Customer Uptrading, Relational Frictions, and Exporters' Growth

Javier Boncompte[1] and Oscar Perelló[2,3]

[1]University College London
[2]London School of Economics
[3]Bank of Spain

November, 2025

Abstract

How do exporters grow their customer networks when maintaining relationships is costly? We study the role of customer churning in exporters' growth. Using detailed firm-to-firm data from Chilean customs, we show that fast-growing exporters systematically drop buyers that purchase smaller volumes and replace them with large customers, a process we term *Customer Uptrading*. A formal decomposition reveals that uptrading, rather than selling more to existing customers or expanding the number of buyers, is the main driver of exporters' growth. Exploiting variation in direct flight availability, we find that exporters maintain longer relationships when better connected to their buyers, linking uptrading to the upkeep costs of managing multiple trade relationships. We rationalize these findings with a dynamic model of network formation in which firms engage in costly customer search and actively decide which relationships to keep or sever, taking into account the upkeep costs of their network. The model predicts that more productive firms both search more intensively and replace more customers than less productive ones, highlighting the central role of search in exporters' growth and also its limits.

*We acknowledge the generous support of the International Growth Centre (Small Research Grant, BGD 24042).
Contact information: javier.boncompte.19@ucl.ac.uk; oscar.perello.19@ucl.ac.uk.

1. Introduction

Firm-to-firm connections are increasingly recognized as fundamental drivers of heterogeneity in firm size, aggregate productivity, and international trade flows. Despite sharp declines in transportation and communication costs, trade networks remain sparse and dominated by few, highly connected large firms across most sectors, which points to substantial relational costs. At the same time, these patterns have heightened concerns about industry concentration and the role of imperfect competition in global markets. Understanding how firms form and manage their customer portfolios is therefore central to ongoing debates on trade facilitation, deep economic integration, and industrial policy, and particularly for identifying the most effective actions for export promotion.

Exporting firms must engage in a range of activities to transact with customers, including finding suitable trade partners, handling orders for existing buyers, and negotiating prices with each of them. These customer management activities are inherently dynamic: searching for customers does not instantly result in new matches, firms may drop older customers if they are no longer profitable, and contracts often require renegotiation under evolving conditions. Yet, due to data limitations and theoretical challenges, most studies on exporters' performance have taken a static approach or abstracted from the role of customer relationships. As a result, our understanding of how firms expand and succeed in foreign markets remains limited.

This paper provides an empirical, theoretical, and quantitative analysis of the role of customer portfolio management in exporters' growth. Using panel data on Chilean exporters and their foreign buyers, we show that growing exporters replace older customers with more profitable matches while increasing both average prices and price dispersion across customers. We develop a dynamic export model with search frictions, managerial costs of customer relationships, and bilateral bargaining that rationalizes these patterns. Each period, firms decide how much to invest in customer search, which customers to retain, and what prices to charge. While additional customers enhance exporters' sales and negotiating positions, they also increase managerial costs. The model characterizes firms' dynamic export strategies and provides a framework to quantify the role of managerial costs in export growth. We then evaluate policies aimed at reducing search and managerial costs or inducing market entry.

Our first contribution is to establish two novel facts on the dynamics of export relationships, unveiling the relevance of the *churning margin* for export growth and the prominence of bilateral price negotiations. We exploit rich Chilean customs data covering the universe of export transactions from 2002 to 2019. Importantly, this dataset includes the identities of both Chilean exporters and their foreign buyers, enabling us to track export relationships over time for each HS 8-digit product and destination country. We match this dataset with records from the Tax Authority of Chile, which provide additional information on exporters' sales, age, and primary industry of activity.

Fact 1 shows that growing exporters systematically replace customers with more profitable matches. In contrast, underperforming exporters add buyers that purchase smaller amounts than their terminated relationships. To quantify the importance of this channel, we exploit the panel structure of the data and conduct a formal variance decomposition of export growth at the firm-product level. This analysis separates changes in the number of customers (extensive margin), changes in average sales to existing customers (intensive margin), and a new channel capturing differences in average sales to new versus dropped relationships (churning margin). We find that the traditional extensive and intensive margins roughly account for 20% and 40% of export growth, respectively, while the *churning margin* explains the remaining 40%. Our results highlight the relevance of customer portfolio management as a driver of export growth.

Fact 2 documents that growing exporters increase their average price and the dispersion of prices within products and across customers over time. The same pattern arises when restricting the analysis to the subset of old customers, indicating price changes are not solely driven by differences between new and terminated export relationships. This, in turn, suggests that exporters not only discriminate prices across buyers for the same product but also renegotiate prices on a recurring basis, presumably under evolving bargaining positions. Overall, this highlights the role of bilateral and dynamic price setting in export markets.

Our second contribution is to develop a dynamic model of exporting that accounts for these empirical facts. In the model, heterogeneous sellers transact with heterogeneous buyers under search frictions, upkeep costs of managing customer relationships, and bilateral pricing. Each period, exporters decide their optimal search effort to find customers, which customers to retain in their portfolio, and negotiate prices bilaterally with each of them. Firms engage in costly searches to find new, potentially better matches, which increase their sales and strengthen their negotiating position with each inframarginal buyer. However, dealing with multiple customers entails managerial costs, and firms may only retain the most profitable relationships they can handle. Ultimately, the profitability of an additional customer depends on the productivity and relative market power of both the exporter and the importer.

We model the search process using a continuous effort variable, whose intensity determines the probability of finding new matches and the cost borne by the exporter. Our framework thus features search frictions that add a random component to network formation: at any given period, the allocation of matches may not be optimal for exporters. Conditional on finding a new potential customer, exporters can add it to their portfolio, churn an existing customer, or ignore it. Exporters balance the additional upkeep costs of managing relationships with the benefits of a larger customer network for sales and negotiations. Once firms have defined their customer portfolios, they engage in simultaneous bilateral negotiations to set prices and quantities. We model these negotiations using the Nash-in-Nash protocol, where each exporter-importer pair negotiates prices under Nash bargaining and takes other prices as given, even though prices are jointly determined in equilibrium. The model is solved by backward induction, starting with the negotiation stage conditional on a customer network.

The model illustrates novel economic mechanisms for export relationships. Exporters charge higher prices to less productive importers, while more productive exporters charge lower prices even when they apply higher markups. The highest export prices are thus observed in matches between two unproductive firms. More productive exporters are more likely to add or churn potential matches, as a larger pool of customers is profitable for them, and they consequently make greater search investments. While costly searching alone would make relationships sticky, the presence of upkeep costs implies that exporters optimally drop customers. This, in turn, helps rationalize the well-documented pattern of short-lived export relationships. Upkeep costs limit the ability of firms to sell abroad, even if they successfully search for potential customers, and hinder their negotiating position in imperfectly competitive markets. This suggests that policies facilitating the search and matching process may have limited impact if upkeep costs remain high.

Our third contribution is to quantify the role of customer management costs in export growth. The estimation strategy leverages the rich microdata on Chilean firms and their foreign buyers. Using model-driven equations, we back out the elasticity of substitution for exported intermediate goods from variation in prices across sellers within buyers, as well as the relative market power of sellers and buyers from transactional price data. We then estimate the costs of searching for customers and managing customer relationships using the simulated method of moments. Our quantification compares export performance across the firm size distribution and aggregate trade outcomes with and without the presence of upkeep costs.

The model allows us to perform counterfactuals that consider policies aimed at reducing different costs associated with customer relationships. We interpret changes in search costs as reflecting traditional trade facilitation policies, such as trade fairs and foreign governmental offices, or advances in communication technologies. In contrast, training programs and management technologies that enhance firms' ability to deal with multiple customers simultaneously are interpreted as reductions in upkeep costs. We evaluate the effects of these policies on exporters' performance and aggregate trade, considering both individual and package reforms. We also interact these actions with industrial policies that induce entry on either side of the market.

This paper bridges and advances three strands of literature. First, we contribute to the broad literature on firm growth, and particularly to studies examining export performance. Hottman et al. (2016) shows that demand factors are an important driver of differences in firm outcomes, while Bernard et al. (2022) extends this analysis to the role of customer linkages. A series of papers support the role of customer accumulation as a primary determinant of exporters' growth (Albornoz et al. 2012; Chaney 2014; Carballo et al. 2018; Piveteau 2021), the role of sunk export investments for firm and aggregate trade dynamics (Das et al. 2007; Alessandria and Choi 2007; Impullitti et al. 2013; Gumpert et al. 2020; Alessandria et al. 2021), and the role of search frictions for the formation and evolution of trade relationships (Eaton et al. 2021, 2022). Recent work has also explored the use of marketing and pricing strategies in firms' export success (Fitzgerald et al. 2024).

We advance this literature by unveiling the role of customer churning in exporters' growth and introducing upkeep costs as a key determinant of customer management over time. As in Eaton et al. (2022), our model features search frictions and bilateral price negotiations, although we adopt a Nash-in-Nash approach instead of the Rolodex protocol, enabling the simultaneous determination of prices without assuming buyer-seller coordination. More importantly, upkeep costs generate endogenous customer churning, which rationalizes the observed patterns in the data and governs the evolution of export relationships.

Second, we contribute to the literature on endogenous production networks, which considers the implications for firm and aggregate outcomes (Bernard et al. 2018a, 2019; Dhyne et al. 2021; Bernard et al. 2022; Manova et al. 2024), as well as the transmission of microeconomic shocks to macroeconomic fluctuations (Acemoglu et al. 2012; Baqaee and Farhi 2019, 2020). From a dynamic perspective, Lim (2018) proposes a model in which the value of relationships evolves due to idiosyncratic shocks, while Huneeus (2018) introduces adjustment costs that induce firms to make forward-looking decisions. More closely related to our paper, Aekka and Khanna (2024) model dynamic relationships under search frictions, such that firms may not match with their optimal set of partners. We adopt a similar framework but incorporate upkeep costs and bilateral bargaining into the activities firms undertake to transact with customers. This allows us to quantify the relative importance of search and matching versus relationship management costs for export growth, and examining how the market structure shapes these effects.

Finally, we contribute to the emerging literature on imperfect competition in international markets, and particularly in seller-buyer relationships. Works in this area have examined strategic interactions among final producers in oligopolistic environments (Bernard et al. 2003; Atkeson and Burstein 2008; Neary 2016), imperfect competition upstream and downstream in fixed production networks (Morlacco 2019; Alviarez et al. 2023), and imperfect competition upstream in endogenous production networks (Huang et al. 2024). By embedding a Nash-in-Nash bargaining protocol into a model with continuous search effort and random matching, we expand this literature in two ways. First, we incorporate upstream and downstream market power into a model with endogenous network formation. Second, we extend pricing interactions to a dynamic setting, where firms renegotiate over the life cycle of relationships, under potentially different market conditions.

The rest of the paper is organized as follows. Section 2 describes the data and presents stylized facts on exporters' growth. Section 3 develops a dynamic model of exporting with search costs, upkeep managerial costs, and bilateral bargaining. Section 4 estimates the model and quantifies the role of managerial costs and market power for export performance. The final section concludes.

2. Empirical Evidence

2.1. Data

Export Relationships. We exploit rich data for Chile that allows us to examine the universe of firm-to-firm export transactions over a long panel. We obtain the value, quantity, and unit value for all export flows from the Chilean Customs Service (*Servicio Nacional de Aduanas*) for 2010–2019. These records identify the HS 8-digit product, destination country, foreign buyer, and domestic seller for each transaction. We also collect information on seller size, industry, and city where the firm is located from the Business Statistics of the Chilean Tax Authority (*Servicio de Impuestos Internos*) for the same period. We match these datasets using unique tax identifiers (RUT).[1]

We define an export relationship as a triplet of Chilean seller, HS 8-digit product, and foreign buyer. This level of aggregation allows us to compare across relationships trading the same detailed product. In the main analysis, we define *new* relationships as those active in period t that were inactive in $t-1$, and *dropped* relationships as those active in t that will be inactive in $t+1$. We assess robustness to alternative definitions for both relationships themselves and their *new* or *dropped* status.[2]

Panel A of Table 1 reports summary statistics for exporters. The average exporter serves about four destinations and maintains five relationships per destination, reflecting combinations of roughly three different products and two buyers. There is, however, substantial heterogeneity across exporters: the median firm serves only two destinations with two relationships each. Panel B further characterizes export relationships. The average relationship lasts less than two

[1]We apply a harmonization routine to the digitized names of foreign buyers to address misreporting and common spelling mistakes (see Appendix A).

[2]We alternatively define relationships at the Chilean seller–foreign buyer level, and use longer windows to classify *new* and *dropped* relationships as those inactive for n consecutive periods before or after year t. Results are consistent across definitions.

years and is shorter for newly formed links. Consequently, separation rates are high: about 60% overall and nearly 70% for new relationships.

TABLE 1. Summary Statistics

	2010		2019	
	Mean	Median	Mean	Median
Panel A. Chilean Exporters				
# Exporters	7,948		9,243	
# Destinations per exporter	3.87	2	3.68	1
# Products per exporter-destination	3.28	2	3.23	1
# Buyers per exporter-destination	2.46	1	2.55	1
# Relationships per exporter-destination	5.47	2	5.34	2
Sales per exporter-destination (USD)	2,176,183	49,554	2,205,163	50,390
Panel B. Export Relationships				
# Relationships	170,841		181,980	
Length of relationships	1.41	1	1.37	1
Length of *new* relationships	1.26	1	1.24	1
Probability relationships break	0.59	1	0.63	1
Probability *new* relationships break	0.74	1	0.76	1
Sales per relationship (USD)	391,573	9,600	412,272	11,153
Panel C. International Flights				
# Chilean towns *(with exporters)*	204		230	
# Chilean towns with flights	9		10	
# Destination countries	189		191	
# Destination countries with flights	31		26	
# Town - destination pairs	4,411		5,081	
# Town - destination pairs with flights	45		42	

Notes: This table presents summary statistics for the first and last year in the data. Panel A reports both the mean and median for the distribution of Chilean exporters. Panel B reports the average for different outcomes of export relationships, defined at the Chilean seller–product (HS 8-digit)–foreign buyer level. Panel C presents statistics on the connectivity of Chilean cities with destination countries, considering direct flights.

Flights and Gravity. We collect data on all flights operating in Chile from the Civil Aeronautics Board (*Junta Aeronáutica Civil*) for the same period (2010–2019). The data is reported monthly and includes the Chilean city of departure, the foreign city of arrival, operating airlines, route distance, and passenger flow. We collapse the dataset to the year–Chilean city–destination country level and compute a dummy indicating whether exporters from a given Chilean city are connected to buyers in a destination country by a direct flight in a given year. To explore the intensive margin of connectivity, we also compute the number of flights operating on each route. In total, over 40 export routes between Chilean cities and destination countries have direct flight connections (Panel C of Table 1).

Finally, we use information on gravity variables from the CEPII database (Gaulier and Zignago 2010). These include GDP per capita across countries and proxies for the relational costs faced by Chilean sellers in each destination: geographic distance to capture travel logistics, common language and religion to measure communication costs, and legal origins to reflect institutional differences.

2.2. Customer Uptrading

We document a novel fact on exporters' customer relationships: growing exporters replace older customers with more profitable matches, and this customer *uptrading* margin explains a major share of the variation in exporters' growth.

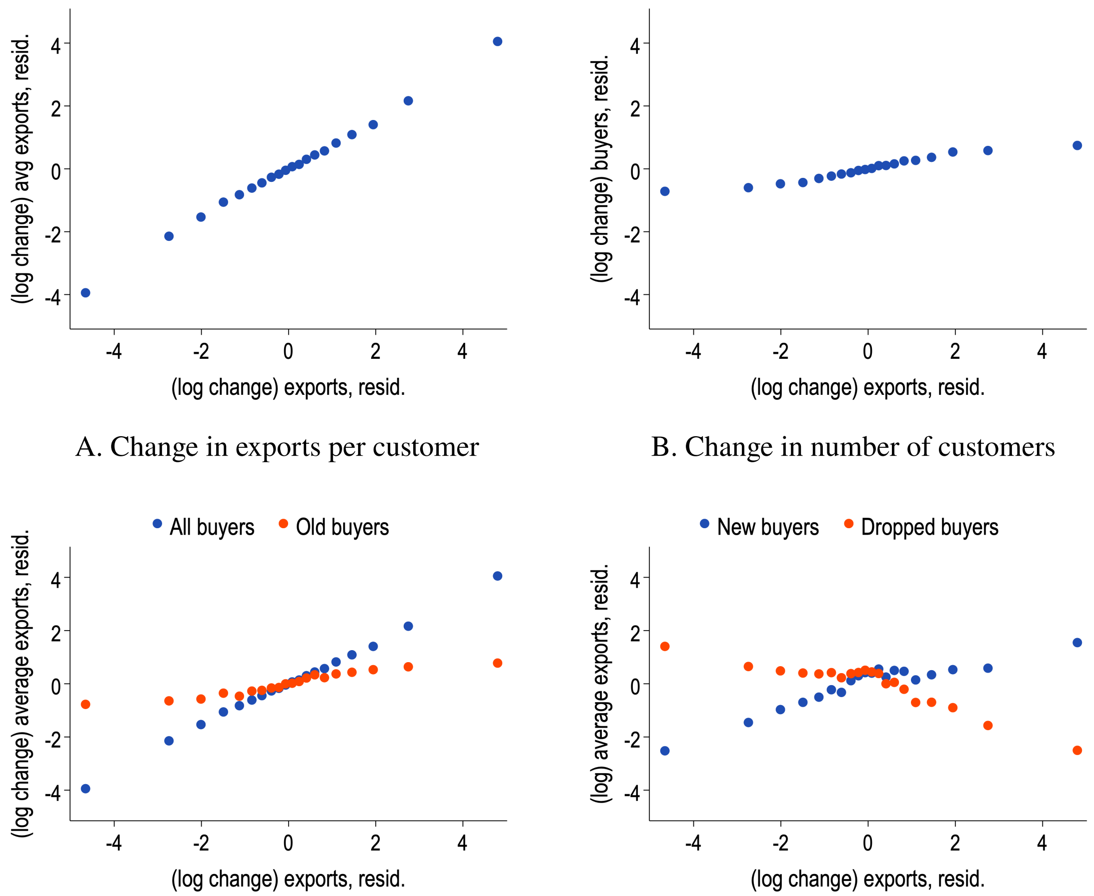
Empirical Patterns. We begin by describing how changes in exports within firms over time relate to changes in exports per customer and in the number of customers. We sort firm–product (HS8) pairs into 20 bins by their change in exports over a four-year horizon (2015–2019). All variables are demeaned by product to adjust for sector-specific trends, so a firm with a log change of zero has the average change among firms selling the same product. We then plot the relationship between export growth and changes in exports per customer (Figure 1A) and changes in the number of customers (Figure 1B). These figures point to the dominance of the *intensive* margin (linear slope of 0.81) over the *extensive* margin (linear slope of 0.19), suggesting that exporters primarily grow by selling more to each customer rather than by expanding their customer portfolios.

One must be cautious in interpreting the prominent role of the intensive margin. In a dynamic setting, an increase in exports per customer masks two qualitatively different channels: higher sales to existing customers (*upselling*) and compositional shifts in the customer base, where exporters replace customers with more profitable matches (*uptrading*). In fact, over a four-year horizon, roughly 80% of exporter–product pairs churn at least one customer. To explore these channels, we first plot changes in average exports for the subset of *old* customers (Figure 1C) and note that upselling to them only partially explains the variation in exports per customer (Figure 1A).[3] We next compare average exports to *new* customers with previous sales to *dropped* customers (Figure 1D). This reveals that growing exporters' sales to new customers exceed those to dropped ones, thereby raising average exports per customer, whereas the opposite holds for contracting exporters.

These empirical patterns indicate that a rise in average exports per customer reflects both *upselling* and *uptrading*. Exporters can therefore grow by adding customers, selling more to

[3]Consistent with our definition of *new* relationships in Section 2.1, we consider *old* relationships as those active in period $t-1$ and t. Here, however, a period is defined as a four-year window.

FIGURE 1. Change in Exports at the Firm–Product Level



A. Change in exports per customer

B. Change in number of customers

C. Change in exports per old customer

D. Exports per customer, new vs. dropped

Notes. Firm-product pairs are sorted into 20 bins by their change in exports over a 4-year horizon (2015-2019). Each dot displays the value of the variable on the vertical axis for the average firm in each bin. All variables are residualized by product (HS-8).

existing ones, or replacing underperforming customers with better matches. We next develop a formal decomposition of exporters' growth to assess the relative importance of each margin in explaining heterogeneous performance across firms.

Decomposing Exporters' Growth. We decompose exporters' growth into the extensive margin of the number of customers and the intensive margin of sales per customer, further distinguishing between *upselling* and *uptrading* strategies in the latter.

Exports by a firm–product pair i in period t can be expressed as $X_{it} = N_{it}\overline{X}_{it}$, where N_{it} is the number of customers and $\overline{X}_{it}$ the average sales per customer. The (log) change in exports between periods t and $t+j$ can then be written as:

$$\Delta_{t,t+j} \log X_i = \underbrace{\Delta_{t,t+j} \log N_i}_{\text{Extensive Margin}} + \underbrace{\Delta_{t,t+j} \log \overline{X}_i}_{\text{Intensive Margin}} . \tag{1}$$

We show that the intensive margin can be exactly decomposed into *upselling* and *uptrading* margins (Appendix B), yielding the following three-term formula:

$$\Delta_{t,t+j} \log X_i = \underbrace{\Delta_{t,t+j} \log N_i}_{\text{Extensive Margin}} + \underbrace{\frac{\Delta_{t,t+j}\overline{X}_i^{Upsale}}{M_i}}_{\text{Customer Upselling}} + \underbrace{\frac{\Delta_{t,t+j}\overline{X}_i^{Uptrade}}{M_i}}_{\text{Customer Uptrading}} . \tag{2}$$

The *upselling* component is:

$$\Delta_{t,t+j}\overline{X}_i^{Upsale} = \Delta_{t,t+j}\Big(\alpha_{it}^{Old} \cdot \overline{X}_{it}^{Old}\Big),$$

measuring the change in average sales to old customers (those active in both t and $t+j$), weighted by their share in the customer portfolio in each period, $\alpha_{i\tau}^{Old} \equiv N_{i\tau}^{Old}/N_{i\tau}$. The *uptrading* component is:

$$\Delta_{t,t+j}\overline{X}_i^{Uptrade} = \alpha_{it+j}^{New} \cdot \overline{X}_{it+j}^{New} - \alpha_{it}^{Drop} \cdot \overline{X}_{it}^{Drop},$$

which captures the net effect of replacing dropped customers with new customers that have different average sales, weighting by the shares that dropped customers represented in period t, $\alpha_{it}^{Drop} \equiv N_{it}^{Drop}/N_{it}$ and that *new* customers represent in $t+j$, $\alpha_{it+j}^{New} \equiv N_{it+j}^{New}/N_{it+j}$. Finally, M_i is the logarithmic mean of $\overline{X}_{it}$ and $\overline{X}_{it+j}$, which ensures that the *upselling* and *uptrading* components in (2) sum exactly to the intensive margin in (1).[4]

Table 2 reports the results from regressing each element of this decomposition on the log-change in exports, so the coefficients can be interpreted as the share of variation in exporters' growth accounted for by each margin. Column (1) presents the baseline specification; Column (2) adds product (HS8) fixed effects to control for secular growth in each sector; Column (3) instead includes firm fixed effects that absorb firm-specific shocks common across products; and Column (4) includes both sets of fixed effects. We find consistent results across specifications. Customer *uptrading* is the main driver of export growth, accounting for roughly two-thirds of the variation in exporters' growth, while *upselling* to old customers accounts for only 13%. This implies an aggregate contribution of about 80% for the intensive margin of sales per customer, with the extensive margin of the number of customers accounting for the remaining 20%.[5]

[4]Formally, the logarithmic mean of two variables $a, b > 0$ is defined as $M(a,b) \equiv \frac{a-b}{\ln a - \ln b}$.

[5]Cross-sectional decompositions typically find a greater role for the extensive margin of buyers (Carballo

Table 2. The Margins of Exporters' Growth

	(1)	(2)	(3)	(4)
Extensive Margin				
Number of customers	0.199	0.205	0.193	0.196
Intensive Margin				
Customer Upselling	0.129	0.121	0.133	0.124
Customer Uptrading	0.671	0.674	0.674	0.680
Product FE	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes
Observations	15,404	14,268	14,002	12,759

Notes: This table reports the contribution of each margin in Equation (2) to export growth from 2015 to 2019 at the firm–product (HS8) level. Contributions are estimated by regressing each component on the log-change in exports and sum to one in each column. Customer upselling corresponds to changes in average exports to existing customers. Customer uptrading reflects the net effect of replacing dropped customers with new customers that have different average exports.

Our results unpack customer *uptrading* as a key channel through which exporters grow. This suggests two things. First, finding new customers can matter for export growth even when the size of the customer portfolio remains unchanged. Second, the systematic replacement of existing customers with better matches points to binding constraints on firms' capacity to sustain multiple relationships. While much attention has focused on search costs as barriers to network formation, our results indicate that firms also face sizable costs in managing existing relationships over time.

2.3. Upkeep Costs

We now examine the role of *upkeep costs* in managing customer relationships as a driver of customer *uptrading*. When these costs are high, firms may choose to replace customers rather than expand their portfolios. Consistent with this mechanism, we show that relationship length and the probability of replacement respond to factors that plausibly affect the cost of managing foreign customers.

Relationship Length. We begin by exploring variation in relationship length across destination countries, using standard gravity variables as proxies for the relational costs Chilean exporters face. Specifically, we consider *geographic distance* to capture travel logistics, a common

et al. 2018; Bernard et al. 2018b). Our results, however, align with the time-varying specification in Carballo et al. (2018), where the intensive margin also accounts for roughly 80% of the variation among exporters from Costa Rica, Ecuador, and Uruguay.

language or *religion* to facilitate communication and trust, and a shared *legal origin* to reflect institutions that ease legal procedures. We regress relationship length on each proxy, defined as the number of consecutive years a seller–product (HS8)–buyer relationship formed in period t will last.[6] Table 3 reports results controlling for GDP per capita in the destination country, year fixed effects, and seller–product fixed effects. All coefficients are significant and in the expected direction: greater geographic distance shortens relationships, while common language, religion, or legal origin expands them. This is consistent with relationships being shorter when they are more costly to manage.

Table 3. Relationship Length and Relational Frictions

	(log) Relationship Length [spbt]			
	(1)	(2)	(3)	(4)
Geographic Distance (log)	-0.042***			
	(0.004)			
Common Language		0.060***		
		(0.006)		
Common Religion			0.091***	
			(0.008)	
Common Legal Origins				0.045***
				(0.006)
GDP per capita	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Seller-Product FE	Yes	Yes	Yes	Yes
Observations	576,235	576,235	574,983	576,235

Notes: The dependent variable is the (log) number of consecutive years a seller–product (HS8)–buyer relationship formed in year t will remain active. Geographic Distance is measured between Santiago (Chile) and the largest city in the destination country. Common Language and Common Religion are indicators for whether the destination shares the same official or primary language or religion. Common Legal Origin is an indicator for whether the legal system shares the same basis. All regressions are at the seller–product (HS8)–buyer–year level over 2010–2015. Standard errors are clustered at the destination country–year level.

We next exploit variation in direct flight connections as a more direct measure of *upkeep costs*. The logic is straightforward: face-to-face meetings, on-site visits, and timely resolutions are easier (and cheaper) when a direct flight is available, reducing the cost of maintaining relationships. Table 4 reports results from regressing relationship length on an indicator for whether the seller's origin city $o(s)$ has a direct flight to the buyer's destination country $d(b)$ in year t. Column (1) includes seller–product fixed effects, so identification comes from variation within a seller across buyers of the same product at different destinations. Column (2)

[6] We define *relationship length* to take the values {1, 2, 3, 4, 5+} years. Since our panel spans from 2010 to 2019, this variable is computed for 2010–2015 to ensure sufficient years ahead for each relationship.

adds product–year fixed effects to control for evolving supply and demand conditions across industries. Columns (3) and (4) further add origin city–year and destination country–year fixed effects to account for local technological or economic developments that may affect relationship length. Finally, Column (5) adds buyer–product fixed effects, so identification comes from the same customer sourcing the same product. Across all specifications, the availability of a direct flight is associated with longer-lasting relationships, supporting the idea that *upkeep costs* drive customer replacement.[7]

Table 4. Relationship Length and Flight Connectivity

	(log) Relationship Length [spbt]				
	(1)	(2)	(3)	(4)	(5)
D(Flight = 1) [c(s)d(b)t]	0.077***	0.075***	0.073***	0.036***	0.071**
	(0.018)	(0.013)	(0.013)	(0.013)	(0.030)
Year FE	Yes	No	No	No	No
Seller-Product FE	Yes	Yes	Yes	Yes	Yes
Product-Year FE	No	Yes	Yes	Yes	Yes
Origin City-Year FE	No	No	Yes	Yes	Yes
Destination Country-Year FE	No	No	No	Yes	Yes
Buyer-Product FE	No	No	No	No	Yes
Observations	592,768	587,463	587,384	587,331	191,854

Notes: The dependent variable is the (log) number of consecutive years a seller–product (HS8)–buyer relationship formed in year t will remain active. The main regressor is an indicator for whether the seller's origin city $c(s)$ has a direct flight connection to the buyer's destination country $d(b)$ in year t. All regressions are at the seller–product–buyer–year level over 2010–2015. Standard errors are clustered at the origin city–destination country–year level.

Probability of Breaks. We complement this analysis by measuring how the probability that an export relationship breaks varies with the availability of a direct flight connection. For this, we use an indicator equal to one if a seller–product (HS8)–buyer link formed in t is terminated in $t + 1$. We then regress this variable on the indicator for a direct flight connection between the seller's town and the destination country, using the same set of fixed effects as in the previous specification. Table 5 shows that a direct flight significantly reduces the probability that a relationship ends in $t + 1$ by roughly 5 percentage points. This reinforces the interpretation that lower *upkeep costs* make relationships more durable, while higher upkeep costs make them more likely to break.

[7]Appendix A provides additional evidence on the role of flight connectivity. Results are robust to using the more demanding seller–product–year fixed effect and to restricting the sample to sellers active at the beginning of the panel (2010), ruling out market entry effects.

Table 5. Probability of Breaks and Flight Connectivity

	D(Break = 1) [spbt]				
	(1)	(2)	(3)	(4)	(5)
D(Flight = 1) [c(s)d(b)t]	-0.059***	-0.059***	-0.059***	-0.027**	-0.050*
	(0.017)	(0.012)	(0.011)	(0.011)	(0.027)
Year FE	Yes	No	No	No	No
Seller-Product FE	Yes	Yes	Yes	Yes	Yes
Product-Year FE	No	Yes	Yes	Yes	Yes
Origin City-Year FE	No	No	Yes	Yes	Yes
Destination Country-Year FE	No	No	No	Yes	Yes
Buyer-Product FE	No	No	No	No	Yes
Observations	592,768	587,463	587,384	587,331	191,854

Notes: The dependent variable is an indicator for whether a seller–product (HS8)–buyer relationship formed in period t ends in $t+1$. The main regressor is an indicator for whether the seller's origin city $c(s)$ has a direct flight connection to the buyer's destination country $d(b)$ in year t. All regressions are at the seller–product–buyer–year level over 2010–2015. Standard errors are clustered at the origin city–destination country–year level.

Taken together, these results suggest that *upkeep costs* shape the dynamics of export relationships: when they are high, sellers may opt to drop existing customers when better matches are available. This, in turn, helps explain the prominence of customer *uptrading* as a channel of exporters' growth. We next propose a dynamic model of exporting that rationalizes these patterns and quantifies the role of upkeep costs.

3. Model

We interpret these findings through a structural model that emphasizes two key features of exporters' growth: First, the customer replacement patterns documented above suggests that sellers are constantly searching for new buyers in the hope of finding more and better trade partners. Second, these search frictions combined with the relationship upkeep costs previously identified, give rise to an *uptrading dynamic*, in which exporters' search outcomes determine whether they expand their network, replace existing customers, or leave their customer portfolio unchanged.

Our setup is a continuous-time model in which single-product sellers choose the intensity of a costly search effort to find potential new buyers in the global market. These buyers combine multiple inputs from different sellers to produce a final good to be sold in a downstream market. In each period, a firm can generate at most one new lead or none at all, depending on its search effort. When a seller meets a potential buyer, it evaluates the expected profits from starting a trade relationship with it. This calculation accounts for both the direct profits from the transaction and the additional costs of managing a larger portfolio of business relationships. The seller then compares the profitability of every possible combination of its existing trade partners and the new lead. Based on this assessment, the seller can choose one of three actions: *grow* its network by adding the new lead to its customer portfolio, *churn* its portfolio by replacing the least profitable customer with the new lead (keeping the number of customers constant), or *ignore* the lead and keep its current pool of customers unchanged.

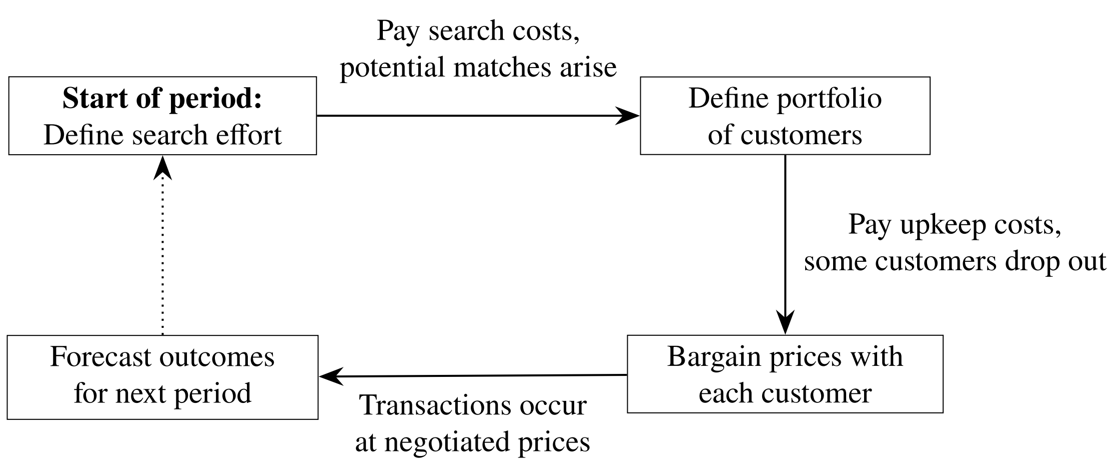


FIGURE 2. Model overview from sellers' perspective at each period

3.1. Sellers

There is a continuum of heterogeneous sellers producing intermediate goods. Each seller owns a blueprint for a single variety ω and draws its marginal production cost c_x from a distribution $G(c_x)$. When choosing the intensity of search effort (ϵ), each seller x incurs an increasing and convex cost (κ) proportional to its efforts. Sellers form expectations about future profits after a new match, $\bar{\Pi}(\Omega_x)$, knowing they will optimize their customer portfolios (Ω_x) based on the outcomes of their searches. Because they have limited information about foreign markets, sellers cannot target specific buyers and understand that matches occur at random, although greater effort raises the probability of securing a new lead.

$$\epsilon^* = \arg\max_{\epsilon} \mathbb{E}\left[\bar{\Pi}(\Omega_x)\right] - \kappa(\epsilon) \tag{3}$$

The optimal portfolio decision after meeting a new lead depends on two factors: the additional transaction profits of trading with the new potential buyer and the increase in per-period upkeep costs (λ) for maintaining the seller's business network. When a search succeeds, the seller meets a lead ℓ and chooses one of three actions: (i) trade with ℓ and expand the network, (ii) replace an incumbent customer with ℓ, or (iii) ignore the match and don't engage in trade with the lead. Expanding the network raises revenue but also increases maintenance and upkeep costs, reflecting the greater difficulty of serving a larger customer base. When ℓ is a higher-value customer than the marginal incumbent but not enough to offset the added upkeep cost, replacing an existing customer will yield higher profits than expanding the trade network. If ℓ is less profitable than even the weakest incumbent, the seller keeps the customer base unchanged and ignores the match. This decision framework leads to the following portfolio optimization problem of the seller:

$$\bar{\Pi}(\Omega_x|\ell) = \underset{\Omega_x' \subseteq \Omega_x \cup \{\ell\}}{Max} \quad \Pi(\Omega_x') - \lambda(n = |\Omega_x'|) \tag{4}$$

3.2. Buyers

Buyers, on the other hand, source multiple intermediate inputs from different sellers to assemble a final product, y, they sell in a downstream market where consumers choose among a continuum of differentiated final goods. Consumers in the downstream market have a constant elasticity of substitution σ. This formulation captures how consumers are willing to substitute across products while still valuing variety. Therefore, demand for the importer's good y is a function of its price (p_y), the downstream market price index (P) and the total consumers' expenditure (E) on the whole range of final goods.

(5)
$$q_y = p_y{}^{-\sigma} P^{\sigma-1} E$$

To produce these goods, buyers incur no labor costs and use a CES technology that combines the intermediate inputs supplied by different sellers with a constant elasticity of substitution across inputs, η. This implies each buyer has a cost index c_y defined by the aggregation of the input prices of each of its suppliers in its network (Ω_y).

(6)
$$c_y = \left(\sum_{x \in \Omega_y} p_{xy}{}^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

Under monopolistic competition in the downstream market, buyers set prices by applying a fixed markup over their cost index:

(7)
$$p_y = \left(\frac{\sigma}{\sigma - 1} \right) c_y$$

And demand for the good of a seller x from a buyer y is then given by:

(8)
$$q_{xy}(p_{xy}) = p_{xy}{}^{-\eta} c_y{}^{\eta-1} E_y$$

3.3. Bilateral profits

Assuming monopolistic competition in the upstream market for intermediate goods, sellers also set prices[8] using a fixed markup rule over their marginal cost (c_x) and the match specific quality shock (γ_{xy}).

(9)
$$p_{xy} = \left(\frac{\eta}{\eta - 1} \right) \gamma_{xy} c_x \quad \text{for all } y$$

Then the transaction profits for the seller are:

[8]We also study an extension of the model with multilateral bargaining.

$$\Pi_{xy} = \left(\frac{1}{\eta}\right)\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}\left[\frac{\eta}{\eta-1}c_x\right]^{1-\eta} c_y^{\eta-\sigma} P^{\sigma-1} E = A \times c_x^{1-\eta} c_y^{\eta-\sigma} \tag{10}$$

Profits from a bilateral transaction depend only on the costs of the seller and the buyer, and they are independent of the seller's other transactions. The following proposition summarizes these results.

PROPOSITION 1. (BILATERAL PROFITS) *The transaction profits of the seller are a strictly decreasing function of the buyer's cost index* c_y.

3.4. Portfolio optimization

We can use Equation 10 to characterize the seller's decision making about its portfolio choices after finding a new lead. Proposition 1 establishes that, all else equal, a seller prefers matching customers with lower cost indices. A new lead is therefore ignored only if two conditions are met simultaneously. First, the lead's cost index must exceed that of every incumbent customer. Second, the profits from trading with the lead must be less than the additional upkeep costs required to maintain a larger network. If either condition fails, the seller improves its portfolio, either by expanding the network to include the lead or by replacing the incumbent with the highest cost index.

The decision to expand or replace customers depends on the transaction profits of the lead and of the seller's worst buyer (Π_{xy}^{min}). That is, the incumbent customer with the highest cost index. If the transaction profits of trading with the new lead are higher than those of trading with its worst customer, but neither of them exceeds the marginal upkeep cost of expanding the network, the seller replaces this worst customer with any new lead whose cost index is lower. If, instead, the transaction profits of trading with the lead exceed the marginal upkeep cost, then the seller chooses to include the new lead and expand its customer portfolio.

PROPOSITION 2. (PORTFOLIO CHOICE) *The seller's optimal portfolio policy follows a threshold rule based on the lead's cost index.*

$$\Omega_x^*(\Omega_x, \ell) = \begin{cases} \Omega_x \cup \{\ell\} & \text{if} \quad \Pi_{x\ell} \geq \frac{\partial\lambda}{\partial n} & (Expand) \\ \Omega_x \cup \{\ell\}/\{\omega\} & \text{if} \quad \exists \omega \in \Omega_x / \Pi_{x\omega} \leq \Pi_{x\ell} < \frac{\partial\lambda}{\partial n} & (Churn) \\ \Omega_x & \text{if} \quad \Pi_{x\ell} < \min\left(\Pi_{xy}^{min}, \frac{\partial\lambda}{\partial n}\right) & (Ignore) \end{cases} \tag{11}$$

The intuition behind this is illustrated in Figure 3, which depicts the optimal action of a seller x when matched with a potential new buyer ℓ with transaction profits $\Pi_{x\ell}$.

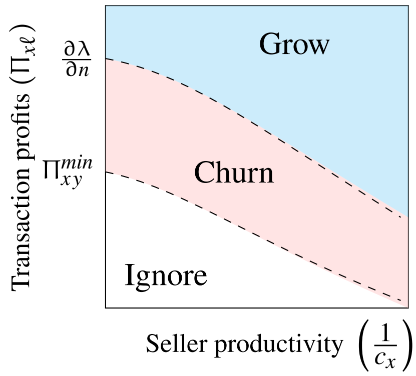


FIGURE 3. Example of a seller's optimal portfolio choices

We further assume that upkeep costs take the form

$$\lambda(n_x = |\Omega_x|) = n_x^{\lambda_0} \tag{12}$$

In this case, an exporter expands its network only if:

$$c_\ell \geq \bar{c_\ell} = \left[\frac{\lambda_0}{A} c_x^{\eta-1} n_x^{\lambda_0 - 1}\right]^{\frac{1}{\eta-\sigma}} \tag{Expand}$$

And churns its portfolio if

$$c_\omega < c_\ell < \bar{c_\ell} \tag{Churn}$$

3.5. Optimal search effort

A firm's choice of search effort intensity depends on the costs and the expected rewards of these efforts. We assume these costs to be separately additive from the firm's operating profits and to be an *m-power* function on intensity effort (see Equation 13 below).

$$\kappa(\epsilon) = \kappa_0 \epsilon^m \tag{13}$$

The rewards from a firm's search efforts depend on two elements: the probability of finding a new match and the portfolio decision taken once a lead is found. Equation 11 characterizes the seller's choice given its least profitable customer ω, and allows us to write the expected profits of seller x after matching with a new lead ℓ.

Proposition 3. (Seller Profits) *The seller's profit conditional on finding a new lead (potential customer) ℓ can be expressed as:*

$$\begin{aligned}\mathbb{E}\left[\pi(\Omega_x)|\ell\right] &= \pi(\Omega_x) + \mathbb{P}\left(Upselling\right)\mathbb{E}\left[\Delta\pi|\Omega_x\right] \\ &\quad + \mathbb{P}\left(Churn\right)\left(\pi_{x\ell} - \pi_{x\omega}\right) + \mathbb{P}\left(Expand\right)\left(\pi_{x\ell} - \frac{\partial\lambda}{\partial n}(|\Omega_x|)\right)\end{aligned}$$

The evolution of a seller's profits depends on its previous customer portfolio (Ω_x) and on whether it expands sales along one or more of three growth margins: *upselling* to existing customers, *uptrading* by replacing an old customer with the new lead, or *expanding* the customer base by adding the new lead.

We model the probability of forming a new match using an equally *m-powered* exponential distribution in search intensity:

$$\mathbb{P}(Match = 1|\epsilon) = 1 - e^{-(\epsilon^m)} \quad \text{with } \epsilon \in [0, \infty] \tag{14}$$

Combining this with Proposition 3, we can solve for the firm's optimal search effort.

Proposition 4. (optimal effort) *The optimal search effort ϵ^* is given by*

$$\epsilon^* = \sqrt[m]{\log\left(\mathbb{E}\left[\pi(\Omega_x)|\ell\right]\right) - \log(\kappa_0)}$$

These parameters rule exporters' growth trajectories.

3.6. System transitions

The analysis above shows that the dynamics of the system are driven by the distribution of potential new buyers, which shapes sellers' profit expectations and search efforts. From the seller's perspective, buyers are fully characterized by their cost index c_y. We therefore define the distribution of new buyers as the distribution of their cost indices, which we assume follows a Pareto distribution with two parameters.

$$M(c_y) \sim Pareto(\alpha, \beta) \tag{15}$$

We can now rewrite the seller's expected profits after finding a lead (Equation 3) as

$$
\begin{aligned}
(16) \qquad \mathbb{E}\left[\pi(\Omega_x)|\ell\right] =& A \times c_x^{1-\eta}\left(\sum_{y\in\Omega_x} c_y^{\eta-\sigma} + e^{-\phi\bar{c_\ell}}\left[-\left(\frac{\alpha\beta^\alpha}{\eta-\sigma-\alpha}\right)\bar{c_\ell}^{\eta-\sigma-\alpha} - \lambda_0 n_x^{\lambda_0-1}\right]\right. \\
&\left. + \left(e^{-\phi\bar{c_\ell}} - e^{-\phi c_\omega}\right)\left[-\left(\frac{\alpha\beta^\alpha}{\eta-\sigma-\alpha}\right)\left(\bar{c_\ell}^{\eta-\sigma-\alpha} - c_\omega^{\eta-\sigma-\alpha}\right)\right]\right)
\end{aligned}
$$

Which we can use to characterize the transition probabilities. For example, the probability of having a new lead of type ℓ in the next period is defined[9] as:

$$
(17) \qquad \mathbb{P}(\ell \in \Omega_x') = \begin{cases} \left(1 - e^{-(\epsilon^*)^m}\right) M(c_\ell) & \text{if } c_\ell > \min\left(c_\omega, \bar{c_\ell}\right) \\ 0 & \text{otherwise} \end{cases}
$$

Finally, we define the network's steady state as the one in which the probability

$$
\mathbb{P}_t(\Omega_x'|\Omega_x) = \mathbb{P}_{t+1}(\Omega_x'|\Omega_x)
$$

[9]Other transition probabilities can be written in an analogous way.

4. Quantitative analysis (in progress)

4.1. Model simulations

In this section we present the results from numerical simulations of our model to better understand the model behavior and its dynamics. For this exercise, we use parameters values previously present in the literature and we are particularly interested in the behavior of the equilibrium prices, the portfolio management decisions and the choice of search efforts.

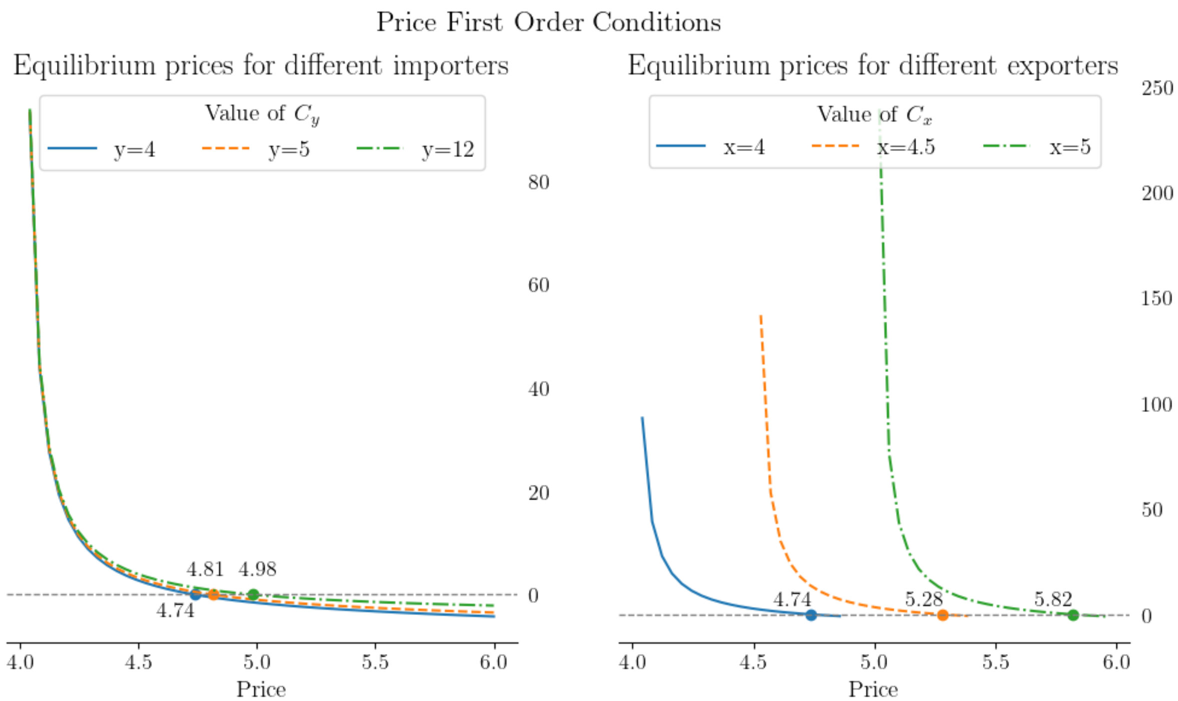


FIGURE 4. Equilibrium prices at different cost-indexes

Figure 4 shows the value of the first order conditions of the bargaining problem at different prices, as described in equation **??**. We can see the value of the first order condition is a monotonically decreasing function of prices, which is consistent with the uniqueness result of the Nash-in-Nash bargaining solution (Collard-Wexler et al. 2019). Moreover, we observe that prices are increasing functions of the parties cost-indexes. That is, an exporter charges a higher markup to less efficient importers. Similarly, more efficient importers are able to get lower prices from their suppliers.

For an exporter with marginal cost c_x, figure 5 illustrates the expected profits of trading with a new lead characterized by an ex-ante cost index c_y. While exporters achieve higher markups with high-cost importers, the overall profits decline as the parties' cost indexes increase. This

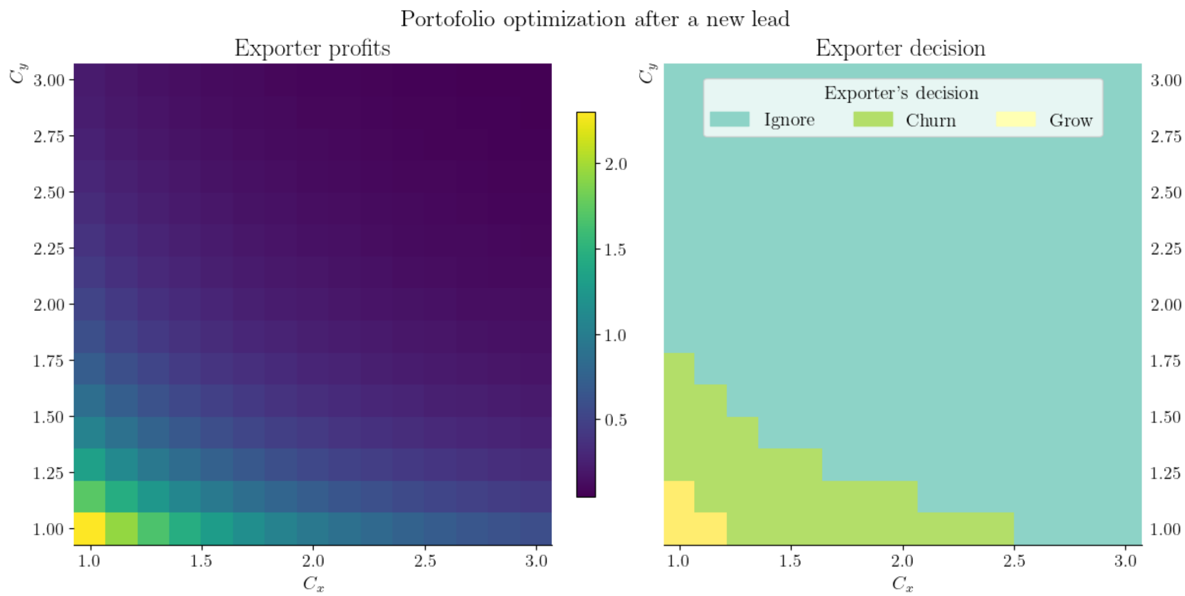


FIGURE 5. Portfolio decisions of the exporter

is because higher cost-index importers must charge higher prices, leading to reduced sales volumes. These lower volumes weaken the importers' bargaining positions in the upstream market, prompting exporters to impose higher markups to offset the diminished trade volume.

As a result, the decision to expand the exporter's network is reserved for instances where the exporter encounters a highly productive importer with significant sales potential. Otherwise, the firm may opt to drop an existing customer with a high cost index and replace it with the new client (*Churn*)—but only if the profits from the new relationship exceed the associated upkeep costs. If the expected profits fall below this threshold, the exporter will choose not to engage in trade and will *Ignore* the new lead.

These decision thresholds are illustrated in the second chart of figure 5. The figure demonstrates that more productive firms exhibit higher decision thresholds, reflecting their greater expected value from a new match. This advantage arises through two mechanisms: (1) they can engage profitably with a broader range of firms, and (2) they can achieve higher profits from trading with the same importer compared to less productive exporters with higher costs.

Finally, we focus on exporters' search behavior, depicted in figure 6. As expected, firms increase their search efforts when faced with lower search costs (κ). Similarly, exporters with lower marginal costs also search more actively. This creates a positive feedback loop for highly productive firms: these firms search more for new clients because they achieve higher profits from any new match and can trade with a broader range of partners. Moreover, although not shown in the figure, more productive firms have a higher probability of being included in the trade networks of potential leads, providing an additional channel for growth and reinforcing their competitive advantage.

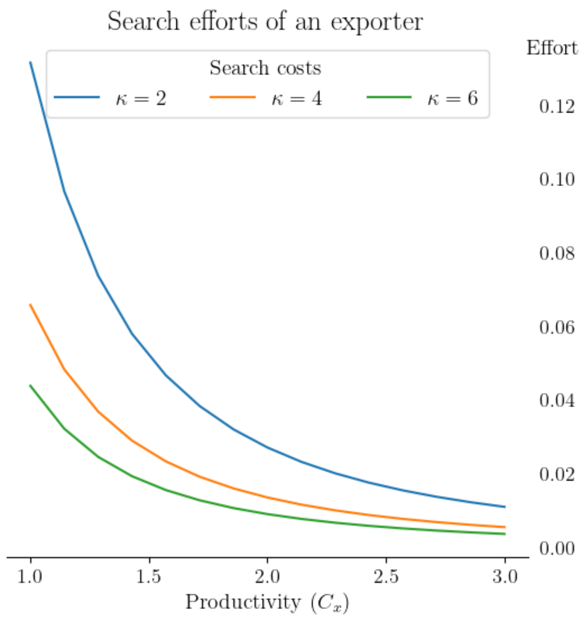


FIGURE 6. Exporters with lower marginal-costs search more

4.2. Estimation and counterfactuals (in progress)

Our estimation strategy leverages the rich microdata on Chilean firms and their foreign buyers. We use model equations to estimate the elasticities of substitution and the parameter governing the relative market power of sellers and buyers. We then estimate the costs of searching for customers and managing customer relationships using the simulated method of moments. Our quantification analysis examines the impact of customer management costs on export performance across the firm size distribution. We then perform four counterfactuals: (i) reductions in search costs, representing trade facilitation policies or advances in communication technologies; (ii) reductions in upkeep costs, reflecting training programs and technologies that improve firms' customer management; (iii) market entry on either side of the market, interpreted as industrial policies enhancing competition; and (iv) package reforms combining policies to examine their joint effects.

5. Conclusion

Exporters engage in a range of activities to transact with customers, including finding suitable partners, managing orders from existing buyers, and negotiating prices over time. This paper combines rich panel data on the foreign buyers of Chilean exporters with a dynamic model of exporting to examine the role of customer management activities in export growth. We show that growing exporters replace older customers with more profitable matches while increasing both average prices and price dispersion. Our model features search frictions, upkeep costs of managing customers, and bilateral bargaining, such that additional customers enhance exporters' sales and negotiating positions but increase managerial costs. This setting allows us to characterize firms' dynamic export strategies and quantify the role of managing customer relationships in export growth.

Our analysis examines the effect of different policies associated with customer management on exporters' performance. We compare standard trade facilitation policies, which reduce search and matching costs, with policies that enhance firms' managerial skills to handle multiple customers, considering both individual and combined actions. We then interact these measures with policies that induce entry on either side of the market. By unveiling the role of customer relationships in imperfectly competitive international markets, this paper advances our understanding of how exporters succeed and informs ongoing debates on trade facilitation, deep economic integration, and industrial policy.

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A. Empirical Appendix

A.1. Data Management

We first merge the following datasets using the unique tax identifier (RUT) for Chilean firms.

- **Customs Service of Chile** (*Servicio Nacional de Aduanas*)
  - Exporter tax ID, foreign buyer name, destination country, product (HS8), value, quantity, and unit value for the universe of export transactions (2010–2019).
- **Tax Authority of Chile** (*Servicio de Impuestos Internos*)
  - Firm tax ID, industry, size (sales bins), number of employees, age, and location (city) for the universe of Chilean firms (2010–2019).

We then implement a simple harmonization routine for foreign buyer names. This addresses misreporting and common spelling mistakes in digitized records while preserving most observations in the data.

- Drop observations without a name ($< 10\%$).
- Remove non-numerical characters and spaces within names.
- Remove spaces at the beginning and end of each name.
- Trim names to their first 30 characters.
- Standardize common abbreviations for Limited, Corporation, Company, Incorporated, etc.
- Collapse buyers with the same name within destination country–HS8 product–exporter combinations.

Finally, we merge in information on flights operating between each Chilean city and destination country in a given year from the **Civil Aeronautics Board of Chile** (*Junta Aeronáutica Civil*) and standard gravity variables for geographic distance, language, religion, legal system and GDP per capita for all destination countries from the **CEPII database**.

A.2. Additional Evidence on Upkeep Costs

TABLE A1. Relationship Length with Seller-Product-Year FE

	(log) Relationship Length [spbt]			
	(1)	(2)	(3)	(4)
D(Flight = 1) [c(s)d(b)t]	0.076***	0.037***	0.047**	0.066**
	(0.014)	(0.014)	(0.021)	(0.033)
Seller-Product-Year FE	Yes	Yes	Yes	Yes
Origin City-Year FE	No	Yes	Yes	Yes
Destination Country-Year FE	No	Yes	Yes	Yes
Buyer FE	No	No	Yes	No
Buyer-Product FE	No	No	No	Yes
Observations	520,537	520,484	419,525	160,192

Notes: The dependent variable is the (log) number of consecutive years a seller–product (HS8)–buyer relationship survives, considering relationships formed in period t. The key regressor is an indicator for whether the seller's origin city $c(s)$ has a direct flight connection to the buyer's destination country $d(b)$ in year t. All regressions are at the seller–product–buyer–year level over 2010–2015. Standard errors are clustered at the origin city–destination country–year level.

TABLE A2. Relationship Length with Subsample of Initial Sellers (2010)

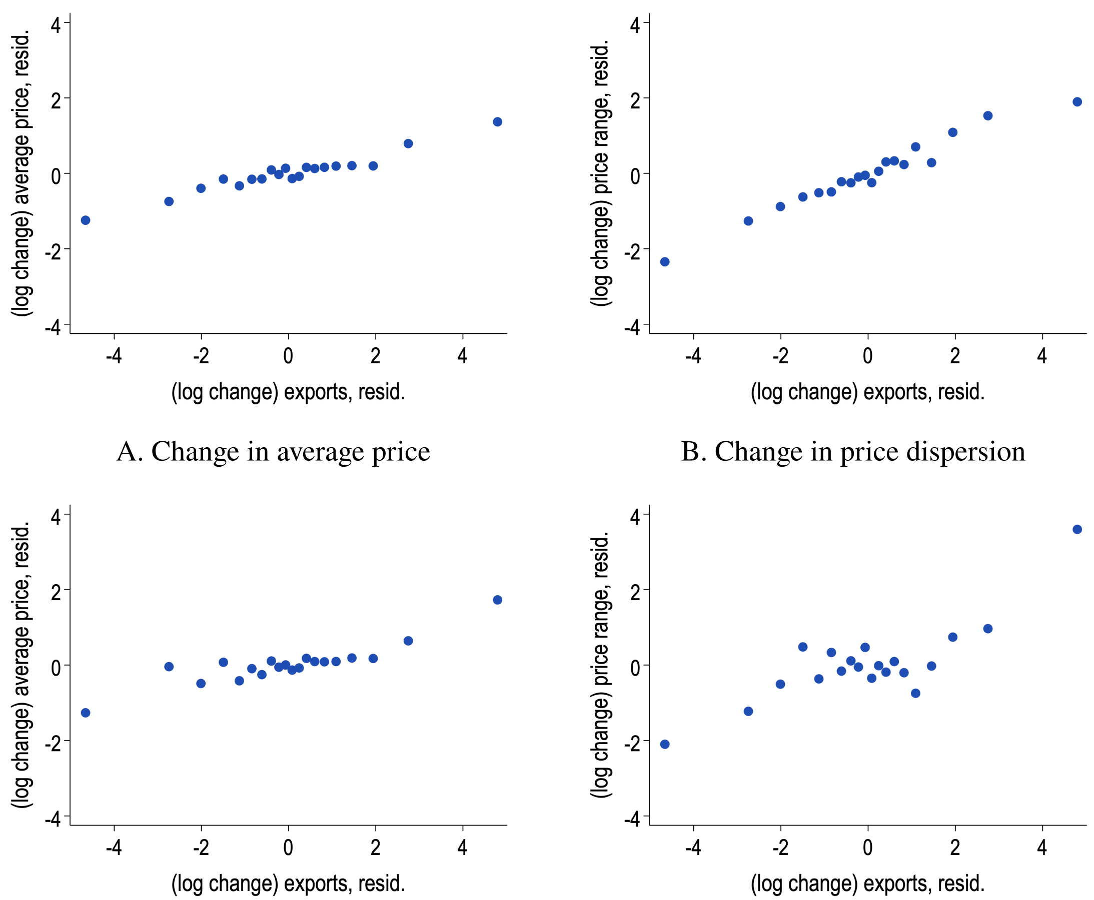
	(log) Relationship Length [spbt]				
	(1)	(2)	(3)	(4)	(5)
D(Flight = 1) [c(s)d(b)t]	0.081***	0.077***	0.074***	0.038***	0.076**
	(0.018)	(0.013)	(0.013)	(0.013)	(0.034)
Year FE	Yes	No	No	No	No
Seller-Product FE	Yes	Yes	Yes	Yes	Yes
Product-Year FE	No	Yes	Yes	Yes	Yes
Origin City-Year FE	No	No	Yes	Yes	Yes
Destination Country-Year FE	No	No	No	Yes	Yes
Buyer-Product FE	No	No	No	No	Yes
Observations	533,205	527,891	527,833	527,777	162,656

Notes: The dependent variable is the (log) number of consecutive years a seller–product (HS8)–buyer relationship survives, considering relationships formed in period t. The key regressor is an indicator for whether the seller's origin city $c(s)$ has a direct flight connection to the buyer's destination country $d(b)$ in year t. All regressions are at the seller–product–buyer–year level over 2010–2015. Standard errors are clustered at the origin city–destination country–year level.

A.3. Evidence on Export Prices

We explore how export prices evolve over time and find that growing exporters increase both their average price and the dispersion of prices across customers. We focus on a four-year horizon (2015–2019) at the firm–product level and demean all variables by product (HS8). Figure A1A shows that growing exporters raised their prices relative to downsizing exporters, while Figure A1B shows that they also widened the range of prices charged across customers. We then restrict attention to *old* customers (relationships that remain active in both periods) in Figures A1C and A1D. A similar trend emerges, consistent with changes in the bargaining position of exporters and their customers over time.

FIGURE A1. Changes in Export Prices at the Firm-Product Level



A. Change in average price

B. Change in price dispersion

C. Change in average price, old customers

D. Change in price dispersion, old customers

Note. Firm-product pairs are sorted into 20 bins by their change in exports over a 4-year horizon (2015-19). Each dot displays the value of the variable on the vertical axis for the average firm in each bin. All variables are residualized by product (HS-8).

B. Decomposition of Exporters' Growth

Total exports by a firm-product pair i in period t can be expressed as:

$$X_{it} = \overline{X}_{it} N_{it},$$

where $\overline{X}_{it}$ denotes average exports per customer and N_{it} is the number of customers. The log-change in exports by i from period t to $t+j$ is then given by:

$$\text{(A1)} \qquad \Delta_{t,t+j} \log X_i = \underbrace{\Delta_{t,t+j} \log N_i}_{\text{Extensive Margin}} + \underbrace{\Delta_{t,t+j} \log \overline{X}_i}_{\text{Intensive Margin}}$$

We split the intensive margin into a *customer upselling* component (sales growth to continuing customers) and a *customer uptrading* component (net effect of adding new customers and dropping others). We first transform $\Delta_{t,t+j} \log \overline{X}_i$ into absolute changes $\Delta_{t,t+j}\overline{X}_i$ to separate these components, and then express the result back in log-change form. Formally:

$$\text{(A2)} \qquad \Delta_{t,t+j} \log \overline{X}_i = \frac{\Delta_{t,t+j}\overline{X}_i}{M_i},$$

where $M_i \equiv L(\overline{X}_{i,t+j}, \overline{X}_{i,t})$ is the logarithmic mean $L(a,b) \equiv \frac{a-b}{\ln a - \ln b}$ for $a, b > 0$.

The numerator $\Delta_{t,t+j}\overline{X}_i$ can be expressed in terms of exports to *new* customers in $t+j$, sales to *dropped* customers in t that are no longer active in $t+j$, and exports to *old* customers that remain active in both t and $t+j$.

$$\begin{aligned}
\underbrace{\Delta_{t,t+j}\left(\overline{X}_i\right)}_{\substack{\text{Change in average}\\ \text{exports per customer}}} &\equiv \overline{X}_{it+j} - \overline{X}_{it} \\
&= \frac{X^{New}_{it+j} + X^{Old}_{it+j}}{N_{it+j}} - \frac{X^{Drop}_{it} + X^{Old}_{it}}{N_{fpt}} \\
\text{(A3)} \qquad &= \left\{ \frac{N^{Old}_{it+j}}{N_{it+j}} \frac{X^{Old}_{it+j}}{N^{Old}_{it+j}} - \frac{N^{Old}_{it}}{N_{it}} \frac{X^{Old}_{it}}{N^{Old}_{it}} \right\} + \left\{ \frac{N^{New}_{it+j}}{N_{it+j}} \frac{X^{New}_{it+j}}{N^{New}_{it+j}} - \frac{N^{Drop}_{it}}{N_{it}} \frac{X^{Drop}_{it}}{N^{Drop}_{it}} \right\} \\
&= \underbrace{\Delta_{t,t+j}\left(\alpha^{Old}_i * \overline{X}^{Old}_i\right)}_{\text{Customer Upselling}} + \underbrace{\left[\alpha^{New}_{it+j} * \overline{X}^{New}_{it+j} - \alpha^{Dropped}_{it} * \overline{X}^{Drop}_{it}\right]}_{\text{Customer Uptrading}}
\end{aligned}$$

Denoting the customer upselling component as $\Delta_{t,t+j}\overline{X}^{Upsale}_i$ and the customer uptrading component as $\Delta_{t,t+j}\overline{X}_i^{Uptrade}$ in (A3), we can write the log-change in the intensive margin as:

$$\text{(A4)} \qquad \Delta_{t,t+j} \log \overline{X}_i = \frac{\Delta_{t,t+j}\overline{X}_i}{M_i} = \frac{\Delta_{t,t+j}\overline{X}_i^{Upsale}}{M_i} + \frac{\Delta_{t,t+j}\overline{X}_i^{Uptrade}}{M_i}$$

Substituting (A4) into (A1) yields the following three-term decomposition for the total change in exports of firm i from period t to $t + j$:

$$\text{(A5)} \qquad \Delta_{t,t+j} \log X_i = \underbrace{\Delta_{t,t+j} \log N_i}_{\text{Extensive Margin}} + \underbrace{\frac{\Delta_{t,t+j}\overline{X}_i^{Upsale}}{M_i}}_{\text{Customer Upselling}} + \underbrace{\frac{\Delta_{t,t+j}\overline{X}_i^{Uptrade}}{M_i}}_{\text{Customer Uptrading}}$$

Note that the *upselling* and *uptrading* components are scaled by the logarithmic mean of average exports per customer, calculated over all customers in the portfolio in each period. This adjustment ensures that the sum of the two components is exactly equal to the intensive margin in Equation (A1). Moreover, since this is an exact decomposition, the contributions of all three margins to the variance of export growth across units are guaranteed to sum to one.