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International trade finance and learning dynamics[☆], [☆☆]

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ABSTRACT

We study how relationship-specific learning affects the joint dynamics of exports and trade finance. Using micro-level Chilean data, we document that new exporters initially rely on cash-in-advance payments and gradually transition to providing trade credit as relationships mature, with faster transitions in riskier destinations and for less experienced firms. Motivated by this, we develop a general equilibrium trade model that integrates learning about foreign demand and counterparty risk together with firms' endogenous export and trade finance choices. We use the model to investigate the role of learning and risks in shaping export adjustments and quantify the impact of shocks to the cost of trade finance on aggregate exports. We find that the response to these shocks depends on the riskiness of the destination and is amplified by the disruption of long-term trading relationships.

1. Introduction

Credit arrangements between firms, or trade finance, play an important role in facilitating international transactions, given the inherent risks and costs associated with international trade. In particular, exporters and importers face the possibility that a foreign counterparty will not honor its payment or delivery obligations (Antras and Foley, 2015, Schmidt-Eisenlohr, 2013). They also face uncertainty about local tastes and market conditions, which can make demand for newly introduced products abroad highly unpredictable (Albornoz et al., 2012, Allen, 2014, Eaton et al., 2025). In addition, the time elapsed between shipment and settlement is typically longer in international trade than in domestic trade, increasing working capital requirements (Anderson and Van Wincoop, 2004, Kohn et al., 2016). Due to this combination of default risk, demand uncertainty, and liquidity needs, most firms rely on some form of trade finance (Auboin, 2009).

Existing work has mostly focused on characterizing the static trade-offs across trade finance instruments, but risks and financing needs are not static and instead evolve over time as trading relationships mature and exporters learn about the foreign demand

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for their products and the reliability of their counterparties.[1] Motivated by this observation, we study how learning about product demand and counterparty risk shapes the choice of trade finance, exporters' decisions, and aggregate trade flows. First, we document the joint dynamics of exports and trade finance, and show how they vary with destination- and firm-level characteristics. Second, we develop a general equilibrium quantitative trade model that combines learning about demand and counterparty risk (previously analyzed separately) with endogenous trade finance choices. Third, we calibrate the model using the empirically estimated joint evolution of exports and financing terms to separately identify the two learning processes. Finally, we use the model to quantify the aggregate effects of shocks to the cost of trade finance on exports, and the role of learning and risks in driving export dynamics. To the best of our knowledge, we are the first to quantify the aggregate effects of trade finance choices.

We start by documenting stylized facts on trade finance and presenting evidence on the role of relationship length and learning. We use transaction-level Chilean customs data covering the universe of exporting firms from 2005 to 2019. Open account (OA), in which the importer pays after shipment, is the dominant arrangement. For the average exporter, OA shipments account for nearly two-thirds of annual export value, compared with about one-third shipped cash-in-advance (CIA), in which the importer pays before shipment.[2] We find that reliance on CIA is higher among small and inexperienced exporters and among firms serving riskier destinations (proxied by a weaker rule of law index), suggesting that firms use CIA to limit counterparty risk. We also find that CIA is used more for differentiated than for non-differentiated products, a pattern that is consistent with exporters of differentiated goods having greater ability to impose financing terms that limit their exposure to non-payment while they learn about the trustworthiness of their foreign buyers.[3],[4]

We then characterize how trade finance and export volumes evolve within destination-product export spells. Both the share of export value conducted on OA terms and export volumes rise with spell duration: over the first five years, the OA share increases by about 2 percentage points and export volumes increase by roughly 26.5 percent. However, these averages hide substantial heterogeneity. The shift toward OA is markedly stronger in riskier and financially less-developed destinations and among small and inexperienced firms. Export growth is also more responsive to spell duration in riskier destinations, in less financially developed markets, and among experienced exporters. Taken together, these patterns are consistent with a learning mechanism in which firms gradually update beliefs about counterparty trustworthiness over time, with more scope for learning early in the relationship. Moreover, we show that initial trade finance choices are also predictive of subsequent export growth. Over a 5-year horizon, export volumes rise by 27 percent for exporters that start a spell with at least a 50 percent OA share, versus 22 percent for exporters that start with lower OA reliance.[5]

To account for these empirical patterns, we develop a dynamic model of international trade with heterogeneous firms in a small open economy, in the spirit of Melitz (2003). A continuum of monopolistically competitive firms produces differentiated varieties that can be sold domestically and abroad, with foreign sales subject to fixed and variable export costs. Relative to the standard framework, our model adds two key ingredients. First, exporting is subject to both demand and counterparty (default) risks that exporters learn about over the course of an export spell. Second, exporters choose the method of payment for each shipment to manage these risks. 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 be untrustworthy and fail to pay after receiving the goods. To model demand risk, we follow Albornoz et al. (2012) and Berman et al. (2019) and assume that demand abroad is uncertain, with some products turning out to be unpopular and low demand. Thus, our model combines two sources of risk that have been previously investigated in isolation.

This model highlights a new channel through which trade finance facilitates trade: it allows entrants to experiment and learn while limiting exposure to risk. In equilibrium, new exporters optimally start with higher CIA to reduce their risk exposure while learning about local demand and about their counterparties' trustworthiness through "passive learning".[6] As information accumulates, exporters gradually switch toward OA, which raises export volumes but increases direct exposure to default. Since using OA terms exposes exporters directly to counterparty risk, learning about counterparty trustworthiness is faster when using OA, which further expands sales. A key implication is that even if CIA is used less frequently than OA, it can be crucial for lowering export entry barriers: absent CIA, some firms would not export because initial OA exposure would be too risky.

We calibrate the model to Chilean micro data and show that it reproduces the empirical patterns we report. As in the data, new exporters are more likely to use CIA terms and then gradually transition toward OA. The model also matches both export quantity dynamics and the differential export growth between firms that start with high versus low OA use well. These dynamics are tightly linked to the learning parameters, with learning about demand primarily governing export volume growth, whereas learning about counterparty risk mainly affecting the evolution of payment terms. Quantitatively, learning is an important driver of export dynamics

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

[2] Bank-intermediated transactions account for only 4 percent of export value and, thus, we focus on OA and CIA throughout the paper.

[3] These patterns are consistent with earlier findings; see, for example, Ahn (2011), Ahn (2021), Antras and Foley (2015), and Schmidt-Eisenlohr (2013).

[4] Firms with close ties to institutional creditors (banks) may have better access to other sources of financing that affect payment terms (Acosta-Henao et al., 2023, Petersen and Rajan, 1994). We abstract from this channel.

[5] While Benguria et al. (2023) documents similar patterns in trade finance dynamics, our contribution is to study these dynamics jointly with export volume growth.

[6] Even though when using CIA terms firms do not expose themselves to counterparty risk, they can still learn the nature of and the extent of importers' business, their treatment of 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).

and generates an endogenous decline in effective trade costs over time consistent with a reduction in iceberg costs, as emphasized by Ruhl and Willis (2017), Alessandria et al. (2021a,b).

We use the calibrated model to study aggregate trade dynamics following shocks to foreign and domestic financing costs, focusing on how endogenous trade finance choices and learning about demand and counterparty risk shape the response of exports. Following a permanent 2.5 percentage point increase in the foreign financing cost, aggregate export sales and exporter entry fall sharply on impact, followed by a partial recovery as firms gradually transition toward OA and slowly rebuild their relationships. We find that responses to financing shocks are highly asymmetric. A permanent decrease of the same magnitude in the foreign financing cost induces additional entry and an initial increase in exports, with gains that grow over time because relationship-specific learning is gradual. In contrast, a comparable increase in domestic financing costs generates more muted short-run effects, as exporters substitute toward CIA rather than exiting from exporting, which dampens the initial adjustment. The shock to domestic financing costs also produces little subsequent recovery because reduced OA use limits learning and slows the rebuilding of relationships. Overall, these asymmetries underscore the importance of learning and long-term relationships for the transmission of financing shocks to aggregate exports.

Finally, we use the model as a laboratory to study (i) how destination-level counterparty risk shapes the export response to shocks to the cost of trade finance, and (ii) the role of learning about demand and counterparty risk in driving the response of exports. In the first exercise, we show that risky destinations (that is, those where exporters are less likely to match with a trustworthy importer) respond differently from safe destinations. Exports to risky destinations are more exposed to shocks to foreign financing costs because exporters serving those markets rely more on CIA terms. By contrast, exports to relatively safe destinations are more sensitive to domestic financing cost shocks, since exporters there rely more heavily on OA financing.

In the second exercise, we study how learning about counterparty and demand risks shapes export dynamics. To do so, we analyze the effects of shocks to domestic and foreign funding costs in counterfactual economies that abstract from counterparty risk and demand risk, respectively. We find that the presence of these two types of risk increases the persistence in exports dynamics and dampens their response to shocks. The intuition is that, under two-dimensional risk, the value of maintaining an existing relationship is higher because finding a new match with sufficiently low counterparty and demand risk is difficult. As a result, firms are less likely to terminate current relationships following a negative shock.

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 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 and 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. 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. Furthermore, they do not attempt to quantify the impact of trade finance in driving aggregate export dynamics, as we do.

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 these papers in several aspects. First, empirically, our focus is on the joint determination of trade finance and exports. Second, to explain our findings, we develop a small open economy model that features both learning about counterparty risk and demand risk, combining two popular learning explanations for the observed exporters' dynamics. Our model emphasizes two novel dynamic trade-offs associated with the choice of trade finance (since learning about counterparty risk is faster under OA terms) and the entry decision (since a firm can choose whether to enter into an exporting relationship or continue to search for a different trade partner).[7] Finally, we quantify the role of trade finance in shaping the aggregate response of exports following shocks to foreign and domestic external financing costs.

Our paper also contributes 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.[8] Several mechanisms have 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., 2024, Piveteau, 2021, and Arkolakis, 2010). We focus instead on 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.

Other papers have studied 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., 2025, and Timoshenko, 2015). In contrast, 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.

[7] Antras and Foley (2015) and Benguria et al. (2023) abstract from entry decisions and model trade financing decisions as static choices.

[8] 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.

Table 1
Relative use of CIA and OA.

	All	Product type		Financial dev.		Destination risk		Size		Experience	
		Diff.	Non-diff.	Low	High	Risky	Safe	Small	Large	Low	High
OA	0.63	0.62	0.74	0.65	0.64	0.63	0.72	0.55	0.72	0.57	0.81
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CIA	0.33	0.34	0.21	0.32	0.31	0.34	0.22	0.42	0.23	0.39	0.14
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firms	3354	2,794	1496	2689	2441	2991	1818	1677	1677	2474	880

Notes: Entries report the annual value share of transactions conducted using cash-in-advance (CIA), open account (OA), or bank credit (BC), relative to total exports at the firm–destination–product level. Shares add up to 1, so BC is omitted. Product types classified following Rauch (1999) classification into non-differentiated (commodities and standardized) and differentiated goods. Destinations classified as high (low) financial development based on domestic credit-to-GDP ratios and as safe (risky) based on Law and Order index. A firm can have spells in both categories. Firms classified as large if they employ more than 50 workers and as experienced if they export to at least five destinations. Standard errors reported in parentheses.

2. Empirical evidence

In this section, we use data from Chile to document a series of stylized facts regarding the cross-section and dynamics of trade finance arrangements, export volume, and exit rates. In Section 4, we use these moments to discipline a general equilibrium quantitative model with heterogeneous firms. Our primary data are drawn from the customs export declarations collected by the National Customs Service. The data records all export transactions by firms, including information on prices, quantities, destinations, and financing terms for each transaction. Appendix A.1 describes the data cleaning procedure and presents descriptive statistics.[9]

2.1. Relative use of trade finance

Table 1 reports the average relative use of CIA terms and OA terms by firms in our sample.[10] 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 63% of the annual export value compared to 33% accounted by CIA. The prominent role of OA as a method of payment has been noted in earlier work, including Antras and Foley (2015) and Benguria et al. (2023).

Splitting the sample into differentiated and non-differentiated goods, we find a relatively higher share of CIA terms for exporters that produce differentiated products. Since CIA terms shift the financing burden to the importer, this pattern is consistent with the idea that exporters of differentiated products, facing lower substitutability and greater bargaining power, are better able to impose financing terms that protect them from counterparty risk as they learn about the trustworthiness of their foreign counterparts. This evidence aligns closely with the contractual friction emphasized in the theoretical framework in this paper and provides empirical motivation for the assumption that exporters may be able to make take-it-or-leave-it offers regarding trade finance arrangements.

We also consider how the use of trade finance arrangements varies with the characteristics of the destination and the firm. Table 1 suggests that on average exporters to risky destinations tend to rely more on CIA terms. This result is intuitive, since high risk captures the difficulty of enforcing contracts in those locations and the relative ease with which the importer can renege on its promise. 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 are likely to cancel each other out. Regarding firm characteristics, we observe 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 42% compared to only 23% for large exporters. Similarly, the share of CIA terms for an inexperienced exporter is 39% while it is only 14% for an experienced one.

2.2. Dynamics of trade finance and quantities

We next turn to the analysis of trade finance and export volume dynamics, focusing on whether exporters switch from CIA to OA terms over the course of an export spell and how these dynamics jointly evolve with export volumes. We analyze the dynamics of

[9] 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.

[10] For expositional clarity, we omit the relative use of bank credit, so the shares add up to less than 1. We compute the share of trade finance as the annual value of transactions using a given payment method (CIA and OA) divided by the annual value of exports for each firm-destination-product-year. We then average these values for each firm and report the coefficient C and standard error of a regression $\omega_i = C + \epsilon_i, \quad \omega_i \in \{CIA, OA\}$ across firms. Results are robust if we compute shares based on the number of transactions instead of the value.

trade finance and export volumes over the number of days with trade within a spell.[11] Let i denote an exporting firm, j a destination country, and k a product. We estimate:

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

where w_n^{ijk} is either the share of OA or the logarithm of exported volumes 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-product-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^{ijk} is an indicator variable equal to 1 for the spells that we observe in the first year of the sample and zero otherwise. Similarly, right-censored^{ijk} is an indicator variable equal to 1 for spells in the last year of the sample and zero otherwise. Finally, ε_n^{ijk} is idiosyncratic noise.

Table 2, Panel (a), presents the results for the evolution of OA. In Column 1, 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 during a 5-year export spell, on average, we observe shipments on 31.4 separate days, this translates into an increase in the share of OA transactions by 2.0% over the first five years of the spell.[12] We then investigate how the characteristics of the firm and destination markets affect the evolution of the financing terms and export volumes. To do so, we augment Eq. (1) and interact the length of the trading relationship with indicators for destinations with high financial development and strong rule of law, and indicators for large and experienced firms.[13] In Columns 2 to 6, we observe that the dynamics of OA are substantially more pronounced in risky and less financially developed economies, and for more inexperienced exporters. On average, the share of OA increases by 3.1% (3.4%) over the first 5 years of exporting to risky (financially underdeveloped) destinations, while it increases by only 0.8% (1.1%) for safe (financially developed) destinations. Additionally, the share of OA increases by 3.8% over the first five years of an average export spell for inexperienced firms, while it only increases by 1.9% for experienced ones.[14] These results suggest that learning plays an important role in shaping trade finance dynamics, especially in high-risk countries and for less experienced exporters, where the use of OA as a payment method increases significantly more along the export spell than in safer countries or for more experienced exporters.

Table 2, Panel (b), shows the elasticity of export volumes with respect to the number of transactions. We find that quantities grow rapidly along an export period, in line with earlier findings in the literature (see, for example, Ruhl and Willis, 2017): the positive and significant coefficient in Column 1 implies that, on average, the export volume increases by approximately 26.5 percent over a five-year export period. Columns 2 to 6 show that the export elasticity is lower in safer destinations (i.e., high rule of law). When we control for safety, our results suggest that export spells 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. We also find an economically and statistically significant role for experience in explaining the dynamics of volumes over export spells, but not for the firm's size – a proxy for productivity. This suggests that firms with exporting "know-how" are able to expand their exports faster over time than firms with less experience operating in foreign markets.[15,16] The difference in the rates of increase of trade finance and export volumes along an export spell suggests that they might be driven by different forces. In the theory section, we incorporate two mechanisms – learning about local demand and importers' trustworthiness – to explain the joint evolution of export volumes and financing terms.

2.3. Initial provision of trade finance, exports, and exit rates

We now investigate how the credit arrangement used at the onset of an export spell is correlated with subsequent exported volumes and exit rates. To do so, we allow the relationship between the number of transactions and export volumes to vary with the initial provision of OA. Specifically, we define a spell to have high (low) initial use of OA if 50 percent or more (less than 50 percent) of export sales are financed through OA in the first year of an export spell, and we estimate:

$$\ln Q_n^{ijk} = \beta^{high\,OA} \log n^{ijk} \times OA_0^{ijk} + \beta^{low\,OA} \log n^{ijk} \times \left(1 - OA_0^{ijk}\right) + c^{ijk} + d_t^j + e_t^{ik} + \varepsilon_n^{ijk}, \tag{2}$$

where OA_0^{ijk} is an indicator for whether the spell has a high initial share of OA. Other terms are defined as in Eq. (1). Table 3 reports the results.

[11] Following Fitzgerald et al. (2024) an export 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. As Benguria et al. (2023), we aggregate all transactions that occur on a given day. We refer to the nth day during an export spell as the nth transaction.

[12] See the Appendix, Table A.2 for descriptive statistics on trading days for Chilean exporters.

[13] Appendix A.1.1 presents the raw correlation between these variables.

[14] 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.

[15] We estimate alternative specifications including destination-product-year fixed effects instead of destination-year fixed effects. The results are qualitatively similar to the baseline specification although coefficients are estimated with lower precision. These results are reported in the Online Appendix.

[16] Importers' liquidity constraints might be a driver of the joint dynamics for trade finance and volume; however, to the extent that these frictions are determined at the destination-level (or product-destination level), this source of dynamics should be absorbed by the destination–time (product-destination-time) fixed effects.

Table 2
Dynamics of trade finance and export volumes.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Dependent variable share of open account in exports						
Transactions	0.0059***	0.0099***	0.0091***	0.0059***	0.0111***	0.0147***
	(0.0004)	(0.0007)	(0.0006)	(0.0020)	(0.0016)	(0.0024)
Transactions × Fin Dev		−0.0066***				−0.0028**
		(0.0008)				(0.0012)
Transactions × Safe			−0.0068***			−0.0051***
			(0.0008)			(0.0011)
Transactions × Large				0.0000		0.0004
				(0.0021)		(0.0021)
Transactions × Experience					−0.0055***	−0.0053***
					(0.0017)	(0.0017)
Observations	1,978,600	1,941,024	1,953,364	1,978,600	1,978,600	1,933,911
Distinct Spells	56,848	54,868	55,103	56,848	56,848	54,318
R^2	0.6487	0.6463	0.6483	0.6487	0.6487	0.6460
Panel (b): Dependent variable logarithm of exported volumes						
Transactions	0.0769***	0.0769***	0.0844***	0.0702***	0.0221***	0.0274***
	(0.0021)	(0.0034)	(0.0029)	(0.0078)	(0.0081)	(0.0104)
Transactions × Fin Dev		0.0001				0.0173***
		(0.0040)				(0.0055)
Transactions × Safe			−0.0149***			−0.0269***
			(0.0038)			(0.0053)
Transactions × Large				0.0071		−0.0045
				(0.0081)		(0.0084)
Transactions × Experience					0.0582***	0.0596***
					(0.0084)	(0.0087)
Observations	1,974,992	1,937,450	1,949,779	1,974,992	1,974,992	1,930,337
Distinct Spells	56,577	54,603	54,834	56,577	56,577	54,053
R^2	0.8705	0.8697	0.8698	0.8705	0.8705	0.8695

Note: The table reports estimates from specification (1) extended to include $\beta^z \log n^{ijk} \times z^{ijk}$, where the vector z^{ijk} includes interaction terms capturing destination and firm characteristics. See notes to Table 1 for definitions of the variables. The estimation period is 2005–2019. Robust standard errors reported in parentheses. *** denotes significance at 1% level.

Table 3
Initial trade finance provision and dynamic of exported-quantities.

	$X = 50\%$	$X = 90\%$
$(OA < X) \times$ Transactions	0.0678***	0.0675***
	(0.0032)	(0.0029)
$(OA \geq X) \times$ Transactions	0.0784***	0.0793***
	(0.0022)	(0.0022)
P-value: Test of coefficient equality		
$(OA < X) \times$ Transactions $= (OA \geq X) \times$ Transactions	0.0002	0.0000
R^2	0.8705	0.8705

Note: The table reports estimates from specification (2). The estimation period is 2005–2019, observations 1,974,992, and distinct spells 56,577. Robust standard errors reported in parentheses. *** denotes significance at 1% level.

The elasticity of exports with respect to the number of transactions is approximately 15 percent higher (1.1pp.) for export spells that begin financing at least 50 percent of their exports with OA terms. That is, export volumes increase by 27 percent over a five-year period for exporters starting with a high share of OA terms, while only by 22 percent for those with a lower reliance on OA.[17] The results are similar when using instead a threshold of 90 percent of OA terms.

We next quantify the relationship between export survival and the initial choice of payment method. We estimate a linear probability model for export exit at the firm–destination–product–year level. Let $Exit_t^{ijk}$ be an indicator equal to one if firm i exports product k to destination j in year $t-1$ but not in year t, and zero otherwise. We estimate

$$Exit_t^{ijk} = \beta^{exit,OA}\, OA_0^{ijk} + \beta^{exit,n} \log n_t^{ijk} + \beta^{exit,OA\times n} \log n_t^{ijk} \times OA_0^{ijk} + d_t^j + e_t^{ik} + \varepsilon_t^{ijk}, \tag{3}$$

[17] Exporters starting with a high share of OA (CIA) trade on average 32.5 (25.4) days in 5 years.

Table 4
Dynamics of exit rates and initial trade finance provision.

	$X = 50\%$		$X = 90\%$	
	(1)	(2)	(3)	(4)
$(OA \geq X)$	−0.0387*** (0.0048)		−0.0021 (0.0044)	
Transactions	−0.1990*** (0.0033)	0.3908*** (0.0063)	−0.1885*** (0.0030)	0.3839*** (0.0060)
$(OA \geq X) \times$ Transactions	0.0162*** (0.0040)	−0.0115*** (0.0040)	0.0033 (0.0028)	−0.0033 (0.0036)
Firm-dest-prod FE	No	Yes	No	Yes
Observations	243,620	211,017	243,620	211,017
R^2	0.5362	0.6970	0.5359	0.6970

Note: The table reports estimates from specification (3). The estimation period is 2005–2019. Robust standard errors reported in parentheses. *** denotes significance at 1% level.

where n_t^{ijk} denotes the cumulative number of transactions up-to year t. The coefficient $\beta^{exit,OA}$ captures the difference in exit probabilities between export spells that begin with high versus low initial reliance on OA terms. The coefficient $\beta^{exit,n}$ measures how exit probabilities evolve with transaction intensity within the year, while $\beta^{exit,OA\times n}$ captures how the exit effect of initial OA provision varies with relationship maturity. A positive interaction coefficient implies that the exit-reducing effect of early OA provision attenuates as the trading relationship deepens. We estimate specifications with and without firm–destination–product fixed effects. The former allows us to examine whether OA affects exits within spells, while the latter captures how selection across destinations is associated with firms' decisions to provide OA.

As shown in Table 4, Column 1, export relationships that begin with a share of OA greater than 50% are approximately 3.9 percentage points less likely to exit than those with a lower use of OA at the beginning of the relationship, although this effect dissipates as the number of transactions increases. The coefficient associated with the number of transactions implies that the exit rate is initially high and then gradually decreases over time, consistent with the literature on exporter dynamics (see, for example, Kohn et al., 2016 or Ruhl and Willis, 2017). The previous results are driven by the selection of the firms in the export spells. Once we control for firm-destination-product fixed effects, Column 2, shows that the exit probability is increasing on the number of transactions within export spells. The results on the role of the number of transactions are similar when using instead a threshold of 90 percent of OA terms (Columns 3 and 4), but the role of the initial provision of OA becomes non-significant and quantitatively smaller.

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 that produce differentiated varieties that are owned by the consumer. Firms can sell their production in domestic and foreign markets, with exports subject to 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.

This standard 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.[18] While both risks have been individually studied in earlier literature, our contribution is modeling them jointly and analyzing their relevance for exporters' extensive and intensive margin decisions. 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 consumer

There is a representative domestic 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

$$C = \left\{ \int_0^1 \left[y_d(i) \right]^{\frac{\sigma-1}{\sigma}} d\omega + y_m^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

[18] Throughout, we abstract from the possibility that exporters may breach their contractual obligations. Although our choice is mostly motivated to gain tractability, this assumption can also be introduced by the fact that exporters are mainly large firms, so we assume that the reputational loss of defaulting is larger than the gains of defaulting by itself. In addition, Chile is considered a safe country where contractual arrangements are relatively well enforced.

where $y_d(i)$ denotes the quantity of domestic variety produced by the domestic firm i and y_m is the imported bundle of foreign varieties.[19]

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.

For simplicity, we assume that in each period the representative consumer spends its income across domestic and foreign varieties of goods. 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. The domestic representative consumer maximizes consumption specified in (4) subject to the budget constraint,

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

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

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

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

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_f, is given by

$$C_f = \left\{ \int_0^1 \left(y_d^f(i)\right)^{\frac{\sigma-1}{\sigma}} di + \int u(i) \left[y_f(i)\right]^{\frac{\sigma-1}{\sigma}} di \right\}^{\frac{\sigma}{\sigma-1}},$$

where $y_d^f(i)$ denotes her consumption of a foreign domestic variety and $y_f(i)$ denotes her consumption of an imported variety exported from the domestic economy. Finally, $u(i)$ are demand shifters that can take the value of 0 or 1 and are not observed 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

$$y_f(i) = (p_f)^{-\sigma} C_f, \tag{8}$$

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

3.2. Domestic firms

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

Technology Each firm produces a unique variety using linear production technology

$$y = zn,$$

where z is the productivity of a firm 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 $\log(z) \sim N(\mu_z, \sigma_z^2)$, with μ_z chosen so that $\mathbb{E}[z] = 1$.

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 Eq. (6). The foreign demand for a variety produced by the firm i is initially uncertain. In each period, the foreign demand of the firm is given by Eq. (8) or 0 depending on the value taken by the demand shifter, $u(i)$.

[19] 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.

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, it is given by Eq. (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 Eq. (8)) with probability $\delta \in (0, 1)$ and equal to 0 otherwise (i.e., $u(i) = 0$). Unsold goods perish, that is, they do not provide value to any party involved. We denote by 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 counterparty risk. To export, a firm must match with an importer in a foreign country. There are 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 $\mu \in (0, 1)$.[20] We denote by χ an exporter's belief that the counterparty in the foreign economy is trustworthy. 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.[21] Demand and counterparty risks are independent. Moreover, exporters observe whether goods are sold or not and thus can determine whether the importer stole the shipment.

Export shipping lags and working capital Motivated by the literature that documents substantial shipping lags associated with international trade (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_d. Instead, if payment for exports is made in advance (i.e., before shipment), then an importer borrows to finance the advanced payment at the foreign interest rate r_f. We assume that $r_f > r_d$, an assumption that will allow us later to match the share of exports sold on credit observed in our data.[22] The inventory cost is high when payments are not frequent. This can be particularly true when searching and matching with trading partners takes time. There is no delay associated with 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, CIA and OA.

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 CIA while the second one corresponds to OA.

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

$$\gamma^{OA}(\chi, \lambda) = \left[\chi + \mu(1-\chi)\right]\left[\lambda + \delta(1-\lambda)\right]. \tag{9}$$

The exporter's problem is to choose payment to the importer s and sales volume y to solve

$$\max_{s,y} \frac{\gamma^{OA}(\chi, \lambda)}{1 + r_d}\xi s - \frac{\tau w}{z} y - wF, \tag{10}$$

[20] 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.

[21] 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.

[22] This assumption can be motivated by the observation that in the case of Chilean data, exporters are larger than importers, so exporters would be expected to have access to better financing terms than importers. In addition exporters often are able to use account receivables as collateral for the loans. Furthermore, the difference between r_f and r_d can be further motivated by the fact that CIA payments represent the foreign funding costs that importers bear and the inventory cost of holding cash-in-advance.

$$\text{s.t. } [\lambda + \delta(1-\lambda)][p(y)\,y - s] \geq 0, \tag{11}$$

where ξ is the real exchange rate and $p(y)$ is the price implied by the foreign demand (Eq. (8)) as a function of y when the product sells (i.e., $u = 1$). Eq. (10) 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_d, since the payment is received at the end of the period. Eq. (11) 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 the importer is supposed to make to the exporter. Note that this constraint implies that if an importer is unsuccessful in selling the contract, then it will not pay the exporter.

Optimal contract under CIA terms Consider the optimal contract when an exporter sells its goods using CIA arrangements. In this case, since the exporter receives payment before shipping the goods, the exporter is not exposed to demand or counterparty risk. However, the demand risk is now faced directly by the importer, who will require compensation for it. Let

$$\gamma^{CIA}(\lambda) = \lambda + \delta(1-\lambda). \tag{12}$$

Then, the exporter's problem is given by

$$\max_{s,y} \xi s - \frac{\tau w}{z} y - wF, \tag{13}$$

$$\text{s.t. } \gamma^{CIA}(\lambda)p(y)y - (1+r_f)s \geq 0. \tag{14}$$

Eq. (13) 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. Eq. (14) 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_f 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. In our model, learning introduces a dynamic aspect to the choice of financing terms. This contrasts to Antras and Foley (2015) and Benguria et al. (2023), where the choices of financing terms are static.

Consider first learning about demand. In 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 updates its beliefs upward, 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.

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} denote 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 them. However, we assume that, with probability μ, an untrustworthy importer escapes with unsold goods. Instead, a trustworthy importer always reports the sales and returns the unsold goods to the exporter.[23]

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*.[24] In particular, we assume that when an exporter interacts with an untrustworthy importer using CIA terms, it fails to detect 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

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

[23] As with many assumptions of our model, this one is also not essential, and 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 our numerical experiments show that exporters always exit the market once they learn that the good is unpopular, the exact nature of learning in this case is unlikely to affect our results.

[24] This is to differentiate it from the "active learning" where an exporter directly exposes itself to counterparty risk using OA terms.

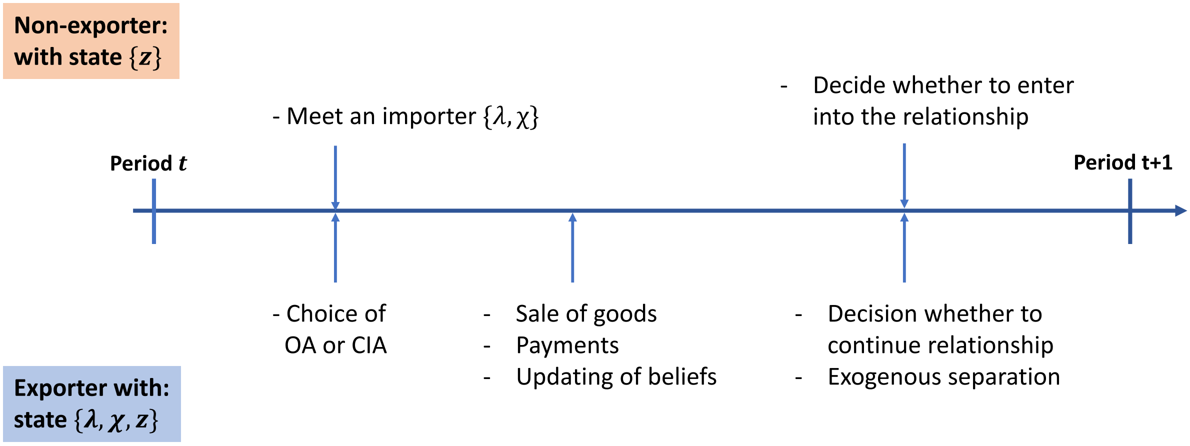


Fig. 1. Timeline.

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.[25] In addition, the exporter may also observe how high labor turnover is (which might be informative about the importer's attitude toward 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 relationship with an importer, it will start exporting in the next period.[26]

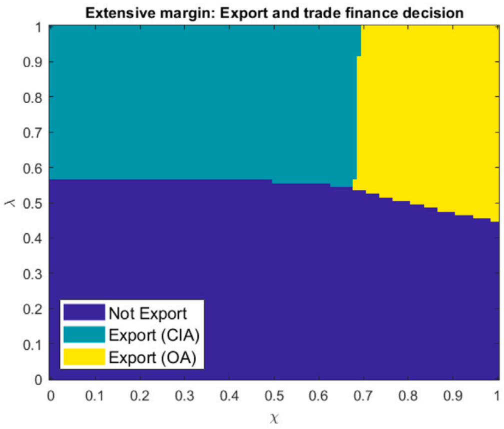
At the end of each period, exporters update their beliefs and based on their updated beliefs decide whether to continue exporting in the next period. In addition, relationships are subject to exogenous separation shocks. That is, with probability $1 - \kappa \in (0, 1)$, a relationship dissolves (equivalently, relationships survive with probability κ). 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.[27]

Fig. 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.

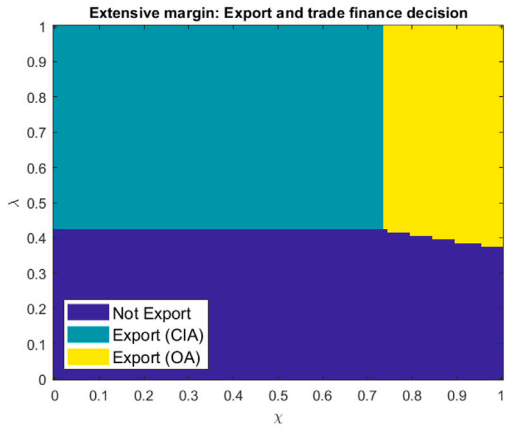
[25] Giannetti et al. (2011) points out that the concern whether the customer is a fictitious firm is a common concern among firms extending trade credit, particularly among those firms that sell highly liquid products.

[26] 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.

[27] This assumption ensures 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 $\{\lambda, \chi\} = \{1, 1\}$.



(a) Optimal decisions



(b) Static decisions

Fig. 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.

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

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

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

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

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

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

Thus, we see that the exporter's decision 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 $\{\lambda, \chi\}$.

To better understand firms' incentives to start exporting and the dynamic considerations involved, in Fig. 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.

Table 5
Calibrated parameters.

Parameter	Value	Target moment	Data	Model
β	0.9	Pre-assigned		
σ	4	Pre-assigned		
r_d	0	Pre-assigned		
τ	4.478	Average export intensity	0.20	0.20
F	0.140	Share of exporters	0.10	0.10
κ	0.950	Exporters' exit rate	0.13	0.13
$\sigma_{log(z)}$	0.095	Exporters' labor premium	4.21	4.20
$r_f - r_d$	0.032	Share of CIA among exporters	0.34	0.35
		Learning and risks		
δ	0.544	New exporters 5-year increase in export quantity	0.27	0.27
μ	0.881	5-year differential increase in export quantity (OA - CIA)	0.05	0.05
μ_{CIA}	0.936	New exporters 5-year increase in OA share	0.02	0.02
		Initial Beliefs Distribution		
α_b	1.234	The conditional size premium of new exporters using CIA	−0.02	−0.02
β_b	0.977	The conditional size premium of exporters using CIA	−0.10	−0.05

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 trustworthiness 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_d and r_f 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: (i) Policy and value functions solve the problem of firms taken as given demand functions and aggregate prices; (ii) Policy functions solve the representative consumer's problem taking as given firms' decisions; (iii) The labor market clears: $\int_S \left[n_d(s) + e(s)\left(n_f(s) + F\right)\right] d\nu = 1$; (iv) The domestic final goods market clears: $C = w + \Pi$; and (v) Measure ν is stationary.

4. Calibration

In this section, we calibrate the model to match key features of Chilean micro data and examine its implications for the dynamics of sales and trade finance, and other non-targeted moments. In the following section, we quantitatively investigate the roles of risk and learning in driving trade finance and export dynamics.

Table 5 reports the calibrated parameters. We use standard values for the discount rate, $\beta = 0.9$, and the elasticity of substitution, $\sigma = 4$. We also normalize the domestic interest rate to zero, $r_d = 0$.[28] 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 $\sigma_{log(z)}$ (to be estimated) and, for each choice $\sigma_{log(z)}$, we normalize the mean of the firms' productivity distribution to be equal to 1. The remaining parameters are chosen to match key cross-sectional and dynamic data moments.

We follow much of the quantitative trade literature (see, for example, Alessandria and Choi, 2014 or Ruhl and Willis, 2017), in choosing $\{\tau, F, \kappa, \sigma_{\log(z)}\}$ to match (i) the average export intensity, (ii) the share of firms in the economy that export, (iii) the exit rate of exporters' from the foreign market, and (iv) the exporters' size premium captured by the number of employees.[29]

The next set of paramaters, $\{r_f - r, \delta, \mu, \mu_{CIA}\}$, is 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 export spells, (iii) the difference in average increase in export sales from period 1 to period 6 of export 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 export spells.[30]

28 The results do not depend on the choice of r_d. See the Online Appendix for more details.

29 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 average across years. We compute the exit rate of exporters for each year of the export 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.

30 We compute the average share of CIA by calculating first the share of exported value using OA and CIA terms (thus, ignoring bank intermediation 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 export 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 exports spells in the data according to their use of trade finance terms in the first year of spells. In particular, if the

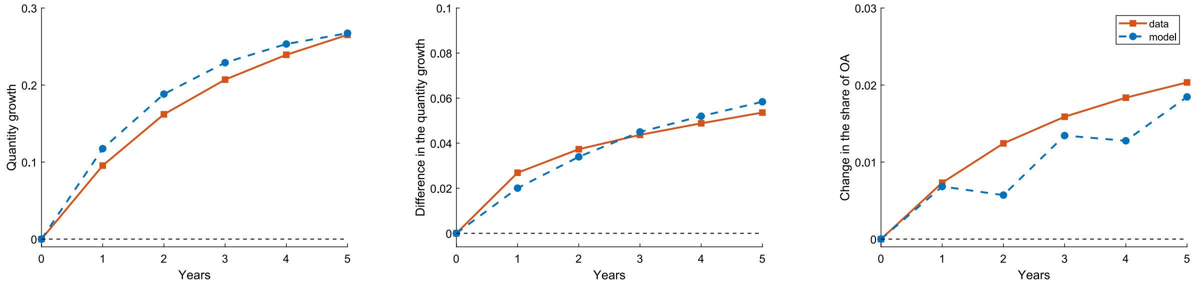


Fig. 3. Trade finance and export dynamics.

Table 6
Open account persistence.

	Data	Model
OA_{t-1}	0.72***	0.76***
	(0.003)	(0.003)
Years	0.008***	0.005***
	(0.001)	(0.001)
Observations	177,991	447,612
R^2	0.53	0.94

Note: The table reports the coefficients from regressing the share of OA in its own lag and the log of the number of years a relationship lasts. Robust standard errors reported in parentheses. *** denotes significance at 1% level.

Finally, to calibrate the initial beliefs distributions, we assume that the initial beliefs about demand and counterparty risks are drawn from identical beta distributions. More precisely, we assume that the initial beliefs about demand and counterparty trustworthiness are drawn from a Beta distribution with parameters α_b and β_b (which we denote by $\mathcal{B}(\alpha_b, \beta_b)$). This leaves us with two shape parameters of the Beta distribution to calibrate. We target the conditional size premia of new exporters that use CIA and of exporters that use predominantly CIA, obtained from regressing firms' log-size (measured in the number of employees) on dummies for exporters, new exporters, new exporters that use predominantly CIA terms, exporters that use predominantly CIA terms, and time and firm fixed effects.[31] To match these target moments we run an equivalent regression in the model.[32]

Fig. 3 contrasts the dynamics of trade finance and the dynamics of export volume implied by the model with those observed in the data (solid red lines). Our model delivers dynamics that closely match 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 OA. Our model matches well the overall increase in the share of OA terms, though it slightly underpredicts the rate of switching in the initial years.[33]

4.1. Untargeted moments

This section reports the fit of the model in other dimensions not targeted in the calibration. Table 6 shows that, both in the data and in the model, the financing terms are a persistent feature of the trading relationships. In the data (model), firms that finance their trading relationships through OA terms in a given year are 72% (76%) more likely to continue using OA the following year of their trading spell. Additionally, as expected, the share of OA increases over time in both the model and the data.

Table 7 compares the average growth in export intensity for firms that export for at least five consecutive periods in both the model and the data.[34] Export intensity increases by 0.8 (1.2) percentage points in the data (model) after one year of exporting and

share of OA (CIA) is greater than 50 percent first year, we classify this spells 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 export spell.

31 The regression can be found in Appendix A.2.

32 The idea is that, via the lens of our model, after controlling for time and firm fixed effect, the remaining differences in the size should be driven by differences in beliefs. Then, we can choose the mean and the variance of the belief distribution (which are functions of α_b and β_b) to match these moments. In particular, the mean of the belief distribution directly affects the size of new exporters that use CIA relative to non-exporters. Similarly, the variance governs how fast the exporters that start using CIA switch to OA and how much smaller are those that do not switch quickly. In particular, if there are a lot of exporters that start exporting with low beliefs then these exporters will be smaller than exporters that use OA even after several periods.

33 As shown, this model matches well export and trade finance dynamics, but it also counterfactually predicts that prices decrease over time. In the Online Appendix, we clarify the implications of our model on price dynamics, show how they compare to the data, and present an extended model that matches the price dynamics and delivers aggregate implications that are quantitatively close to those generated by our baseline model.

34 For details about the computation of export intensity in the data, see Appendix A.3.

Table 7
Export intensity.

Moment	Data	Model
Export intensity growth over 1 year	0.008	0.012
Export intensity growth over 2 years	0.013	0.020
Export intensity growth over 3 years	0.017	0.025
Export intensity growth over 4 years	0.019	0.028
Export intensity growth over 5 years	0.022	0.029

Note: The data column is obtained by multiplying log of years 2 to 6 by $\hat{\beta}$ from column (3) in Table A.5. For further details see Appendix A.3.

Table 8
Dynamics of exit rates and initial trade finance provision.

	Model ($X = 100\%$)		Data ($X = 90\%$)	
	(1)	(2)	(3)	(4)
$(OA \geq X)$	0.018***		−0.0021	
	(0.002)		(0.004)	
Transactions	−0.026***	0.111***	−0.189***	0.384***
	(0.001)	(0.001)	(0.003)	(0.006)
$(OA \geq X) \times$ Transactions	−0.007***	0.014***	0.003	−0.003
	(0.001)	(0.001)	(0.003)	(0.004)
Firm-dest-prod FE			No	Yes
Firm FE	No	Yes		
Observations	548,575	548,575	243,620	211,017
R^2	0.010	0.285	0.536	0.697

Note: The table reports estimates from specification (3) for data (See Table 8) and from similar specification, at firm-level, for model. Specification for the model includes time fixed effects and controls for time-varying productivity. Robust standard errors reported in parentheses. *** denotes significance at 1% level.

by 2.2 (2.9) percentage points after five years of exporting. Overall, the model generates dynamics in export intensity that closely match those observed in the data.[35]

We further validate the model by estimating the linear probability specification in Eq. (3) using simulated data and comparing the results with their empirical counterparts. In columns 1 and 3 of Table 8, we report results from regressions that exploit variation across export spells in the simulated and in the actual data, respectively.[36] The model successfully reproduces the negative relationship between the number of transactions and exit probabilities observed in the data: as the number of transactions increases, the probability of exit declines. Columns (2) and (4), instead, exploit variation within an export spell, by additionally controlling for selection into export destinations. Under this specification, within-export-spells dynamics, the probability of exit increases with tenure both in the model and the data and export spells become more likely to end as relationships mature. In both cases, however, the model underestimates the magnitude of the relationship. The model further generates only modest differences in exit rates between firms that begin with high versus low levels of OA usage, consistent with the empirical evidence where no statistically significant role is found.

5. Shocks to financing costs and aggregate dynamics

In this section, we study the aggregate trade dynamics in response to 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 2.5 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 these changes are asymmetric. Next, we discuss the impact of a permanent increase of 2.5 percentage points in the cost of domestic funding r_d. We then examine how these implications vary with the risks exporters face at their destination markets. Finally, we explore the role of learning in driving these dynamics.

[35] Using simulated data from the model, we compute cumulative changes in export intensity and average them over the first five years after a firm begins exporting; for the empirical counterpart, we calculate cumulative changes in export intensity after controlling for firm fixed effects, consistent with the model's focus on within-firm evolution of export intensity; see Table A.5 in the Appendix for more details.

[36] In the regressions using simulated data, productivity is controlled for explicitly, whereas in the empirical specification it is absorbed by firm–product–year fixed effects; in the quantitative model, the firm-destination match incorporates endogenous selection, which is the key margin of interest in this exercise; controlling for firm fixed effects would eliminate this variation and is therefore avoided.

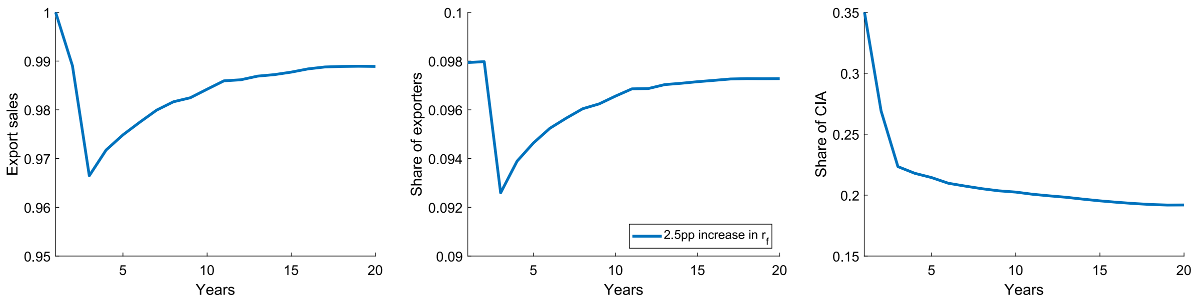


Fig. 4. Effects of a permanent increase in r_f of 2.5pp.

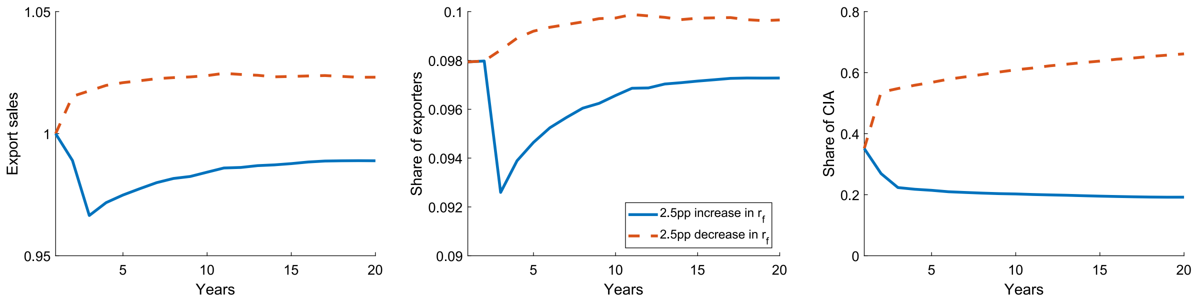


Fig. 5. Asymmetric effects of changes in r_f.

5.1. Permanent increase in foreign funding costs

Fig. 4 shows the effects of a permanent increase in foreign financing costs by 2.5 percentage points on the behavior of export sales, the share of exporters, and the use of CIA terms. We see that, following an increase in r_f, there is a sharp decline in these three variables. In particular, on impact, exports decrease by more than 3%, the share of exporters decreases by 0.54pp (a decrease of 5.5%), and the proportion of exporters using CIA drops from 35% to 22% during the first two years and then gradually decreases to a level of around 19%. Instead, export sales and the share of exporters gradually recover toward 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 1% and the share of exporters lower by 0.07pp (or 0.7%) compared to their initial steady state values, respectively. Thus, the long-run decline in export sales is about 70% smaller than in the short-run, while the share of exporters recovers most of its initial drop.

To understand these dynamics, note that an increase in foreign funding costs destroys relationships. Before the shock, exporters who 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 CIA terms. An increase in r_f renders many of such export matches unprofitable, 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 foreign financing costs also affects entry decisions. Firms that believe that their good will be popular (high λ) decide not to enter unless matched with importers that are likely to be trustworthy (high χ). This decreases the value of waiting for a new match for domestic firms. As a result, firms that are matched with relatively trustworthy importers decide to enter the foreign market rather than wait for another match, even if their beliefs about the ability to sell their goods are 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 therefore 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 they learn about their counterparty trustworthiness and demand for the goods.

To summarize, a positive shock to the foreign financing costs 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 funding costs

In this section, we analyze the dynamics of trade and trade finance in response to a permanent decrease of 2.5 percentage points in foreign financing costs and contrast them with the dynamics following an increase in these costs.

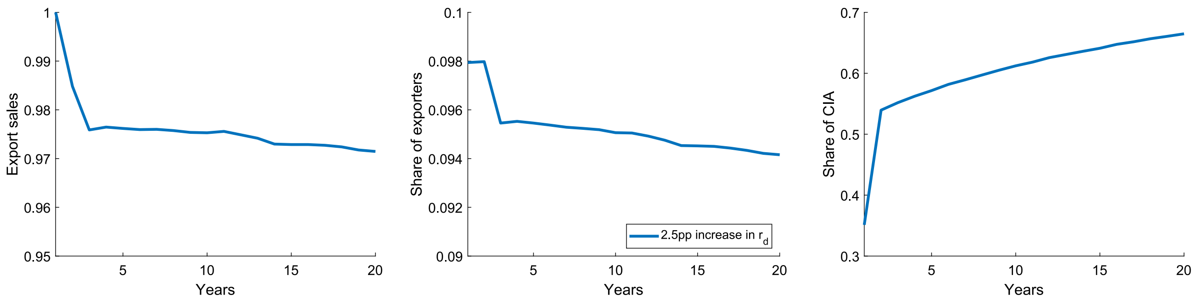


Fig. 6. Effects of a permanent increase in r_d of 2.5pp.

Fig. 5 shows the behavior of export sales, the share of exporters and the share of exporters using CIA terms, following a 2.5 percentage point decrease in r_f (red dashed line) and a 2.5 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 lower than the long-run response. 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. Although 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. However, as explained above, an increase in r_f destroys existing relationships on impact, leading to a large drop in exports and the share of exporters, followed by a gradual rebuilding of relationships.

5.3. Permanent increase in domestic financing costs

Finally, we consider the effects on exports and trade finance dynamics of a permanent increase in domestic financing costs of 2.5 percentage points. Fig. 6 shows that, following an increase in r_d, exports and the share of exporters decrease by around 2.9% and 0.4 pp, respectively. In addition, the share of exports sold using CIA terms increases on impact by about 19 percentage points, from roughly 35% to 54% (about 50% increase relative to its initial level), and then increases slowly, reaching about 66% after 20 periods. In general, we see that the effects of an increase in r_d are lower in the short-run 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 because they perceive exporting using OA terms to be too risky. On the other hand, an increase in r_d directly affects 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, after 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 in relationships even if they learn that their counterpart 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 $\mu < \mu_{CIA}$.

To summarize, a positive shock to the domestic financing cost has large immediate and permanent negative effects on exports.[37]

5.4. 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 distribution for counterparty's trustworthiness (χ) and associate a more risky destination with markets in which exporters are less likely to meet a trustworthy importer. We discipline this distribution using the steady state share of CIA in the data. Fig. 7 reports three Beta distributions for χ: a safe destination, $\mathcal{B}_\chi(1.48, 0.98)$, chosen so that steady state CIA average usage is 27%; a risky destination, $\mathcal{B}_\chi(1.23, 1.14)$, chosen so that steady state CIA average usage is 46%; and the benchmark $\mathcal{B}_\chi(1.23, 0.98)$, chosen so that steady state average CIA usage is 35%.[38] We also consider more extreme distributions: the "very high risk" case is calibrated to produce a steady state average CIA usage of 58%, while the "very low risk" case is calibrated to produce a steady state average CIA usage of 22%.

[37] Given the immediate and permanent impact described here, in the case of shocks to domestic financing costs, we do not observe the asymmetric dynamics that we observe in the case of shocks to foreign financing costs.

[38] When considering only export spells to risky destinations, the average share of CIA is 0.46, while the analogous number for exports to safe destinations is 28%.

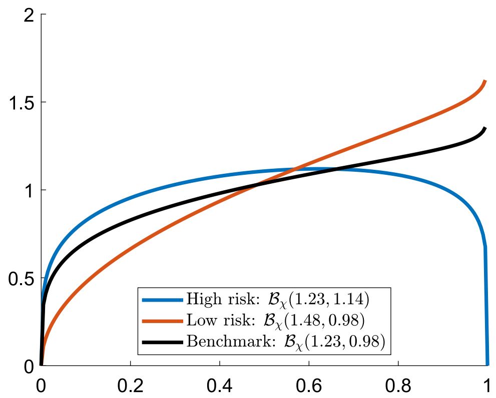


Fig. 7. Alternative risk distributions.

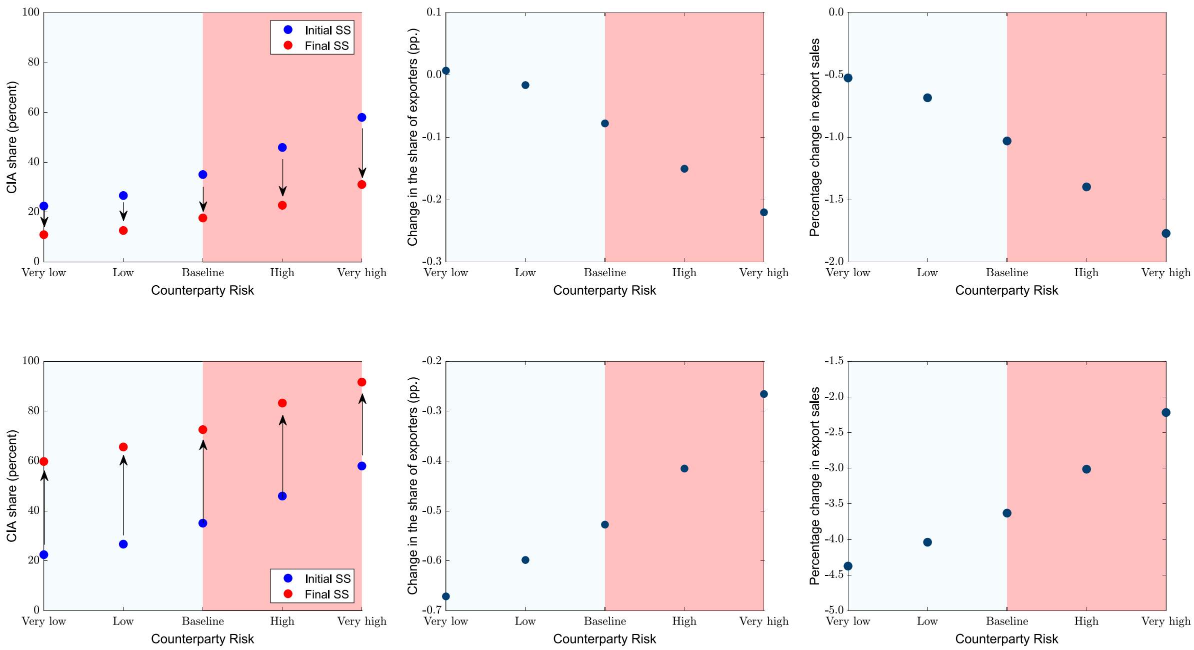


Fig. 8. Counterparty risk and long run effects of increases in r_f and r_d.

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

5.4.1. Long-run effects

Fig. 8 shows the long-run effects on exports and trade finance of a permanent increase of 2.5 pp (percentage points) in foreign financing costs, r_f (top three panels) and of a permanent increase of 2.5 pp in domestic financing costs, r_d (bottom three panels).

The top three panels of Fig. 8 show the effects of an increase in the foreign financing cost, r_f, by 2.5 pp. A permanent increase in r_f in the "very low risk" economy causes a drop of 0.25 pp in export sales, almost no change in the share of exporters, and a decrease in the share of CIA terms of 11 pp (from 22% to 11%). In contrast, in the "very high risk" economy, it leads to a drop of 1.8 pp in export sales, a decrease in the share of exporters of 0.22 pp, and a drop in the share of CIA terms of 30 pp (from 58% to 28%). Thus, an increase in foreign financing costs has a much greater impact on exports in riskier economies. This pattern is consistent with firms relying more on CIA terms in riskier destinations, which makes exporters more sensitive to changes in r_f.

The bottom three panels of Fig. 8 show the effects of an increase in domestic financing costs, r_d, by 2.5 pp. We see that a permanent increase in r_d in the "very low risk" economy leads to a drop of 3.4 pp in export sales, a decline in the share of exporters of 0.67 pp, and an increase in the share of CIA terms of 38 pp (from 22% to 60%). In contrast, in the "very high risk" economy, it

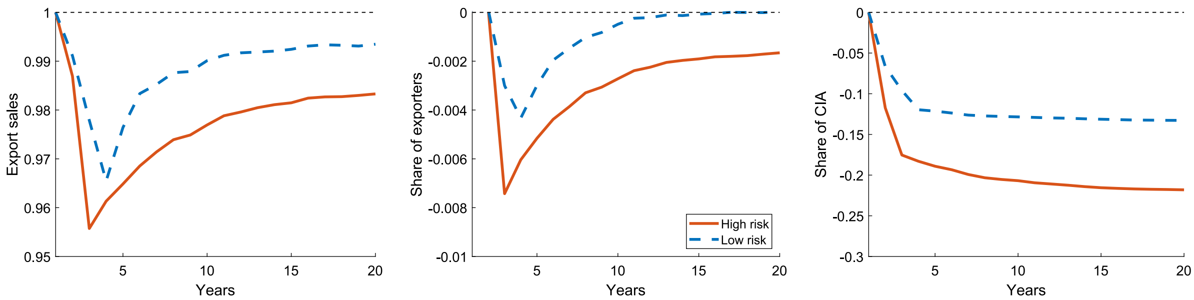


Fig. 9. Counterparty risk and effects of a permanent increase in r_f of 2.5 pp.

leads to a drop of 1.6 pp in export sales, a decrease in the share of exporters of 0.27 pp, and an increase in the share of CIA terms of 32 pp (from 58% to 90%). Thus, an increase in domestic financing costs has a 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).

In summary, 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 because, 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.

5.4.2. 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.

Fig. 9 shows the dynamics of aggregate exports, the share of exporters, and the share of CIA in response to an increase of 2.5 pp in foreign financing costs, in risky (solid red line) and safe (blue dashed line) destinations. A key insight is that exports and share of exporters recover faster in low-risk destinations, so the gap between the risky and safe responses widens over time. In the safe destination, aggregate exports drop by 3.5 pp in the short run but 20 years afterwards they recover about 4/5 of the initial drop (i.e., end up 0.7 pp below their initial steady state). Instead, in the risky destination, exports initially drop by 4.4 pp but 20 years later only recover about 60% of the initial drop (i.e., end up to 1.7 pp below their initial steady state value). Similar observations apply to the dynamics of share of exporters. In particular, in the safe destination the share of exporters drops by 0.4 pp and then recovers completely, in the risky destination it drops by 0.7 pp but then recovers only up to 0.2 pp below its initial steady state (a recovery of 71%).

To understand the lower recovery in exports to risky destinations, note that these destinations feature a larger mass of matches with low χ, for which exporting is viable only under CIA. When r_f increases, these CIA-reliant relationships are disproportionately destroyed, and re-entry is slow because the probability of meeting an importer with sufficiently high χ to make the use of OA terms profitable is low. In contrast, in safe destinations, exporters are more likely to match with sufficiently trustworthy importers over time, which leads to a faster recovery of share of exporters and export sales.

In the case of an increase of 2.5 pp in domestic financing costs, instead, exports and the share of exporters initially experience a sharp drop and then continue to decrease over time.[39] The initial drop is higher for exports to the safe destination, as these are more reliant on OA terms, which now become costlier. This difference widens over time as new exporters to safe destination predominantly rely on OA terms and, thus, they now delay entry till they find a better match to compensate for the increase in the cost of OA terms.

5.5. The role of learning dynamics

Above, we showed that shocks to foreign and domestic financing costs can have nonlinear, asymmetric effects on exports and trade finance dynamics. We now explore the role of learning, both about demand and counterparty risks, in generating these dynamics. Toward this goal, we revisit the impact of domestic and foreign financing shocks in two alternative versions of our model, in which we eliminate learning about demand risk and counterparty risk, respectively. In the first case, we set $\delta = 1$, which eliminates demand risk since it implies that the product always sells. Thus, in this version of the model there is only learning about counterparty risk. In the second case, we set $\mu = \mu_{CIA} = 1$, which eliminates the counterparty risk, since it implies that the untrustworthy importer always pays back its credit. Hence, in this version of the model, there is only learning about demand risk. Comparing the dynamics implied by these counterfactual economies with our benchmark model clarifies the role of learning about demand and counterparty risk in shaping the response to financing costs shocks.[40]

[39] The dynamics of exports in response to an increase in r_d are depicted in the Online Appendix.

[40] We keep all other parameters at their baseline values.

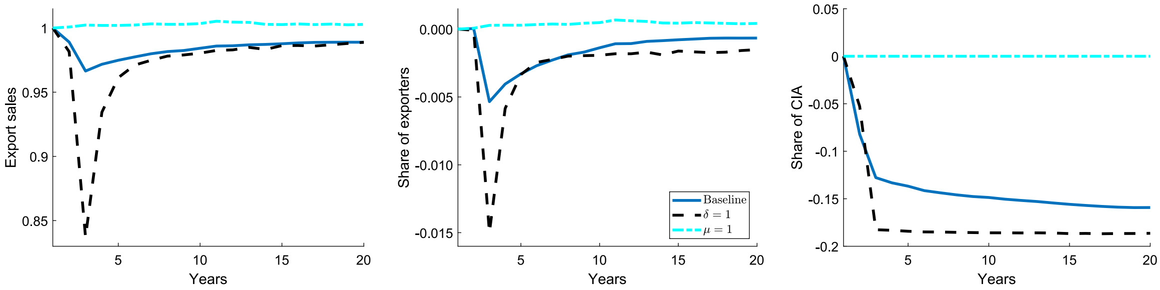


Fig. 10. Effects of a permanent increase in r_f of 2.5pp.

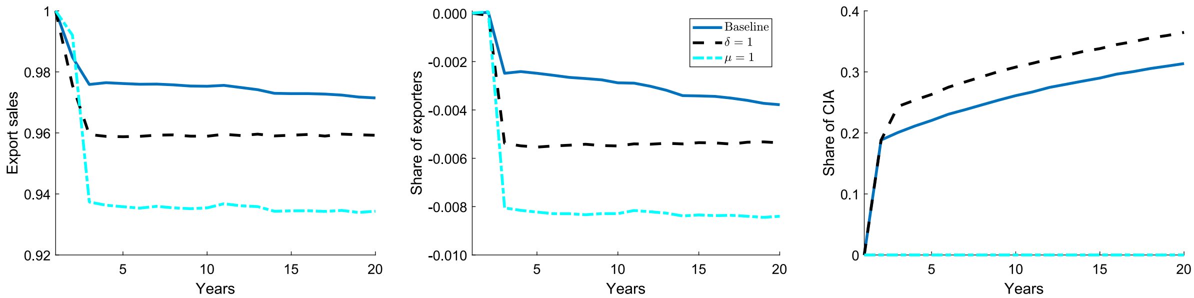


Fig. 11. Effects of a permanent increase in r_d of 2.5pp.

Before considering the dynamic responses, it is useful to first understand how shutting down demand or counterparty risk affects export decisions. Eliminating demand risk ($\delta = 1$) makes exporting more profitable and leads to a higher share of exporters in the initial steady state (0.106 instead of 0.098 in the baseline). At the same time, it reduces the share of exporters using CIA terms from 0.35 to 0.21. The reason for this is that the option value of waiting and searching for a more trustworthy importer is now higher than in the baseline model, since in the baseline model firms deciding to search had to hope for a match with a low counterparty risk (high μ_0) and a low demand risk (high λ_0). In contrast, when counterparty risk is absent ($\mu = \mu_{CIA} = 1$), the share of exporters increases only slightly as demand risk is the only factor driving the export entry decision and all exporters use OA terms.

Fig. 10 shows the aggregate responses to a 2.5pp increase in foreign financing costs in the baseline model (solid line), in the model without demand risk (dashed line) and in the model without counterparty risk (dashed-dotted line). As expected, in the absence of counterparty risk, a shock to foreign financing costs has no effect on exports, since no exporter uses CIA terms. However, in the absence of demand risk, the response to the shock on impact is much larger than in the baseline model, but it is followed by rapid recovery. Despite the more negative initial impact, after a few years the impact of the shock on export sales and share of exporters is about the same as in the baseline model.

The reason behind this collapse and subsequent rapid recovery, in the absence of demand risk, is the greater value of searching for a new counterparty relative to the baseline model. In particular, in the baseline model, firms in matches that use CIA and have a high belief in the popularity of their product are willing to continue exporting despite the increase in r_f because finding a new match that is both trustworthy and has a high demand is relatively unlikely. In contrast, in the absence of demand risk, firms need to worry only about finding a match who is relatively trustworthy, which is more likely than finding a match that is both trustworthy and has a high demand, as in the baseline model. As a result, following a shock to r_f, many exporters decide that it is worthwhile to break up their current relationships and search for a new counterparty under OA terms. Since it is more likely to find a satisfactory match when $\delta = 1$ than in the baseline model, firms quickly find new matches and start exporting again. Thus, in the absence of demand risk, we see a larger initial negative effect followed by a very quick recovery. In sum, adding demand risk on top of counterparty risk adds persistence to the exporting relationship, which dampens the adjustment to shocks.

Fig. 11 shows the aggregate responses to a 2.5pp increase in domestic financing costs r_d. Export sales and the share of exporters drop the most in the model without counterparty risk, followed by the model without demand risk, and then by the baseline model. This ordering reflects the usage of OA in the initial steady state, which is the highest in the model without counterparty risk and the lowest in the baseline model. As in the baseline model, the initial shock leads to a permanent decrease in export sales and the share of exporters, as the shock to r_d decreases the total surplus from exporting.

Overall, we see that the two-dimensional learning plays an important role in shaping the dynamics of exports following shocks to the financing costs of firms. In particular, learning about demand and counterparty risks dampens the response to shocks and adds persistence to the dynamics of exports.

Table A.1
Descriptive statistics.

	Mean	SD	p5	p10	p25	p50	p75	p90	p95	Obs
Sales (MM USD)	21.73	157.80	0.21	0.35	0.91	2.75	10.30	35.78	72.85	3,354
Exports (MM USD)	0.28	1.48	0.00	0.00	0.01	0.04	0.14	0.48	0.96	3,354
Exports/Sales	0.16	0.22	0.00	0.00	0.01	0.05	0.21	0.51	0.67	3,354
Employees	169.90	438.22	7.00	9.00	19.03	51.00	141.50	387.47	653.79	3,352
Destinations	8.68	13.86	1.00	1.00	1.00	3.00	10.00	24.00	37.00	3,354
Products	12.27	23.52	1.00	1.00	2.00	4.00	13.00	30.00	49.00	3,354
Destinations-Products	31.85	72.73	1.00	1.00	2.00	8.00	29.00	85.00	140.00	3,354
Destinations-Products-Year	82.99	214.95	1.00	1.00	3.00	13.00	65.00	231.00	387.00	3354

Table A.2
Average number of days with transactions within export spells.

Year	All	OA	CIA
1	3.46	3.57	2.93
2	4.76	4.92	3.91
3	6.55	6.73	5.39
4	7.69	7.97	6.22
5	8.97	9.31	6.96
Sum	31.43	32.50	25.41

6. Conclusions

This paper investigates how learning about demand and counterparty risk within trading relationships shapes the joint dynamics of export performance and trade finance choices. Using detailed Chilean customs data, we documented that new exporters predominantly rely on cash-in-advance (CIA) terms and gradually transition to open account (OA) arrangements as relationships mature. These dynamics are more pronounced for inexperienced firms and in riskier destinations, emphasizing the role of relationship-specific learning in mitigating uncertainty and facilitating export growth.

To account for these patterns, we developed a dynamic general equilibrium model of international trade that integrates endogenous trade finance decisions with learning about demand and counterparty risk —two dimensions previously studied in isolation. Calibrated to micro-level data, the model replicates key empirical regularities and highlights the importance of learning in reducing effective trade costs over time. Our quantitative analysis shows that shocks to trade finance costs can have substantial and asymmetric effects on aggregate exports, particularly when long-term relationships are disrupted.

These findings suggest that trade finance arrangements are not merely contractual details but are central to understanding export dynamics and the transmission of financial shocks. By quantifying the aggregate implications of trade finance choices, our work contributes to a deeper understanding of the frictions that shape international trade and offers a framework for evaluating policies aimed at supporting exporters in the face of financial volatility.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

A.1. Data

Our work combines several datasets to perform our empirical analysis. We merge 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 drop a small number of transactions that use a combination of financing terms for the same transaction. We also drop firm-year observations for which the ratio of exports to total sales exceeds one, consider firms in the manufacturing sector and limit our attention to firms with at least five employees. We exclude pandemic years and focus on the period spanning from 2005 to 2019. Table A.1 provides descriptive statistics of the firm-level data. Table A.2 shows the average number of days that exporting firms have positive transactions in each year of their export spell.

Table A.3
Cross-country and cross-firm correlation of interaction variables.

	Cross-country		Cross-firm	
	(1) Financial Development	(2) Low Risk	(3) Size	(4) Experience
Financial Development	1	0.66	–	–
Low Risk	0.66	1	–	–
Size	–	–	1	0.35
Experience	–	–	0.35	1
Observations	134		3,354	

Note: 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. Correlations are computed across 134 countries and 3354 firms.

Table A.4
Conditional size premium regressions.

	(1) $\ln(\text{Employees}_{it})$	(2) $\ln(\text{Employees}_{it})$	(3) $\ln(\text{Employees}_{it})$	(4) $\ln(\text{Employees}_{it})$
Exporter_{it}	0.3793***	0.4727***	0.4764***	0.4049***
	(0.0093)	(0.0107)	(0.0108)	(0.0148)
New Exporter_{it}		−0.2371***	−0.2330***	−0.2258***
		(0.0139)	(0.0140)	(0.0140)
$\text{New Exporter}_{it} \times \mathbb{I}_{(\text{Share CIA} \geq 50)_{it}}$			−0.0400***	−0.0212
			(0.0141)	(0.0144)
$\mathbb{I}_{(\text{Share CIA} \geq 50)_{it}}$				−0.0998***
				(0.0142)
Observations	205,469	205,469	205,469	205,469
R^2	0.7826	0.7829	0.7830	0.7830

All regressions include year and firm fixed effects. Standard errors in parentheses. *** $p < 0.01$.

A.1.1. Destination and firms' characteristics

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.[41] 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".[42,43] We define a destination as low risk if the index is above the median and as high risk otherwise. 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 A.3 reports a strong positive correlation of 0.66 between the above-median financial development dummy and the above-median rule-of-law dummy at the country level. Columns (3) and (4), shows a positive correlation, albeit smaller than in the previous case.

A.2. Conditional size premium

To obtain the conditional size premium, we ran the following regressions

$$\ln(\text{Employees}_{it}) = \text{Exporter}_{it} + \text{New Exporter}_{it} + \text{New Exporter}_{it} \times \mathbb{I}_{(\text{Share CIA} \geq 50)_{it}} + \mathbb{I}_{(\text{Share CIA} \geq 50)_{it}} + \delta_t + f_i + \varepsilon_{it}$$

The results are reported in Table A.4. We consider the specification in columns (4) and target the coefficients on $\text{New Exporter}_{it} \times \mathbb{I}_{(\text{Share CIA} \geq 50)_{it}}$ and $\mathbb{I}_{(\text{Share CIA} \geq 50)_{it}}$.

[41] Results are robust to using the Financial Development Index constructed by the IMF.
[42] For details, see https://www.prsgroup.com/explore-our-products/icrg/ .
[43] 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 A.5
Export intensity over an export spell.

	(1)	(2)	(3)
$\ln(\text{years}_{ft})$	0.0126*	0.0084*	0.0120**
	(0.0074)	(0.0044)	(0.0051)
Firm FE	No	Yes	Yes
Year FE	No	No	Yes
R^2	0.2289	0.8150	0.8201

Note: The table reports linear estimated coefficient of export-intensity on years, for firms that export at least 5 periods, only along their first 5 years of exporting. Robust standard errors reported in parentheses. **, and * denote significance at the 5% and 10% levels, respectively.

A.3. Export intensity

Table 7 shows the average cumulative change in export intensity in the model, for firms that export for at least 5 periods, and contrasts it with the growth in export intensity in the data. To calculate export intensity in the data, we utilize the same source of variation used in the model—that is, within firms we calculate the evolution of export intensity. In practice, this is implemented by estimating the following regression:

$$x_{ft} = \beta \ln t_{ft} + \text{left censoring}_{ft} + \text{right censoring}_{ft} + \alpha_f + \mu_t + \epsilon_{ft}, \tag{15}$$

where $x_{ft} = \frac{\text{Exports}_{ft}}{\text{Sales}_{ft}}$, Exports_{ft} and Sales_{ft} are total exports and sales of f in year t, t_{ft} is the number of years since the firm started exporting.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jinteco.2026.104286.

Data availability

Replication package for "International Trade Finance and Learning Dynamics" (Original data) (Mendeley Data)

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