Red Nacional de
Investigadores
en Economía

International Trade Finance and Learning Dynamics

David Kohn (Central Bank of Chile and Pontificia Universidad Católica de Chile)

Emiliano Luttini (World Bank)

Michal Szkup (University of British Columbia)

Shengxing Zhang (Carnegie Mellon University, Tepper School of Business)

DOCUMENTO DE TRABAJO N° 346

Diciembre de 2024

Citar como:
Kohn, David, Emiliano Luttini, Michal Szkup, Shengxing Zhang (2024). International Trade Finance and Learning Dynamics. Documento de trabajo RedNIE N°346.

International Trade Finance and Learning Dynamics*

David Kohn
Central Bank of Chile and Pontificia Universidad Católica de Chile

Emiliano Luttini
World Bank

Michal Szkup
University of British Columbia

Shengxing Zhang
Carnegie Mellon University, Tepper School of Business

October 2024

Abstract

We study how trade finance and long-term relationships between exporters and importers facilitate international trade by allowing exporters to learn about demand uncertainty and counterparty 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. These dynamics affect export growth and are more salient for firms with less exporting experience and selling to riskier destinations. We set up an international trade model in which firms make exporting and trade financing decisions subject to demand and counterparty risks and estimate it using microdata. We then use the model to quantify the relative importance of demand and counterparty risks and investigate how trade finance choices and learning affect the dynamics of exports. Our model implies that the response of aggregate exports and the number of exporters to shocks to aggregate interest rates can overshoot in the short run if long-term relationships and relationship-specific knowledge are destroyed. Building relationships takes time, making the response to these shocks sluggish and persistent. Crucially, these responses depend on the riskiness of trade destinations.

Keywords: export dynamics, trade finance, learning, demand risk, counterparty risk.

*We thank George Alessandria, Treb Allen, Pol Antràs, Doireann Fitzgerald, Alvaro Garcia-Marin, Leticia Juarez, Amartya Lahiri, John van Reenen, Tim Schmidt-Eisenlohr, and Shangjin Wei for helpful comments. We also thank participants at numerous seminars and conferences. We thank Rachel Coroseo, Valeria Logan and Jose Elías Rishmawi for their excellent research assistance. The views expressed are those of the authors and do not necessarily represent the views of the Central Bank of Chile or its board members.

1 Introduction

Credit arrangements between firms, or trade finance, are pivotal in facilitating international transactions, given the inherent risks and costs associated with international trade. There are two main sources of risk that firms face when engaging in international trade. First, the risk that their counterparty will default on its obligations (see, for example, Antras and Foley (2015) or Schmidt-Eisenlohr (2013)). Second, foreign demand for new products is uncertain due to uncertainty about local tastes and market conditions (see, for example,Albornoz et al. (2012), Allen (2014), Eaton et al. (2021)). In addition, international trade is associated with long delays between the shipment of goods and the payment for them, implying that international trade is associated with higher working capital needs (Anderson and Van Wincoop (2004) or Kohn et al. (2016)). To balance the risks and needs associated with international trade, most firms use some form of trade finance (Auboin (2009)).

Importantly, these needs and risks evolve during trading relationships as firms learn more about the demand for their products and their counterparties' trustworthiness. Therefore, 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. To do so, we (i) document jointly the dynamics of export volume and trade finance and show how these dynamics depend on export destination and firm characteristics; (ii) propose a model to explain these dynamics that combines learning about demand and counterparty risks (previously studied in isolation) with trade finance choices; (iii) estimate the model using an identification scheme that allows us to disentangle learning about demand and counterparty risk in the data (utilizing data on export and trade finance dynamics); and (iv) use the model to investigate the aggregate effects of shocks to interest rates on exports and analyze how these effects depend on countries characteristics such as their perceived riskiness of export destinations.

While earlier work has emphasized the static trade-offs associated with trade finance choices, we instead focus on their dynamic implications.[1] We find empirically that new exporters are more likely to ask importers to pay for goods in advance (Cash-in-Advance arrangements – CIA) and gradually switch to offering trade credit (Open Account arrangements – OA). We then propose a model that can explain this pattern. In our model, new exporters are more likely to use CIA terms, which protects them from counterpart risk (i.e., the risk that the importer does not pay for the goods) and allows them to learn about the local demand for their products. As exporters learn more about their counterparties and

[1] Notable exceptions are Antras and Foley (2015) and Benguria et al. (2023) who focus on learning about counterparty risk in stylized frameworks.

their local demand, they switch from demanding cash-in-advance to offering trade credit, which encourages importers to buy more from exporters. By switching to OA, exporters directly expose themselves to counterparty risk, which allows them to learn even more about their counterparties' credibility. Thus, by facilitating learning, long-term relationships can potentially mitigate the risks firms face, reducing the costs of international trade and shaping their export decisions.

We begin by documenting stylized facts regarding 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 transaction-level export data linked with firms' balance sheets. The data covers the years 2005 to 2019 and includes all exports by Chilean firms at the transaction level. We find that Chilean exporters tend to offer trade credit to foreign importers. In particular, an average exporter uses OA terms (i.e., extends trade credit) in 64% of its transactions, while 83% of all shipments are sold on open account terms (reflecting the fact that firms that export many products to many destinations are more likely to use OA terms). The respective numbers for CIA terms are 32% and 13%.[2] However, exporters that begin exporting to a new market and new exporters (i.e., firms that did not export before to any destination) rely much more heavily on cash in advance, with CIA accounting for 19% and 38% of their total sales, respectively. We also find that small firms (less than 50 employees), inexperienced exporters (exporters selling to less than five markets), and those selling to more risky destinations rely more heavily on CIA arrangements.[3] [4]

To investigate the importance of learning, we then empirically analyze how trade finance arrangements evolve over firms' export spells at the destination-product level. Following Benguria et al. (2023), we perform regressions at the transaction-day level, controlling for a rich set of fixed effects. We find 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 percentage points over the first five years of an exporting spell after. We also show that the gradual switching from CIA to OA over the export spell is substantially more pronounced in risky and financially underdeveloped destinations, as well as among inexperienced and small firms. In particular, the share of shipments sold on cash in advance decreases by 5 percentage points

[2]The remaining transactions involve bank intermediation. Since such transactions account only for 4% of total transactions, throughout the paper we focus mostly on OA and CIA terms. We abstract from alternative combinations of methods of payments as they are not quantitatively relevant in our data.

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

[4]Firms with close ties with a institutional creditors (i.e. Banks) might have better access to other sources of financing such as trade credit (Acosta-Henao et al. (2023), Petersen and Rajan (1994)). We abstract from this channel.

over the first five years of an exporting spell for inexperienced firms exporting to risky and financially underdeveloped destinations.

We then apply the same approach to quantify export dynamics through the duration of a trading relationship and investigate how export dynamics are affected by destinations' and firms' characteristics. We find that exports tend to grow on average by 26% over the first five years of an exporting spell and that export growth is faster in risky destinations and among experienced exporters. We also investigate how initial trade finance choices affect firms' subsequent choices of export quantities and find that exporters who start exporting using predominantly OA terms grow substantially faster than those that initally rely mostly on CIA terms. Finally, we investigate how exporters' initial choices of financing terms affect their likelihood of exiting from exporting. These novel findings are consistent with learning, though they are silent on its exact nature.

To investigate the role of learning about the demand and counterparty risks in accounting for our empirical findings, we set up a dynamic model of international trade with heterogeneous firms. We consider a small open economy in the spirit of Melitz (2003). The domestic economy is populated by a continuum of monopolistically competitive firms that produce differentiated varieties that can be sold domestically and abroad with exports subject to fixed and variable costs. While otherwise standard, our model features two novel components. First, we assume that exporting is subject to demand and counterparty risks that exporters learn about throughout their exporting spells. Second, exporters can choose financing terms of their shipments to mitigate the risks they face.

To model counterparty risk, we follow Antras and Foley (2015) and Schmidt-Eisenlohr (2013), and assume that exporters need to form a match with an importer who may prove untrustworthy and refuse to pay for the received goods. To model demand risk, as in Albornoz et al. (2012) and Berman et al. (2019), we assume that foreign demand for exporters' goods is uncertain, with some products turning out to be unpopular. Thus our model combines two sources of risk that have been previously investigated separately (with the trade finance literature focusing on the counterparty risk while the export dynamics literature focuses on demand risk). As in Antras and Foley (2015) and Schmidt-Eisenlohr (2013), we allow firms to manage these risks by optimally choosing trade finance arrangements. In particular, in our model, 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 directly exposes exporters to risk.

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 tend to initially sell their goods in foreign destinations using CIA terms, which allows them to learn about local demand and reduce demand uncertainty. Moreover, by using CIA terms firms also learn about their counterparty trustworthiness (what we refer to as "passive learning").[5] This learning decreases the amount of risk firms are exposed to and leads them to gradually switch from CIA to OA terms. This tends to increase the volume of exports (since OA is cheaper from importers' perspective), but exposes exporters directly to counterparty risk. Exposing to the counterparty risk allows exporters to learn even faster about the importer's credibility and 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 export entry barriers, as many firms would not decide to export if they had to use OA financing terms as these financing terms are initially associated with a higher risk.

We then calibrate our model using Chilean microdata. We show that our model matches well the documented empirical patterns. In particular, as in the data, new exporters are more likely to use CIA terms and then gradually switch to offering trade credit (OA terms). Similarly, our model matches well overall export quantity dynamics and the difference in the export growth for firms that begin exporting using OA and CIA terms. We also show how the exporter dynamics depends crucially on the parameters governing learning about demand and counterparty risks, with the former having a stronger impact on export volume dynamics while the latter affecting relatively more the dynamics of trade finance. Overall, we find that learning can be a quantitatively important source of export dynamics and can provide an endogenous theory of iceberg cost reduction over time (as considered in Ruhl and Willis (2017), Alessandria et al. (2021a), and Alessandria et al. (2021b)).

We then use the calibrated model to evaluate the response of export dynamics to aggregate shocks. We find that in response to an increase in foreign financing costs both the aggregate export sales and the number of exporters sharply decline. However, both export sales and the share of exporters recover over time, so the long-run decline in both indicators is about 50% smaller than in the short run. In other words, an increase in foreign financing cost has much larger effects in the short run than in the long run. This nonmonotone response is driven by destruction and rebuilding of trade relationships. More precisely,

[5]Even though when using CIA terms firms do not expose themselves directly to counterparty risk, they can still learn the nature of and the extent of importers' business, their treatment of their other contractors, or whether the importer is a proper firm. Antras and Foley (2015) make the same assumption when considering a dynamic model, though we differ from them by assuming that the speed of learning about the counterparty risk is (weakly) faster when exporters directly expose themselves to it by using OA terms (with this assumption being supported by our estimation results).

while relationships in which exporters have relatively low beliefs about their counterparties trustworthiness dissolve immediately after the shock (since CIA terms become more costly), rebuilding relationships and finding new trustworthy importers takes time. As a consequence, export sales and share of exporters initially overshoot their long-run level before slowly recovering towards it. We also show that the response to changes in foreign financing costs is asymmetric and a decrease in the foreign financing costs leads to a monotone convergence towards the final steady state (that is, in this case, the short run response is smaller that the long run response). Finally, we consider a shock to domestic financing costs and find that in this case the economy transitions to the final steady state almost immediately.

In the final section of the paper, we investigate how the aggregate effects of shocks to financing costs depend on the destination's characteristics. We find that shocks to foreign financing costs have a stronger impact in risky destinations since firms that export to those destinations rely more on CIA terms, which requires importers to finance working capital associated with international transactions. On the other hand, shocks to domestic financing costs have stronger effects on exports to safe destinations since firms that export to those destinations rely more on OA terms. Overall, our quantitative results show that trade finance choices are important for aggregate trade flows, and the extent of their importance depends on the characteristics of trade partners.

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 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. Benguria et al. (2023) document similar empirical findings for trade finance dynamics to the ones documented here using Colombian and Chilean data and provides a model that can rationalize these findings. 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 stylized models and abstract from learning about demand risk. In contrast, we consider a small open model that emphasizes learning about both counterparty and demand risk as key drivers of exporters dynamics and use the model to quantify the impact of risks and trade finance in driving aggregate dynamics. We also document novel empirical facts about the impact of trade finance on exports growth and exit rates.

The closest papers to ours are Antras and Foley (2015) and Benguria et al. (2023). Antras and Foley (2015) study trade finance dynamics in a stylized model of learning about counterparty risk via repeated interactions and provide evidence supporting this channel based on data from a single large exporter. Benguria et al. (2023) documents trade finance dynamics using detailed Colombian and Chilean data and uses a stylized model in the spirit of Antras and Foley (2015) and Garcia-Marin et al. (2019) to rationalize their empirical findings. We differ from those papers in several aspects. First, we provide novel evidence regarding trade finance choices on export volume dynamics and export exit rates. Second, to explain our findings, we develop a small open economy model that features not only learning about counterparty risk but also demand risk, combining two popular learning explanations for the observed exporters dynamics. Finally, we estimate our model and use it to quantify the role of trade finance in shaping the aggregate response of exports following shocks to foreign and domestic interest rates.

Our paper contributes also to a large literature on export dynamics. Ruhl and Willis (2017) document using Colombian data how export volume, export intensity, and exporters' hazard rate evolve following entry into a foreign market.[6] Several mechanisms has been proposed to 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. (2021b) consider stochastically decreasing trade costs. Other papers investigate the role of market-specific investments in advertising and customer-capital accumulation (Fitzgerald et al. (2023), Piveteau (2021), and Arkolakis (2010)). We contribute to this literature by considering learning about counterparty and demand risks as drivers of exporter dynamics and document novel facts about the joint dynamics of export quantities and trade finance.

We are not the first ones to consider learning as a driver of export dynamics. Albornoz et al. (2012) argue that export dynamics can be explained by firms' learning about the 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 Bastos et al. (2018), Eaton et al. (2021), and Timoshenko (2015)). Instead, we consider two-dimensional learning about demand and counterparty risk and focus on the interaction between export and trade finance dynamics both at the firm and aggregate levels.

The rest of the paper is organized as follows. In Section 2, we present the empirical evidence on trade finance and export dynamics. In Section 3, we develop our theory of two-dimensional learning about demand uncertainty and counterparty risks. In Section 4,

[6] See Lawless (2009) for additional evidence about dynamics of exporters' entry across foreign markets and Berman et al. (2015) for the analysis of joint dynamics of domestic and foreign sales.

we estimate the model and discuss how we identify its key parameters. In Section 5, we use the model to investigate the response of exports to shocks to interest rates in the domestic and foreign economies. In Section 6, we show how the riskiness of the trade destinations determines the choices of trade finance and shapes the aggregate response of the economy to interest rate shocks. Section 7 concludes.

2 Empirical evidence

In this section, we document stylized facts regarding trade credit arrangements, trade finance and export volume dynamics, and hazard rates. We aim to provide suggestive evidence on the importance of long-term relationships and learning. The estimates we obtain below are then used as estimation targets for our model described in Section 3.

Data Our primary data is drawn from the customs export declarations collected by the National Customs Service of Chile. The data records all export transactions by Chilean firms, including information on prices, quantities, destinations, and, crucially, the financing terms for each transaction. We merge the Customs data using firms' identifiers with firms' administrative tax records to obtain information about exporters' sales, materials used, and the number of workers employed. For each firm, we keep only years during which the firm is "active," that is, it reports sales and purchases of materials, pays payroll taxes, and presents annual income tax (Form 22) and monthly tax payments to the Chilean Internal Revenue Service (Form 29). We also drop firm-year observations for which the ratio of exports to total sales exceeds one. Finally, we consider only firms in the manufacturing sector and limit our attention to firms with at least five employees.[7] The database classifies goods according to an 8-digit Harmonized System classification system. We exclude pandemic years and focus on the period spanning from 2005 to 2019. Table 1 provides descriptive statistics of the firm-level data.[8]

[7]Results are robust to considering firms with more than ten employees, as common in studies that rely on Chile's annual manufacturing survey, ENIA.

[8]This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, under collaboration agreements signed with these institutions. To secure the privacy of workers and firms, the CBC mandates that the development, extraction and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. The authors implemented all the analysis and did not involve nor compromise the institutions involved. The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

Table 1: Descriptive statistics

	Mean	SD	p1	p5	p10	p25	p50	p75	p90	p95	p99	Obs
Sales (MM USD)	21.04	145.19	0.06	0.19	0.31	0.84	2.62	9.88	34.63	73.07	327.79	3,757
Exports (MM USD)	0.27	1.42	0.00	0.00	0.00	0.01	0.04	0.14	0.48	0.93	3.56	3,757
Exports / Sales	0.16	0.22	0.00	0.00	0.00	0.01	0.05	0.23	0.53	0.68	0.87	3,757
Employees	167.57	429.62	5.00	7.00	9.00	19.00	51.00	142.38	382.42	632.50	2090.12	3,755
Destinations	8.36	13.55	1.00	1.00	1.00	1.00	3.00	9.00	22.00	36.00	67.00	3,757
Products	11.71	22.60	1.00	1.00	1.00	2.00	4.00	12.00	29.00	45.00	105.00	3,757
Destinations-Products	30.22	70.03	1.00	1.00	1.00	2.00	7.00	27.00	80.00	132.00	309.00	3,757
Destinations-Products-Year	77.84	206.24	1.00	1.00	1.00	3.00	12.00	58.00	212.00	370.00	916.00	3,757
Log Labor Productivity	10.99	1.04	8.61	9.43	9.81	10.31	10.93	11.61	12.29	12.79	13.75	3,755

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 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 trade credit arrangements used by exporters. Hoefele et al. (2016) uses the World Bank Enterprise Survey, 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 the World Bank Enterprise Survey 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) and Benguria et al. (2023) use similar customs data for Chile merged with the annual manufacturing survey for the years 2003-2007; instead, we access tax administrative data with more accurate firm-level information, wider coverage of firms, and consider a longer sample period (2005-2019), which is particularly suited for studying export and trade finance dynamics.[9]

2.1 Trade finance by firm and destination characteristics

We begin by investigating the firms' relative use of trade finance arrangements. In Table 2, we report the relative use of CIA terms (when the importer pays for the good in advance), OA terms (when the importer pays for the good after their shipment), and bank intermediation

[9]Benguria et al. (2023) complement their analysis by using custom import data for Colombia. That data has the advantage that it contains information on foreign counterparties of Colombian importers. However, the downside of that data is the lack of production-side information.

(that is, letters of credit and other bank financing) by firms in our sample.[10] We measure the share of each payment method as the annual value of transactions using a given payment method (e.g., CIA) divided by the annual value of exports for each firm, destination and product.[11]

Table 2: Relative use of CIA, OA, and BI by exporters

Relative use of	CIA	OA	BI
All firms	0.32	0.64	0.04
New exporters, 1st year	0.38	0.58	0.05
Firm new market, 1st year	0.21	0.73	0.06
Firm-destination-product-year	0.13	0.83	0.04

Note: Share of each payment method computed as the annual value of transactions using a given payment method (cash in advance, CIA, open account, OA, or bank intermediation, BI) divided by the annual value of exports for each firm-destination-product triple. The first row reports the average across firms, where for each firm we first take the average across destination-product-year observations; the second row reports the average across firms for their first year, destination and product of exporting; the third row averages across the first years of exports to any new market; the fourth row is the average across all firm-destination-product-year observations.

Three observations emerge from these tables. First, OA terms are the most popular financing terms among Chilean exporters, followed by CIA terms. For an average exporter, export sales on OA terms account for 64% of the annual export value compared to 32% accounted by CIA. The infrequent use of the letter of credit 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 **?**, Table 1).

The second observation is that CIA plays a much more important role for new exporters during the first year of exporting to their first destination. In particular, 38% of export sales during the first year of exporting occur on CIA terms among these firms while the average across all annual observations is only 13%.[12] 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.

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

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

[12]Notice that the 13% CIA share across all transactions is lower than the average at the firm-level (i.e., 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.

Finally, we see that when firms enter a new export market –not necessarily their first one–, they initially rely on CIA payments more than the average across firm-destination-product-years, but less than new exporters. This suggests that even experienced exporters often rely on CIA terms when entering a new market, though to a lesser degree than first-time exporters.

The last two observations suggest that exporting experience is essential in determining firms' use of trade finance arrangements. Our findings are 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.

We next turn our attention to investigating how the use of trade finance arrangements varies with destination characteristics such as financial development and riskiness, whose importance has been emphasized in earlier literature (see Antras and Foley (2015) and Schmidt-Eisenlohr (2013)).[13] 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 the credit-to-GDP ratio is above the median and as having low financial development otherwise.[14] We measure countries' riskiness using the Law and Order index from the International Country Risk Guide, a component of the political risk index produced by the PRS Group. This index measures the "strength and impartiality of the legal system" and "an assessment of popular observance of the law".[15,16] We define a destination as low risk if the index is above the median and as high risk otherwise.

Table 3 indicates that, on average, exporters to risky destinations tend to rely more on CIA terms. The result is intuitive since high riskiness captures the difficulty of enforcing contracts in those locations and the relative ease with which the importer can renege on its promise. Instead, we do not find much difference in terms of financial development: while low financial development correlates closely with the riskiness of destinations, these are also destinations in which the cost of credit is higher, making it more costly to use CIA terms. Thus, these effects likely cancel out each other. These results are consistent with the findings of the previous literature mentioned above.

[13] See also Hoefele et al. (2016), Garcia-Marin et al. (2019), and Benguria et al. (2023).

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

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

[16] 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).

Table 3: Relative use of CIA, OA, and BI by destination

	CIA	OA	BI	# Firms	# Spells
Low Fin. Development	0.31	0.66	0.03	2,983	139,733
High Fin. Development	0.31	0.64	0.05	2,712	143,333
Risky destination	0.34	0.63	0.03	3,333	191,546
Safe destination	0.21	0.72	0.06	2,014	92,451

Note: Share of each payment method computed as the annual value of transactions using a given payment method (cash in advance, CIA, open account, OA, or bank intermediation, BI) divided by the annual value of exports for each firm-destination-product triple. We average across firms exporting to low (high) financial development and risky (safe) risk destinations after averaging across destination-product-years for each firm. # Spells denotes the amount of exporting spells at the firm-destination-product level in each of the table's categories.

Next, we report how trade finance arrangements vary across firms' size and export experience. We define a firm as large if it has, on average, more than 50 employees over the period it appears in our sample; otherwise, we classify the firm as small. We define a firm as experienced if, on average, it exports to more than five different markets in our sample. Table 4 provides information about the relative use of different financing terms among firms that differ in terms of size and experience.

Table 4: Relative use of CIA, OA, and BI by exporters characteristics

	CIA	OA	BI	# Firms	# Spells
Small firms	0.41	0.56	0.03	1,880	42,199
Large firms	0.23	0.72	0.05	1,877	250,256
Inexperienced	0.38	0.58	0.04	2,807	44,977
Experienced	0.14	0.81	0.05	950	247,478

Note: Share of each payment method computed as the annual value of transactions using a given payment method (cash in advance, CIA, open account, OA, or bank intermediation, BI) divided by the annual value of exports for each firm-destination-product triple. 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 exporting to at least 5 markets over the sample period. # Spells denotes the amount of exporting spells at the firm-destination-product level in each of the table's categories.

We see that small firms and inexperienced exporters tend to rely significantly more on CIA terms. In particular, the share of CIA terms for a small exporter is 41% compared to only 23% for large exporters. Similarly, the share of CIA terms for an inexperienced exporter is 38% while it is only 14% for an experienced one. Finally, as in Tables 2 and 3, we see that bank intermediation accounts for only a small share of transactions.

Overall, the cross-sectional results suggest that while open account is the most common payment method among Chilean exporters, CIA terms are associated with a significant share of sales to risky destinations as well as among small and inexperienced exporters –particularly those that start to export for the very first time. In contrast, bank intermediation accounts only for a small fraction of transactions. 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. Given the relatively low importance of bank intermediation, we focus below on OA and CIA terms.

2.2 Dynamics of trade finance

We next analyze exporters' use of trade finance along export spells defined at the firm-destination-product level.[17] In particular, we investigate whether exporters switch from using CIA to providing more trade credit (OA) during their export spells and whether these dynamics depend on the characteristics of firms or the destination markets. We later investigate whether our model can explain these dynamics.[18]

Table 5 reports the unconditional average dynamics of how the share of export values in which their payment method is OA or CIA evolves. While the share of OA increases by 8 percentage points and CIA decreases by 7 percentage points, unconditional averages present the pitfall that selection into export markets based on persistent unobserved heterogeneity may generate a relationship between tenure in a destination market and firms' choices. In the next section, we isolate the role of the number of transactions from selection by looking at the evolution of trade finance within an exporting spell. In addition, to avoid confounding market and firm-product variables, we quantify the trade finance dynamics orthogonal to market and firm productivity shocks. For this purpose, we remove the time effect common to firms exporting the same product to a given market and the time effect common to the same firm-product pair across destinations. The empirical specification implements this through a set of fixed effects at the firm-product-year and market-product-year levels. Finally, following Fitzgerald et al. (2023), we control for censoring of export spells arising due to the finite time coverage of our data.

[17]Results are robust if we define spells at the firm-destination level instead.

[18]Three terms that we use throughout this section require precise definitions: exporting spell, tenure, and transactions. For the first two terms, we follow the definitions provided by Fitzgerald et al. (2023). An exporting spell is defined as an episode that begins when a firm continuously exports a product to a destination and ends in the year when it stops exporting. If a firm exports for several years, stops for one year, and resumes exporting to the same product-destination pair, the spell ends in the year with no exports, and a new spell begins in the following year. Finally, tenure is defined as the exporting years within a given spell. As Benguria et al. (2023), we also aggregate all transactions on a given day so that our highest frequency is daily. Abusing language, we refer to the n-th day during an export spell as the n-th transaction.

Table 5: Unconditional average dynamics of CIA and OA

Tenure	Share OA	Share CIA	Observations
1	0.80	0.16	113,550
	(0.39)	(0.36)	
2	0.83	0.13	55,010
	(0.35)	(0.32)	
3	0.85	0.11	36,495
	(0.33)	(0.29)	
4	0.87	0.10	27,040
	(0.31)	(0.28)	
5	0.88	0.09	21,054
	(0.30)	(0.27)	
6	0.88	0.09	16,847
	(0.30)	(0.26)	

Note: Share of each payment method computed as the annual value of transactions using a given payment method (cash in advance, CIA, or open account, OA) divided by the annual value of exports for each firm-destination-product triple. We average across destination-product-years for each exporting year within a spell. The table is truncated at the spells' sixth year. Standard deviations are reported in parentheses.

2.2.1 Dynamics of trade finance within exporting spells

We analyze the dynamics of trade finance over the number of days with trade within a spell. Let i denote an exporting firm, j a destination country, and k a product. For each variable of interest w_t^{ijk}, we estimate:

$$w_n^{ijk} = \beta \log n^{ijk} + c^{ijk} + d_t^j + e_t^{ik} + \text{left-censored}^{ijk} + \text{right-censored}^{ijk} + \varepsilon_t^{ijk}, \qquad (1)$$

where w_t^{ijk} is either the share of CIA or OA in transactions recorded on the nth day of export spell, c^{ijk} is the firm-destination-product fixed effect, d_t^j is the destination-year fixed effect, e_t^{ik} is the firm-destination-year fixed effect, n^{ijk} measures the number of transactions in destination j of a firm i exporting product k in the current spell. The variable left-censored is an indicator variable equal to 1 for spells that we observe in the first year of the sample and zero otherwise. Similarly, right-censored is an indicator variable equal to 1 for spells that we observe in the last year of the sample and zero otherwise. Finally, ε_t^{ijk} is idiosyncratic noise.

Table 6, column 1, presents the results for the evolution of OA in panel (a) and for the evolution of CIA in panel (b). The coefficient on the length of the export spell is positive and highly significant implying that the share of exports financed through OA increases over the length of an export spell. Since, on average, during a 5-year long exporting spell we observe shipments on 32 separate days (see Table 1 in the appendix), this translates into an increase in the share of OA transactions by about 2% over the first five years of an exporting spell. As observed by Benguria et al. (2023), this increase is typically concentrated in the first two years of the spell. We also observe that for the firms in the top 10% in terms of frequency of shipments, the increase in the proportion of OA terms is about 2.4% while for those in the bottom 10% is less than 1%. Conversely, the share of exports financed through CIA decreases over the exporting spell.

As firms' productivity and their experience as exporters matter in the selection of payment methods, they are likely to affect payment dynamics. By the same token, exports to risky and financially developed countries are likely to differ in payment dynamics. We turn next to investigating these issues.

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

We augment Equation (1) to investigate how firm and destination market characteristics affect the evolution of the methods of payment. To do so, we consider the following regression,

$$\begin{aligned} w_n^{ijk} = &\beta \log n^{ijk} + \beta^z \log n^{ijk} \times z^{ijk} + c^{ijk} + d_t^j + e_t^{ik} \\ &+ \text{left-censored}^{ijk} + \text{right-censored}^{ijk} + \varepsilon_t^{ijk} \end{aligned} \tag{2}$$

where z^{ijk} includes dummy variables for export destinations with high financial development and a high rule of law and order index (defined relative to the cross-country medians), as well as for large firms (with more than 50 employees) and experienced firms (exporting to more than five markets). The equation does not include dummies as independent regressors z^{ijk} as they are implicitly included in the firm-destination-product fixed effects. The results of this regression are presented in columns (2) to (4) of Table 6.

We observe that the dynamics of CIA/OA are substantially more pronounced in risky and less financially developed economies. On average, the share of OA increases by 3.3% over the first 5 years of exporting for risky and financially underdeveloped destinations, while it increases by only 0.6% for financially developed and safe destinations. For firms in the top 10% in distribution of shipments' frequency the proportion of OA terms in transactions increases by 4.1% in risky and financially underdeveloped destinations over the first 5 years compared to about 0.8% in safe and financially developed countries. In contrast, these numbers are 1.5% and 0.3%, respectively, for the firms in the bottom 10%. Turning our attention to dynamics of CIA (Panel b), we see that these dynamics reflect the dynamics of OA terms, with the share of CIA decreasing by 3.3% in the first five years of an average

Table 6: Dynamic of trade finance and its determinants

	(1)	(2)	(3)	(4)
Panel (a): Dependent variable share of open account in exports				
Transactions	0.0056***	0.0096***	0.0091***	0.0141***
	(0.0004)	(0.0005)	(0.0018)	(0.0018)
Transactions × High Fin. Development		-0.0021**		-0.0020**
		(0.0009)		(0.0009)
Transactions × Safe		-0.0057***		-0.0058***
		(0.0009)		(0.0009)
Transactions × Large			0.0003	-0.0006
			(0.0015)	(0.0015)
Transactions × Experienced			-0.0041***	-0.0042***
			(0.0015)	(0.0015)
R^2	0.6509	0.648	0.6509	0.648
Panel (b): Dependent variable share cash in advance in exports				
Transactions	-0.0044***	-0.0096***	-0.0074***	-0.0126***
	(0.0003)	(0.0004)	(0.0014)	(0.0015)
Transactions × High Fin. Development		0.0019***		0.0018**
		(0.0007)		(0.0007)
Transactions × Safe		0.0085***		0.0086***
		(0.0007)		(0.0007)
Transactions × Large			0.0003	0.0005
			(0.0012)	(0.0012)
Transactions × Experienced			0.003**	0.0028**
			(0.0012)	(0.0012)
R^2	0.6178	0.6172	0.6178	0.6172
Distinct Spells	60,457	57,754	60,457	57,754
Observations	2,075,945	2,028,673	2,075,945	2,028,673

Note: We estimate the relation $w_n^{ijk} = \beta \log n^{ijk} + \beta^z \log n^{ijk} \times z^{ijk} + c^{ijk} + d_t^j + e_t^{ik} + \text{left-censored}^{ijk} + \text{right-censored}^{ijk} + \varepsilon_t^{ijk}$, where w_t^{ijk} is either the share of cash in advance or open account, c^{ijk} is the firm-destination-product fixed effect, d_t^j is the destination-time fixed effect, e_t^{Iknow} is the firm-product-year fixed effect, and n^{ijk} measures the cumulative number of months with transactions, z^{ijk} are interaction terms. The variables left-censored and right-censored are indicator variables equal to 1 for spells that we observe in the first year of the sample, 2005, zero otherwise, and equal to 1 for spells that we observe in the last year of the sample, 2019, zero otherwise, respectively. High Fin. Development is a dummy variable for export destinations with high domestic credit-to-GDP ratios. Safe is a dummy for destinations with high Law and Order index scores. Large equals one for firms with more than 50 employees, and Experienced is defined as firms exporting to more than five markets. Column 1 presents the results of β with no interaction terms in the regression. Columns 2-to-4 present the results of the interaction regressions. The estimation period is 2005-2019. Robust standard errors are in parentheses. ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

exporting spell for a risky and financially underdeveloped destination, and by less than 0.1% for financially developed and safer destinations. These results are consistent with the results of Antras and Foley (2015) and Benguria et al. (2023).

Next, we consider how the dynamics of trade finance vary with firms' characteristics, such as experience and size. We classify a firm as experienced if it exports on average to more than five markets during the sample period. Otherwise, we classify it as inexperienced. We preserve the threshold for large firms at 50 employees. Table 6, column 3, shows that the share of OA increases by 3.2% over the first five years of an average exporting spell for small and inexperienced firms, while it only increases by 1.8% for larger and experienced firms. Conversely, the share of CIA decreases by 2.6% and 1.5%, respectively. These novel effects are mostly driven by our proxy of experience.[19]

Finally, column 4 of Table 6 shows that the share of OA increases by 5% over the first 5 years of an average exporting spell for a small and inexperienced firm selling to a risky and financially underdeveloped destination. This occurs in less than two years for an exporting spell in the top 1% of the distribution of days exported. Instead, for a large and experienced firm selling to a safe and financially developed destination, this change is only 0.5%. The respective numbers for the decrease in the share of CIA are -4.3% and -0.4%.

The above results suggest that learning plays an important role in driving trade finance dynamics. These results are consistent with the implications of the theory that we develop in Section 3, where firms selling to high-risk or low financially-developed countries tend to sell a higher share of their exports using CIA arrangements compared to firms that begin exporting to low-risk or high financial development countries.

2.3 Export dynamics

We turn to quantify the evolution of firms' exports along the life of a trading relationship. We also zoom in on how the market and firms' characteristics and the initial provision of trade credit determine the evolution of exported quantities and exit rates over an exporting spell. This novel evidence on the association between export and trade finance dynamics will later inform our modeling choices.

2.3.1 Export dynamics, destination and firm characteristics

To document how exports evolve over an exporting spell, we employ the same empirical approach as we did for trade finance dynamics to analyze the dynamics of export volumes

[19] In a similar spirit, Araujo et al. (2016) finds that experience is an important driver of export quantity dynamics. Our results complement their findings by showing that experience also affects the dynamics of trade finance.

over the length of a spell.[20] Specifically, we estimate Equation (1) for the log of exported quantities instead of the method of payment shares. Table 7 presents estimates on how export volumes evolve over an exporting spell.

Consistent with earlier literature (see, for example, Ruhl and Willis (2017)), we find that export volumes increase rapidly over the duration of an exporting spell. In particular, as shown in the first column of Table 7, the elasticity of export volumes with respect to the number of transactions within an exporting spell is large, approximately 0.075, and significant at the one percent level. This implies that, on average, export transaction volume increases by about 26 percent over a five-year long export spell. An important question is the extent to which the growth of export volume over the exporting spell varies with the initial choice of payment method. We specifically address this issue in section 2.3.2, where we examine the relationship between export volumes and the initial share of trade finance within an exporting spell.

Table 7 indicates that the elasticity of exports with respect to the number of transactions varies with destination characteristics. Column two shows that the elasticity is lower in safer or less financially developed destinations. Conditional on the level of financial development at the export's destination, the magnitude associated with the rule of law coefficient (Safe in the table) suggests significant scope for learning along the relationship length in markets with lower rule of law. When we control for the rule of law, our results indicate that exporting spells can grow faster in more financially developed markets, suggesting that importers in less financially developed markets face higher interest rates, ultimately impairing firms' ability to import. These two mechanisms are at the core of our theoretical model and quantitative exercises in Sections 3 and 4.

In column three of Table 7, we investigate whether size – a proxy for productivity – and experience affect how exported volumes evolve along an exporting spell. We find an economically and statistically significant role for experience in explaining the dynamics of volumes over export spells, but not so for the firm's size. This suggests firms with the exporting "know-how" are able to expand their exports faster over time than firms with less experience operating in foreign markets. We do not find empirical evidence that firm size interacts with relationship length: there is no additional role for productivity besides what the firm-product-destination fixed effects already control for in the regression.

When we consider the firm and destination characteristics in the regression, we find that our estimates' magnitude and statistical significance remain virtually unchanged, as shown in column four. The lack of difference across our estimates suggests that firm and destination

[20] This approach has the advantage of not being subject to the bias that can arise when analyzing the evolution of exports using calendar months or years.

characteristics are two independent factors that affect how exported volumes evolve along the exporting spell.

Table 7: Dynamic of exported-quantities and its determinants

	(1)	(2)	(3)	(4)
Transactions	0.0751***	0.078***	0.0257**	0.0286***
	(0.002)	(0.0031)	(0.0101)	(0.0104)
Transactions × High Fin. Development		0.0187***		0.0171***
		(0.0051)		(0.0051)
Transactions × Safe		-0.0296***		-0.0289***
		(0.0051)		(0.0051)
Transactions × Large			-0.0084	-0.006
			(0.0087)	(0.0088)
Transactions × Experienced			0.0612***	0.0596***
			(0.0083)	(0.0084)
R^2	0.8706	0.8696	0.8706	0.8696
Distinct spells	60,187	57,490	60,187	57,490
Observations	2,072,346	2,025,108	2,072,346	2,025,108

Note: We estimate the relation $\log Q_n^{ijk} = \beta \log n^{ijk} + \beta^z \log n^{ijk} \times z^{ijk} + c^{ijk} + d_t^j + e_t^{ik} + \text{left-censored}^{ijk} + \text{right-censored}^{ijk} + \varepsilon_t^{ijk}$, where, Q_n^{ijk} represents exported quantities, 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 months with transactions, z^{ijk} are interaction terms. The variables left-censored and right-censored are indicator variables equal to 1 for spells that we observe in the first year of the sample, 2005, zero otherwise, and equal to 1 for spells that we observe in the last year of the sample, 2019, zero otherwise, respectively. High Fin. Development is a dummy variable for export destinations with high domestic credit-to-GDP ratios. Safe is a dummy for destinations with high Law and Order index scores. Large equals one for firms with more than 50 employees, and Experienced is defined as firms exporting to more than five markets. Column 1 presents the results of β with no interaction terms in the regression. Columns 2-to-4 present the results of the interaction regressions. The estimation period is 2005-2019. Robust standard errors are in parentheses. ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

2.3.2 Initial provision of trade credit, exports, and exit rates

A direct link between exporting activity and trade finance can be established by analyzing whether the initial method of payment choice is associated with export decisions. Therefore, we investigate how the credit arrangement used at the onset of the exporting spell is correlated with subsequent exported volumes and hazard rates.

We estimate the same regression as in the previous section, but distinguish between spells that started with high and low OA levels. Specifically, we define a spell to have high (low) initial use OA if 50% or more (less than 50%) of export sales on the first day of an exporting spell has used OA financing arrangements. For robustness, we also use 90% cutoff when classifying export spells.

We report the results of these regressions in the first two columns of Table 8. The elasticity of exports to the number of transactions is roughly twice as large for spells that begin using at least 50 percent of open account terms than those that start below this threshold. A similar result is found when splitting the sample between spells where the share of open account terms during the first year exceeds 90 percent. Thus, a higher provision of open account is associated with higher export growth.

Table 8: Initial trade credit provision and dynamic of exported-quantities

	Share open account			
	$> 50\%$	$< 50\%$	$> 90\%$	$< 90\%$
Transactions	0.0752***	0.0371***	0.0744***	0.0416***
	(0.0022)	(0.0059)	(0.0023)	(0.0047)
Observations	1,781,677	220,855	1,663,450	339,320
R^2	0.8648	0.9096	0.8646	0.9
Distinct spells	49,972	10,284	47,546	13,101

Note: We split the sample in exporting spells that start with high and low open account terms and estimate the relation $\log Q_n^{ijk} = \beta \log n^{ijk} + c^{ijk} + d_t^j + e_t^{ik} + \text{left-censored}^{ijk} + \text{right-censored}^{ijk} + \varepsilon_t^{ijk}$, where, Q_n^{ijk} represents exported quantities, 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 months with transactions. The variables left-censored and right-censored are indicator variables equal to 1 for spells that we observe in the first year of the sample, 2005, zero otherwise, and equal to 1 for spells that we observe in the last year of the sample, 2019, zero otherwise, respectively. Column 1 presents the results of β for instances where 50 percent or more of the export value is paid through open account terms. Column 2 presents the results for operations where less than 50 percent is paid through open account terms. Column 3 repeats the exercise for instances where 90 percent or more of the export value is paid through open account terms and column 4 where less than 90 percent is paid through open account. The estimation period is 2005-2019. Robust standard errors are in parentheses. ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

We next investigate how initial trade finance choices are associated with subsequent exit rates. Column 1 of Table 9 reports the probability of ending an exporting spell conditional on tenure. We see that the exit rate is initially high and then gradually decreases over time. The dynamics of exit rates are consistent with the exporter dynamics literature (see, for example, Kohn et al. (2016) or Ruhl and Willis (2017)) although the exit rates are higher than those reported by that literature. This difference stems from the fact that we compute exit rates at the firm-destination-product level rather than at the firm level as typically done in that literature.

We then investigate how export exit rates are are associated with initial trade finance choices. Columns two and three show that firms that initially rely relatively little on OA terms have 7% higher exit rate in the first year of exporting spells than exporters that initially use predominantly OA terms. The difference in exit rates is gradually declining to about 1% in the fifth year. Columns four and five of Table 9 report similar patterns when we use 90% threshold to classify the spells though the differences are unsurprisingly lower.

Table 9: Initial trade credit provision and exit rates

Tenure	Exit rate	Share open account			
		$> 50\%$	$< 50\%$	$> 90\%$	$< 90\%$
1	64.02	62.64	69.59	63.29	66.79
	(2.81)	(2.97)	(2.72)	(2.86)	(3.07)
2	41.10	40.35	45.21	40.68	43.07
	(2.21)	(2.16)	(3.55)	(2.21)	(3.24)
3	29.29	28.64	33.61	28.78	31.89
	(2.35)	(2.47)	(3.37)	(2.48)	(2.89)
4	23.52	23.17	26.63	23.44	24.83
	(2.80)	(2.81)	(4.75)	(2.78)	(4.51)
5	19.63	19.49	20.43	19.61	19.64
	(3.13)	(3.80)	(2.55)	(3.81)	(3.28)
6	15.90	15.70	16.98	15.87	15.98
	(2.19)	(2.10)	(4.29)	(2.08)	(4.29)

Note: Exit rates are calculated as the number of exits in each spell year relative to the number of observations in the spell year. For instance, a 64.02 percent exit rate means that 64.02 percent of spells do not survive after the first year. Columns three to six condition on the payment choice over the first spell year. For example, a 62.64 percent exit rate for a share open account less than 50 percent means that spells that start with less than 50 percent open account have a 62.64 percent probability of ending. The share of open account (OA) is calculated as the annual value of transactions using this payment method divided by the annual value of exports for each firm-destination-product triple. The table is truncated at the spells' sixth year. Standard deviations are reported in parentheses.

Taken together, the results of this section provide novel evidence that the initial choices of payment methods are associated to the intensive and extensive margins of an exporting spell.

In the remainder of the paper, we develop, calibrate, and simulate an international trade model in which exporters face risks about the demand for their products and the trustworthiness of their counterparties, and learn about these risks within their exporting relationships. We will use the estimates obtained in this section to discipline our model and show that our model implies dynamics that are consistent with the dynamics documented in this section.

3 Model

We consider a small open economy model in the spirit of Melitz (2003). There are two types of agents in the domestic economy: a representative consumer and a continuum of firms indexed by i producing differentiated varieties that are owned by the consumer. Firms can sell their production in domestic and foreign markets with exports being subject to a variable and fixed cost. The rest of the world consists of a foreign representative consumer that demands domestic varieties and a large number of importers that buy goods from domestic firms and sell them to the foreign consumer.

While otherwise standard, the model features two novel components. First, exports are subject to both counterparty risk (the risk that foreign importers may not pay for received goods) and demand risk (uncertainty about foreign consumer's demand for domestic varieties) that evolve over the export spells.[21] Second, to manage the exposure to those risks, we allow exporters to choose different financing terms as in Antras and Foley (2015) and Schmidt-Eisenlohr (2013). The learning dynamics are the only driver of dynamics in the model.

3.1 Representative consumers

There is a domestic representative consumer that derives utility from consuming domestic and imported varieties according to

$$U = \log(C),$$

where C is the composite of domestic and foreign varieties given by

$$C = \left\{ (1-\alpha) \int_0^1 \left[y_d\left(i\right) \right]^{\frac{\sigma-1}{\sigma}} d\omega + \alpha y_m^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}},$$

where $y_d\left(i\right)$ denotes a quantity of domestic variety produced by a domestic firm i and y_m is the imported bundle of foreign varieties.[22] Parameter α measures the extent of home bias in the economy.

The representative consumer has two sources of income. First, she obtains wage income, w, from supplying inelastically one unit of labor to the labor market. Second, the consumer receives profits from the domestic firms with the total aggregate profits denoted by Π. Both the wage and the total profits are expressed in units of the domestic final consumption good.

[21] While both risks have been individually studied in earlier literature, our approach integrates them. The importance of counterparty risk has been highlighted by Antras (2015), Antras and Foley (2015), Schmidt-Eisenlohr (2013) and Benguria et al. (2023) among others. Demand risk has been explored by Albornoz et al. (2012), Berman et al. (2019), and Timoshenko (2015), among others. We consider both risks together and analyze their relevance for exporters' extensive and intensive margin decisions.

[22] Since the foreign economy is not explicitly modeled, we assume that the domestic representative consumer imports a single foreign good which can be thought of as an optimal bundle of foreign goods.

For simplicity, we assume that in each period the representative consumer spends its income on the consumption of domestic and foreign varieties. We denote the price of the variety produced by a domestic firm i by $p_d(i)$, where $p_d(i)$ is denominated in units of the domestic final consumption good. Similarly, we denote by p_m the price of the imported variety, measured in units of the foreign final consumption good. It follows that the domestic representative consumer's problem is given by

$$\max_{\{(y_d(i))_{i\in[0,1]}, y_m\}} \log(C) \tag{3}$$

$$s.t.\;\; C = \left\{(1-\alpha)\int_0^1 \left[y_d(i)\right]^{\frac{\sigma-1}{\sigma}} di + \alpha y_m^{\frac{\sigma-1}{\sigma}}\right\}^{\frac{\sigma}{\sigma-1}} \tag{4}$$

$$\int_0^1 p_d(i)\, y_d(i)\, di + \xi p_m y_m = w + \Pi, \tag{5}$$

where ξ is the real exchange rate defined as the price of the foreign final good in terms of the domestic final good. Equation (5) is the budget constraint which states that the representative consumer's expenditure on domestic and imported varieties has to be equal to the consumer's total income. Note that prices in Equation (5) are in units of the final consumption good of their origin. Solving the above consumer's problem yields standard demand functions for domestic and imported varieties given by

$$y_d(i) = (1-\alpha)^{\sigma}\left(p_d(i)\right)^{-\sigma} C \tag{6}$$

$$y_m = \alpha^{\sigma}\left(\xi p_m\right)^{-\sigma} C, \tag{7}$$

where C is the consumption of the final domestic good, which is equal to $w + \Pi$.

While we consider a small open economy, it is useful to discuss how foreign demand for domestic varieties is determined. We assume that there is a foreign representative consumer that is analogous to the domestic one but with one key difference. The foreign consumer's demand for imported varieties is subject to demand shifters, which we interpret as uncertain local tastes. Specifically, foreign consumer's consumption of the composite final good, denoted by C^*, is given by

$$C^* = \left\{(1-\alpha^*)\left(y_d^*\right)^{\frac{\sigma-1}{\sigma}} di + \alpha^* \int u(i)\left[y_f(i)\right]^{\frac{\sigma-1}{\sigma}} di\right\}^{\frac{\sigma}{\sigma-1}},$$

where $y_d^*(i)$ denotes her consumption of a foreign domestic variety, $y_f(i)$ denotes her consumption of an imported variety exported from the domestic economy and α^* measures the extent of home bias in the foreign economy. Finally, $u(i)$ are demand shifters that can take the value of 0 or 1 and are unobserved by domestic firms giving rise to demand risk as described below. Note that when $u(i) = 1$, the demand for domestic exports is given by

$$y_f(i) = \alpha^{*\sigma}(p_f)^{-\sigma}C^* \tag{8}$$

where p_f denotes the price of export variety i (denominated in foreign consumption goods). Otherwise, when $u(i) = 0$, the demand for domestic variety produced by firm i is 0. Since we consider a small open economy, C^* is taken as given.

3.2 Domestic firms

There is a continuum of monopolistically competitive firms indexed by i, $i \in [0, 1]$. Each firm produces a unique variety and chooses how much to sell domestically and abroad.

Technology Each firm produces a unique variety using a linear production technology

$$y = zn, \tag{9}$$

where z is a firm's productivity and n is the labor input. Firms have heterogeneous productivity and their productivity is constant over time. We assume that the productivity among domestic firms is log-normally distributed with $\log(z) \sim N(0, \sigma_z)$.

Domestic and foreign demand Firms choose how much to sell domestically and abroad. In both markets, firms face downward sloping demand curves. The domestic demand is given by Equation (6). The foreign demand for a variety produced by firm i is initially uncertain. Each period the firm's foreign demand is given either by Equation (8) or 0 depending on the value taken by the demand shifter, $u(i)$. Domestic firms cannot sell directly in the foreign market. Instead, they need to find an importer who then sells the goods on their behalf. As we explain below, this exposes exporters to counterparty risk: that is, the risk that an importer does not fulfill his contractual obligations.

Risks and costs of exporting As in Melitz (2003), exporting is subject to a fixed cost, F, and a variable iceberg cost, τ. The presence of these costs implies that only relatively productive firms will export. In addition, we assume that exporting is associated with risks and additional costs due to working capital needs.

More specifically, we assume that exporters face two types of risk. First, they face demand risk. In particular, when exporters start exporting they do not know whether their product will turn out to be popular in the foreign market. The demand for a popular good is always "high," that is, is given by Equation (8) (meaning that $u(i) = 1$ in each period). The demand for an unpopular good is high (i.e., $u(i) = 1$ and the demand is given by Equation (8)) with probability $\delta \in (0, 1)$ and equal to 0 otherwise (i.e., $u(i) = 0$). Unsold goods perish, that is, they provide no value to any party involved. We denote with λ the exporter's belief that its variety is popular. Each time a firm enters a foreign market it faces a new draw of goods' popularity, but the goods popularity stays constant over the export spell.

In addition, exporters face a counterparty risk. To export a firm needs to be matched with an importer in a foreign country. There is a large number of importers and each exporter is matched with a single importer. The importer can be trustworthy or untrustworthy. A trustworthy importer always fulfills its contractual obligations unless it cannot sell the goods (the foreign demand for the product is zero). The untrustworthy importer, instead, may renege on the contract. In particular, if the goods were sold on trade credit, the untrustworthy importer pays for the goods only with probability $\mu \in (0, 1)$.[23] We denote with χ an exporter's belief that the counterparty in the foreign economy is credible. Each time a firm enters an export market it is matched with a new importer and stays in the relationship with this importer throughout the export spell.[24] The demand and counterparty risks are independent. Moreover, whether goods are sold or not is observable by exporters. Thus, exporters can determine whether goods are sold and whether the importer decided to steal the shipment.

Export shipping lags and working capital Motivated by the literature that documents substantial shipping lags associated with international trade (see, for example, Djankov et al. (2010) or Hummels and Schaur (2013)), we assume that there is a lag between production and foreign sales. In particular, we assume that production takes place at the beginning of a period while sales in the foreign country occur later on. This implies that exports are associated with working capital needs as firms have to finance production before export sales are realized. If the goods are sold on credit, then an exporter borrows to finance its working capital needs at the domestic interest rate, r. Instead, if payment for exports is made in advance (i.e., before shipment), then an importer borrows to finance the advanced payment at the rate r^*. We assume that $r^* > r$, an assumption that will allow us later to match the share of exports sold on credit observed in our data. There is no delay associated with

[23] We assume that untrustworthy importers are behavioral types that do not choose when to renege on their contractual obligations. Instead, they do it randomly with a positive probability. Following Antras and Foley (2015), we can interpret μ as the probability with which an opportunity to divert or abscond with goods arises.

[24] Thus, to switch importers, a firm first needs to break its current relationship with an importer, exit the export market, and only then look for a new importer.

domestic sales and, hence, production for the domestic market does not require working capital.

Trade finance arrangements To manage the risks and working capital costs associated with international trade, exporters can use different trade finance arrangements. Motivated by our empirical findings, as in Antras (2015), we focus on the two most common trade finance arrangements, namely, cash in advance (CIA) and open account (OA).

More specifically, we assume that to export in a given period a firm has to sign a contract with the importer with which it is matched specifying: (i) the quantity of goods to be delivered, y, (ii) the payment for the goods that the exporter will receive (denominated in foreign final goods), s, and (iii) the timing of payment for the goods by an importer. The payment can happen before shipment (i.e., before production takes place) or after shipment (after the goods are sold). The first timing corresponds to cash in advance (CIA) financing terms while the second one corresponds to open account (OA) terms.

Assumption 1. *We assume that: (i) all contracts are one-period, (ii) exporters have all the market power in negotiating contract terms with importers, and (iii) importers' outside options are zero.*

3.2.1 Trade finance contracts and learning dynamics

Optimal contract under OA terms Suppose first that an exporter decides to sell its goods on OA terms (i.e., payment occurs after the goods are sold). In this case, the exporter not only exposes itself to demand and counterparty risks but also needs to finance the working capital needed for production. Suppose that exporters current belief about demand is λ while the belief about counterparty trustworthiness is χ. Then the probability that the exporter gets paid is

$$\gamma^{OA}(\chi, \lambda) = [\chi + \mu(1-\chi)][\lambda + \delta(1-\lambda)]. \tag{10}$$

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

$$\max_{s,y} \frac{\gamma^{OA}(\chi, \lambda)}{1+r}\xi s - \frac{\tau w}{z} y - wF, \tag{11}$$

$$\text{s.t. } [\lambda + \delta(1-\lambda)][p(y)\,y - s] \geq 0, \tag{12}$$

where ξ is the real exchange rate and $p(y)$ is the price implied by the foreign demand (Equation (8)) as a function of y when the product sells (i.e., $u = 1$). Equation (11) is the expected payoff to an exporter with beliefs $\{\chi, \lambda\}$ when the exporter agrees to deliver y units to its counterparty and is promised to receive payment of s (denominated in foreign final goods) with the payment discounted at the domestic borrowing rate, r, since the payment is received at the end of the period. Equation (12) is the importer's participation constraint, which states that the importer's expected revenues from selling the goods must be at least as large as the contractual payment she is supposed to make to the exporter. Note that this constraint implies that if an importer is unsuccessful in selling the contract, then she will not pay the exporter.

Optimal contract under CIA terms Next, consider the optimal contract when an exporter decides to sell her goods using CIA arrangements. In this case, since the exporter receives the payment before shipping the goods, she is not exposed to either demand or counterparty risk. On the other hand, the demand risk is now faced directly by the importer, who will require compensation for it. Let

$$\gamma^{CIA}(\lambda) \equiv [\lambda + \delta(1 - \lambda)] \tag{13}$$

Then, the exporter's problem is given by

$$\max_{s,y} \xi s - \frac{\tau w}{z} y - wF \tag{14}$$

$$\text{s.t. } \gamma^{CIA}(\lambda) p(y) y - (1 + r^*) s \geq 0, \tag{15}$$

Equation (14) is the payoff to an exporter. Notice that an exporter's beliefs do not appear in its objective function since, in this case, the payment is received before shipment of the goods. Equation (15) is the importer's participation constraint. It differs from the importer's participation constraint under OA terms in two respects. First, the payment s is made in advance, regardless of whether the importer is able to sell the goods later on. Second, it is now the importer who has to borrow at interest rate r^* in order to pay in advance for the goods.

Learning about demand and counterparty risk Before discussing the optimal choice of financing terms, we describe how exporters learn about demand and counterparty risk. As we will see, in our model, learning introduces a dynamic aspect to the choice of financing terms. This is in contrast to Antras and Foley (2015) and Benguria et al. (2023), where choices of financing terms are static.

Consider first learning about demand. Each period, an exporter observes whether the goods it shipped to the foreign country were successfully sold. Based on that observation, the exporter updates its beliefs following Bayes rule. Let λ denote the exporter's belief at the beginning of the period and λ' denote the exporter's belief at the end of the period. Then

$$\lambda'(\lambda) = \begin{cases} \frac{\lambda}{\lambda+(1-\lambda)\delta}, & \text{if the product sells,} \\ 0, & \text{otherwise} \end{cases}$$

Since only an unpopular product ever fails to sell, it follows that in this case $\lambda' = 0$. Otherwise, if the product sells, the exporter revises its beliefs upwards since observing high demand is more likely when the product is popular. Since foreign sales are observable, learning about demand does not depend on the choice of trade finance arrangements.

Next, consider learning about the counterparty risk. Suppose first that an exporter uses OA terms, in which case it is directly exposed to counterparty risk. The exporter updates its belief based on the importer's fulfillment of contractual obligations (or lack thereof). Let χ denote the exporter's belief about counterparty's trustworthiness at the beginning of a period and χ'_{OA} denotes the exporter's belief at the end of a period (after an importer attempted to sell the goods), where we use subscript OA to indicate that those posterior beliefs are achieved when using OA terms. Then

$$\chi'_{OA}(\chi) = \begin{cases} \frac{\chi}{\chi+(1-\chi)\mu}, & \text{if credit repaid} \\ 0, & \text{otherwise} \end{cases}$$

If exported goods do not sell, neither type of importer pays for the good. However, we assume that with probability μ, an untrustworthy importer absconds with unsold goods. Instead, a trustworthy importer always reports it sales and returns the unsold goods to the exporter.[25]

Finally, consider an exporter that this period decided to use CIA terms. In that case, an exporter does not expose itself to counterparty risk and, hence, cannot update its beliefs about counterparty risk based on the importer's behavior after the sale of goods. We assume that, nevertheless, an exporter can learn about an importer's type simply from their interactions. We refer to this as *passive learning.*[26] In particular, we assume that when

[25]As with many assumptions of our model, this one is also not essential. In particular, it can be relaxed by assuming that exporters do not learn anything if sales were unsuccessful at the cost of increasing the complexity of the model and its numerical implementation. However, since in our numerical experiments, we find that exporters always leave the market once they learn that the good is unpopular, the exact nature of learning in this case is unlikely to affect our results.

[26]This is to differentiate it from the "active learning" where an exporter directly exposes itself to counter-

an exporter interacts with an untrustworthy importer using CIA terms, it learns about the importer's untrustworthiness with probability $\mu_{CIA} \in (0,1)$. That is, the posterior belief about an importer's trustworthiness, χ' given that the exporter uses CIA terms and given that its initial beliefs are χ is given by

$$\chi'_{CIA}(\chi) = \begin{cases} \frac{\chi}{\chi+(1-\chi)\mu_{CIA}}, & \text{if the untrustworthy type is not detected} \\ 0, & \text{otherwise} \end{cases}$$

Passive learning is meant to capture the fact that by interacting with an importer, an exporter might be able to learn whether the importer is trustworthy or not by observing the importer's behavior. For example, an exporter is able to verify that the importer is not a fictitious firm, observe how the importer is fulfilling her other contractual obligations (such as those to workers), etc.[27] In addition, the exporter may also observe how high labor turnover is (which might be informative about the importer's attitude towards labor contracts). However, such indirect learning is likely not as effective as learning under direct exposure to counterparty risk when using OA financing terms. Therefore, we assume that $\mu < \mu_{CIA}$.

Implications of passive learning The assumption that $\mu < \mu_{CIA}$ implies that learning about counterparty risk is slower when using CIA terms than when using OA terms. This in turn implies that trade finance choices are dynamic. This is because exporters' future beliefs, which determine the future value from exporting, depend now on an exporters' current choices of financing terms. As discussed below, we find strong support for this assumption when estimating the parameters of our model. The dynamic aspect of trade finance choices is absent in Antras and Foley (2015) and Benguria et al. (2023), where the speed of learning about counterparty risk is assumed independent of the trade finance use.

3.2.2 Export entry, export exit, and timeline

The entry decision into exporting is driven by new draws of beliefs $\{\lambda, \chi\}$. Each period, each non-exporter draws new beliefs, which represents meeting a new potential importer. Based on its new beliefs, a non-exporter decides whether to enter into a relationship with an importer it is matched with and start exporting. If an exporter decides to enter into a

party risk using OA terms.

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

relationship with an importer, it will start exporting in the next period.[28]

At the end of each period, exporters update their beliefs and based on their updated beliefs decide whether to continue exporting in the next period. In addition, relationships are subject to exogenous separation shocks. That is, with probability $\kappa \in (0, 1)$, a relationship dissolves for exogenous reasons. In that case, a current exporter becomes a non-exporter in the next period even if, based on its beliefs, it would like to continue exporting.[29]

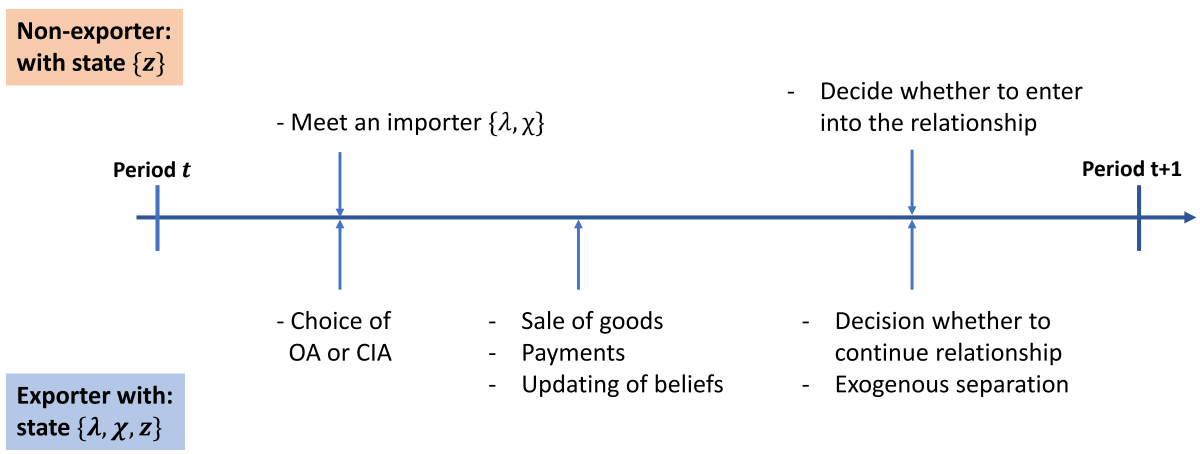


Figure 1: Timeline

Figure 1 illustrates the timeline of the model. Consider first a firm that enters the period as a non-exporter. At the beginning of the period, this firm meets a new importer and draws new beliefs $\{\lambda, \chi\}$. Based on those beliefs, the firm decides whether to enter into a relationship with the importer. If the firm enters into a relationship, it starts exporting in the next period. Otherwise, it remains a non-exporter and faces the same problem in the next period. Consider now an exporter who starts this period with beliefs $\{\lambda, \chi\}$. The exporter decides the export contract details, particularly whether to export this period using OA or CIA terms. After this, the exporter ships goods to an importer who sells them in the foreign market. Once the sales occur and the contract is settled, the exporter updates its beliefs. Finally, at the end of the period, the exporter decides whether to continue the relationship, and the exogenous separation shock occurs.

[28] We make this assumption for two reasons. First, this allows us to identify export spells in the model in a way that is consistent with how we do it in the data. That is, in the model, any two export spells will be separated by at least one period of non-exporting. Second, it implies that the continuation value for non-exporters and exporters is identical, substantially simplifying the numerical analysis.

[29] In a model where every period firms are matched with new importers, this assumption is needed to ensure that there are meaningful dynamics and a non-degenerate distribution of beliefs in the steady state. Otherwise, the distribution of exporters' beliefs will converge to a mass point at $\{\lambda, \chi\} = \{1, 1\}$.

3.3 Recursive formulation and equilibrium

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

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

If the firm decides to export then it becomes an exporter the next period with state $\{z, \lambda, \chi\}$. If it decides not to export, it faces the same problem the next period but with new draws of beliefs.

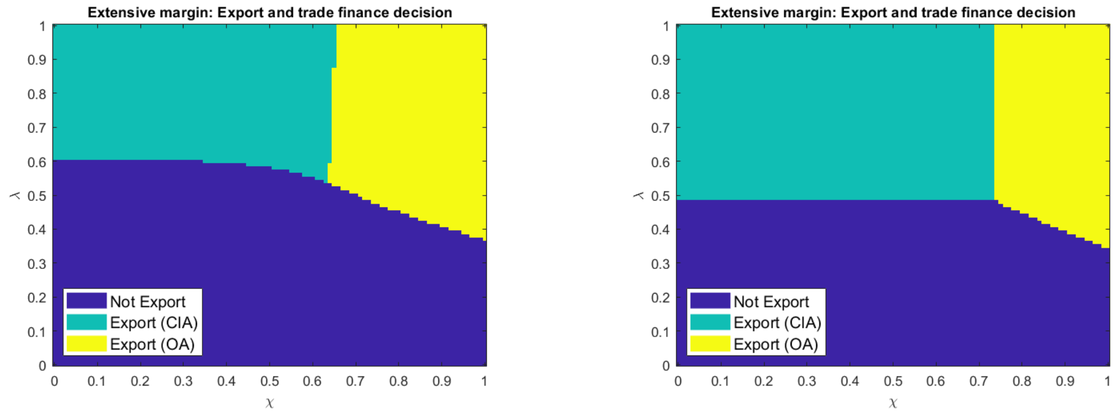
Let $V^E(z, \lambda, \chi)$ denote the value function of an exporter with state $\{z, \lambda, \chi\}$ that is choosing whether to use CIA or OA terms. Let $\pi^X(z, \lambda, \chi)$ denote expected profits from choosing financing option X, where $X \in \{CIA, OA\}$. After profits are realized, an exporter updates its beliefs and, if hit by an exogenous separation shock it leaves the export market, which occurs with probability $(1 - \kappa)$. In that case, the firm will be a non-exporter in the following period. Otherwise, based on the updated beliefs, the exporter decides whether to stay in the current relationship and export, or leave. Let $V^C(z, \lambda, \chi)$ denote the value function of the exporter at that point it time. Then, $V^E(z, \lambda, \chi)$ is given by

$$\begin{aligned} V^E(z, \lambda, \chi) = \max_{\{\text{CIA,OA}\}} & \\ \Big\{ \pi^{CIA}(z, \lambda, \chi) &+ \kappa \mathbb{E}\left[V^C\left(z, \lambda'_{CIA}(\lambda), \chi'_{CIA}(\chi)\right)\right] + (1-\kappa)\beta\mathbb{E}\left[V^N\left(z, \lambda'_{CIA}(\lambda), \chi'_{CIA}(\chi)\right)\right], \\ \pi^{OA}(z, \lambda, \chi) &+ \kappa \mathbb{E}\left[V^C\left(z, \lambda'_{OA}(\lambda), \chi'_{OA}(\chi)\right)\right] + (1-\kappa)\beta\mathbb{E}\left[V^N\left(z, \lambda'_{OA}(\lambda), \chi'_{OA}(\chi)\right)\right] \Big\} \end{aligned} \tag{16}$$

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 $X \in \{CIA, OA\}$, and $V^C(z, \lambda, \chi)$ is simply equal to

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

Thus, we see that the exporter's decision on whether to exit the relationship or continue 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) Optimal decisions

(b) Static decisions

Figure 2: The extensive margins of export and financing choices. The left panel depicts the optimal dynamic choice of exporting and financing terms. The right panel depicts the static choice of exporting and financing terms (based on the comparison of static export profits). Both policies are computed using calibrated parameters and equilibrium prices.

To better understand firms' incentives to start exporting and the dynamic considerations involved, in Figure 2 we depict firms' export entry/exit policy function (for a fixed productivity level) as a function of their current beliefs when (i) firms behave optimally taking into account dynamic aspects of their entry decisions (Panel A) and (ii) when firms make these decisions myopically by considering only their current static export profits (Panel B).

Contrasting the optimal dynamic export decision with the non-optimal static one, we observe two major differences. First, the optimal entry policy implies entry for fewer belief pairs. This is because the optimal decision takes into account the firms' option value of waiting. By waiting, a firm may get matched with a better importer and start its export spell with more favorable beliefs. Second, the optimal entry-exit decision also implies more use of OA terms. This is because the optimal decision takes into account the faster learning under OA terms and the opportunity cost of staying in a relationship that ultimately dissolves due to importer's untrustworthiness.

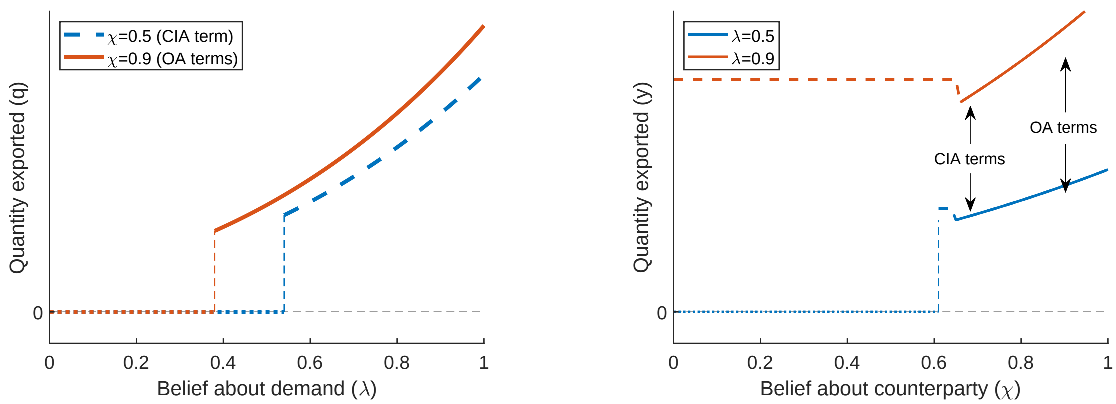
Having described the extensive margin decisions, we now briefly discuss the impact of risk on exporters' intensive margin choices. It is straightforward to see that the exporter's static problem (as described by Equations (11)-(12) for OA terms and Equations (14)-(15) for CIA terms) can be simplified to

$$\max_{y} \frac{\xi}{\phi(\lambda, \chi)} p(y)y - \frac{\tau w}{z} y - wF \tag{17}$$

where, as before, $p(y)$ is the price implied by the foreign demand (Equation (8)) and ϕ is a "wedge" that depends on an exporter's beliefs and its choice of financing $I \in \{\text{CIA}, \text{OA}\}$, and is defined as

$$\phi(\lambda, \chi) = \mathbb{1}_{\{I=\text{CIA}\}} \frac{1+r^*}{\gamma^{CIA}(\lambda)} + \mathbb{1}_{\{I=\text{OA}\}} \frac{1+r}{\gamma^{OA}(\lambda, \chi)}$$

Thus, the static profit maximization problem faced by exporters is as in standard Meltiz-style models, except for the presence of the wedge that captures the static impact of risk on exporters' choices. Since $\phi > 1$, it follows that the risks depress the quantities exporters ship. Moreover, since ϕ is increasing in λ and χ, it follows that optimal export quantities are also increasing in λ in χ.



(a) Dynamic entry/exit decision

(b) Static entry/exit decision

Figure 3: The extensive margins of export and payment choices. The left panel shows optimal export quantity as a function of belief about demand, λ, holding belief about counterparty constant at $\chi = 0.5$ (blue line) and $\chi = 0.9$ (red line). The right panel depicts optimal export quantity as a function of χ holding belief about demand constant at $\lambda = 0.5$ and $\lambda = 0.9$. In both panels, solid lines indicate the optimal choice of OA, dashed lines indicate the optimal choice of CIA, and dotted lines indicate the optimal choice of non-exporting. All policies are computed using calibrated parameters and equilibrium prices.

Figure 3 depicts the optimal export quantity. The left panel shows how the optimal export quantity varies with the belief about demand, λ, holding the belief about counterparty risk fixed at $\chi = 0.5$ (blue dashed line) and $\chi = 0.9$ (red solid line).[30] For both values of counterparty risk, firms choose to export only when λ is high enough, with the quantity of export increasing with λ. However, when $\chi = 0.9$, firms start to export at lower values of λ, use OA terms (as indicated by the solid line), and export more for any given λ than when $\chi = 0.5$. This is driven by the fact that OA terms are associated with cheaper external financing that encourages exporters to produce more for the foreign market (and dominates the negative effect of exposure to counterparty risk).

[30]In both panels, the dashed lines depict the optimal choice of CIA terms while the solid lines depict the optimal choice of OA terms

The right panel, instead, depicts the optimal export quantity as a function of counterparty risk, χ, holding demand risk constant at $\lambda = 0.5$ (red line) and $\lambda = 0.9$ (blue line). When demand risk is low ($\lambda = 0.9$), firms export for all values of χ, though for low values of χ they use CIA terms (red-dashed line) before switching to OA terms. Since under CIA terms firms are protected from counterparty risk, the optimal export quantity is initially flat in χ. For high enough χ, exporters optimally switch to OA terms. The switch to OA terms is associated with an initial drop in exported quantities as exporters scale down their exports due to exposure to counterparty risk.[31] Afterward, export quantity is increasing in χ. The export quantity varies with χ in a similar fashion when demand risk is relatively high ($\lambda = 0.5$) but with one key difference. Namely, for a wide range of values for χ, firms choose not to export when they face substantial demand uncertainty.

3.3.1 Equilibrium

Let $\mathcal{S} = \mathcal{Z} \times \Lambda \times \mathcal{X}$ denote the state space where $\mathcal{Z}$ is the set of possible productivity realizations, Λ is the set of possible beliefs about the popularity of a product, $\mathcal{X}$ is the set of possible beliefs about the credibility of a counterpart. Let ν denote a measure over $\mathcal{S}$. Assume that the price of the imported good, p_m, is constant and given. Finally, let e denote firms extensive margin export decision and o their choice of trade finance arrangements.

Let r and r^* be given. A stationary equilibrium consists of aggregate prices $\{w, \xi\}$, policy functions $\{p_d, y_d, n_d, p_f, y_f, n_f, e, o, y_m, C\}$, value functions V^n and V^e, and a measure $\nu \to [0, 1]$ such that

1. Policy and value functions solve firms' problem taken as given demand functions and aggregate prices.

2. Policy functions solve the representative consumer's problem taking as given firms' decisions.

3. Labor market clears:

$$\int_{\mathcal{S}} [n_d(s) + e(s)(n_f(s) + F)]\, d\nu = 1.$$

[31] That export quantity jumps down upon the switch to OA terms implies that export profits also drop upon the switch of financing terms. Firms find this optimal because of dynamic considerations as they trade off lower profits today for faster learning and higher expected profits in the future. Under static export financing choices, as depicted in the right panel of Figure 2, there would be no jump in quantities upon a switch of financing terms and export quantities would always be monotone functions of beliefs about counterparty risk.

4. Domestic final good market clears (i.e., C satisfies the representative consumer's budget constraint)

$$C = w + \Pi$$

5. Measure ν is stationary.

4 Quantitative Analysis

In the remainder of the paper, we quantitatively investigate the role of learning in driving trade finance and export dynamics. We begin by calibrating our model using Chilean micro data. We then discuss how our model allows us to disentangle the importance of learning about the popularity of the product and the trustworthiness of counterparties in trade finance and export dynamics. In the following sections, we investigate the aggregate implications of these channels by considering the response of the economy to shocks to domestic foreign funding costs. Finally, we examine how these implications vary with the type of risks exporters face at their destination markets.

4.1 Calibration

In this section, we calibrate the model to match key features of Chilean micro data. We then use the calibrated model to contrast the dynamics of export volume and trade finance with the data (Section 2), and show how changes in the parameters governing the speed of learning affect these dynamics.

Table 10 reports the parameters that we use in our quantitative analysis. We use standard values for the discount rate, $\beta = 0.9$, and elasticity of substitution, $\sigma = 4$. The prior beliefs about demand and counterparty trustworthiness are chosen to be uniform over the unit interval, which correspond to beta distributions with parameters $\{1, 1\}$. Thus, we denote the prior belief about demand risk by $\mathcal{B}_\lambda(1, 1)$ and the prior belief about counterparty trustworthiness by $\mathcal{B}_\chi(1, 1)$.[32] We assume that firms' productivity, z, is distributed in the cross-section according to a log-normal distribution. We denote the variance of $log(z)$ by $\sigma_{log(z)}$ and for each choice of $\sigma_{log(z)}$ we normalize the mean of firms' productivity distribution to be equal to 1. Parameters $\{\tau, F, \kappa, \sigma_{log(z)}, r_f - r\}$ are chosen to match key cross-sectional moments and the parameters governing the speed of learning and risks (δ, μ, μ_{CIA}) are chosen to match the dynamics of exports and trade finance over a typical export spell.

[32] In Section 6, we consider how changes in the parameters of the Beta distribution affect the response of the domestic economy to aggregate shocks.

Table 10: **Estimated Parameters**

Parameter	Value	Target moment	Data	Model
β	0.9	Pre-assigned		
σ	4	Pre-assigned		
λ_0	$\mathcal{B}_\lambda(1,1)$	Pre-assigned		
χ_0	$\mathcal{B}_\chi(1,1)$	Pre-assigned		
τ	4.523	Average export intensity	0.20	0.20
F	0.125	Share of exporters	0.09	0.09
κ	0.899	Exporters' exit rate	0.13	0.12
$\sigma_{log(z)}$	0.105	Exporters' labor premium	4.27	4.28
$r_f - r$	0.084	Share of CIA among exporters	0.33	0.32
		Learning and risks		
δ	0.563	New exporters 5-year increase in export quantity	0.26	0.26
μ	0.704	5-year differential increase in export quantity (OA - CIA)	0.13	0.13
μ_{CIA}	0.869	New exporters 5-year increase in OA share	0.02	0.02

We follow much of the quantitative trade literature (see, for example, Alessandria and Choi (2014b,a), Ruhl and Willis (2017), or Kohn et al. (2016)), in choosing $\{\tau, F, \kappa, \sigma_{\log(z)}\}$ to match (i) the average export intensity, (ii) the share of exporters in the economy, (iii) the exit rate of exporters' from the foreign market, and (iv) the exporters' size premium captured by the number of employees.[33]

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, trade finance dynamics, and export dynamics to discipline them. Specifically, we choose $\{r_f - r, \delta, \mu, \mu_{CIA}\}$ to match (i) the average share of CIA among exporters, (ii) the average increase in export sales from period 1 to period 6 of exporting spells, (iii) the difference in average increase in export sales from period 1 to period 6 of exporting spells among exporters that use OA vs. those that use CIA, and (iv) the average increase in the share of OA from period 1 to period 6 of exporting spells.[34]

[33]For average export intensity (i.e. exports/sales), we compute the simple average across firms for each year in the sample and then average across years. For the share of exporters, we compute the share of exporters in each year and then the average across years. We compute the exit rate of exporters for each year of the exporting spell, conditional on firm survival in the sample, and average across years of spell from year 6 onwards -when the exit rate stabilizes-. For computing the exporters' labor premium in the data, we calculate the number of employees for each firm-year and its export status, we then compute an average across time for each firm when it is exporting and when it is non-exporting, we then compute the median across exporters and across non-exporters at the firm-level, and finally we compute the ratio between this measure for exporters and non-exporters.

[34]We compute the average share of CIA by calculating first the share of exported value using OA and CIA terms (thus, ignoring bank intermediation from which we abstract from in the model) at the firm-year level. We then first average across years and then across firms. To compute the 5-year increase in quantity exported we multiply the coefficient of the baseline regression of quantities by the log of the average number of days exported during the first 5 years of an exporting spell. To compute the difference in export quantity growth over the first 5-years for exporters that initially use predominantly OA and CIA terms, we follow the same steps but first we classify export spells in the data according to their use of trade finance terms in

The parameters δ, μ and μ_{CIA} jointly affect the export volume and trade finance dynamics in our model, but they all have distinct effects on each of these dimensions. In particular, as discussed in more detail in Section 4.3, changes in δ have stronger effects on average export growth, changes in μ affect predominantly the difference in the growth of export sales of firms that begin exporting on OA terms versus those that begin exporting on CIA terms. Finally, μ_{CIA} has stronger effects on the rate at which firms switch from CIA terms to OA terms. [35]

4.2 Dynamics of sales and trade finance

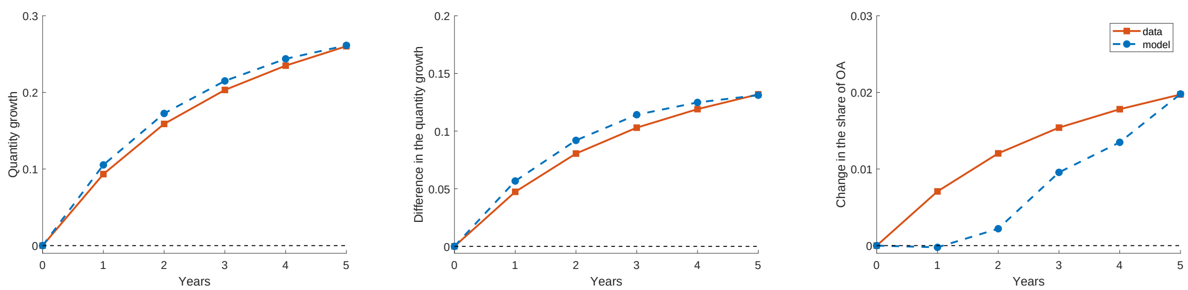


Figure 4: Trade finance and export dynamics

Figure 4 contrasts the dynamics of trade finance and export volume dynamics implied by the model with those observed in the data (solid red lines). Our model delivers dynamics comparable to those observed in the data. In particular, our model matches well the gradual increase in export volume for new exporters and the higher increase in export volume across exporters that start exporting primarily with Open Account. Our model matches well the overall increase in the share of OA terms, though it predicts a lower rate of switching in the initial years than predicted in the data. In the next section, we explain how various aspects of learning affect these dynamics.

4.3 Changes in the speed of learning and export dynamics

In this section, we explain how changes in the parameters governing the speed of learning (δ, μ, and μ_{CIA}) affect the dynamics of the share of CIA and the average export volume among

the first year of spells. In particular, if the share of OA (CIA) is greater than 50 percent in the first year, we classify this spell as OA (CIA) spell. We then compute the growth of export quantities for OA and CIA spells as in the case of all spells and take the difference. Finally, for the average increase in the share of OA, we use the coefficient of the baseline daily regressions and multiply it by the average number of days transacted over the first five years of the exporting spell.

[35]Note that, in absence of learning, our model would imply no dynamics over the course of export spells (with exit from exporting driven only by the exogenous separation shocks).

new exporters. As we show, each parameter has a distinct effect on these dynamics, which allows us to identify them. Figure 5 depicts our results.

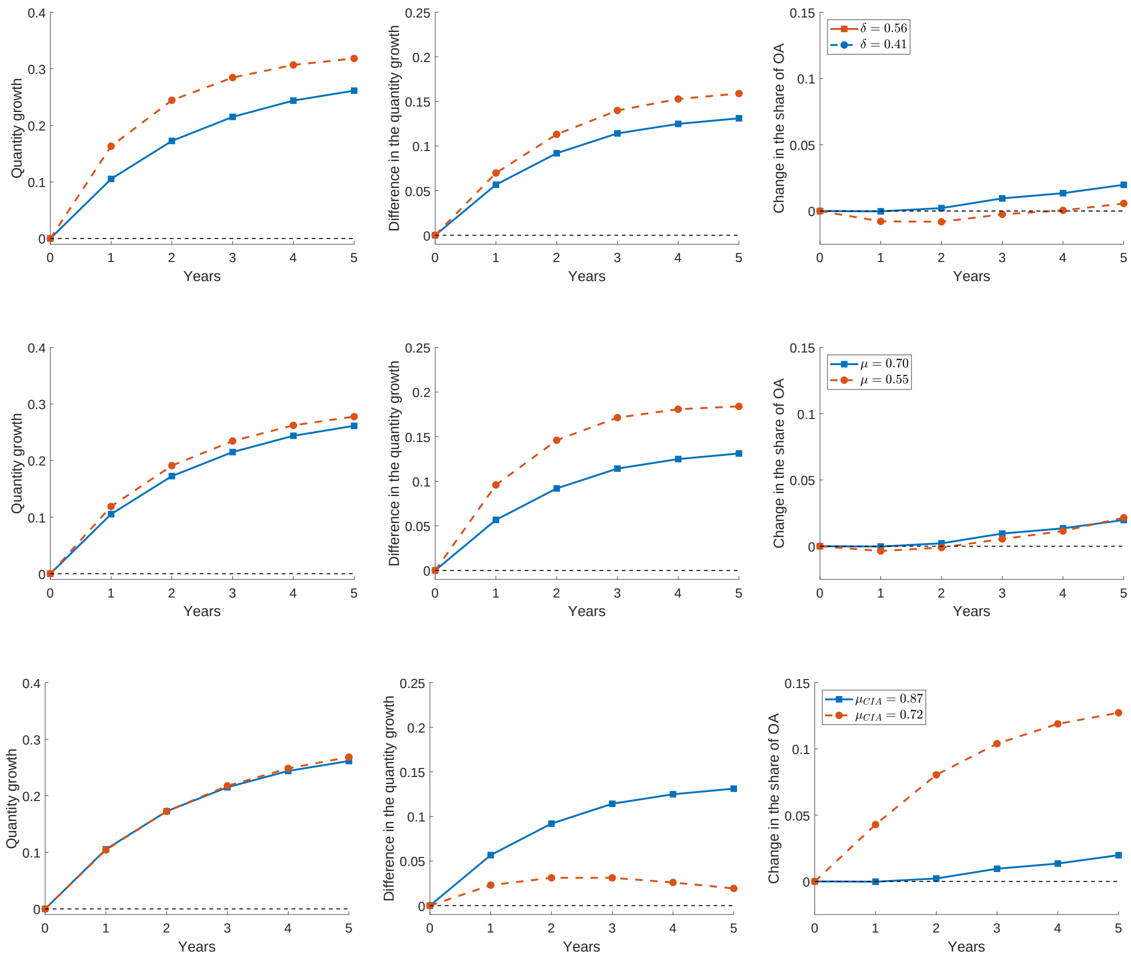


Figure 5: Trade finance and export dynamics under alternative parameters

Consider first changes in the probability that an unpopular product is sold, δ, depicted in the top row of Figure 5. Note that δ governs both the extent of the demand risk and the speed at which exporters learn about the current foreign demand for their product (with lower δ corresponding to faster learning). Because of that, a decrease in δ from 0.56 (our estimated value) to 0.41 has a large impact on the dynamics of exports. More specifically, a lower δ implies a faster resolution of the demand uncertainty, which effectively leads to a faster decrease in the cost of exporting (i.e., decrease in the wedge $\phi(\lambda, \chi)$) and translates into faster export growth. On the other hand, changes in δ have more modest effects on the difference in export growth under OA and CIA terms (the middle panel) since changes in δ affect in a similar fashion all exporters irrespectively of financing terms used. For the same reasons, changes in δ have only a small effect on the use of trade finance.

Next, consider changes in the probability that a non-credible importer fulfills its contract, μ, depicted in the middle row of Figure 5. Note that μ governs both the extent of the counterparty risk and the speed at which exporters learn about the counterparty risk under OA terms. Decreasing μ from 0.7 (our estimated value) to 0.55 has a large impact on the difference in the speed of export growth under OA and CIA terms. This is because a decrease in μ increases the speed of learning for firms that use OA terms (the middle panel). On the other hand, we see minor effects on the overall export quantity growth. This is because a lower μ means that OA terms are more risky than before (lower likelihood of being repaid) and, thus, fewer new exporters use OA terms. As learning is slower under CIA terms, this counteracts the faster growth rate (due to faster learning) of firms that use OA terms leaving the overall growth rate of exports unchanged. Finally, a change in μ has little impact on trade finance dynamics since changes in μ have no direct impact on firms using CIA terms.

Lastly, consider changes in the parameter that governs the speed of learning about whether the importer is credible or not when using CIA, μ_{CIA}, depicted in the bottom row of Figure 5. We see that trade finance dynamics are very sensitive to changes in μ_{CIA} (the right panel). This is because μ_{CIA} directly controls the speed with which firms learn about their counterparty's trustworthiness, which determines the rate at which firms switch from CIA to OA terms. We also note that a decrease in μ_{CIA} decreases the difference in the speed of export growth under OA and CIA terms. This occurs for two reasons. First, a decrease in μ_{CIA} (holding μ constant) decreases the difference in the speed of learning about counterparty risk between CIA and OA terms. Second, many firms that previously would start exporting using OA terms choose instead to start exporting using CIA terms. This implies that, on average, firms that start exporting under OA terms have now higher beliefs about their counterparties, which decreases the average rate of export growth under OA terms. Finally, a decrease in μ_{CIA} has little effect on the growth of quantity exported. This is due to two opposing forces. On the one hand, firms that use CIA terms learn faster, which tends to increase export growth. On the other hand, firms that would start exporting using OA terms but instead switch now to using CIA terms face less risk than before when they begin exporting. Therefore, these "switchers" start by exporting closer to their optimal scale (i.e., the scale when all uncertainty is resolved) and, as a consequence, they grow at a slower rate which depresses the overall export growth rate. Under the parameters considered, these two forces almost exactly offset each other.

Overall, Figure 5 suggests that changes in each of the parameters governing the speed of learning and the extent of risk (i.e., δ, μ, and μ_{CIA}) have differential effects on trade finance and export volume dynamics. In particular, we see that changes in δ have particularly strong effects on overall export growth. Changes in μ mostly affect the difference in export growth under CIA and OA terms, while changes in μ_{CIA} strongly affect trade finance dynamics and the difference in the export growth under CIA and OA terms. These differential effects explain why we are able to identify the learning parameters in the data from the export and trade finance dynamics.

5 Shocks to financing costs and aggregate dynamics

Above, we discussed how changes in the parameters of the model affect the dynamics of export sales and trade finance use. In this section, we focus instead on the aggregate trade dynamics following shocks to foreign and domestic funding costs, r_f and r_d, respectively. We first describe how our economy adjusts to a permanent increase of 5 percentage points in the foreign funding cost. We then contrast the effects of an increase and a decrease in r_f, and highlight that the responses to those changes are asymmetric. Finally, we discuss the impact of a permanent increase of 5 percentage points in the domestic funding cost, r_d.

5.1 Permanent increase in foreign funding costs

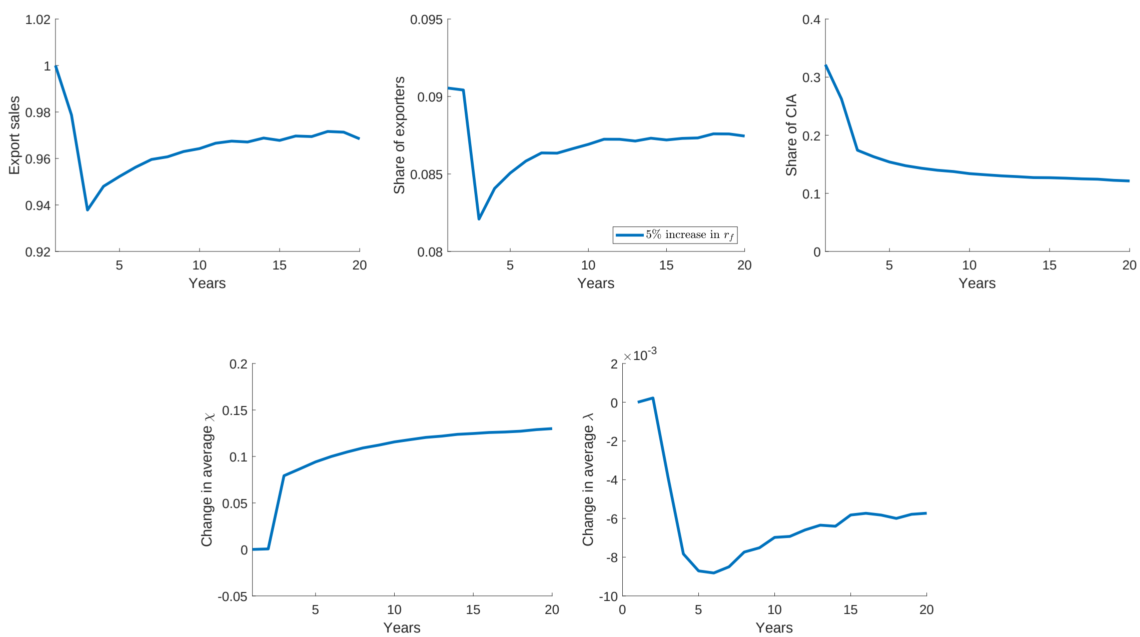


Figure 6: Effects of a permanent increase in r_f of 5pp.

Figure 6 depicts the effects of a permanent increase in the foreign financing cost by 5 percentage points. The top row shows the behavior of export sales, the share of exporters, and the use of cash-in-advance terms. We see that following an increase in r_f, there is a sharp decline in these three variables. In particular, on impact, exports decline by 5%, the share of exporters decreases by 0.7pp (a decline of 7.6%) and the proportion of exporters using cash-in-advance drops from 33% to 20% over the first two years and then continues declining gradually to a level of around 13%. Instead, export sales and the share of exporters gradually recover towards their new steady state values and eventually settle at levels below the initial steady state but above their short-run levels, with export sales lower by 3% and the share of exporters lower by 0.35pp (or 3.8%) compared to their initial steady-state values, respectively. Thus, the long-run decline in export sales and the share of exporters are about 50% smaller than in the short-run.

To understand these dynamics, note that an increase in the foreign funding costs destroys relationships. Before the shock, exporters that have relatively high beliefs about the demand for their products (high λ) but relatively low beliefs about the trustworthiness of their counterparties (low χ) exported using cash-in-advance terms. An increase in r_f turns unprofitable many of such exporting matches, leading to a substantial exit from the export market and a decline in export sales on impact. In addition, a significant proportion of exporters that used CIA terms switch on impact to OA terms, deciding to expose themselves to higher risk rather than compensate importers for their higher financing costs. This leads to a sharp initial decline in the share of CIA.

The increase in the foreign financing cost also affects entry decisions. Firms that believe that their good will turn out to be popular (high λ) decide not to enter unless matched with importers who are likely to be trustworthy (high χ). This decreases the value of waiting for a new match for the domestic firms. As a result, firms that are matched with relatively trustworthy exporters decide to enter the foreign market rather than wait for another match even if their beliefs about the ability to sell their goods is relatively low. These firms use OA terms which tends to further decrease the share of CIA. However, since OA terms are more risky ($\mu < \mu_{CIA}$) many new exporters leave soon after entering the foreign market, and, thus, the further decrease in the share of CIA terms is gradual. This also explains the slow recovery of the share of exporters and contributes to the gradual recovery of export sales. The latter is also driven by gradual learning dynamics where new exporters initially start by exporting relatively little but expand their sales as their learn about their counterparty trustworthiness and demand for the goods.

The bottom row of Figure 6 depicts the effect of a change in the foreign funding costs on the exporters' average belief about popularity of their products (λ) and the trustworthiness of their counterparties (χ). These figures confirm the above intuition. On impact, an increase in r_f destroys the exporting relationships in which exporters have relatively low beliefs about their counterparty's trustworthiness but high beliefs about the popularity of their goods, resulting in an increase in the exporters' average beliefs about counterparty χ and a decrease in the average beliefs about the demand λ. Afterwards, the dynamics of λ and χ are driven by the entry of new domestic firms into the export market and learning. More specifically, after an increase in r_f, the new entrants tend to have lower λ and higher χ leading to a further increase in average χ and, initially, a further decrease in average λ. In the following periods, χ and λ slowly increase driven by learning.

To summarize, a positive shock to the foreign financing cost has large immediate negative effects on exports in the short run, as it destroys some of the existing relationships, followed by a slow recovery driven by entry and learning dynamics.

5.2 Asymmetric response to changes in foreign financing costs

In this section, we analyze the dynamics of trade and trade finance in response to a permanent decrease of 5 percentage points in foreign financing costs and contrast them with the dynamics following an increase in these costs. Figure 7 reports our findings.

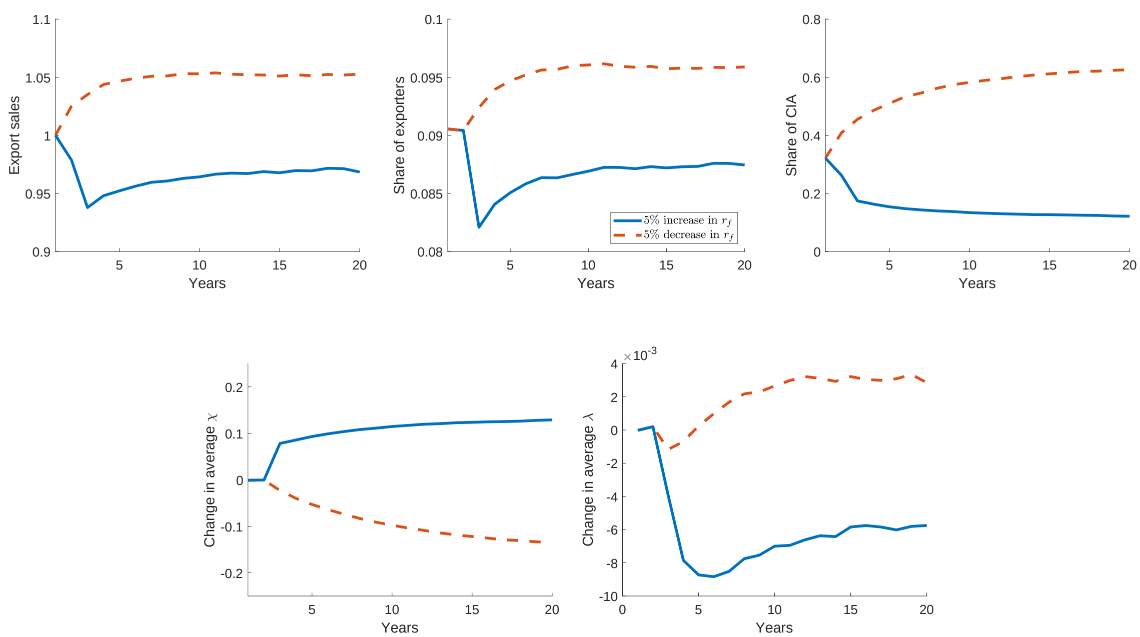


Figure 7: Asymmetric effects of changes in r_f

The top row of Figure 7 depicts the behavior of export sales, the share of exporters, and the share of exporters using CIA terms following a 5 percentage point decrease in r_f (red dashed line) and a 5 percentage point increase in r_f (blue solid line). We see that following a decrease in r_f, export sales, the share of exporters and the share of CIA all increase on impact and then gradually increase further. Thus, the short-run response of exports is smaller than the response in the long-run. This is in contrast to an increase in r_f to which the economy responds in a non-linear fashion with an initial large decline in exports followed by a slow recovery.

This asymmetry in the response of the economy to foreign financing cost shocks is driven by the asymmetric nature of export relationships. While relationships can dissolve quickly, it takes time to build new relationships and acquire relationship-specific knowledge. A decrease in foreign financing costs reduces the impact of counterparty risk and encourages more entry leading to an initial positive effect on exports. However, since building relationship-specific knowledge takes time, it takes time before the full positive effects of these shocks materialize. On the other hand, as explained above, an increase in r_f destroys the existing relationships on impact, leading to a large drop in exports and share of exporters, followed by the gradual rebuilding of relationships.

5.3 Permanent increase in domestic financing costs

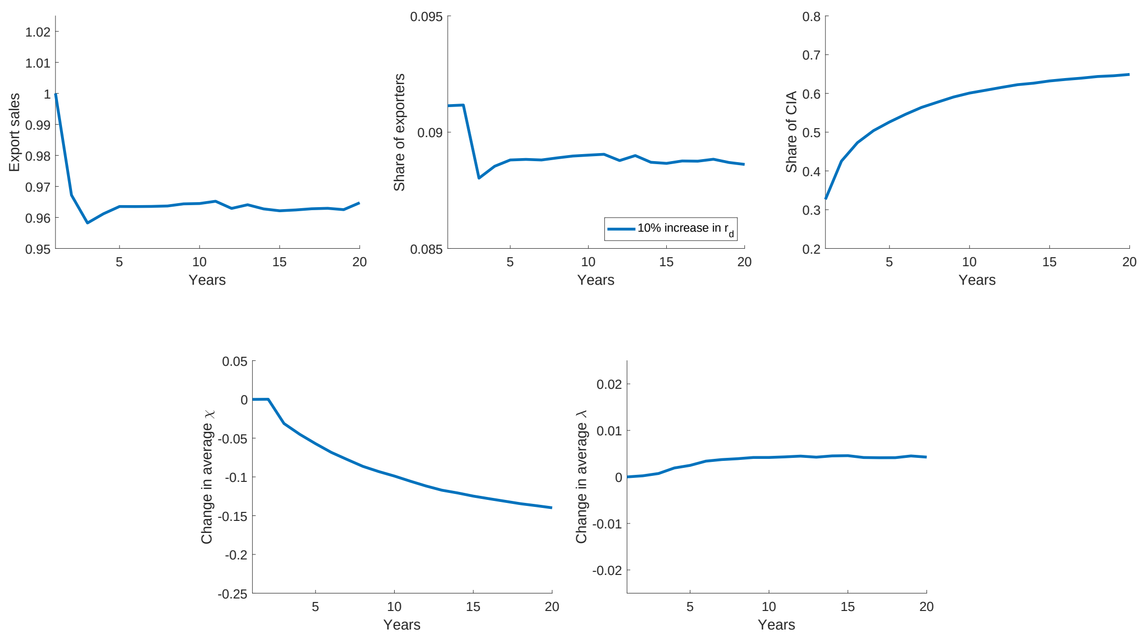


Figure 8: Effects of a permanent increase in r_d of 5pp.

Finally, now consider the effects on exports and trade finance dynamics of a permanent increase in domestic financing costs of 5 percentage points with Figure 8 depicting our results. The top row shows the behavior of export sales, the share of exporters, and the use of CIA. We see that following an increase in r_d, there is a substantial decline in exports and the share of exporters by around 4% and 0.3pp (close to 3%), respectively. In addition, the share of exports sold using CIA terms jumps up on impact by 10% and then increases slowly, reaching about 65% after twenty periods. Overall, we see that the effects of an increase in r_d are much smaller than in the case of an increase in r_f. The reason for this is that an increase in r_f makes it more costly for exporters to protect themselves from the counterparty risk they face. As a consequence, following an increase in r_f, many of the exporters that use CIA exit as they perceive exporting using OA terms too risky. On the other hand, an increase in r_d affects directly only those exporters using OA terms. These exporters can switch to CIA terms, a change that increases the cost of exporting but leads to a decrease in the risks they face. Thus, following an increase r_d, there is much less exit and a smaller decline in export sales.

Unlike in the case of an increase in foreign financing costs, there is also little recovery afterwards. In other words, export sales and the share of exporters almost immediately adjust to their final steady-state levels. The reason behind the relatively flat behavior of exports and the share of exporters following the initial decline is that, in this case, we observe less destruction of relationships than in the case of an increase in foreign financing costs. In particular, exporters stay now in relationships even if they learn that their counterparty is untrustworthy. This is because the value of finding a new trustworthy importer is now much lower given the higher cost associated with OA terms. Moreover, learning about counterparty risk is slower under CIA terms since $\mu < \mu_{CIA}$. These factors also explain why the share of CIA continues to increase while the average belief about the counterparty continues to decline for quite some time following the initial shock.

To summarize, a positive shock to the domestic financing cost has large immediate and permanent negative effects on exports.[36]

6 Shocks to financing costs and counterparty risk

In this section, we investigate how the extent of counterparty risk faced by exporters in foreign destinations affects the response of exports to interest rate shocks. To do so, we vary the probability distributions for trustworthiness (χ) and associate a more risky destination with markets in which exporters are less likely to meet a trustworthy importer. In particular, we associate a risky destination with a distribution $\mathcal{B}_\chi(1, 1.25)$ and a safe destination with a distribution $\mathcal{B}_\chi(1.25, 1)$, which imply initial shares of CIA of 24% and 52%, respectively. These numbers are comparable to those found in Chilean data, with firms selling only to safe

[36]Given the immediate and permanent impact described here, in the case of shocks to domestic financing costs we don´t observe the asymmetric dynamics that we observe in the case of shocks to foreign financing costs.

destinations featuring an average CIA of 28%, and those selling only to risky destinations featuring an average CIA of 46% of their total value exported.[37]

The distributions we consider are shown in Figure 9. In addition, when considering the long-run (i.e., steady state) effects we also consider more extreme distributions (namely, $\mathcal{B}_\chi(1.5, 1)$ and $\mathcal{B}_\chi(1, 1.5)$) to investigate whether long-run effects vary in a monotone way with counterparty risk in a foreign destination.

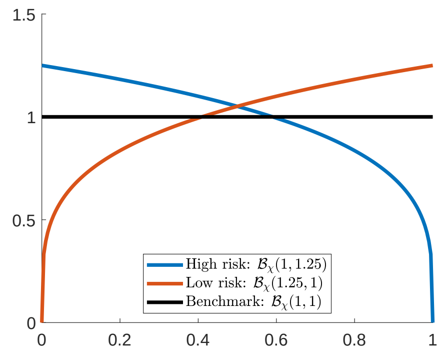


Figure 9: Alternative risk distributions

We consider shocks that permanently increase either domestic or foreign funding costs. We begin first by examining their long-run effects. That is, we compare how the new steady state value differ from the initial steady state values as the distribution of beliefs about importers' trustworthiness varies. We then investigate how the transitional dynamics are affected by the extent of counterparty risk.

6.1 Long-run effects

In this section, we contrast the steady-state values implied by the model under alternative distributions of risks, attempting to capture the long-run effects of a permanent increase in domestic and foreign interest rates, r_f and r_d. Figure 10 shows the long-run effects on exports and trade finance of a permanent increase of 5 percentage points in foreign financing costs, r_f (top three panels) and of a permanent increase of 5 percentage points in domestic financing costs, r_d (bottom three panels).

Consider first the top three panels of Figure 10 that depict the effects of an increase in the foreign financing cost, r_f. We see that a permanent increase in r_f in the less risky economy (i.e., the economy with $B_\chi(1.25, 1)$) leads to a decline in the share of exporters of 0.2pp, a drop of 2% in export sales, and a decrease in the share of CIA terms of 17pp (from 24% to

[37]These values are computed by focusing only on transactions using OA and CIA terms –excluding those using bank intermediation–. When including bank intermediation, the respective numbers are 26% and 45%.

7%). The effects of a shock to foreign funding costs are even smaller in the destination where counterparty risk is less of a concern (i.e., the economy with $B_\chi(1.5, 1)$). In contrast, the same shock in the more risk economy (i.e., with $B_\chi(1, 1.25)$) leads to a decline in the share of exporters of 0.6pp, a drop of almost 5% in export sales, and a decrease in the share of CIA terms of 28pp (from 52% to 24%). The effects are even larger in the destination where exporters face more counterparty risk (i.e, the economy with $B_\chi(1, 1).5)$.Thus, an increase in foreign financing costs has a much larger impact on exports in the riskier economies. These results are not surprising since firms rely more on CIA terms in more risky destinations, which makes exporters more sensitive to changes in r_f.

Consider next the bottom three panels of Figure 10 that show the effects of an increase in domestic function costs, r_d. We see that a permanent increase in r_d in the less risky economy (i.e., the economy with $B_\chi(1.25, 1)$) leads to a decline in export share of 0.5pp, a drop of 5.2% in export sales, and an increase in the share of CIA terms of 33pp (from 24% to 57%). The effects are even larger in the destination where counterparty risk is less of a concern (i.e., the economy with $B_\chi(1.5, 1)$). In contrast, the same shock in the more risk economy (i.e., with $B_\chi(1, 1.25)$) leads to an increase in the share of exporters of 0.1pp, a drop of 2% in export sales, and an increase in the share of CIA terms of 31pp (from 52% to 83%). The effects are even smaller in the more risky destination. Thus, an increase in domestic funding costs has a much larger effect on exports in the safer economies because trade with those destinations tends to rely more on domestic financing (i.e., OA payment methods).

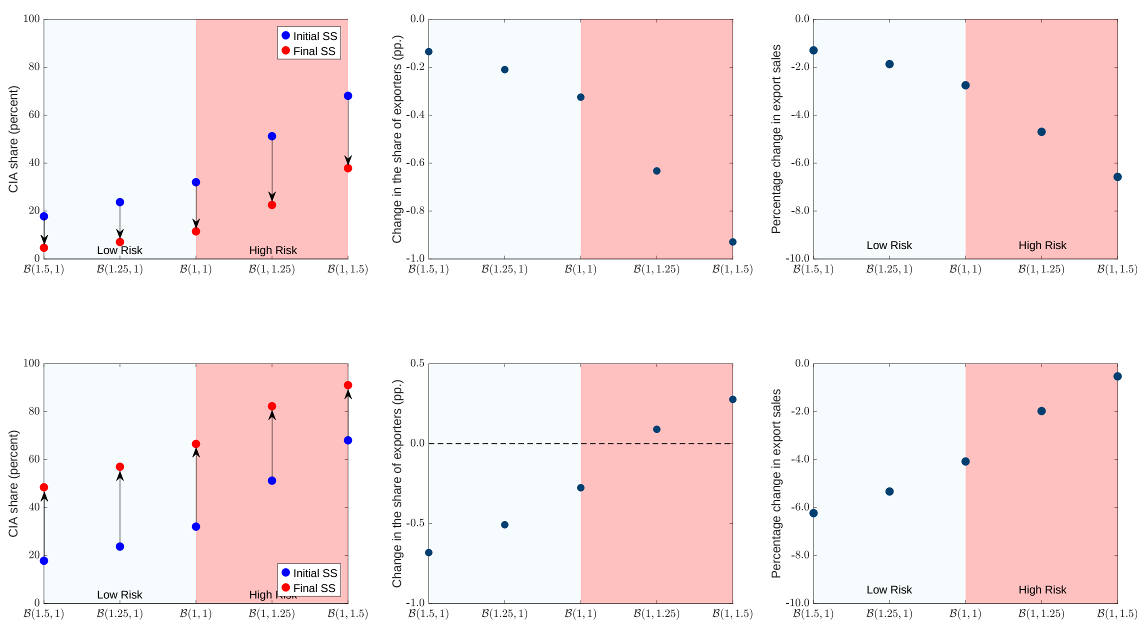


Figure 10: Counterparty risk and long run effects of increases in r_f and r_d.

Summing up the above results, we see that risky and safe destinations respond differently to financing shocks. In particular, exports to destinations with more counterparty risk tend to be more vulnerable to shocks that affect foreign financing costs as, in those cases, exporters depend more on CIA terms. Instead, exports to destinations with relatively little counterparty risk are more vulnerable to domestic funding shocks since exporters to those destinations rely particularly heavily on OA terms.

6.2 Transitional dynamics

We now investigate the transitional dynamics of exports and trade finance in safe and risky destinations in response to permanent increases in domestic and foreign interest rates.

Figure 11 shows the dynamics of aggregate exports, the share of exporters, and the share of CIA in response to an increase of 5pp in foreign financing costs, in risky (solid blue line) and safe (red dashed line) destinations. As we saw above, the share of exporters and exports to high-risk destinations decline more in the long run following a shock to r_f since exporters to these destinations rely more on CIA terms and, hence, on foreign funding. For the same reason, this is also true in the short run. However, studying transitional dynamics provides a new insight: exports and the share of exporters recover faster in low-risk destinations, implying that the difference between the response of aggregate export sales and the share of exporters in risky and safe economies widens over time. While in the short-run, the share of exporters drops by 0.65pp in the safe destination and 0.9pp in the risky destination (0.25pp higher impact), in the long run the share of exporters drops by only 0.2pp in the safe destination and by 0.6pp in the risky one (0.4pp higher impact). The same is true for aggregate exports: while in the short-run, exports drop by 5% in the safe destination and 7% in the risky destination, in the long run exports drop by only 2% in the safe destination and by 5% in the risky destination.

To understand the relative lack of recovery in exports to risky destinations, note that exporters to risky destinations are more likely to be matched with importers believed to be untrustworthy. In such cases, exporters will only export if they can use CIA terms. When CIA terms become more expensive, many of the relationships that rely on CIA terms dissolve. However, the firms that exit from exporting are relatively unlikely to find an importer who is trustworthy enough to make it profitable to export using OA terms. Thus, the share of exporters and export sales do not recover much over time. In contrast, in safe destinations, firms that initially exit due to an increase in the cost of CIA are more likely to find trustworthy importers over time and start exporting. As a result, aggregate export sales and the share of exporters recover more in the safe economy.

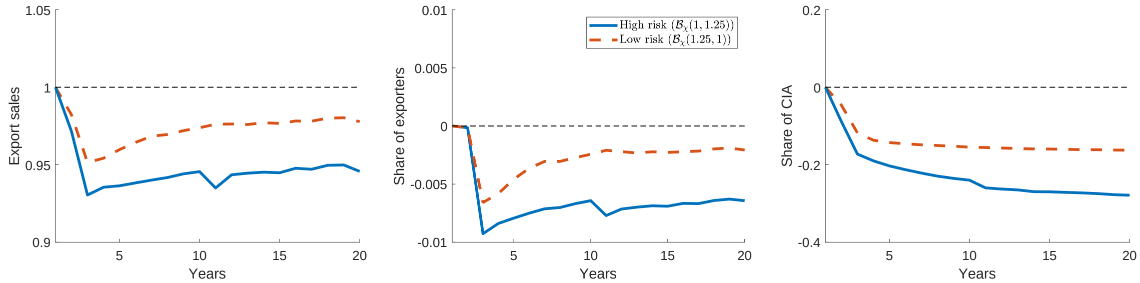


Figure 11: Counterparty risk and effects of a permanent increase in r_f of 5pp.

Figure 12 shows the dynamics of aggregate exports, the share of exporters, and the share of CIA in response to an increase of 5pp in domestic financing costs, in risky (solid blue line) and safe (dashed red line) destinations. We see that, as in the long run, the share of exports and aggregate exports decline more on impact in the safe destination. In this case, however, exports and the share of exporters recover faster in the high-risk destination, implying that the difference between the response of exports to high-risk and low-risk destinations widens over time. While in the short-run, the share of exporters drops by 0.14pp in the risky destination and 0.36pp in the risky destination (0.22pp higher impact), in the long run the share of exporters actually increases by 0.11pp in the risky destination and it decreases by 0.5pp in the safer one (0.61pp higher impact). The same is true for aggregate exports: while in the short-run, exports drop by 3% in the risky destination and 5% in the safer destination, in the long-run export sales drop by only 1.5% in the risky destination and by 5% in the safer destination.

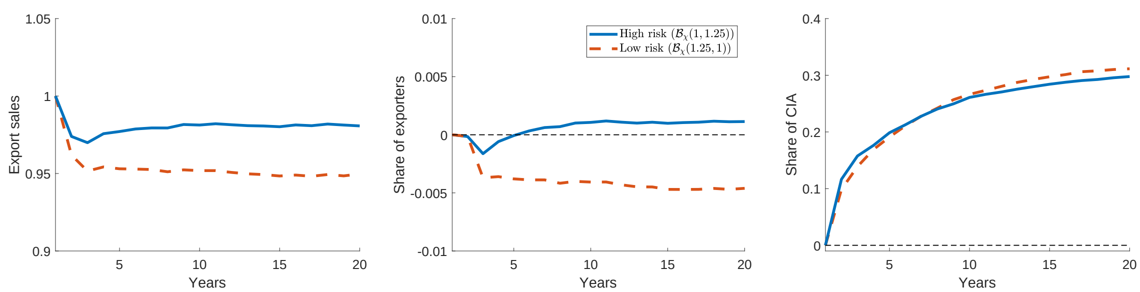


Figure 12: Counterparty risk and effects of a permanent increase in r_d of 5pp.

To understand why exports behave differently in both economies along the transition, note that an increase in r_d discourages entry using OA terms. In both economies, this implies that firms that are matched with trustworthy importers are less willing to start exporting (export for fewer values of λ). This, in turn, decreases non-exporters' option value for waiting for trustworthy importers. As a result, non-exporters become more willing to enter a match with untrustworthy importers and start exporting using CIA terms. These changes to export entry/exit policy have differential impacts on the safe and the risky economies. Since most of the importers are believed to be trustworthy in the safe destination, the change in entry/exit policy leads to a permanent decrease in exports. In contrast, in the risky destination, many importers are considered untrustworthy, so the change in entry policy leads to more entry and a gradual increase in the share of exporters.[38]

7 Conclusions

This paper investigates how learning and long-run relationships between exporters and importers affect trade finance and export decisions, and how these choices, in turn, affect aggregate export dynamics. Using detailed micro-level Chilean data, we document that (i) new exporters are more likely to use cash-in-advance arrangements and gradually switch to providing trade credit as they continue to export, (ii) these dynamics are more pronounced in risky destinations and among smaller firms, and (iii) firms that start to export using OA terms expand their foreign sales faster and are less likely to exit.

We then set up a small open economy model consistent with our empirical findings that features demand and counterparty risk. In the model, domestic exporters need to form a match with a foreign importer who may be untrustowrthy and/or unsuccessful in selling domestically produced varieties. Exporters have a choice to sell their goods on credit (OA terms) or demand advanced payment (CIA terms). The former is associated with lower financing costs but exposes exporters to risk. We calibrate the model to the data and show that it can match our main empirical findings.

In the final part of the paper, we use the model to investigate the response of the economy to aggregate shocks to foreign and domestic funding costs. We show that the response of domestic exporters is not only sluggish as learning and building relationships takes time but also asymmetric across positive and negative shocks. On the other hand, we find that the response to domestic funding shock is fast, with the economy quickly converging to its new steady state. Finally, we investigate how the extent of counterparty risk in the destination affects these results by varying the distribution of importers' trustworthiness.

[38]Export sales nevertheless drop since firms tend to export less when using CIA terms due to the higher cost of foreign external financing.

References

Acosta-Henao, M., S. Pratap and M. Taboada, “Four facts about relationship lending: The case of Chile 2012-2019,” *Journal of Corporate Finance* 80 (2023), 102415.

Ahn, J., “A Theory of Domestic and International Trade Finance,” IMF Working Paper No. 11/262, 2011.

Albornoz, F., H. F. C. Pardo, G. Corcos and E. Ornelas, “Sequential exporting,” *Journal of International Economics* 88 (2012), 17–31.

Alessandria, G., C. Arkolakis and K. J. Ruhl, “Firm dynamics and trade,” *Annual Review of Economics* 13 (2021a), 253–280.

Alessandria, G. and H. Choi, “Do falling iceberg costs explain recent US export growth?,” *Journal of International Economics* 94 (2014a), 311–325.

———, “Establishment heterogeneity, exporter dynamics, and the effects of trade liberalization,” *Journal of International Economics* 94 (2014b), 207–223.

Alessandria, G., H. Choi and K. J. Ruhl, “Trade adjustment dynamics and the welfare gains from trade,” *Journal of International Economics* 131 (2021b), 103458.

Allen, T., “Information frictions in trade,” *Econometrica* 82 (2014), 2041–2083.

Anderson, J. E. and E. Van Wincoop, “Trade costs,” *Journal of Economic Literature* 42 (2004), 691–751.

Antras, P., *Global production: Firms, contracts, and trade structure* (Princeton University Press, 2015).

Antras, P. and C. F. Foley, “Poultry in motion: a study of international trade finance practices,” *Journal of Political Economy* 123 (2015), 853–901.

Araujo, L., G. Mion and E. Ornelas, “Institutions and export dynamics,” *Journal of International Economics* 98 (2016), 2–20.

Arkolakis, C., “Market penetration costs and the new consumers margin in international trade,” *Journal of political economy* 118 (2010), 1151–1199.

Auboin, M., “Restoring trade finance during a period of financial crisis: stock-taking of recent initiatives,” (2009).

Bastos, P., D. A. Dias and O. A. Timoshenko, “Learning, prices and firm dynamics,” *Canadian Journal of Economics* 51 (2018), 1257–1311.

Benguria, F., A. Garcia-Marin and T. Schmidt-Eisenlohr, “Trade Credit and Relationships,” (2023).

Berman, N., A. Berthou and J. Héricourt, “Export dynamics and sales at home,” *Journal of International Economics* 96 (2015), 298–310.

Berman, N., V. Rebeyrol and V. Vicard, "Demand learning and firm dynamics: evidence from exporters," *Review of Economics and Statistics* 101 (2019), 91–106.

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

Djankov, S., C. Freund and C. S. Pham, "Trading on time," *The review of Economics and Statistics* 92 (2010), 166–173.

Domínguez, J. C., J. Eaton, M. Eslava and J. Tybout, "Search and learning in export markets: Evidence from interviews with Colombian exporters," *Review of International Economics* forthcoming (2023).

Eaton, J., M. Eslava, D. Jinkins, C. J. Krizan and J. R. Tybout, "A search and learning model of export dynamics," Technical Report, National Bureau of Economic Research, 2021.

Fitzgerald, D., S. Haller and Y. Yedid-Levi, "How exporters grow," *Review of Economic Studies* forthcoming (2023).

Garcia-Marin, A., S. Justel and T. Schmidt-Eisenlohr, "Trade credit, markups, and relationships," (2019).

Giannetti, M., M. Burkart and T. Ellingsen, "What you sell is what you lend? Explaining trade credit contracts," *The Review of Financial Studies* 24 (2011), 1261–1298.

Hoefele, A., T. Schmidt-Eisenlohr and Z. Yu, "Payment choice in international trade: Theory and evidence from cross-country firm-level data," *Canadian Journal of Economics* 49 (2016), 296–319.

Hummels, D. L. and G. Schaur, "Time as a trade barrier," *American Economic Review* 103 (2013), 2935–2959.

Kaufmann, D., A. Kraay and M. Mastruzzi, "The worldwide governance indicators: Methodology and analytical issues," *Hague Journal on the Rule of Law* 3 (2011), 220–246.

Kohn, D., F. Leibovici and M. Szkup, "Financial frictions and new exporter dynamics," *International Economic Review* 57 (2016), 453–486.

Lawless, M., "Firm export dynamics and the geography of trade," *Journal of International Economics* 77 (2009), 245–254.

Melitz, M. J., "The impact of trade on intra-industry reallocations and aggregate industry productivity," *Econometrica* 71 (2003), 1695–1725.

Niepmann, F. and T. Schmidt-Eisenlohr, "International trade, risk and the role of banks," *Journal of International Economics* 107 (2017a), 111–126.

———, "No guarantees, no trade: How banks affect export patterns," *Journal of International Economics* 108 (2017b), 338–350.

Petersen, M. A. and R. G. Rajan, "The benefits of lending relationships: Evidence from small business data," *The journal of finance* 49 (1994), 3–37.

Piveteau, P., "An empirical dynamic model of trade with consumer accumulation," *American Economic Journal: Microeconomics* 13 (2021), 23–63.

Rho, Y. and J. Rodrigue, "Firm-level investment and export dynamics," *International Economic Review* 57 (2016), 271–304.

Ruhl, K. J. and J. L. Willis, "New exporter dynamics," *International Economic Review* 58 (2017), 703–726.

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

Timoshenko, O. A., "Product switching in a model of learning," *Journal of International Economics* 95 (2015), 233–249.

Appendix

Table 1: Number of days with exports by year within exporting spell

Tenure	Mean	SD	p5	p10	p25	p50	p75	p90	p95	p99	Observations
1	3.46	6.38	1	1	1	2	3	6	10	27	57235
2	4.76	9.37	1	1	1	2	4	10	17	43	41077
3	6.55	11.82	1	1	1	3	7	15	24	57	22591
4	7.7	13.38	1	1	2	3	8	18	28	63	14690
5	8.98	15.28	1	1	2	4	9	21	32	74	10383
6	9.86	16.38	1	1	2	4	11	24	36	76	7654
7	11.55	18.83	1	1	2	5	12	27	42	89	5832
8	12.04	20.34	1	1	2	6	13	29	44	99	4409
9	10.91	16.04	1	1	2	5	12	27	40	72	3113
10	11.71	16.95	1	1	3	6	14	29	44	78	2328
11	12.47	17.73	1	1	3	6	15	33	47	84	1722
12	13.02	19.20	1	1	2	6	15	35	50	88	1223
13	13.53	18.89	1	1	3	6	16	36	51	87	806
14	10	12.25	1	2	3	5	12	24	34	65	304