International Trade Finance and Learning Dynamics*

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Abstract

We study how the use of trade finance and the development of long-term relationships between exporters and importers facilitate international trade by allowing exporters to learn about demand uncertainty and counter-party risk. Using detailed micro-level Chilean data, we document that new exporters are more likely to use cash-in-advance (CIA) arrangements and gradually switch to providing trade credit as they continue to export. The initial use of CIA also depends on firms' former exporting experience and the perceived riskiness of the destination. We set up an international trade model in which firms make exporting and trade financing decisions subject to demand and counter-party risks, estimate it to Chilean micro data and use it to quantify the relative importance of demand and counter-party risks and how trade finance choices affect the dynamics of export and learning about the risks within the relationship. Our model implies that the response of aggregate export volume and the number of exporters to aggregate shocks can overshoot in the short run if the shocks destroy long-term relationships and relationship-specific knowledge. The response can be sluggish and persistent because building up relationships takes time. The trade finance choices inform researchers of the learning dynamics and facilitate firms' learning decisions.

Keywords: exports, trade finance, learning, demand uncertainty, counterparty risk.
JEL: F1, F4, G32.

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1 Introduction

Credit arrangements, or trade finance, are pivotal in facilitating transactions in international trade, given its inherent risks and costs. First, firms engaging in international trade face counterparty risk, that is the risk that their counterparty will default on its obligations (see, for example, Antras and Foley (2015) or Schmidt-Eisenlohr (2013)). Second, demand for new foreign products in new destinations is uncertain, and it may sell worse than expected due to uncertain local tastes and market conditions (see, for example, Allen (2014)). At the same time, international trade is associated with long delays between shipment of goods and payment for these goods as well as direct trade costs such as shipping costs Anderson and Van Wincoop (2004). As a consequence, the vast majority of international trade involves some form of trade finance (Auboin, 2009).

Firms' choices of trade finance arrangements need to balance the needs and risks of both counterparties, which may change as firms engage in international trade and learn more about the demand for their products and their counterparties' trustworthiness. In this paper, we investigate how learning about counterparty risk and product demand interacts with trade finance choices and how these interactions affect firm-level export decisions and aggregate trade flows.

While earlier work emphasized static trade-offs associated with trade finance choices, we focus on their dynamic implications.[1] We uncover a channel through which trade finance facilitates learning and, hence, international trade. We show that new exporters typically demand importers to pay in advance (Cash-in-Advance arrangements – CIA) which protects these firms from counterpart risk but allows them to learn about the local demand. As uncertainty about local demand diminishes, exporters switch from demanding Cash-in-Advance to offering trade credit (Open Account arrangements –OA). This encourages importers to buy more from exporters, particularly in those destinations where credit is costly. By switching to OA, exporters expose themselves to counterparty risk and, hence, learn over time about their counterparties' credibility. Thus, long-term relationships can potentially mitigate the risk faced by firms, reducing the costs of international trade and affecting their export decisions.

We first document stylized facts regarding the use of trade credit arrangements and provide evidence for the importance of long-term relationships and learning. To do so, we use detailed micro-level Chilean data that includes both custom-level export data and firms'

[1] Notable exceptions are Antras and Foley (2015) and Garcia-Marin et al. (2019) who consider learning about counterparty risk in a partial equilibrium framework. In contrast, we consider two-dimensional learning about demand and counterparty risk and investigate how this learning affects both trade finance choices and exporting decisions. As explained below, the two sources of uncertainty present in our model play a key role driving the dynamics of international trade and trade finance.

balance sheets. The data covers the years 2005 to 2019 and includes all exports by Chilean firms at the transaction level. We find that, at the product-destination level, firms tend to offer trade credit to their counterparties (80% of all shipments are sold on OA). However, exporters that begin exporting to a new market and new exporters (i.e., firms that did not export before to any destination) in particular rely much more heavily on cash in advance with CIA accounting for 34% of their total sales in the latter case. We also find that small firms (less than 50 employees) and inexperienced exporters (exporters selling to less than five markets) also rely more heavily on CIA arrangements.[2]

In order to investigate the importance of learning, we then analyze empirically how the use of trade finance arrangements evolves during firms' export spells at the destination-product level. To account for firms' selection that may induce dynamics in trade finance choices, we follow the approach implemented by Fitzgerald et al. (2023) and control for the tenure in a given market (which captures dynamics) as well as the spell length (which controls for selection on unobserved persistent heterogeneity). Using this approach, we find that exporters tend to initially rely more on CIA financing terms and gradually switch to OA as they keep exporting their products to a new destination. These dynamics are more pronounced in risky destinations and financially underdeveloped economies as well as among inexperienced and small firms. Overall, these results are consistent with learning though they are silent on the exact nature of such learning.

We then set up a dynamic model of international trade with heterogeneous firms to investigate the role of learning about the demand and counter-party risks in accounting for our empirical findings. Our model consists of multiple countries and monopolistically competitive sectors populated with a continuum of firms that produce differentiated varieties which can be sold domestically and abroad. As in Melitz (2003), exporting is subject to fixed and variable trade costs. Firms use labor as their only input. Deviating from the standard Melitz (2003), we assume that when a firm exports to a particular destination it is matched with a specific importer for the duration of its export spell as in the dynamic version of the model developed in Antras (2015).

Following the large literature that emphasizes the riskiness of exporting activities (see, for example, Antras (2015)), we assume that exporting is subject to two types of risks. First, as in Antras and Foley (2015) or Schmidt-Eisenlohr (2013), firms face the risk that the matched importer may prove unreliable, posing a risk of non-payment for the received goods (counterparty risk). Second, as in Albornoz et al. (2012) or Berman et al. (2019), the foreign demand for exporters' goods is uncertain with some products turning up to be unpopular

[2]These results are consistent with earlier findings. See, for example, Ahn (2011), Ahn (2021), Antras and Foley (2015), and Schmidt-Eisenlohr (2013).

(demand risk). Thus our model combines two sources of risk that have been investigated separately in trade finance (counterparty risk) and export dynamics (demand uncertainty) literature. Following the growing literature on trade finance, we allow firms to manage these risks by optimally choosing trade finance arrangements. In particular, exporters can choose to sell their goods on cash in advance (CIA) terms which protects them from both the counterparty risk and demand risk as exporters are paid in advance, but is costly to the importer resulting in a lower volume of exports. Alternatively, exporters can choose to sell goods on credit using open account (OA) terms which leads to higher export volume due to lower costs for importers but exposes exporters to counterparty and demand risk.[3].

Our model emphasizes a new channel through which trade finance facilitates international trade by allowing new exporters to learn gradually about the risks they face while minimizing exposure to these risks. In particular, in our model, new exporters initially sell their goods in foreign destinations using CIA terms, which allows them to learn about local demand and reduce demand uncertainty without exposing themselves to any risk. As they learn more about the local market, demand uncertainty decreases and they gradually switch from CIA to OA terms. This tends to increase the volume of exports (since OA is typically cheaper from importers' perspective) which exposes exporters to counterparty risk, but also allows them to learn about the importer's credibility. This learning, by reducing counterparty risk, leads to a further increase in foreign sales. Thus, our model implies that even if CIA terms are less common than OA terms, they are important for lowering entry barriers for exporters as many firms would not decide to export if they had to use OA financing terms because of the high risk initially associated with these terms.

We then calibrate our model using Chilean data. We find that both sources of learning are important drivers of export volume and trade finance dynamics. In particular, we show that learning, by decreasing the implied financing wedge, can be a quantitatively important source of export dynamics. We also show that our model matches well the documented empirical patterns. In particular, we find that new exporters are more likely to use CIA terms and then gradually switch to offering trade credit (OA terms). We also show how the speed of trade finance dynamics depends crucially on the parameters governing learning about demand and counterparty risks, with the former having a relatively stronger impact on export volume dynamics while the latter affecting relatively more dynamics of trade finance. Thus, our quantitative results show that the new channel implied by our model is important for aggregate trade flows.

[3]Note that while the existing literature on trade finance emphasizes the choice of trade finance arrangement as a way of managing counterparty risk, in our model firms also use it to limit their exposure to the risk arising from an uncertain demand

We use the calibrated model to evaluate the response of export dynamics to aggregate shocks. We find that the response of aggregate export volume and the number of exporters to aggregate shocks can overshoot in the short run if the shocks destroy long-term relationships and relationship-specific knowledge. The response can be sluggish and persistent because building up relationships takes time. The trade finance choices inform researchers of the learning dynamics and facilitate firms' learning decisions.

Literature Review — Our paper contributes to recent literature that studies the role of trade finance in facilitating international trade. Ahn (2011), Antras and Foley (2015), and Schmidt-Eisenlohr (2013) were the first ones to develop equilibrium theoretical models of trade finance in the international trade context. These papers emphasize counterparty risk as the main determinant of firm-to-firm financial arrangements. Antras and Foley (2015) and Schmidt-Eisenlohr (2013) also provide empirical evidence based on micro-level and aggregate data, respectively, consistent with the predictions of their models. Demir and Javorcik (2018) and Garcia-Marin et al. (2019) extend these models to study the effect of an increase in competition. Finally, Niepmann and Schmidt-Eisenlohr (2017a,b) emphasize the importance of direct financial intermediation by banks for international firm-to-firm transactions. These papers consider partial equilibrium models and typically abstract from learning about counter-party risk.[4] In contrast, we document empirically the significance of relationship-specific knowledge and use our model to quantify its importance. We also emphasize learning about foreign demand as another key determinant of trade finance.

We also contribute to the large literature on export dynamics. Ruhl and Willis (2017) document using Colombian data how export volume, export intensity, and exporters' hazard rate change following entry into a foreign market. Several mechanisms can account for these dynamics. Kohn et al. (2016) focus on the role of financial frictions, Rho and Rodrigue (2016) emphasize capital accumulation, and Alessandria et al. (2021) consider stochastically decreasing trade costs. Other papers investigate the role of market-specific investments such as advertising (Fitzgerald et al. (2023)) and customer-capital accumulation (Piveteau (2021)). We contribute to this literature by considering the dynamics of trade finance and its interaction with the dynamics of exports as well as by focusing on learning as the driver of these dynamics.

We are not the first ones to consider learning as the driver of export dynamics. Albornoz et al. (2012) argue that export dynamics can be explained by firms' learning about the

[4] A notable exception is Antras and Foley (2015) who also considers repeated interactions. We differ from that paper by investigating the relative importance of learning about demand and counterparty risk, providing novel evidence regarding the importance of long-term relationships, and quantifying the sources of learning and their effect on export dynamics.

profitability of exporting.Araujo et al. (2016) propose a model of export dynamics driven by learning about counterparty risk. Finally, Berman et al. (2019) provide evidence that learning about demand is an important driver of firms' dynamics (see also Eaton et al. (2021) and Timoshenko (2015)). We instead focus on the interaction between export and trade finance dynamics, consider two-dimensional learning about demand and counter-party risk and investigate their relative importance.

2 Empirical evidence

In this section, we document stylized facts regarding the use of trade credit arrangements and provide evidence for the importance of long-term relationships and learning.

We use detailed firm-level customs data that record all export transactions by Chilean firms, including information on prices, quantities, destinations, and, crucially, on the terms of financing for each transaction. We merge these data using firms' identifiers with administrative tax records to obtain information about exporters' sales, materials used, and number of workers employed. We consider only firms in the manufacturing sector and limit our attention to firms with at least five employees. While the data covers years 2005 to 2021, we exclude pandemic years and focus instead on the period 2005 to 2019.

Compared to the previous literature that studied trade finance in the context of international trade, our dataset has several advantages. Compared to Antras and Foley (2015) who consider a single large exporter, we have data on all export transactions and their financing terms for the universe of manufacturing firms in Chile. Thus, we can explore how trade finance use depends on firms' and destinations' characteristics. However, unlike Antras and Foley (2015), we do not observe the importer's information, and thus, we have to perform our analysis at the product-market level. In contrast to Niepmann and Schmidt-Eisenlohr (2017a,b) who use detailed data on banking credit, our data has a broader scope and covers all types of trade credit arrangements used by exporters. Hoefele et al. (2016) uses the World Bank Enterprise Survey (WBES), which is a comprehensive firm-level survey conducted in a wide range of developing countries but is missing the time dimension (i.e., it is a cross-section of firms). In addition, in WBES data set, the timing of payments is reported only at the firm level. Demir and Javorcik (2018) use similar data but focus only on the textile industry. Finally, Garcia-Marin et al. (2019) use similar customs data for Chile merged with the annual manufacturing survey (ENIA); instead, we have access to the tax administrative data with more accurate firm-level information. Table 11 in the Appendix provides some descriptive statistics of the firm-level data.

2.1 Trade finance use by firm, destination and product characteristics

We begin by investigating the relative use of trade finance arrangements by firms. In Tables 1 and 2, we report the relative use of cash in advance, open account, and bank credit (that is, letters of credit and other bank financing) by firms in our sample.[5] We measure the share of each payment method as the annual value of transactions using a given payment method (i.e. CIA) divided by the annual value of exports for each firm, destination and product.[6]

Table 1: Relative use of CIA, OA, and BC by exporters.

Relative use of	CIA	OA	BC
All firms	0.32	0.64	0.04
Firms-destination-product-years	0.13	0.83	0.04
Exporters to a new market, first year	0.19	0.75	0.06
New exporters, first year	0.38	0.57	0.05

Note: The share of each payment method is computed as the annual value of transactions using a given payment method (i.e. CIA) divided by the annual value of exports for each firm-destination-product couple. The first row reports the average across observations, the second row reports the average across firms after averaging across destination-product-years for each firm, the third row averages across the first years of exports of new products to a new market, the fourth row reports the average across the first years of exports for each firm,

Table 2: Relative use of CIA, OA, and BC by exporters, distribution.

	N	Average	std	min	p10	p25	p50	p75	p90	Max
CIA	3,812	0.32	0.37	0.00	0.00	0.00	0.14	0.60	1.00	1.00
OA	3,812	0.64	0.38	0.00	0.00	0.33	0.80	0.99	1.00	1.00
BC	3,812	0.04	0.13	0.00	0.00	0.00	0.00	0.01	0.11	1.00

Three observations emerge from these tables. First, open account terms are the most popular financing terms among Chilean exporters followed by cash-in-advance terms. On average, export sales on OA terms account for 64% of the annual export value compared to 32% accounted by CIA. Finally, we observe very few firms using financing terms that involve bank intermediation (75 percent of firms use less than 1 percent of bank financing, as Table 2 shows). Thus, at least in Chile, we find that bank intermediation is much less important than emphasized by earlier literature. The infrequent use of the letter of credit

[5]A small number of transactions use a combination of financing terms. We ignore those transactions throughout our empirical analysis.

[6]Results are robust when computing the relative use as shares of number of transactions using a particular payment method.

is consistent with Antras and Foley (2015) who report that only 5% of transactions of a major US-based poultry producer occur using the letter of credit. It is also consistent with data from Turkey and Colombia, where post-shipment payment accounts for 79% to 90% of international transactions value (See Ahn 2021, Table 1).

The second observation that emerges is that cash in advance plays a much more important role for new exporters, that is exporters who start to export to their first destination. In particular, 38% of export sales during the first year of exporting occur on cash-in-advance terms among these firms while the average across all annual observations is only 13%.[7] Thus the relative use of cash in advance terms more than triples for these firms. This suggests that firms with little to no exporting experience prefer to use financing terms that protect them from unexpected default by the importer of their goods.

Finally, we observe that when firms enter a export new market they rely on cash-in-advance payments more than the average across firm-destination-product-years, but less than firms that start exporting to their first destination-product. This suggests that even experienced exporters often use CIA terms when entering a new market, though to a lesser degree than first-time exporters.

Overall, the last two observations suggest that exporting experience plays an important role in determining firms' use of trade finance arrangements. This is consistent with recent survey results of Colombian managers described in Domínguez et al. (2023) which suggest that managers view exporting as a learning experience, not only about a particular destination but also about the process of exporting more broadly.

Table 3: Relative use of CIA, OA, and BC by firms.

Relative use of	CIA	OA	BC
Large firms	0.23	0.72	0.05
Small firms	0.41	0.56	0.03
Experienced	0.12	0.83	0.05
Inexperienced	0.37	0.59	0.04

Note: Share of each payment method computed as the annual value of transactions using a given payment method (i.e. CIA) divided by the annual value of exports for each firm-destination-product couple. We average across firms after averaging across destination-product-years for each firm. Firms are classified as large if they have more than 50 workers on average, small otherwise. Experienced firms are those that export to at least 5 markets on average.

We next turn our attention to investigate how the use of trade finance arrangements vary

[7] Notice that the 11% average CIA share is lower than the average when first averaging observations for each firm and then averaging across firms. This is because firms exporting many products, to many markets, and for many years tend to rely more on OA, and thus these observations are over-represented when taking the simple average across observations as in the second row of Table 1.

across firms that differ in terms of size and export experience. We define a firm to be large if it has on average more than 50 employees over the period it appears in our sample, otherwise a firm is classified as small. We define a firm to be experienced if it on average exports to more than 5 different markets over the period it appears in our sample. Table 3 provides information about the relative use of different financing terms among firms in terms of size and experience.

We see that the use of bank intermediation does not vary much with firms' size or export experience, with a small share of sales using letters of credits. However, small firms and inexperienced exporters rely more on cash-in-advance payments. This is consistent with the results reported in Table 1 since new exporters tend to be small and, by definition, tend to be inexperienced.

Table 4: Relative use of CIA, OA, and BC by destinations.

Relative use of	CIA	OA	BC
High Fin. Development	0.31	0.65	0.04
Low Fin. Development	0.31	0.66	0.03
Low Risk	0.22	0.72	0.06
High Risk	0.34	0.63	0.03

Next, in Table 4, we report how the use of trade finance arrangements varies with destination characteristics such as financial development and riskiness, whose importance have been emphasized in earlier literature (see Antras and Foley (2015) and Schmidt-Eisenlohr (2013)). We measure financial development at each destination using the ratio of domestic credit to the private sector divided by GDP, which is a standard measure in the literature, and classify destinations as having high financial development if credit-to-GDP ratio is above the median and as having low financial development otherwise.[8] We measure countries' riskiness using the Law and Order index from the International Country Risk Guide which is a component of the political risk index produced by the PRS Group for 141 countries. This index measures the "strength and impartiality of the legal system" and "an assessment of popular observance of the law".[9,10] We define a destination to be of low risk if the index is above the median and as featuring high risk otherwise.

Table 4 indicates that on average exporters to destinations that have low financial development or are perceived to be of high risk rely more on cash in advance terms. This is

[8]Results are robust to using instead the Financial Development Index constructed by the IMF.

[9]For more information, see `https://www.prsgroup.com/explore-our-products/icrg/` .

[10]Results are robust to measuring country riskiness using the Investment Profile component of the Law and Order index instead, as in Antras and Foley (2015), or the Rule of Law index from the World Governance Indicators by Kaufmann et al. (2011).

intuitive since low financial development and high riskiness capture the difficulty of enforcing contracts in those locations and the relative ease with which the importer can renege on its promise. These findings are consistent with previous findings in the literature and with our model implications, as we show in the quantitative section.

Finally, in Table 5, we report how the use of trade finance arrangements varies across product characteristics. First, following Rauch (1999), we classify goods into differentiated goods, standardized (goods with a reference price), and commodities. We also classify product according to their use (i.e., capital, intermediate, and consumption goods). We see that firms exporting differentiated and capital goods are substantially more likely to use CIA terms than firms that exports standardized goods, commodities, or consumption goods. Among consumption goods, we find that durable goods are more often sold using CIA terms than sem-durable or non-durable goods.

Table 5: Relative use of CIA, OA, and BC by product characteristics.

Relative use of	CIA	OA	BC
Differentiated	0.34	0.63	0.03
Standardized	0.21	0.75	0.04
Commodities	0.21	0.76	0.03
Capital goods	0.39	0.59	0.03
Intermediate goods	0.30	0.67	0.04
Consumption goods	0.23	0.73	0.04
Durable Consumption goods	0.30	0.68	0.02
Semi-durable Consumption goods	0.25	0.72	0.03
Non-durable Consumption goods	0.17	0.77	0.06

Overall, the cross-section results suggest that while open account is the most common payment method among Chilean exporters, cash-in-advance terms are associated with a significant share of sales among small and inexperienced exporters –particularly those that start to export for the very first time– as well as among risky destinations. In what follows, we investigate how these firm-level and destination-level characteristics affect the choice of financing terms upon entry and trade finance dynamics.

2.2 Dynamics of trade finance

We next analyze the use of trade finance by exporters during their export spells, which are defined at the firm-destination-product level. In particular, we investigate whether exporters switch to providing more trade credit during their export spells (i.e., switch from using cash in advance to using open account) and whether these dynamics depend on the characteristics of firms, destinations, or products. In the following sections, we investigate whether our model can explain these dynamics.

We perform the analysis both at the yearly level (aggregating all transactions yearly) and at the more disaggregated transactions level. We face the challenge that selection into export markets based on persistent unobserved heterogeneity may generate a relationship between tenure in a destination market and firms' choices. To isolate actual firm-level dynamics, we control for selection by conditioning dynamics on firm-product-market fixed effects. To control for exogenous changes in destination markets that can contribute to post-entry dynamics, we use destination-year fixed effects. These sets of fixed effects help us isolate learning from other factors that might be driving trade finance dynamics.

2.2.1 Dynamics of trade finance by year

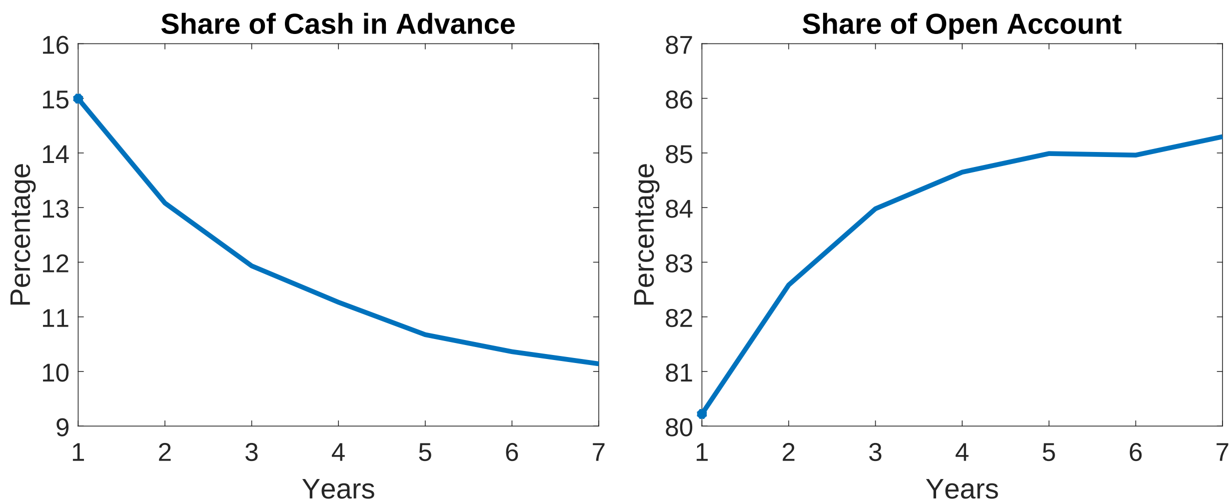
Let i denote an exporting firm, j a destination country, and k a product. For each variable of interest w_t^{ijk} (i.e. share of cash-in-advance), we estimate:

$$w_t^{ijk} = \beta a_t^{ijk} + c^{ijk} + d_t^j + e_t^{ik} + +\varepsilon_t^{ijk}, \tag{1}$$

where c^{ijk} is the firm-destination-product fixed effect, d_t^j is the destination-time fixed effect, e_t^{ik} is the firm-destination-time fixed effect, $\boldsymbol{a}_t^{ijk}$ is a vector of indicators for the tenure in destination j of a firm i exporting product k in the current spell (so that there is a separate indicator for the first year of an export spell, second year, etc.), and ε_t^{ijk} is idiosyncratic noise.

Figure 1 depicts the estimated dynamics over time with the left panel showing the dynamics of the share of cash-in-advance sales and the right panel depicting the dynamics of the share of open account sales. The dynamics are for exporter-destination pairs that maintain trading relationships for 7 years or more. This figure shows that the share of value sold on cash-in-advance decreases over the duration of export spells (conversely, the share of open account sales increases over time). In particular, the share of shipments sold on cash in advance decreases by 2% while the share of shipments sold on open account increases by 2.5% , after controlling for fixed effects.

To further control for selection, we follow Fitzgerald et al. (2023) and condition export spells dynamics on the duration of export spells at the firm-product-market level. That is, we condition on the number of years a given firm-product pair survived in a particular market. To implement the above approach, we let $\boldsymbol{a}_t^{ijk}$ be a vector of indicators for the tenure in destination j of a firm i and product k in the current spell, as before. Next, we define



(a) Share of Cash-in-Advance Payment **(b) Share of Open Account**

Figure 1: Dynamics of trade finance.

$\boldsymbol{\ell}_t^{ijk}$ to be the vector of indicators for the duration of relevant export spells (so that we have indicators for one-year spells, two-year spells, and so on). Then, let $\boldsymbol{s}_t^{ijk}$ be the Kronecker product of $\boldsymbol{\ell}_t^{ijk}$ and $\boldsymbol{a}_t^{ijk}$, that is, $\boldsymbol{s}_t^{ij} = \boldsymbol{\ell}_t^{ijk} \bigotimes \boldsymbol{a}_t^{ijk}$. Since tenure in a given export spell has to be lower than the length of the spell, we drop redundant interactions. Using this notation, our regression is then given by

$$w_t^{ijk} = \beta(\ell_t^{ijk} \otimes a_t^{ijk}) + c^{ijk} + d_t^j + e_t^{ik} + \varepsilon_t^{ijk}, \tag{2}$$

where w_t^{ijk} is a given variable of interest (i.e. CIA share), c^{ijk} is the firm-destination-product fixed effect, d_t^j is the destination-time fixed effect, e_t^{ik} is the firm-destination-time fixed effect, and ε_t^{ijk} is idiosyncratic noise.

Figure 2 depicts the estimated dynamics for spells of different length with the left panel depicting the dynamics of the share of cash in advance and the right panel depicting the dynamics of the share of open account. Figure 2 shows that there is substantial heterogeneity in the use of cash in advance and open account upon entry which is correlated with the length of export spells. Trading relationships with shorter spells tend to begin with a higher CIA payment share. This result suggests that controlling for unobserved persistent heterogeneity is important for estimating the dynamics of trade finance.

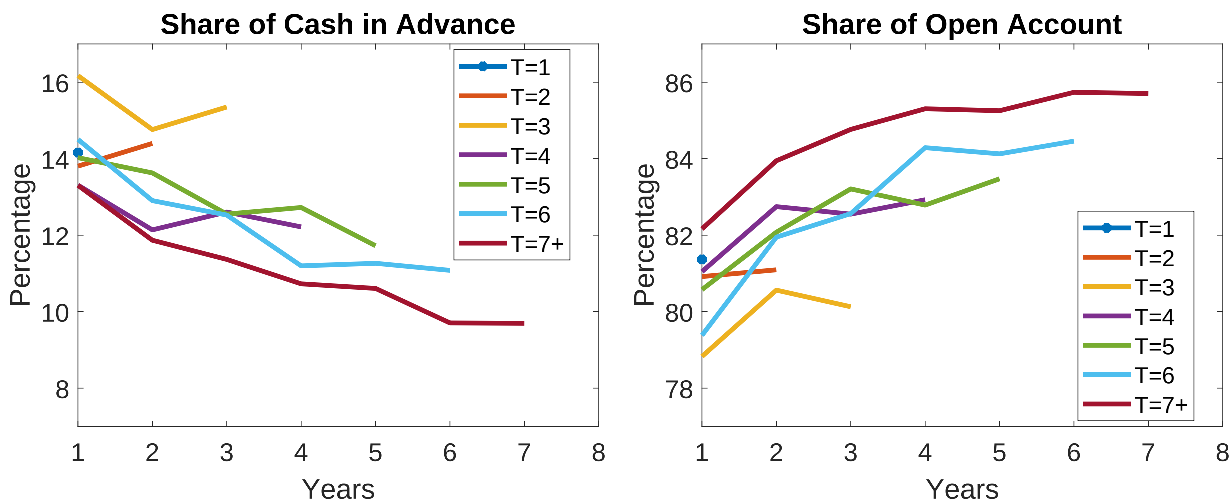


Figure 2: Dynamics of trade finance.

2.2.2 Dynamics of trade finance by transactions

We next perform the regression analysis at the more disaggregated transaction level.[11]. We show that our previous findings are robust at this more disaggregated level.

We estimate

$$w_n^{ijk} = \beta \log(n^{ijk}) + c^{ijk} + d_t^j + e_t^{ik} + \varepsilon_t^{ijk}, \tag{3}$$

where, c^{ijk} is the firm-destination-product fixed effect, d_t^j is the destination-time fixed effect, e_t^{ik} is the firm-product-year fixed effect, and n^{ijk} measures the cumulative number of transactions (first transaction, second, etc). Table 6 presents the main findings.

Table 6: The change in the use CIA/OA as the # of transactions increases

	Share of CIA			Share of OA		
	(1)	(2)	(3)	(4)	(5)	(6)
log(# Cum.Trans.)	−0.019	−0.0034	−0.0045	0.018	0.0077	0.0057
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0004)
Firm-dest-prod FE	-	Yes	Yes	-	Yes	Yes
Firm-year-prod FE	-	-	Yes	-	-	Yes
Dest-year FE	-	-	Yes	-	-	Yes

We observe that the share of CIA decreases in the number of transactions (i.e., the length of relationship). In particular, after the first 100 transactions (which takes, on average, two years of exporting), the share of CIA decreases by 9% if we do not control for selection

[11] Results here are complementary to those in Garcia-Marin et al. 2019

(col. (1)) or 2% once we control for selection (col. (3)); conversely, following the first 100 transactions, the share of OA increases by 8.5% if we do not control for selection (col. (4)) or 3% once we control for selection (col. (6)).

Thus, the results using transaction-level data are consistent with results based on calendar years. In particular, they imply that the share of CIA falls as relationships develop. Notice that also in this case selection matters: it is important to control for firm-destination-product fixed effects.

2.2.3 Dynamics of trade finance by firm, destination and product characteristics

Our model suggests that the dynamics of trade finance are more pronounced in risky destinations and those with lower financial development. To test these predictions we divide countries into high risk and low risk countries using the law and order indicator described above and modify (3) by including the interaction of the cumulative transactions with an indicator variable that captures either riskiness or financial development of the destination. The results of this regression are presented in Table 7. Consistent with our theoretical model, firms selling to high risk or low financially-developed countries tend to sell a higher share of their exports with using cash-in-advance arrangements compared to firms that begin exporting to low risk or high financial development countries.

Table 7: The change in the use CIA/OA in countries with low and high financial development.

	Share of CIA		**Share of OA**	
log(# Cum.Trans.)	-0.012	-0.008	0.013	0.009
	(0.0007)	(0.0004)	(0.0009)	(0.0005)
log(# Cum.Trans.)×Fin.Dev.	0.009		-0.0083	
	(0.0007)		(0.0009)	
log(# Cum.Trans.)×Safe		0.0083		-0.007
		(0.0005)		(0.0006)
Firm-dest-prod FE	Yes	Yes	Yes	Yes
Firm-year-prod FE	Yes	Yes	Yes	Yes
Dest-year FE	Yes	Yes	Yes	Yes

We observe that the dynamics of CIA/OA substantially more pronounced in less financially developed economies: After 100 transactions, the share of CIA falls by nearly 6% in financially underdevloped countries compared to only 1.5% in financially developed economies. Moreover, the dynamics of CIA/OA substantially more pronounced in more risky destinations: After 100 transactions, the share of CIA falls by nearly 4% in risky countries compared to no change in safe countries. Thus, we see that dynamics of trade finance use are more pronounced in countries that are less financially developed and more risky.

Next, we consider how the dynamics of trade finance vary with firms' characteristics such as experience and size. As before, we classify a firm to be experienced if, at the time of entry into a new export market, it is exporting to more than five markets. Otherwise, a firm is classified as inexperienced. Table 8 presents our results. We see that the dynamics of CIA/OA substantially more pronounced among inexperienced firms (firms that export to fewer than 5 markets): After 100 transactions, the share of CIA falls by 3.1% among inexperienced firms compared to only 0.5% among experienced firms.

Table 8: The change in the use CIA/OA in among experienced and inexperienced firms.

	Share of CIA	**Share of OA**
	(1)	(2)
log(# Cum.Trans.)	−0.0052	0.0068
	(0.0003)	(0.0004)
log(# Cum.Trans.)×Experience	0.004	−0.006
	(0.0004)	(0.0005)
Firm-dest-prod FE	Yes	Yes
Firm-year-prod FE	Yes	Yes
Dest-year FE	Yes	Yes

Overall, the above results suggest that learning plays an important role in driving trade finance dynamics, as we show below in the quantitative analysis.

2.3 Initial choice of trade finance

In this section, we investigate potential factors that drive the heterogeneity in the use of trade finance among exporters upon entry to a new market. To do so, we regress the share of exported value that is financed in advance (i.e. use cash in advance arrangements) in the first year of an exporting spell to a given market on the riskiness and financial development of destinations, as well as on firms' size, experience, and labor productivity.[12] We report our results in Table 9.

Table 9 suggest that destination characteristics (such as riskiness and financial development) and firms' characteristics (such as export experience, size, and labor productivity) are important determinants of the share of export sales on cash in advance terms in the first

[12]All variables except for labor productivity are indicators equal to 1 if a given variable is above the median and 0 otherwise.

Table 9: **Share of cash in advance upon entry to a new export market.**

	Initial CIA			
	(1)	(2)	(3)	(4)
Riskiness (-)	-0.119***			-0.136***
Fin. Development	0.023***	-0.051***		0.016***
Experience	-0.100***	-0.115***	-0.130***	
Size	-0.070***	-0.070***	-0.069***	
Labor Productivity	-0.031***	-0.029***	-0.026***	-0.034***
Constant	0.915***	0.883***	0.807***	0.850***
N	32,806	33,628	35,772	32,806
R2	0.057	0.044	0.039	0.037

Note: Riskiness (-) is a dummy variable equal to 1 if the Law and Order index for a given destination is above the median (safer destinations); Fin. Development is a dummy variable equal to 1 if Credit/GDP for a given destination is above the median; Size and Experience are dummy variables equal to 1 if the firm has more than 50 workers and exports to more than 5 markets upon entry, respectively; Labor productivity is the log of real sales divided by the number of workers (continuous variable with mean equal to 18.83).

year following entry into a new destination-product market. Column (1) indicates that a small and inexperienced firm (i.e. a firm with less than 50 workers and exporting to less than 5 markets), exporting to risky and low-credit destinations, finances on average 33% of its annual exports by cash-in-advance payments.[13] Instead, if that same firm exports to a safe destination, the share of CIA is 21%; if it exports to a financially developed destination, where importers are better able to cope with payments in advance, the share of CIA is 2.3% larger. Size and experience also play important roles: A large and experienced firm, exporting to a risky and non-financially developed destination, finances only 16% of its exports by CIA. The model we present in this paper rationalized these empirical observation assuming that firms face demand uncertainty and counterparty risk when exporting to a new destination.

Columns (2) to (4) show that firms' size, productivity, and experience, as well as destination country's riskiness are consistently highly statistically significant and their coefficient vary relatively little across the different specifications. Instead, our measure of financial development, credit-to-GDP ratio, features a negative sign when we do not explicitly control for riskiness of the destination: since these two measures are positively correlated, financially developed destinations are also likely to be less risky and, hence, exports to those destinations are likely to feature more open account financing.

In the following sections we develop, calibrate and simulate an international trade model with learning that implies similar dynamics to the ones documented in this section.

[13] The mean of log labor productivity is 18.83. Then 0.33=0.915-0.031*18.83.

3 Model

We consider a small open economy in the spirit of Melitz (2003) with S sectors monopolistically competitive sectors. There are three types of agents: a representative consumer, a continuum of firms producing differentiated goods, and the rest of the world. Firms can sell their products domestically or export with exports being subject to variable and fixed trade costs. In addition, exporters face both counterparty and demand risks.[14] To manage their risk exposure, firms choose different financing terms for their exports, as in Antras (2015).

3.1 Representative consumer

There is a representative consumer who derives utility from consuming goods from S sectors. Her utility is

$$U = \sum_{s=1}^{S} \beta_s \log Q_s$$

where $\sum_{s=1}^{S} \beta_s = 1$ and

$$Q_s = \left[\int_{\omega \in \Omega_s} \left(u_s(\omega) q_s(\omega) \right)^{(\sigma_s - 1)/\sigma_s} d\omega \right]^{\sigma_s/(\sigma_s - 1)}, \ \sigma_s > 1,$$

where $u_s(\omega)$ is the realized value of good ω in sector s and Ω_t is the set of all varieties (both domestic and foreign available in the domestic economy in period t).

The preference features a unit elasticity of substitution across sectors, so industry spending shares are constant. Within each sector, there is a continuum of varieties with greater-than-one-elasticity of substitution between varieties. Given the preferences, consumers in country j optimally allocate a fraction β_s of their total spending $E_j$to goods in sector s.

In each country and sector s, consumers allocate spending across varieties to minimize the cost of consuming Q_s. The problem is given by

$$\begin{aligned}
\min E_s = P_s Q_s &= \int_{\omega \in \Omega_s} p_s(\omega) q_s(\omega) d\omega \\
s.t. & \\
Q_s &= \left[\int_{\omega \in \Omega_s} \left(\mathbb{E}[u_s(\omega)] q_s(\omega) \right)^{(\sigma_s - 1)/\sigma_s} d\omega \right]^{\sigma_s/(\sigma_s - 1)}
\end{aligned}$$

[14] Our model is unique in combining both demand and counterparty risk, the two sources of risk emphasized by earlier literature. The importance of counterparty risk was emphasized earlier by Antras (2015), Antras and Foley (2015), and Schmidt-Eisenlohr (2013). The demand risk has been studied by Albornoz et al. (2012), Berman et al. (2019), and Timoshenko (2015) among others

The solution to the above representative consumer problem gives rise to the following demand for variety ω:

$$q_s(\omega) = p_s(\omega)^{-\sigma_s} P_s^{\sigma_s - 1} \eta_s(\omega)^{(\sigma_s - 1)} E_s$$

where $p_s(\omega)$ is the price for variety ω, P_s is the ideal price index

$$P_s = \left[\int_{\omega \in \Omega_s} \left(\frac{p_s(\omega)}{\eta_s(\omega)} \right)^{1-\sigma_s} d\omega \right]^{1/(1-\sigma_s)} .$$

3.2 Firms

Firms are monopolistically competitive. There is a unit measure of domestic firms in each sector. Each firm produces a unique variety using a linear production technology

$$y = zn,$$

where z is firm's productivity and n is the labor input. Firms are heterogeneous with respect to their productivity with their productivity constant over time. Let G_s be the CDF od the distribution of productivity in sector s. We assume that the distribution of productivity within each sector among domestic firms is Pareto with shape parameter $\kappa > \sigma - 1$, so that

$$G_s(z) = 1 - \left(\frac{\underline{z}}{z} \right)^{\kappa}, \text{ for } z \geq \underline{z}_i > 0.$$

Firms choose whether to sell goods domestically or export. Domestic sales are associated with no additional cost above the production cost. Instead, exporting, as in Melitz (2003), is subject to a fixed cost, F, and variable cost τ. The presence of variable cost τ implies that the marginal cost of production for the foreign market is higher than for domestic market. Let $C_f(q)$ denote the cost for firm i of producing q units of good in foreign market. Then

$$C_f(y) = \left(F + \tau \frac{y}{z} \right) w,$$

where w is the wage rate. The cost of producing for the domestic market is simply $C_d(y) = \frac{y}{z} w$.

An exporter is also subject to an endogenous cost, ϕ, that arises from demand and counterparty risks and which, in expectation, decrease revenue from exporting. The expected profit for a firm with productivity z is given by

$$\pi(z) = \max_{p,y_s} \frac{1}{\phi}\xi p y_s - C_f(y_s)$$
$$s.t. y_s = p^{-\sigma_s}(P_s^*)^{\sigma_s-1}E_s^*$$

where ξ is the real exchange rate, P_s^* is the price of composite good produced by sector s in the foreign country, and E_s^* is the total expenditure on varieties in sector s by the foreign representative consumer. The optimal price that solves the producer's problem is

$$p_s = \frac{\sigma}{\sigma-1}\frac{\tau\phi}{z}w$$

and the implied profits are

$$\pi = \left(\frac{\sigma-1}{\sigma}\frac{z\eta}{w\tau}\right)^{\sigma-1}\phi^{-\sigma}\frac{\beta_s}{\sigma}E_s^*(P_s^*)^{\sigma_s-1} - wF$$

Finally, we assume that if a firm decides to export today it will start exporting (i.e., will make its first sells in foreign market) the next period.[15]

3.2.1 Trade finance decision, learning and dynamics

We have not explained above how the endogenous wedge ϕ arises from risks in export. There are two sources of uncertainty: the importer's credibility and the demand for the project in the exporting destination. Let χ denote exporter's belief that the counterparty in the foreign economy is credible. A credible importer always repays the debt while non-credible importer repays the debt with probability μ.[16] The demand for the good can be either high or low, corresponding to the demand shifter $u_s(\omega)$ being 1 or 0. Let λ denote the exporter's belief that the product is popular thus more likely to deliver high demand.[17] If the product is popular it is always in high demand; if the product is unpopular, it is in high demand with probability δ, otherwise, it is in low demand.

When a domestic firm decides to export abroad, it enters into a contract with an importer in the foreign market. The contract specifies:

[15] We make this timing assumption to make the problem computationally simpler. See below for more details.

[16] Following Antras and Foley (2015), $1-\mu$ can be interpreted as the probability that an opportunity to divert funds arises.

[17] Alternatively, we could assume that importer could be a good or bad at marketing. An importer that is good at marketing would be able to always sell the good while an importer that is bad at marketing will be able to sell the good with probability δ. An implicit assumption is that the importer does not know its own type. This is true in all the versions of the model.

- Quantity of goods to be delivered, q_j
- Payment for the goods that exporter will receive, s_j
- The timing of payment for the goods by an importer

Assumption 1. *We assume that:*

1. *Exporter has all the market power*
2. *Importers outside option is zero.*

As in Antras (2015), we consider two types of short-term contracts, open account (OA) and cash-in-advance (CIA). They differ in the payment timing. Under OA, the exporter first delivers the goods to an importer and only gets paid after the importer receives the goods or sells the good. Under CIA, the importer pays first for the goods and receives the good later. We now discuss the optimal contracts under OA and CIA financing terms.

Optimal contract under OA terms Suppose first that an exporter decides to sell its goods on credit (i.e., use OA). In this case he needs to finance its working capital by using intra-period external finance. The domestic intra-period interest rate is r. Moreover, exporter exposes itself to the risk that the importer does not pay for the goods. In particular, exporter gets paid only with probability

$$\gamma^{OA} = [\chi + \mu (1 - \chi)] [\lambda + \delta (1 - \lambda)]$$

Therefore, exporter's problem is to choose s_j and y to solve

$$\max_{s,q} \frac{\gamma^{OA} s}{1 + r} - wF - \frac{\tau w}{z} y \tag{4}$$

$$s.t.\ \ [\lambda + \delta (1 - \lambda)] [p (y) y - s] \geq 0 \tag{5}$$

$$\text{and foreign demand}$$

Here, Equation (4) is the expected payoff earned by an exporter. In particular, if the contract specifies that the exporter delivers y goods then $wF + \frac{\tau w}{z} y$ is the cost of delivering these goods that has to borne at the beginning of the period. Exporter is paid s_j at the end of the period with probability γ^{OA} and it discounts this payments at the borrowing rate $(1 + r)$. Equation (5) in turn is importer's participation constraint which states that importers' revenues from selling the goods must be at least as large as the contractual payment he is supposed to make to an exporter. Note that this constraint implies that if an importer is unsuccessful in selling the contract then it will not pay anything to the exporter. Since exporters have all the bargaining power, it follows that the participation constraint will always bind, that is

$$s = p(q)\,q$$

Substituting this expression for s into Equation (4) we obtain

$$\begin{aligned} &\max_{y} \frac{\gamma^{OA}}{1+r} p(y)\,y - wF - \frac{\tau w}{z} y \\ &s.t.\ \text{foreign demand} \end{aligned} \tag{6}$$

Thus, we see that under OA terms the wedge ϕ that arises due to the presence of counterparty and demand risk satisfies

$$\frac{1}{\phi} = \frac{\gamma^{OA}}{1+r} \tag{7}$$

Optimal contract under CIA terms Next, consider the optimal contract when the exporter decides to sell its goods using cash-in-advance (CIA) arrangements. In this case, since the exporter receives payment before shipping the goods, it is not exposed to either demand or counterparty risk. However, CIA terms are costly to an importer. First, an importer needs to use external finance to pay for the goods at the rate r^*. In addition, the importer faces a risk that it will not be able to sell the goods and will want to be compensated for it.[18,19]

$$\gamma^{CIA} = [\lambda + \delta(1-\lambda)]$$

denote the probability that the importer manages to successfully sell the goods. Then, the participation constraint of an importer is given by

$$\gamma_i p(y)\,y - (1+r^*)\,s \geq 0 \tag{8}$$

Since exporters have all the bargaining power, the above participation constraint has to be satisfied as equality. Therefore,

$$s = \frac{\gamma^{CIA} p(y)\,y}{1+r^*}$$

[18] Under OA terms, the importer also faces demand risk, but if the good does not sell the importer pays nothing to the exporter since there is no revenue to share.

[19] By paying early, an importer also exposes itself to the risk that an exporter will not ship the goods as agreed upon (as in Antras and Foley (2015)). We abstract away from this case and assume that exporters always honor the contracts. This is motivated by the fact that we are using data from Chile which is a country with strong contractual enforcement laws.

It follows, that the optimal choice of quantity of goods shipped under OA solves

$$\max_{y} \frac{\gamma^{CIA}}{1+r^{*}} p(y)\, y - wF - \frac{\tau w}{z} y \qquad (9)$$
$$s.t.\ \text{foreign demand}$$

Learning about demand and counterparty uncertainty Exporters learn over time about credibility of their counterparty and demand for their goods. If exporter uses CIA, then at the end of the period it updates its beliefs about the demand for its good. If the transaction was successful then the next period belief is given by

$$\lambda' = \frac{\lambda}{\lambda + (1-\lambda)\,\delta}$$

On the other hand, the exporter cannot infer anything about the imports credibility and so

$$\chi' = \chi$$

Under OA, an exporter is exposed to both the demand and counterparty risk. In particular, after receiving payment for its goods, the exporters updates its beliefs about demand and importer's credibility. In particular, since the two dimensions of uncertainty are independent, we have

$$\lambda_{t+1} = \begin{cases} \frac{\lambda_t}{\lambda_t + (1-\lambda_t)\delta} & \text{if the product sells} \\ 0 & \text{otherwise} \end{cases}$$

and

$$\chi_{t+1} = \begin{cases} \frac{\chi_t}{\chi_t + (1-\chi_t)\mu} & \text{if OA is repaid} \\ 0 & \text{otherwise} \end{cases}$$

Moreover, we assume that learning about importers' type depends on the choice of financing: If the exporter uses CIA, even though there is no direct exposure to counterparty risk, we assume there is still learning though a lower rate $\mu^{CIA} \leq \mu$:

$$\chi_{t+1} = \begin{cases} \frac{\chi_t}{\chi_t + (1-\chi_t)\mu^{CIA}} & \text{if the untrustworthy type is not detected} \\ 0 & \text{otherwise} \end{cases}$$

We refer to this as "passive learning." Passive learning is meant to capture that by interacting with importer, an exporter might be able to learn whether the importer is trustworthy or not. For example, an exporter is able to verify that importer is not a fictitious firm, be able to observe how importer is fulfilling its other contractual obligations (such as those to workers), etc.[20] But such learning is likely not as effective compared to learning compared to learning under direct exposure to counterparty risk when using OA financing terms since repayment in that case is a strong signal of importer's trustworthiness. If $\mu^{CIA} = 1$, there is no passive learning.

3.3 Entry and exit of a trading relationship

We assume that exporters' productivity is constant and the entry decision into export is driven by new draws of beliefs. The new draw of beliefs represents meeting a new potential importer. We also allow for exogenous separation, driven by an exogenous probability κ that the firm will stop exporting any given period regardless of the beliefs and productivity.

The timing within the period is such that the decision whether to export or not is the same for non-exporters and continuing exporters when they have the same beliefs. The timing serving the purpose is that non-exporters observe at the beginning of each period their new realization of beliefs that represent information about the demand for their goods in the foreign markets, λ, and information about their potential counterparty, χ. However, once they decide to export they start exporting the next period with a one-period lag. At the beginning of a period, an exporter, new and continuing alike, chooses whether to export this period using OA or CIA. Finally, at the end of the period, after updating beliefs about λ and χ, exporters decide whether to continue exporting the next period, or whether to stop exporting. As we will see, this implies that continuing and new exporters' entry decisions are the same. Figure 3 illustrates the timeline of the model.

[20]Giannetti et al. (2011) points out that the concern whether the customer is a fictitious firm is a common concerns among firms extending trade credit, particularly among those firms that sells highly liquid products.

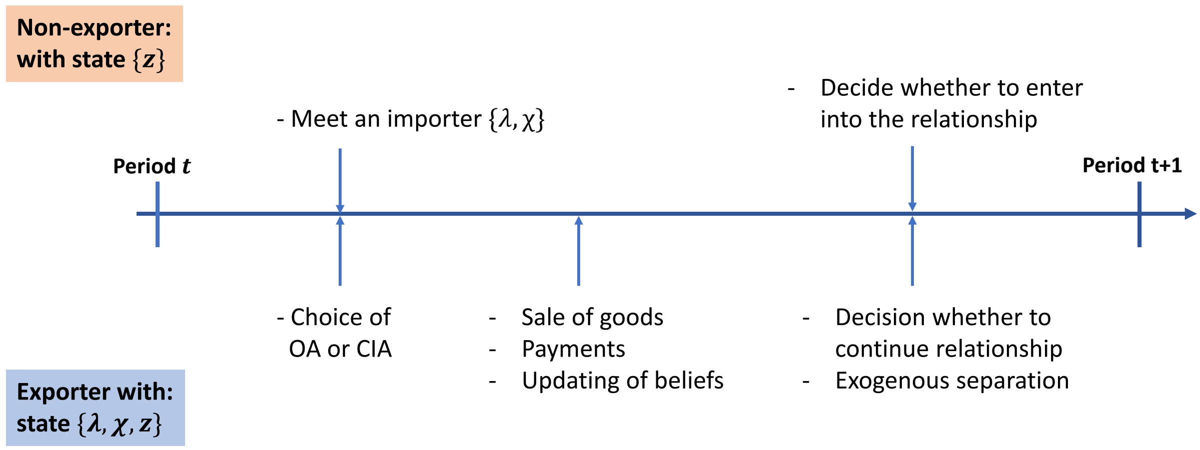


Figure 3: Timeline

Let $V^N(z, \lambda, \chi)$ be the value function of a non-exporter that chooses whether to export or not, given productivity z, and beliefs $\{\lambda, \chi\}$. Then

$$V^N(z, \lambda, \chi) = \max_{\{\text{Not export, Export}\}} \beta \left\{ \mathbb{E}_{z', \lambda', \chi'} \left[V^N(z', \lambda', \chi') \right], V^E(z, \lambda, \chi) \right\}$$

If the firm decides to export then it becomes an exporter the next period with the state $\{z, \lambda, \chi\}$ (assuming that productivity is non-stochastic for now). If it decides not to export, it faces the same problem the next period but with new draws of beliefs.

Next, let $V^E(z, \lambda, \chi)$ denote the value function of an exporter with state $\{z, \lambda, \chi\}$ that is choosing whether to use CIA or OA. Let $\pi_{ij}^X(z, \lambda, \chi)$ denote expected profits from choosing financing option X, where $X \in \{CIA, OA\}$. After profits are realized, an exporter updates his beliefs and if hit by an exogenous shock it leaves the export market, which occurs with probability $(1 - \kappa)$. In that case, the firm will be a non-exporter next period. Otherwise, based on the updated beliefs, the firm decided whether to stay in the current relationship and export or leave. Finally, let $V^C(z, \lambda, \chi)$ denotes the value function of an exporter at the end of the period after sales have been realized that is choosing whether to continue the relationship or not given $\{z, \lambda, \chi\}$.

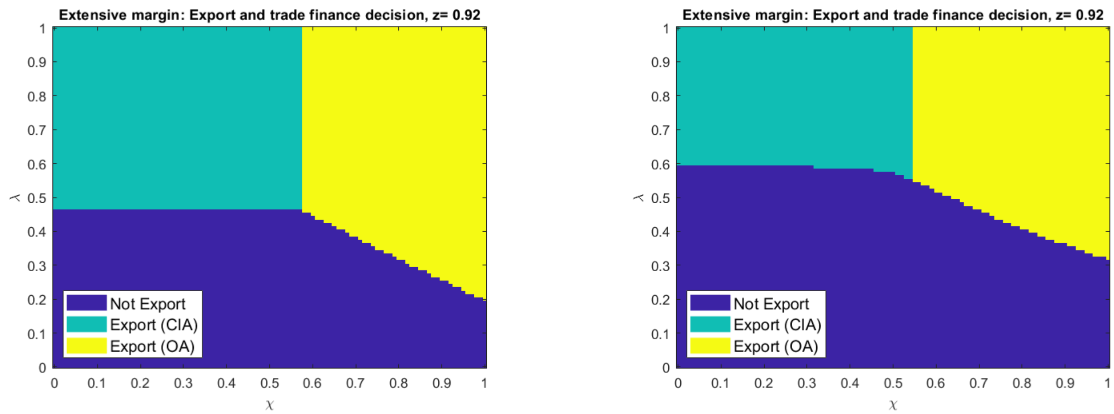
Thus, $V^E(z, \lambda, \chi)$ is given by

$$V^E(z, \lambda, \chi) = \max \left\{ \pi_{ij}^{CIA}(z, \lambda, \chi) + \kappa \mathbb{E}^{CIA} \left[V^C(z', \lambda', \chi') \right], \pi_{ij}^{OA}(z, \lambda, \chi) + \kappa \mathbb{E}^{OA} \left[V^C(z', \lambda', \chi') \right] \right\}$$
$$+ (1 - \kappa) \mathbb{E} \left[V^N(z', \lambda', \chi') \right],$$

where we use superscript X in $\mathbb{E}^X[\cdot]$ to indicate that learning (and hence the future values of λ and χ) depends on the financing choice X, and $V^C(z, \lambda, \chi)$ is simply equal to

$$V^C(z, \lambda, \chi) = \max_{\{\text{Exit, Continue}\}} \left\{ \mathbb{E}_{\{\lambda', \chi'\}} \left[V^N(z, \lambda', \chi') \right], V^E(z, \lambda, \chi) \right\}$$

Thus, we see that, the exporter decision whether to exit the relationship or continue it is identical to the decision of a non-exporter which is deciding whether to enter the export market or not conditional on having beliefs $\{\lambda, \chi\}$.



(a) Static entry decision **(b) Dynamic entry decision**

Figure 4: The Extensive Margins of Export and Payment Choices

To better understand firms' incentive to start exporting and the dynamic considerations involved, in Figure 4 we depict the extensive margin decision of firms as function of their productivity and current beliefs when firms behave optimally taking into account dynamic aspects of their entry decisions (Panel B) and when firms make these decisions myopically by caring only about their current static export profits (Panel A). Comparing the optimal dynamics extensive margin export decision with the non-optimal static one, there are two major differences. First, we note that under the dynamic extensive margin decision fewer firms decide to export. This is because there is an option value to waiting as firms that wait might be matched with better counterparties the next period and are willing to forgo positive profits from exporting to the option to wait. Second, we note the dynamics entry/exit decision also imply more use of OA terms. This is because optimal extensive margin export decision take into account that under OA terms firms learn faster about their counterparty credibility. Thus, we see that dynamic considerations play important role in our model.

4 Quantitative Analysis

In this section, we investigate quantitatively how well our model can match trade finance dynamics, the importance of speed of learning on these dynamics, and consider their aggregate implications.

To do so, we calibrate the model to match key features of Chilean plant-level data. We then use the calibrated model to contrast the dynamics of export volume and trade finance with the data. We then analyze how changes in parameters governing speed of learning δ, μ, and μ^{CIA} affect these dynamics. Finally, we investigate the importance of having access to CIA terms for exporters by considering an exogenous shock that makes CIA terms prohibitively expensive

Table 10: Estimated Parameters

Parameter	Value	Target moment	Data	Model
β	0.9	Pre-assigned		
σ	4	Pre-assigned		
λ_0	U[0,1]	Pre-assigned		
χ_0	U[0,1]	Pre-assigned		
τ	4.38	Average export intensity	0.16	0.16
F	0.09	Share of exporters	0.11	0.11
κ	0.91	Exporters' exit rate	0.11	0.11
$\sigma_{log(z)}$	0.16	Exporters' domestic sales premium	5.69	5.71
$r_f - r$	0.103	Share of CIA among exporters	0.32	0.32
		Learning and risks		
δ	0.54	New exporters 6-period increase in exports	0.28	0.28
μ	0.7	New exporters 6-period increase in sales with OA	0.35	0.35
μ_{CIA}	0.78	New exporters 6-period increase in OA share	0.05	0.05

Table 10 reports the parameters that we use in our quantitative analysis. We use a standard values for the discount rate, β, and elasticity of substitution, σ. The prior beliefs are fixed to be uniform over the unit interval. The remaining parameters are chosen to match the key cross-sectional moments (τ, F, κ, $\sigma_{log(z)}$, $r_f - r$) and the growth rates of export volume and trade finance (δ, μ, μ_{CIA}).

As is standard (see, for example, Alessandria and Choi (2014) or Ruhl and Willis (2017)), we choose $\{\tau, F, \kappa, \sigma_{\log(z)}\}$ to match (i) average export intensity, (ii) the share of firms in the economy that export, (iii) the exit rate of exporters' from the foreign market, and (iv) exporters' domestic sales premium (as measured by the ratio of the average domestic sales of exporters and the average domestic sales of non-exporters), respectively.

The remaining parameters, $\{r_f - r, \delta, \mu, \mu_{CIA}\}$ are particular to our model and we use moments related to the use of trade finance and trade finance dynamics to discipline them. Specifically, we choose $\{r_f - r, \delta, \mu, \mu_{CIA}\}$ to match (i) the share of CIA terms among exporters, (ii) the average increase in export sales over first six periods of export spell, (iii) the average increase in export sales over first six periods of export spell among exporters that use OA terms, (iv) the average increase in export sales over first six periods of export spell among exporters that use CIA terms. While δ, μ and μ_{CIA} all affect export volume dynamics they affect different aspects of it. In particular, changes in δ affect the average growth of export sales but do not lead to differences in the growth of export sales under CIA and OA terms since exporters face demand risk irrespective of the financing terms they use. On the other hand, μ since is giverns the speed of learning about counterparty risk under OA terms affects predominantly the growth of export sales of firms that sell their goods abroad using OA terms, while the opposite is true for μ_{CIA}.[21]

4.1 Dynamics of sales and trade finance

Figure 5 contrasts the predictions of our model to the data by comparing the use of trade finance and export dynamics within exporters' cohorts. We see that learning about the local demand and counterparty's credibility plays a key role in generating the empirical pattern of CIA utilization. Our model delivers dynamics comparable to those observed in the data. In particular, our model captures well the gradual decline in the share of CIA as well as the gradual increase in exports.

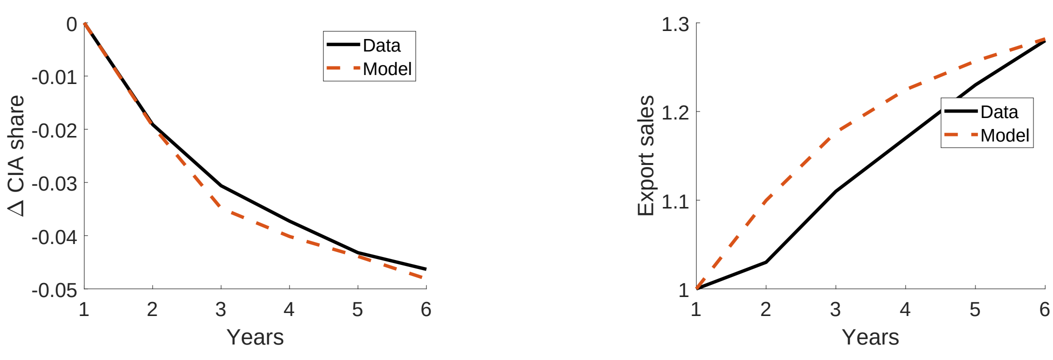


Figure 5: Trade finance and export dynamics

[21] In 4.2 we discuss in details how changes in speed of learning affect not only export sales dynamics but also the dynamics of trade finance.

4.2 Changes in the speed of learning and export dynamics

In this section, we consider how changes in the parameters governing the speed of learning (δ, μ, and μ_{CIA}) affect dynamics of the share and average export volume among new exporter. Figure 6 depicts our results.

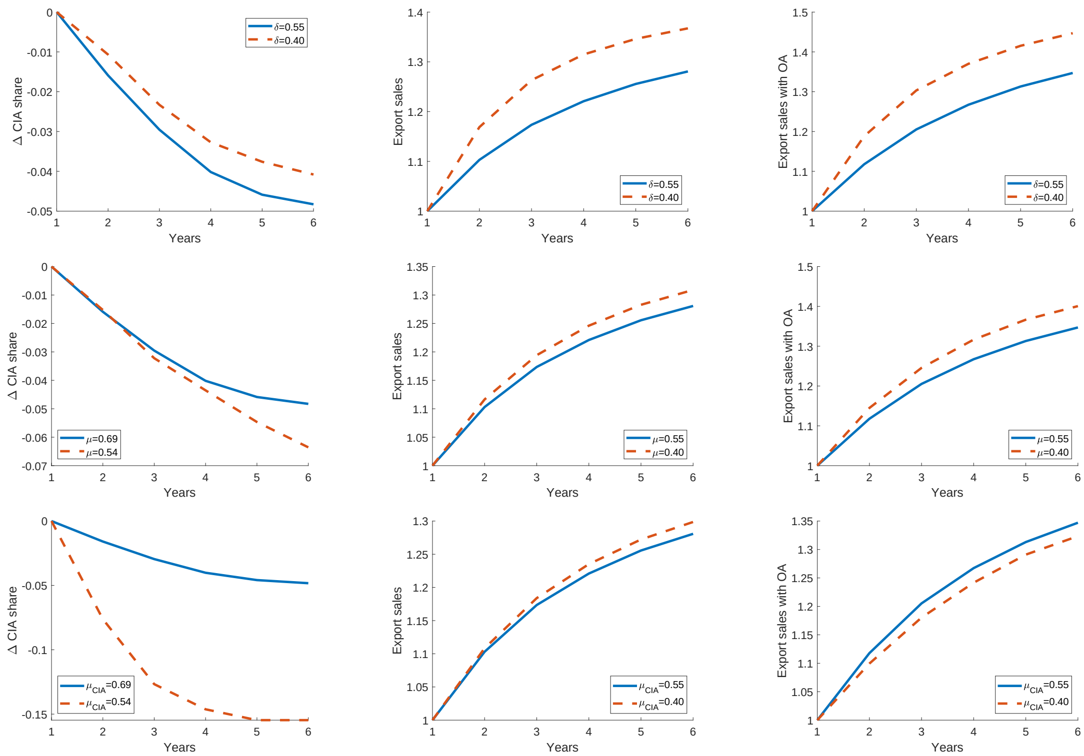


Figure 6: Trade finance and export dynamics under alternative parameters

Consider first changes in the probability that an unpopular product sells δ (the top row of Figure 6), which governs how fast exporters learn about the current foreign demand for their product with lower δ corresponding to faster learning. We see that a decrease in δ from 0.7 to 0.4 has large impact on dynamics of exports. The reason for this is that lower δ implies that the uncertainty about foreign demand faced by exporters decreases faster over their exporting spells effectively decreasing the cost of exporting (i.e., the wedge γ^X, $X \in \{CIA, OA\}$). This faster learning is associated with higher exit rate among new exporters as new exporters which learn that their product is not popular in the foreign economy decide to stop exporting. On the other hand, changes in δ have only modest effects on the dynamics of trade finance use since exporters face demand risk regardless of the financing terms they use.

Consider next changes in the probability that a noncredible importer is monitored μ (the middle row of Figure 6), which governs how fast exporters learn about the counterparty risk under OA financing terms with lower μ corresponding to faster learning. We see that decreasing μ from 0.8 to 0.6 has substantial impact on dynamics of trade finance use. This is because with lower μ, firms have more incentives to switch to OA as it allows them to learn faster about counterpart risk. This is valuable for two reasons. First, faster learning means that the effective cost of exporting (as captured by the wedge γ) decreases faster for those firms that are matched with credible exporters. Second, faster learning is valuable since staying in the relationship with a non-credible counterparty has an opportunity cost (an exporter could break the match and look for a new importer). On the other hand, we see that the effect on export dynamics is much more modest than in the case of changes in δ. The reason for this is that changes in μ only affect the growth of firms that use OA financing terms. Moreover, firms that learn that their counterparty is not trustworthy might decide to continue to export but switch from OA terms to CIA . This switch however is associated with a decrease in export sales as exporting on CIA terms is costly (due to high cost of external financing for importers who need to be compensated for those costs).

Finally, consider changes in the parameter that governs the speed learning whether the importer is credible or not when using CIA payments μ_{CIA} (the bottom row of Figure 6). We see that trade finance dynamics are very sensitive to changes in μ_{CIA}. This is because the μ_{CIA} directly controls the speed with which firms will switch from CIA terms to OA terms.[22] On the other hand, changes in μ_{CIA} have negligible effects on export dynamics.

Overall, Figure 6 suggests that changes in δ, μ, and μ_{CIA} affect differently trade finance and export volume dynamics. In particular, we see that changes in δ have the opposite effects on trade finance dynamics compared to changes in μ and μ_{CIA}. On the other hand, changes in μ_{CIA} have stronger effect on trade finance dynamics than changes in μ, but much less effect on the dynamics of export volume. These differences explain also why we are able to estimate those parameters separately in the data.

4.3 Trade finance dynamics by destination and product characteristics

In the empirical analysis, we showed that firms tend to use more CIA when selling to riskier destinations or selling differentiated products. The interpretation is that CIA allows firms to limit the exposure to counterparty risk, in the first case, and to a more uncertain demand, in the second case. Moreover, trade finance dynamics is steeper (there is a faster change from

[22] Note that for high values of μ_{CIA}, the share of CIA among new exporters might be increasing over time. This is because there are more new exporters who start exporting using OA terms but switch to using CIA terms (as these firms still find it profitable to export under CIA terms that protects them from counterparty risk) than firms that switch from CIA to OA (after learning that their counterparty is trustworthy).

CIA to OA) in these cases.

Figure 7 shows trade finance and export dynamics for risky and safe destinations, proxied by the expected value of the prior distribution for ξ. We find that there is a steeper switch to OA in riskier (low χ) destinations as in the data. Moreover, the average CIA share is higher in risky destinations: 0.34 (0.41 for new exporters) in risky vs. 0.27 (0.28 for new exporters) in safe destinations.

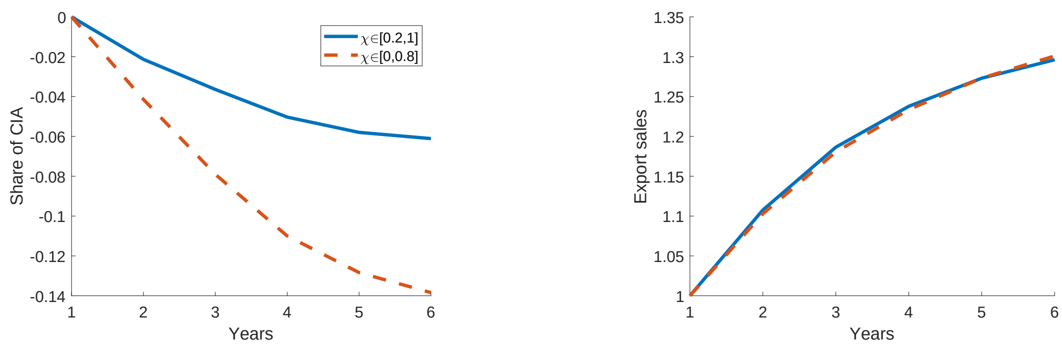


Figure 7: Trade finance and export dynamics by destination

Figure 8 shows trade finance and export dynamics for products with more uncertain demand, proxied by the standard deviation of the prior distribution for δ. We find that there is a steeper switch to OA in products with more uncertain demand (high σ_λ) as in the data. Moreover, the average CIA share is higher for products with more uncertain demand: 0.32 (0.37 for new exporters) in product with more uncertain demand vs. 0.27 (0.29 for new exporters) for the others.

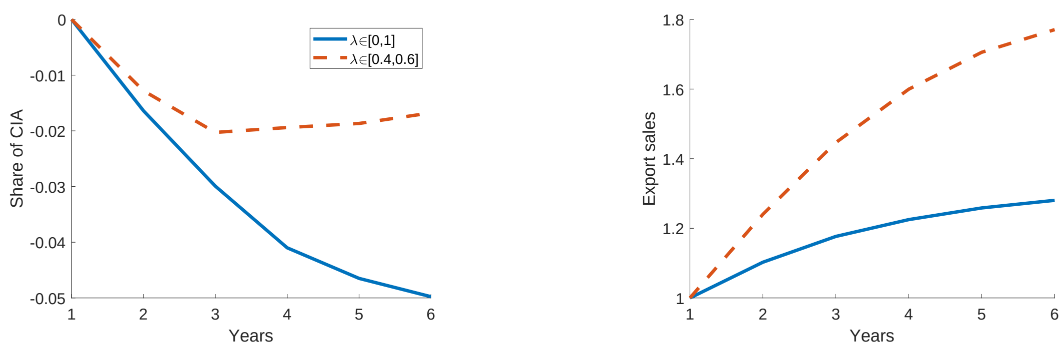


Figure 8: Trade finance and export dynamics by product

4.4 Importance of CIA to firm-level export dynamics

Finally, in this section we investigate the importance of CIA payments for firms in our economy. To do so, we contrast our baseline economy with one for which the foreign interest rate r_f is prohibitively high.

Figure 9 shows the export dynamics and extensive margin (survival ratio of exporters) for these two economies, besides the behaviour of average beliefs for exporters. We observe that in the case of no CIA, firms start smaller (although the ones that do export grow faster), but there are fewer exporters and also a lower probability of surviving. Exporters tend to sell lower-quality products to foreign destinations. And they export only if they are optimistic about the importers' credibility (high χ).

As Figure 4 illustrates, CIA payments allow exporters with good-quality products (high λ) but matched with importers with low credibility (low χ) to export. In a dynamic environment, it also allows exporters who use CIA payments to learn about product demand and importers' credibility.

Without CIA payments, firms are faced with higher risk on average in using OA. When the credit risk is too high, firms cannot switch to CIA payments to reduce credit risks. Firms with high λ and low χ have to exit. This is why the survival rate is lower without CIA payments. Firms wait until they draw a sufficiently high χ before starting to export. Thus, the lack of CIA payments discourages entry, which translates into a smaller share of exporters. Without CIA payment, it is more costly to learn about product demand as high credit risk may cut short a trading relationship. This is why exporters sell products with lower quality on average when CIA payments are too costly.

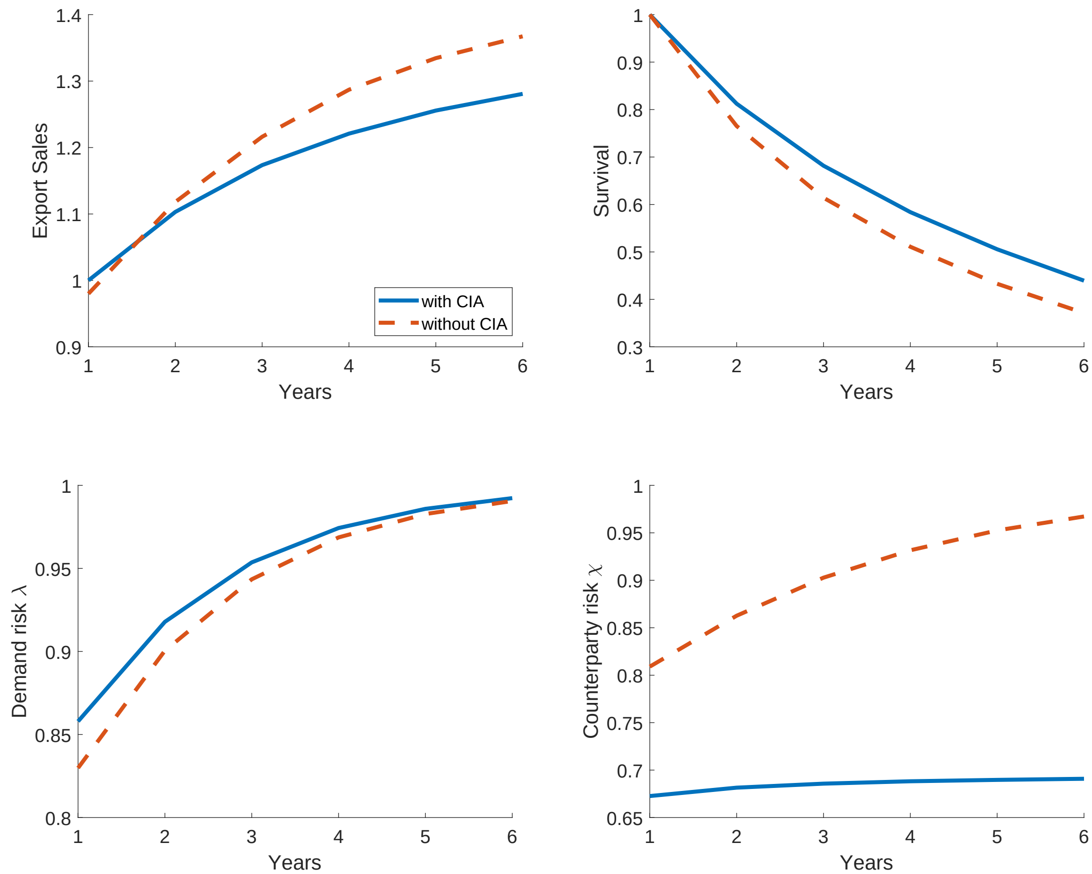


Figure 9: Importance of CIA

4.5 Aggregate trade dynamics in response to permanent changes in foreign funding cost r_f

To further understand the consequence of payment frictions, we study the aggregate response of trade dynamics to an unexpected permanent change in the cost of using CIA payments r_f. To analyze the aggregate response, we compute the dynamic general equilibrium where the domestic wage and consumption are endogenous.

Figure 10 illustrates the non-linear dynamics triggered by an unexpected permanent increase in foreign funding cost r_f. Besides the long-run declines in export volume and the number of exporters, the short-run declines are stronger. As we discussed in Section 4.4 about the entry and exit decisions at the firm level, the survival rate of trading relationships is lower when CIA is too costly to use. Exporter-importer matches with high credit risk but high product demand are forced to terminate their matches when the high funding cost r_f becomes very high. The knowledge accumulated within the match is destroyed when the relationship is terminated and it takes time to build up the relationship-specific knowledge once it is destroyed.

The overshooting in the short-run response is stronger when the increase in r_f is large. The long-run responses to a 10% increase in r_f and a 15% increase in r_f are similar in magnitude while the short-run response decline in export volume and exporter share is stronger with a 15% increase in r_f, since relationships are only destroyed when r_f is sufficiently high.

The aggregate response is not only non-linear but also asymmetric. Figure 11 illustrates the responses to a 5% increase in r_f and a 5% decrease in r_f. The consequent trade dynamics are asymmetric. Only the response to the rate increase overshoots in the short run. The response to the rate decrease is sluggish and converges gradually to the long-run steady state. Whether the short-run response overshoots or not depends on whether trading relationships and relationship-specific knowledge are destroyed in the short run. While a rate increase makes it more costly to CIA payments and thus destroys some exporter-importer matches, a rate decrease only reduces trading frictions and encourages more entry.

One common feature between the impulse responses to rate increases and rate decreases is that the response is sluggish. It takes more than five periods for the model to converge to the new steady state. That's because it takes time for newly established trading relationships to accumulate relationship-specific knowledge through learning.

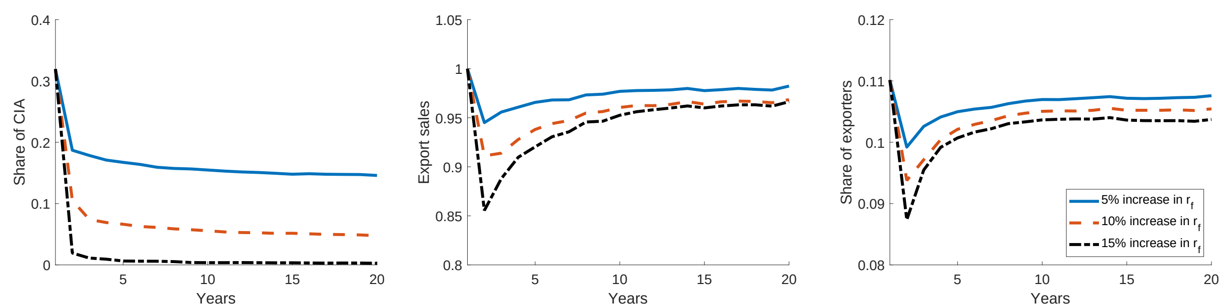


Figure 10: Effects of a permanent increase in r_f

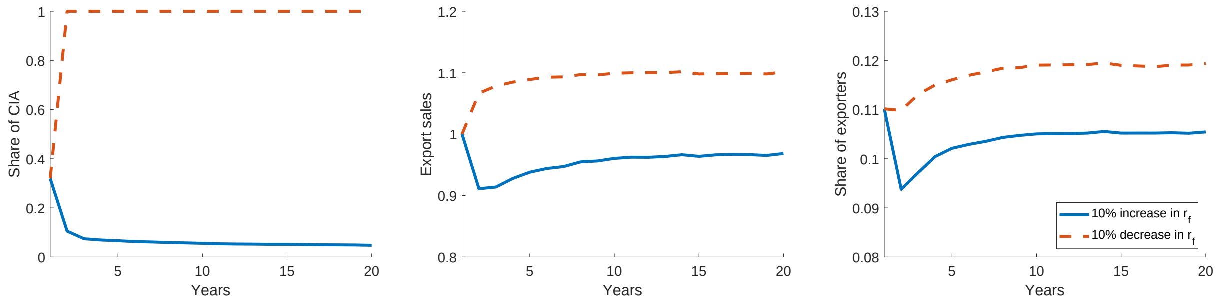


Figure 11: Asymmetric effects of r_f increases vs r_f decreases

5 Conclusion

This paper delves into the role of trade finance choices and the evolution of long-term relationships between exporters and importers. We explore how these aspects facilitate international trade by enabling exporters to understand demand uncertainties and counter-party risks. Using detailed micro-level Chilean data, we document that new exporters are more likely to use cash-in-advance arrangements and gradually switch to providing trade credit as they continue to export. We set up an international trade model in which firms make exporting and trade financing decisions while learning about demand and counter-party risks and show that the model produces dynamics consistent with our empirical findings. We then investigate the consequences of changes in learning parameters and accessibility of CIA. We find that access to CIA terms encourages entry and decreases the exit rate from exporting increasing the share of exporters in the economy, which has significant welfare effects. The cost of accessing CIA and OA also influences trade dynamics in the aggregate.

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Table 11: Descriptive Statistics at the Firm Level

	Mean	SD	Min	p1	p5	p10	p25	p50	p75	p90	p95	p99	Max	Obs
Sales (MM USD)	20.80	144.16	0.01	0.06	0.17	0.30	0.82	2.56	9.66	33.84	71.94	326.49	7490.60	3,812
Exports (MM USD)	0.27	1.42	0.00	0.00	0.00	0.00	0.01	0.04	0.14	0.48	0.93	3.56	43.38	3,812
Exports / Sales	0.05	0.10	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.12	0.20	0.50	0.99	3,812
Employees	165.64	426.86	5.00	5.00	7.00	8.89	18.33	50.00	139.92	376.50	623.80	2051.82	9853.45	3,812
Destinations	8.21	13.40	1.00	1.00	1.00	1.00	1.00	3.00	9.00	22.00	35.00	67.00	150.00	3,812
Products	11.44	22.40	1.00	1.00	1.00	1.00	2.00	4.00	11.00	28.00	44.00	105.00	319.00	3,812
Destinations-Products	29.57	69.50	1.00	1.00	1.00	1.00	2.00	7.00	27.00	78.00	130.00	305.00	1279.00	3,812
Destinations-Products-Year	75.88	204.61	1.00	1.00	1.00	1.00	3.00	11.00	56.00	207.00	368.00	916.00	4565.00	3,812
Log Labor Productivity	10.97	1.04	6.19	8.52	9.42	9.78	10.29	10.92	11.58	12.25	12.77	13.73	15.62	3,812