18). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Trade credit shares are computed as the ratio of the FOB value of trade credit 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%; †: p-value = 13.6%.

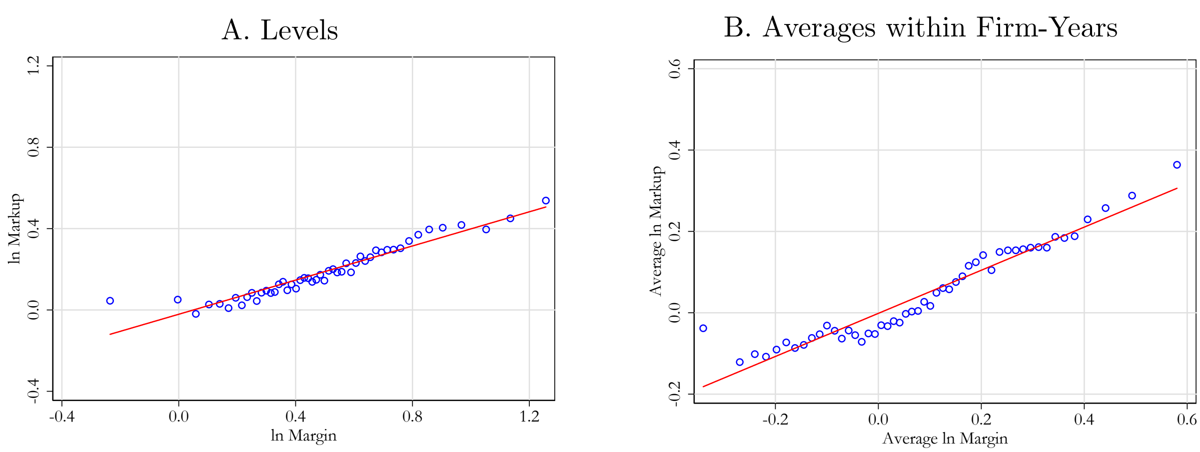
Average product margin. An additional proxy for markups that we can compute in our sample is product-level price-cost margins. ENIA reports the variable production cost per product, defined as the sum of raw material and direct labor costs involved in the production of each product. Product margins can be derived by dividing prices (unit values) over this reported measure of average variable cost. Note that the average variable cost is self-reported by managers, making the application of rules of thumb likely.

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

Figure D.3 shows binscatter plots 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 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 of 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.[9]

Columns 7-8 of table D.2 estimate our baseline level regression using the average price-cost margins. Using margins as a proxy for markups delivers qualitatively similar results, with a highly significant coefficient estimate for the markup in the 2SLS specification.

Figure D.3. Firm-Product level Markup and Sales-Cost Margin



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

Censoring. The dependent variable throughout our analysis is the share of trade credit in sales at the firm-product-destination-year level, which be construction lies in the range zero to one. Since average trade credit is relatively high in our sample (83%, as shown in table 1), using the trade credit share as the main dependent variable limits the potential response of

[9] 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 the sales-cost margin may be a poorer approximation of markups in the short run. However, if managers do not make systematic mistakes when reporting average variable costs, the measurement error cancels out when averaging over longer periods.

trade credit use to markups for firm-products with initially high trade credit use. In table D.3 we revisit the question on the magnitude of the markup mechanism using a logit transformation on the trade credit share, to pull out its variation over all of the real numbers. We run the following specification:

$$\ln\left(\frac{\rho_{ijpy}}{1-\rho_{ijpy}}\right) = \beta_1 \ \ln(\mu_{ipy}) + \gamma_1 \ \ln(L_{iy}) + \delta_i + \delta_p + \delta_{jy} + \epsilon_{ijpy}, \quad \text{(D.1)}$$

where ρ denotes the trade credit share. In this alternative specification, the marginal response of the trade credit 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 trade credit share can be computed as $\beta_1 \times \rho_{ijpy} \times (1-\rho_{ijpy})$. Plugging in the coefficients from table D.3, leads to an estimated implied trade credit share-markup elasticity of 0.06 (OLS), and 0.38 (IV) for firm-products with trade credit shares equal to the mean (83 percent in our sample). These marginal effects are more than three times larger than those implied by the baseline coefficients in columns 1 and 4 of table 2.

Table D.3. Logistic Trade credit Share Transformation

Specification	OLS (1)	2SLS (2)
ln(Markup)	.442***	2.703***
	(.110)	(.686)
Implied Avg. Markup Semi-elasticity	0.062	0.378
First-Stage F-Statistic	—	185.4
Firm FE	✓	✓
HS8 FE	✓	✓
Country-Year FE	✓	✓
Observations	93,556	90,727
R^2	.675	.405

Notes: The table reports the coefficient estimates from equation (D.1). All regressions are run at the firm-product-destination level (with products defined at the HS8-level). Trade credit shares are computed as the ratio of the FOB value of trade credit 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%.