Trade Credit and Relationships*

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Abstract

Exploiting transaction-level international trade data, this paper documents new facts about trade credit. Trade credit use increases with firm-to-firm relationship length, an effect that varies with countries' rule of law, and is stronger for trade in more complex products and trade between unrelated parties. A model featuring diversion risk, learning, and a financing cost advantage of trade credit can rationalize these patterns. Initially, payment risk is a key factor limiting trade credit use. Through learning, this risk declines and firms switch to trade credit. Long-term trade relationships give rise to a financial benefit: saving financing costs through trade credit.

Keywords: trade credit, relationships, learning, financing costs, risk

JEL Classification: F12, F14, G21, G32

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1 Introduction

Most domestic and international firm-to-firm transactions rely on trade credit, where sellers grant buyers time to pay the invoice after delivery.[1] As a consequence, trade credit is the most important source of short-term finance (Rajan and Zingales, 1998), and its availability has important consequences for corporate default (Jacobson and von Schedvin, 2015; Barrot, 2016; Amberg et al., 2021), macroeconomic stability (Hardy et al., 2022), monetary policy transmission (Nilsen, 2002; Adelino et al., 2023), global value chains (Kalemli-Ozcan et al., 2014; Antràs, 2023; Kim and Shin, 2023), and prices (Amberg et al., 2020).

When do firms provide trade credit to their customers? While earlier work on domestic and international trade credit has identified key determinants across firms, products, and countries (see e.g. Petersen and Rajan, 1997; Giannetti et al., 2011; Klapper et al., 2012; Ahn, 2014; Antràs and Foley, 2015; Demir and Javorcik, 2018; Giannetti et al., 2021), the role of relationship dynamics is less well understood.[2] At the same time, a growing literature in international trade has argued that relationships are central to both domestic and international trade (Bernard and Moxnes, 2018). Motivated by these observations, this paper uses transaction-level international trade data from Colombia and Chile to shed light on the link between trade credit and relationships.[3] It shows how firm-to-firm relationships affect the provision of trade credit and develops a theory featuring diversion risk, learning, and a financing cost advantage of trade credit to rationalize the observed patterns. The model implies a new, financial benefit of long-term trade relationships: the ability to save

[1] Trade credit is also referred to as open account. In balance sheet data, trade credit is reflected in accounts payable (trade credit received) and accounts receivable (trade credit granted).

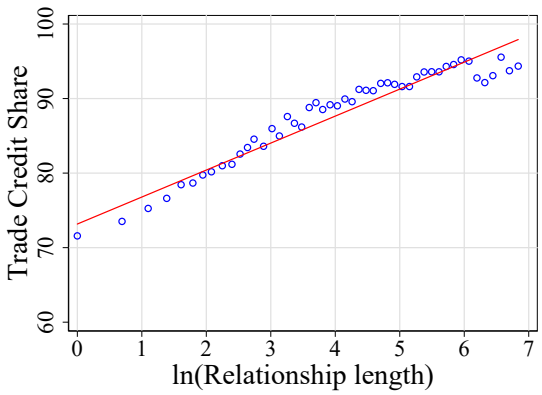
[2] An important exception is Antràs and Foley (2015). We discuss this paper in detail below.

[3] For the United States, comparable data is not available. The U.S. Census' transaction-level customs data does not have information on trade credit or other payment forms used, while firm-level balance sheet data from Compustat does not have information about trade credit at the relationship or transaction level.

on financing costs through the use of trade credit.

The paper starts by documenting a striking positive relationship between trade credit use and relationship length (illustrated in Figure 1 for Colombia). The longer a Colombian firm is importing from a given foreign supplier, the more likely that supplier will provide trade credit to the Colombian importer.[4]

Figure 1. Trade Credit Increases with Relationship Length



Notes: The figure shows a binscatter plot between the trade credit share and log relationship length for Colombian imports. Relationship length is measured by the number of transactions between a Colombian importing firm and a foreign supplier. Relationship length is censored at ln(relationship) = 7, i.e., at 1096 interactions within a relationship.

Exploiting the rich information contained in the two transaction-level data sets, we generate additional facts that help us to zoom in on the mechanism behind this striking pattern: First, while firms switch their payment terms within a relationship from cash in advance to trade credit quite frequently, they rarely switch in the opposite direction. Second, relationship length affects the payment choice more for imports from source countries with stronger

[4] As we show later, we find a corresponding result for Chile. The longer a Chilean exporters is exporting a product to a given destination country, the more likely it provides trade credit to its foreign buyer.

contract enforcement and for exports to destination countries with weaker contract enforcement, for trade in products with more scope for quality differentiation, and for trade between unrelated parties. Third, trade credit use increases rapidly at the beginning of relationships and tends to level off as relationships age. Finally, learning (proxied by relationship length) is particularly important for the choice of payment terms in younger relationships, whereas the financing cost advantage (proxied by estimated markups) dominates this choice in older relationships.

The paper presents a model of payment term choice that can rationalize these facts in a setup that combines a financing cost advantage of trade credit as in Garcia-Marin et al. (2023) with elements of the learning model in Antràs and Foley (2015). A financing cost advantage of trade credit arises when exporters charge positive markups to importers, and there are financial frictions such that the borrowing rate exceeds the deposit rate. Then, trade credit has lower financing costs than cash in advance because it requires less gross borrowing – for cash in advance, the importer needs to borrow the full invoice amount, whereas, under trade credit, the exporter only needs to finance the production costs. Learning matters in the model because there are two types of firms, reliable and unreliable, and because each payment term gives rise to diversion risk: A buyer may not pay after receiving goods on trade credit, and a seller may not deliver after getting paid cash in advance.

Through repeated interactions, firms learn about the type of their trading partner. As firms learn, the importance of diversion risk declines and the financing cost advantage of trade credit starts to dominate. Consequently, a sizable fraction of new relationships relies on cash in advance. In contrast, transactions within old firm-to-firm relationships are exclusively based on trade credit (as in Figure 1). As trade credit has a financing cost advantage over cash in advance, the model, therefore, implies a new benefit of long-term trade relationships:

the ability to save on financing costs by employing the most efficient payment term, trade credit.

Literature. The analysis speaks to two strands of the literature: research studying international trade finance and trade credit, and work on relationships and learning.

Several papers study payment terms theoretically in an international context (Schmidt-Eisenlohr, 2013; Ahn, 2014; Antràs and Foley, 2015; Niepmann and Schmidt-Eisenlohr, 2017a; Fischer, 2020). This paper adds to this literature by providing a joint analysis of learning dynamics and a financing cost advantage of trade credit and showing how these two channels interact in a meaningful way to explain the empirical patterns we uncover. This paper also extends the empirical literature on payment choice in international trade (see, e.g., Ahn, 2014; Antràs and Foley, 2015; Hoefele et al., 2016; Niepmann and Schmidt-Eisenlohr, 2017b; Demir and Javorcik, 2018; Garcia-Marin et al., 2023) by generating new facts on trade credit use within relationships for the universes of Colombian import and Chilean export transactions, respectively. More broadly, the paper adds to the work on trade and financial frictions (see e.g. Ahn et al., 2011; Amiti and Weinstein, 2011; Chor and Manova, 2012; Manova, 2013; Paravisini et al., 2015; Niepmann and Schmidt-Eisenlohr, 2017b; Leibovici, 2021; Paravisini et al., 2023; Federico et al., 2023).

This paper is closely related to earlier work by Antràs and Foley (2015), who study the sales of a single large U.S. exporter and find that the firm's sales shifted toward trade credit over time. Empirically, our paper goes beyond this earlier work in four dimensions. First, it documents that trade credit use increases with relationship age for the universe of Colombian import and Chilean export transactions. Second, it shows that these dynamics differ systematically with contract enforcement across countries, vary with product charac-

teristics, and are concentrated in trade between unrelated parties.Third, it decomposes the learning dynamics into importer-, exporter- and relationship-level effects.[5] Fourth, it estimates markups and test for the relative importance of the financing cost and diversion risk channels over the life cycle of a relationship.

Theoretically, our paper rationalizes why trade credit increases with relationship length. Antràs and Foley (2015) generate a similar prediction in a simplified model where there is no diversion risk on the seller side.[6] In contrast, our paper derives a general result, showing that a preference for trade credit arises over time when there is a financing cost advantage of trade credit as in Garcia-Marin et al. (2023). In the absence of this additional channel, learning eliminates diversion risk but does not deliver a clear prediction on the preference between trade credit and cash in advance.[7]

The paper complements earlier theoretical work on domestic trade credit that studies other ways through which relationships may interact with trade credit. Wilner (2000) develops a model where long-term relationships make trade credit desirable, because they improve outcomes for debtors during renegotiations. Cuñat (2007) develops a related idea, arguing that suppliers may provide liquidity insurance to buyers within longer-term trade credit relationships. More recently, Hardy et al. (2022) study the insurance properties of trade credit in a model of supply chains, showing that trade credit can have a role as a macroeconomic stabilizer. While our paper has an international focus, the idea that older relationships facilitate trade transactions by reducing diversion risk should also be relevant for domestic

[5]This is possible with the Colombian firm-to-firm data but not with data that only captures exports of a single firm.

[6]In their model, by construction, learning can only be beneficial for trade credit, as cash in advance is always risk-free.

[7]Assuming that firms' financing costs for exporters and importers are drawn from similar distributions, the model in Schmidt-Eisenlohr (2013) and Antràs and Foley (2015) predicts that, in the absence of diversion risk, both cash in advance and trade credit would be used for an equal share of transactions.

trade credit provision. For reviews of the wider literature on domestic trade credit see, for example, Petersen and Rajan (1997), Cuñat and García-Appendini (2012), and Giannetti (2023).

There is an increasing understanding that firm-to-firm relationships are central to international trade. A growing number of empirical papers have contributed to this assessment, relying increasingly on 'two-sided' trade data, where buyers and sellers have unique identifiers, allowing a deeper dive into global value chains than earlier work that relied on data where only one firm was identified (see Bernard and Moxnes, 2018, for a survey).[8] This paper adds to this literature by looking at trade credit use within Colombian import relationships at the firm-pair level. The paper also contributes to the literature on learning and international trade, which has argued for an important role of learning about demand or supply factors, as well as about trading partners. The learning model in the present paper is based on the idea of learning about trading partners and directly builds on earlier work by Araujo et al. (2016) and Antràs and Foley (2015).

The analysis suggests an additional benefit of long-term relationships: the ability to save on financing costs by employing the most efficient payment term, trade credit. This adds to earlier work that showed that long-term relationships trade more, have higher survival rates, are more resilient in crisis times (Monarch and Schmidt-Eisenlohr, 2018), are better able to share risk in the presence of exchange-rate shocks (Heise, 2015), and can overcome enforcement frictions (Macchiavello and Morjaria, 2015).

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 describes the data.

[8] See, also Blum et al. (2013), Eaton et al. (2014), Heise (2015), Kamal and Sundaram (2016), Bernard et al. (2018), Monarch and Schmidt-Eisenlohr (2018), Carballo et al. (2018), Benguria (2021), and Monarch (2022).

Section 4 discusses the empirical specifications we use to test the predictions of the model. Section 5 presents the empirical results. Finally, Section 6 discusses implications and routes for future research.

2 A Model of Trade Credit and Relationships

In this section, we develop a model of trade finance that features a financing cost advantage of trade credit as in Garcia-Marin et al. (2023) and learning dynamics similar to Antràs and Foley (2015). As we show in the following, both mechanisms are needed jointly to rationalize the dynamic patterns we uncover in the data.

2.1 Baseline Model

One exporter is matched with one importer. Both firms are risk neutral. There are two periods. In period 0, the exporter produces the goods and sends them to the importer. In period 1, the importer sells the goods to a final consumer. Because of this time gap between production and final sale, firms need to agree on payment terms. Firms have two options. First, importers can pay in advance (cash in advance) before receiving the goods. Second, importers can pay after delivery (on trade credit). An exporter produces output for a total cost of C and sells it to the importer. The importer can then sell the goods to final consumers and generate revenues R. To finance their transactions, the exporter (importer) can borrow from banks at an interest rate r_b^E (r_b^I), and deposit surplus funds at banks for a deposit rate of r_d.[9] Assume that the borrowing rates r_b^E and r_b^I exceed the deposit rate

[9] The assumption that the exporter's outside option is the deposit rate could be relaxed, as the mechanism works as long as the exporter's marginal return to capital is below the importer's borrowing rate.

r_d.[10] In the following we use the superscript "I" for all variables referring to the importer or the destination country and superscript "E" for all variables referring to the exporter or the source country.

The exporter makes a take-it-or-leave-it offer to the importer, who can choose to accept or reject the offer. Additionally assume that firms charge a constant markup over production costs to final consumers given by μ so that $R = \mu C$. Throughout the analysis, we focus on the interesting case where the markup, μ, is sufficiently large such that both trade credit and cash in advance generate positive profits, $R > (1 + r_b^E)C$ and $R > (1 + r_b^I)C$, which implies $\mu > 1 + r_b^E$ and $\mu > 1 + r_b^I$. Let $\Pi^{i,j}$ denote the profit under trade credit or cash in advance ($i \in \{TC, CIA\}$) of the importer or exporter ($j \in \{I, E\}$).

Diversion risk. As firms cannot commit to their actions ex ante, each payment term gives rise to diversion risk: Importers that receive trade credit may divert goods without paying, and exporters that receive advance payments may divert cash without delivering the goods.[11] Assume that a fraction η^E (η^I) of exporters (importers) is reliable; that is, these firms always fulfill their contracts. If a firm is unreliable, it does not fulfill its contract voluntarily but diverts goods or funds whenever it gets the opportunity to do so. Assume that an unreliable exporter and importer get the opportunity to divert goods or funds with probability $1 - \phi^E > 0$ and $1 - \phi^I > 0$, respectively. Throughout the analysis, we focus on the case where it is optimal for unreliable firms to imitate reliable firms.[12]

[10] This interest rate spread can, for example, be rationalized by banks' overhead costs. Alternatively, it can be micro-founded in a model with diversion risk (see Garcia-Marin et al., 2023).

[11] In contrast to Burkart and Ellingsen (2004), we do not assume that goods are harder to divert than cash. Introducing this asymmetry would provide an additional rationale to use trade credit rather than cash in advance.

[12] Garcia-Marin et al. (2023) show that for a sufficiently high shares of reliable firms, η (η^*), this pooling case is consistent with optimal behavior by both types of firms. Then, it is sufficient to derive the optimal choice of a reliable firm.

Trade Credit. Under trade credit, the exporter maximizes:

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

where P^{TC} is the payment from the importer to the exporter, and $\tilde{\eta}^I = \eta^I + (1-\eta^I)\phi^I$ is the expected probability of payment, which is given by the probability of being matched with a reliable buyer plus the probability of being matched with an unreliable buyer who does not get a chance to divert funds. Because production takes place in period 0 while the payment is only received in period 1, the exporter has to borrow the production costs C from a bank and pay the interest rate r_b^E. The optimization is subject to the participation constraint of the importer. Solving for the optimal payment, P^{TC}, that respects the participation constraint implies $P^{TC} = R$, delivering profits for a reliable exporter of:

$$\mathrm{E}[\Pi^{TC,E}] = \tilde{\eta}^I R - (1 + r_b^E)C. \tag{1}$$

This expression is intuitive: exporter profits under trade credit decrease with the probability that the importer diverts funds, $1 - \tilde{\eta}^I$, and with the interest rate that the exporter has to pay to finance the trade, $1 + r_b^E$.

Cash in Advance. Under cash in advance, the reliable exporter maximizes:

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

with $\tilde{\eta}^E = \eta^E + (1-\eta^E)\phi^E$. In period 0 the exporter gets paid P^{CIA} and incurs production costs, C. Because the price charged to the importer exceeds production costs, the exporter has surplus funds and deposits them at a bank for interest rate r_d. Under cash in advance, there is a risk that an importer is matched with an unreliable exporter who may not deliver the goods. Thus, the importer generates revenues, R, only with probability $\tilde{\eta}^E$. The importer pays P^{CIA} in period 0, borrowing from a bank at interest rate r_b^I. Solving for the optimal payment, P^{CIA}, that makes the importer's participation constraint bind, delivers $P^{CIA} = \frac{\tilde{\eta}^E}{1+r_b^I}R$. With expected exporter profits for a reliable exporter of:

$$\mathrm{E}[\Pi^{CIA,E}] \quad = \quad (1+r_d)\left(\frac{\tilde{\eta}^E}{1+r_b^I}R - C\right). \tag{2}$$

With cash in advance, the expected exporter profits decline with the risk that the exporter diverts funds, $1-\tilde{\eta}^E$, and with the importer's borrowing cost, $1+r_b^I$, as both factors raise the compensation required by the importer. Equation (2) represents the expected profits that are relevant for the payment choice of all exporters, as we assumed that conditions are such that an unreliable exporter always imitates a reliable exporter.[13]

2.2 Trade Credit and Repeated Interactions

Consider now the case where an importer and an exporter interact repeatedly. Importantly, we assume that an exporter cannot offer a dynamic contract to solve the commitment problem that underlies the diversion risk.[14] However, as firms interact repeatedly, they update their belief about each other's reliability. Assume that with every successful transaction, a

[13] That is, while an unreliable exporter only pays the production costs, C, with probability ϕ^E, to imitate the reliable exporter, she will choose her payment terms as if she always paid production costs, C.

[14] See Schmidt-Eisenlohr (2011), Olsen (2016), and Fischer (2020) for an analysis of optimal dynamic contracts in this environment.

firm's belief about its trading partner's reliability improves. That is, assume that $\partial\eta_k^E/\partial k > 0$ ($\partial\eta_k^I/\partial k > 0$), where k is the number of previous interactions and η_k^E (η_k^I) is the probability that an exporter (importer) is reliable after k interactions.

The dynamics do not necessarily have to arise from learning about the trading partner's reliability. Any dynamic process that raises the expected reliability of the trading partner over time would generate similar predictions. For example, firms may be more willing to fulfill their contracts due to relationship-specific investments or learning-by-doing. In Appendix A, we provide one example of Bayesian learning that can micro-found the assumed learning dynamics.

We allow the speed of learning to differ between importers and exporters, with η_k^I and η_k^E, representing the belief about the probability that an importer or exporter is reliable after k interactions, respectively. The optimal payment choice is then determined by:

$$\frac{\Pi^{TC,E} - \Pi^{CIA,E}}{C} = \frac{\Delta\Pi^E}{C} = \tilde{\eta}_k^I\ \mu - (1 + r_b^E) - (1 + r_d)\left(\frac{\tilde{\eta}_k^E}{1 + r_b^I}\ \mu - 1\right).$$

where $\tilde{\eta}_k^E$ and $\tilde{\eta}_k^I$ now depend on k. Taking the derivative with respect to k delivers:

$$\frac{\partial(\Delta\Pi^E/C)}{\partial k} \quad = \quad \mu\left((1-\phi^I)\frac{\partial\eta_k^I}{\partial k} - \frac{1+r_d}{1+r_b^I}\ (1-\phi^E)\ \frac{\partial\eta_k^E}{\partial k}\right). \tag{3}$$

This derivative is positive if $\frac{\partial\eta_k^I}{\partial k} > \frac{1+r_d}{1+r_b^I}\ \frac{1-\phi^E}{1-\phi^I}\ \frac{\partial\eta_k^E}{\partial k}$. If learning about the importer is sufficiently fast relative to learning about the exporter, then trade credit becomes more attractive as two firms repeatedly trade with each other.

Learning about the importer is key because diversion risk under trade credit only depends on the reliability of the importer (η_k^I). Thus, for the financing cost advantage of trade credit to dominate over time, diversion risk under trade credit needs to decline through learning

about the importer. Specifically, learning about the importer cannot be too slow relative to learning about the exporter, as the latter makes cash in advance more attractive. Importantly, the condition implied by (3) allows for some asymmetry in the speed of learning, that is trade credit use increases with relationship length even if learning about the exporter is a bit faster (as long as $r_b^I > r_d$).[15] This result is summarized in Proposition 1.

Proposition 1 (Trade Credit and Learning)
Suppose learning about the importer is sufficiently fast, that is: $\frac{\partial \eta_k^I}{\partial k} > \frac{1+r_d}{1+r_b^I} \frac{1-\phi^E}{1-\phi^I} \frac{\partial \eta_k^E}{\partial k}$. *Then, payment is more likely on trade credit terms, the longer the two firms have traded.*

Proof. Follows directly from equation (3). ■

The proposition is quite intuitive. The longer two firms trade with each other, the more likely they will fulfill their contracts. The key advantage of trade credit is that it saves on financing costs compared to cash in advance. Through learning, diversion risk becomes less of an issue and financing costs differences matter more for the payment choice. Therefore, as firms learn that their trading partners are reliable, they increasingly prefer trade credit over cash in advance.

In the symmetric case, where the speed of learning about importers is equal to the speed of learning about exporters ($\frac{\partial \eta_k^I}{\partial k} = \frac{\partial \eta_k^E}{\partial k}$), diversion risk is the same on both sides ($1 - \phi^E = 1 - \phi^I$), and the borrowing and deposit rates are equal across countries, the condition in the proposition simplifies to: $r_b > r_d$. We summarize this insight in the following corollary.

[15] The speed of learning could be a function of the payment terms. In particular, there could be more learning about the exporter under cash in advance and more learning about the importer under trade credit, due to the asymmetry in diversion risk. For tractability, we focus on the case where learning is independent of the payment terms. The key assumption is that there is learning in both directions and that the speed of learning is not too dissimilar.

Corollary 1 (Trade Credit and Learning, Symmetric Case)
Suppose the exporter and importer face the same speeds of learning, diversion risk, and interest rates. Then, as long as the borrowing rate exceeds the deposit rate, $r_b > r_d$, payment is more likely on trade credit terms, the longer the two firms have traded.

That is, all else equal, the financing cost advantage of trade credit unequivocally pulls the payment terms toward trade credit over time. As we show later, this stark result is fully reflected in the data, where payment term switches toward trade credit are quite common whereas switches in the opposite direction are rare.

2.3 Trade Credit, Learning, and Diversion Risk

Does the strength of a country's legal institutions affect the relationship between repeated interactions and trade credit? This seems plausible, as learning reduces diversion risk in the model and thereby works as a substitute for imperfect contract enforcement. In particular, if contracts were perfectly enforceable and there was hence no diversion risk, learning would not matter. To check for this mechanism in the model, start with equation (3) and take the cross-derivative with respect to ϕ^E, the probability that there is no diversion opportunity for the exporter, to get:

$$\frac{\partial^2(\Delta\Pi^E/C)}{\partial k \partial \phi^E} = \mu \left(\underbrace{\frac{\partial \eta_k^E}{\partial k}}_{\text{Direct Effect}} \underbrace{-(1-\phi^E)\frac{\partial^2 \eta_k^E}{\partial k \partial \phi^E}}_{\text{Indirect Effect}} \right) \frac{1+r_d}{1+r_b^I}, \tag{4}$$

There are two effects. First, a direct effect: If there is less diversion risk in the source country, there is a stronger positive effect from learning on the use of trade credit. To understand the intuition, recall that trade credit becomes more attractive as the exporter learns that the importer is more reliable, because with trade credit there is a risk that

the importer does not pay. If there is less diversion risk in the source country, learning is less about the exporter and more about the importer, which increases the positive effect of learning on trade credit.

The second effect depends on how the speed of learning changes with diversion risk $\left(\frac{\partial^2 \eta_k^E}{\partial k \partial \phi^E}\right)$. Under standard Bayesian learning, when there is more diversion risk, learning is faster initially but slower later on, such that the sign of the cross-derivative changes in k. However, one would typically expect the direct effect to dominate the indirect effect, which we put as a condition into the proposition below.

For the proposition, we also derive the effect of changes to diversion risk in the destination country, which yields the opposite prediction: more diversion risk in the destination country increases the positive effect of learning on trade credit, because then learning is more about the importer, which benefits trade credit.[16]

Proposition 2 (Trade Credit, Learning, and Diversion Risk)
Suppose $(1-\phi^E)\frac{\partial^2 \eta_k^E}{\partial k \partial \phi^E} < \frac{\partial \eta_k^E}{\partial k}$ *and* $(1-\phi^I)\frac{\partial^2 \eta_k^I}{\partial k \partial \phi^I} < \frac{\partial \eta_k^I}{\partial k}$. *Then, the effect of learning on trade credit decreases (increases) in the diversion risk in the source (destination) country.*

Proof. Follows directly from equations (4) and (5). ■

2.4 Trade Credit, Learning, and Product Complexity

Does the effect of learning on trade credit vary across products of different complexity? This could be the case, because diversion is likely easier for more complex products, as courts

[16]Specifically, we start with equation (3) and take the cross-derivatives with respect to ϕ^I, the probability that there is no diversion opportunity for the importer, to get:

$$\frac{\partial^2(\Delta\Pi^E/C)}{\partial k \partial \phi^I} = \mu \left(\underbrace{-\frac{\partial \eta_k^I}{\partial k}}_{\text{Direct Effect}} \underbrace{+(1-\phi^I)\frac{\partial^2 \eta_k^I}{\partial k \partial \phi^I}}_{\text{Indirect Effect}} \right). \tag{5}$$

may have a harder time verifying successful transactions. In particular, quality may be more difficult to check for more complex products. Following Hoefele et al. (2016), assume that product complexity is captured by parameter $\gamma \in [0, 1]$, where a higher γ represents a more complex product. Assume further that the exporter and importer now have an opportunity to divert funds or goods with probability $1-(\phi^i)^\gamma$. That is, there are more opportunities for diversion when firms are trading in complex products. Focusing for tractability on the case with symmetric financing costs ($r_b^E = r_b^I$) and symmetric diversion risk $1-(\phi^E)^\gamma = 1-(\phi^I)^\gamma$, the optimal decision becomes:

$$\frac{\Delta\Pi^E}{C} = \tilde{\eta}_k^I(\gamma)\ \mu - (1 + r_b^E) - (1 + r_d)\left(\frac{\tilde{\eta}_k^E(\gamma)}{1 + r_b^I}\ \mu - 1\right).$$

with $\tilde{\eta}_k^E(\gamma) = \eta_k^E + (1 - \eta_k^E)\phi^\gamma$ and $\tilde{\eta}_k^I(\gamma) = \eta_k^I + (1 - \eta_k^I)\phi^\gamma$. Taking the derivative with respect to k delivers:

$$\frac{\partial(\Delta\Pi^E/C)}{\partial k} \quad = \quad \mu(1 - \phi^\gamma)\ \left[\frac{\partial\eta_k^I}{\partial k} - \frac{1 + r_d}{1 + r_b^I}\ \frac{\partial\eta_k^E}{\partial k}\right]. \tag{6}$$

Then taking the cross-derivative with respect to γ and k, and rearranging delivers:

$$\frac{\partial^2(\Delta\Pi^E/C)}{\partial k\partial\gamma} \quad = \quad -\mu\phi^\gamma\ \left[\frac{\partial\eta_k^I}{\partial k} - \frac{1 + r_d}{1 + r_b^I}\ \frac{\partial\eta_k^E}{\partial k}\right]\ \ln(\phi). \tag{7}$$

which is greater or equal to zero as $\ln\phi \leq 0$. That is, the effect of learning on the difference between trade credit and cash in advance is stronger for more complex products (higher γ). This result is summarized in the following proposition:

Proposition 3 (Trade Credit, Learning, and Product Complexity)
Suppose the importer and the exporter face the same financing costs and diversion risk, and learning about the importer is sufficiently fast ($\frac{\partial\eta_k^I}{\partial k} > \frac{1+r_d}{1+r_b^I}\ \frac{\partial\eta_k^E}{\partial k}$). Then, trade credit use

increases with relationship length, and the strength of this effect increases with the complexity of the product that is traded.

Proof. Follows directly from equations (6) and (7). ■

Proposition 3 is quite intuitive: Diversion is easier for more complex products and hence learning, which reduces diversion risk, has a stronger effect on firms' payment choices.

2.5 Relationship Length and Markups

How do relationship length and markups interact? Recall that the model features two frictions: Diversion risk and financial intermediation costs. These two frictions lead to two dynamic predictions that we derive formally below. First, the role of relationship lengths for the payment terms choice decreases over time, as firms learn about their trading partners and diversion risk becomes less of a concern. Second, as diversion risk declines, the financial friction becomes relatively more important, making markups more central for the payment choice in older relationships.

Trade Credit and a Declining Speed of Learning. Equation (3) shows that the difference in profits between trade credit and cash in advance increases with relationship length, k. Taking the second derivative of equation (3) with respect to relationship length k delivers:

$$\frac{\partial^2(\Delta\Pi^E/C)}{\partial k^2} = \mu\left((1-\phi^I)\frac{\partial^2\eta_k^I}{\partial k^2} - \frac{1+r_d}{1+r_b^I}\,(1-\phi^E)\,\frac{\partial^2\eta_k^E}{\partial k^2}\right). \tag{8}$$

This derivative is negative if: $-\frac{\partial^2\eta_k^I}{\partial k^2} > -\frac{1+r_d}{1+r_b^I}\,\frac{1-\phi^E}{1-\phi^I}\,\frac{\partial^2\eta_k^E}{\partial k^2}$. Now, assume that the speed of learning decreases over time, a standard feature of most types of learning, and consider

the case where the speed of learning is symmetric, so that: $\frac{\partial^2 \eta_k^I}{\partial k^2} = \frac{\partial^2 \eta_k^E}{\partial k^2}$.[17] Then, the above condition simplifies to: $(1-\phi^I) > \frac{1+r_d}{1+r_b^I}(1-\phi^E)$. In this case, the effect of repeated interactions on the trade credit choice declines over time as long as diversion risk across countries is not too different and the importer's borrowing rate exceeds the exporter's deposit rate, $r_b^I > r_d$.

Trade Credit, Learning, and Markups. Next, take the cross-derivative of equation (3) with respect to the markup μ to get:

$$\frac{\partial^2(\Delta\Pi^E/C)}{\partial k \partial \mu} = \left((1-\phi^I)\frac{\partial \eta_k^I}{\partial k} - \frac{1+r_d}{1+r_b^I}\,(1-\phi^E)\,\frac{\partial \eta_k^E}{\partial k}\right), \tag{9}$$

which is positive if: $\frac{\partial \eta_k^I}{\partial k} > \frac{1+r_d}{1+r_b^I}\,\frac{1-\phi^E}{1-\phi^I}\,\frac{\partial \eta_k^E}{\partial k}$. The following proposition summarizes the two results on the speed of learning and on learning and markups:

Proposition 4 (Repeated Interactions, Learning, and Markups)

1. *Suppose the speed of learning declines in the length of a relationship and learning speeds are not too different* ($-\frac{\partial^2 \eta_k^I}{\partial k^2} > -\frac{1+r_d}{1+r_b^I}\,\frac{1-\phi^E}{1-\phi^I}\,\frac{\partial^2 \eta_k^E}{\partial k^2}$). *Then, the effect of learning on the payment choice declines in the number of interactions k.*

2. *Suppose learning about the importer is sufficiently fast* ($\frac{\partial \eta_k^I}{\partial k} > \frac{1+r_d}{1+r_b^I}\,\frac{1-\phi^E}{1-\phi^I}\,\frac{\partial \eta_k^E}{\partial k}$). *Then, the effect of the markup on the payment choice increases with the number of interactions k.*

Proof. Follows directly from equations (8) and (9). ■

Proposition 4 formalizes the intuition provided at the beginning of this section. As firms continually trade with each other, learning becomes less important and financing costs and therefore markups become more important for choosing the payment term. In the limit,

[17] See Appendix A for details on how to micro found the assumption that the speed of learning decreases over time with a model of Bayesian learning.

when a firm has perfectly learned the type of its trading partner, the payment choice only depends on financing costs and thus trade credit tends to dominate. Importantly, Proposition 4 provides clear testable predictions for this mechanism that we can take to the data.

3 Data

Our primary dataset is transaction-level import data from Colombia from 2007-2016. A key advantage of the Colombian data is that it provides firm identifiers for both Colombian importers and foreign exporters, which allows studying relationships at the importer-exporter-(product) level. This information is crucial for testing how payment choices change as relationships evolve.

In addition, we use transaction–level export data from Chile for 2003-2007. In the Chilean data, only exporters are identified at the firm level, while importers can only be identified as a country-HS8 pair. However, the Chilean customs data can be matched to manufacturing survey data that allows estimating markups and productivity, which is essential for testing the predictions of Proposition 4. We describe both Colombian and Chilean data in detail below.

3.1 Colombian Import Data

Data for Colombian imports are collected by the Colombian customs agency, DIAN (*Direccion de Impuestos y Aduanas Nacionales*), and records the universe of international transactions entering the country. For each transaction, the data provide information on the importer's name and tax ID and the name and address of the exporting firm in the source country. Importantly, the identifying variables for importers and exporters are recorded

consistently across years, allowing us to track these firms uniquely over the sample period. For each transaction, the data details the transaction date, the 10-digit HS code to which the product belongs, the FOB value of the merchandise, and the financing mode of the import transaction. In particular, the data contain information allowing us to determine if the transaction was paid post–shipment (trade credit), with cash in advance, a letter of credit, or other payment terms.

We create a consistent identifier for foreign exporters to Colombia following Benguria (2021, 2022). This procedure follows the method used by the U.S. Census Bureau to identify foreign suppliers in US imports as described by Kamal and Monarch (2018). Specifically, a foreign exporter ID is constructed as a string combining a two–digit ISO country code, the first three characters of the city in which the exporter is located, the first three characters in the first word of the exporter's name, the first three characters in the second word of the exporter's name, and the first four characters in the first number found on the street address of the exporter.[18]

We aggregate the data such that each observation corresponds to a Colombian importer, foreign exporter, HS10 product, and day.[19] We refer to these observations as transactions. We exclude from the sample transactions that do not involve a payment as well as transaction in which the payment term variable does not unambiguously correspond to trade credit, cash in advance, or letter of credit.[20] The sample used in the analysis has about 16.1 million transactions and represents 87% of transactions that involve a payment.

[18]This procedure is implemented after removing punctuation marks from names and addresses and standardizing common prefixes and suffixes such as "inc", "llc", etc.

[19]In the raw data, in some cases a firm has multiple transactions of the same product on the same day.

[20]Specifically, 4.6% of transactions involve no payment (IMPORTACION QUE NO GENERA PAGO AL EXTERIOR), 3.8% of transactions fall into the category foreign direct investment (INVERSION EXTRANJERA DIRECTA), and 3.3% of transactions have a mixture of payment terms (COMBINACION DE ALGUNA DE LAS ANTERIORES FORMAS DE PAGO). For a full list of excluded categories amd their shares see table C.1.

3.2 Matched Production-Export Data for Chile

Transaction-level export data for Chile are provided by the Chilean National Customs Service and are available for the 90 main destinations of Chilean exports, accounting for over 99.7% of the total value of exports over our sample period. For each export transaction, the dataset details the identity of the exporting firm, the destination country, the 8-digit HS code to which the product belongs, the date of the transaction, the FOB value of the merchandise, and the financing mode of the export transaction (trade credit, cash in advance, letters of credit, or other payment terms).

We merge the export dataset with the Chilean Annual Manufacturing Survey (ENIA), which provides production information. ENIA is collected by the Chilean National Statistical Agency (INE) and covers the universe of manufacturing entities with 10 or more employees. It surveys approximately 5,000 manufacturing establishments annually, of which approximately 20 percent are exporters. Firms in ENIA are identified with the same identifier provided in the customs data, allowing us to match both datasets. ENIA provides detailed information on firm-level outcomes (e.g., sales, inputs expenditures, employment, investment), on each product sold by each firm (value and volume), and on each input purchased by each firm (value and volume), which we use in our estimation of markups and productivity.

We aggregate the data such that each observation corresponds to a Chilean exporter, HS8 product, destination, and day and refer to these observations as transactions. As with the Colombian data, we exclude from the sample transactions that do not involve payment and transactions with payment terms other than trade credit, cash in advance, or letters of credit. These excluded transactions account for 0.6% of the total. The sample used in the analysis has 604 thousand transactions, and accounts for approximately 80% of the value of Chilean (non-copper) exports.

4 Empirical Approach

This section presents the empirical methodology to test the predictions on trade credit and relationship length.

4.1 Relationship Definition

To test the predictions of the model, we define relationships in two ways. In the Colombian import data, we define a relationship as all imports of a Colombian firm from the same foreign exporting firm. In the Chilean data, we define a relationship as all exports of a Chilean firm of the same product to the same destination country.

4.2 Trade Credit and Relationship Length

Proposition 1 predicts that the use of trade credit increases in the length of a trading relationship. Considering our baseline sample of Colombian imports, the main regression exploits within-relationship variation and takes the following form:

$$\rho_{iept} \quad = \quad \alpha_1 \ \ln(\text{Rel. Length})_{iet} + \psi_{iep} + \nu_{iept}, \tag{10}$$

where ρ_{iept} is a dummy variable that equals one if a transaction between Colombian importer i and foreign exporter e in product p on day t is settled with trade credit and zero otherwise. Rel. Length$_{iet}$ captures the length of a relationship. It is calculated as the cumulative number of transactions between importer i and exporter e through date t. Specification (10) controls for importer–exporter–product fixed-effects (ψ_{iep}). In alternative specifications, we also include importer-product-year and/or exporter–year fixed-effects. Proposition 1 predicts

that $\alpha_1 > 0$: The use of trade credit should increase in the length of the relationship.[21]

Interactions with Country, Product, and Firm Characteristics. To test Proposition 2 on learning and diversion risk, we modify specification (10), adding interactions between the length of the relationship and proxies for diversion risk in the source country s:

$$\begin{aligned} \rho_{iept} &= \alpha_1 \ \ln(\text{Rel. Length})_{iet} \ \times (\text{High Div. Risk})_s \\ &\quad + \alpha_2 \ \ln(\text{Rel. Length})_{iet} \ \times (\text{Low Div. Risk})_s + \psi_{iep} + \nu_{iept}, \end{aligned} \tag{12}$$

where $(\text{High Div. Risk})_s$ and $(\text{Low Div. Risk})_s$ are dummy variables that equal one if a source country s has an above and below median value of diversion risk, respectively, and are zero otherwise.[22] Proposition 2 predicts that $\alpha_1 < \alpha_2$: The effect of learning on trade credit use should be stronger for imports from source countries with low diversion risk.[23]

To test the predictions of Proposition 3 on product complexity, we modify specification (10) again, interacting $\ln(\text{Rel. Length})_{iet}$ with dummy variables that indicate whether a

[21] We also test Proposition 1 using the Chilean export data, estimating:

$$\rho_{edpt} = \alpha_1 \ \ln(\text{Rel. Length})_{edpt} + \psi_{edp} + \nu_{edpt}, \tag{11}$$

Now, ρ_{edpt} equals one if exporter e exports product p to destination country d on date t using trade credit and zero otherwise. Because we do not observe the identity of the importing firm in the Chilean export data, relationship length is computed as the cumulative number of transactions of exporter e of product p to destination d through date t.

[22] As discussed in detail later, we proxy diversion risk by the rule of law index from the World Bank, assuming that diversion risk declines in the rule of law.

[23] We also test Proposition 2 using the Chilean export data, estimating:

$$\begin{aligned} \rho_{edpt} &= \alpha_1 \ \ln(\text{Rel. Length})_{edpt} \ \times (\text{Low Div. Risk})_d + \alpha_2 \ \ln(\text{Rel. Length})_{edpt} \ \times (\text{High Div. Risk})_d \\ &\quad + \psi_{edp} + \nu_{edpt}, \end{aligned}$$

where $(\text{High Div. Risk})_d$ and $(\text{Low Div. Risk})_d$ are dummy variables that indicate high or low levels of diversion risk in the destination country d. In this case, the theory predicts that the effect of learning on trade credit use should be stronger for exports to destinations with high diversion risk, which implies $\alpha_1 < \alpha_2$.

product has a high (Long_Ladder$_p$) or low (Short_Ladder$_p$) scope for quality differentiation as defined in Khandelwal (2010). The estimation equation reads:

$$\begin{aligned}\rho_{iept} &= \alpha_1 \ln(\text{Rel. Length})_{iet} \times (\text{Long Ladder})_p + \alpha_2 \ln(\text{Rel. Length})_{iet} \times (\text{Short Ladder})_p \\ &\quad + \psi_{iep} + \nu_{iept}. \end{aligned} \tag{13}$$

Proposition 3 predicts that $\alpha_1 > \alpha_2$, that is, the use of trade credit should increase more with relationship length for imports of more complex products, as there is a larger role for learning.[24]

Finally, we test whether effects of relationship length on the trade credit choice depends on the multinational status of the importing firm, estimating the following specification:

$$\begin{aligned}\rho_{iept} &= \alpha_1 \ \ln(\text{Rel. Length})_{iept} \ \times (\text{non-MN})_i + \alpha_2 \ \ln(\text{Rel. Length})_{iept} \ \times (\text{MN})_i \\ &\quad + \psi_{iep} + \nu_{iept}, \end{aligned} \tag{14}$$

where $(\text{MN})_i$ and $(\text{non-MN})_i$ are dummies that equal one if a Colombian importer is a subsidiary of a foreign multinational or not, respectively. To construct these dummies, we use S&P's Capital IQ to obtain a list of all firms in Colombia (and Chile) that are affiliates of multinational companies headquartered abroad. We match these firms to the customs data based on their names, using a record linking algorithm and manually inspecting the results.

As diversion risk should mostly matter for unrelated-party trade, we except effects to be

[24] We also test Proposition 3 using the Chilean export data, estimating:

$$\begin{aligned}\rho_{edpt} &= \alpha_1 \ \ln(\text{Rel. Length})_{edpt} \ \times (\text{Long Ladder})_p + \alpha_2 \ \ln(\text{Rel. Length})_{edpt} \ \times (\text{Short Ladder})_p \\ &\quad + \psi_{edp} + \nu_{edpt}. \end{aligned}$$

Proposition 3 implies $\alpha_1 > \alpha_2$, the same as for imports.

stronger for importers that do not belong to a foreign multinational, which implies $\alpha_1 > \alpha_2 \approx 0$.[25]

4.3 Trade Credit, Learning, and Markups

Proposition 4 predicts that the effect of learning on the payment choice declines with the number of transactions, whereas the effect of the financing cost advantage increases with the number of transactions. To test these predictions, we estimate the following specification for different subsamples:

$$\rho_{edpt} = \alpha_1 \ \ln(\text{Rel. Length})_{edpt} + \alpha_2 \ \ln(\text{Markups})_{ipt} + \psi_{edp} + \nu_{edpt}, \tag{15}$$

Specification (15) regresses the trade credit share simultaneously on the log of relationship length and on the log of markups to determine the relative importance of the enforcement friction and the financing cost advantage over the life cycle of a relationship. As the information needed to estimate markups and productivity is only available in the Chilean manufacturing survey, we focus this part of our analysis on Chilean export data.

Proposition 4 predicts a higher magnitude for α_1 early on in the relationships. In contrast, the magnitude for α_2 should increase with the number of transactions as the effect of learning becomes less important. We test this prediction by splitting the data between the first nine transactions in a relationship and all subsequent trades.

To address the endogeneity of markups, we follow Garcia-Marin et al. (2023) implement-

[25] We also run a parallel regression using the Chilean export data, estimating:

$$\rho_{edpt} = \alpha_1 \ \ln(\text{Rel. Length})_{edpt} \times (\text{non-MN})_e + \alpha_2 \ \ln(\text{Rel. Length})_{edpt} \times (\text{MN})_e + \psi_{edp} + \nu_{edpt},$$

where $(\text{MN})_e$ and $(\text{non-MN})_e$ are dummies that equal one if the Chilean exporter is a subsidiary of a foreign multinational or not, respectively.

ing a 2SLS strategy. Specifically, we use firm-product physical total factor productivity (TFPQ) as an instrument for markups. This instrument is consistent with (most) models with variable markups that predict that more efficient firms charge higher markups.[26] 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, which may lead to confound measured productivity and markups (see De Loecker and Goldberg, 2014). Appendix B details the procedure for computing firm-product markups, which follows De Loecker et al. (2016).

5 Results

This section presents our empirical analysis. We start by providing descriptive evidence on the use of trade credit and other payment terms. We then provide econometric evidence on the link between relationship length and payment terms, as well as results on trade credit and the interaction between relationship length and the strength of contract enforcement, product complexity, and markups. Finally, we discuss our robustness analysis.

5.1 Descriptive Evidence

We begin by comparing the shares of different payment terms in the overall sample in Table 1. Trade credit is the dominant payment term. About 88.1% of import transactions in Colombia are paid with trade credit, followed by cash in advance (10.2%) and letters of credit (1.7%).[27] We find a very similar pattern for Chilean exports in panel B.

[26] See, for example, Atkeson and Burstein (2008) and Melitz and Ottaviano (2008), among others.

[27] Recall that, as mentioned in Section 3, we exclude from our sample payment terms that do not fall under these three categories, so here we report percentages out of the total of the sum of these three categories.

Table 2 reports the frequency of each payment term for different points over the life cycle of a relationship. For both countries, trade credit shares for the first transaction are lowest and then rise over the life of a relationship. In the case of Colombia (see panel A), the first transaction in a relationship is paid with trade credit most of the time (74.3%), followed by cash in advance (23.4%). The use of trade credit increases to 79.7% and 82.6% in the fifth and tenth transactions of a relationship, respectively. From the eleventh transaction onward, the trade credit share reaches 90.5%, which is 16.2 percentage points higher than the trade credit share in the first transaction. Most of this increase in the trade credit share comes at the expense of cash in advance, whose share drops by 15.4 percentage points to reach 8.0%. The data on Chilean exports (see panel B) show a similar pattern, with the trade credit share going from 80.8% in the first transaction to 90.9% from the eleventh transaction onward.

Table 1. Summary Statistics

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
A. Colombian Imports						
Trade Credit Dummy	88.1	32.4	100	100	100	16,082,792
Cash in Advance Dummy	10.2	30.3	0	0	0	16,082,792
Letter of Credit Dummy	1.7	13.0	0	0	0	16,082,792
Import Value (US$)	20446.0	265362.3	219.66	1351.91	8105.02	16,082,792
B. Chilean Exports						
Trade Credit Dummy	89.1	31.1	100.0	100.0	100.0	604,843
Cash in advance Dummy	5.2	22.3	0.0	0.0	0.0	604,843
Letters of Credit Dummy	5.6	23.0	0.0	0.0	0.0	604,843
Export Value (US$)	138,205	1,196,335	3,700.0	14,439.5	49,484.9	604,843

Notes: The table lists the summary statistics for the variables used in the paper's baseline analysis sample. Panel A comprises transaction-level data for the universe of Colombian importers from 2007 to 2016. Panel B comprises transaction-level data for the universe of Chilean manufacturing exporters that can be matched to the Chilean Annual Manufacturing Survey (ENIA) from 2003 to 2007.

Table 2. Payment Terms and Relationship Length

	Trade Credit	Cash in Advance	Letter of Credit
A. Colombian Imports			
First transaction	74.3	23.4	2.3
Fifth transaction	79.7	18.1	2.2
Tenth transaction	82.6	15.3	2.0
Eleventh transaction and beyond	90.5	8.0	1.6
B. Chilean Exports			
First transaction	80.8	11.9	7.3
Fifth transaction	85.7	8.3	6.0
Tenth transaction	87.1	7.0	5.9
Eleventh transaction and beyond	90.9	3.8	5.3

Notes: The table shows the percentage of transactions financed through trade credit terms (column 1), cash in advance terms (column 2), letter of credit terms (column 3), and other forms of payment (column 4) in the first, fifth, or tenth transaction in a relationship.

Figure 2 provides further evidence on the link between payment terms and relationship length. It shows a binscatter plot for the logarithm of relationship length —defined as the log cumulative number of transactions occurring from the beginning of a relationship– and the average use of the three main payment terms in Colombia (top panel) and Chile (bottom panel).

Chart A on the left of each panel shows that the use of trade credit increases almost monotonically with the length of the relationship. Chart B in the middle shows that the opposite is true for the share of transactions paid cash in advance. Finally, Chart C on the right shows that the share of letters of credit also decreases with relationship length, but to a much lesser extent than cash in advance. This evidence is consistent with Proposition 1, suggesting that firms are more likely to use trade credit as they learn about the reliability of their trading partners.

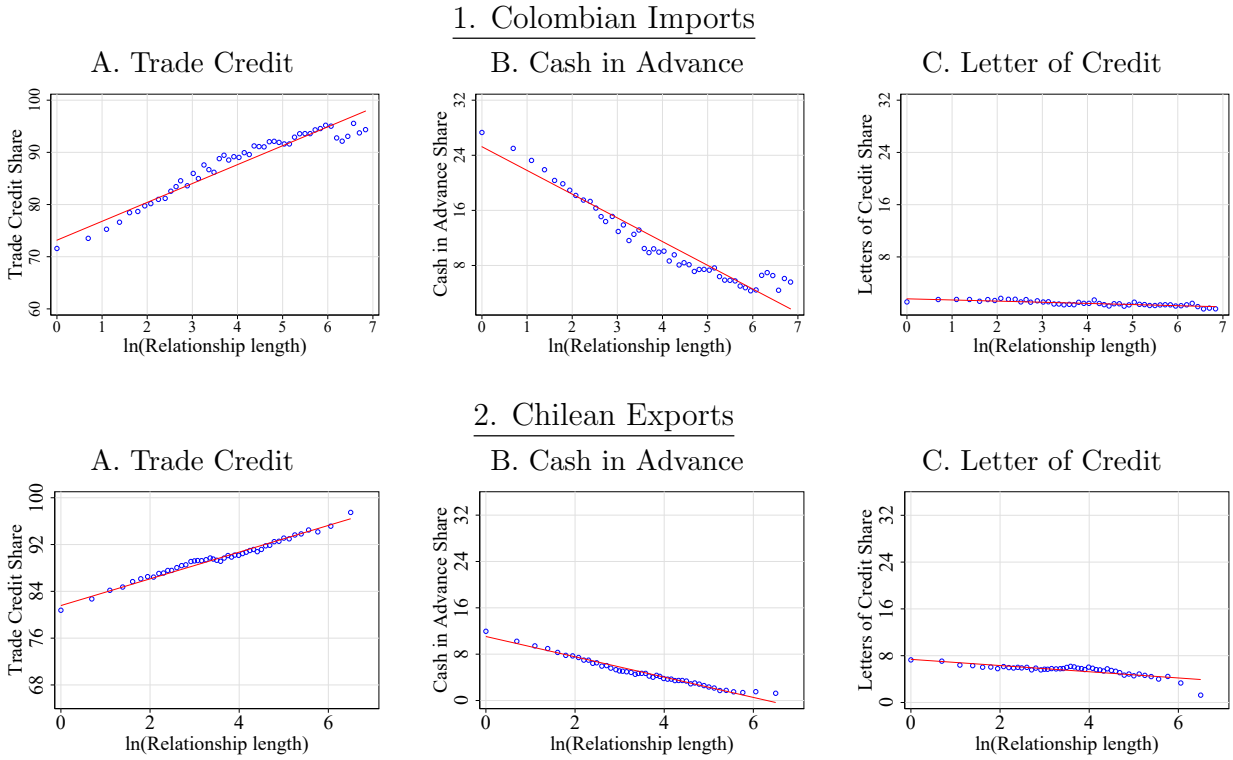
We can also compute transition probabilities between payment terms in consecutive trans-

actions within a relationship (see Table 3). For relationships that use cash in advance, it is common to transition to trade credit in the next transaction. In contrast, switches in the opposite direction, from trade credit to cash in advance, are very rare. For the case of Colombian imports (panel A), 7.2% of relationships that utilize cash in advance switch to trade credit for the next transaction, while only 0.7% of relationships that use trade credit switch to cash in advance. These patterns are qualitatively similar in the Chilean export data.

This asymmetric pattern, where many more relationships switch toward trade credit than toward other payment terms, is consistent with the financing cost advantage of trade credit: as the enforcement friction wanes with relationship length and learning, the advantage of trade credit in terms of financing costs starts to dominate, generating switches from cash in advance to trade credit but not in the opposite direction.

Antràs and Foley (2015) derive a similar prediction by assuming that there is no commitment problem for the seller, which seems plausible in their specific application to a very large U.S. poultry exporter but is unrealistic when looking at the universe of importers or exporters. A generalization of their setup to two-sided learning generates symmetric switches of payment terms: If financing costs are lower in the importer (exporter) country, firms switch to cash in advance (trade credit) over time. Only the financing cost advantage of trade credit introduces the asymmetry necessary to generate a broad-based increase in the use of trade credit within relationships over time in a model with two-sided learning.

Figure 2. Trade Credit Share and Relationship Length



Notes: The figure plots the frequency of each of the three main payment terms in the Colombian and Chilean data for 50 bins of the measure of relationship length (defined as the cumulative number of transactions occurring from the beginning of the relationship). Relationship length is censored at ln(relationship) = 7, i.e., at 1096 interactions within a relationship.

Table 3. Transitions Between Payments Forms

	Payment term in $t+1$:		
	Trade Credit	Cash in Advance	Letter of Credit
A. Colombian Imports			
Payment term in t:			
Trade Credit	99.1	0.7	0.1
Cash in Advance	7.2	92.6	0.2
Letter of Credit	7.8	1.2	91.0
B. Chilean Exports			
Payment term in t:			
Trade Credit	94.9	2.7	2.4
Cash in advance	30.9	65.7	3.4
Letters of Credit	31.0	4.1	64.9

Notes: The table shows transition probabilities in payment terms within relationships. Consider any two consecutive transactions within a relationship labeled t and $t+1$. Each cell shows the fraction of consecutive transactions that transition from the payment term shown in the corresponding row to the payment term shown in the corresponding column.

5.2 Main Results on Relationship Length

According to Proposition 1, trade credit use should increase with relationship length. Table 4 tests this prediction by estimating equation (10). Panel A reports results for Colombian imports. Column 1 includes importer-exporter-product fixed effects, while columns 2 and 3 sequentially add source country-year and firm-product-year fixed effects to control for country-specific and firm-product-specific time-varying shocks. Across all specifications, the coefficient on relationship length is positive and statistically significant, in line with Proposition 1.

One concern is that the results in columns 1 to 3 may be affected by survival bias. This would bias results if, for example, short-lived relationships were less likely to rely on trade credit than longer-lasting relationships. To address this concern, column 4 re-estimates the specification in column 3 using a sample of the first twenty transactions in relationships with at least twenty trades. This sample – which we denote as 'balanced' – is not subject to survival bias because, by definition, all relations survive the entire sample period. The fact that the coefficient in column 4 is positive and has a similar magnitude as the one in column 3, where the full sample is used, suggests that survival bias does not drive our results.

Panel B reports the results based on the sample of Chilean exports, where trade credit use also increases with relationship length. Even though the Chilean data measure relationships at a more aggregate level, the estimated coefficients in our preferred specifications, columns 3 and 4, are of similar magnitude across the two data sets.

Within–Relationship Trade Credit Dynamics. We can also estimate equation (10) replacing the continuous measure of relationship length by a categorical variable to allow

Table 4. Relationship Length and Trade Credit Share

	(1)	(2)	(3)	(4)
A. Colombian Imports				
ln(Relationship Length)	0.211***	0.637***	0.472***	0.401***
	(0.026)	(0.021)	(0.016)	(0.048)
Sample	All	All	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes	Yes	Yes
Source Country-Year FE	—	Yes	Yes	Yes
Importer-HS10-Year FE	—	—	Yes	Yes
Observations	13,645,337	13,645,081	12,947,042	994,519
B. Chilean Exports				
ln(Relationship Length)	1.443***	0.784***	0.924***	0.618***
	(0.120)	(0.130)	(0.121)	(0.217)
Sample	All	All	All	Balanced
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Exporter-HS8-Year FE	—	—	Yes	Yes
Observations	604,843	604,843	604,843	47,177

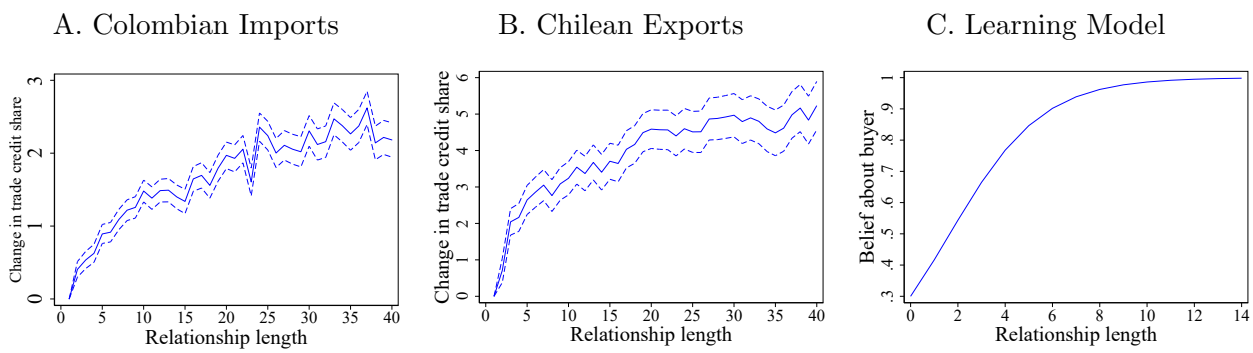
Notes: The table reports the coefficient estimates from equation (10) for Colombian import data (panel A), and from equation (11) for Chilean export data (panel B). In each regression, the dependent variable is (100 ×) a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The independent variable is relationship length, measured as the log of the cumulative count of transactions within a relationship. The sample in columns 1 through 3 considers all observations in each dataset, while the sample in column 4 comprises the first twenty transactions in relationships with at least twenty trades ("Balanced"). Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

for a more flexible relationship between trade credit use and relationship length. We are particularly interested in documenting whether payment terms change more frequently early on in a relationship, as this would provide strong support to a learning interpretation.

Results are presented graphically in Figure 3 for Colombia (panel A) and Chile (panel B). The fixed effects used are the same as those in column 1 in Table 4 and the sample is restricted to the first 40 interactions in a relationship. The figure shows a steep increase in the use of trade credit at the beginning of the relationship, with the slope flattening out as

the relationship progresses. This path is very consistent with a model of Bayesian learning (panel C), where learning is faster early in a relationship and then slows down.[28] This result confirms the prediction in Proposition 4: If the speed of learning declines in the number of transactions, firms should switch more toward trade credit at the beginning of a relationship. The effect is quantitatively meaningful. Based on panel A, the trade credit share rises by 1.5 percentage points between the first and the tenth transactions.

Figure 3. Within–Relationships Dynamics



Notes: The figure shows the estimated within-relationship trajectory for trade credit share in the sample of Colombian importers (panel A) and Chilean exporters (panel B). We define relationships as importer-exporter combinations in the Colombian data and exporter-product combinations in a particular destination country in the Chilean data. The trajectories correspond to the estimated linear regression coefficients of a specification between the trade credit share and categorical variables taking the value one for different transaction counts within a relationship. The dotted lines represent 90 percent confidence intervals. Panel C illustrates the typical Bayesian learning process (with parameters $\hat{\eta} = 0.3$ and $\lambda = 0.6$, see Appendix A for details).

5.3 Additional Results on Relationship Length

In the following, we test the additional predictions of the model on relationship length and its interactions with diversion risk, product complexity, and markups in Propositions 2 to 4.

[28] See Appendix A for an example of Bayesian learning that can micro-found the assumed learning dynamics and for further details on the simulation that generates panel B.

Relationship Length and Diversion Risk. We begin by testing Proposition 2, which predicts that the effect of learning on the trade credit choice is larger for source countries with less diversion risk and for destination countries with more diversion risk. Table 5 presents results from regressions where we interact relationship length with two dummy variables that indicate if a country has high or low diversion risk.[29] Results are consistent with the theoretical prediction. In the case of Colombian imports (panel A), the effect of relationship length on the probability of trade credit use is about 30% larger (according to column 4) for source countries with high diversion risk than for countries with low diversion risk. This makes sense because, in the model, source countries with low diversion risk have a higher initial share of cash in advance, which leaves more space for learning to shift the payment terms to trade credit over time.

[29] We define a country to have high (low) diversion risk if it has a below (above) median rule of law index from the World Bank's *World Government Indicator*.

Table 5. Relationship Length and Contract Enforcement

	(1)	(2)	(3)	(4)
A. Colombian Imports				
ln(Relationship Length) × (High Div. Risk)	0.179***	0.599***	0.428***	0.357***
	(0.027)	(0.022)	(0.018)	(0.068)
ln(Relationship Length) × (Low Div. Risk)	0.253***	0.679***	0.521***	0.454***
	(0.025)	(0.024)	(0.018)	(0.065)
Sample	All	All	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes	Yes	Yes
Source Country-Year FE	—	Yes	Yes	Yes
Importer-HS10-Year FE	—	—	Yes	Yes
Observations	13,644,789	13,644,553	12,946,532	994,476
B. Chilean Exports				
ln(Relationship Length) × (High Div. Risk)	1.958***	1.216***	1.164***	1.068***
	(0.180)	(0.199)	(0.178)	(0.346)
ln(Relationship Length) × (Low Div. Risk)	0.843***	0.353**	0.684***	0.199
	(0.113)	(0.154)	(0.164)	(0.266)
Sample	All	All	All	Balanced
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Exporter-HS8-Year FE	—	—	Yes	Yes
Observations	604,843	604,843	604,843	47,177

Notes: The table reports the coefficient estimates from equation (12) for Colombian import data (panel A), and from equation (13) for Chilean export data (panel B). In each regression, the dependent variable is (100 ×) a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right side of the regression includes interactions between relationship length (measured as the log of the cumulative count of transactions within a relationship) and indicators for whether the source country (in panel A) or the destination country (in panel B) has high or low diversion risk (a below or above median rule of law index). The sample in columns 1 through 3 considers all observations in each dataset, while the sample in column 4 comprises the first twenty transactions in relationships with at least twenty trades ("Balanced"). Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

For Chilean exports (in panel B), we find the expected opposite pattern. The effect of relationship length is at least twice as strong for destinations with a high diversion risk than for destinations with low diversion risk. Even more, in the balanced sample (column 4), relationship length only has a statistically significant effect on the trade credit share for

destinations with high diversion risk.

Relationship Length and Product Complexity. Proposition 3 predicts that the effect of learning on the use of trade credit should be stronger for more complex products. We test this prediction measuring product complexity by the degree of vertical differentiation (i.e. the length of quality ladders) as defined and measured in Khandelwal (2010). This is based on the notion that in industries with vertically differentiated goods, there is more scope for a breach of contract, because product quality is difficult to verify in courts. With cash in advance, the exporter may reduce the quality of the goods she is shipping, while, with trade credit, the importer may dispute the quality of the goods she received and withhold payment.

Table 6 tests these predictions, interacting relationship length with dummy variables that indicate if good have above- or below-median length quality ladders. Across all specifications, the effect of relationship length on trade credit is stronger for more vertically differentiated products, as predicted by the model.

Table 6. Relationship Length and Trade Credit by Product Type

	(1)	(2)	(3)	(4)
A. Colombian Imports				
ln(Relationship Length) × Long Quality Ladder	0.265***	0.689***	0.502***	0.462***
	(0.045)	(0.039)	(0.028)	(0.029)
ln(Relationship Length) × Short Quality Ladder	0.127***	0.606***	0.457***	0.433***
	(0.040)	(0.033)	(0.026)	(0.027)
Sample	All	All	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes	Yes	Yes
Source Country-Year FE	—	Yes	Yes	Yes
Importer-HS10-Year FE	—	—	Yes	Yes
Observations	9,744,531	9,744,297	9,227,462	8,366,908
B. Chilean Exports				
ln(Relationship Length) × Long Quality Ladder	2.781***	1.630***	2.194***	2.107***
	(0.474)	(0.451)	(0.395)	(0.743)
ln(Relationship Length) × Short Quality Ladder	2.046***	1.108***	0.793*	0.826
	(0.404)	(0.409)	(0.442)	(0.633)
Sample	All	All	All	Balanced
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Exporter-HS8-Year FE	—	—	Yes	Yes
Observations	182,966	182,966	182,966	27,674

Notes: The table reports the coefficient estimates from equation (13) for Colombian import data (panel A) and from equation (14) for Chilean export data (panel B). In each regression, the dependent variable is (100 ×) a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right side of the regression includes interactions between relationship length (measured as the log of the cumulative count of transactions within a relationship) and indicators for whether the product has an above- or below-median length quality ladder. The sample in columns 1 through 3 considers all observations in each dataset, while the sample in column 4 comprises the first twenty transactions in relationships with at least twenty trades ("Balanced"). Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Relationship Length and Related Party Status. In the model, diversion risk is key to explaining trade credit dynamics within relationships over time. To provide additional evidence for this channel, we exploit information on the multinational status of Colombian importers and Chilean exporters. Intuitively, diversion risk should be most severe for trade between unrelated parties, while trade within a multinational group should be much less

affected by this friction.

While we cannot directly observe whether a trade transaction is between related or unrelated parties, we can proxy for related-party trade with information on the multinational status of a firm. Specifically, in the Colombian and Chilean data, we can check if firms are subsidiaries of a foreign parent or not. If a firm is a subsidiary of a foreign parent, we expect it to do more related-party trade.

Using this definition, we start by looking at baseline shares of trade credit. In Colombia, 97% of import transactions of firms that are subsidiaries of a foreign multinational use trade credit. This contrasts with a trade credit share of 87% among all other Colombian importers.[30] As shown in table 7, the econometric evidence also aligns well with our expectations. While relationship length matters for trade credit use within firms that are not subsidiaries of foreign affiliates, in row 1, effects are much smaller or insignificant for affiliates of foreign firms, as shown in row 2. This implies that the trade credit dynamics we identify are concentrated within trade between unrelated parties, a finding that is consistent with a central role for diversion risk.

[30]The corresponding trade credit shares in the sample of Chilean exporters are 94% trade for Chilean subsidiaries of foreign multinationals, and 88% for all other Chilean exporters.

Table 7. Relationship Length and Trade Credit Share by Multinational Affiliate Status

	Colombian Imports		Chilean Exports	
	(1)	(2)	(3)	(4)
ln(Relationship Length) × non-MN	0.505***	0.431***	1.001***	0.785***
	(0.017)	(0.051)	(0.129)	(0.207)
ln(Relationship Length) × MN	0.097***	0.005	0.096	0.443
	(0.024)	(0.120)	(0.301)	(0.0454)
Sample	All	Balanced	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes	—	—
Source Country-Year FE	Yes	Yes	—	—
Importer-HS10-Year FE	Yes	Yes	—	—
Exporter-Destination Country-HS8 FE	—	—	Yes	Yes
Destination Country-Year FE	—	—	Yes	Yes
Exporter-HS8-Year FE	—	—	Yes	Yes
Observations	12,947,028	994,514	604,846	98,684

Notes: The table replicates table 4 interacting log relationship length with two indicator variables taking the value one if the Colombian importer (panel A) or the Chilean exporter (panel B) are affiliates of a multinational corporation. In each regression, the dependent variable is (100 ×) a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The independent variable is relationship length, measured as the log of the cumulative count of transactions within a relationship. The sample in columns 1 through 3 considers all observations in each dataset, while the sample in column 4 comprises the first twenty transactions in relationships with at least twenty trades ("Balanced"). Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Importer Experience, Exporter Experience, and Relationship Length. In line with Proposition 1, we have established that payment terms depend on the length of a relationship between an importer and an exporter. The payment terms could, however, also depend on the experience of an importer sourcing from a certain country (regardless of which exporting firm it trades with) or on how long a firm has been an importer, regardless of where it imports from. Additionally, the foreign exporter's experience selling to Colombia could affect the payment terms. Our detailed data allow us to disentangle these different effects. In Table 8, we estimate regressions similar to equation (10), adding to the right-hand side

the log cumulative number of transactions of an importer ("importer experience"), the log cumulative number of transactions of an importer with a given source country ("country-specific importer experience"), and the log cumulative number of transactions of an exporter with Colombia ("exporter experience"). The results indicate that the most important determinant of the payment contract is the length of a relationship between an importer and an exporter, and not the importer's or exporter's experience independently.

Table 8. Trade Credit, Importer Experience, Exporter Experience, and Relationship Length in Colombian Imports

	(1)	(2)
ln(Relationship Length)	1.003***	0.672***
	(0.044)	(0.107)
ln(Importer Experience)	-0.275***	0.090
	(0.033)	(0.097)
ln(Country–Specific Importer Experience)	-0.022**	-0.029
	(0.009)	(0.056)
ln(Exporter Experience)	-0.494***	-0.367***
	(0.043)	(0.115)
Sample	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes
Source Country-Year FE	Yes	Yes
Importer-HS10-Year FE	Yes	Yes
Observations	12,947,042	994,519

Notes: This table shows the results of a transaction–level regression in which the dependent variable is (100 ×) a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right-hand side includes measures of relationship length, importer experience, and exporter experience. Standard errors (in parentheses) are clustered at the exporter-importer-product level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Relationship Length and Markups. Finally, we test the predictions of Proposition 4 to shed light on the relative importance of learning and diversion risk and the financing cost

advantage of trade credit over the life cycle of a relationship. Table 9 presents the results.[31] Consider first columns 1 and 2, which show that both the number of previous interactions and the markup are positive and statistically significant when entering the estimation simultaneously. Magnitudes for the coefficient on log relationship length are similar to those reported in Table 4.

Table 9. Trade Credit, Markup and Relationship Length in Chilean Exports: 2SLS Results

	(1)	(2)	(3)	(4)
ln(Relationship Length)	1.237***	0.623***	1.277***	0.0702
	(0.136)	(0.151)	(0.156)	(0.355)
ln(Markup)	6.280**	6.738**	1.858	11.44**
	(3.093)	(3.233)	(5.261)	(5.124)
First-Stage F-Statistic	71.0	75.3	118.3	22.5
Relationships	All	All	<10 trades	≥10 trades
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Observations	202,507	202,507	109,950	92,557

Notes: The table reports the coefficient estimates from equation (15) for transaction-level Chilean export data. In each regression, the dependent variable is (100 ×) a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right side of the regression includes relationship length and firm–product markups. All columns use firm-product TFPQ to instrument for markups. The table only shows second-stage results (together with the corresponding cluster-robust Kleibergen-Paap rKWald F-statistic). The Stock-Yogo value for 10% maximal IV bias is 16.4. Markups are computed at the firm-product level (products are defined at the 5-digit CPC level). Column 1 controls for the logarithm of firm employment. Standard errors (in parentheses) are clustered at the firm-product-destination level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Proposition 4 predicts that the effect of learning on the trade credit choice declines in the number of transactions while the effect of the markup increases. To test these predictions, we split the data into two samples: the first 9 transactions in a relationship and all trades

[31] To compare the strength of both mechanisms over the full life cycle of a relationship, the analysis focuses on the set of relationships that started in 2003 or later.

after the first 9 transactions. Results are presented in columns 3 and 4 of Table 9. For the first nine trades, the coefficient on relationship length is twice as large as the average effect in column 2, while the coefficient on markups is insignificant (column 3). In contrast, when we move beyond the ninth transaction (column 4), the coefficient on relationship length is no longer significant – with a magnitude very precisely estimated at zero,– while the positive coefficient on markups becomes statistically significant and is 50 percent larger than the average effect estimated in column 3. These results suggest that in line with Proposition 4, the effect of learning is more important at the beginning of a relationship. At the same time, the financing cost advantage of trade credit, captured by markups, matters more in older relationships.

Alternative Ways of Measuring Relationship Length. In our main analysis, we define the length of a relationship as the number of transactions between firms (Colombian data) or as the number of times an exporter has sold a specific product to a destination (Chilean data). Alternatively, we can define the length of a relationship as the cumulative value of sales that have taken place within a relationship or as the number of days that have passed since the first transaction within a relationship. As shown in table D.1, results are not sensitive to the way in which we define the length of a relationship.

6 Concluding Remarks

Exploiting Colombian and Chilean transaction-level international trade data, this paper documents new facts about trade credit use: Trade credit use increases with firm-to-firm relationship length, an effect that is stronger for exports to destination countries with weaker contract enforcement and for imports from source countries with stronger contract enforce-

ment, Consistent with diversion risk, relationship length also plays a bigger role for trade in more complex goods and for trade between unrelated parties.

We present a model featuring enforcement frictions, learning, and a financing cost advantage of trade credit that can rationalize these patterns. Initially, as there is uncertainty about the reliability of the trading partner, payment risk is a key factor limiting the use of trade credit. Through learning this uncertainty resolves within a relationship over time. For older relationships, the payment choice is therefore only determined by the financing cost advantage of trade credit and all relationships rely on trade credit in the long run.

Our findings thus uncover an important role of firm-to-firm relationships for firms' finances: by facilitating the use of trade credit in cross-border transactions, long-term relationships reduce borrowing costs and thereby improve firms' financial performance.

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A Micro Foundation: A Learning Model

In this section, we discuss an example of a learning model that can micro-found the dynamics discussed in Section 2. The exposition below is based on Monarch and Schmidt-Eisenlohr (2018) and Araujo et al. (2016).[1] We use the same setup as in the baseline model with two types of firms: reliable and unreliable. λ and λ^* now reflect the probability that the seller or buyer do not have an opportunity to cheat in a given period. Let $\hat{\eta}$ denote the population mean of reliable firms.

Bayesian Updating Initially, a seller believes (correctly) that the probability a buyer is reliable is equal to the population mean, $\widehat{\eta}$.[2] Every period that a relationship survives, the seller updates her belief about the buyer according to Bayes' rule. A successful interaction signals that the buyer is either reliable or did not have an opportunity to cheat. Learning is therefore not instantaneous but takes time. However, learning is the fastest initially, as the probability that the trading partner is unreliable is the highest then.

If a seller has successfully sold to a buyer for k periods, the posterior probability that the buyer is reliable can be derived as:

$$\eta_k = \frac{\widehat{\eta}}{\widehat{\eta} + (1 - \widehat{\eta})\,\lambda^k}. \tag{1}$$

Importantly, the probability only changes with the length of time that a seller has been selling to the same buyer. It is easy to see that for large k, η_k converges to 1; that is, the seller is almost certain that the buyer is reliable. To shed further light on this, we can take

[1] See also Antràs and Foley (2015) and Macchiavello and Morjaria (2015) for similar setups.
[2] In this section, we drop the star superscript for buyers.

the derivative of η_k with respect to k:

$$\frac{\partial \eta_k}{\partial k} = -\ln(\lambda)\ \hat{\eta}\ (1-\hat{\eta}) \left(\frac{1}{\widehat{\eta} + (1-\widehat{\eta})\ \lambda^k} \right)^2 \lambda^k > 0. \tag{2}$$

Not surprisingly, this derivative is always positive. That is, with every successful interaction, the seller's belief about the buyer's reliability improves. Now, taking the second derivative delivers:

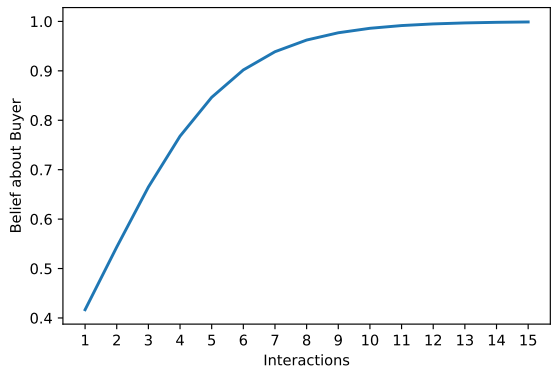
$$\frac{\partial^2 \eta_k}{\partial k^2} = -(\ln(\lambda))^2\ \hat{\eta}\ (1-\hat{\eta})\lambda^k \left[\frac{1}{\widehat{\eta} + (1-\widehat{\eta})\ \lambda^k} \right]^2 \frac{\hat{\eta} - (1-\hat{\eta})\lambda^k}{\hat{\eta} + (1-\hat{\eta})\lambda^k}, \tag{3}$$

which is smaller than zero for all k if

$$\hat{\eta} > \frac{\lambda}{1+\lambda}. \tag{4}$$

That is, as long as condition (4) holds, the second derivative of the belief with respect to k is negative and the learning speed declines over time. Below, we present a graphical example on how learning looks like in this environment where we pick $\hat{\eta}$ such that condition (4) holds.

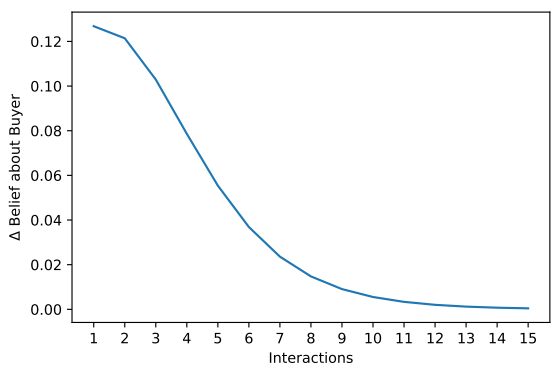
Figure A.1. Bayesian Learning: Level of Belief



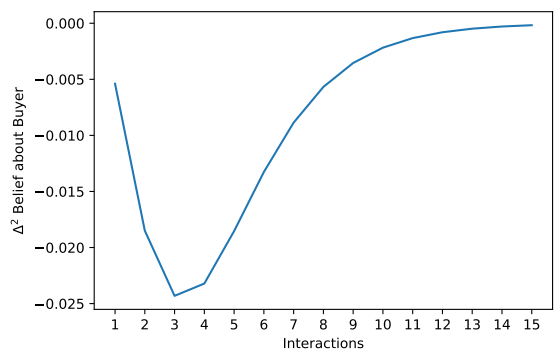
Notes: This figure illustrates the learning process in our example. Parameters are: $\hat{\eta} = 0.3$ and $\lambda = 0.6$.

Figure A.2. Bayesian Learning: Speed of Learning

A: First Difference of Belief



B: Second Difference of Belief



Notes: This figure illustrates the speed of learning in our example. Panel A shows the first difference in the belief about the buyer. Parameters are: $\hat{\eta} = 0.3$ and $\lambda = 0.6$.

The above discussion showed how learning about the buyer works when transactions are done with trade credit and the buyer has an incentive to deviate from the contract. To generate two-sided learning in this setup, there also needs an opportunity to deviate for the seller under trade credit. This could be modeled by following Antràs and Foley (2015) and

allowing the seller to default on the bank loan that she draws to pre-finance production costs. In that case, if defaults to the bank are public information, the buyer learns about the seller even in the case of trade credit. The reverse mechanism would hold for the seller learning about the buyer with cash in advance.

B Markups Estimation

To test the financing motive for trade credit use, we calculate markups following De Loecker et al. (2016). This method requires minimal working assumptions, is flexible about the underlying demand system, and delivers a simple representation of the price-cost markup, which equals the product between the input-output elasticity for a flexible input V (θ^V_{ipt}) and the inverse of the corresponding input's expenditure share relative to the sales of product p (s^V_{ipt}). While the expenditure share is available in the Chilean manufacturing data (more details below), the input-output elasticity requires estimating the production function. For this, we assume an output-specific Cobb-Douglas technology with labor, capital, and materials as production inputs. We avoid the incidence of input and output price biases (discussed in detail in De Loecker and Goldberg, 2014) using firm-specific price deflators to measure output and material expenditure in physical units. Identification of the production function coefficients in multi-product firms directly follows De Loecker et al. (2016), and it requires assuming that multi-product firms use the same technology as single-product firms to produce each output. In particular, the method identifies the production function coefficients for all firm-products using information for single-product firms.[3] We estimate the produc-

[3]The main limitation of this approach is that it restricts economies of scope on the production side, but as Garcia-Marin et al. (2020) show for the same data we use in this paper, considering alternative markup measures not subject to this issue (such as reported average costs and firm-level markups) leads to similar results when analyzing the financing motive for trade credit use.

tion function coefficients following the methodology proposed by Ackerberg et al. (2015) to control for the endogeneity of firms' input choices.[4]

Once we estimate the input-output elasticity for each variable input, we compute the expenditure share, which is only directly available at the firm level. We assign inputs expenditure across outputs, assuming that firms allocate inputs in the same proportion across outputs. To determine the proportion of inputs used to produce each output, we rely on a unique feature of the Chilean manufacturing survey following Garcia-Marin and Voigtländer (2019): The survey lists the total variable costs (labor cost and material expenditure) for each product the firms produce. This information allows computing product-specific input usage. Once we obtain the levels of inputs for each firm-product pair, we compute the expenditure share by taking the ratio between material inputs expenditure and product-specific revenues.

Table B.1 shows summary statistics for the estimated markups. In the survey, outputs and inputs are defined according to the Central Product Classification (CPC) at the 8-digit level, corresponding to 1,190 products over 2003-2007.[5] 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.

[4]In addition, we 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 firms switching non-randomly from single to multi-product status (see De Loecker et al., 2016, for details).

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

Table B.1. Summary Statistics Estimated Markups

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Markups (in logs)	0.153	0.373	-0.125	0.105	0.383	26,584

Notes: The table lists summary statistics for the estimated markup. Markups are computed for the universe of Chilean manufacturing exporters that can be matched to the Chilean Annual Manufacturing Survey (ENIA), over the period 2003-2007.

C Payment Terms Categories in Colombian Import Data

Table C.1. Classification of Payments Terms in Colombian Imports Data

Our classification	Category in Colombian data	Share of transactions (%)
Cash in advance		
	Pagos anticipados (Payment in advance)	8.5
Letters of credit		
	Carta de credito sobre el exterior (Foreign letter of credit)	1.4
Trade credit (open account)		
	Giro directo (Direct payment)	68.6
	Financiacion directa del proveedor (Direct financing by foreign supplier)	4.5
Excluded		
	Mecanismo de compensacion o cuenta de compensacion en el exterior (Compensation mechanism or foreign compensation account)	4.9
	Financiacion del intermediario del mercado cambiario (Financing from the foreign exchange market intermediary)	0.2
	Credito externo de mediano y largo plazo (Long or medium term foreign credit)	0.1
	Arrendamiento financiero leasing (Leasing)	0.1
	Inversion extranjera directa (Foreign direct investment)	3.8
	Combinacion de alguna de las anteriores formas de pago (Combination of any of the previous categories)	3.3
	Importacion que no genera pago al exterior (Imports that do not require foreign payment)	4.6

Notes: The table shows our classification of the original payment term categories in Colombian import data, and the share of transactions in each category during the sample period.

D Additional Results

Table D.1. Robustness: Alternative Relationship Length Measures

	(1)	(2)	(3)	(4)
A. Colombian Imports				
ln(Cumulative FOB Sales)	0.407***	0.232***	—	—
	(0.014)	(0.041)		
ln(# Days since first trade)	—	—	0.388***	0.284***
			(0.016)	(0.045)
Sample	All	Balanced	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes	Yes	Yes
Source Country-Year FE	Yes	Yes	Yes	Yes
Importer-HS10-Year FE	Yes	Yes	Yes	Yes
Observations	12,947,042	994,519	12,947,042	994,519
B. Chilean Exports				
ln(Cumulative FOB Sales)	0.326***	0.318***	—	—
	(0.045)	(0.103)		
ln(# Days since first trade)	—	—	0.172***	0.137***
			(0.022)	(0.045)
Sample	All	Balanced	All	Balanced
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	Yes	Yes	Yes	Yes
Exporter-HS8-Year FE	Yes	Yes	Yes	Yes
Observations	604,843	47,177	604,843	47,177

Notes: The table replicates the last 2 columns in Table 4 using two alternative relationship length measures: Cumulative FOB sales (columns 1 and 2) and days since the first trade in the relationship (columns 3 and 4). In all regressions, the dependent variable is (100 ×) a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The sample in columns 1 and 3 considers all observations in each dataset, while the sample in columns 2 and 4 comprises the first 20 transactions in relationships with at least 20 trades ("Balanced"). Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.