Essays on Firm Learning and Trade Dynamics

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Abstract

In the first chapter of this dissertation, I present a model of exporting with demand uncertainty where incumbent firms in a market reveal signals about a common component of demand that potential entrants observe and use to update their beliefs. Using transaction-level Chilean export data, I estimate these signals within disaggregate product-destination markets and their effect on new exporters along three margins: entry into new markets, the quantity of output sold, and the duration of trade spells. A one-standard-deviation increase in the signal revealed by incumbents is associated with a 3.8% increase in entry rates among potential entrants, along with a 9.8% increase in first-year sales and 0.8% increase in duration for new entrants. The effects of these signals are larger in countries which are further away from Chile, in countries where Spanish is not an official language, and for less differentiated products.

In the second chapter, I examine whether a similar mechanism is present for importing firms whereby they infer information about the quality of imported intermediates and capital goods from the sourcing behavior of their compatriots. Using data on Chilean importers and controlling for heterogeneous export capacities across sectors, source countries, and time, I show that the probability of a firm sourcing a product from a particular origin country, the quantity imported, and relationship survival time increase with the number of compatriots sourcing the same product from the same origin country and the value imported in the previous year. Specifically, entry is 6.6% more likely, import values are 8.0% higher, and relationship survival times are 4.4% longer for product-market pairs in which there is at least one incumbent Chilean firm sourcing the same product from the same origin in the previous year.

In the final chapter, I use results from the first two chapters to estimate the effect of exporting on importing, and vice versa, within a firm-country pair. That is, when a firm begins to export its output to a foreign country, is it more likely to begin importing from that country? Additionally, for a firm which begins to import from a particular country, is the same firm more likely to begin exporting to that country? Because the decision to engage in these two activities is endogenous, I use the presence of firms exporting (importing) the same products to (from) the same country to instrument for initial export (import) entry to estimate the effect of exporting (importing) on importing (exporting). Positive and significant OLS estimates imply that a firm beginning to export to a country is 5.2% more likely in the year after that firm begins importing from that country, with smaller and insignificant effects in the other direction. However, insignificant 2SLS results using six different measures of incumbent presence as instruments indicate that entry into either of these activities within a firm-country pair does not make the other more likely in the following years.

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Chapter 1

Learning, Externalities, and Export Dynamics

1.1 Introduction

International trade is rife with uncertainty. Among other issues, firms have imperfect information about foreign demand, as well as the quality and reliability of foreign inputs. Whereas previous work has shown that firms overcome this uncertainty through repeated interactions and learning from their own experiences, I study how firms overcome this uncertainty prior to their own entry into a market by learning from the actions of their compatriots. Using transaction-level export data from Chile, I examine how the degree of incumbent presence and the information those incumbents reveal within disaggregate product-markets affect three margins of exporting: entry rates, sales, and export spell duration. While multiple mechanisms could generate a positive relationship between incumbent presence and these three margins of exporting, I rule out competing alternatives and show that results are driven by potential entrants learning about demand conditions from the outcomes of incumbents.

My first contribution is to generalize models of firm learning by introducing a component of demand that is common across Chilean firms selling the same product to consumers in the same country. In other learning models, each firm faces its own idiosyncratic demand shock, for which the firm has some prior distribution of beliefs. Many firms may enter a market, but those who experience low enough demand shocks exit, whereas those who face higher-than-expected shocks revise their beliefs upwards and grow in subsequent years. The key is that firms revise their beliefs about demand after themselves entering a market and receiving information. In the model presented here, firms are able to learn about the common component of demand by viewing the actions of others, *without themselves needing to enter,* generating information spillovers across firms. Therefore, when incumbents are present and reveal information, potential entrants have more accurate and precise beliefs about demand.

My second contribution is to quantify the effects of these information spillovers by examining how entry rates, first-year sales, and export duration vary across markets within firm-product-years with the information revealed by incumbent firms in a market. The model delivers the testable implication that when incumbents reveal strong signals about demand, beliefs will be higher (and therefore entry more likely, sales larger, and export duration longer). Consistent with this prediction, I find that a one-standard-deviation increase in the signal revealed by incumbents for a HS 8-digit product in a destination country increases entry rates by 3.8%, first-year sales by 9.8%, and export spell duration by 0.8%. Furthermore, I perform falsification tests that rule out alternative explanations for these results. For example, the positive correlation between incumbent presence and these three margins of exporting could be driven by decreases in trade costs. If incumbent firms establish contacts, develop a reputation, or deepen transportation networks, subsequent entrants may face lower fixed or variable trade costs. However, I show that the effects of the revealed signal decay rapidly with aggregation. Beyond the HS 6-digit level, revealed signals no longer have a positive and significant effect on any of these three margins, which would be unlikely if these effects were driven by decreasing trade costs.

My third contribution is to measure how these spillovers vary by destination country and product type. I find that the effects of these spillovers are larger when considering countries which are further away from Chile and which do not have Spanish as an official language. If these are markets with which exporters are initially less familiar, the presence of an incumbent has a larger effect than in closer, more similar, and more familiar markets. The spillover effects are also larger for more homogeneous products. When there is less inter-firm variation in demand (as there likely is for homogeneous compared to differentiated products), information gained from observing incumbents is more valuable. In determining the efficacy of different export promotion policies, policymakers should take into account these heterogeneous multiplier effects caused by information spillovers.[1]

Many governments around the world employ export promotion agencies and spend large amounts to aid firms in becoming or remaining exporters.[2] In the US alone, the Export-Import Bank, Department of Commerce, Department of Agriculture, Overseas Price Investment Corporation, Small Business Administration, Department of State, Trade and Development Agency, Office of the US Trade Representative, and the Department of the Treasury are all involved in export promotion, with more than $500 million spent by the Department of Agriculture on market development and export financing programs in 2012 alone (Ilias et al. (2013)). An extensive literature exists studying the effectiveness of export promotion for different margins of exporting in many different countries, largely finding positive results.[3] Although export promotion has largely been shown to be effective, that does not mean resources are flowing to their most valuable use. As expected, Volpe Martincus and Carballo (2010) show that different promotion activities have heterogeneous payoffs. Quantifying these differential payoffs and understanding how the benefits of these activities spillover from program recipients to non-recipients selling different types of products in various destination countries remains an important avenue of research to maximize the value of

[1] Export promotion comes in a variety of forms including providing financing to internationally-engaged firms, guaranteeing payments by foreign firms, carrying out studies on foreign markets, tax incentives, and hosting conferences where exporters can meet foreign buyers. According to the 2016 Small Business Exporting Survey (SBES) conducted jointly by the National Small Business Association (NSBA) and the Small Business Exporters Association in the United States, almost 50% of non-exporting firms surveyed claimed to be interested in exporting but did not, one of the primary stated reasons for which was a lack of knowledge. In responses to the 2013 SBES, firms stated that one "of the top three responses among both exporters and non-exporters when asked what types of federal government support would be the most beneficial to their company had to do with better availability of information." Export promotion can provide these firms with the information they need to successfully enter foreign markets and then provide information to others.

[2] Furthermore, real public spending on export promotion has been increasing over recent years. In a report released by Informa Economics in 2017, the authors show that spending on export promotion in the US, the EU, Australia, Brazil, Canada, Chile, China, New Zealand, South Africa, and Turkey increased by 45% between 2011 and 2016.

[3] Countries studied include Belgium in Broocks and Van Biesebroeck (2017), Canada in Van Biesebroeck et al. (2016), Colombia in Volpe Martincus and Carballo (2010), Costa Rica in Volpe Martincus and Carballo (2012), Chile in Alvarez and Crespi (2000), Denmark in Hiller (2012) and Munch and Schaur (2015), Ireland in Görg, Henry, and Strobl, Peru in Volpe Martincus and Carballo (2008), and Uruguay in Volpe Martincus and Carballo (2010). As an example of results, Volpe Martincus and Carballo (2008) argue that export promotion is associated with Peruvian firms exporting more products to more destinations and Broocks and Van Biesebroeck (2017) find that export promotion increases the likelihood that firms in the Flanders region of Belgium export outside of the EU single market.

government export promotion in helping firms overcome international uncertainty.[4]

The rest of the paper is arranged as follows. Section 2 provides a review of the literature regarding externalities and export dynamics. In section 3, I describe the data and highlight that overall firm-level export dynamics in Chile are consistent with those reported elsewhere. Section 4 presents a model with demand uncertainty and outlines the channel through which potential entrants may learn from incumbents. In section 5, I discuss my methodology for deriving signals revealed by incumbent exporters, outline my empirical strategy, and present results. In section 6, I use alternative signals to support claims that the baseline results are driven by learning rather than an alternative mechanism such as reductions in fixed costs or transportations costs.

1.2 Literature Review

The idea that firms may learn from the process of exporting and become more productive as a result is an old one, with empirical investigations dating back to Bernard and Jensen (1999). However, trade economists are increasingly interested and have the tools to examine whether there are spillovers across firms and whether exporters selling new products to new markets are affected by pioneering exporters selling similar products to similar markets. Aitken et al. (1997) show that the entry of pioneers into export markets reduces the entry costs for subsequent exporters to that market.

This work is most closely related to Alvarez et al. (2008), Koenig (2009), Koenig et al. (2010), Poncet and Mayneris (2013), and Fernandes and Tang (2014). Also using Chilean customs data, Alvarez et al. (2008) find that Chilean firms are more likely to enter disaggregate product-markets to which more of their compatriots are already exporting. Koenig (2009), Koenig et al. (2010), and Poncet and Mayneris (2013) use French customs data to show that French exporters are more likely to enter a market where other firms from the same French department export, although there is no effect on the quantity exported. The authors interpret this as pioneering exporters reducing the fixed costs of exporting for fol-

[4] If the effectiveness of export promotion is estimated as the difference in outcomes between treated and non-treated firms, but some of the benefits of treatment accrue to non-treated firms, estimates of effectiveness will decrease with the effects of information spillovers.

lowers, but not variable costs. In all four of these papers, the authors focus on simply the number of incumbents already serving a market, ignoring the possibility that incumbents may reveal negative signals and deter potential entry. Fernandes and Tang (2014) focus on local spillovers in China whereby firms learn about aggregate demand in foreign markets from firms located in the same city exporting to those countries. By contrast, I focus on learning in disaggregate foreign markets from all compatriots selling there, not just those geographically close.

The use of firm-level data over the last fifteen years has brought to light several facts about export dynamics common across countries. One of these is the presence of churning in export markets, as shown in Iacovone and Javorcik (2010). Rather than selling the same products to the same destinations year after year, firms continuously add and drop products and destinations to their export portfolio. As a result, export spells are short on average, as first shown by Besedeš and Prusa (2006) for exports to the US.[5] Second, although many export spells end up being short, some spells survive and exist for a decade or longer. There is negative duration dependence of export spells: a majority of export spells end within a single year. However, for those that survive, the hazard rate declines with each additional year of survival, as in Cadot et al. (2011). Finally, in export spells that last multiple years, growth in sales is higher on average in the early years before declining in the later years, as shown using French data by Berman et al. (2017). Those authors also show that it is common for the quantity that a firm exports to a particular market to decrease over the export spell, even for spells that continue for many years. While the magnitudes vary by level of data aggregation and country, I show that these facts also hold for Chilean exports.

Many hypotheses have been put forth to explain these patterns, including credit constraints, working capital constraints, and uncertainty about demand in foreign markets. In the presence of credit constraints, a firm may begin an export spell with low sales since it cannot secure the financing required to produce and sell as much as it would when unconstrained. As it continues to export, lenders may become more confident in the firm's ability to pay off its debt and be willing to lend it more, allowing it to expand and increase exports,

[5]The definition of an export spell varies from paper to paper with the dimensions of available data. In this paper, I define an export spell as one firm continuously selling the same product to the same destination country in consecutive years.

as described by Bellone et al. (2010). Blum et al. (2013) develop a model with fixed capital but uncertain demand in the home market to explain why firms rapidly enter and exit export markets. In their model, firms commit to production prior to knowing how high domestic demand will be. Once that uncertainty is realized, any excess production is exported. Therefore, firms export in some years but do not in others. While both of these phenomena may help to partially explain firm-level and aggregate export dynamics, results presented here include firm-product-year fixed effects so that I am comparing outcomes across markets within a firm-product-year, where credit and capital constraints do not vary. Furthermore, neither credit nor capital constrants can rationalize why sales may decline consistently for long-lived export spells.

In this paper, I focus on the uncertainty about demand in foreign markets, the role it plays in generating the trends described above, and how it can be reduced by potential entrants learning from incumbent exporters. Introducing uncertainty about demand into a model of exporting generates all of the observed facts described above, even when controlling for the presence of credit and capital constraints, as for example in Berman et al. (2017). In an environment where firms learn about uncertain demand, many firms will begin to export in the hopes that they are profitable. Some firms will receive signals that demand for their products is lower than expected. Of these, some will discontinue exporting whereas others scale back operations. Those firms which receive better-than-expected signals about demand will increase their beliefs, leading them to sell more in future periods. If the export spell survives long and the firm receives enough signals, export volumes will evolve until they reach what would be their optimal level in the absence of uncertainty. Finally, as beliefs about demand improve, it will take an increasingly negative shock to drive the surviving firms out of the market, leading to the declining hazard rates. In the next section, I describe the dataset and document these facts using Chilean export data.

1.3 Data and Descriptive Statistics

The main source of data that I use is transaction-level export data covering the years 2002 through 2014 from Servicio Nacional de Aduanas, Chilean customs.[6] In the original data, a unit of observation contains a firm identifier (RUT), HS 8-digit product code, the nominal value, quantity, and weight of products sold, the destination country, and the date of the transaction. I aggregate together observations involving the same firm, product, and destination in a given year.[7]

Once aggregated, I then define each export spell as the same firm exporting the same product to the same destination country in a string of consecutive years. A spell therefore ends when a calendar year passes without a transaction involving that firm-product-destination triplet. However, if that same triplet re-emerges, it is classified as the beginning of a new export spell, but also as the resumption of a previously-observed trade relationship.[8] Therefore, the same trade relationship may show up in the data as two separate spells. If hypothetical firm Chilean Copper sells copper to the US in 2005 and 2010, these transactions constitute a single trade relationship but two export spells. There is no consensus in the literature about how to deal with trade relationships which appear multiple times. Should the re-entry of a previously existing spell be included in an analysis of new entrants? Or should it be excluded since it may differ dynamically from new spells as it has occurred before and the firm may retain information from its prior experience? I opt to include repeat spells in my baseline analysis, but results are robust when only considering relationships which are observed for the first time.

The final dataset contains 1,113,159 firm-product-destination-year level export flows originating from Chile, embodying 607,703 export spells of 522,553 trade relationships. These

[6]Supplementary data come from many different sources: I use data on price indices and GDP from the World Bank, gravity data from CEPII, information about product types from the Rauch classification, estimates of elasticities of substitution from Soderberry (2015) and Broda et al. (2017), and tariff data from TRAINS. All nominal values are expressed in 2008 US$. As described by Mayer and Zignago (2011), the distance between two countries is the weighted distance between the sets of the the most populous cities in each country. Although tariffs are set at the HS 6-digit level, I use the simple average tariff set for all HS 6-digit products within a HS 4-digit group to obtain better coverage.

[7]However, I retain and use information from the date of each transaction to control for when in the calendar year export spells begin, allowing me to address the partial year effects discussed in Bernard et al. (2017).

[8]A trade relationship is a firm-product-destination triplet.

1.1 million observations contain roughly 13 million (12,814,364) transactions worth $677 billion. The average firm exports 8.5 products to 3.6 destinations over the period of the sample, whereas the median firm exports 2 products to a single destination. These differences between the mean and median statistics are driven by the disproportionate share of exports contributed by the largest firms. Freund and Pierola (2015) and Bernard et al. (2009) show that exports at the country level are dominated by the largest firms. Using U.S. data, the latter find that 81% of US exports in 2000 came from the top 1% of firms, 93% came from the top 5%, and 96% came from the top 10%. Those numbers are similar for Chile. In this sample, the top 1%, 5%, and 10% of firms account for 85%, 95%, and 98% of export value.

The key variation that I exploit is differences in the presence of incumbent Chilean exporters across markets and the signals revealed by those incumbents.[9] For example, there are some markets to which many Chilean firms export and some to which none do. Furthermore, the information revealed by the incumbent firms also varies by market. Signals about demand may be strong in one market but weak in another. Table 1.1 summarizes the number of incumbents present in each market in the year prior to new entry by other firms. For 51% of markets entered, there is zero incumbent presence in that market in the year before, while the average number of incumbent firms within a market entered is 2.4. I exploit this lagged variation and the signals about market conditions revealed by incumbents, which are exogenous from the point of view of potential entrants, to see how the potential entrants respond in terms of entry rates, sales, and duration.[10]

Next, I quantify the three features of the data that I describe above and provide more detail on each. Recall that the three trends are: 1) firms frequently enter and exit markets, leading to short average export spells, 2) conditional survival rates begin low and increase as export spells age, and 3) conditional on survival, growth is large in the beginning of an export spell but slows as the spell ages. Furthermore, despite spells growing on average, a large share of long-lasting spells experience a decrease in quantities sold over their duration.

Figure 1.1 provides four histograms of export spell duration. Even though the data is ag-

[9]For the rest of the paper, a market refers to a product-destination country pair unless otherwise made clear.

[10]I use observations from the first year of the dataset to define these spillover measures. However, since these observations are left-censored and I am unable to observe when those spells begin, I discard them when describing the stylized facts and in regressions below.

gregated to the firm-product-destination-year level, one of the benefits of having transaction-level data is that I am able to see how many transactions occur within a year and when each occurs for each trading relationship, allowing me to determine the duration of each spell to the day. I define the length of each spell as the number of days between the final transaction and the initial transaction as long as no calendar year passes without a transaction occurring.[11] Panels (A) and (B) depict the count distribution of export duration, or the fraction of the total number of spells that survive for a particular length. For spells with a single transaction, I define the duration of that spell as zero. As is clear from the mass of observations in the left of panel (A), a majority of export spells involve just a single transaction. In panel (B), I ignore observations with zero duration and show the histogram of duration for spells with more than one transaction. The frequency decreases nearly (but not perfectly) monotonically in duration. There are many short spells, but few that survive beyond six years. Panels (C) and (D) depict the value distribution, or the sales-weighted share, of export spells that survive to a particular length.[12]

The second fact observed for many countries is that export spells, for almost any level of aggregation, exhibit increasing conditional survival rates. The conditional survival rate for each age a of spells is defined as the percent of spells that survive to age $a+1$ conditional on surviving to a. Naturally, overall survival rates will decrease as age goes up, but the conditional survival rates increase: the longer a spell lasts, the more likely it is to survive into the next year. In Figure 2.2, I graph the conditional survival rates of spells between the ages zero (those in the first year) and nine that are active in 2012. The point for each age represents the fraction of spells of that age which appear again in the data in 2013. Of the spells which begin in 2012 (and are therefore zero years old), only 48% survive until a second

[11] Most studies measure age as the discrete number of years a spell has been active (0, 1, 2, ...), but I am able to measure in days, providing a finer measure of duration and a greater degree of variation. However, it also provides a more accurate picture of the true length of export spells. For example, suppose that Firm A exports grapes to South Africa on January 1, 2003 and December 31, 2003. This export spell would be coded as lasting 364 days in my data and as lasting one year in studies which measure duration in years rather than days. Suppose Firm B exports grapes to South Africa on December 31, 2002 and January 1, 2003. This spell would be coded as lasting two days in my data, but two years in other studies, even though it clearly lasts a much shorter time than the spell involving Firm A. Measuring spell duration in days limits the likelihood of duration mismeasurement.

[12] Weights in panel (C) are determined by the first-year sales of an export spell, whereas those in panel (D) are by the lifetime sales of the export spell. Because longer spells involve higher sales, the mass of the distribution shifts to the right.

year. As spells age, that survival rate increases (almost monotonically) so that more than 80% of spells above age five survive in the next year. Learning about uncertain demand may be one driver of this trend: many spells end after one year when firms infer that demand is lower than expected and exporting to that market is not profitable. In the model, for those that do survive, larger negative shocks are required to achieve the same change in beliefs (due to the decreasing value of information as a result of the large amount of information already accumulated). Therefore, a smaller fraction of older spells cease each year.

The third finding that I also document for Chilean exporting spells is the presence of declining growth rates (in absolute value) within spells. That is, even after controlling for the partial year effects documented by Bernard et al. (2017), growth rates are large in the first couple of years (in absolute value) but decrease as the spell ages. As pointed out by Berman et al. (2017), not only does growth slow, but a large fraction of spells with duration of ten years actually experience a decrease in the quantity sold, both of which are consistent with learning.

I show that the value traded within an export spell grows over time on average, but that the growth decelerates. I follow Monarch and Schmidt-Eisenlohr (2017) and regress the value exported within a trade relationship (firm f-product k-destination d triplet) in a given year t on a set of age dummies and relationship fixed effects with the following specification:

$$\ln(\text{Sales})_{fkdt} = \sum_{a=1}^{A} \beta_a \mathbf{1}[\text{Age}_{fkdt} = a] + \alpha_{fkd} + \epsilon_{fkdt}. \tag{1.1}$$

I estimate seven versions of this regression, with each using only observations from spells which have a duration of exactly A=4, 5, ..., 10 years.[13] Results are available in Table 1.2 and I plot the estimated β_a coefficients from each regression separately in Figure 1.3 to see how the value traded evolves within a relationship over time. In order to avoid incorrectly identifying growth rates between the first two years of a spell due to partial year effects, I omit the first year of a spell. The estimated coefficients then can be interpreted as sales relative to the second year of the spell being active. As can be seen in Figure 1.3, the value traded increases most rapidly in the first years of an export spell. In the penultimate year,

[13]Observations are weighted according to their sales value.

values decrease slightly, before falling much further in the last year.[14]

While credit constraints and capital constraints may be important determinants of firm behavior, they cannot account for the fact that even among long-lasting spells, the value traded decreases over time for a large fraction of spells, showing that learning may be an important determinant of export dynamics. Following Berman et al. (2017) and examining spells which last exactly ten years, I examine how spells evolve over their lifetime in Figure 1.4 below.[15] On average, the quantity sold within an export spell increases over time relative to the quantity sold in the second period, as indicated by the blue diamonds in the figure. However, these averages mask substantial heterogeneity in the evolution of quantity sold across spells. The upper and lower bounds of the bar represent the 25th and 75th percentiles of the distribution of relative quantity for spells of a particular age, with the white line being the median. As export spells age, the relative quantity at the 75th percentile is increasing. However, the 25th percentile relative quantity is decreasing, with the median relatively flat (first increasing, then decreasing). All of the spells included survived for exactly ten years, but 41% of the $fkdt$ observations have lower sales than they did in the second active year of the spell. These trends are all consistent with there being uncertainty in international markets where firms receive signals about demand each year. Those who receive positive signals expand in subsequent years, whereas those who receive negative signals contract (and feasibly exit if the signal is low enough).

These three empirical regularities are all consistent with firms learning about demand once they enter a market or the presence of other idiosyncratic shocks. However, in this paper, I model and control for these potential shocks and show that learning occurs prior to entry as well through the observation of outcomes for incumbent firms in a market. This learning will affect entry rates, sales, and the duration of export spell for potential entrants. In the next section, I develop a model motivated by these facts and examine how spillovers across firms may affect these trends.

[14]Part of the decrease in the final year will also be due to the partial year effect.

[15]Once again, I omit the first year and normalize everything with respect to the second-year quantity.

1.4 Model

The partial equilibrium model features heterogeneous firms as in Melitz (2003) and generalizes uncertainty introduced into similar models by Arkolakis et al. (2017) and Berman et al. (2017). Firms learn passively about demand through market interactions similar to how firms learn about cost in Jovanovic (1982). Whereas the models above feature firms who learn from their own experiences, the novel feature of the model presented here is that firms learn about a common component of demand from the outcomes of their compatriot firms in foreign markets without themselves having to enter the market, similar to Rodrik and Hausman (2003) where firms learn about costs from each other. The introduction of the demand component that is common across firms within a market generates information spillovers, the value of which will vary with the level of uncertainty in a destination country.

1.4.1 Consumers

Time is discrete and measured in years. Consumers have Cobb-Douglas preferences across industries where the subutility function in each industry-destination-year is a CES aggregate over firm (f)-product (k) pairs with heterogeneous demand shifters, as in Arkolakis et al. (2017):

$$C_{idt} = \left(\int_{fk \in \Omega_{idt}} e^{\frac{a_{fkdt}}{\sigma_i}} c_{fkdt}^{\frac{\sigma_i - 1}{\sigma_i}} d(fk) \right)^{\frac{\sigma_i}{\sigma_i - 1}}, \tag{1.2}$$

where c_{fkdt} is the consumption of an individual variety of product k produced by firm f by consumers in destination country d in year t, σ_i is the elasticity of substitution in industry i, and a_{fkdt} is the demand shock for a particular variety.[16] Consumers solve a two-stage utility maximization problem. First, conditional on any allocation of expenditure across industries, spending is allocated across varieties within industries. Second, they solve for the optimal allocation across industries. The solution to this problem yields the following demand for a variety in a given market:

$$c_{fkdt} = e^{a_{fkdt}} p_{fkdt}^{-\sigma_i} P_{idt}^{\sigma_i - 1} Y_{idt}, \tag{1.3}$$

[16] Note that inclusion in a HS 8-digit product code implies a particular HS 3-digit industry i.

where p_{fkdt} is the price of that variety, P_{idt} is the price index, and Y_{idt} is the income spent on industry i in d during time t. Note that the price index will incorporate the prices of all varieties bought in a destination, not just those sold by Chilean firms. See Appendix 4.1.1 for more detail and the derivation of the demand curve.

Uncertainty is reflected in the ex ante unknown demand shock a_{fkdt}, which has three components. The first is a permanent component that varies at the product-destination level (θ_{kd}) and is therefore common to all Chilean firms. For example, θ_{kd} may be large for all Chilean firms for $k =$ beef and $d =$ the United States, but may be much smaller for $d =$ India. Second, there is a permanent component that varies at the firm-product-destination level (θ_{fkd}) which controls for differences in tastes for the output of different producers which may be related to quality, how close the variety is to the consumer's ideal variety, or other exogenous differences. For example, all else equal, consumers in America may have greater preferences for beef produced organically and humanely relative to beef produced on a factory farm. Finally, there is random noise (ϵ_{fkdt}) at the firm-product-destination-year level, so that the final demand shock can be written as

$$a_{fkdt} = \underbrace{\theta_{kd}}_{\sim N(\bar{\theta},\sigma^2_{\theta_1})} + \underbrace{\theta_{fkd}}_{\sim N(0,\sigma^2_{\theta_2})} + \underbrace{\epsilon_{fkdt}}_{\sim N(0,\sigma^2_{\epsilon})}, \tag{1.4}$$

where I assume that each of the components is independent of the two others. Define the time-invariant component of demand for a variety as $\theta_{kd} + \theta_{fkd}$. As a preview of what is to come, firms will be able to infer information about θ_{kd} from the actions of their compatriots and then update their beliefs about demand without themselves having to enter a market, generating spillovers and potential market failures if firms do not internalize the value of information they reveal to others.

1.4.2 Producers

Firms are monopolistically-competitive and have constant (but heterogeneous) marginal costs that are known at the time of production. Productivity is denoted by ϕ_{fkt}. Firms observe noisy signals of demand when they or their compatriots operate in a market and face a signal extraction problem in trying to pin down the permanent component of demand. Each year, firms select the optimal set of product-destination markets in which to sell their output given their information sets and the sunk and fixed costs of exporting to each market.[17,18] Conditional on that set of segmented markets served, the firm maximizes expected profits by choosing the quantity to sell in each market subject to expected inverse demand in that market. That is, firms solve the following profit maximization problem:

$$\begin{aligned} \max_{q_{fkdt}} \quad & \mathrm{E}(\pi_{fkdt}) = q_{fkdt} E(p_{fkdt}) - q_{fkdt} \frac{w_{it}\tau_{idt}\tau_{HS4dt}}{\phi_{fkt}} - f_{fkdt} \\ & \text{where} \ \ \mathrm{E}(p_{fkdt}) = \mathrm{E}(e^{a_{fkdt}}) q_{fkdt}^{\frac{-1}{\sigma_i}} P_{idt}^{\frac{\sigma_i - 1}{\sigma_i}} Y_{idt}^{\frac{1}{\sigma_i}}. \end{aligned} \tag{1.5}$$

Taking first order conditions, the optimal quantity sold by firm f is:

$$q_{fkdt} = \left(\frac{\sigma_i - 1}{\sigma_i}\right)^{\sigma_i} \left[\mathrm{E}\left(e^{a_{fkdt}}\right)\right]^{\sigma_i} \left(\frac{\phi_{fkt}}{w_{it}\tau_{idt}\tau_{HS4dt}}\right)^{\sigma_i} P_{idt}^{\sigma_i - 1} Y_{idt}. \tag{1.6}$$

Elasticities of substitution are constant within each HS 3-digit industry i. The iceberg cost of transporting any product from industry i to country d in time t is τ_{idt} and τ_{HS4dt} is the tariff levied by importing country d on products from a particular HS 4-digit category in year t. The key takeaway here is that firms sell larger quantities in markets where expected demand ($b_{fkdt} \equiv \mathrm{E}(e^{a_{fkdt}})$) is higher. Once a firm chooses the optimal quantity and demand shocks are realized, the price of each product adjusts so that markets clear. Given this quantity and a given demand shock, the price of a variety can be expressed as:

$$p_{fkdt} = \left(\frac{\sigma_i}{\sigma_i - 1}\right) \frac{w_{it}\tau_{idt}\tau_{HS4dt}}{\phi_{fkt}} \frac{e^{a_{fkdt}}}{\mathrm{E}(e^{a_{fkdt}})} \tag{1.7}$$

Using the market-clearing price and known values for the other right-hand side variables,

[17] The fixed cost of a spell may include an implicit component arising from how expected profits in other product-markets respond to the firm engaging in a particular export spell. For example, the fixed costs of a spell will be lower if the firm expects that its experience with a given spell will generate an option value with respect to selling to other product-market pairs. The larger is this expected option value, the lower are fixed costs.

[18] I do not analytically solve for the optimal bundle of markets the firm exports to because of dynamic entry considerations and path-dependence as described in Albornoz et al. (2012), Defever et al. (2015), and Morales et al. (2017). Instead, I take is as given that the firm is solving this profit-maximization problem as in Tintelnot (2017) and is behaving accordingly. Firms enter a particular set of markets taking into account the effects of the information they reveal. However, conditional on the set of markets served in a given year, my assumption is that with constant marginal cost and passive learning, the decision about how much to produce and sell in each market-year is a static decision, as in Arkolakis et al. (2017).

firms are able to infer $e^{a_{fkdt}}$, a noisy signal of the true underlying demand for its product, $(\theta_{kd} + \theta_{fkd})$. Firms use these signals of demand to update their beliefs about the permanent demand for each of the products they sell to each destination country. Learning spillovers will exist if potential entrants to a product-market are able to observe the signals revealed by the pioneering firms in each market[19]. If pioneering firms reveal signals that demand is high, and demand within a market is correlated across firms because of the permanent component that is common among Chilean producers, then that will cause potential entrants to revise their beliefs about demand upward.[20] Given expected demand, the expected profit of a trade relationship in a given year is:

$$\mathrm{E}\Big(\pi_{fkdt}\Big) = \frac{(\sigma_i - 1)^{\sigma_i - 1}}{\sigma_i^{\sigma_i}} b_{fkdt}^{\sigma_i} \Big(\frac{\phi_{fkt}}{w_{it}\tau_{idt}\tau_{HS4dt}}\Big)^{\sigma_i - 1} Y_{dit} P_{dit}^{\sigma_i - 1} - f_{fkdt}. \tag{1.8}$$

I assume the exporting country is small relative to the rest of the world so that entry by firms does not affect price indices abroad. As a result, information revealed by incumbent firms which induces entry by followers will not lower the price index, so incumbents need not take into account the effects of the information they reveal on other Chilean firms when making their decisions.

1.4.3 Beliefs

Recall from Equation 1.4 that there are three components of the demand shock for a given product and that each of these components is distributed normally and independently. Firms are assumed to know these three distributions for the market they are considering entering, but they do not know the exact value of the permanent component of demand for their product. For a firm which is considering entering a new product-market that it has never served and which has no incumbent Chilean firms selling to it, beliefs about demand (a_{fkdt})

[19]In the model, ϕ_{fkt} is assumed to be public information so that so that potential entrants are able to infer the demand shock. In the empirical section, I relax that assumption and show that it is not necessary when estimating signals of demand.

[20]For some products, it may be the case that firms decide prices, with quantities adjusting so that the market clears. If so, the optimal price set by the firm is $p_{fkdt} = \Big(\frac{\sigma_i}{\sigma_i - 1}\Big)\frac{w_{it}\tau_{idt}\tau_{HS4dt}}{\phi_{fkt}}$, which varies across markets only to the extent that trade costs vary by country. That is, the optimal price is independent of firm beliefs about demand. I focus on quantities so that the decision variable is a function of expected demand.

are distributed normally with mean μ_{fkdt} and variance ν_{fkdt}, where

$$\mu_{fkdt} = \overline{\theta}_{kd} \quad \text{and} \quad \nu_{fkdt} = \sigma^2_{\theta_1} + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}. \tag{1.9}$$

If there are information spillovers across firms, potential entrants will update their beliefs about the distribution of demand shocks as they observe information revealed by export pioneers. Suppose that there is a potential entrant who observes F neighbors exporting to the foreign country-product pair. The potential entrant accrues information by observing the demand shock of each incumbent firm in each previous year that incumbent exports to this market. Suppose that the firm observes the set of demand shocks $[a^f_1 \ a^f_2 \ ... \ a^f_{n_f}]' \ \ \forall f = 1, 2, ..., F$, where n_f, the number of years firm f exports the product to this market, may vary due to differences in export duration across firms within a product-market. Define $a^f = [a^f_1 \ a^f_2 \ ... \ a^f_{n_f}]'$ as the realizations of demand shocks for firm f within a product-market. This means that a firm's beliefs about demand will change according to the success and failure of its competitors. A potential entrant will update beliefs using Bayes' Rule each time it observes a competitor export. Given $a^f \ \ \forall f = 1, 2, ...F$, a potential entrant's posterior beliefs are distributed normally with mean μ_{fkdt} and variance ν_{fkdt} where

$$\mu_{fkdt} = \frac{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F} n_f \sigma^2_{\theta_1}} \overline{\theta}_{kd} + \sum_{f=1}^{F} \frac{n_f \sigma^2_{\theta_1}}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F} n_f \sigma^2_{\theta_1}} \overline{a}^f(n_f) \quad \text{and} \tag{1.10}$$

$$\nu_{fkdt} = \frac{\sigma^2_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F} n_f \sigma^2_{\theta_1}} + \sigma^2_{\theta_2} + \sigma^2_{\epsilon} < \sigma^2_{\theta_1} + \sigma^2_{\theta_2} + \sigma^2_{\epsilon} \ \text{ if } \ F > 0. \tag{1.11}$$

See Appendix 4.1.2 for more details about this derivation. Note from Equation 1.10 that the posterior mean increases with the average signal revealed by incumbent firms:

$$\frac{\partial \mu_{fkdt}}{\partial \overline{a}^f(n_f)} = \frac{n_f \sigma^2_{\theta_1}}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F} n_f \sigma^2_{\theta_1}} > 0. \tag{1.12}$$

This increase will be relatively larger when inter-firm product variation and idiosyncratic noise are low (low $\sigma^2_{\theta_2}$ and σ^2_{ϵ}) and when there is high variation in the permanent component that is shared across firms (high $\sigma^2_{\theta_2}$), i.e., when there is a higher signal-to-noise ratio. Furthermore, note from Equation 1.11 that the variance is decreasing in the number of firms a potential entrant observes in a market and the number of times each firm is observed. As a firm observes more incumbents and receives more signals, beliefs become more precise. See Appendix 4.1.3 for more details on these comparative statics.

The weight given to prior beliefs is decreasing in the number of firms that potential entrants observe and the number of times that each firm is observed. To see this, define the weight given to the prior as $\omega = \frac{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F} n_f \sigma^2_{\theta_1}}$. As the number of incumbent firms (F) or the number of times a particular firm is observed (n_f), the numerator is unchanged but the denominator strictly increases, so the fraction decreases. Intuitively, less weight is given to prior beliefs when more information is revealed prior to entry.

Given a particular posterior distribution of beliefs, I write expected demand as[21]:

$$b_{fkdt} \equiv \mathrm{E}\Big(e^{a_{fkdt}}\Big) = \exp\Big(\mu_{fkdt} + \frac{\nu_{fkdt}}{2}\Big). \tag{1.13}$$

Note that due to the log-normality of demand shocks, a decrease in variance with no change in the mean of the normally-distributed shocks actually decreases expected demand. Because of the log-normality, beliefs (and therefore expected profits) increase when the variance increases, keeping the mean constant. This is because the gains from more likely, large, positive shocks outweighs the losses from more likely, low, negative shocks. Expected profits are a convex function of beliefs (see Equation 1.8, combined with the assumption that the elasticity of substitution is greater than one). Variable profits increase without bound with beliefs, but are bounded from below by zero. Increasing uncertainty means a firm is more likely to get a large positive draw, with little change in the downside risk. Therefore, for a given better-than-expected signal, there are two competing effects of having more incumbents reveal that signal: first, potential entrants place more weight on the signal because it is more precise as it is revealed by more incumbents, which causes the expected mean to increase more. Second, more incumbents implies more precise beliefs and therefore lower variance, which causes the expected exponentiated demand shock to decrease. Therefore, it is theoretically ambiguous whether more firms revealing a given signal will increase or

[21] To be clear about terminology, expected demand refers to the expected value of the exponentiated demand shock (b_{fkdt}). The posterior mean and variance refer to μ_{fkdt} and ν_{fkdt}, the arguments of the expected demand.

decrease overall beliefs about demand and therefore increase or decrease entry rates, sales, and duration, which I test in the empirical section.

In the baseline results, I assume that firms observe signals revealed by incumbent firms in only the immediately preceding year when updating beliefs. Therefore, μ_{fkdt} and ν_{fkdt} can be simplified to:

$$\mu_{fkdt} = \frac{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + F\sigma^2_{\theta_1}}\overline{\theta}_{kd} + \frac{F\sigma^2_{\theta_1}}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + F\sigma^2_{\theta_1}}\overline{a}^f \quad \text{and} \tag{1.14}$$

$$\nu_{fkdt} = \frac{\sigma^2_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + F\sigma^2_{\theta_1}} + \sigma^2_{\theta_2} + \sigma^2_{\epsilon} < \sigma^2_{\theta_1} + \sigma^2_{\theta_2} + \sigma^2_{\epsilon} \text{ if } F > 0 \tag{1.15}$$

The first thing I examine is how expected demand changes with signals revealed by incumbent firms.

$$\frac{\partial b_{fkdt}}{\partial \overline{a}_{fkdt}} = \underbrace{\left(\frac{F\sigma^2_{\theta_1}}{\sigma^2_{\theta_2} + \sigma^2_{\epsilon} + F\sigma^2_{\theta_1}}\right)}_{>0} \underbrace{b_{fkdt}}_{>0} > 0 \tag{1.16}$$

Therefore, when a higher average signal is revealed by incumbent firms, expected demand increases, keeping everything else constant. The next thing I examine is how the change differs depending on the number of firms which reveal the signal.

$$\frac{\partial^2 b_{fkdt}}{\partial \overline{a}_{fkdt}\partial F} = \underbrace{\frac{b_{fkdt}\sigma^2_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + F\sigma^2_{\theta_1}}}_{>0} \left[1 + \underbrace{\frac{F\sigma^2_{\theta_1}}{\sigma^2_{\theta_2} + \sigma^2_{\epsilon} + F\sigma^2_{\theta_1}}}_{>0} \left(\overline{a} - \overline{\theta} - \frac{1}{2}\sigma^2_{\theta_1}\right)\right] \gtreqless 0 \tag{1.17}$$

See Appendix 4.1.4 for more details and the intuition behind this theoretically-ambiguous result. In Appendix 4.1.5, I show how results change if the shared component of demand is persistent rather than permanent and follows an AR(1) process. In that case, potential entrants will place greater weight on more recent signals. Having established how expected demand responds to the number of incumbents and the signals those incumbents reveal in a market, I next show how changes in expected demand affect the entry rates, initial sales, and duration of potential entrants in the model.

1.4.4 Learning from Others

Extensive Margin - Entry

First consider the probability that a given firm is active in a particular market in a given year, conditional on not selling to that market in the previous year. The probability that a firm decides to enter depends on whether or not the expected marginal profit of the spell exceeds the fixed costs of beginning the spell:

$$\text{Prob}(\text{Entry}_{fkdt} = 1) = \Phi\left(\frac{(\sigma_i - 1)^{\sigma_i - 1}}{\sigma_i^{\sigma_i}}\Big(\frac{\phi_{fkt}}{w_{it}\tau_{idt}\tau_{HS4dt}}\Big)^{\sigma_i} P_{idt}^{\sigma_i - 1} Y_{idt} b_{fkdt}^{\sigma_i} > f_{fkdt}\right), \qquad (1.18)$$

where Φ is the standard normal cumulative distributive function. This probability is increasing in expected demand so that incumbents revealing larger-than-expected signals about demand increase the likelihood that potential entrants enter that market.

Intensive Margin - Volume

Second, information from incumbent firms may influence the quantity new entrants sell in a market. Recall the expression for the optimal quantity sold by a firm in a product-market-year in Equation 1.6 above. When potential exporters observe signals that lead to higher expected demand, first-year sales will be higher:

$$\frac{\partial q_{fkdt}}{\partial b_{fkdt}} = \sigma_i \left(\frac{\sigma_i - 1}{\sigma_i}\right)^{\sigma_i} b_{fkdt}^{\sigma_i - 1}\Big(\frac{\phi_{fkt}}{w_{it}\tau_{idt}\tau_{HS4dt}}\Big)^{\sigma_i} P_{idt}^{\sigma_i - 1} Y_{idt} > 0 \qquad (1.19)$$

Therefore, when there are incumbents revealing higher-than-expected signals about demand, new entrants sell a larger quantity in their first year. I focus on first-year sales of a spell to isolate learning from others, as years beyond that will feature firms using information they uncover themselves in addition to information unveiled by their compatriots in that year.

Intensive Margin - Duration

Third, changes in beliefs caused by information gained from observing pioneering exporters may also affect the duration of new export spells. For spells which are active, the probability that the spell terminates is given by:

$$\text{Probability}(\text{Exit}_{fkdt} = 1) = \Phi\left(\frac{(\sigma_i - 1)^{\sigma_i - 1}}{\sigma_i^{\sigma_i}} \left(\frac{\phi_{fkt}}{w_{it}\tau_{idt}\tau_{HS4dt}} \right)^{\sigma_i} P_{idt}^{\sigma_i - 1} Y_{idt} b_{fkdt}^{\sigma_i} < f_{fkdt} \right). \tag{1.20}$$

If firms continue to consider the signals they received prior to entry, then stronger signals prior to entry will lead to higher expected demand throughout the duration of the spell. With higher expected demand, it is more likely that variable profits will exceed the fixed costs of the spell, meaning it is less likely to end. The prior three results lead to Propositions 1 and 2:

Proposition 1. *For a given number of incumbents in a disaggregate product-market, entry rates, first-year sales, and spell duration increase with the signals revealed by those incumbents.*

Proposition 2. *Entry rates, first-year sales, and export duration may increase or decrease with the average signal revealed as the number of incumbents also rises.*

1.5 Constructing Signals, Methodology, and Empirical Results

Empirically testing Propositions 1 and 2 requires having credible signals about demand in each market. In this section, I describe a two-stage strategy for estimating those signals and using them to test for the presence of spillovers across exporting firms along three separate margins.

1.5.1 Constructing Signals

Taking logs of the firm's optimal quantity defined by Equation 1.6 above yields:

$$\ln(q_{fkdt}) = \overbrace{\sigma_i \ln\Big(\frac{\sigma_i - 1}{\sigma_i}\Big) - \sigma_i \ln(\tau_{idt}) + (\sigma_i - 1)\ln P_{idt} + \ln Y_{idt}}^{\alpha_{idt}} - \sigma_i \ln(\text{Tariff}_{HS4dt})$$
$$+ \underbrace{\sigma_i \ln(\phi_{fkt}) - \sigma_i \ln(w_{ft})}_{\alpha_{fkt}} + \sigma_i \Bigg(\mathrm{E}\Big(e^{a_{fkdt}}\Big)\Bigg). \tag{1.21}$$

Using the insight from Berman et al. (2017), the quantity sold by a firm in a market can be broken down into two main components: variables which vary by industry-market-year (idt) and those which vary by firm-product-year (fkt). I estimate signals of demand by regressing the quantity sold within a trade relationship in a given year on idt and fkt fixed effects in addition to the tariff levied by a country at the HS 4-digit level in that year.[22] The former set of fixed effects controls for market conditions which do not vary by exporting firm such as consumer spending, the price index, exchange rate fluctuations, and iceberg transportation costs which differ by industry-destination-year. The latter set controls for firm variables such as productivity and input costs which I can include because trade data features firms selling the same product to multiple destinations in the same year. I also include the tariffs charged in each destination market, as quantities likely decrease with the taxes charged by the government of the importing country.[23] The primary identification assumption is that the residual from Equation 1.21 above is uncorrelated with the variables the fixed effects control for such as firm productivity, input costs, price indices, consumer spending, and transportation costs. As pointed out by Berman et al. (2017), this requires that more productive firms which sell larger quantities do so because they have lower prices, not because they have higher ex ante beliefs about demand on average.

Because of the inclusion of fkt fixed effects, the average residual within a firm-product-year will be equal to zero by construction. Potential entrants are not learning about the productivity of incumbent firms. Rather, they are looking at how sales vary across destinations within a firm-product-year and using those deviations to construct their signals.

[22] I use the `reghdfe` command courtesy of Correia (2017) to estimate the linear model with high-dimensional fixed effects.

[23] I also include controls for the time in the year in which the export spell begins, as spells which begin later will naturally have smaller values, as pointed out by Bernard et al. (2017).

Potential entrants will be interested in the average signal revealed by all of the incumbents within a product-market-year kdt, which is not necessarily equal to zero. If there is a particular location where many firms are selling relatively high quantities, that will be a signal to potential entrants that demand is higher in that location than in others.[24]

Once quantities have been purged of fixed effects, each incumbent export spell will yield a residual I use as a signal. Controlling for the fixed effects above, this residual represents how much more or less a firm exports than would be expected given market size, transportation costs, tariffs, firm productivity, input costs, etc. I use this residual variation in quantities sold to construct signals about demand for Chilean varieties for each year in each market that Chilean exporters are active.

Define the signal revealed by firm f selling product k to destination d at time t as

$$\text{Signal}_{fkdt} = \widehat{\text{E}(e^{a_{fkdt}})} = \frac{\ln q_{fkdt} - \hat{\alpha}_{idt} - \hat{\alpha}_{fkt} - \hat{\beta}_1 \text{FirstMonth}_{fkdt} - \hat{\beta}_2 \text{Tariffs}_{HS4dt}}{\widehat{\sigma}_i}, \quad (1.22)$$

where I use estimates of the elasticity of substitution at the HS 3-digit level from Broda et al. (2017). If each incumbent firm f reveals a signal in product-market-year kdt, the average signal revealed by incumbents for that product-market-year is:

$$\text{Signal}_{kdt} = \frac{1}{F_{kdt}} \sum_{f=1}^{F_{kdt}} \text{Signal}_{fkdt}, \quad (1.23)$$

where F_{kdt} is the number of incumbent firms which reveal a signal in a particular market.[25,26]

[24] To fix ideas, suppose there are two countries which are identical in terms of income, price indices, transportation costs, tariffs, etc. Consider a firm which produces a product at constant marginal cost and sells the product to both of these countries. If variation in how much the firm sells to each market is driven by differences in beliefs and the firm sells more in one country than the other, its beliefs about demand conditions there must be higher than in the other country. This could be the case if there were already incumbent Chilean firms selling to either market and reveal positive signals about the first market or negative signals about the second.

[25] When there are no incumbents in a market-year, the signal variable is assigned a value of 0.

[26] The number of incumbent firms which reveal a signal in a market-year is not necessarily equal to the number of Chilean firms which export to that market in the previous year. Note that the signal revealed by a particular firm is relative to sales by that same firm of the same product in other locations. Therefore, if there is a firm which sells a product only to the location in question, no information is gained by potential entrants because there is nothing with which to compare the level of sales. To see this another way, note that the fkt fixed effect for that firm will be such that the residual will be equal to zero, meaning no signal is revealed. Basically, when there is only one observation within a particular fkt, potential entrants are unable to separate how much of the sales is due to productivity versus the strength of demand. Therefore, I

The signal within a particular market is the average amount all firms sell in that market relative to their sales of the same product to other destination countries in that year. Potential entrants are unable to determine how much of the sales of other firms is due to productivity of the other firms and how much is due to the strength of demand. Consider a low-productivity firm which sells high output in two separate countries due to high demand in both. The signals revealed by this firm will not show that demand is high in both places, but that it is relatively high where the incumbent sells more and relatively low where the incumbent sells less.[27]

Figure 1.5 plots the estimated signals across product-destination-years. The minimum and maximum values are approximately -5 and 5, but the majority of observations fall within a standard deviation of zero. With these estimates in hand, I examine how entry, sales volume, and exit decisions of potential entrants vary with the information uncovered by and the number of incumbent firms.

1.5.2 Extensive Margin

I begin by focusing on the extensive margin and how a firm's decision to begin an export spell in a particular market is affected by the presence of incumbent Chilean firms already selling to that same market in the preceding year. First, define entry at the firm-product-destination-year level as:

$$\text{Entry}_{fkdt} = \begin{cases} 1 \text{ if } \text{Sales}_{fkdt-2} = 0, \quad \text{Sales}_{fkdt-1} = 0, \quad \& \quad \text{Sales}_{fkdt} > 0 \\ 0 \text{ if } \text{Sales}_{fkdt-2} = 0, \quad \text{Sales}_{fkdt-1} = 0, \quad \& \quad \text{Sales}_{fkdt} = 0 \\ . \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{Otherwise} \end{cases} \tag{1.24}$$

Note that the entry variable is not defined for continuing export spells because $\text{Sales}_{fkdt-1} > 0$ and $\text{Sales}_{fkdt} > 0$. Because those firms are already serving those markets, they do not have

include only those firms which reveal signals. Essentially, in order to be included in the set of firms revealing a signal in product-market-year kdt, firm f' must have positive sales in that market ($\text{Quantity}_{f'kdt} > 0$) and at least one other market k' ($\text{Quantity}_{f'k'dt} > 0$) in the same year.

[27] Suppose both countries are identical in all respects but that the firm sells 20% more in one of the markets (120 units versus 100 units). The average sales within that fkt are 110 units, so the signals revealed is +9% ($\frac{120-110}{110}$) in the market with higher volume and -9% in the market with lower volume.

the opportunity to enter again without first ending the current export spell.

With only export data, I do not observe firm age, share of production exported, overall production, or when firms begin to produce new products, only when they begin to export them. In order to include only observations for which I am certain a firm produces a product, I drop all observations that occur prior to the first year a firm exports a product to any destination. For example, suppose I observe a single-product firm export blueberries to Germany, France, and Belgium in the years indicated by Table 1.3. According to the above definition of entry, this data will be coded as shown in Table 1.4.

Equipped with only trade data, I am unable to determine if this firm existed, produced blueberries, and/or ever considered exporting blueberries in 2002 and 2003 and therefore do not include those observations in the regressions. Starting in 2004, the observations are included because I know that the firm is capable of producing the product beyond that point. I also omit all observations beyond the last year the firm is observed in the sample due to possible firm closing, disengagement from exporting in general, mergers, or any other reason the firm may no longer appear in the data. The sample is therefore defined for all firm-product-destination-year observations after which a firm is known to produce a particular product and is still engaged in exporting. By observing where and when firms export to, I am also able to infer each market-year to which each firm does not export. I expand the sample to include these observations which never appear in the data so that for the hypothetical firm above, the entry variable would be coded as (. . 0 0 0 0 0 0) for all destinations other than Germany, France, and Belgium.

The fact that I observe cross-section variation in the entry decision of firms across markets within a firm-product-year allows me to correlate that decision with incumbent firm presence across markets rather than having to rely on time-series variation of incumbent presence within a firm-product-destination as in Koenig (2009) and Koenig et al. (2010). The reliance on time-series variation in entry in these papers means that those authors are able to include only trade relationships that are observed in the data. They are trying to explain why firms enter the markets they do *when* they do. By utilizing cross-section variation across markets within a firm-product-year, I am able to examine why firms enter the set of product-markets that they do.[28]

There are 247,435 firm-product pairs observed in the thirteen years of the dataset. If I include all possible firm-product-destination-year observations for each firm-product pair that is observed at any point in the data, there would be (247,435×13 years×191 countries) = 614,381,105 firm-product-destination-year level observations when examining extensive margin effects. To decrease the computational burden, I focus on the top 20 importing countries of Chilean exports in the baseline analysis, leaving me with 48,887,280 observations.[29,30] While these 20 importing countries are only 10.5% of export destinations, they account for 88.4% of the value of all Chilean exports over the course of the sample.[31]

The nature of trade data provides an advantage over balance sheet data by allowing me to observe the same firm beginning to sell the same product in multiple destination countries during the same calendar year. By including firm-product-year fixed effects, I can control for differences in productivity at the firm-product-year level which is certainly an important determinant of export entry at the firm-product-destination-year level (Melitz (2003)). In addition, including industry-market-year fixed effects will control for differences in market size, transportation costs, and differences in the competitive environment and price indices across sectors and destination markets.

To examine the effect of incumbent exporters and the information they reveal on the probability that other firms enter that same market in the following year, I estimate the

[28]In this way, this is similar to the specifications in Fernandes and Tang (2014). The main differences are that my analysis incorporates the product dimension into the data and omits intra-Chilean geographical considerations, whereas they exclude the product dimension and include intra-Chinese geographical considerations and focus on local learning from firms in the same city. This paper examines spillovers across all firms within Chile about demand in specific product-market pairs. Fernandes and Tang (2014) examines spillovers across firms within a localized unit about aggregate demand in foreign markets.

[29]These countries include Argentina, Belgium, Brazil, Canada, China, Colombia, France, Germany, India, Italy, Japan, Mexico, the Netherlands, Peru, Spain, South Korea, Taiwan, the UK, the United States, and Venezuela. I only reduce the sample to the top twenty importing countries while focusing on the extensive margin. The intensive margin discussion below features all importing countries.

[30]Although there are nearly 49 million observations in the sample, most regression results will have roughly a third of that after enforcing the requirements described in the paragraph above.

[31]Because I focus on the top twenty recipient countries, results reported below could underestimate the overall importance of learning from others if uncertainty in these countries is lower than in more peripheral countries that import Chilean products. In the appendix, I also report results for the next twenty importing countries, where estimates are indeed higher.

following regression via OLS:

$$\text{Entry}_{fkdt} = \beta_1 \text{Signal}_{kdt-1} + \beta_2 \Big(\text{Signal}_{kdt-1} \times \text{Firms}_{kdt-1} \Big) + \beta_3 \text{Tariff}_{HS4dt} + \alpha_{idt} + \alpha_{fkt} + \alpha_{fd} + \epsilon_{fkdt}, \tag{1.25}$$

where Signal_{kdt-1}, as defined in Equation 1.22, is the average signal revealed by other Chilean exporters which sold the same product to the same destination market in the prior year, Firms_{kdt-1} is the number of firms which sold product k to destination d in the prior year (F_{kdt}), and β_1 is the coefficient of interest. All potential entrants face the same number of Chilean firms exporting that product in the previous year to the market in question. Because the regressor of interest varies at the kdt level, at the minimum I should cluster standard errors at the kdt level. In order to allow for correlation across years within the same market and across similar products within the same country, I more conservatively cluster by HS 2-digit chapter-destination pair.[32]

The coefficient of interest, β_1, is the percentage point change in the probability that a firm enters a particular market associated with a one-standard-deviation increase in the revealed signal. If there are spillovers across firms whereby potential entrants are able to learn from incumbents, β_1 should be positive. For the same reason as in the estimation of the signals above, α_{idt} are HS3-destination-year fixed effects to account for market size, differential industry spending, transportation costs, price indices, and exchange rate differences, while α_{fkt} are firm-product-year fixed effects which flexibly control for changes in productivity, input bundle costs, and other sources of unobserved firm heterogeneity over time. These firm-product-year fixed effects help control for selection into markets on the basis of productivity typical in the new trade models with heterogeneous firms as in Melitz (2003) and Melitz and Ottaviano (2008). I do not observe ownership variables for any firms and therefore include firm-destination fixed effects (α_{fd}) to control for the possibility that some of these firms are multinationals exporting back to their home country, making entry more likely in that particular country. If that is the case, learning about demand could be much less important for these firms, as they could be more concerned with learning about supply-side conditions

[32]In all results, the signal variables have been normalized so that the reported coefficients should be interpreted as the effect of a one standard deviation increase in the revealed signal on the probability of entry.

in Chile.

Baseline Results

Results of estimating Equation 1.25 are presented in Table 1.5. The first column includes the direct effect of the revealed signal, whereas the second includes the direct effect and its interaction with the number of firms revealing the signal. In the first column, a one-standard-deviation increase in the signal revealed by incumbent firms is associated with a 0.06 percentage point increase in the probability that a firm begins a particular export spell. In Column 2, the direct effect of the signal variable is statistically insignificant but the joint effect with the interaction is statistically and economically significant: compared to a market in which there are no incumbents and therefore no signals are revealed, a firm is 0.02 (0.04-0.02) percentage points more likely to enter a market where a single incumbent reveals a signal that is one standard deviation above the average, with the effects increasing with the number of firms. On the face of it, these seem like small effects. However, for the 15 million observations included in these regressions, the entry rate is 1.6%. Using the results from Column 1 then, a one standard deviation increase in revealed signal by incumbents is associated with a 3.8% $\left(=\frac{0.0006}{0.016}\right)$ increase in the probability that a potential entrant enters a particular market. For Column 2, a single incumbent firm revealing a signal one standard deviation higher than average is associated with a 1.3% $\left(=\frac{0.0002}{0.016}\right)$ increase in the probability that a potential entrant actually enters the market, with this value increasing in the number of firms revealing the signal.[33]

In Columns 3 and 4, I replace the continuous measure of the signal with three dummies: one each for whether the average signal is negative, zero (no signal is revealed), or positive.[34] As expected, observing a positive average signal is associated with an increase in the

[33]To account for the presence of generated regressors and sampling variance in the second stage of these regressions, I bootstrap standard errors to avoid inconsistent estimates which would make rejection of the null hypothesis more likely (Pagan (1984) and Murphy and Topel (1985)) following a strategy similar to that of Ashraf and Galor (2013). For each replication, I sample the original dataset with replacement by cluster and estimate the signals using the new set of observations. Using the set of estimated signals from the new set of observations, I replicate the second stage to estimate and store a standard error for each coefficient. The coefficients reported in the tables below are from the original dataset, while the reported standard errors are the average over 100 bootstrap replications of this process. In addition, I report the 95% confidence interval for each standard error.

[34]Roughly half of the observations receive no signal prior to entry, whereas a quarter each receive positive

probability of entry of 0.63 percentage points $\left(39\%{=}\frac{0.0063}{0.016}\right)$ compared to a potential entrant observing a negative average signal. However, what is unexpected is that entry probabilities are 0.34 percentage points $\left(21\%{=}\frac{0.0034}{0.016}\right)$ lower for markets with no signals revealed compared to markets where negative signals are revealed. In Column 4, I interact each of the three signal dummies with the number of firms revealing that signal. As in Column 2, the effect of observing a positive signal is increasing with the number of firms revealing that signal. Once again, entry probabilities are higher when a negative signal is revealed relative to no signals. One potential explanation for the negative coefficient on the dummy for no signal revealed is that learning about demand may not be the only spillover across exporting firms. There could be economies of scale in transportation or reputation effects that make matching more likely when there is already an incumbent Chilean firm selling to that market generating these results. Alternatively, firms may be learning about what is unpopular in a market and selling a similar product with different attributes, a mechanism which would be more prevalent for differentiated than homogeneous products, which I test for below.

Destination Characteristics

Tables 1.6 and 1.7 extend the results of Table 1.5 by allowing the estimated coefficients to vary with the distance to and official language of the importing country. The reason for including these gravity variables is that if firms are learning about demand or other conditions in foreign markets, learning from others may be more important in more culturally and geographically distant countries with which firms are less familiar. It is not a stretch to imagine that a Chilean firm exporting blueberries is relatively familiar with Argentine preferences even if the firm has never exported to Argentina so that the effects of other Chilean firms selling blueberries to Argentina would be small. However, if that same firm observes a compatriot exporting to Sweden, that may yield more information than if the other firm were only exporting to Argentina.

The direct effects of distance and language on entry are subsumed by the *idt* fixed effects but the interaction with the spillover is identified by seeing to what extent the effect of incumbent presence on the entry decision of potential entrants varies with the distance to

and negative average signals.

and language of the market in question. The primary takeaway from Table 1.6 is that these estimated effects are larger in countries that are further away from Chile with which Chilean firms are likely less familiar and therefore information gleaned from spillovers is more valuable. In Column 1 of Table 1.6, I interact the signal revealed by incumbents with the distance to the destination country. In line with Proposition 1, entry is more likely in markets where positive signals have been revealed, and the effect is stronger in more distant markets. Compared to a market in which no signal is revealed, a one standard deviation increase in signal revealed increases the entry probability by 0.02 percentage points (1.3%) in Argentina (the closest country) but by 0.10 percentage points (6.3%) in China (the country furthest away). Column 2 shows that the estimated effect is larger when the signal is revealed by more firms with the positive coefficient on the triple interaction term, whereas Columns 3 and 4 corroborate the results using dummies representing no signal, positive average signal, or negative average signal instead of the level of the signal. For example, results in Column 3 show that a positive signal revealed in Argentina is associated with a $0.0011 * 7.05 = 0.8$ percentage point increase in the probability that a potential entrant begins to export to that market, whereas a positive signal revealed in China is associated with a $0.0011 * 9.84 = 1.1$ percentage point increase in the probability that a potential entrant begins an export spell there.

In Table 1.7, I examine how the effect of signals revealed by incumbents on the entry rates of potential entrants differ with the language spoken in the importing country. In Column 1, I interact the direct effect of the signal with a dummy indicating whether Spanish is an official language of the importing country. A one standard deviation increase in the revealed signal is associated with a 0.08 percentage point ($\frac{0.008}{0.016} = 5\%$) increase in the probability of entry in a country which does not speak Spanish, but only a 0.05 percentage point ($\frac{0.0005}{0.016} = 3.1\%$) increase in a country where Spanish is an official language. Column 2 includes a triple interaction term between the signal, the number of incumbents, and the language dummy so that the marginal effect of an increase in the revealed signal depends on the number of incumbents and whether or not Spanish is spoken in the foreign country. When there are fewer than four incumbents, the marginal effect of an increase in the revealed signal is higher in countries which do not speak Spanish, however that reverses when the number of incumbents increases further. Columns 3 and 4 replace the continuous measure of the revealed signal with a set of dummies indicating whether or not the average revealed signal is negative, zero, or positive, with similar results obtaining.

Product Characteristics

In Table 1.8, I examine how the effect of signals revealed by incumbents on the entry rates of potential entrants differ with the type of product being traded. If these spillovers differ by product type and the degree of substitutability, policymakers can use this information to increase the efficacy of export promotion. In the first column, I interact the signal variable with the HS 3-digit elasticity of substitution estimated by Broda et al. (2017). The positive estimated coefficient implies that a one standard deviation increase in revealed signal is associated with a 0.07 percentage point (4.3%) increase in entry probability for a firm selling wooden caskets or jewelry boxes (a relatively differentiated product with σ=2.9), but a 0.4 percentage point (26%) increase in entry for a firm selling cotton (a relatively homogeneous product with σ=6.4). That is, a given increase in signal is associated with greater increases in entry rates for more homogeneous products. If a potential entrant is considering beginning an export spell with a homogeneous product such as cotton, observing signals from incumbent firms will provide meaningful information to that firm if those same consumers similarly value the cotton of the potential entrant. However, the success or failure of incumbents firms may be less important when it comes to differentiated products because the variety produced by a particular incumbent may be very dissimilar to the variety of a potential entrant. For example, if a potential entrant is considering beginning an export spell involving an artisan casket made with valuable wood, that firm will have less to learn from incumbents if the firms already present only sell mass-produced caskets with lower quality inputs. It will be more difficult for this potential entrant to extrapolate how high demand for its higher quality product will be than for the producer of cotton based off the actions of incumbent firms. Therefore, the less differentiated a product is (and the higher is the elasticity of substitution σ), the more potential entrants have to learn from incumbents because there is less inter-firm variation in demand shocks and a higher signal-to-noise ratio.

In Column 2, I exclude all observations for which the product is classified by Rauch (1999) as homogeneous to allow for the possibility that markets involving homogeneous goods are in some fundamental way different from those involving reference-priced or differentiated goods and as a consequence driving the results in the first two columns.[35] The estimates are identical across the two different samples, confirming that the initial results were not driven by the inclusion of homogeneous products: the less differentiated a product is (higher σ), the larger the effect of a given signal on the entry rates of potential entrants.

In Column 3 and 4 of Table 1.8, I continue to exclude homogeneous products but replace the elasticity of substitution with two dummy variables indicating whether a particular product is classified by Rauch (1999) as reference-priced or differentiated. If reference-priced goods have higher elasticities of substitution on average than differentiated products, than the results corroborate findings in the first four columns: a one standard deviation increase in the signal revealed by incumbents for a reference-priced product is associated with a much larger increase in the probability that a potential entrant enters (0.26 percentage points) than that same one standard deviation increase for a differentiated product (0.01 percentage points). Intuitively, firms have less to learn from their compatriots when they produce more dissimilar products.

To summarize the results in this section, an increase in the average signal revealed in a market is associated with an increase in the likelihood of entry by other Chilean firms into that same market, with the effects larger for more distant countries, for countries where Spanish is not an official language, for homogeneous products, and when the signal is revealed by more firms. In the next subsection, I examine how incumbent presence affects two intensive margins of exporting: how much new exporters sell and how long their export spells last.

1.5.3 Intensive Margin - Sales Volume

In order to see how incumbent firms affect the intensive margin decision of new entrants in export markets, I analyze the quantity of output sold in the first year of an export spell

[35]For example, in a world where homogeneous goods are truly homogeneous and the Armington assumption does not hold, firms may face very little uncertainty with regards to demand and must act as perfectly competitive price takers rather than monopolistically-competitive producers with market power. In this case, these firms would observe the price and choose the quantity to sell conditional on that price.

and how that varies with the number of Chilean incumbents serving that market and the signals those firms reveal in the prior year. I focus on first-year sales in which firms have information only from others. Including observations beyond the first year would confound learning from others with a firm learning from its own experience. I lag signals one period to allow time for information to become available and so that variation in incumbent presence is exogenous to the firm beginning a new export spell.

The results in this section should be interpreted as explaining variation in quantities sold across markets conditional on the set of product-markets served by a firm in a given year. All else equal, firms are more likely to sell to locations where expected demand is highest within a product-year, which also means sales in those locations will be higher due to higher expected demand. I observe sales only for markets to which firms actually export, but not what they would sell in markets that they do not enter.

To test for spillovers from incumbent firms in disaggregated product-markets to new entrants along the intensive margin, I estimate the following regression:

$$\begin{aligned}\ln(\text{Quantity})_{fkdt} = \eta_1 \text{Signal}_{kdt-1} + \eta_2 \Big(\text{Signal}_{kdt-1} \times \text{Firms}_{kdt-1}\Big) \\ + \eta_3 \text{Tariff}_{HS4dt} + \alpha_m + \alpha_{idt} + \alpha_{fkt} + \epsilon_{fkdt}\end{aligned} \tag{1.26}$$

The dependent variable is the quantity of output sold by firm f of product k to destination d in time t. The signal variables are defined as they were in the analysis of the extensive margin decision and η_1 and η_2 are the coefficients of interest. They answer the following question: how do export quantities across locations within a firm-product-market vary with the signal revealed by and the number of incumbent Chilean firms, controlling for market-specific factors such as GDP which may also drive differences in quantities. Quantities sold by firms across markets may vary due to differences in spending, market size, transportation costs, which is controlled for with the idt fixed effects, or due to differences in firm productivity or input costs, which is controlled for with the fkt fixed effects. To address the partial year effect documented by Bernard et al. (2017), α_m is a set of month dummies which controls for the month of the year in which a particular export spell begins. Export values in a calendar year will naturally be higher on average for spells that begin in January compared to spells that begin in December; the set of month fixed effects α_m control for these differences.

Baseline Results

Baseline results are presented in Table 1.9. Looking first at column 1 where I include only the direct effect of the revealed signal, a one-standard-deviation increase in the revealed signal in a market is associated with a 9.8% ($e^{0.0931} = 1.0975$) increase in the quantity of exports to that market compared to a market in which no signals are revealed or where the average signal is zero, once again providing evidence in favor of Proposition 1.[36] Recall that the theoretical sign of η_2 is ambiguous due to competing effects of having more incumbents. Allowing for the effect to vary with the number of firms revealing the signal, I interact the signal with the number of incumbents in the previous year in Column 2. Now, for a given positive average signal, first-year sales are predicted to be 0.8% ($e^{0.0076} = 1.0076$) higher in a market where there is one more incumbent firm revealing that signal. The qualitative findings are in line with what Fernandes and Tang (2014) find for local spillovers among Chinese exporters.

Country Characteristics

As with the extensive margin, I also estimate heterogeneous effects across destination countries by distance from Chile. In Column 1 of Table 1.10, I include an interaction term between the revealed signal and the distance between Chile and the destination country. As with the heterogeneity results in the extensive margin section, the direct effect of distance on initial sales is subsumed by the *idt* fixed effect, but the coefficient on the interaction between the revealed signal and distance to the country is identified by differences in initial sales with respect to a given signal for countries located various distances from Chile. For Argentina, the closest country to Chile, a one standard deviation in signal increases initial sales by 1.9% $\Big(\exp(-0.3514+(0.0525*7.05)\Big)$, whereas that same increase in signal increases sales by 18.0% $\Big(\exp(-0.3514 + (0.0525 * 9.84)\Big)$ in China, the country furthest away from Chile. In Column 2, I add the triple interaction between signal, the number of firms revealing

[36]As with the extensive margin, standard errors are bootstrapped to account for generated regressors in the second stage. I report the average and 95% confidence interval from 500 replications.

that signal, and the distance to the destination country, with results consistent with earlier results: a given signal has a stronger effect when it is revealed by more incumbents.

Next, I examine how these spillovers vary with the the official language spoken in each destination country. Spanish$_d$ is a dummy variable equal to 1 if at least one of the official languages spoken in country d is Spanish. In Column 1 of Table 1.11, I include the revealed signal and its interaction with the Spanish-language dummy. For countries where Spanish is not an official language, a one-standard- deviation increase in revealed signal increases first-year sales by 15.9% $\Big(\exp(0.1477)\Big)$, whereas that increase is 5.3% $\Big(\exp(0.0521)\Big)$ in countries where Spanish is spoken. Looking at column 2 where the triple interaction with the number of incumbents is included, effects are larger in both countries when the signal is revealed by more firms.

Product Characteristics

In addition to heterogeneity across countries, I examine whether spillovers differ with respect to first-year sales across types of products and with the elasticity of substitution in a particular industry in Columns 1 and 2 of Table 1.12. In Column 1, I include interactions of the signal variable with each of the three Rauch dummies. As with the extensive margin where changes in entry rates in response to signals were smaller for differentiated products, similar results hold for the intensive margin decision. A one-standard-deviation increase in the average revealed signal is associated with an 18.9% (17.6%)[2.7%] increase in first-year sales for export spells involving homogeneous (reference-priced) [differentiated] products. In Column 2, the interaction with the number of firms is included, at which point the effect of a signal increase for differentiated products is no longer statistically significant. In summary, for products for which inter-firm differentiation is large, the success or failure of incumbents is less useful as a predictive tool for potential entrants to learn about their own market outlook since the products are inherently more different from one another.[37]

[37] As discussed in the results for the extensive margin, these results would obtain if the Armington assumption holds for all classes of products so that even homogeneous products are differentiated by their country of origin in consumer tastes. In this case, it would be more informative for a producer of a homogeneous good to see a neighbor exporting to a particular country than it is for a producer of a differentiated product, as they are selling virtually identical products from the point of view of a consumer, manifesting as a decrease in σ_{ϵ_2}

To conclude the section on first-year sales, I interact the signal with the elasticity of substitution in Table 1.13 to provide corroboration for the results in Table 1.12 in seeing how responses to signals vary with product substitutability. Consider again two separate industries: cotton ($\sigma = 6.4$) versus wooden caskets/jewelry boxes ($\sigma = 2.9$). For cotton, the more homogeneous of the two products, a one standard deviation increase in signal increases first-year sales by 38.6%, whereas the same increase in signal increases casket sales by only 8.5%. Because there is less inter-firm variation in the quality or attributes of cotton, potential entrants get a more accurate picture of demand for their product by observing their compatriots.

Overall, the results from this section show that firms sell more output in the newly-entered markets in which they have seen more positive signals revealed by more incumbent Chilean firms. These effects are larger in more distant countries, countries where Spanish is not an official language, and for more homogeneous products, all of which is consistent with firms learning from the experience of others and with learning being more impactful in more unfamiliar markets.

1.5.4 Intensive Margin - Export Duration

Finally, I examine how the signals revealed by incumbents in a particular market affect the duration of new exporters selling to that market. Specifications are nearly identical to Equation 1.26 which I used to measure the volume of sales: the differences are that I omit the month dummies but add the volume of sales in the first year, as larger sales have been shown to be strongly predictive of spell survival. The dependent variable is the time between the first and last transactions of an export spell as long as there is no calendar year gap between transactions. This variable is measured continuously as the number of days for which that spell is active. In order to look at elasticities as well as level effects, I also use the inverse hyperbolic sine transformation of this variable because of spells with zero duration (i.e. spells for which there is only one transaction and therefore duration is zero).[38] Results

[38]The inverse hyperbolic sine function was developed by Johnson in 1949 and has been used empirically going at least as far back as Burbidge et al. (1988). The function is defined as $\text{IHS}(x) = \ln(x + \sqrt{x^2+1})$, which behaves much like the logarithm beyond very small values of x and is defined for $x \leq 0$. As with logged variables, differences in variables which have been IHS-transformed can be interpreted as percentage

for the effect of signals on the duration margin of exporting are in columns 3-6 of Table 1.9, columns 3 and 4 of Tables 1.10-1.12, and column 2 of 1.13.

In Column 3 of Table 1.9, a one-standard-deviation increase in the revealed signal is associated with a 0.8% increase in the eventual duration of an export spell relative to that same firm beginning to export to an otherwise identical market in which no signal was revealed in the previous year. Column 4 introduces the interaction of the signal with the number of firms revealing that signal with results similar to the sales volume results: the effect of a given signal is larger when revealed by more firms, although the interaction term is not statistically significant. Now, in order for a one-standard-deviation increase in the observed signal to have the same effect as above, it would need to be revealed by five incumbent firms. Columns 5 and 6 show the results when the dependent variable is measured in levels rather than using the IHS transformation, with results qualitatively similar: a one standard deviation increase in the signal increases duration by 0.0189 years, or 6.9 days. Overall, the estimated effects of information spillovers are smaller for the duration margin of exporting compared to the entry or quantity decisions.

Destination Characteristics

As with the sales volume decision, Columns 3 and 4 of Table 1.10 show that the effects of a given signal are larger in more distant countries which do not speak Spanish. Making the same comparison between the effects in Argentina and China as above, a one standard deviation increase in the signal revealed in Argentina results in a 0.2% ($-0.0527+(0.0072\times7.05)$) decrease in duration compared to that same increase in signal resulting in a $(-0.0527+(0.0072\times9.84))=1.8\%$ increase in duration in China (Column 3). For the differences in languages spoken across countries, results in Column 3 of Table 1.11 show that a signal one-standard-deviation above average in a country in which Spanish is not spoken increases duration by 1.22% compared to an increase of 0.54% in a country in which Spanish is spoken. Once again, these results suggest that any spillovers that exist across Chilean exporters allowing potential entrants to learn about market conditions prior to entry are larger in markets with which Chilean firms are likely less familiar to begin with.

changes and can therefore be used to estimate elasticities.

Product Characteristics

The second halves of Tables 1.12 and 1.13 show heterogeneous duration responses as a function of product type. Although the standalone signal is insignificant for homogeneous products in Column 3, the interaction becomes significant in Column 4 so that more firms revealing a positive signal induce longer export spells. The effect on reference-price products is also statistically significant although there is little gained with the presence of additional firms. For differentiated products, there is no statistically significant effect of revealed signals on subsequent export duration. Similar results obtain in Table 1.13: signals have stronger effects on spells involving products with higher elasticities of substitution, i.e. those which are more homogeneous. Results for all three margins are consistent with firms learning about demand from others: when incumbent exporters in a market reveal strong signals about demand, entry rates, first-year sales, and export duration increase for followers.

In these baseline results, I assume firms observe signals from only the directly preceding year. In Appendix Table 4.1.5, I include signals from multiple years and show that more recent signals will have larger effects on entry rates, sales, and export duration than more distant signals if demand is persistent rather than permanent. In the next section, I provide evidence that these spillovers are the result of learning rather than some alternative mechanism.

1.6 Evidence for the Learning Mechanism

1.6.1 More Aggregate Signals

Without a structural model, it is impossible to ascertain that learning about demand from other firms is present or that it is the only factor generating these results. In the results above, the wide array of fixed effects controlled for factors at the firm-year level such as credit constraints, capital contraints, and managerial aptitude which may also lead to short export spells, increasing conditional survival rates, and heterogeneous growth within spells. However, alternative mechanisms which increase entry, sales, and duration with the presence of incumbent firms in a market may also be at play. For example, if a large incumbent presence is correlated with more developed transportation and distribution networks so that new entrants can benefit from lower transportation and distribution costs, incumbent presence would affect entry rates and sales in the absence of learning about demand. If incumbent firms establish business relationships in a foreign country which increases Chilean reputation and the willingness of people and firms in that country to buy from Chilean firms, similar results would obtain. In this section, I construct estimates for signals at various levels of aggregation to show that these effects are confined to narrow HS 8-digit product categories, which would not be the case if these alternative mechanisms were driving the results.[39]

Recall the construction of the average signal revealed above:

$$\text{Signal}_{kdt} = \frac{1}{F_{kdt}} \sum_{f=1}^{F_{kdt}} \text{Signal}_{fkdt}, \tag{1.27}$$

where k is an HS 8-digit product. In the construction of these signals, I assumed that firms only use information from other firms selling the same HS 8-digit product to a particular market. However, if an improving transportation network or business environment between a destination and Chile decreasing fixed and/or variable trade costs is driving these results, similar results should obtain if I use signals at higher levels of aggregation. Consider for example HS 4-digit product code 0808, which includes fresh apples and pears. Nested in this 4-digit code is 6-digit code 080810, fresh apples. Within this 6-digit code, there are multiple HS 8-digit codes for different types of apples: Fuji, Red Delicious, Granny Smith, etc. If decreases in trade costs through lower transportation costs, higher ease of finding business partners, or another similar mechanism is driving the results above, the signal from other products within the same HS 6-digit category should be as powerful as the signal for the HS 8-digit product itself. I construct alternative signals for each HS 8-digit product-destination-year as the signals revealed by all other HS 8-digit products within the same HS 6-digit and 4-digit product-destination-year:

$$\text{Signal}_{HS(a,-k)dt} = \frac{1}{F_{HS(a,-k)dt}} \sum_{F_{HS(a,-k)dt}} \text{Signal}_{fHS(a,-k)dt}, \tag{1.28}$$

[39] Furthermore, if the results were driven by decreases in the fixed costs of exporting, that should have effects for the extensive margin but neither of the intensive margins.

where $a = 6, 4$. If we focus on Red Delicious apples, $\text{Signal}_{HS(6,\text{-RedDelicious})dt}$ is the average signal revealed by firms in a market for all apples other than Red Delicious, and $\text{Signal}_{HS(4,\text{-RedDelicious})dt}$ is the average signal revealed by firms in a market for all pears and non-Red Delicious apples.

If learning about uncertain demand within disaggregated markets is not present, the estimates should be similar across levels of aggregation: in terms of decreasing trade costs, it should not matter if incumbents are selling exactly your product or one similar to it for these effects to manifest. However, if it is learning about demand, the disaggregate signal should be more important. Furthermore, if the results were being driven by incumbent presence decreasing fixed trade costs, there should be no effect on first-year sales.

Tables 1.14 and 1.15 report results for using signals at various levels of aggregation, first in isolation and then adding them sequentially. Columns 1-3 show results for the extensive margin, columns 4-6 for first-year sales, and columns 7-9 for duration. The first column under each margin reports baseline results that have already been reported for the purpose of comparison. The story is the same across all three margins. When considering each signal in isolation (Table 1.14), the disaggregate HS8-destination-year signal has the significant effects discussed in detail above. However, the HS6 (HS4)-destination-year signals are all smaller, statistically insignificant, and some are even negative. As I successively add more aggregate signals in Table 1.15, the original coefficients are preserved at the HS8-destination-year level, with signals at higher levels of aggregation having no effect on these three margins of exporting. Therefore, it is only when firms observe signals about the precise product that they are considering exporting that these positive spillovers exist, not for similar products within nested product categories, providing evidence that decreases in trade costs are not driving results.

1.6.2 Firm Size

In the model, firms are assumed to know the productivity of other firms and can perfectly observe the signals revealed by incumbents. In reality, firms will be unable to observe the productivities of other firms and may not observe quantities sold by them either. The data is available to these firms if they want to look for it, but it may represent a significant fixed cost to invest the resources in obtaining it. In a Melitz-type setting, more productive firms will have higher variable profits and be able to cover the fixed costs of this research process. If larger firms are predominantly the ones observing these signals, the signals should have a greater effect on them than on small firms. In Table 1.16, I test for this along the three margins by interacting the signal variable with a time-varying proxy for firm size.[40]

The direct effects are now estimated to be negative but the estimated coefficients on all three interaction terms are positive, meaning that the effects of information are larger for firms with greater export values. For a firm of the median size (IHS(FirmSize)$_{ft}$=11.9), a one-standard-deviation increase in the signal increases the entry probability by 4.2%, first-year sales by 7.1%, and duration bv 0.5%.

1.6.3 Different Extensive Margin Subsample

Recall from the discussion in the section on extensive margin results that I only use the top 20 importing countries in terms of value. Since these are the markets that Chilean firms export the most to, uncertainty may be lower here than in other destinations. I re-estimate Equation 1.25 on the next twenty importing countries in terms of value. If Chilean firms are less familiar with these countries, the value of information should be greater. Columns 1 and 2 report baseline results discussed above and Columns 3 and 4 present the new estimates. Consistent with learning being more important in more peripheral countries, the effect of a given signal is larger in the second sample.

1.7 Quantifying the Value of Information

In this section, I quantify the aggregate value of these spillovers by estimating what the export sales of entering cohorts would be in the absence of any incumbent presence and revealed signals. I re-estimate Equation 1.26, replacing ln(Quantity)$_{fkdt}$ on the left-hand side with ln(Revenue)$_{fkdt}$, and use the estimates to construct predicted values of how much firms would sell if there had been no incumbents selling the same product to the same market

[40]Firm size is constructed as the inverse hyperbolic sine of export value within a firm-year. I lag this firm size variable by one year so that it is not a function of how much the firm sells in a new spell.

in the previous year. Conditional on no information acquired, predicted revenue is given by:

$$\ln(\widehat{\text{Revenue}})_{fkdt}|_{\text{Signal}_{kdt-1}=\text{Firms}_{kdt-1}=0} = \widehat{\eta}_3 \text{Tariff}_{HS4dt} + \widehat{\alpha_m} + \widehat{\alpha}_{idt} + \widehat{\alpha}_{fkt} + \widehat{\epsilon}_{fkdt}. \tag{1.29}$$

Conditional on the observed set of export spells (i.e., considering only the effect of information on the intensive margin), I predict the aggregate export value of newly-formed trade spells using estimates from Equation 1.29 and compare those to the observed aggregates in the data. Graphical results are presented in Figure 1.6. Although some export spells will involve higher values because of the removal of negative signals, the overall average effect of removing information is to decrease the aggregate value of a new cohort's sales by 8.7%. As discussed above in the extensive margin section, firms are more likely to begin export spells in markets where positive signals are revealed. Therefore, conditioning on the observed set of trade spells, the effects of positive signals will outweigh the effects of negative signals and aggregate exports will be lower in the absence of information.

1.8 Conclusion

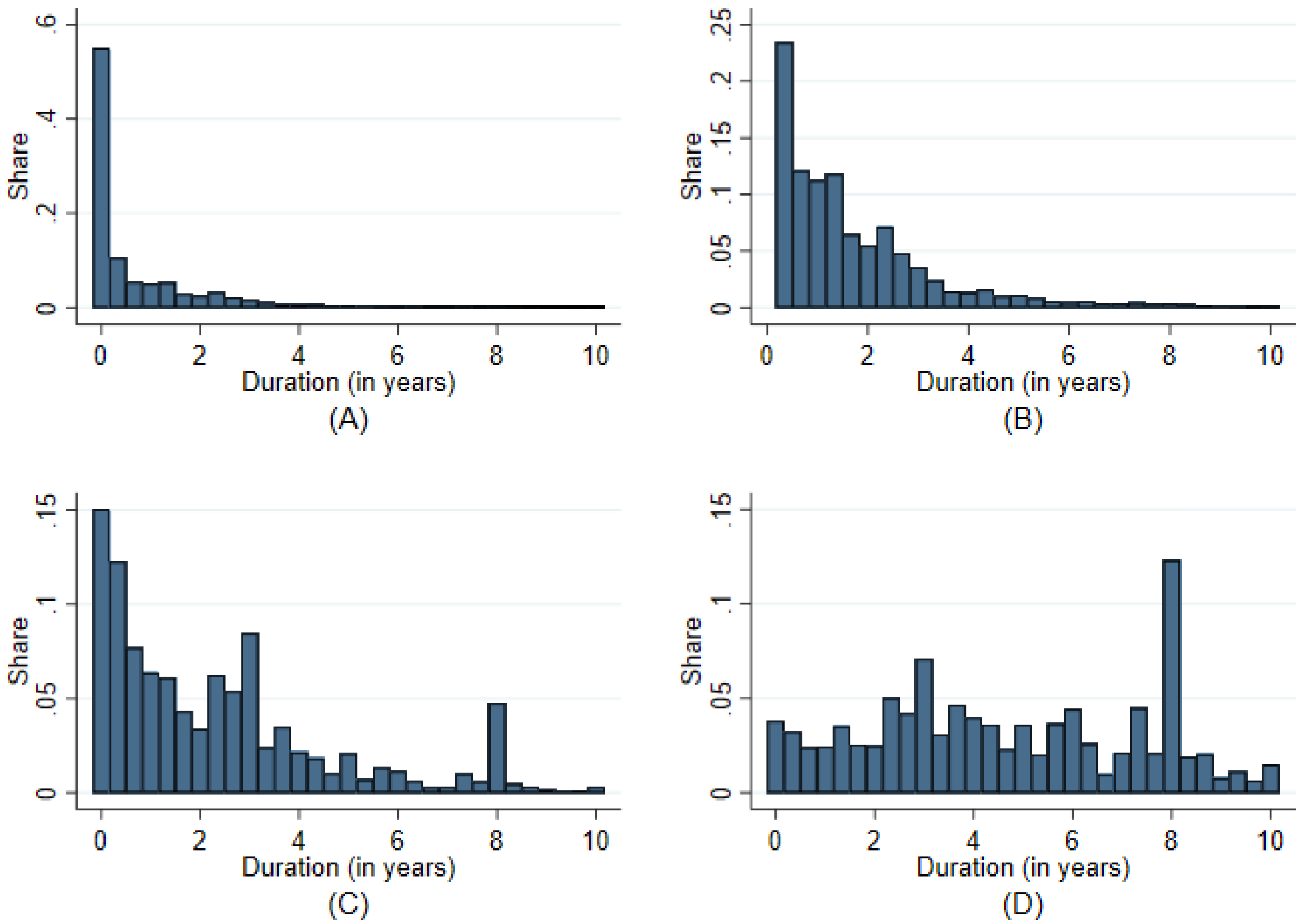
In this chapter, I show that potential entrants respond to the signals revealed by incumbent firms and are more inclined to enter markets where stronger signals are revealed. Conditional on the set of markets entered by a particular firm in a given year, the firm sells more output for a longer period of time on average to countries where stronger signals are revealed by more incumbents. Finally, these spillovers are confined to narrow HS 8-digit products and vary systematically with characteristics of the destination market and product type: effects are larger for export spells involving homogeneous products, more distant countries, and countries without Spanish as an official language. If policymakers are evaluating the effect of export promotion by examining the differences in outcomes between recipient firms and non-recipients, estimates of the effects of promotion will be biased downward in the presence of spillovers. Different export promotion policies will propagate to non-recipients according to these heterogeneous spillovers, leading to multiplier effects, which policymakers should take into consideration when allocating these scarce resources.

These results may help to explain some of the findings in the literature on the effectiveness of export promotion. For example, Volpe Martincus and Carballo (2010) use data on Uruguayan firms to show that export promotion is more successful at inducing producers of differentiated products to enter more markets but has virtually no effect on the entry decision for producers of homogeneous products. If the effect of promotion is measured as the difference of outcomes between treated and untreated firms and the possibility of spillovers are ignored, spillover effects will be included in the estimated effects of promotion, something Volpe Martincus and Carballo mention directly in footnote 23: "In particular, we do not consider information spillovers. It is well known that firms may learn about export opportunities from other firms through employee circulation, customs documents, customer lists, and other referrals. . . . If these spillovers were to be associated with participation in export promotion activities, i.e., unassisted firms obtain business information from assisted firms, then the treatment effects, as estimated here, would be underestimated." However, if spillovers are larger for homogeneous goods, as I find, then the difference in effectiveness of export promotion between differentiated and homogeneous products will be overstated if these spillovers are ignored.

If the goal of export promotion agencies is to increase some combination of aggregate exports, the total number of countries exported to, the number of exporting firms, and/or the number of exported products, more research is needed to inform these policymakers of the nuanced ways in which information flows across firms and how these flows vary with market and product characteristics. Furthermore, as pointed out by Wei et al. (2017), the presence of information spillovers and learning does not imply a market failure: equilibrium entry will not necessarily be below the socially optimal level. For a market failure to exist, the authors note, it must be the case that the sum of expected benefits to potential exporters outweigh the cost of uncovering information and that no firm by itself would be willing to incur entry costs in a product-market. More work is needed to determine if entry rates are socially suboptimal.

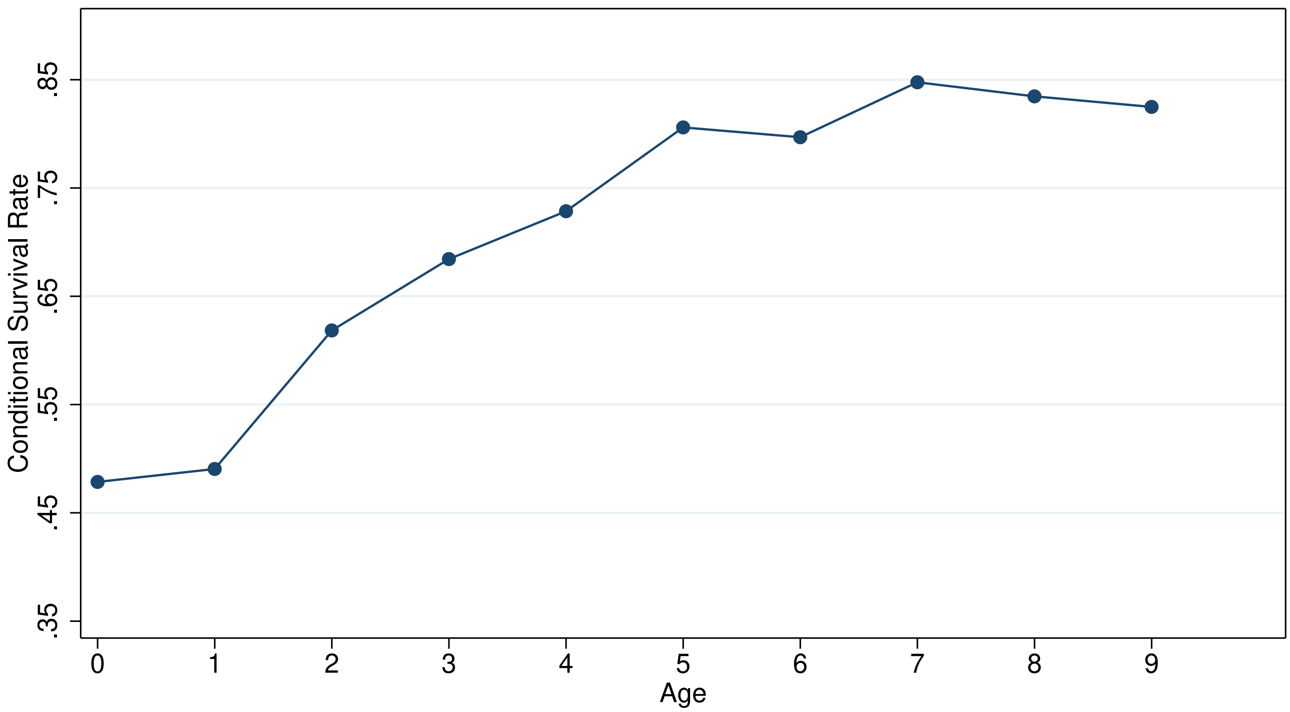
1.9 Figures and Tables

Figure 1.1: Export Spell Duration Histograms



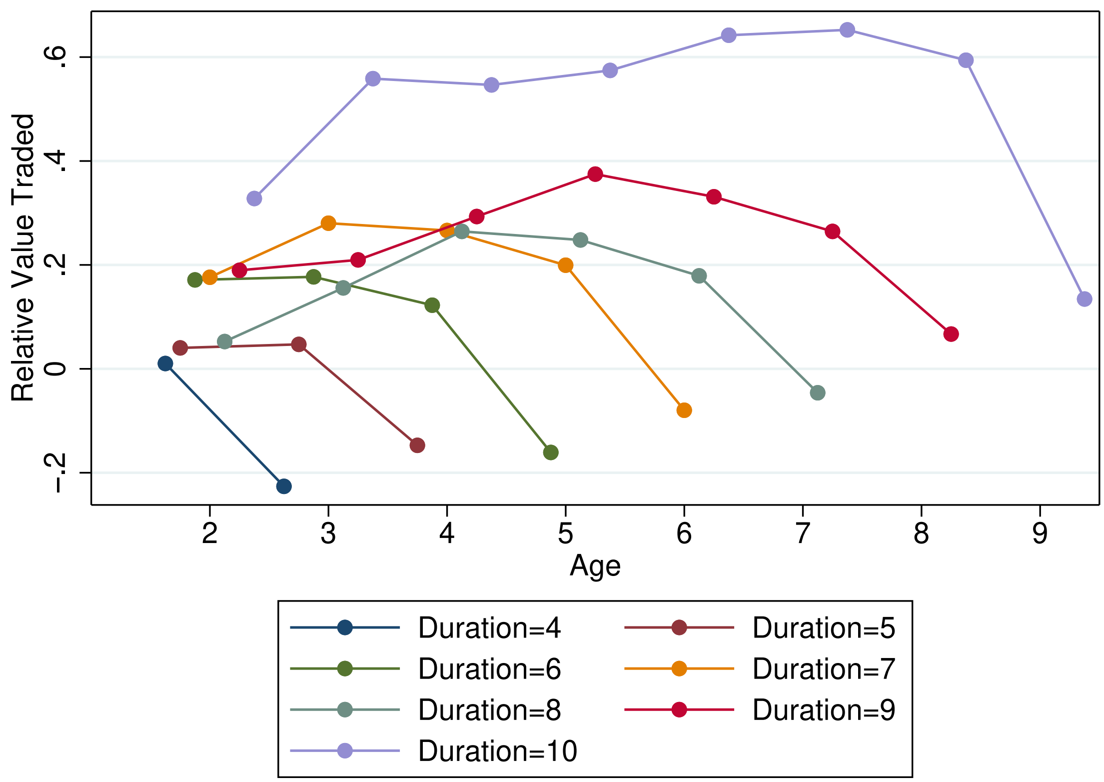
Panel (A) shows the histogram of export spell durations for all spells, including those with only one transaction and are therefore assigned duration of zero years. Panel (B) excludes spells with a single transaction and focuses only on spells with at least two transactions and therefore positive duration. Panel (C) includes all spells and weights each observation according to first-year sales. Because older spells have larger spells on average, the distribution shifts to the right. Panel (D) includes all spells and weights each observation according to the lifetime sales in the spell, resulting in a further shift in the distribution to the right, since larger spells tend to last longer as well.

Figure 1.2: Export Spell Conditional Survival Rates



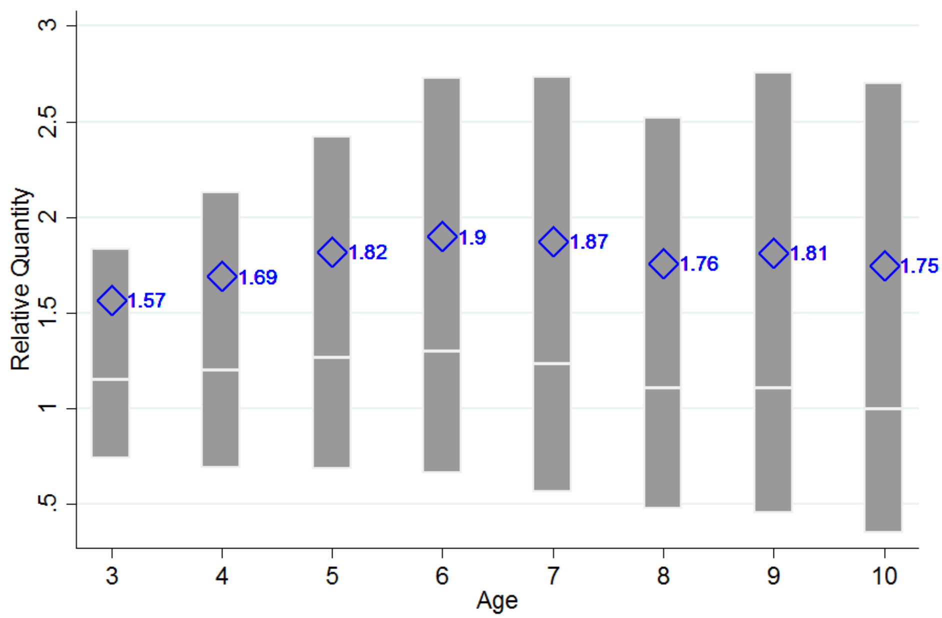
Each point represents the fraction of spells of age a active in 2012 which survive until 2013. For example, only 48% of spells of age 0 (those in their first year) survive whereas 85% of spells that are seven years old survive.

Figure 1.3: Relative Value Traded Over the Life of an Export Spell



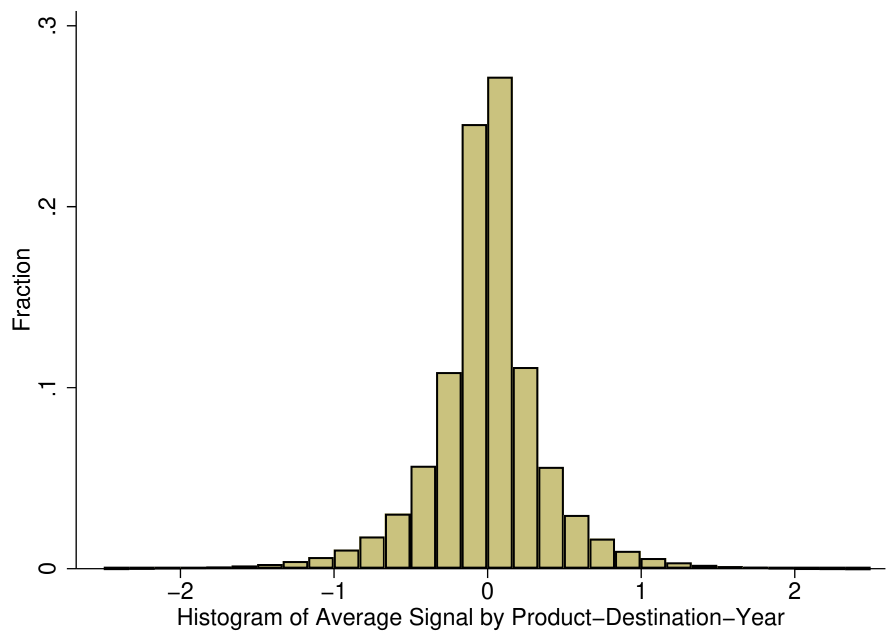
The points on each curve are estimated coefficients from a regression of sales on age dummies and relationship fixed effects. Each curve shows how the average sales evolve within an export spell for spells of different length. Observations are weighted by sales.

Figure 1.4: The Distribution of Changes in Values Exported for Long Spells



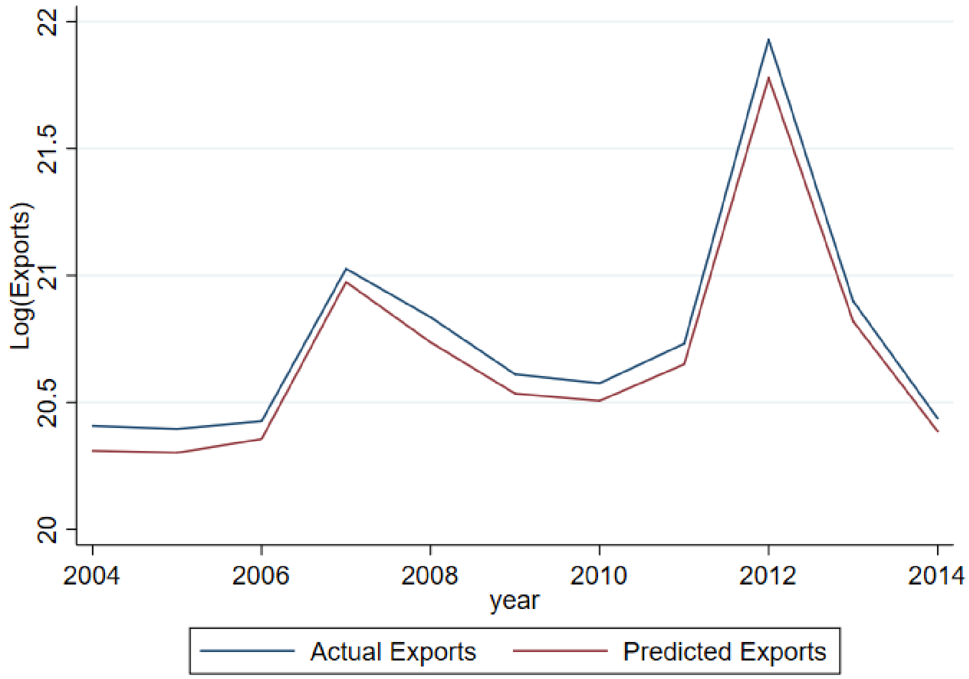
For each age, the bar shows the interquartile range for the quantities sold relative to second-year sales. That bottom of the bar is the 25th percentile, the white dash is the median, and the top of the bar is the 75th percentile, with the blue diamonds representing the means. Although the mean grows over time, median relative sales remain close to one.

Figure 1.5: Histogram of Estimated Average Signal Revealed by Product-Market-Year



This table plots the average signal revealed within each product-destination-year triplet in which information is revealed. The minimum and maximum values are approximately -5 and 5, but there are few observations less than -1 or greater than 1, so I restrict the domain to the area with the vast majority of observations.

Figure 1.6: Quantifying Counterfactual Exports of New Cohorts in the Absence of Information



Using the coefficients estimated from Equation 1.29, this graph shows the actual aggregate sales of first-year trade spells for each entering cohort of exporters and the predicted amount conditional on them not observing any information from the previous year. On average, removing the effect of signals leads to a reduction of about 8.7% of aggregate export sales.

Table 1.1: Descriptive Statistics for Incumbent Exporter Presence by Product-Market-Year

Number of Incumbents	Share	
0 incumbents	50.77%	Median: 0
1 incumbents	18.26%	Mean: 2.41
2 incumbents	9.31%	25th percentile: 0
3-5 incumbents	11.53%	75th percentile: 2
6-10 incumbents	5.41%	95th percentile: 10
11+ incumbents	4.71%	99th percentile: 32
Observations: 270,210		

The unit of observation is a product-market-year in which there is at least one new entrant. The number of incumbents shows the how many firms were active selling the same product to the same market in the previous year.

Table 1.2: Growth in Value Over the Life of Export Spell of Different Durations

	ln(Sales)$_{fkdt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}(\text{Age=2})_{fkdt}$	0.0103	0.0403***	0.1712***	0.1763***	0.0525*	0.1897***	0.3279***
	(0.0106)	(0.0122)	(0.0184)	(0.0232)	(0.0242)	(0.0308)	(0.0555)
$\mathbb{1}(\text{Age=3})_{fkdt}$	-0.2262***	0.0471***	0.1770***	0.2803***	0.1557***	0.2097***	0.5586***
	(0.0117)	(0.0122)	(0.0180)	(0.0224)	(0.0232)	(0.0299)	(0.0527)
$\mathbb{1}(\text{Age=4})_{fkdt}$		-0.1472***	0.1225***	0.2663***	0.2646***	0.2932***	0.5464***
		(0.0135)	(0.0185)	(0.0225)	(0.0228)	(0.0289)	(0.0518)
$\mathbb{1}(\text{Age=5})_{fkdt}$			-0.1609***	0.1995***	0.2480***	0.3748***	0.5744***
			(0.0209)	(0.0236)	(0.0233)	(0.0289)	(0.0498)
$\mathbb{1}(\text{Age=6})_{fkdt}$				-0.0797**	0.1790***	0.3312***	0.6421***
				(0.0262)	(0.0239)	(0.0292)	(0.0501)
$\mathbb{1}(\text{Age=7})_{fkdt}$					-0.0460	0.2645***	0.6524***
					(0.0262)	(0.0301)	(0.0519)
$\mathbb{1}(\text{Age=8})_{fkdt}$						0.0669*	0.5940***
						(0.0334)	(0.0538)
$\mathbb{1}(\text{Age=9})_{fkdt}$							0.1344*
							(0.0592)
N	44,502	42,688	25,305	20,292	21,511	15,440	6,615

Standard errors in parentheses are clustered by fkd. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Spells of age 0 (i.e. those in their first year) are excluded to avoid conflating growth with partial-year effects. The omitted category is sales in the second year of the spell (when age equals one) so that coefficients can be interpreted as log differences in sales relative to sales in the second year of a spell. Each column only includes spells which last exactly the number of years of the final regressor included to account for heterogeneous growth dynamics across spells of different length. For example, the first column only includes observations for spells which last exactly four years, whereas the last column only includes observations for spells which last exactly ten years.

Table 1.3: Defining Entry for the Extensive Margin - Example

	2002	2003	2004	2005	2006	2007	2008	2009
Germany			*	*	*	*	*	*
France				*	*			*
Belgium					*	*	*	*

An asterisk denotes positive export flows of a particular product by a hypothetical firm to the three destinations.

Table 1.4: Defining Entry for the Sample of Generated Observations - Example

	2002	2003	2004	2005	2006	2007	2008	2009
Germany	.	.	1	.	.	.	.	.
France	.	.	0	1	.	.	.	1
Belgium	.	.	0	0	1	.	.	.
All Others	.	.	0	0	0	0	0	0

1 denotes an observation that I classify as entering a market. 0 denotes an observation I classify as not entring a market. A period denotes a missing observation because the firm has never exported this product, it is already in the market, or the firm no longer exports.

Table 1.5: Baseline Extensive Margin Exporting Results

	(1)	(2)	(3)	(4)
	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}
Signal_{kdt-1}	0.0006^{***}	-0.0002		
	(0.00011)	(0.00012)		
	[0.00010-0.00012]	[0.00010-]0.00014]		
Signal_{kdt-1} $\times$ Firms_{kdt-1}		0.0004^{***}		
		(0.00005)		
		[0.00004-0.00006]		
Zero Signal_{kdt-1}			-0.0034^{***}	-0.0029^{***}
			(0.00062)	(0.00050)
			[0.00058-0.00068]	[0.00044-0.00057]
Positive Signal_{kdt-1}			0.0063^{***}	0.0029^{***}
			(0.00103)	(0.00055)
			[0.00092-0.00115]	[0.00048-0.00062]
Negative Signal_{kdt-1} $\times$ Firms_{kdt-1}				0.0011^{***}
				(0.00008)
				[0.00007-0.00010]
Positive Signal_{kdt-1} $\times$ Firms_{kdt-1}				0.0012^{***}
				(0.00007)
				[0.00006-0.00008]
N	15,298,772	15,298,772	15,298,772	15,298,772
R^2	0.309	0.309	0.309	0.310
adj. R^2	0.256	0.256	0.256	0.258

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fd, fkt, and idt fixed effects as well as HS 4-digit tariffs by country-year. Entry_{fkdt} is a dummy variable equal to 1 if firm f begins to sell product k in destination d at time t if they did not already do so in the previous two years. The signal variables in columns 1 and 2 are constructed from Equation 1.21 whereas the signal variables in columns 3 and 4 are dummies according to whether no signal is revealed, the average revealed signal is positive, or the average revealed signal is negative. Results are from estimating Equation 2.26. I exclude firm-product-year observations that occur before the first time a firm exports a particular product and firm-year observations after the final year a firm exports.

Table 1.6: Extensive Margin Exporting Results - Distance

	(1)	(2)	(3)	(4)
	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}
Signal_{kdt-1}	-0.0018	-0.0013		
	(0.0012)	(0.00104)		
	[0.0010-0.0013]	[0.00090-0.00121]		
Signal_{kdt-1} $\times$ $\ln(\text{Distance})_d$	0.00028	-0.00013		
	(0.00014)	(0.00012)		
	[0.00012-0.00016]	[0.00010-0.00014]		
Signal_{kdt-1} $\times$ Firms_{kdt-1} $\times$ $\ln(\text{Distance})_d$		0.000046*		
		(0.000005)		
		[0.000004-0.000006]		
Negative Signal_{kdt-1} $\times$ $\ln(\text{Distance})_d$			0.0003***	0.0003***
			(0.00009)	(0.000063)
			[0.00007-0.000012]	[0.000057-0.000071]
Positive Signal_{kdt-1} $\times$ $\ln(\text{Distance})_d$			0.0011***	0.0004***
			(0.00012)	(0.00006)
			[0.00011-0.00013	[0.00005-0.00007]
Negative Signal$kdt-1$ $\times$ Firms_{kdt-1} $\times$ $\ln(\text{Distance})_d$				0.0001***
				(0.000001)
				[0.000001-0.000001]
Positive Signal_{kdt-1} $\times$ Firms_{kdt-1} $\times$ $\ln(\text{Distance})_d$				0.0001***
				(0.00001)
				[0.000001 0.000001]
N	15,298,772	15,298,772	15,298,772	15,298,772
R^2	0.309	0.309	0.309	0.310
adj. R^2	0.256	0.256	0.256	0.258

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fd, fkt, and idt fixed effects as well as HS 4-digit tariffs by country-year. Entry_{fkdt} is a dummy variable equal to 1 if firm f begins to sell product k in destination d at time t if they did not already do so in the previous two years. The distance variable ranges from a low of 7.05 for Argentina to a high of 9.84 for China. The signal variables in columns 1 and 2 are constructed from Equation 1.21 whereas the signal variables in columns 3 and 4 are dummies according to whether no signal is revealed, the average revealed signal is positive, or the average revealed signal is negative. Results are from estimating Equation 2.26. I exclude firm-product-year observations that occur before the first time a firm exports a particular product and firm-year observations after the final year a firm exports.

Table 1.7: Extensive Margin Exporting Results - Language

	(1)	(2)	(3)	(4)
	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}
Signal_{kdt-1}	0.0008**	-0.0000		
$\times\ \mathbb{1}(\text{Spanish}_d{=}0)$	(0.00026)	(0.00022)		
Signal_{kdt-1}	0.0004***	-0.0004		
$\times\ \mathbb{1}(\text{Spanish}_d{=}1)$	(0.00012)	(0.00021)		
Signal_{kdt-1}		0.0004***		
$\times\ \text{Firms}_{kdt-1} \times (\text{Spanish}_d{=}0)$		(0.00007)		
Signal_{kdt-1}		0.0005***		
$\times\ \text{Firms}_{kdt-1} \times (\text{Spanish}_d{=}1)$		(0.00009)		
Zero Signal_{kdt-1}			-0.0024**	-0.0017**
$\times\ \mathbb{1}(\text{Spanish}_d{=}1)$			(0.00077)	(0.00070)
Positive Signal_{kdt-1}			0.0036***	0.0013*
$\times\ \mathbb{1}(\text{Spanish}_d{=}1)$			(0.00108)	(0.00066)
Negative Signal $_{kdt-1}$				0.0011***
$\times\ \text{Firms}_{kdt-1} \times (\text{Spanish}_d{=}0)$				(0.00011)
Negative Signal_{kdt-1}				0.0013***
$\times\ \text{Firms}_{kdt-1} \times (\text{Spanish}_d{=}1)$				(0.00011)
Positive Signal_{kdt-1}				0.0013***
$\times\ \text{Firms}_{kdt-1} \times (\text{Spanish}_d{=}0)$				(0.00008)
Positive Signal_{kdt-1}				0.0014***
$\times\ \text{Firms}_{kdt-1} \times (\text{Spanish}_d{=}1)$				(0.00014)
N	15,298,772	15,298,772	15,298,772	15,298,772
R^2	0.309	0.309	0.309	0.310
adj. R^2	0.256	0.256	0.256	0.258

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the upper bound of the 95% confidence interval of 100 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fd, fkt, and idt fixed effects as well as HS 4-digit tariffs by country-year. Entry_{fkdt} is a dummy variable equal to 1 if firm f begins to sell product k in destination d at time t if they did not already do so in the previous two years. The signal variables in columns 1 and 2 are constructed from Equation 1.21 whereas the signal variables in columns 3 and 4 are dummies according to whether no signal is revealed, the average revealed signal is positive, or the average revealed signal is negative. Results are from estimating Equation 2.26. I exclude firm-product-year observations that occur before the first time a firm exports a particular product and firm-year observations after the final year a firm exports.

Table 1.8: Extensive Margin Exporting Results - Product Characteristics

	(1)	(2)	(3)	(4)
	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}	Entry_{fkdt}
Signal_{kdt-1}	-0.0023***	-0.0023**		
	(0.0006)	(0.0006)		
	[0.0005-0.0006]	[0.0005-0.0008]		
Signal_{kdt-1}	0.0010***	0.0010***		
$\times\ \sigma_{HS3dt}$	(0.0002)	(0.00021)		
	[0.00018-0.00023]	[0.0002-0.0003]		
Signal_{kdt-1}			0.0026***	0.0012*
$\times$ Reference_k			(0.0005)	(0.0004)
			[0.0004-0.0006]	[0.0003-0.0005]
Signal_{kdt-1}			0.0001	-0.0000
$\times$ Differentiated_k			(0.0001)	(0.0001)
			[0.00006-0.0001]	[0.00009-0.00015]
Signal_{kdt-1}				0.0004***
$\times$ Firms_{kdt-1} $\times$ Reference_k				(0.00005)
				[0.00004-0.00007]
Signal_{kdt-1}				0.0001
$\times$ Firms_{kdt-1} $\times$ Differentiated_k				(0.00005)
				[0.00003-0.00007]
N	15,298,772	14,919,937	12,025,911	12,025,911
R^2	0.309	0.312	0.319	0.319
adj. R^2	0.256	0.259	0.265	0.265

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fd, fkt, and idt fixed effects as well as HS 4-digit tariffs by country-year. Entry_{fkdt} is a dummy variable equal to 1 if firm f begins to sell product k in destination d at time t if they did not already do so in the previous two years. Estimates for the elasticity of substitution at the HS 3-digit level come from Broda et al. (2017), whereas product types are defined according to the Rauch classification. The signal variables in columns 1 and 2 are constructed from Equation 1.21. Results are from estimating Equation 2.26. Columns 2, 3, and 4 exclude homogeneous products. I exclude firm-product-year observations that occur before the first time a firm exports a particular product and firm-year observations after the final year a firm exports.

Table 1.9: Baseline Intensive Margin Exporting Results

	$\ln(\text{Quantity})_{fkdt}$		$\text{IHS}(\text{Duration})_{fkdt}$		Duration_{fkdt}	
	(1)	(2)	(3)	(4)	(5)	(6)
Signal_{kdt-1}	0.0931***	0.0530***	0.0083*	0.0069	0.0189**	0.0154
	(0.0113)	(0.0105)	(0.0029)	(0.0033)	(0.0063)	(0.0071)
	[0.0099-0.0127]	[0.0092-0.0119]	[0.0026-0.0033]	[0.0029-0.0037]	[0.0055-0.0073]	[0.0060-0.0082]
Signal_{kdt-1} $\times$ Firms_{kdt-1}		0.0076***		0.0003		0.0007
		(0.0012)		(0.0004)		(0.0007)
		[0.0010-0.0015]		[0.0003-0.0004]		[0.0005-0.0010]
$\ln(\text{Sales})_{fkdt}$			0.1313***	0.1311***	0.2321***	0.2317***
			(0.0025)	(0.0025)	(0.0045)	(0.0045)
Tariff_{HS4dt}	-0.0018	-0.0019	-0.0003	-0.0003	0.0007	0.0007
	(0.0020)	(0.0020)	(0.0006)	(0.0006)	(0.0014)	(0.0014)
N	163,652	163,652	163,652	163,652	163,652	163,652
R^2	0.872	0.872	0.676	0.676	0.686	0.686
adj. R^2	0.796	0.797	0.486	0.486	0.503	0.503

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 500 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All six columns contain fkt and idt fixed effects, while only the first two have dummies for the first month in the year in which an export spell occurs. $\ln(\text{Quantity})_{fkdt}$ is the number of units sold in the first year of an export spell, $\text{IHS}(\text{Duration})_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell, and Duration_{fkdt} is the duration of the spell in levels. The signal variables are constructed from Equation 1.21. Results in columns 1 and 2 are from estimating Equation 2.28, whereas those in columns 3 through 6 add to that first-year sales and remove the first month dummies. For the quantity margin, I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 1.10: Intensive Margin Exporting Results - Distance

	$\ln(\text{Quantity})_{fkdt}$		$\text{IHS}(\text{Duration})_{fkdt}$	
	(1)	(2)	(3)	(4)
Signal_{kdt-1}	-0.3514**	-0.1523	-0.0527	-0.0474
	(0.1088)	(0.0997)	(0.0281)	(0.0288)
	[0.0921-0.1278]	[0.0840-0.1186]	[0.0239-0.0332]	[0.0245-0.0338]
Signal_{kdt-1} $\ln(\text{Distance})_d$	0.0525***	0.0247	0.0065	0.009*
	(0.0128)	(0.0115)	(0.0033)	(0.0034)
	[0.0107-0.0147]	[0.0098-0.0136]	[0.0028-0.0039]	[0.0029-0.0040]
Signal_{kdt-1} $\times \text{Firms}_{kdt-1} \times \ln(\text{Distance})_d$		0.0008***		0.00002
		(0.0001)		(0.00004)
		[0.0001-0.0002]		[0.00003-0.00005]
$\ln(\text{Sales})_{fkdt}$			0.1311***	0.1311***
			(0.0025)	(0.0025)
Tariff_{HS4dt}	-0.0018	-0.0019	-0.0003	-0.0003
	(0.0020)	(0.0020)	(0.0006)	(0.0006)
N	163,644	163,644	163,644	163,644
R^2	0.872	0.872	0.676	0.676
adj. R^2	0.796	0.797	0.486	0.486

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 500 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fkt and idt fixed effects, while only the first two have dummies for the first month in the year in which an export spell occurs. $\ln(\text{Quantity})_{fkdt}$ is the number of units sold in the first year of an export spell and $\text{IHS}(\text{Duration})_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. The distance variable ranges from a low of 7.05 for Argentina to a high of 9.84 for China. The signal variables are constructed from Equation 1.21. Results in columns 1 and 2 are from estimating Equation 2.28, whereas those in columns 3 and 4 add to that first-year sales and remove the first month dummies. For the quantity margin, I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 1.11: Intensive Margin Exporting Results - Language

	$\ln(\text{Quantity})_{fkdt}$		$\text{IHS}(\text{Duration})_{fkdt}$	
	(1)	(2)	(3)	(4)
Signal_{kdt-1}	0.1477***	0.0885***	0.0122*	0.0106
$\times \mathbb{1}(\text{Spanish}_d{=}0)$	(0.0159)	(0.0148)	(0.0044)	(0.0051)
	[0.0137-	[0.0127-	[0.0037-	[0.0042-
	[0.0183]	0.0174]	0.0052]	0.0061]
Signal_{kdt-1}	0.0521**	0.0158	0.0054	0.0037
$\times \mathbb{1}(\text{Spanish}_d{=}1)$	(0.01340)	(0.0157)	(0.0038)	(0.0048)
	[0.0117-	[0.0131-	[0.0033-	[0.0040-
	0.0166]	0.0189]	0.0044]	0.0059]
Signal_{kdt-1}		0.0066***		0.0002
$\times \text{Firms}_{kdt-1} \times \mathbb{1}(\text{Spanish}_d{=}0)$		(0.0012)		(0.0004)
		[0.0010-		[0.0003-
		0.0015]		0.0005]
Signal_{kdt-1}		0.0141*		0.0007
$\times \text{Firms}_{kdt-1} \times \mathbb{1}(\text{Spanish}_d{=}1)$		(0.0043)		(0.0013)
		[0.0032-		[0.0009-
		0.0057]		0.0018]
$\ln(\text{Sales})_{fkdt}$			0.1312***	0.1311***
			(0.0025)	(0.0025)
Tariff_{HS4dt}	-0.0017	-0.0018	-0.0003	-0.0003
	(0.0020)	(0.0020)	(0.0006)	(0.0006)
N	163,644	163,644	163,644	163,644
R^2	0.872	0.872	0.676	0.676
adj. R^2	0.797	0.797	0.486	0.486

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 500 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fkt and idt fixed effects, while only the first two have dummies for the first month in the year in which an export spell occurs. $\ln(\text{Quantity})_{fkdt}$ is the number of units sold in the first year of an export spell and $\text{IHS}(\text{Duration})_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. The signal variables are constructed from Equation 1.21. Results in columns 1 and 2 are from estimating Equation 2.28, whereas those in columns 3 and 4 add to that first-year sales and remove the first month dummies. For the quantity margin, I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 1.12: Intensive Margin Exporting Results - Rauch Classification

	$\ln(\text{Quantity})_{fkdt}$		$\text{IHS}(\text{Duration})_{fkdt}$	
	(1)	(2)	(3)	(4)
Signal_{kdt-1}	0.1729***	0.0472	0.0066	-0.0289
$\times$ Homogeneous_k	(0.0431)	(0.0645)	(0.0161)	(0.0245)
	[0.0293-0.0616]	[0.0445-0.0905]	[0.0103-0.0232]	[0.0167-0.0331]
Signal_{kdt-1}	0.1626***	0.0940***	0.0146**	0.0136*
$\times$ Reference_k	(0.0151)	(0.0141)	(0.0044)	(0.0053)
	[0.0130-0.0174]	[0.0119-0.0168]	[0.0037-0.0052]	[0.0043-0.0062]
Signal_{kdt-1}	0.0262	0.0128	0.0030	0.0005
$\times$ Differentiated_k	(0.0168)	(0.0252)	(0.0044)	(0.0066)
	[0.0137-0.0209]	[0.0201-0.0313]	[0.0037-0.0053]	[0.0053-0.0084]
Signal_{kdt-1}		0.0584		0.0164
$\times$ Firms_{kdt-1} $\times$ Homogeneous_k		(0.0272)		(0.0109)
		[0.0190-0.0382]		[0.0078-0.0149]
Signal_{kdt-1}		0.0060***		0.0001
$\times$ Firms_{kdt-1} $\times$ Reference_k		(0.0012)		(0.0004)
		[0.0009-0.0014]		[0.0003-0.0005]
Signal_{kdt-1}		0.0071		0.0013
$\times$ Firms_{kdt-1} $\times$ Differentiated_k		(0.0101)		(0.0027)
		[0.0073-0.0136]		[0.0020-0.0038]
$\ln(\text{Sales})_{fkdt}$			0.1310***	0.1309***
			(0.0028)	(0.0028)
Tariff_{HS4dt}	-0.0005	-0.0003	0.0004	0.0004
	(0.0034)	(0.0033)	(0.0010)	(0.0010)
N	137,999	137,999	137,999	137,999
R^2	0.869	0.869	0.662	0.662
adj. R^2	0.797	0.798	0.477	0.477

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 500 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fkt and idt fixed effects, while only the first two have dummies for the first month in the year in which an export spell occurs. $\ln(\text{Quantity})_{fkdt}$ is the number of units sold in the first year of an export spell and $\text{IHS}(\text{Duration})_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. Product types are defined according to the Rauch classification. The signal variables are constructed from Equation 1.21. Results in columns 1 and 2 are from estimating Equation 2.28, whereas those in columns 3 and 4 add to that first-year sales and remove the first month dummies.

Table 1.13: Intensive Margin Exporting Results - Elasticity of Substitution

	$\ln(\text{Quantity})_{fkdt}$	$\text{IHS}(\text{Duration})_{fkdt}$
	(1)	(2)
Signal_{kdt-1}	-0.1216***	-0.0148
	(0.0257)	(0.0067)
	[0.0216-0.0308]	[0.0057-0.0078]
$\text{Signal}_{kdt-1} \times \sigma_{HS3}$	0.0700***	0.0076**
	(0.0076)	(0.0020)
	[0.0061-0.0095]	[0.0016-0.0024]
$\ln(\text{Sales})_{fkdt}$		0.1308***
		(0.0025)
Tariff_{HS4dt}	-0.0017	-0.0003
	(0.0020)	(0.0006)
N	163,652	163,652
R^2	0.872	0.676
adj. R^2	0.797	0.486

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 500 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Both columns contain fkt and idt fixed effects, while only the first two have dummies for the first month in the year in which an export spell occurs. $\ln(\text{Quantity})_{fkdt}$ is the number of units sold in the first year of an export spell and $\text{IHS}(\text{Duration})_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. Estimates for the elasticity of substitution at the HS 3-digit level come from Broda et al. (2017). The signal variables are constructed from Equation 1.21. Results in column 1 are from estimating Equation 2.28, whereas those in column 2 add to that first-year sales and remove the first month dummies. For the quantity margin, I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 1.14: Varying the Level of Signal Aggregation - 1

	Entry$_{fkdt}$			ln(Quantity)$_{fkdt}$			IHS(Duration)$_{fkdt}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Signal$_{kdt-1}$	0.0006***			0.0931***			0.0083*		
	(0.00011)			(0.0113)			(0.0029)		
	[0.00010-0.00012]			[0.0099-0.0127]			[0.0026-0.0033]		
Signal$_{HS(6,-k)dt-1}$		0.0002			-0.0167			0.0001	
		(0.00009)			(0.0105)			(0.0033)	
		[0.00007-0.00013]			[0.0092-0.0121]			[0.0028-0.0038]	
Signal$_{HS(4,-k)dt-1}$			0.0001			-0.0223			-0.0011
			(0.00010)			(0.0117)			(0.0031)
			[0.00007-0.00015]			[0.0104-0.0137]			[0.0028-0.0035]
N	15,298,772	15,298,772	15,298,772	163,652	163,652	163,652	163,652	163,652	163,651
R^2	0.309	0.309	0.309	0.872	0.871	0.871	0.676	0.676	0.676
adj. R^2	0.256	0.256	0.256	0.796	0.796	0.796	0.486	0.486	0.486

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 (500) bootstrap replications in Columns 1-3 (4-9). The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All five columns contain fkt and idt fixed effects in addition to tariff controls (Tariff$_{HS4dt}$). Columns 1-3 contain fd fixed effects, columns 4-6 contain dummies for the first month in the year in which an export spell occurs, and Columns 7-9 contain controls for first-year sales. Entry$_{fkdt}$ is a dummy variable equal to 1 if firm f begins to sell product k to destination d at time t if it did not already do so in either of the previous two years. ln(Quantity)$_{fkdt}$ is the number of units sold in the first year of an export spell and IHS(Duration)$_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. The signal variables are constructed from Equation 1.21 and 1.28. Results are from estimating Equations 2.26 and 2.28 with various definitions of the signal variable. I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 1.15: Varying the Level of Signal Aggregation - 2

	Entry$_{fkdt}$			ln(Quantity)$_{fkdt}$			IHS(Duration)$_{fkdt}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Signal$_{kdt-1}$	0.0006***	0.0006***	0.0006***	0.0931***	0.0925***	0.0925***	0.0083**	0.0085**	0.0085**
	(0.00011)	(0.00012)	(0.00012)	(0.0113)	(0.0102)	(0.0103)	(0.0029)	(0.0028)	(0.0029)
	[0.00010-	[0.00011-	[0.00011-	[0.0099-	[0.0091-	[0.0092	[0.0026-	[0.0025-	[0.0025-
	0.00012]	0.00013]	0.00013]	0.0127]	0.0115]	0.0115]	0.0033]	0.0032]	0.0032]
Signal$_{HS(6,-k)dt-1}$		0.0002	0.0002		-0.0046	-0.0044		0.0012	0.0012
		(0.00010)	(0.00010)		(0.0101)	(0.0112)		(0.0034)	(0.0035)
		[0.00008-	[0.00008-		[0.0088-	[0.0097-		[0.0029-	[0.0030
		0.00013]	0.00014]		0.0117]	0.0131]		0.0039]	0.0043]
Signal$_{HS(4,-k)dt-1}$			0.0001			-0.0004			0.0000
			(0.00010)			(0.0122)			(0.0033)
			[0.00007-			[0.0105-			[0.0029-
			0.00015]			0.0150]			0.0038]
N	15,298,772	15,298,772	15,298,772	163,652	163,652	163,652	163,652	163,652	163,651
R^2	0.309	0.309	0.309	0.872	0.872	0.872	0.676	0.676	0.676
adj. R^2	0.256	0.256	0.256	0.796	0.796	0.796	0.486	0.486	0.486

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 (500) bootstrap replications in Columns 1-3 (4-9). The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All five columns contain fkt and idt fixed effects in addition to tariff controls (Tariff$_{HS4dt}$). Columns 1-3 contain fd fixed effects, columns 4-6 contain dummies for the first month in the year in which an export spell occurs, and Columns 7-9 contain controls for first-year sales. Entry$_{fkdt}$ is a dummy variable equal to 1 if firm f begins to sell product k to destination d at time t if it did not already do so in either of the previous two years. ln(Quantity)$_{fkdt}$ is the number of units sold in the first year of an export spell and IHS(Duration)$_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. The signal variables are constructed from Equation 1.21 and 1.28. Results are from estimating Equations 2.26 and 2.28 with various definitions of the signal variable. I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 1.16: Heterogeneous Effects by Firm Size - All Three Margins

	(1)	(1)	(2)
	Entry_{fkdt}	$\ln(\text{Quantity})_{fkdt}$	$\text{IHS}(\text{Duration})_{fkdt}$
Signal_{kdt-1}	-0.0005*	-0.0452	-0.0076
	(0.00019)	(0.0503)	(0.0145)
	[0.00017-0.00023]	[0.0444-0.0594]	[0.0127-0.0173]
Signal_{kdt-1}	0.0001***	0.0097*	0.0011
$\times\text{IHS}(\text{FirmSize})_{ft-1}$	(0.00001)	(0.0036)	(0.0011)
	[0.00001-0.00001]	[0.0032-0.0042]	[0.0009-0.0013]
Tariff_{HS4dt}	-0.0000	-0.0018	-0.0003
	(0.0000)	(0.0020)	(0.0006)
$\ln(\text{Sales})_{fkdt}$			0.1312***
			(0.0025)
N	15,298,772	163,652	163,652
R^2	0.309	0.872	0.676
adj. R^2	0.256	0.796	0.486

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All three columns include fkt and idt fixed effects and the first column includes fd fixed effects. Entry_{fkdt} is a dummy variable indicating whether or not an exporter enters market in a particular year, $\ln(\text{Quantity})_{fkdt}$is the number of units sold in the first year of an export spell, and $\text{IHS}(\text{Duration})_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. The signal variables are constructed from Equation 1.21. Results in column 1 are from estimating Equation 2.28, whereas those in column 2 add to that first-year sales and remove the first month dummies. For the quantity margin, I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 1.17: Extensive Margin Exporting Results for an Alternative Sample

	Entry_{fkdt}			
	Top 20 Destinations		Destinations 20-40	
	(1)	(2)	(3)	(4)
Signal_{kdt-1}	0.0006***	-0.0002	0.0007***	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Signal_{kdt-1}		0.0004***		0.0005***
$\times$ Firms_{kdt-1}		(0.0001)		(0.0001)
Observations	15,298,772	15,298,772	6,274,535	6,274,535
R^2	0.256	0.256	0.301	0.301

Standard errors in parentheses are clustered by country-sector (HS 2-digit). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns include fkt, idt, and fd fixed effects, in addition to tariff controls (Tariff_{HS4dt}). Entry_{fkdt} is a dummy variable indicating whether or not an exporter enters market in a particular year. The signal variables are constructed from Equation 1.21. Results are from estimating Equation 2.28. The first two columns replicate the baseline extensive margin results for the original sample of the top 20 importing countries of Chilean exports. The third and fourth columns use countries that rank between the 21st and 40th most popular destinations of Chilean exports.

Chapter 2

Import Sourcing and Learning from Others

2.1 Introduction

In the second chapter of this dissertation, I test whether or not similar learning spillovers documented in the last chapter for exporters are present among importing firms. That is, do importing firms learn about the heterogeneous quality of inputs from various sources through the signals revealed by their compatriots prior to themselves entering a market? If so, how does it affect their importing behavior in terms of entry, volume, and duration of import spell?

This first contribution of this chapter is to document a series of empirical facts about import spells analogous to those in the last chapter for exporting that are suggestive of firms learning about the quality of the intermediate inputs and capital goods that they import. First, import spells are short on average.[1] For a cohort of new import spells, a majority will end within a year of beginning. Second, conditional survival rates are increasing. For the minority of spells which survive beyond that uncertain first year, the probability of survival

[1]In the last chapter, an export spell was defined as one firm exporting the same product to the same destination country in consecutive years. I define an import spell as the same importing firm buying the same product from the same origin country in consecutive years. Data for exporting firms in the origin countries is unavailable, so a firm which imports a product from an origin may do so from more than one firm.

from year-to-year increases with the length of that import spell, meaning the oldest spells are the least likely to terminate in a given year. Third, the evolution of value traded within durable import spells (i.e., those which last ten years) fluctuate dramatically across trade relationships. The import value within some spells grows steadily throughout those ten years, remains constant in others, and shrinks for a nontrivial fraction.

I discuss each of these three trends in more detail below, but taken together, they are consistent with an environment of uncertainty in which importers do not know the quality of the goods they import. For a new cohort of import spells, some fraction of importers will be unhappy with the quality of the intermediates they receive (once they begin importing and are able to observe that quality). Those are the spells which end within the first year. This selection that drives out the least profitable import relationships generates increasing conditional survival rates. Each year, the spells that survive are those for which the signals about quality are highest. After a longer period of observing positive quality, importing firms are less likely to cease a trade relationship in response to a given negative shock. Additionally, the importers that receive better-than-expected signals in the early years of a relationship are those which will import more in the subsequent years. For those with worse-than-expected signals, but not bad enough to cause them to terminate the relationship, the value they import may stay constant or even decrease over time.

To account for these empirical trends, the second contribution of the paper is in developing a model in which firms import varieties of intermediate inputs of uncertain quality from around the world but can learn from one another. There is an idiosyncratic firm-variety match value which governs the productivity of that variety for the firm, but there is a common component of quality about which the firm can infer information from the actions of other Chilean firms importing that variety. In short, if there are more firms importing greater quantities of that variety, that will be a positive signal about the quality of that variety, making the firm more likely to begin importing that particular variety, import greater quantities of it, and have a longer trade relationship. In the presence of information spillovers, potential importers can infer some information about the quality of a particular input without ever having to import it themselves. Therefore, learning can occur prior to entry, in addition to the post-entry learning which has been discussed in the literature.[2]

While there is an extensive literature documenting spillovers among exporting firms, there is much less evidence for importers. Alvarez et al. (2008), Koenig (2009), Koenig et al. (2010), Poncet and Mayneris (2013), Fernandes and Tang (2014), and the previous chapter of this dissertation examine how the propensity to export to a destination and the intensive margin decision of how much to sell depend on the presence of compatriots firm selling the same product to the same market. Koenig (2009) and Koenig et al. (2010) interpret incumbent presence as decreasing the fixed costs of entry for exporting, as a greater incumbent presence increases the entry rates but does not affect sales volume. Fernandes and Tang (2014) interpret incumbent presence as revealing information about heterogeneous aggregate demand across different markets. They find that potential entrants are more likely to enter and sell greater values in markets with higher growth over the previous two years, although they do not disaggregate markets along the product dimension. In the preceding chapter, I show that Chilean firms are more likely to enter and have greater sales in markets where incumbent Chilean firms sell relatively greater quantities in the previous years.

Among others, Monarch and Schmidt-Eisenlohr (2018) and Rauch and Watson (1999) document trends consistent with firms learning about import quality and reliability from their own experience. Firms begin import spells with smaller orders to gauge whether suppliers are reliable. As order are filled, the importer becomes more confident in the quality and reliability of the supplier, importing more each period. However, evidence for import spillovers across firms is much scarcer. Bisztray et al. (2018) use Hungarian data and show that firms are more likely to source imports from a particular country if there are other firms within the same building, across the street, or within a few buildings importing from that country. Hu and Tan (2017) use prices as signals about the quality of imports and show that Chinese firms are more likely to source inputs from countries from which other local firms buy that product. Using a similar empirical strategy but with different signals about quality, I show that spillovers are present throughout Chile, not just from neighboring importers.

In the previous chapter, I used quantities sold by an exporter purged of a variety of fixed effects as a signal of uncertain demand across markets. I relied on firms selling the same

[2] See for example Monarch and Schmidt-Eisenlohr (2018) and Rauch and Watson (2003).

product to different countries and the key variation I exploited was differences in quantities sold across destinations within a firm-product-year.[3] Exporting firms facing segmented markets will sell to each country where they expect profits to be positive. For the largest, most productive firms, this typically involves selling to many countries, generating differences in revealed signals across product-market-years. However, the same is not true of importers, which are more likely to source a product from just a single destination country. Therefore, I am unable to use analogous purged import quantities as signals of quality.[4] Instead, I use the number of Chilean importers which import a particular good from a particular source in a year and the overall value imported by Chilean firms in that year.[5]

As a brief summary of results, I find that firms are 6.6% more likely to enter, have 8.0% greater import values, and survive 4.4% longer in markets where there is positive incumbent Chilean presence in the previous year compared to markets in which there is no incumbent presence. Entry, import values, and survival increase with the value imported by incumbent firms, but increasing the number of incumbent firms can have a positive or negative effect on these three margins of importing. A doubling of import value by incumbent firms from a particular source increases the likelihood of a new entrant choosing to buy from that country by 0.6%, first-year values by 33.4%, and survival time by 1.7%. However, the presence of one additional incumbent sourcing from a market in the previous year is associated with an increase in the import probability of 0.1%, a decrease in import volume of 0.05%, and in increase in surival times of 0.02%.

If importing a higher quality or a greater variety of intermediate inputs increases firm productivity, but firms do not take into account the value of the information they reveal to their compatriots about the quality of different intermediates, this generates an additional motive for import promotion policies that help firms overcome the obstacles of importing.

[3]The basic intuition is that, controlling for differences in market size, a firm sells greater quantities to one market than to another because it anticipates that demand is higher in the former.

[4]Consider a firm which produces steel. If this firm is productive and is optimistic about demand for its product, it will export widely to many countries. However, for a firm which imports steel, it will likely choose to do so from only one source. Whereas the steel exporter may sell to more than 20 destination countries, it is unlikely for a steel importer to ever import from that many source countries.

[5]The idea here is that more firms and a greater import value will be indicative of a more reliable, higher quality input after controlling for differences in the size or origin countries, exports from source countries to the rest of the world, and the presence of the firm already importing from that market.

If the returns to these policies have a multiplier effect through non-treated firms importing higher quality or more varieties, increases in aggregate productivity will be greater than predicted in the absence of spillovers.

In the next section, I describe the data that I use and discuss in more detail the stylized facts outlined above. In Section 3, I present a model in which information externalities exist because incumbent importers reveal information about the quality of inputs through their actions. Based off of comparative statics derived from the model, I discuss my empirical strategy and results in Section 4, concluding with a remark on the policy relevance of the results and potential avenues for future research.

2.2 Data, Descriptive Statistics, and Trends

I construct import spells using transaction-level import data spanning the years 2002 to 2014 from Servicio Nacional de Aduanas, Chilean customs. Each original transaction identifies the HS 8-digit product being imported, the importing firm, the country of origin, the date the transaction occurs, and the quantity and value being imported.[6] An import spell is identified as one firm importing the same HS 8-digit product from the same origin country in consecutive years.[7]

The transaction-level import data includes all transactions that clear Chilean customs. These transactions include those done by conventional firms, but also imports by household consumers. Each firm/household consumer in the data is identified by a unique RUT (Rol Único Nacional) code, but I do not observe whether each code is a firm or an individual. I make two restrictions in the sample to ensure that the focus of the analysis is on learning about input quality done by producing firms rather than household consumers or retailers. Imports are classified broadly into five categories: intermediate inputs, capital goods, raw materials, consumer goods, and oil. The first restriction is that I focus only on capital and

[6]It was mentioned above but worth highlighting: I do not observe information about the exporting firm in the source country. Therefore, a firm importing a product from an origin country may import from more than one firm.

[7]If there is a calendar year break during which a firm does not import a particular product from a particular source country, but the the firm resumes importing the following year, I consider that to be a new import spell.

intermediate goods. Learning from others is unlikely to be unimportant for oil, so those observations are discarded. Consumers are more likely to purchase consumer goods than intermediate inputs or capital goods, so this leaves me with observations which are more likely to be firms for products where learning is important. Second, I omit identifiers for which the overall import value is less than $5,000 over the course of the sample. Therefore, the regressions below report results including observations with identifiers which import more than $5,000 of capital goods and intermediate inputs. There are 155,312 unique RUT codes in the original data, but these restrictions reduce that number to 62,163.

After enforcing these two restrictions, the final dataset contains 2,902,708 firm-product-origin-year flows of imports into Chile. These 2.9 million observations represent 1,728,290 import spells, 1,400,323 import relationships (where a relationship is a firm-product-origin triple), and 16,276,866 transactions of $221 billion worth of imports. The average firm imports 14.3 products from a combined 3.2 origin countries, whereas the median firm imports a single product from a single origin country over the course of the sample. As has been documented for exports by Freund and Pierola (2015), Bernard et al. (2009), and Hamilton (2019), the differences in outcomes for the mean and median trading firms are driven by the disproportionate share of trade generated by the largest firms. In the first chapter of this dissertation, I show that the top 1% of Chilean firms in terms of export revenue account for 85% of overall Chilean exports, whereas the top 5% account for 95% and the top 10% account for 98%. For the subsample of imports considered here, the top 1%, 5%, and 10% of firms account for 72%, 93%, and 97% of the value of goods imported.

2.2.1 Stylized Facts of Importing

The three stylized facts that I document for Chilean importing are:

1. Import spells are short on average
2. Conditional survival rates are increasing
3. Conditional on extended survival, import spells exhibit large differences in their growth trajectories.

The first of these trends was initially documented by Besedeš and Prusa (2006) using US import data. The data they use is aggregated to the product-origin-year level so that the behavior of individual firms is unobserved, but despite this aggregation, more than 50% of import spells fail to live beyond the first year. Using a finer measure of duration, I find that the median import spell survival time is zero years and that the mean is 0.61 years. These low values are driven by the fact that so many of the spells in the data have a single transaction, but even when discarding those and focusing on spells with at least two transactions, survival times remain low. After that restriction, the median spell survival is 1.08 years whereas the mean is 1.69 years. Two histograms displaying the distribution of import spell survival times, the first for all import spells and the second for those with strictly positive duration, are shown in Figures 2.1a and 2.1b.[8]

Secondly, Besedeš and Prusa (2006), Monarch and Schmidt-Eisenlohr (2018), and Cadot et al. (2011) show that there is negative duration dependence for trade spells, the first two using imports and the latter using exports. That is, the longer a particular trade spell is active, the less likely it is to cease in a given year, which yields increasing conditional survival rates.[9] In Figure 2.2 below, I plot this conditional survival rate for spells between the ages of zero (those in their first year) and nine that are active in 2012. Each point represents the fraction of spells of that age which were active in 2012 which survived and appeared once again in the data in 2013. Of the spells which were newly-formed in 2012 (those that are zero years old), roughly 30% survive until the second year. However, as the age increases, the conditional survival rate increases monotonically. Of the spells which survive to a second year, 50% survive until the third. By the time firms are in their fifth year, conditional

[8]Whereas Besedeš and Prusa (2006) and many of the more recent papers which examine trade duration observe annual level data and therefore measure duration discretely in years, I am able to more finely measure duration because I observe the day that each transaction takes places. The duration for a particular spell is measured as the number of days between the first transaction and the final transaction without a calendar year gap intervening. Therefore, spells with only a single transaction are assigned a duration of zero. This finer measure of detail also prevents mismeasurement that results when using annual data. For example, consider two possible import schedules. In the first, a firm imports a product on January 1, 2002 and December 31, 2002, whereas in the second, a firm imports a product on December 31, 2002 and January 1, 2003. I will measure duration in the first case as $\frac{364}{365} \approx 1$ year and in the second as $\frac{1}{365} \approx 0$ years. However, someone using annual data will measure the first as one year and the second as two, even though the second lasts only two days.

[9]The average conditional survival rate for each age a of spells is the percent of spells of that age to survive to age $a+1$. Of course, overall survival rates decrease with age, but conditional survival rates are increasing.

survival rates exceed 75% and increase slightly beyond that.

Lastly, the third of these trends is that even among long-lasting import spells, growth trajectories are highly variable. For some spells, the yearly value traded increases by more than an order of magnitude, whereas for others it shrinks by more than 50%. To show this heterogeneity, I examine how the distribution of relative quantities imported varies for import spells with a duration of exactly ten years in Figure 2.3 below in an exercise similar to that done in Berman et al. (2018). Each bar represents the interquartile range of the relative quantity imported compared to the amount imported in the second year of the spell, where the white line in each bar is the median.[10] For these spells which last ten years, the median import quantity remains relatively stable over the eight years of imports when these spells are between three and ten years old. However, firms at the 75th percentile import between 3 and 8 times the original quantity, whereas firms at the 25th percentile import between 40% and 60% of the original quantity. Furthermore, 41% of these firm-product-origin-year observations have quantities imported that are lower in years three through ten of the spell than they were in year two. While some firms import greater and greater quantities, some quantities shrink continuously throughout a long-lived import spell.

These three trends are consistent with firms learning about the quality of the intermediate inputs and capital goods that they import from abroad through their own experiences. A cohort of firms may begin importing a particular product. Some of them will received better-than-expected signals about the quality of the input, whereas others will receive worse. Those with better-than-expected signals will continue to buy the product, buy more of it, and be more likely to survive in future years. Those with worse-than-expected signals will shrink and perhaps stop buying the product entirely. Therefore, there is selection in the composition of spells that are active so that those with better signals are the spells that survive and contribute to the increasing conditional survival rates shown above.

There are numerous possibilities that would allow firms to also learn or in some other way benefit from the experiences of compatriots purchasing imports from the same source countries. If a firm is considering importing a particular intermediate input, it may make its

[10] I use the second year of the spell to normalize subsequent imports rather than the first to account for the partial year effect documented by Bernard et al. (2017).

sourcing decision based off of other firms buying the same input from abroad. If most of that firm's compatriots who buy that input buy from the same source, that may be a signal that that variety is of a higher quality. Alternatively, a heavy presence of compatriot incumbents buying from a market may develop relationship capital which reduces the fixed and variable costs of importing, which may induce others to make the same sourcing decisions.

2.3 Model

In this section, I develop a model with information spillovers in which potential importers of a particular input observe signals about the quality of that input through the actions of their compatriots. At the end of the section, I provide a discussion of changes that could be made to the model to allow for the alternative mechanisms mentioned above.

2.3.1 Demand

Consumers in each country have CES preferences over different varieties of a non-tradable final consumption good. Demand for any one of these varieties is given by

$$d_i = p_i^{-\sigma} P^{\sigma-1} Y, \tag{2.1}$$

where p_i is the price of that variety, $P = \left(\int_0^D p_i^{1-\sigma} di \right)^{\frac{1}{1-\sigma}}$ is the price index of the measure D of varieties consumed, Y is aggregate income, and σ is the elasticity of substitution across varieties in consumption.

2.3.2 Supply

There are two types of producers in the economy, each of which is monopolistically competitive: one that produces a variety of intermediate input using labor and another which produces a variety of a final consumption good using a bundle of intermediate inputs.

Intermediate Inputs

Intermediate good producers must pay a fixed cost to enter the market and then use labor to produce their variety at constant marginal cost. Each worker produces β units (assumed to be homogeneous across firms) of the intermediate variety so that total labor demand by the producer of variety j is:

$$L_j(q_j) = F_j + \frac{1}{\beta}q_j, \tag{2.2}$$

where F_j is the number of workers firm j must hire to cover the fixed cost of developing its own blueprint for production. There is no fixed cost for final good producer i to buy variety j from a domestic intermediate good producer, so that each of the latter supplies its variety to each of the former. Define q_{ij} as the quantity of the intermediate input supplied to final good producer i by intermediate producer j. The total amount of the input supplied by firm j can be found by integrating over the continuum of domestic buyers, $q_j = \int_0^M q_{ij}di$, where M is the measure of final good producers in the economy.[11] Define the measure of intermediate input producers as M_d. The domestic labor market-clearing condition requires that the labor employed by all intermediate input producers is equal to the population endowment, $\overline{L}$: $\int_0^{M_d} L_j dj = \overline{L}$. Assuming intermediate producers are identical yields the measure of domestic intermediate producers to be $M_d = \frac{\overline{L}}{F_j + \frac{1}{\beta}q_j}$.

Final Good Producers

To begin, I outline the behavior of final goods producers in the absence of uncertainty about input quality to illustrate the mechanisms of the model. Afterwards, I introduce uncertainty and the the effects it has on firm behavior. Final goods producers buy inputs from the intermediate sector and use them to produce final output according to a CES production function:

$$q_i = \phi_i \left(\int_0^{M_i(\phi)} e^{\frac{a_{ij}}{\eta}} m_{ij}^{\frac{\eta-1}{\eta}} dj \right)^{\frac{\eta}{\eta-1}}, \tag{2.3}$$

[11] For simplicity of exposition, I assume that the producers of intermediate inputs do not export, so all of their output must be sold to domestic firms.

where ϕ_i is the productivity of firm i, $M_i(\phi)$ is the measure of inputs used by firm i, a_{ij} is a random productivity shifter specific to each firm pair which is unknown to the importer prior to purchasing it, m_{ij} is the input demand by final good producer i for intermediate variety j, and $\eta > 1$ is the elasticity of substitution across intermediates in production.[12]

After production takes places, final good producers solve the following problem and maximize variable profits by choosing the price at which to sell their output:

$$\begin{aligned} \max_{p_i} \quad & \pi_i = q_i(p_i)p_i - C_i q_i(p_i) \\ & \text{subject to} \quad q_i = p_i^{-\sigma} P^{\sigma-1} Y, \end{aligned} \tag{2.4}$$

where C_i is marginal cost. Taking first-order conditions yields the standard markup on marginal cost: $p_i = \left(\frac{\sigma}{\sigma-1}\right) C_i$. Whereas marginal cost is usually assumed to be exogenous, it is endogeneous here, varies across firms, and is a function of intrinsic firm productivity. Conditional on charging this price, consumers demand

$$d_i = \left[C_i \left(\frac{\sigma}{\sigma - 1} \right) \right]^{-\sigma} P^{\sigma-1} Y \tag{2.5}$$

units of the good. Plugging these values into the variable profit function yields:

$$\pi_i = \frac{(\sigma-1)^{(\sigma-1)}}{\sigma^{\sigma}} C_i^{1-\sigma} P^{\sigma-1} Y. \tag{2.6}$$

Assuming $\sigma > 1$, profits are decreasing in marginal cost.

Before production takes place, firms must source their bundle of intermediate input varieties from suppliers, taking into account the quantity of the final good each firm plans on selling to final consumers (from Equation 2.5). Each firm will choose the bundle of intermediates which minimizes total costs, subject to producing the optimal quantity. The firms do this in two stages, first determining the measure of varieties to use in production and then determining how much of each variety to buy. Solving backwards, the firm decides how much of each variety to buy, conditional on the number of varieties, and then determines

[12] $M_i(\phi)$ will consist of intermediates sourced domestically ($M_d(\phi) = M_d$) and intermediates imported from each source country o ($M_o(\phi)$): $M_i(\phi) = M_d + \sum_{o=1}^{O} M_o(\phi)$.

that optimal number of varieties. Conditional on $M_i(\phi)$, the firm solves:

$$\begin{aligned} \min_{m_{ij}\in[0,M_i(\phi)]} \quad & \text{VariableCost}_i = \Big(\int_0^{M_i(\phi)} p_j m_{ij} dj \Big) \\ & \text{subject to} \quad q_i = \phi_i \left(\int_0^{M_i(\phi)} e^{\frac{a_{ij}}{\eta}} m_{ij}^{\frac{\eta-1}{\eta}} dj \right)^{\frac{\eta}{\eta-1}}, \end{aligned} \tag{2.7}$$

Taking first order conditions yields input demand for each variety from each final good producer to be

$$m_{ij} = \frac{e^{a_{ij}} c_i^{\eta} q_i p_{ij}^{-\eta}}{\phi_i}, \tag{2.8}$$

where c_i is the cost index of purchasing one bundle of intermediate inputs, with marginal cost $C_i = \frac{c_i}{\phi_i}$.[13] Demand for a particular variety is increasing in the productivity shifter for that variety, in the overall cost index, and in the quantity produced for final consumption, but decreasing in its price and firm productivity. Marginal cost C_i can be derived by taking the derivative of the variable cost function with respect to quantity, evaluated at the optimal input demand bundle:

$$C_i = \frac{\partial \text{VariableCost}_i}{\partial q_i} = \frac{c_i}{\phi_i} = \frac{1}{\phi_i} \left(\int_0^{M_i} p_j^{1-\eta} e^{a_{ij}} dj \right)^{\frac{1}{1-\eta}} \tag{2.9}$$

This marginal cost is decreasing in each productivity shifter and in the measure of intermediate varieties used in production ($\frac{\partial C_i}{\partial a_{ij}} < 0$ and $\frac{\partial C_i}{\partial M_i} < 0$). However, the decrease with respect to the number of varieties is increasing ($\frac{\partial^2 C_i}{\partial M_i^2} > 0$), so that there are decreasing returns to sourcing a greater variety of intermediates. See Section 4.2 for more details on these comparative statics.

A firm's total costs is:

$$\text{TotalCost}_i = \left(\frac{\sigma}{\sigma - 1} \right)^{-\sigma} P^{\sigma-1} Y \phi^{\sigma-1} c_i^{1-\sigma} - F - \sum_{o=1}^{O} \Big(F_o + \int_0^{M_{oi}} F_{oj} dj \Big), \tag{2.10}$$

[13] Analogous to the consumer price index with CES preferences, the cost index is $c_i = \Big(\int p_j^{1-\eta} e^{a_{ij}} dj \Big)^{\frac{1}{1-\eta}}$.

where the second term, F, is the fixed entry cost to begin production. The third term captures the downside of increasing the measure of intermediate inputs used. Final goods producers must pay a fixed entry cost to access inputs from a new source country o (F_o) and for each additional variety from that country (F_{oj}). Taking the bundle of inputs the firm would buy as a function of the measure of varieties used into account, the firm then chooses the measure of varieties to access to maximize overall profits:

$$\max_{\{M_{oi}\}\forall o=1,2,..O} \quad \Pi_i = \frac{(\sigma-1)^{(\sigma-1)}}{\sigma^\sigma} P^{\sigma-1} Y \left[\left(\frac{1}{\phi}\right) \left(\int_0^{M_i(\phi)} p_j^{1-\eta} e^{a_{ij}} dj \right)^{\frac{1}{1-\eta}} \right]^{1-\sigma} - F - \sum_{o=1}^{O} \left(F_o + \int_0^{M_{oi}} F_{oj} dj \right) \tag{2.11}$$

The first term on the right-hand side of the equation captures variable profits, which are strictly increasing as the number of varieties increases. As $M_i(\phi)$ increases, marginal costs fall, firm i sells a greater quantity, and profits increase.

The effect of increasing the overall measure of varieties used by a firm on profits can be decomposed as follows:

$$\frac{\partial \Pi_i}{\partial M_i(\phi)} = \underbrace{\frac{(\sigma-1)^{(\sigma-1)}}{\sigma^\sigma} \phi_i^{\sigma-1} P^{\sigma-1} Y \left(\int_0^{M_i(\phi)} p_j^{1-\eta} e^{a_{ij}} dj \right)^{\frac{\eta-\sigma}{1-\eta}} p_j^{1-\eta} e^{a_{ij}}}_{>0} - F_o - F_{oj}. \tag{2.12}$$

The first term captures the net effect of an increase in intermediate varieties used on profits through a decrease in the cost index and an increase in sales, which is strictly positive. With a lower cost index, firms pay less for the intermediate bundle and increase sales, increasing profits. However, this is negated by the fixed cost expenditure required to access that input (F_{oj}), with an additional country entry cost (F_o) if it is the first variety imported from that country.

Unlike the decision to export to different markets when marginal costs are constant, the decision to import an intermediate input from one source is not independent of a firm's decision to import the same intermediate from another source or from the decision to import other intermediates. Because the benefits of adding a new intermediate depend on the varieties already used and the benefits of inframarginal varieties are affected by the addition of new products, each possible sourcing strategy must be considered as a whole, rather than looking individually at each part of it, as described by Antras, Fort, and Tintelnot (2017). Define the sourcing strategy of firm i as the set of countries from which the firm imports intermediate inputs. If firms import a single variety from each source country, the presence of O possible source countries yields 2^O possible sourcing strategies for a firm in a given year. Rather than solving for a firm's optimal sourcing strategy by solving for the expected profits from each of these 2^O options, I assume the firm is already following its optimal sourcing strategy and then derive comparative statics subject to that optimal behavior.

Define a firm's optimal import strategy as s_i^*, which is the solution to the following optimization problem:

$$s_i^* = \underset{s_i \in \mathcal{S}}{\operatorname{argmax}} \ \Pi_i(s_i) = q_i(s_i)p_i(q_i) - C_i(s_i)q_i(s_i), \tag{2.13}$$

where the dependence of marginal cost on s_i comes from the sourcing decision affecting the number of varieties and therefore the cost index, and the dependence of quantities sold on s_i comes indirectly through the reduction in costs and therefore the reduction in prices charged to consumers. If firms can import more than one product from a given source country, the set of possible sourcing decisions, $\mathcal{S}$, will be greater than the 2^O referenced in the paragraph above, and will be infinite when varieties from each source are measured continuously. Rather than a vector of ones and zeros indicating any importing from a particular source, the optimal sourcing strategy is a vector of the measure of goods imported from each source:

$$s_i^* = \begin{bmatrix} M_1^*(i) & M_2^*(i) & ... & M_O^*(i) \end{bmatrix}, \tag{2.14}$$

where entry $M_o^*(i) = 0$ when country o is not included in firm i's optimal sourcing strategy. Define the returns of sourcing one more variety from country o, conditional on the existing sourcing strategy for all countries other than o, as the change in profits when increasing the measure of varieties used, the result from Equation 2.12:

$$R_{oi}(s_i) = \Delta\Pi_i(s_i) = \frac{(\sigma-1)^{(\sigma-1)}}{\sigma^\sigma}\phi_i^{\sigma-1}P^{\sigma-1}Y p_j^{1-\eta}e^{a_{ij}}\left(\int_0^{M_i(s_i)} p_j^{1-\eta}e^{a_{ij}}dj\right)^{\frac{\eta-\sigma}{1-\eta}} - F_o - F_{oj}. \tag{2.15}$$

Conditional on the optimal sourcing strategy, the returns of importing an additional variety from any source country must be non-positive: zero for countries from which imports are positive and negative for countries from which imports are zero:

$$R_{oi}(s_i)\begin{cases} = 0 \text{ if } M_{oi}(s_i) > 0 \\ < 0 \text{ if } M_{oi}(s_i) = 0 \end{cases} \tag{2.16}$$

Because of the fixed costs required to purchase intermediate inputs from a foreign country, only the most productive firms will import, as is familiar from Melitz (2003) and the many extensions which have followed. Only these productive firms sell a large enough quantity for the savings on marginal cost from using more varieties to outweigh the fixed cost of acquiring that input.

Introducing Uncertainty

Now assume that firms do not observe the quality of an intermediate input prior to buying it, but learn about the quality after production. Firms commit to purchasing a bundle of intermediate inputs prior to knowing the realizations of the a terms. At this point, I introduce an additional subscript to make notation as clear as possible: a_{iko} is the productivity of intermediate k imported from country o by firm f. Each a_{iko} consists of two components, one that is common among Chilean importers and one that is specific to the importing firm-product-origin country triplet. That is,

$$a_{iko} = \underbrace{a_{ko}}_{\sim N(\mu,\sigma_1)} + \underbrace{\epsilon_{iko}}_{\sim N(0,\sigma_2)}. \tag{2.17}$$

The shared component of productivity reflects quality differences across source countries, whereas the firm-specific component reflects an idiosyncratic match value which differs across firms. Firms are assumed to know the distributions from which these realizations are drawn, but not the individual realizations themselves. In the absence of using information provided by compatriots, beliefs about this productivity shifter are distributed normally with mean μ and variance $\sigma_1 + \sigma_2$. However, if firms use information revealed by compatriots, and the presence of incumbent firms sourcing a particular product k from a particular origin o are positively correlated with that variety's quality, the number of incumbent firms and the overall value they import will be a signal about the common quality of that variety, a_{ko}. If many firms import large values of this product, this serves as a positive signal: that the quality is high, the price is low, the supplier is reliable, or some combination of the three. Therefore, a larger incumbent presence may lead potential importers to improve beliefs about a_{ko}.

Consider a firm which had a particular sourcing strategy in the previous year, learned about the quality of those varieties imported (and therefore knows marginal cost as a function of those qualities), and is now deciding which varieties to buy in the current year. Conditional on the prior sourcing strategy for which marginal cost is known, the expected returns to buying the marginal variety from each source country are:

$$\mathrm{E}(R_{oi}(s_i)) = \mathrm{E}(e^{a_{iko}})\frac{(\sigma-1)^{(\sigma-1)}}{\sigma^{\sigma}}\phi_i^{\sigma-1}P^{\sigma-1}Yp_j^{1-\eta}c_i(s_i)^{\frac{\eta-\sigma}{1-\eta}} - F_{oj}, \tag{2.18}$$

where an increase in expected quality increases expected returns $\left(\frac{\partial \mathrm{E}(R_{oi}(s_i))}{\partial \mathrm{E}(e^{a_{iko}})} > 0\right)$, and therefore increases the probability of a potential importer to source product k from origin o.[14] Therefore, if the expected returns to an input are increasing in the quality of an input, and firms infer information about the quality of an input from the number of incumbent firms sourcing input k from o and the value they import, new entrants will be more likely to source k from o as well.

In addition to being more likely to source from a country, firms will also import greater quantities from markets where signaled quality is higher. Recall from Equation 2.8 above that demand for an intermediate depends on quality, the input bundle cost index, productivity,

[14] Note that this statement is conditional on the sourcing strategy from the previous year, or at least a sourcing strategy for which the firm knows the productivity of the other inputs. Otherwise, the expectation of marginal cost will further depend on beliefs about the quality of that particular variety.

the intended quantity to produce for final consumers, and the price of the variety. If quality is unobserved prior to an import spell beginning, input demand will instead be determined by expectations about quality rather than quality itself:

$$m_{iko} = \mathrm{E}(a_{iko})\phi_i^{-1}c_i^{\eta}q_i p_{iko}^{-\sigma}, \tag{2.19}$$

and firms will import more from markets where expected quality is higher $\left(\frac{\partial m_{iko}}{\partial \mathrm{E}(a_{iko})} > 0\right)$. Once again, this comparative static requires assuming that firms know the quality of the other inputs they are sourcing and therefore know marginal cost, with this one additional variety not affecting c_i.

As described, the effects of incumbent firms on new entrants are embodied in information spillovers about input quality. Alternatively, incumbent firms may develop reputations which make it easier for newcomers to do business with firms from countries with a higher Chilean presence, thereby decreasing trade costs, which could induce similar patterns in the data. In the empirical section, I discuss controls which limit the extent to which the latter could explain my findings.

2.4 Empirical Strategy and Results

2.4.1 Extensive Margin

I first examine how the sourcing decision of a firm buying a particular intermediate input or capital good varies with the degree to which other Chilean firms buy that same product from different source countries in the previous year. Entry is defined within a firm-product-origin-year as:

$$\mathrm{Entry}_{fkot} = \begin{cases} 1 \text{ if } \mathrm{Value}_{fkot-2} = 0, \quad \mathrm{Value}_{fkot-1} = 0, \quad \& \quad \mathrm{Value}_{fkot} > 0 \\ 0 \text{ if } \mathrm{Value}_{fkot-2} = 0, \quad \mathrm{Value}_{fkot-1} = 0, \quad \& \quad \mathrm{Value}_{fkot} = 0 \\ . \qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{Otherwise.} \end{cases} \tag{2.20}$$

Note that a firm is only considered to enter a market if it has not imported from that market for at least two years. This is to prevent firms which continuously enter and exit a market from being included in the regressions. If these firms retain information from their previous incursions in the market, learning from others may be less important for them. Therefore, I focus only on firms which have not imported this product from this source for at least two years, with the intention that the firms included are those making their entry for the first time.

I use cross-section variation in incumbent presence to explain why Chilean firms import from the particular set of countries that they do as opposed to time-series variation to explain when Chilean begin to import from the countries they do. To do so, I create $fkot$ observations which never actually appear in the customs data. For each firm-product pair that I observe in the sample (i.e., for each product that each firm imports from at least one source country in at least one year), I create observations for all other source country-year pairs from which this firm could source the product over the course of the sample.

Consider a hypothetical firm Chilean Garments which imports thread from the United States starting in 2005, China starting in 2006, Japan starting in 2007, and never imports after 2007. Define a firm's sourcing strategy for product k in a given year as the set of source countries from which it imports this product in a particular year as:

$$\Omega_{fkt} = \{o : \text{Value}_{fkot} > 0\} \tag{2.21}$$

For Chilean Garments, $\Omega_{fk2005} = \{\text{United States}\}$, $\Omega_{fk2006} = \{\text{United States, China}\}$, $\Omega_{fk2007} = \{\text{United States, China, Japan}\}$. The firm's sourcing strategy for product k over the course of the sample is the set of all source countries from which it imports this product at least once:

$$\Omega_{fk} = \{o : \text{Value}_{fko} > 0\}, \tag{2.22}$$

where $\text{Value}_{fko} = \sum_{t=2002}^{2014} \text{Value}_{fkot}$, $\Omega_{fk} = \{\text{United States, China, Japan}\}$ for Chilean Garments and the size of the set $O_{fk} = |\Omega_{fk}|$ is the number of countries firm f imports this product from. Define Γ_{fk} as a $T \times O_{fk}$ matrix of ones and zeros indicating whether firm f

imported k from o in t. For Chilean Garments,

$$\Gamma_{fk} = \begin{pmatrix} \gamma_{fkUS,t=2002} & \gamma_{fkChina,t=2002} & \gamma_{fkJapan,t=2002} \\ \vdots & \vdots & \vdots \\ \gamma_{fkUS,t=2005} & \gamma_{fkChina,t=2005} & \gamma_{fkJapan,t=2005} \\ \gamma_{fkUS,t=2006} & \gamma_{fkChina,t=2006} & \gamma_{fkJapan,t=2006} \\ \gamma_{fkUS,t=2007} & \gamma_{fkChina,t=2007} & \gamma_{fkJapan,t=2007} \\ \vdots & \vdots & \vdots \\ \gamma_{fkUS,t=2014} & \gamma_{fkChina,t=2014} & \gamma_{fkJapan,t=2014} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{pmatrix}. \tag{2.23}$$

The only observations which appear in the original data are those for which $\Gamma_{fk}(t, o) = 1$. Therefore, there would be six observations pertaining to Chilean Garments in the original data. The first expansion that I make is to create observations for source-year pairs for the years Chilean Garments did not import from the source countries that it imports from at some point during the sample (these are the observations equal to 0 in Γ_{fk}). This creates cross-section variation in entry in 2005 and 2006 because Chilean Garments begins to import from a new source when they could have chosen an alternative new source.[15] I leverage differences in incumbent presence across the potential source countries as one possible explanation for why firms choose the sourcing strategies they choose. Perhaps Chilean Garments entered the US first in 2005 because many other Chilean firms imported thread from the US and this was interpreted as a positive signal of quality.

Define the set of all possible source countries as Ω_k. The second expansion that I make is to create $fkot$ observations for Chilean Garments for all countries which they **never** import product k from. Define this set of countries as

$$\Omega_{-fk} = \Omega_k \setminus \Omega_{fk}. \tag{2.24}$$

[15] At this point, there is not cross-section variation in entry in 2007. Although Chilean Garments begins to import from Japan in this year, it cannot "begin" to import from China or the US because it is already buying from those markets.

If $|\Omega_k|$ is the number of countries which at some point export k in the sample, I create a $T \times |\Omega_k| - |\Omega_{fk}|$ matrix of zeros, call it Γ_{-fk}, to indicate Chilean Garments imported from none of these countries. Combining Γ_{fk} and Γ_{-fk} yields a $T \times |\Omega_k|$ matrix of ones and zeros from which I define the entry variable above.

$$\Gamma'_{fk} = \begin{pmatrix} \Gamma_{fk} & \Gamma_{-fk} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 0 \end{pmatrix} \tag{2.25}$$

The creation of these observations generates additional cross-section variation in 2005 and 2006 because of the fact that Chilean Garments did not import from any of the other possible source countries, in addition to creating initial variation for 2007. Whereas previous papers such as Koenig (2009) and Koenig et al. (2010) study time-series variation in an exporting firm's decision to enter the markets they do **when** they do, I try to account for **which** countries importing firms begin to source from as a function of the presence of other Chilean firms importing the same products from them as well.

In the reduced sample which only includes intermediate inputs and capital goods for entities with greater than \$5,000 worth of imports, there are 888,207 firm-product pairs. Making the above expansions to the data will generate 888,207 $\times$ 13 years $\times$ 162 source countries = 1.8 billion $fkot$ observations. To decrease the computational burden, the sample is further reduced in the following ways.

As in the preceding chapter, the first restriction I make is to limit the sample to the twenty countries with the greatest exports to Chile. Although these twenty represent 12.3% $(= \frac{20}{162})$ of the countries from which firms export to Chile, it covers 89.6% of the value imported in the sample and 80.2% of global GDP in 2002.[16,17]

Because I rely on import data and do not use firm-level balance-sheet data, I am unable to observe firm size (in terms of workers or overall sales) or the years for which a particular firm exists. A firm which begins to import thread in 2005 may be an older, established firm trying to expand its operations or it could be a startup in its first year of existence. In the latter case, I would not want to include observations in the regressions below for the years 2002, 2003, and 2004 because the firm did not exist and count not feasibly import thread in those years. To prevent this from happening, I exclude all observations for a particular firm prior to its first import experience in the sample.

Third, a firm which imports in 2005 but in no years beyond that may have stopped importing for a number of reasons: more attractive varieties are available from domestic firms, wholesalers import and offer lower prices, the firm no longer produces the product for which they required that intermediate input, the firm merges with another and has a new identifying RUT code, or the firm goes out of business. I exclude all observations for a particular firm after its last import experience in the sample to allow for these possibilities.

To measure the effect of incumbent Chilean firms importing a product from a particular source country on the probability of a new importer importing from that same country, I estimate the following regression:

$$\begin{aligned}\text{Entry}_{fkot} = \beta_1 \text{Firms}_{kot-1} + \beta_2 \text{IHS(Value)}_{kot-1} + \beta_3 \Big(\text{Firms}_{kot-1} \times \text{IHS(Value)}_{kot-1}\Big) \\ + \text{Controls}_{fkot} + \alpha_{iot} + \alpha_{fkt} + \alpha_{fo} + \epsilon_{fkot},\end{aligned} \tag{2.26}$$

where Firms_{kot-1} is the number of firms in Chile which import HS 8-digit product k from origin country o in the preceding year and $\text{IHS(Value)}_{kot-1}$ is the inverse hyperbolic sine of the FOB (free on board) value of imports of HS 8-digit product k by Chilean firms in the preceding year.[18] These variables of interest are lagged one year to allow time for information

[16] These twenty countries include Argentina, Brazil, Canada, China, Colombia, Finland, France, Germany, India, Italy, Japan, Mexico, Paraguay, Peru, Spain, South Korea, Sweden, Thailand, the UK, the United States. With the exception of Thaliand, Paraguay, Finland, Sweden, the remaining sixteen countries are also in the top 20 recipients of Chilean exports.

[17] This restriction is only made for the extensive margin analysis. For the intensive margin and duration analysis below, I use the full sample of exporting countries.

[18] Recall from the first chapter of this dissertation that the inverse hyperbolic sine (IHS) function, developed in Johnson (1949) and used empirically in Burbidge et al. (1988), is defined as $\text{IHS}(x) = \ln(x + \sqrt{x^2 + 1})$.

to accrue and to reduce concerns about the reflection problem identified by Manski (1993) concerning peer effects. Because these two variables of interest do not vary across potential importers within a *kot* triplet, standard errors should be clustered at a minimum by *kot*. To allow for more general correlation patterns across observations, I conservatively cluster by HS 2-digit chapter-origin country pairs.

I include three sets of fixed effects which may also drive differential sourcing patterns by firms. The first is an HS 3-digit industry-origin-year triplet to control for differences across origin countries in terms of market size, distance from Chile (geographic or cultural), and/or number of suppliers which may cause a firm to choose to source an input from one country rather than another. To the extent that transportation costs are constant within an HS 3-digit industry-origin-year, this will also control for transportation cost differences across markets. The second is a firm-product-year fixed effect to control for differences across firms in terms of productivity or other unobserved heterogeneity which may generate differential importing patters. If more productive firms find it worthwhile to import more products from more origin countries, these fixed effects will control for those differences. The third is a firm-origin fixed effect to control for potential relationships between firms and source countries which may make importing more likely. For example, if an importing firm in Chile is an affiliate of a multinational in the United States, it may be more likely to begin importing from the United States, either within the firm or at arm's length.[19] As alluded to already, I do not observe balance sheet data or any variables which define a firm's multinational status, but the firm-origin fixed-effects control for these possible relationships. The main controls I include are the number of products and the overall value of imports imported by firm f from the same market o in the previous year: if a firm is already sourcing other inputs from a particular country, it may be more likely to choose that country as its source when it begins importing an additional product.

As with logged variables, differences in variables which have been IHS-transformed can be interpreted as percentage changes and can therefore be used to measure elasticities and semi-elasticities. The benefit of using the inverse hyperbolic sine function is that it is defined for non-positive values of x. By using the inverse hyperbolic sine function, I can include the origin-product-year triplets for which entrants are the first Chilean firms sourcing that product from that market (i.e., there is no Chilean incumbent presence in that market in the previous year).

[19] To estimate this regression with multidimensional fixed effects, I use the `reghdfe` command courtesy of Correia (2017), as in the previous chapter.

Baseline Results

Table 2.1 below reports results from estimating Equation 2.26 with various measures of incumbent presence. In Column 1, each additional incumbent Chilean firm sourcing product k from country o in the prior year is associated with a 0.002 percentage point increase in the probability that a firm newly-sourcing this product chooses to import from source o. On the face of it, this seems like a small effect. However, recall that many of the observations used in the regression represent feasible import spells which never actually materialize. Taking into account the generated observations, the average entry rate in the sample is 2.9%. Therefore, the estimated coefficient implies an increase in the entry probability of 0.1%. On average, there are 14.3 Chilean firms that import from each product-origin-year triplet.[20] Therefore, the probability of entering markets with the average number of incumbents is 1% higher than entering a market in which there are no incumbents. In Column 2, I add the overall value of product k imported by all Chilean firms from o in the previous year, as having many importers is not necessarily a strong sign if each of them has very low imports. The estimated coefficient of 0.00015 implies that the entry probability of a potential importer is 0.5% higher when the value imported by incumbents the previous year doubles.[21] In Column 3, I include both of these measures directly and their interaction, with the effects of both diminishing with the prevalence of the other. However, the interaction effect is statistically insignificant.

In Column 4, the right-hand side variable measuring incumbent presence is a dummy equal to one if there is at least one Chilean firm which imports k from o in $t-1$, whereas Column 5 has four bins for 1-5, 6-20, 21-50, and greater than 50 incumbents. Compared to markets in which there are no incumbents, entry rates are 6.9% ($\frac{0.00199}{0.029}$) higher in markets with strictly positive incumbent presence according to results in Column 4. In Column 5, entry rates are 7.0%, 15.3%, 18.3%, and 22.1% higher in markets with 1-5, 6-20, 21-50, and greater than 50 incumbents compared to markets with no incumbent presence.

[20] This is the average only for the subsample of observations that include the top 20 exporting countries. It is smaller for the intensive margin when the remaining countries are reintroduced.

[21] For the average observation in this subsample, the incumbents in the previous year imported \$468,600 worth of product k from o in $t-1$. Going from zero incumbents (and therefore zero value imported) to an average amount of imports is associated with a 7.1% increase in the probability of entry for a potential importer (7.1%=$\frac{\text{IHS}(468{,}600)*0.00015}{0.029} = \frac{13.8*0.00015}{0.029}$)

Results in Table 2.1 may be biased upwards due to omitted variable bias caused by excluding the supply capacity for each industry-origin-year in the data. If the steel industry in the United States is particularly productive compared to steel producers in other countries and exports to many firms around the world, this could cause both an increase in the number of Chilean firms sourcing steel from the US in the previous year and an increase in the probability that firms which begin to import steel source from the US. Rather than potential importers learning from their compatriots, the positive estimated β_1 above could be driven by this supply shock which could benefit both incumbent and potential importers. In addition to the total value of the HS 8-digit product imported by Chilean firms in the previous year, which was included in Table 2.1, I include two additional controls which may affect new entry within a particular *iot* but also be positively correlated with incumbent presence sourcing from that market. The first is the overall value of exports from origin o in year t of other HS 8-digit products within the same HS 6-digit heading ($\text{ChileValue}_{HS6-8,ot}$) to Chile.[22] The third proxy for supply capabilities is the remainder of a country's exports within an HS-2 digit sector-year ($\text{ROWValue}_{HS2-8,ot}$).[23] This proxy also controls for more aggregate trends in productivity but additionally introduces and controls for variation in

[22] One example of an HS 6-digit heading is 080810: fresh apples. Within this 6-digit heading are different 8-digit product codes for the various types of apples (Red Delicious, Fuji, Granny Smith). Including sales of similar products from the same heading controls for industry productivity differences beyond narrow 8-digit product categories. For example, if there is a year of weather particularly conducive to apple-growing which expands production and exports of apples, including this second proxy for supply capability will help to separate increases in importing to due learning versus due to more aggregate shocks in origin countries. In addition, if overall preferences for related goods from the same origin among Chilean firms are positively correlated, including this variable helps to control for a higher level of demand for a set of related products.

[23] $\text{ROWValue}_{HS2-8ot}$ is constructed as the remainder of overall 2-digit exports from an industry-origin within a year after subtracting its 6-digit exports to Chile. That is, overall exports can be decomposed into a summation of the different products within an HS 2-digit industry and the countries to which they are exported:

$$\begin{aligned}\text{Value}_{HS2ot} &= \sum_{d} \sum_{k\in \text{HS2}} \text{Value}_{kdt} \\ &= \underbrace{\sum_{d\neq \text{Chile}} \sum_{k\in \text{HS2}} \text{Value}_{kdt} + \sum_{\substack{k\in \text{HS2}\\ k\notin \text{HS6}}} \text{Value}_{k(\text{Chile})t}}_{\text{ROWValue}_{HS2-8,ot}} + \underbrace{\sum_{\substack{k\in \text{HS6}\\ k\notin \text{HS8}}} \text{Value}_{k(\text{Chile})t}}_{\text{ChileValue}_{HS6-8,ot}} + \underbrace{\sum_{k\in \text{HS8}} \text{Value}_{k(\text{Chile})t}}_{\text{Value}_{kot}} \qquad (2.27)\end{aligned}$$

The first two terms in the sum capture what is in $\text{ROWValue}_{HS2-8,ot}$: it is the value of products within an HS2-digit sector exported to all countries other than Chile and the value of products outside of the HS 6-digit heading in question exported to Chile in a particular year. The third and fourth terms each represent the other two controls.

exports to other countries which may be uncorrelated with Chilean demand.

In Table 2.2, I add these controls to the baseline specifications. The coefficient on the number of firms importing the same product from an origin remains constant in Column 1 at 0.002 percentage points, but a doubling of import value is now associated with a 0.6%, as opposed to 0.5%, increase in the probability of sourcing from that country, although the difference is statistically insignificant.

In columns 3 and 4 where incumbent presence is measured using bins, entry rates are 6.6% higher in markets where there is strictly positive incumbent presence compared to markets where there is none. For markets where there are 1-5, 6-20, 21-50, and greater than 50 incumbents, entry rates are 6.8%, 14.9%, 17.8%, and 21.5% larger than in markets where there are none. Overall, including the controls for export capacity and imports of related products leave estimated coefficients slightly smaller but virtually identical. Results from this section show that when firms begin importing a product from a new source country, they are more likely to buy that product from a country where there is a larger presence of incumbent Chilean firms buying the same product.

2.4.2 Intensive Margin - Quantity

In this section, I examine how incumbent presence affects the value of intermediate inputs or capital goods imported by firms which add new sources to their sourcing strategy. I focus on the import values of spells which are in their first year so that I can isolate the effect of incumbent presence without conflating it with the effects of a firm's own experiences later in the spell.

To test for spillovers on the intensive margin of importing from incumbent importers to new entrants, I estimate the following regression:

$$\begin{aligned}\ln(\text{Value})_{fkot} = \eta_1 \text{Firms}_{kot-1} + \eta_2 \text{IHS}(\text{Value})_{kot-1} \\ + \eta_3 \text{Controls}_{kot-1} + \alpha_m + \alpha_{iot} + \alpha_{fkt} + \epsilon_{fkot}\end{aligned} \tag{2.28}$$

The dependent variables is the value of product k imported by firm f from origin o in year t. These values imported may differ with the productivity of the importing firm, the productivity of the exporting firm, market size of the exporting country, transportation costs between origin and destination, or the demand for the product produced by the importing firm, among others. The variables of interest are the number of Chilean incumbents sourcing k from o in the previous year and the total value of all k imported from o in the previous year. The three α terms represent month, firm-product-year, and industry-origin-year fixed effects. The month fixed effects account for the fact that the starting times for import spells are nearly uniformly distributed across the calendar and that spells which begin earlier will naturally have a greater volume, all else equal.[24] The firm-product-year fixed effects control for differences in productivity, bundle of varieties imported, and inputs cost differences across firms which may lead to differences in values imported. The product-origin-year fixed effects control for differences in market size, export capacity, transportation costs, cultural distance, etc., which may generate differences in import values across markets within year or over years within a market. The estimated coefficient η_1 answers the question: how do import values from different source countries vary within a firm-product-year with the number of Chilean firms using the same sourcing strategy in the previous year, controlling for market-specific factors such as size or distance which may also drive differences in quantities.[25]

In addition to the fixed effects above, I include two additional control variables: the number of other products imported and the overall value of imports by firm f from origin country o in the preceding year. If a firm is actively sourcing different intermediates and capital goods from an origin and it has developed ties which make it more confident about the new product, the firm may begin by importing larger quantities.

Baseline Results

Baseline results for estimating Equation 2.28 are presented in the first two columns of Table 2.3.[26,27] In Column 1, an additional ten incumbent firms is associated with a statistically

[24]See Bernard et al. (2017) for a discussion of partial year effects.

[25]The presence of firm-product-year fixed effects implies that η_1 is identified using variation in firms which begin to import the same product from multiple source countries in the same year.

[26]As a reminder, the extensive margin only used observations involving the top 20 exporting countries in terms of value. For the intensive margin, I reintroduce the remainder of the countries from the sample.

[27]With the dependent variable measured in logs, the coefficient for the number of firms is a semielasticity. It answers the question, when the number of incumbent firms increases by one, what is the associated percentage change in import value?

insignificant 0.1% increase in the value imported by the new entrant. While the number of importers does not have a significant effect on quantities, the overall value imported in the previous year does. In column 2, I add the value of product k imported by other Chilean firms from o in the previous year, and when that value doubles, import values are 33.3% higher compared to the other markets from which this firm sources the product.[28] In column 3, I include the interaction between the number of firms and the overall imported value. The effect of both of these indicators of incumbent presence are increasing with the size of the other, although the positive coefficient is statistically insignificant.

In Column 4, incumbent presence is measured with an indicator equal to one if there are any Chilean incumbents sourcing k from o in the prior year. In markets where any incumbents are present, import values within a firm-product-year are 8.6% larger than in markets in which there are no incumbent Chilean firms. In Column 5, incumbent presence is measured using bins. Compared to markets in which there are no incumbents, first year import volumes are 8.9%, 13.9%, 14.7, 21.0% larger in markets with 1-5, 6-20, 21-50, and greater than 50 incumbents.

Recall in the discussion of the extensive margin results that an omitted variable such as overall supply capacity within an industry-origin-year could generate a spurious positive relationship between incumbent presence and new entry even if the former does not affect the latter through learning or another type of spillover. To address this potential omitted variable bias, I include the same two controls which could explain the positive estimated coefficients in the absence of learning or other spillover mechanisms: the sales of other HS 8-digit products within the same overarching HS 6-digit category from o in the previous year, and the remainder of its HS 2-digit exports (both to Chile and to the rest of the world). Similarly here, a higher export capacity in a particular industry-origin-year could also generate both a larger incumbent presence and larger first-year import volumes for new spells, resulting in a positive η_1 even when incumbent presence and volume of new import spells are unrelated. I replicate results from Table 2.3 with the inclusion of these additional

[28] As expected, the coefficients on the variables which capture a firm's previous experience in a market are positive. When a firm imported one additional product from the source in the previous year, imports of the new product are 0.3% higher. When the value a firm imports from the market in the previous year doubles, the value the firm imports of the new product is 1.6%-1.7% higher.

controls in Table 2.4 to show that the volume decision of new entrants is correlated with Chilean incumbent presence even when controlling for overall export capacity.

In column 1, each additional firm (keeping the total value imported constant) now implies a 0.05% reduction in first-year import values for new entrants, perhaps indicative of crowding out among importers. However, the coefficient on the overall value imported is virtually unchanged from column 2 in Table 2.3: import volumes are 33.4% higher when the overall value imported in the previous year is doubled. The direct effect of the number of firms remains negative in column 2, but that is compensated with a positive coefficient on the interaction between the number of firms and the overall value imported. As expected if export capacity increases both incumbent presence and first-year import volumes, the estimated coefficients on the bins in columns 3 and 4 are smaller, albeit still positive and statistically significant, than the results in columns 4 and 5 in Table 2.3 when the controls for origin supply capacity are excluded. Before, import values were 8.6% larger for markets in which there was some incumbent presence. Once controlling for overall supply capacity, import values are 8.0% larger in market for which there was some incumbent presence. Finally, compared to markets with no incumbents, import volumes were 8.3%, 12.5%, 13.0%, and 18.8% larger in markets where there were 1-5, 6-20, 21-50, and greater than 50 incumbents. Once including the additional controls, coefficients are marginally smaller, but the same message applies: conditional on the set of markets from which a firm sources an input, the firm purchases larger volumes from countries in which there was a greater Chilean incumbent presence importing that product in the previous year.

2.4.3 Intensive Margin - Duration

The last margin of importing for which I study the effects of incumbent compatriots in a market is the duration of new import spells. That is, do spells for which incumbent presence is larger prior to that spell beginning survive longer than spells where incumbent presence is lower? The regression specification is nearly identical to Equation 2.28 which was used to look at how import volumes varied with incumbent presence. The only modifications are that I remove the month dummies, as the time of year is less important for the eventual length of the spells as it is in determining the volume within the first year, and I add the sales volume in the first year, as spells which begin with larger sales volume last longer on average. The dependent variable is the inverse hyperbolic sine function of the time between the first transaction of a newly-formed import spell and the last transaction. As with the entry and volume margins, the coefficients estimated for the duration margin are identified using variation in survival times within a firm-product-year. That is, for a firm which begins to import the same product from multiple origin countries during the same year, how do the eventual survival times of those different spells vary with the presence of other Chilean firms in the preceding year? Results are presented Tables 2.5 and 2.6 below.

Baseline Results

Unlike for import values, the coefficient on the number of firms is positive and statistically significant in column 1: each additional incumbent firm is associated with a 0.03% increase in the survival time of the import spell. This coefficient drops to 0.02% in column 2 when the overall value of imports in the previous year is included. When that value doubles, survival times are 1.7% higher, which remains constant in column 3 when the two indicators of incumbent presence are interacted. Expressing incumbent presence with a dummy variable in column 4 shows that survival times are 4.5% higher in markets where there is at least one incumbent in the prior year, whereas using bins in column 5 shows that survival times are 5.1%, 8.0%, 10.7%, and 15.6% in markets where there are 1-5, 6-20, 21-50, and greater than 50 incumbents compared to markets where there are none.

In Table 2.6, I include the remaining two controls for export capacity and demand in Chile for similar goods from the same origin country. Results in columns 1-4 are virtually identical to results in columns 2-5 of Table 2.5: each additional firm is associated with a 0.02% increase in duration in column 1, doubling import value in columns 1 and 2 is associated with 1.7% longer duration, and duration times are 4.4% higher in markets where there is strictly positive incumbent presence. Compared to markets with zero incumbents, survival times are 5.0%, 7.8%, 10.5%, and 15.3% longer when there are 1-5, 6-20, 21-50, and greater than 50 incumbents.

2.5 Conclusion

Results from this chapter show that firms:

1. are more likely to buy an input (extensive margin),

2. buy greater volumes of an input (intensive margin - quantity),

3. and buy an input for a longer time (intensive margin - duration)

from a source in which there is a larger presence of compatriots in the preceding year. Multiple mechanisms could generate these patterns in the data, such as learning about quality from others, economies of scale in transportation, improved bilateral business relationships, positive and persistent supply shocks within a product-origin-year that increase exports, positive and persistent demand shocks among Chilean firms all sourcing the same input, or an unobserved match value between suppliers of one good from a foreign country and consuming firms for that good in Chile, which could generate large incumbent presence and higher entry rates, first-year sales, and durations in the absence of spillover effects.

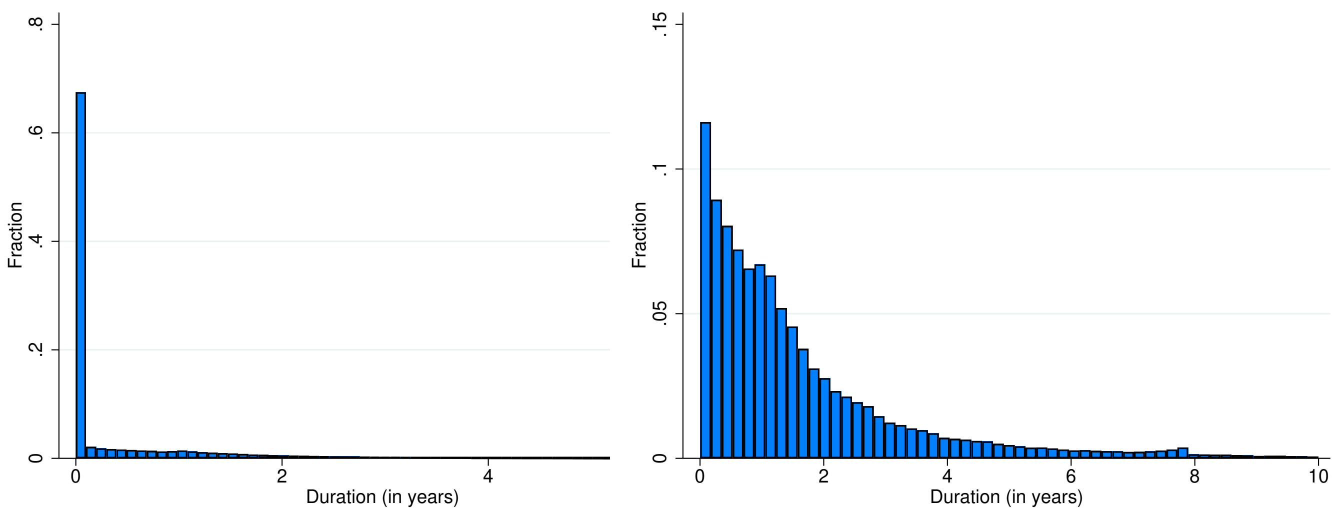
If transportation costs or bilateral business relationships are constant within a industry-origin-year, I can rule out the results presented above being driven by those differences. I control for industry-level exports to the rest of the world for each industry-origin-year, so that differential productivity growth or other positive supply shock across sources can not be driving these results. I include a proxy control for demand by Chilean firms in the value of other HS 8-digit products within the same HS 6-digit category. The main threat to the results presented here are heterogeneous match values between producers of a product in one country and Chilean firms consuming, if they are observable to the Chilean firm yet unobservable to the econometrician. However, these match-value differential would need to be less aggregate than the HS 3-digit for them to overturn results here. That being said, these results should be viewed as an upper bound of learning spillovers in case those effects are present.

One drawback of this chapter is that imports of product k from origin o by a particular importing firm are not broken down by the foreign exporting firm. For example, if I observe a firm import steel from the United States in six consecutive years, that is suggestive of a durable and successful trade relationship. However, it is possible that the importer buys from a particular supplier in the first year, becomes dissatisfied and switches suppliers to another American firm in the second year, becomes dissatisfied with the supplier, and so on, which the present data does not reveal. If there is quality heterogeneity among suppliers from the same origin country, a potential avenue for future research could be to examine the behavior of import spells disaggregated along that additional dimension.

Due to the high costs associated with importing and exporting, learning from others is an important channel through which firms can ease the transition of entering new markets. Trade promotion policy must consider the effect incumbent firms have on potential entrants and the multipliers this information transmission implies for the effectiveness of these policies. For example, if larger firms are better able to access information about the behavior of incumbents, one potential policy to increase the information potential importers and exporters have is to more accessibly circulate information about incumbent presence across markets.

2.6 Figures and Tables

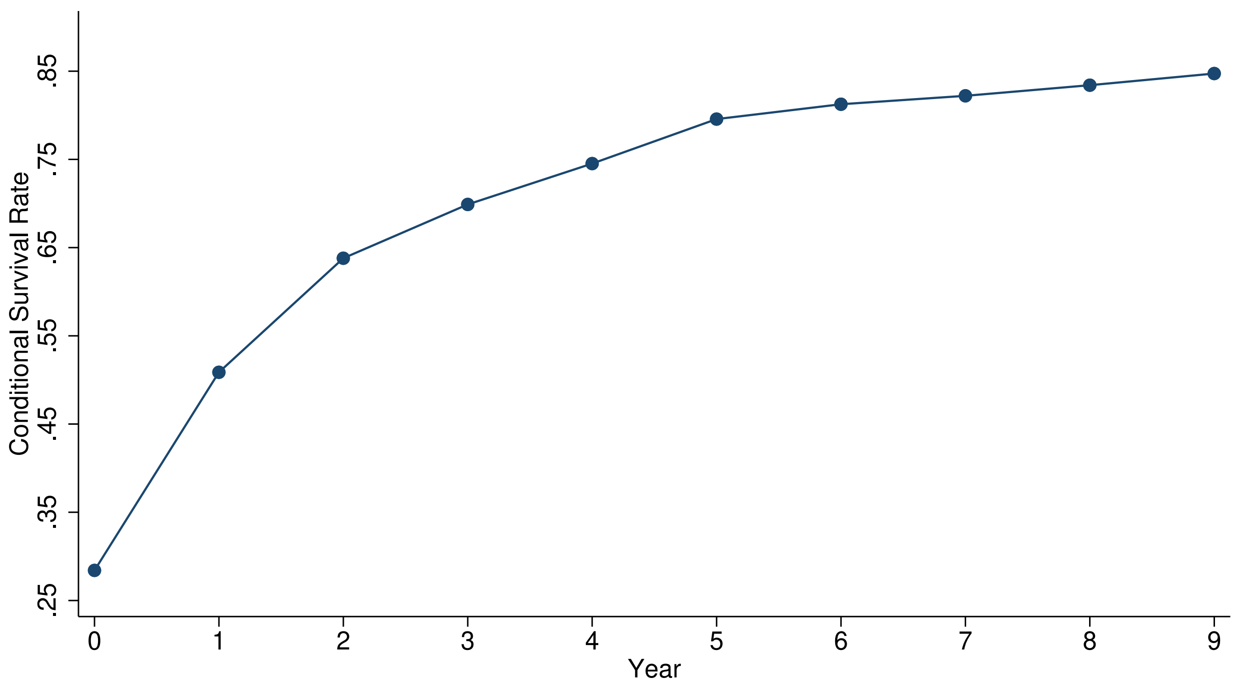
Figure 2.1: Import Spell Duration Histograms



(a) All Spells (b) Spells with Positive Duration

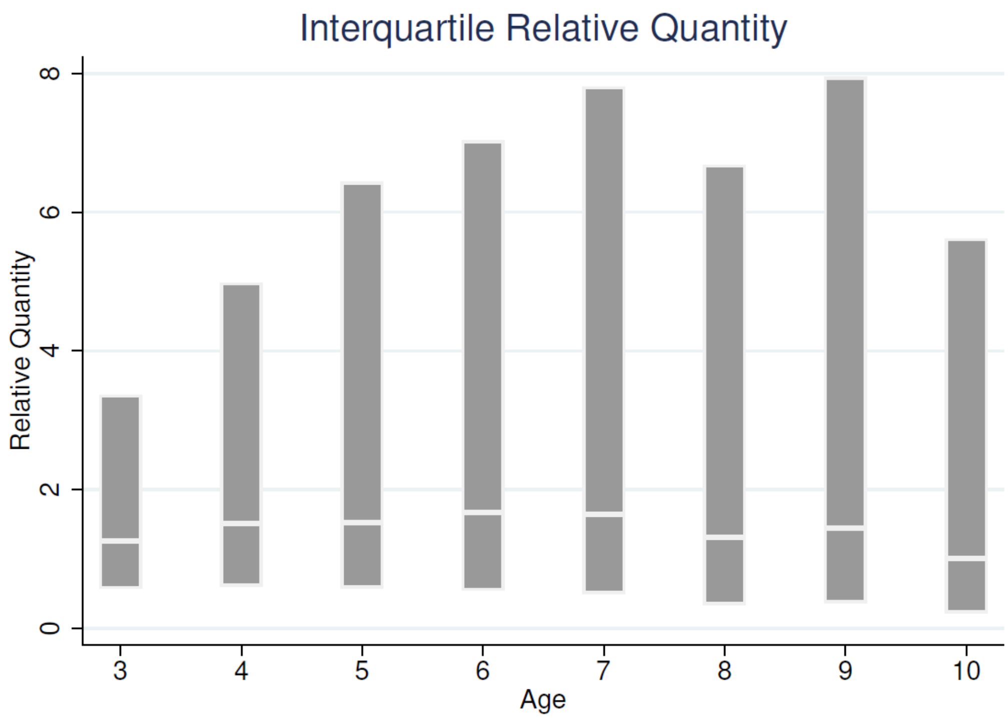
Panel (a) shows the histogram of import spell durations for all spells, including those with only one transaction and are therefore assigned duration of zero years. Panel (b) excludes spells with a single transaction and focuses only on spells with at least two transactiosn and therefore positive duration.

Figure 2.2: Import Spell Conditional Survival Rates



Each point represents the fraction of spells of age a active in 2012 which survive until 2013. For example, roughly 30% of spells of age 0 (those in their first year) survive whereas 83% of spells that are seven years old survive.

Figure 2.3: The Distribution of Changes in Values Imported for Long Spells



For each age, the bar shows the interquartile range for the quantities imported relative to second-year imports. That bottom of the bar is the 25th percentile, the white dash is the median, and the top of the bar is the 75th percentile. Through years three through ten of these import spells, the median relative quantity imported remains close to one, but the 75th percentile fluctuates between 3 and 8 times the original level, while the 25th percentile fluctuates between 40% and 60% of the original level.

Table 2.1: Baseline Extensive Margin Importing Results

	Entry$_{fkot}$				
	(1)	(2)	(3)	(4)	(5)
Firms$_{kot-1}$	0.00002*	0.00002*	0.00003*		
	(0.00001)	(0.00001)	(0.00001)		
IHS(Value)$_{kot-1}$		0.00015***	0.00017***		
		(0.00003)	(0.00003)		
Firms$_{kot-1}$			-0.000001		
$\times$ IHS(Value)$_{kot-1}$			(0.000004)		
$\mathbb{1}$(Firms$_{kot-1} > 0$)				0.00199***	
				(0.00040)	
$\mathbb{1}$(0 <Firms$_{kot-1} < 6$)					0.00203***
					(0.00043)
$\mathbb{1}$(5 <Firms$_{kot-1} < 21$)					0.00443***
					(0.0010)
$\mathbb{1}$(21 <Firms$_{kot-1} < 51$)					0.00530***
					(0.00150)
$\mathbb{1}$(Firms$_{kot-1} > 50$)					0.00642***
					(0.00209)
Products$_{fot-1}$	0.26458***	0.26465***	0.26465***	0.26496***	0.26485***
	(0.00815)	(0.00814)	(0.00814)	(0.00814)	(0.00816)
IHS(Value)$_{fot-1}$	-0.00374***	-0.00375***	-0.00375***	-0.00377***	-0.00377***
	(0.00064)	(0.00064)	(0.00064)	(0.00064)	(0.00064)
N	36,659,280	36,659,280	36,659,280	36,659,280	36,659,280
R^2	0.435	0.435	0.435	0.435	0.435
adj. R^2	0.390	0.390	0.390	0.390	0.390

Standard errors in parentheses are clustered by country-HS 2-digit chapter. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All five columns contain fo, fkt, and iot fixed effects. Entry$_{fkot}$ is a dummy variable equal to 1 if firm f begins to import product k from origin o at time t if they did not do so in the previous two years. Results are from estimating Equation 2.26 using observations from the top 20 exporting countries to Chile in terms of value. I exclude firm-product-year observations that occur prior to a firm's first import experience after a firm's final import experience. 25% of markets entered have zero incumbent presence, 45% have between 1 and 5 firms, 21% have between 6 and 20, 6% have between 21 and 50, and 3% have more than 50.

Table 2.2: Extensive Margin Importing Results with Export Capacity Controls

	Entry$_{fkot}$			
	(1)	(2)	(3)	(4)
Firms$_{kot-1}$	0.00002*	0.00003*		
	(0.00001)	(0.00001)		
IHS(Value)$_{kot-1}$	0.00017***	0.00018***		
	(0.00004)	(0.00004)		
Firms$_{kot-1}$		-0.00000		
$\times$IHS(Value)$_{kot-1}$		(0.00000)		
$\mathbb{1}$(Firms$_{kot-1} > 0$)			0.00192***	
			(0.00039)	
$\mathbb{1}$(0 <Firms$_{kot-1} < 6$)				0.00197***
				(0.00043)
$\mathbb{1}$(5 <Firms$_{kot-1} < 21$)				0.00432***
				(0.00099)
$\mathbb{1}$(20 <Firms$_{kot-1} < 51$)				0.00515***
				(0.00150)
$\mathbb{1}$(Firms$_{kot-1} > 50$)				0.00624**
				(0.00209)
IHS(ChileValue)$_{HS6-8,ot-1}$	-0.00005*	-0.00004	0.00008***	0.00005***
	(0.00003)	(0.00002)	(0.00001)	(0.00001)
IHS(ROWValue)$_{HS2-8,ot-1}$	-0.01662*	-0.01656*	-0.01701*	-0.01668*
	(0.00672)	(0.00672)	(0.00672)	(0.00672)
Products$_{fot-1}$	0.26466***	0.26465***	0.26497***	0.26486***
	(0.00814)	(0.00814)	(0.00814)	(0.00816)
IHS(Value)$_{fot-1}$	-0.00375***	-0.00375***	-0.00377***	-0.00377***
	(0.00064)	(0.00064)	(0.00064)	(0.00064)
N	36,648,784	36,648,784	36,648,784	36,648,784
R^2	0.435	0.435	0.435	0.435
adj. R^2	0.390	0.390	0.390	0.390

Standard errors in parentheses are clustered by country-HS 2-digit chapter. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain fo, fkt, and iot fixed effects. Entry$_{fkot}$ is a dummy variable equal to 1 if firm f begins to import product k from origin o at time t if they did not do so in the previous two years. Results are from estimating Equation 2.26 using observations from the top 20 exporting countries to Chile in terms of value. I exclude firm-product-year observations that occur prior to a firm's first import experience after a firm's final import experience. 25% of markets entered have zero incumbent presence, 45% have between 1 and 5 firms, 21% have between 6 and 20, 6% have between 21 and 50, and 3% have more than 50.

Table 2.3: Baseline Quantity Margin Importing Results

	ln(Value)$_{fkot}$				
	(1)	(2)	(3)	(4)	(5)
Firms$_{kot-1}$	0.0001	-0.0005***	-0.0021		
	(0.0001)	(0.0001)	(0.0011)		
IHS(Value)$_{kot-1}$		0.2867***	0.2865***		
		(0.0038)	(0.0038)		
Firms$_{kot-1}$			0.0001		
$\times$ IHS(Value)$_{kot-1}$			(0.0001)		
$\mathbb{1}(\text{Firms}_{kot-1} > 0)$				0.0827***	
				(0.0204)	
$\mathbb{1}(0 < \text{Firms}_{kot-1} < 6)$					0.0855***
					(0.0209)
$\mathbb{1}(5 < \text{Firms}_{kot-1} < 21)$					0.1301***
					(0.0257)
$\mathbb{1}(20 < \text{Firms}_{kot-1} < 51)$					0.1369***
					(0.0313)
$\mathbb{1}(\text{Firms}_{kot-1} > 50)$					0.1904***
					(0.0394)
Products$_{fot-1}$	0.0029***	0.0028***	0.0028***	0.0028***	0.0028***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
IHS(Value)$_{fot-1}$	0.0165***	0.0159***	0.0160***	0.0166***	0.0165***
	(0.0012)	(0.0011)	(0.0011)	(0.0012)	(0.0012)
N	283,168	283,168	283,168	283,168	283,168
R^2	0.748	0.761	0.761	0.748	0.748
adj. R^2	0.516	0.542	0.542	0.516	0.516

Standard errors in parentheses are clustered by country-HS 2-digit chapter. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All five columns contain first month, fkt, and iot fixed effects. Value$_{fkot}$ is the nominal value of imports of product k by firm f from origin o in year t. Results are from estimating Equation 2.28. 25% of entered markets entered have zero incumbent presence sourcing the same 8-digit product, 45% have between 1 and 5 firms, 21% have between 6 and 20, 6% have between 21 and 50, and 3% have more than 50.

Table 2.4: Quantity Margin Importing Results with Export Capacity Controls

	$\ln(\text{Value})_{fkot}$			
	(1)	(2)	(3)	(4)
Firms_{kot-1}	-0.0005***	-0.0021		
	(0.0001)	(0.0011)		
$\text{IHS(Value)}_{kot-1}$	0.2879***	0.2878***		
	(0.0038)	(0.0038)		
Firms_{kot-1}		0.0001		
$\times$ $\text{IHS(Value)}_{kot-1}$		(0.0001)		
$\mathbb{1}(\text{Firms}_{kot-1} > 0)$			0.0769***	
			(0.0204)	
$\mathbb{1}(0 < \text{Firms}_{kot-1} < 6)$				0.0799***
				(0.0209)
$\mathbb{1}(5 < \text{Firms}_{kot-1} < 21)$				0.1182***
				(0.0258)
$\mathbb{1}(20 < \text{Firms}_{kot-1} < 51)$				0.1226***
				(0.0314)
$\mathbb{1}(\text{Firms}_{kot-1} > 50)$				0.1723***
				(0.0396)
$\text{IHS(ChileValue)}_{HS6-8,ot-1}$	-0.0071***	-0.0071***	0.0109***	0.0103***
	(0.0019)	(0.0019)	(0.0021)	(0.0021)
$\text{IHS(ROWValue)}_{HS2-8,ot-1}$	-0.0834	-0.0837	-0.2177	-0.2169
	(0.1298)	(0.1299)	(0.1263)	(0.1261)
Products_{fot-1}	0.0028***	0.0028***	0.0028***	0.0028***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\text{IHS(Value)}_{fot-1}$	0.0160***	0.0160***	0.0165***	0.0165***
	(0.0011)	(0.0011)	(0.0012)	(0.0012)
N	283,168	283,168	283,168	283,168
R^2	0.762	0.762	0.748	0.748
adj. R^2	0.542	0.542	0.516	0.516

Standard errors in parentheses are clustered by country-HS 2-digit chapter. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain first month, fkt, and iot fixed effects. Value_{fkot} is the nominal value of imports of product k by firm f from origin o in year t. Results are from estimating Equation 2.28. 25% of entered markets entered have zero incumbent presence sourcing the same 8-digit product, 45% have between 1 and 5 firms, 21% have between 6 and 20, 6% have between 21 and 50, and 3% have more than 50.

Table 2.5: Baseline Duration Margin Importing Results

	IHS(Duration)$_{fkot}$				
	(1)	(2)	(3)	(4)	(5)
Firms$_{kot-1}$	0.0003***	0.0002***	0.0012**		
	(0.0000)	(0.0000)	(0.0004)		
IHS(Value)$_{kot-1}$		0.0169***	0.0170***		
		(0.0014)	(0.0014)		
Firms$_{kot-1}$			-0.0001*		
$\times$ IHS(Value)$_{kot-1}$			(0.0000)		
$\mathbb{1}$(Firms$_{kot-1} > 0$)				0.0438***	
				(0.0078)	
$\mathbb{1}$($0 <$Firms$_{kot-1} < 6$)					0.0501***
					(0.0079)
$\mathbb{1}$($5 <$Firms$_{kot-1} < 21$)					0.0774***
					(0.0102)
$\mathbb{1}$($20 <$Firms$_{kot-1} < 51$)					0.1019***
					(0.0126)
$\mathbb{1}$(Firms$_{kot-1} > 50$)					0.1453***
					(0.0160)
Products$_{fot-1}$	0.0027***	0.0026***	0.0026***	0.0025***	0.0026***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
IHS(Value)$_{fot-1}$	0.0170***	0.0158***	0.0158***	0.0159***	0.0158***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
ln(Value)$_{fkot}$	0.1144***	0.1016***	0.1016***	0.1048***	0.1047***
	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
N	283,168	283,168	283,168	283,168	283,168
R^2	0.661	0.668	0.668	0.668	0.668
adj. R^2	0.349	0.363	0.363	0.362	0.363

Standard errors in parentheses are clustered by country-HS 2-digit chapter. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All five columns contain first month, fkt, and iot fixed effects. IHS(Duration)$_{fkot}$ is the inverse hyperbolic sine function of the amount of time that passes between the first transaction of firm f importing product k from origin o in year t of a new export spell and the last transaction. Results are from estimating Equation 2.28. 25% of entered markets entered have zero incumbent presence sourcing the same 8-digit product, 45% have between 1 and 5 firms, 21% have between 6 and 20, 6% have between 21 and 50, and 3% have more than 50.

Table 2.6: Duration Margin Importing Results with Export Capacity Controls

	IHS(Duration)$_{fkot}$			
	(1)	(2)	(3)	(4)
Firms$_{kot-1}$	0.0002***	0.0012**		
	(0.0000)	(0.0004)		
IHS(Value)$_{kot-1}$	0.0167***	0.0167***		
	(0.0014)	(0.0014)		
Firms$_{kot-1}$		-0.0001*		
$\times$ IHS(Value)$_{kot-1}$		(0.0000)		
$\mathbb{1}$(Firms$_{kot-1} > 0$)			0.0426***	
			(0.0078)	
$\mathbb{1}$(0 $<$Firms$_{kot-1} < 6$)				0.0491***
				(0.0079)
$\mathbb{1}$(5 $<$Firms$_{kot-1} < 21$)				0.0754***
				(0.0103)
$\mathbb{1}$(20 $<$Firms$_{kot-1} < 51$)				0.0995***
				(0.0126)
$\mathbb{1}$(Firms$_{kot-1} > 50$)				0.1423***
				(0.0160)
IHS(ChileValue)$_{HS6-8,ot-1}$	0.0013	0.0013	0.0023**	0.0017*
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
IHS(ROWValue)$_{HS2-8,ot-1}$	0.0068	0.0070	-0.0009	-0.0002
	(0.0281)	(0.0280)	(0.0290)	(0.0290)
Products$_{fot-1}$	0.0026***	0.0026***	0.0025***	0.0026***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
IHS(Value)$_{fot-1}$	0.0158***	0.0158***	0.0159***	0.0158***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
ln(Value)$_{fkot}$	0.1016***	0.1017***	0.1047***	0.1046***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
N	283,168	283,168	283,168	283,168
R^2	0.668	0.668	0.668	0.668
adj. R^2	0.363	0.363	0.362	0.363

Standard errors in parentheses are clustered by country-HS 2-digit chapter. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All four columns contain first month, fkt, and iot fixed effects. IHS(Duration)$_{fkot}$ is the inverse hyperbolic sine function of the amount of time that passes between the first transaction of firm f importing product k from origin o in year t of a new export spell and the last transaction. Results are from estimating Equation 2.28. 25% of entered markets entered have zero incumbent presence sourcing the same 8-digit product, 45% have between 1 and 5 firms, 21% have between 6 and 20, 6% have between 21 and 50, and 3% have more than 50.

Chapter 3

Import-Export Coincidence

3.1 Introduction

A firm which imports from a particular origin country is more likely to export its final output back to that country and a firm which exports to a particular destination country is more likely to include that country in the set of countries from which it imports. Does either of these activities cause the other? Or is it simply that more productive firms are more likely to import from and export to more countries, generating a positive correlation between export and import status within a firm-country pair without any causal link between the two activities?

Much of the literature on the relationship between exporting and importing has been at the more aggregate level of the firm. For example, Bas and Strauss-Kahn (2014), Feng et al. (2016), and Elliott et al. (2018) show that firms which import more are associated with greater levels of exporting. This phenomenon could be driven by importing productivity-enhancing intermediate inputs, learning about the logistics of international transactions, or a reduction in the fixed costs of beginning to export once already importing.

Recent work, however, has begun to examine whether the same positive correlation between importing and exporting is present within firm-country pairs (a term I refer to as export-import coincidence), rather than just within the firm more generally. Importing and exporting may be related within firm-country pairs if performing one activity allows a firm to establish contacts in that country, learn how to navigate a particular business environment, or learn about the idiosyncratic preferences of consumers in that country, which reduce the frictions of starting the other activity. Albornoz and García-Lembergman (2016) show that a firm is more likely to import from a country in the year after beginning to export to that destination, although export entry is no more likely after beginning to import, but do not address the joint determination of the two activities within the firm. Campbell (2018) uses variation in tariffs faced by Chinese firms following that country's accession to the WTO to study how variation in import shares across source countries within a firm affects export revenue shares by destination. He finds that firms earn a larger share of their export revenue in countries from which they import a larger share of their intermediate inputs. Whereas that focus is on the intensive margin, I focus on the extensive margin effects of these two activities on one another: does a firm's entry into either activity in a country increase the likelihood of that firm entering the other within that country?

The contribution of this chapter is twofold: first, I establish facts regarding the relationship between importing and exporting within firm-country pairs. For example, relative to the entire sample of firms that both import and export, a firm is roughly twice as likely to export to (import from) a country if that firms imports from (exports to) the same country. The second contribution, motivated by results from the first two chapters of this dissertation, is to provide estimates of the effects of importing on exporting and of exporting on importing within Chilean firm-foreign country pairs. I do this by exploiting variation in different measures of the presence of other Chilean firms buying and selling the same products to and from the same countries to instrument initial import and export entry. Because import and export decisions within a firm are endogenous and jointly determined (see Edwards et al. (2017)), OLS estimates of the effect of importing on exporting and vice versa will be biased upwards. If the presence of firms importing (exporting) the same products from (to) a particular country is correlated with the probability that a different firm begins to import from (export to) that country, but has no independent effect on the potential entrant's probability of beginning to export to (import from) that country, then those variables will be valid instruments to measure the effect of these activities on one another.

I find that the OLS estimates are statistically significant for the effects of import entry on export entry but insignificant in the opposite direction. Whereas a firm beginning to import from a country in one year is associated with a significant 5.2% increase in the likelihood of the same firm exporting to that country in the following year, beginning to export in one year if associated with an insignificant 1.4% increase in the likelihood of importing from that country in the following year. IV estimates fluctuate between being negative and positive, but 11 out of 12 instruments are statistically insignificant, suggesting that export entry does not cause increases in import entry and that import entry does not cause increases in export entry. In the conclusion, I discuss possible mechanisms which may help account for this finding.

In the next section, I discuss how I combine the data sources from the previous two chapters and outline a series of empirical regularities about the coincidence of importing and exporting. Following that, I motivate my use of incumbent importer and exporter presence as instruments for the endogenous entry decisions a firm makes with respect to exporting to or importing from a particular country in order to estimate the extensive margin effects of these activities on one another. Finally, I discuss results, comment, and conclude.

3.2 Sample Construction and Observations

Each observation in the two datasets used in the previous chapters was indexed by firm, product traded, destination/source country, and year.[1] As I am interested in the effects of a firm importing from (exporting to) a country on the propensity of that firm to export to (import from) that same country in general (rather than with respect to a particular product, as two-way trade within a firm-product-country-year is uncommon), I aggregate together observations that involve the same firm, country, and year.[2] Furthermore, I drop observations for firms which only import or only export during the thirteen years included in the sample, leaving 16,777 firms. This number is roughly half of the number of exporters analyzed in the first chapter and a quarter of the number of importers analyzed in the previous chapter. As has been documented in the literature, however, firms which both import and export account for disproportionately massive shares of trade within a country.

[1]See the preceding two chapters for more information about the original transaction-level data.

[2]The country index in Chapter 1 was d (for destination) and and in Chapter 2 was o (for origin). Now that countries are both sources and destinations, I will index countries by c.

In Chile, these firms contribute 97.8% of the value of exports and 89.3% of the value of imports.

3.2.1 Empirical Observations

Observation 1: There is a positive correlation between the number of Chilean importers which source from a country and the number of Chilean exporters which sell to that country. Standard gravity models predict that more trade will occur between larger countries which are closer together. This increase occurs along both the intensive (average size of trade relationships) and the extensive (number of trade relationships) margins. Therefore, this positive correlation between the number of importers and exporters buying from and selling to a country, depicted in Figure 3.1, should come as no surprise. However, less obvious is the degree to which the set of firms which imports from a country overlaps with the set of firms which exports to it.

Observation 2: Compared to the overall population of firms, firms which import from a country are roughly twice as likely to export to that country. While standard gravity models do predict the positive correlation between the number of importers and the number of exporters that trade with a particular country, these models do not predict that the firms that import from a country will necessarily be more likely to export there. Define the unconditional probability that a particular firm exports to destination country c as:

$$\mathrm{P}(\mathrm{Export}_c) = \frac{\text{Number of firms which export to } c}{\text{Number of total exporters}} \tag{3.1}$$

For the 21 countries that at least 5% of Chilean firms that both import from and export to, this probability ranges from a low of 5.6% (Australia) to a high of 37.4% (the US). Now consider the probability that a particular firm exports to destination country c conditional on importing from that country, defined as:

$$\mathrm{P}(\mathrm{Export}_c|\mathrm{Import}_c = 1) = \frac{\text{Number of firms which export to and import from } c}{\text{Number of importers from } c}. \tag{3.2}$$

For the same set of 21 countries, this probability ranges from a low of 7.8% (Taiwan) to a high of 67.6% (Peru) and is higher than the unconditional export probability for each of the 21 countries. That is, a firm is more likely to export to a particular country if it also imports from it. Define the exporting premium of importers as the ratio of Equation 3.2 over Equation 3.1. For these 21 countries, the unweighted average exporting premium of importers is 102%. The converse is also true.

Observation 3: Compared to the overall population of firms, firms which export to a country are roughly twice as likely to import from that country. Analogous to Equation 3.1, define the unconditional probability that a particular firm imports from origin country c as:

$$\mathrm{P}(\mathrm{Import}_c) = \frac{\text{Number of firms which import from } c}{\text{Number of total importers}} \tag{3.3}$$

For the same 21 countries, this probability ranges from a low of 7.9% (Uruguay) to a high of 66.2% (the US). Now consider the probability that a particular firm imports from an origin country c conditional on exporting to that country, defined as:

$$\mathrm{P}(\mathrm{Import}_c|\mathrm{Export}_c = 1) = \frac{\text{Number of firms which import from and export to } c}{\text{Number of exporters to } c}. \tag{3.4}$$

This conditional import probability ranges from a low of 16.6% (Hong Kong) to a high of 82.2% (the US) and is once again higher than the unconditional import probability for each of the 21 countries. Define the importing premium of exporters as the ratio of Equation 3.4 over Equation 3.3. For these 21 countries, the unweighted average importing premium of exporters is 101%. Tables 3.1 and 3.2 presents these probabilities for each country. Figures 3.2 and 3.3 depict these probabilities graphically and indicate a strong degree of coincidence between exporting and importing within firm-country pairs. However, these differences between the conditional and unconditional probabilities are not estimates of the effects of one activity on the other. If a firm jointly determines its importing and exporting strategies, the decision to do either activity may affect or be affected by the decision to do the other, or both activities may be affected by other factors, even without a causal mechanism of one activity causing the other.

Observation 4: Export entry is significantly more likely in the immediate years following *import entry.*[3] To show this, I regress a dummy variable indicating export entry on a set of dummies representing years before and after import entry:

$$\text{Export Entry}_{fct} = \beta_\tau \sum_{\tau=-5}^{5} (\tau \text{ Years after Import Entry})_{fct} + \alpha_{ft} + \alpha_{fc} + \alpha_{ct} + \epsilon_{fct}, \quad (3.6)$$

where the α terms denote firm-year, firm-country, and country-year fixed effects to control for more aggregate factors which may influence export entry such as firm productivity or market size. Results are presented in Table 3.3 and depicted graphically in Figure 3.4.[4] The estimated coefficients are statistically insignificant for years $\tau - 5$ - $\tau - 2$ and for the year of entry τ, but are positive for the three years following import entry. The average entry rate for this subsample is 2.0%, implying that export entry is 17.9% more likely (0.0035/0.0196) in the year following import entry compared to the year before it (with almost identical magnitudes for two and three years after import entry). However, the effect fades beyond four years after import entry such that there are no longer significant effects beyond that point.

Observation 5: Import entry is more likely in the immediate years following import entry. Using the same specification as for Observation 4 but switching import and export entry, estimates show that firms are slightly more likely to import from a country after beginning to export to it.[5] The average import entry rate is 3.1% for this subsample. I reject the null

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[3]Define import entry as

$$\text{Import Entry}_{fct} = \begin{cases} 1 \text{ if ImportValue}_{fct-2} = 0, & \text{ImportValue}_{fct-1} = 0, \quad \& \quad \text{ImportValue}_{fct} > 0 \\ 0 \text{ if ImportValue}_{fct-2} = 0, & \text{ImportValue}_{fct-1} = 0, \quad \& \quad \text{ImportValue}_{fct} = 0 \\ . \quad \text{Otherwise,} & \end{cases} \quad (3.5)$$

and export entry analogously. As in the preceding two chapters, I require two consecutive years of non-activity to classify new trading activity as entry. By doing this, I remove observations for firms which have bought from or sold to a market recently and may experience different entry dynamics as a result. Unlike the previous two chapters, however, I have aggregated observations along the product dimension to examine firm entry into a market generally rather than with regard to a particular product.

[4]The omitted category is the year prior to beginning to import, so that coefficients are interpreted as percentage point changes in the probability of beginning to export compared to the year directly preceding import entry.

[5]Note that the samples will be different for these two regressions (there are 444,000 observations for the former but only 224,000 for the latter). This is because the former includes all fct observations if firm f imports from c at some point, the latter contains fct observations if firm f exports to c at some point, and importing is more likely than exporting within an fc pair throughout the sample. The average exporter in this sample exports to 4.8 countries and the average importer buys from 7.8 countries.

hypothesis that import entry is the same in the year of export entry as in the year prior at the 90% significance level. The 0.23 percentage point increase implies a 7.5% increase in beginning to import in the year of export entry, an effect which increases by 50% in the year after export entry, and is insignificant beyond two years after export entry.

These observations clearly show that the degree of coincidence between importing and exporting within firm-country pairs is greater than if these two activities were independent. Firms are more likely to export after beginning to import and more likely to import after beginning to export, but can either activity be said to cause the other? Or are they both driven by other causes? In the next section, I address the endogenous nature of firms jointly determining to engage in these activities and estimate the effect of import entry on export entry and vice versa using instruments inspired from results in the preceding two chapters.

3.3 Empirical Strategy

Since the decisions to import and export are endogenous, OLS estimates of the effect of these activities on one another will likely be biased upwards. For example, consider the decision of a garment producer in year t planning its import and export strategy for the years $t+1$ and $t+2$. Suppose the firm plans on importing cloth from the United States in $t+1$ and eventually exporting its final output to the United States in $t+2$. OLS coefficients will overstate the effect of importing on exporting if the firm was planning on exporting to the US in the absence of importing or if this was the firm's plan prior to any foreign trade. To overcome this bias, I use a 2SLS estimator to instrument for initial import or export entry with the presence of other Chilean firms buying or selling the same products to or from the same country as the firm in question.

3.3.1 Import Instruments

First I focus on the effect of import entry on the decision to begin exporting within a firm-country pair. A valid instrument must be correlated with a firm's decision to begin importing from a country, but otherwise independent of its decision to begin exporting there. In the preceding chapter, I show that firms are more likely to begin importing a particular product from countries from which other Chilean firms import that same product in the prior year. Using this rationale, I define multiple degrees of exposure potential importers have to a market as functions of this incumbent presence. Define $\{K^m_{fc}\}$ to be the set of products that firm f imports from country c. The first instrument is a dummy indicating whether or not there is any incumbent Chilean presence involved in trading any product in $\{K^m_{fc}\}$ from country c in time $t-1$ ($\mathbb{1}(\text{Incumbent Importer Presence} > 0)_{fct-1}$).[6] As in the previous two chapters, this measure of incumbent presence is lagged one period to allow time for information to accrue to the potential entrant.

The second measure of incumbent importer presence I use as an instrument is a count of the number of Chilean firms which import products in $\{K^m_{fc}\}$ from c in year $t-1$:

$$\text{Importing Firms}_{fct-1} = \sum_{k \in \{K^m_{fc}\}} \text{Importing Firms}_{kct-1}. \tag{3.7}$$

Although there is no variation across firms in terms of the number of incumbent firms which import a given product from a country in a year, the instrument still varies by firm-product-year because of the differences in the portfolio of products that each firm imports.[7] The third measure of incumbent presence I use as an instrument is the value imported by incumbents of products in $\{K^m_{fc}\}$ in year t from country c:

$$\text{Import Value}_{fct-1} = \sum_{k \in \{K^m_{fc}\}} \text{Imported Value}_{kct-1}. \tag{3.8}$$

In the results below, I take the inverse hyperbolic sine transformation of this variable to

[6] There are some firm-country pairs in the sample in which importing never occurs but are present because exporting does. For these observations, the set $\{K^m_{fc}\}$ is empty. In order to define the instruments for these observations, I use the product for which the firm imports the greatest value over the course of the sample. Suppose a firm imports \$1,000 of steel from the US and \$2,000 of lumber from Brazil. In defining this instrument for countries other than Brazil and the US (those from which imports are \$0), I use differences in the presence of other Chilean firms importing lumber from those countries.

[7] Consider two firms: one imports steel from the US whereas the other imports steel and aluminum from the US. If there are two incumbent firms which both import steel and aluminum from the US, the value of the instrument for the former firm will be two, while that for the latter will be four. That is, I am counting the number of firm-product pairs involved in trade of products in $\{K^m_{fc}\}$ from country c in time t, rather than the total number of engaged firms, to account for the fact that firms which sell a greater variety of products may be more likely to be induced to import than firms which import only a single product.

allow for zeros in markets in which there is no incumbent presence.[8]

One potential violation of the exclusion restriction is that omitted time- and country-varying supply shocks could induce Chilean importers to import more from a country, use those imports to produce additional final output, and export that final output back to the original source country, thereby also making export entry more likely for the firm in question. To minimize this possibility, I alternatively define the three instruments described above using only firms which do not also export back to the source country. For example, consider a firm which imports steel from the United States to produce tractors. If steel from the United States becomes cheaper and more Chilean firms begin to import more steel, that may induce a potential steel importer to begin importing steel from the US as well. If those incumbent importers sell their additional output of tractors back to the US, and make entry more likely for potential exporters, there would be a direct causal link between incumbent importer presence and new export entry. To avoid this, I focus only on the incumbent importer presence of firms which do not also export back to the US. Therefore, the exclusion restriction is more likely to be satisfied and incumbent importer presence will only affect new export presence through its effect on import entry.

3.3.2 Export Instruments

To examine the effect of exporting on importing, I use a similar set of variables measuring the presence of other Chilean firms exporting the same set of products to a country to instrument for initial export entry. Define the set of products that firm f exports to country c as $\{K^x_{fc}\}$. The first instrument is a dummy variable indicating whether there is at least one Chilean firm which exports at least one product in $\{K^x_{fc}\}$ to c in the preceding year ($\mathbb{1}(\text{Incumbent Exporter Presence}_{fct} > 0)$).[9] The second is analogous to Equation 3.7 and is equal to the number of firm-product pairs engaged in exporting to country c of products in

[8] See the preceding two chapters for details on the application of the inverse hyperbolic sine function in empirical settings.

[9] As with imports, there are some firm-country pairs in the sample in which exporting never occurs but are present because importing does. For these observations, the set $\{K^x_{fc}\}$ is empty. In order to define the instruments for these observations, I use the product for which the firm exports the greatest value over the course of the sample. Suppose a firm exports $1,000 of apples to the US and $2,000 of pears to Canada. In defining this instrument for countries other than Canada and the US (those to which exports are $0), I use differences in the presence of other Chilean firms exporting pears to those countries.

$\{K^x_{fc}\}$, whereas the third is analogous to Equation 3.8 and measures the value of products in $\{K^x_{fc}\}$ exported by Chilean firms to country c in t. Once again, these variables differ across firms within a country-year due to heterogeneity in the basket of exported goods.

As with the exclusion restriction for import status, one potential situation that violates the exclusion restriction for exporting is if Chilean firms are located in a global value chain such that they export intermediate inputs and re-import goods which embody those intermediates further down the production line. For example, suppose a Chilean firm exports copper to the US, which is used to produce wires and exported back to the same firm in Chile. The fact that this firm exports copper to the US and imports wire from the US may induce other copper producers to export to the US, and may induce other wire importers to import from the US. If other copper producers are also wire importers, there is a causal link between the export status of the incumbent firm and the import status of potential entrants. Therefore, I re-define the three instruments to only include the exports of firms which do not also import from the country in question, breaking that causal link between incumbent exporting and potential import entry of other firms.

The intuition behind these instruments is depicted in Figure 3.6. Incumbent importers affect import entry for other firms, and export entry only through the increased likelihood of beginning to import. Similarly, incumbent exporters affect export entry for others, but import entry only through the increased likelihood of beginning to export. As long as there is no direct link between incumbent exporters and potential import entry, or between incumbent importers and potential export entry, these measures of incumbent presence will be valid instruments to estimate the effect of entry into either activity on the probability of doing the other.

3.4 Results

3.4.1 Import Effects on Exporting

To estimate the effect of importing on exporting, I estimate the following linear probability model:

$$\text{Export Entry}_{fct+1} = \gamma_1 \text{Import Entry}_{fct} + \alpha \text{Export Controls}_{fct} + \alpha_{ft} + \alpha_{fc} + \alpha_{ct} + \epsilon_{fct}. \quad (3.9)$$

I examine variation in export entry in the year following import entry to allow time for import effects to manifest.[10] Once again, the α terms represent firm-year, firm-country, and country-year fixed effects to account for differences in market size, firm productivity, exchange rate fluctuations, and similar determinants of import and export entry which may generate a spurious relationship between the two activities. Export Controls$_{fct}$ includes the number of firms exporting products in $\{K^x_{fc}\}$ to country c in year t and the inverse hyperbolic sine of the value of those exports.

Results are presented in Table 3.4. I first report OLS estimates of Equation 3.9 and then six sets of 2SLS results (one each for the two versions (including all firms and then only those which do not also export to the country) of the three instruments (a dummy indicating positive presence, the number of firms, and total import value)). Given that the average rate of export entry is 6% for these observations, OLS results in Column 1 show that export entry is statistically significantly 5.2% (0.0031/0.0598) more likely in the year following import entry compared to observations where import entry does not occur. Although none are statistically significant, the six 2SLS estimates in Columns 2-7 are negative, suggestive of the positive bias present in the OLS results. Weak instruments do not seem to be an issue here: in four of the six first stages, the F-statistic exceeds 140, while it is 12.06 and 10.46 in the other two cases.[11] Therefore, although export entry is more likely after import entry,

[10] As in the preceding two chapters, I drop observations which occur in years prior to a firm's first international transaction and in years after a firm's final international transaction. The lack of production or balance-sheet data means firm entry, the overall portfolio of products produced, mergers, wages, and measures of firm size unrelated to trade are all unobserved. Requiring observations lie between the first and final trade transactions ensures that I do not include observations when a firm does not exist.

[11] To avoid problems associated with weak instruments, Stock, Wright, and Yogo (2002) argue that the F-statistic must be greater than 10.

these results suggest that the latter does not cause the former.

3.4.2 Export Effects on Importing

Exporting has a similarly insignificant effect on importing. To estimate this effect, I regress the following:

$$\text{Import Entry}_{fct+1} = \beta_1 \text{Export Entry}_{fct} + \beta \text{Import Controls}_{fct} + \delta_{ft} + \delta_{fc} + \delta_{ct} + \epsilon_{fct}. \quad (3.10)$$

Now, export entry is coded as one if sales by firm f to country c are positive in year t but zero in the preceding two years, whereas import entry is classified as one if the firm begins importing from country c at any point in the following year, once again to account for the fact that the effects of exporting on importing may take time to develop. The vector Import Controls$_{fct}$ contains the number of firm-product pairs engaged in trade with country c in year t of products in $\{K^m_{fc}\}$ and the inverse hyperbolic sine of the value of that trade. Results are presented in Table 3.5

Unlike the effect of importing on exporting, the OLS coefficient for the effect of exporting on importing is statistically insignificant. Taking it at face value however, the coefficient of 0.0016, combined with an average import entry rate of 11.8% implies an estimated effect of 1.4%. In addition, in five of the six specifications in which export entry is instrumented for with the measures of incumbent presence defined above, the estimated coefficient is statistically insignificant. The 2SLS estimate on export entry in Column 3 is significant at the 95% confidence level, but the probability of at least one statistically significant, positive coefficient when 12 are estimated in the absence of any causal link between the two is 65.9%. Although some of the IV estimates are larger than the OLS estimates, they are not significantly different from zero. Weak instruments do not seem to be an issue here either, as all six F-statistics are greater than 56.

3.5 Conclusion

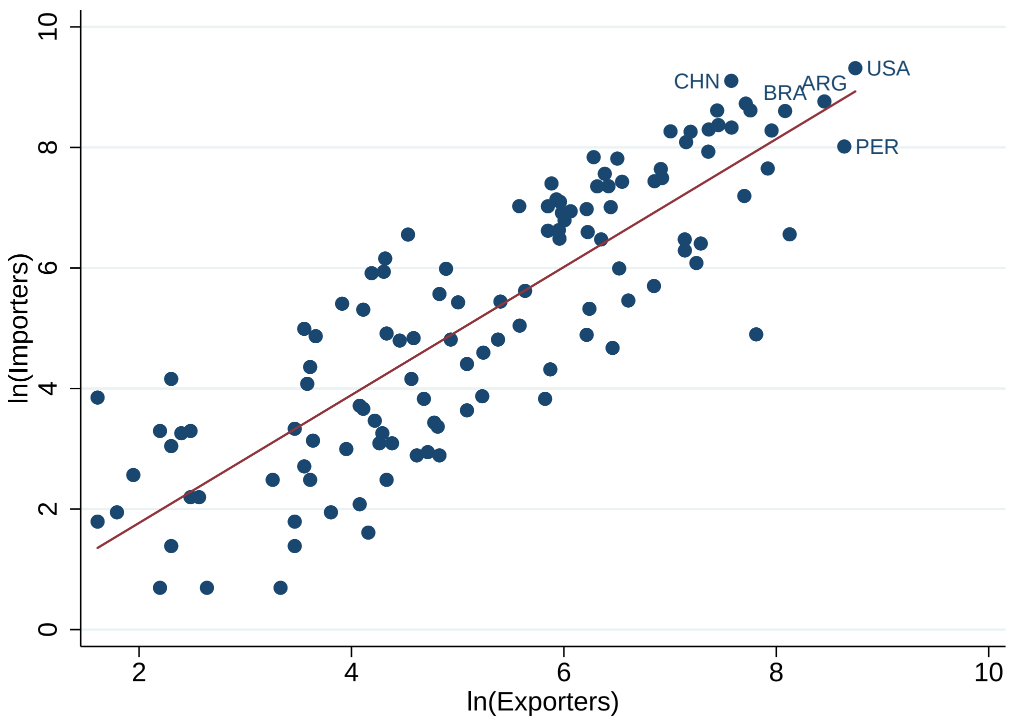
In this chapter, I outline a series of empirical observations regarding the relationship between importing and exporting within firm-country pairs. Although the two activities seem to be linked, these results show that exporting and importing do not have a causal link within firm-country pairs. What then generates the increased propensity by a firm to do one activity if they are already doing the other? In the context of studying export spillovers across firms, Choquette and Meinen (2015) show that firms are more likely to begin exporting to countries when they hire workers who previously worked at firms which exported to those countries. A similar process occuring for importing, whereby firms are also more likely to import from the countries that their new hires imported from at their old jobs, would generate a positive relationship between importing and exporting within firm-country pairs without these two activities directly causing one another.

Alternatively, the information firms must acquire in order to import from and/or export to a country may be complementary. For example, learning about the business environment, customs, or language of a country may help a firm both import and export, even if the exporting itself does not affect the importing and vice versa. If it takes multiple years to perform this research and obtain information, it may appear in the data that whichever activity is performed first is making the other more likely, even though they are both driven by a data-gathering process without affecting each other themselves.

While importing may make exporting more likely in general, such as through the adoption of lower-cost, higher-quality varieties used in the production process that make the firm more competitive globally, these effects are not restricted to the same country from which the imports are sourced. Similarly, beginning to export may make importing more likely through the familiarization within the firm of the requirements of international trade, but neither of those effects are localized within the same country.

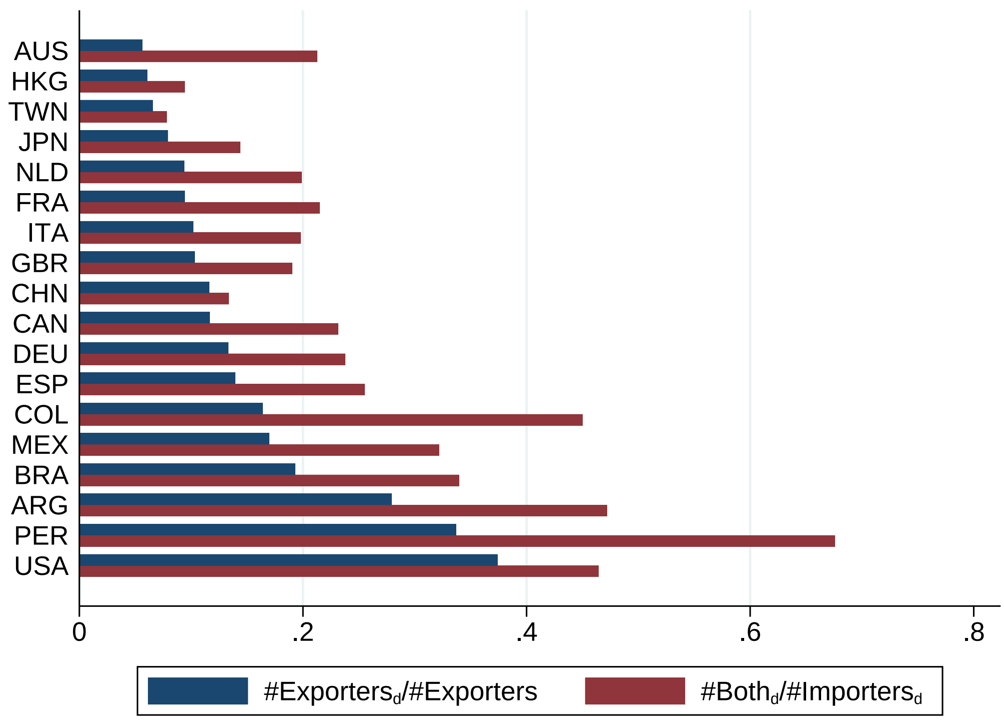
3.6 Figures and Tables

Figure 3.1: The Number of Importing and Exporting Firms by Country



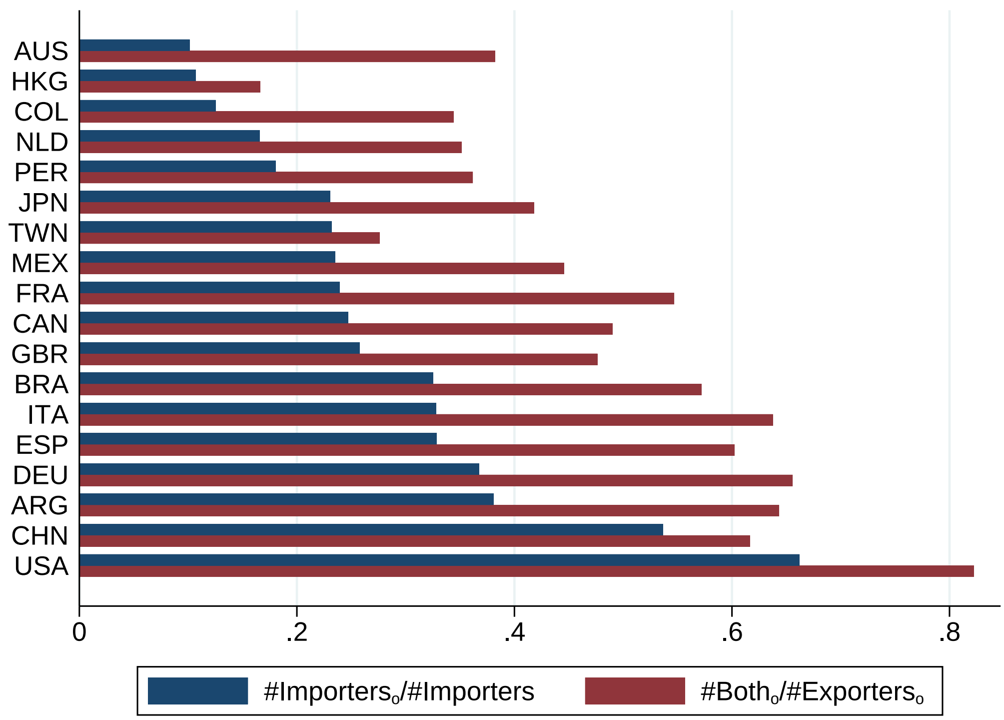
This scatterplot displays the number of firms which export to and import from each country throughout the sample. As expected, the countries with the greatest number of Chilean firms involved in trading are those that are close (Brazil, Argentina, Peru) and those which are large (the US and China).

Figure 3.2: The Exporting Premium for Importers by Country



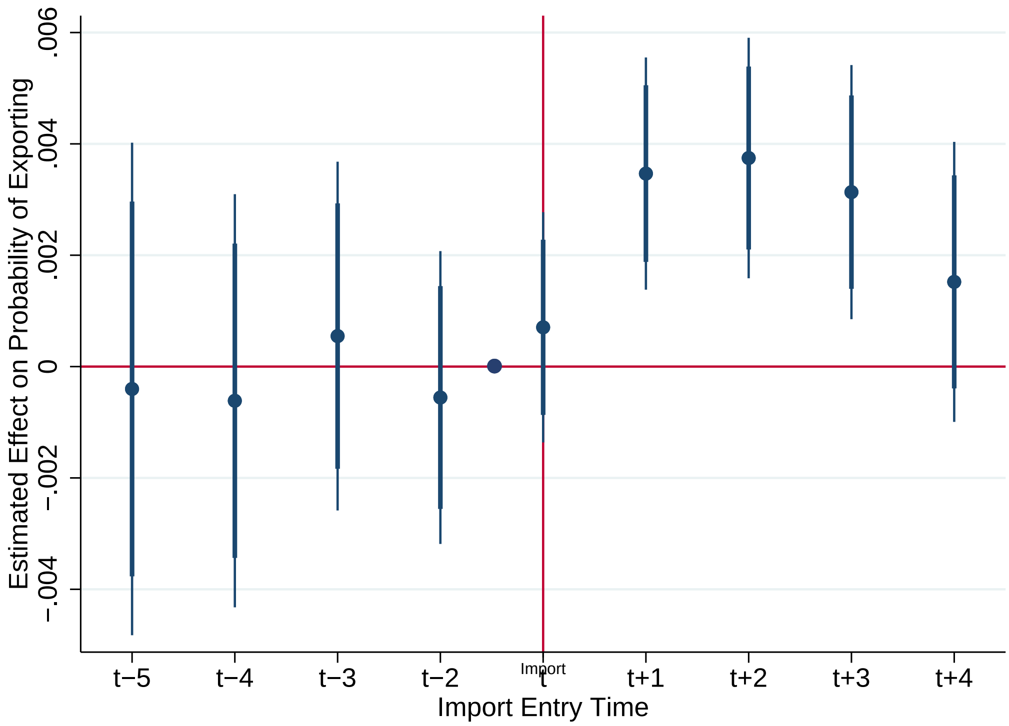
The blue lines in this barchart display the fraction of Chilean exporters (among firms which both import and export at least once) which export to each of the 18 countries which account for at least 1% of the total value of Chilean exports. The red lines depict the fractions of firms which export to each country, conditional on the firm importing from that country. For each of these 18 countries, the likelihood of a firm exporting to a country is higher if that firm also imports from that country, what I refer to as the exporting premium for importers.

Figure 3.3: The Importing Premium for Exporters by Country



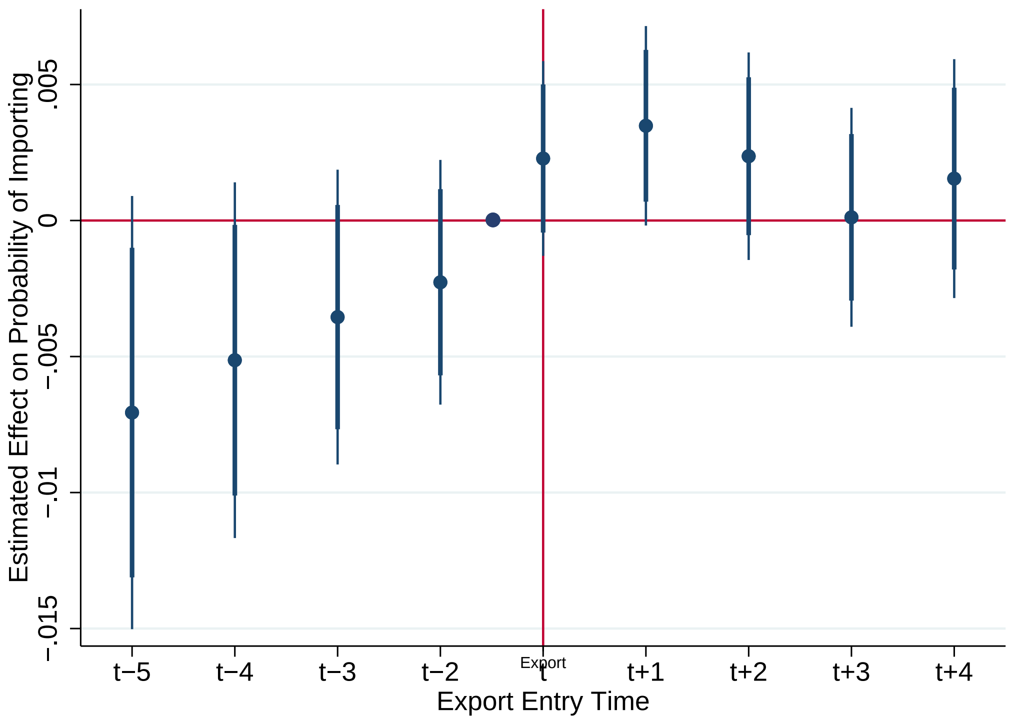
The blue lines in this barchart display the fraction of Chilean importers (among firms which both import and export at least once) which import from each of the 18 countries which account for at least 1% of the total value of Chilean imports. The red lines depict the fraction of firms which import from each country, conditional on the firm exporting to that country. For each of these 18 countries, the likelihood of a firm importing from a country is higher if that firm also exports to that country, what I refer to as the importing premium for exporters.

Figure 3.4: Changes in Export Entry around Import Entry



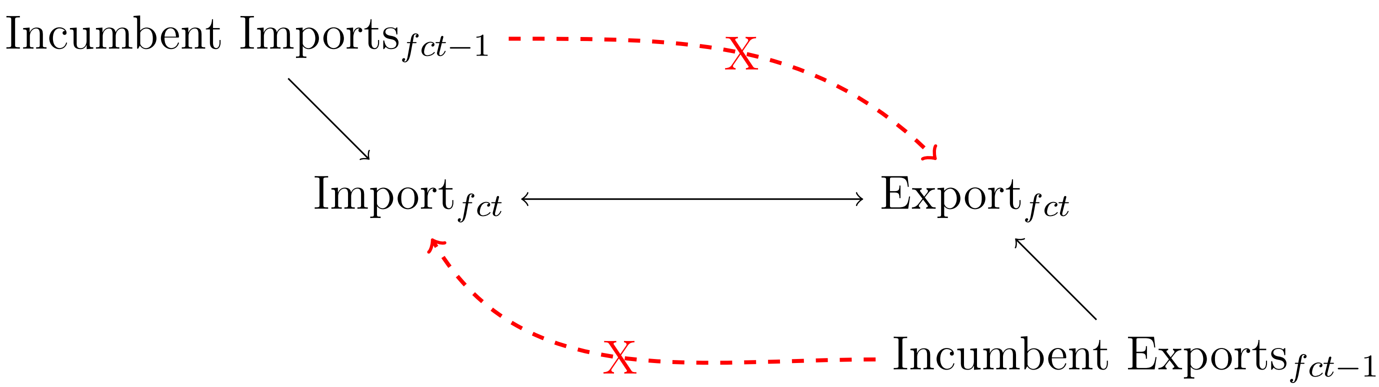
The plotted points depict coefficients from estimating Equation 3.6, with the wider lines denoting the 95% confidence interval and the thinner lines denoting the 99% confidence interval. Import entry occurs at time t and the estimates reflect changes in the probability of beginning to export relative to the probability of exporting in the year prior to import entry. There are no significant changes in the probability of export entry in the five years prior to import entry, but export entry becomes significantly more likely in the year and three years after import entry takes place. Table 3.3 contains more details on the estimation.

Figure 3.5: Changes in Import Entry after Export Entry



The plotted points depict coefficients from estimating Equation 3.6 with import and export entry switched. The wider lines denote the 95% confidence interval and the thinner lines denote the 99% confidence interval. Export entry occurs at time t and the estimates reflect the changes in the probability of beginning to import relative tot he probability of importing in the year prior to export entry. Import entry is significantly less likely five and four years prior to export entry, but is more likely in the year immediately following export entry. Table 3.3 contains more details on the estimation.

Figure 3.6: Causal Chain for Instruments



Firms endogenously choose whether or not to import from or export to a particular country each year. The choice to do one activity may increase the probability of doing the other or both activities may be caused by alternative factors, in which cases OLS estimates suffer from positive bias. To estimate the effect of import entry on exporting and vice versa, I instrument initial import and export entry with different measures of the presence of other Chilean firms exporting and importing the same products to and from the same country. The first exclusion restriction will be satisfied if the imports of other Chilean firms importing the same products affect a potential importer's import decision, but not export decision, while the second will be satisfied if the exports of other Chilean firms selling the same products affect a potential exporter's export decision, but not import decision.

Table 3.1: Exporting Premium for Importers

Country	P(Export)	P(Export|Import)	Exporting Premium for Importers
Argentina	13.3%	24.0%	+80.5%
Australia	5.6%	21.3%	+280.3%
Belgium	6.0%	14.9%	+148.3%
Brazil	19.3%	34.0%	+76.2%
Canada	11.7%	23.1%	+97.4%
China	11.6%	13.4%	+15.5%
Colombia	16.4%	45.0%	+174.4%
France	9.4%	21.5%	+128.7%
Germany	13.3%	23.8%	+78.9%
Hong Kong	6.1%	9.4%	+54.1%
Italy	10.2%	19.8%	+94.1%
Japan	7.9%	14.4%	+89.5%
Mexico	17.0%	32.2%	+89.4%
Netherlands	9.4%	19.9%	+111.7%
Peru	33.7%	67.6%	+100.6%
Spain	13.9%	25.5%	+83.5%
South Korea	7.6%	12.8%	+68.4%
Taiwan	6.6%	7.8%	+18.2%
UK	10.3%	19.1%	+85.4%
USA	37.4%	46.4%	+24.1%
Uruguay	13.1%	43.8%	+234.4%
Average:			+101.6%

Using the sample of Chilean firms that both import and export at least once between 2002 and 2014, the second column shows the fraction of firms which export to each of the 21 countries that account for the greatest share of Chilean trade during this time period. The third column shows the fraction of firms which, conditional on importing from that country, also export to it. The final column displays the ratio of these fractions, what I term the exporting premium for importers, or the increase in likelihood of exporting to a country that a firm imports from. On average, firms are roughly twice as likely to export to a country when they import from it (final row).

Table 3.2: Importing Premium for Exporters

Country	P(Import)	P(Import|Export)	Importing Premium for Exporters
Argentina	36.7%	65.6%	+78.7%
Australia	10.1%	38.2%	+278.2%
Belgium	12.4%	30.8%	+148.4%
Brazil	32.5%	57.2%	+76.0%
Canada	24.7%	49.0%	+98.4%
China	53.6%	61.7%	+15.1%
Colombia	12.5%	34.4%	+175.2%
France	23.9%	54.9%	+129.7%
Germany	36.7%	65.6%	+78.7%
Hong Kong	10.7%	16.6%	+55.1%
Italy	32.8%	63.8%	+94.5%
Japan	23.0%	41.8%	+81.7%
Mexico	23.5%	44.5%	+89.4%
Netherlands	16.6%	35.1%	+111.4%
Peru	18.0%	36.2%	+101.1%
Spain	32.8%	60.2%	+83.5%
South Korea	19.4%	32.7%	+68.5%
Taiwan	23.1%	27.6%	+19.5%
UK	25.7%	47.6%	+85.2%
USA	66.2%	82.2%	+24.2%
Uruguay	7.9%	26.5%	+235.4%
Average:			+101.3%

Using the sample of Chilean firms that both import and export at least once between 2002 and 2014, the second column shows the fraction of firms which import from each of the 21 countries that account for the greatest share of Chilean trade during this time period. The third column shows the fraction of firms which, conditional on exporting to that country, also import from it. The final column displays the ratio of these fractions, what I term the importing premium for exporters, or the increase in likelihood of importing from a country that a firm exports from. On average, firms are roughly twice as likely to import from a country when they export to it (final row).

Table 3.3: Timing of Import and Export Entry Relative to the Other

	(1) Export Entry$_{fct}$		(2) Import Entry$_{fct}$
$\mathbb{1}$(5 years before importing)$_{fct}$	-0.0004	$\mathbb{1}$(5 years before exporting)$_{fct}$	-0.0071*
	(0.0017)		0.0031
$\mathbb{1}$(4 years before importing)$_{fct}$	-0.0006	$\mathbb{1}$(4 years before exporting)$_{fct}$	-0.0051*
	(0.0014)		0.0025
$\mathbb{1}$(3 years before importing)$_{fct}$	0.0005	$\mathbb{1}$(3 years before exporting)$_{fct}$	-0.0035
	(0.0012)		(0.0021)
$\mathbb{1}$(2 years before importing)$_{fct}$	-0.0006	$\mathbb{1}$(2 years before exporting)$_{fct}$	-0.0023
	(0.0010)		(0.0017)
$\mathbb{1}$(1 years before importing)$_{fct}$	Omitted Category	$\mathbb{1}$(1 year before exporting)$_{fct}$	Omitted Category
$\mathbb{1}$(Years of import entry)$_{fct}$	0.0007	$\mathbb{1}$(Year of export entry)$_{fct}$	0.0023
	(0.0008)		(0.0014)
$\mathbb{1}$(1 year after import entry)$_{fct}$	0.0035***	$\mathbb{1}$(1 year after export entry)$_{fct}$	0.0035*
	(0.0008)		(0.0014)
$\mathbb{1}$(2 years after import entry)$_{fct}$	0.0037***	$\mathbb{1}$(2 years after export entry)$_{fct}$	0.0024
	(0.0008)		(0.0015)
$\mathbb{1}$(3 years after import entry)$_{fct}$	0.0031***	$\mathbb{1}$(3 years after export entry)$_{fct}$	0.0001
	(0.0009)		(0.0016)
$\mathbb{1}$(4 years after import entry)$_{fct}$	0.0015	$\mathbb{1}$(4 years after export entry)$_{fct}$	0.0015
	(0.0010)		(0.0017)
N	444,364		224,249
R^2	0.438		0.488
adj. R^2	0.210		0.270

Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results come from estimating Equation 3.6 and both columns contain ft, fc, and ct fixed effects. Using the set of fct observations such that f imports from c at least once in the sample, Column 1 looks at changes in the probability of export entry in the window of time around import entry. Using the set of fct observations such that f exports to c at least one ince the sample, Column 2 looks at changes in the probability of import entry in the window of time around export entry. As import entry is roughly twice as likely in this sample, the first column has twice the observations. I exclude observations prior to and after a firm's first and final international transaction.

Table 3.4: The Effects of Import Entry on Exporting

	Export Entry$_{fct+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Import Entry$_{fct}$	0.0031***	-0.0369	-0.0341	-0.0048	-0.0208	-0.0252	-0.0231
	(0.0008)	(0.0223)	(0.0249)	(0.0375)	(0.0317)	(0.0146)	(0.0153)
Exporting Firms$_{fct-1}$	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
IHS(Exported Value)$_{fct-1}$	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
First Stage Coefficient	-	0.0460***	0.0452***	0.0001***	0.0001**	0.0061***	0.0059***
First Stage t-stat	-	20.22	20.09	3.72	3.41	25.89	25.35
First Stage F statistic	-	145.40	142.85	12.06	10.46	227.27	218.47
N	953,769	953,769	953,769	953,769	953,769	953,769	953,769
R^2	0.398	0.396	0.396	0.398	0.397	0.397	0.397

Standard errors in parentheses are clustered by firm and by country. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results are from estimating Equation 3.9. OLS results are in Column 1, while IV results are in Columns 2-7. All seven columns contain ft, fc, and ct fixed effects. Starting with Column 2, the instrument used is ImporterIncumbentPresence$_{fct}$, NonExportingImporterIncumbentPresence$_{fct}$, IncumbentImportingFirms$_{fct}$, NonExportingIncumbentImportingFirms$_{fct}$, IncumbentImportedValue$_{fct}$, and IncumbentImportedValuebyNonExporters$_{fct}$. I exclude observations prior to and after a firm's first and final international transaction.

Table 3.5: The Effects of Export Entry on Importing

	Import Entry$_{fct+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Export Entry$_{fct}$	0.0016	0.0252	0.0594*	0.0002	0.0023	0.0155	0.0289
	(0.0016)	(0.0333)	(0.0277)	(0.0169)	(0.0150)	(0.0221)	(0.0199)
Importing Firms$_{fct-1}$	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
IHS(Imported Value)$_{fct-1}$	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
First Stage Coefficient	-	0.0395***	0.0463***	0.0017***	0.0018***	0.0052***	0.0058***
First Stage t-stat	-	12.74	12.65	11.15	12.49	15.36	15.01
First Stage F statistic	-	56.49	57.24	56.90	61.66	82.52	80.88
N	946,300	946,300	946,300	946,300	946,300	946,300	946,300
R^2	0.370	0.370	0.370	0.370	0.397	0.370	0.370

Standard errors in parentheses are clustered by firm and by country. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results are from estimating Equation 3.10. OLS results are in Column 1, while IV results are in Columns 2-7. All seven columns contain ft, fc, and ct fixed effects. Starting with Column 2, the instrument used is ExporterIncumbentPresence$_{fct}$, NonImportingExporterIncumbentPresence$_{fct}$, IncumbentExportingFirms$_{fct}$, NonImportingIncumbentExportingFirms$_{fct}$, IncumbentExportedValue$_{fct}$, and IncumbentExportedValuebyNonImporters$_{fct}$. I exclude observations prior to and after a firm's first and final international transaction.

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Chapter 4

Appendices

4.1 Theory Appendix

4.1.1 Deriving the Demand Curve

Destination and year subscripts are suppressed for brevity and the subscript v refers to the variety of product k produced by firm f. Suppose utility has two tiers, Cobb-Douglas in the top and CES in the bottom.

$$U = \prod_{i=1}^{I} C_i^{\alpha_i} \tag{4.1}$$

$$C_i = \left(\int_{v \in \Omega_i} e^{\frac{a_v}{\sigma_i}} c_v^{\frac{\sigma_i - 1}{\sigma_i}} d(v) \right)^{\frac{\sigma_i - 1}{\sigma_i}} \tag{4.2}$$

Conditional on an allocation of income across industries i, consumers solve:

$$\begin{aligned} \max_{(c_v), v \in \Omega_i} \quad & C_i = \left(\int_{v \in \Omega_i} e^{\frac{a_v}{\sigma_i}} c_v^{\frac{\sigma_i - 1}{\sigma_i}} dv \right)^{\frac{\sigma_i - 1}{\sigma_i}} \\ \text{subject to} \quad & \int_{v \in \Omega_i} p_v c_v dv \leq Y \end{aligned} \tag{4.3}$$

Taking first order conditions with respect to each variety yields:

$$\begin{aligned} \frac{\partial C_i}{\partial c_v} : \; e^{\frac{a_v}{\sigma_i}}\Big(\frac{\sigma_i - 1}{\sigma_i}\Big)c_v^{\frac{-1}{\sigma_i}} &= \lambda p_v \\ e^{\frac{a_v}{\sigma_i}}\Big(\frac{\sigma_i - 1}{\sigma_i}\Big)\lambda^{-1}p_v^{-1} &= c_v^{\frac{1}{\sigma_i}} \\ e^{a_v}\Big(\frac{\sigma_i - 1}{\sigma_i}\Big)^{\sigma_i}\lambda^{-\sigma_i}p_v^{-\sigma_i} &= c_v \end{aligned} \tag{4.4}$$

To find the demand curve for a given variety, divide this expression for one variety by that of another:

$$\frac{e^{a_v}\left(\frac{\sigma_i-1}{\sigma_i}\right)^{\sigma_i}\lambda^{-\sigma_i}p_v^{-\sigma_i} = c_v}{e^{a_{v'}}\left(\frac{\sigma_i-1}{\sigma_i}\right)^{\sigma_i}\lambda^{-\sigma_i}p_{v'}^{-\sigma_i} = c_{v'}} \tag{4.5}$$

$$\begin{aligned} c_v &= c_{v'}e^{-a_{v'}}p_{v'}^{\sigma_i}e^{\sigma_i a_v}p_v^{-\sigma_i} && \text{(Multiply by } p_v\text{)} \\ p_v c_v &= c_{v'}e^{-a_{v'}}p_{v'}^{\sigma_i}e^{\sigma_i a_v}p_v^{1-\sigma_i} && \text{(Integrate out variety v)} \\ Y &= c_{v'}e^{-a_{v'}}p_{v'}^{\sigma_i}P^{1-\sigma_i} && \left(\text{Define } P = \Big(\int_{v\in\Omega_i} e^{\sigma_i a_v}p_v^{1-\sigma_i}dv\Big)^{\frac{1}{1-\sigma_i}}\right) \\ c_{v'} &= e^{a_{v'}}p_{v'}^{-\sigma_i}P^{\sigma_i - 1}Y \\ c_v &= e^{a_v}p_v^{-\sigma_i}P^{\sigma_i-1}Y \end{aligned} \tag{4.6}$$

Given this demand curve, the inverse demand curve can be expressed as:

$$p_v = c_v^{\frac{-1}{\sigma_i}}e^{a_v}P^{\frac{\sigma_i - 1}{\sigma_i}}Y^{\frac{1}{\sigma_i}} \tag{4.7}$$

4.1.2 Updating Beliefs

Recall that the demand shock consists of three components:

$$a_{kdt}^f = \theta_{kd} + \theta_{fkd} + \epsilon_{fkdt}, \tag{4.8}$$

and that the distribution of these three components are given by:

$$\theta_{kd} \sim N(\overline{\theta}, \sigma_{\theta_1}^2) \tag{4.9}$$

$$\theta_{fkd} \sim N(0, \sigma^2_{\theta_2}) \tag{4.10}$$

$$\epsilon_{fkdt} \sim N(0, \sigma^2_{\epsilon}). \tag{4.11}$$

For clarity, I omit subscripts where possible and focus on a particular market. Define $a^f = \begin{bmatrix} a^f_1 & a^f_2 & ... & a^f_{n_f} \end{bmatrix}$ as the realizations of demand shocks for firm f that a potential entrant observes, where n_f may differ across firms because of variable export spell duration. If potential entrants observe $a^f \;\forall\; f = 1, 2...F$, what is the posterior distribution of beliefs of θ_{kd} and a_{fkdt}? Given the assumptions about the distributions of the three components, the density function for the component of demand that is common across firms can be written as

$$f(\theta_{kd}) = \frac{1}{\sqrt{2\pi\sigma^2_{\theta_1}}} \exp\left(\frac{-(\theta_{kd} - \overline{\theta})^2}{2\sigma^2_{\theta_1}}\right) \tag{4.12}$$

and the density function for an average signal revealed by a particular firm conditional on that common component can be written as

$$f(\overline{a}^f(n_f) \mid \theta_{kd}) = \frac{1}{\sqrt{2\pi\left(\frac{\sigma^2_{\theta_2} + \sigma^2_{\epsilon}}{n_f}\right)}} \exp\left(\frac{-(\overline{a}^f(n_f) - \theta_{kd})^2}{2\left(\frac{\sigma^2_{\theta_2} + \sigma^2_{\epsilon}}{n_f}\right)}\right). \tag{4.13}$$

Using Bayes' Rule, the density for the posterior distribution of beliefs of the shared component of demand given observed shocks is:

$$
\begin{aligned}
f(\theta_{kd} \mid \overline{a}^f(n_f) \forall f = 1,2,...,F) &= f(\theta_{kd}) \prod_{f=1}^{F} f(\overline{a}^f(n_f) \mid \theta_{kd}) \\
&\propto \frac{1}{\sqrt{2\pi\sigma^2_{\theta_1}}} \exp\left(\frac{-(\theta_{kd} - \overline{\theta})^2}{2\sigma^2_{\theta_1}}\right) \prod_{f=1}^{F} \frac{1}{\sqrt{2\pi\left(\frac{\sigma^2_{\theta_2}+\sigma^2_{\epsilon}}{n_f}\right)}} \exp\left(\frac{-(\overline{a}^f(n_f) - \theta_{kd})^2}{2\left(\frac{\sigma^2_{\theta_2}+\sigma^2_{\epsilon}}{n_f}\right)}\right) \\
&\propto \exp\left(\frac{-(\theta^2_{kd} - 2\theta_{kid}\overline{\theta} + \overline{\theta}^2)}{2\sigma^2_{\theta_1}} - \sum_{f=1}^{F} \frac{\overline{a}^f(n_f)^2 - 2\overline{a}^f(n_f)\theta_{kd} + \theta^2_{kd}}{2\left(\frac{\sigma^2_{\theta_2}+\sigma^2_{\epsilon}}{n_f}\right)}\right) \\
&= \exp\left(\frac{-(\theta^2_{kd} - 2\theta_{kid}\overline{\theta} + \overline{\theta}^2)}{2\sigma^2_{\theta_1}} - \sum_{f=1}^{F} \frac{n_f\overline{a}^f(n_f)^2 - 2n_f\overline{a}^f(n_f)\theta_{kd} + n_f\theta^2_{kd}}{2(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}\right) \\
&= \exp\left(\frac{(-\theta^2_{kd} + 2\theta_{kid}\overline{\theta} - \overline{\theta}^2)(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) - \sum_{f=1}^{F}\left[n_f\overline{a}^f(n_f)^2 - 2n_f\overline{a}^f(n_f)\theta_{kd} + n_f\theta^2_{kd}\right]\sigma^2_{\theta_1}}{2\sigma^2_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}\right) \\
&= \exp\left(\frac{-\theta^2_{kd}\left[(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F} n_f\sigma^2_{\theta_1}\right] + 2\theta_{kd}\left[\overline{\theta}(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F} n_f\overline{a}^f(n_f)\sigma^2_{\theta_1}\right] + \delta}{2\sigma^2_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_{\epsilon})}\right) \\
&= \exp\left(\frac{-\theta^2_{kid} + 2\theta_{kd}\left[\frac{\overline{\theta}(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F}\overline{a}^f(n_f)n_f\sigma^2_{\theta_1}}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F} n_f\sigma^2_{\theta_1}}\right] + \delta}{2\left(\frac{\sigma^2_{\theta_1}(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F} n_f\sigma^2_{\theta_1}}\right)}\right) \\
&= \exp\left(\frac{-\left(\theta_{kd} + \left[\frac{\overline{\theta}(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F}\overline{a}^f(n_f)n_f\sigma^2_{\theta_1}}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F} n_f\sigma^2_{\theta_1}}\right]\right)^2 + \delta}{2\left(\frac{\sigma^2_{\theta_1}(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F} n_f\sigma^2_{\theta_1}}\right)}\right) \\
&\propto \exp\left(\frac{-\left(\theta_{kd} + \left[\frac{\overline{\theta}(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F}\overline{a}^f(n_f)n_f\sigma^2_{\theta_1}}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F} n_f\sigma^2_{\theta_1}}\right]\right)^2}{2\left(\frac{\sigma^2_{\theta_1}(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+\sum_{f=1}^{F} n_f\sigma^2_{\theta_1}}\right)}\right),
\end{aligned}
\tag{4.14}
$$

which is the density function of a normally distributed variable with mean:

$$
\mu = \frac{\overline{\theta}(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F}\overline{a}^f(n_f)n_f\sigma^2_{\theta_1}}{(\sigma^2_{\theta_2} + \sigma^2_{\epsilon}) + \sum_{f=1}^{F} n_f\sigma^2_{\theta_1}}, \tag{4.15}
$$

and variance:

$$\nu = \frac{\sigma^2_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_\epsilon)}{(\sigma^2_{\theta_2} + \sigma^2_\epsilon) + \sum_{f=1}^F n_f \sigma^2_{\theta_1}} \tag{4.16}$$

Given this distribution of beliefs over θ_{kd}, beliefs about demand are then distributed normally with mean μ above and variance $\nu + \sigma^2_{\theta_2} + \sigma^2_\epsilon$. If firms look at signals going back only one year, then the mean and variance reduce to:

$$\mu_{fkdt} = \frac{(\sigma^2_{\theta_2} + \sigma^2_\epsilon)}{(\sigma^2_{\theta_2} + \sigma^2_\epsilon) + F\sigma^2_{\theta_1}}\overline{\theta} + \frac{F\sigma^2_{\theta_1}}{(\sigma^2_{\theta_2} + \sigma^2_\epsilon) + F\sigma^2_{\theta_1}}\overline{a}^f \quad \text{and} \tag{4.17}$$

$$\nu_{fkdt} = \frac{\sigma^2_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_\epsilon)}{(\sigma^2_{\theta_2} + \sigma^2_\epsilon) + F\sigma^2_{\theta_1}} + \sigma^2_{\theta_2} + \sigma^2_\epsilon < \sigma^2_{\theta_1} + \sigma^2_{\theta_2} + \sigma^2_\epsilon \text{ if } F > 0 \tag{4.18}$$

4.1.3 Comparative Statics

Equation 1.12 shows the effects of a change in revealed signal by a particular firm on the expected mean of the demand shock distribution. Taking the second derivative with respect to each of the three variance terms yields the following comparative static results:

$$\frac{\partial \mu_{fkidt}}{\partial \overline{a}^f(n_f)\partial\sigma^2_{\theta_2}} = \frac{\partial \mu_{fkidt}}{\partial \overline{a}^f(n_f)\partial\sigma^2_{\epsilon}} = \frac{-n_f\sigma^2_{\theta_1}}{\left((\sigma^2_{\theta_2} + \sigma^2_\epsilon) + \sum_{f=1}^F n_f \sigma^2_{\theta_1}\right)^2} < 0, \tag{4.19}$$

$$\frac{\partial \mu_{fkidt}}{\partial \overline{a}^f(n_f)\partial\sigma^2_{\theta_1}} = \frac{(\sigma^2_{\theta_2} + \sigma^2_\epsilon)n_f}{\left((\sigma^2_{\theta_2} + \sigma^2_\epsilon) + \sum_{f=1}^F n_f \sigma^2_{\theta_1}\right)^2} > 0. \tag{4.20}$$

Therefore, a given increase in revealed signal by incumbent firms will be larger when inter-firm product variation and idiosyncratic noise are low. Furthermore, it will be smaller when there is low variation in the permanent component of demand which does not vary across firms.

Finally, beliefs will be more precise when more signals are revealed by more firms:

$$\frac{\partial \nu_{fkidt}}{\partial n_f} = \frac{-\sigma^4_{\theta_1}(\sigma^2_{\theta_2} + \sigma^2_\epsilon)}{\left((\sigma^2_{\theta_2} + \sigma^2_\epsilon) + \sum_{f=1}^F n_f \sigma^2_{\theta_1}\right)^2} < 0 \tag{4.21}$$

As the number of firms increases, the numerator in Equation 1.11 remains constant and the denominator strictly increases, meaning the variance falls, independent of the particular realizations of the demand shocks.

4.1.4 Proposition 2

The sign of Equation 1.17 depends on the sign of $(\overline{a}-\overline{\theta}-\frac{1}{2}\sigma^2_{\theta_1})$. Suppose that firms observe a signal larger than the previous mean ($\overline{a} > \overline{\theta}$). Even when that is the case, it is possible that the difference between the average revealed signal and the prior mean is small enough that the difference is more than offset by the decrease in variance. For example, suppose that $\overline{a}$ is just marginally larger than $\overline{\theta}$. If the signal is revealed by many neighbors, the decrease in variance would more than offset the higher mean so that expected demand actually decreases. To be more explicit, incumbent presence affects beliefs about demand in three ways.

First, recall the mean of the expected normal distribution of the demand shock is given by the weighted average of the prior mean and the revealed signal: $\mu = \omega\overline{\theta} + (1-\omega)\overline{a}$.[1] As the observed average signal varies, so too does the expected mean of demand shocks. For example, if firms observe an average signal $\overline{a}$ that is higher than the prior mean, the posterior mean increases, positively affecting expected demand (b_{fkdt}).

Second, the amount by which expected demand changes in response to a given average signal $\overline{a}$ is larger when more incumbents reveal that signal. That is, when potential entrants observe more incumbent firms revealing a given signal, they place more weight on $\overline{a}$ because the observed signal is more precise. That is, $\frac{\partial \omega}{\partial F} > 0$. All else equal, this means that the change in the posterior mean is higher for a given average signal when that signal is revealed by more incumbents.

However, stronger signals revealed by more incumbents will not necessarily lead to an increase in expected demand because an increase in the number of incumbents also leads to a decrease in the variance of the demand shock. Because the normally-distributed demand shock is exponentiated in the consumer utility function, the effective demand shocks are distributed log-normally. Because the log-normal distribution is not mean-preserving and has positive skew where increases in variance lead to potential upside gains that more than

[1]From above, recall that $1-\omega = \frac{F\sigma^2_{\theta_1}}{(\sigma^2_{\theta_2}+\sigma^2_{\epsilon})+F\sigma^2_{\theta_1}}$

compensate for potential downside realizations, risk-neutral firms actually prefer a higher variance. Even though a stronger-than-expected signal revealed by many firms increases the expected mean of the demand shock, decreases in the variance attenuate (and can even overturn) those increases, potentially making firms less likely to enter, decreasing initial sales, and decreasing duration.

4.1.5 Persistent Rather than Permanent Demand

Instead of there being a permanent component of demand, suppose that the shared component is persistent but varies over time:

$$a_{fkdt} = \theta_{kdt} + \underbrace{\theta_{fkd}}_{\sim N(0,\sigma^2_{\theta_2})} + \underbrace{\epsilon_{fkdt}}_{\sim N(0,\sigma^2_{\epsilon})} . \tag{4.22}$$

For example, suppose θ_{kdt} follows an AR(1) process such that $\theta_{kdt} = \rho\theta_{kdt-1} + \epsilon_{kdt}$, where ϵ_{kdt} is distributed normally with mean 0 and variance σ^2_u, with $0 < \rho < 1$. If a potential entrant observes signals a_{kdt-1}, a_{kdt-2},...$a_{kdt-\overline{\tau}}$, in the $\overline{\tau}$ years prior to entry, posterior beliefs will be distributed normally with mean and variance:

$$\mu = \frac{\prod_{\tau=1}^{\overline{\tau}}\left(\frac{\sum_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)\rho^{\tau}\theta_{kd0} + \sum_{\tau=1}^{\overline{\tau}} a_{fkdt-\tau}\left(\frac{1}{\rho^{\tau}}\right)(\sigma^2_{\theta_1} + t\sigma^2_u)\prod_{\tau'\neq\tau}\left(\frac{\sum\limits_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)}{\prod_{\tau=1}^{\overline{\tau}}\left(\frac{\sum_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right) + \sum_{\tau=1}^{\overline{\tau}}\left(\frac{1}{\rho^{2\tau}}\right)(\sigma^2_{\theta_1} + t\sigma^2_u)\prod_{\tau'\neq\tau}\left(\frac{\sum\limits_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)} \tag{4.23}$$

$$\nu = \frac{(\sigma^2_{\theta_1} + t\sigma^2_u)\prod_{\tau=1}^{\overline{\tau}}\left(\frac{\sum_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)}{\prod_{\tau=1}^{\overline{\tau}}\left(\frac{\sum_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right) + \sum_{\tau=1}^{\overline{\tau}}\left(\frac{1}{\rho^{2\tau}}\right)(\sigma^2_{\theta_1} + t\sigma^2_u)\prod_{\tau'\neq\tau}\left(\frac{\sum\limits_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)}. \tag{4.24}$$

The weight given to a signal τ years ago is:

$$\omega(\tau) = \frac{\left(\frac{1}{\rho^{\tau}}\right)(\sigma^2_{\theta_1} + t\sigma^2_u)\prod_{\tau' \neq \tau}\left(\frac{\sum\limits_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)}{\prod\limits_{\tau=1}^{\bar{\tau}}\left(\frac{\sum_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right) + \sum\limits_{\tau=1}^{\bar{\tau}}\left(\frac{1}{\rho^{2\tau}}\right)(\sigma^2_{\theta_1} + t\sigma^2_u)\prod\limits_{\tau' \neq \tau}\left(\frac{\sum\limits_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)}, \tag{4.25}$$

which is decreasing in τ, leading to Proposition 3 below. To see this, note that the first term of $\left(\frac{\sum\limits_{\tau'=0}^{\tau-1}\rho^{\tau'}}{\rho^{\tau}}\sigma^2_u + \sigma^2_{\theta_2} + \sigma^2_{\epsilon}\right)$ is increasing in τ. Assuming $0 < \tau < 1$, the numerator increases and the denominator decreases with τ. Because the weight the signal from a particular year gets is the product of this expression for all other years signals are observed, more recent signals receive higher weights in the updating process.

Proposition 3. *If demand is persistent rather than permanent and firms consider signals from multiple years, an equivalent change in more recent signals will lead to a larger change in beliefs than more distant signals, and therefore larger changes in entry rates, first-year sales, and export duration.*

In Tables 4.1 - 4.3, I show the results of regressions from successively adding signals from each of the last $a = 1, 2, 3, 4, 5$ years. For the extensive margin and sales decisions, estimated effects decreases monotonically with age. While the effect of the signal from the previous year decreases slightly, it remains close to its original level. Overall, the effect of observing a one-standard-deviation larger signal over a period of multiple years has a larger effect than from observing it for a single year. If potential entrants observe year-after-year of above-average signals, that is more assuring than a high average signal for one year because it is less likely to simply be the result of statistical noise.

Table 4.1: Extensive Margin Results with more Distant Signals

	Entry$_{fkdt}$				
	(1)	(2)	(3)	(4)	(5)
Signal$_{kdt-1}$	0.0006***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.00011)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[0.00010-0.00012]	[0.00010-0.00012]	[0.00009-0.00011]	[0.00009-0.00011]	[0.00009-0.00011]
Signal$^{t-1}_{kdt-2}$		0.0004***	0.0004***	0.0004***	0.0003**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
		[0.00008-0.00011]	[0.00007-0.00010]	[0.00007-0.00009]	[0.0007-0.00010]
Signal$^{t-1}_{fkdt-3}$			0.0003***	0.0003***	0.0002*
			(0.0001)	(0.0001)	(0.0001)
			[0.00007-0.00009]	[0.00006-0.00009]	[0.00006-0.00008]
Signal$^{t-1}_{fkdt-4}$				0.0003***	0.0002*
				(0.0001)	(0.0001)
				[0.00007-0.00009]	[0.00006-0.00009]
Signal$^{t-1}_{fkdt-5}$					0.0002*
					(0.0001)
					[0.00007-0.00009]
Sum of Signal Coefficients	0.0006	0.0009	0.0012	0.0015	0.0014
N	15,298,772	15,298,772	14,527,550	13,627,678	12,599,531
R^2	0.309	0.309	0.309	0.312	0.317
adj. R^2	0.256	0.256	0.256	0.259	0.264

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 bootstrap replications. The values in brackets denote the 95% confidence interval of the estimate of the standard error from those bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All six columns contain fd, fkt, and idt fixed effects as well as HS 4-digit tariffs by country-year. Columns 3 through 5 also control for the signal revealed by that particular firm in that market if they were active 3, 4, or 5 years prior to the most recent entry. Entry$_{fkdt}$ is a dummy variable equal to 1 if firm f begins to sell product k in destination d at time t if they did not already do so in the previous two years. Columns 3 through 5 also control for the signal revealed by that particular firm in that market if they were active 3, 4, or 5 years prior to the most recent entry. The signal variables are constructed from Equation 1.21 and 1.28. Signal$_{kdt-a}$ is defined as the average signal revealed in the year $t - a$. Results are from estimating Equation 2.26. I exclude firm-product-year observations that occur before the first time a firm exports a particular product and firm-year observations after the final year a firm exports.

Table 4.2: Intensive Margin with More Distant Signals - Volume

	$\ln(\text{Quantity})_{fkdt}$				
	(1)	(2)	(3)	(4)	(5)
Signal_{kdt-1}	0.0931***	0.0789***	0.0707***	0.0692***	0.0738***
	(0.0113)	(0.0102)	(0.0102)	(0.0104)	(0.0108)
	[0.0099-0.0127]	[0.0093-0.0113]	[0.0091-0.0114]	[0.0089-0.0118]	[0.0096-0.0121]
Signal_{kdt-2}		0.0590***	0.0481***	0.0468***	0.0458***
		(0.0102)	(0.0103)	(0.0105)	(0.0111)
		[0.0089-0.0116]	[0.0089-0.0117]	[0.0090-0.0126]	[0.0094-0.0134]
Signal_{kdt-3}			0.0400***	0.0366**	0.0310*
			(0.0101)	(0.0105)	(0.0111)
			[0.0088-0.0118]	[0.0091-0.0123]	[0.0095-0.0128]
Signal_{kdt-4}				0.0175	0.0105
				(0.0100)	(0.0108)
				[0.0085-0.0117]	[0.0092-0.0131]
Signal_{kdt-5}					0.0171
					(0.0102)
					[0.0084-0.0121]
Tariff_{HS4dt}	-0.0018	-0.0019	-0.0016	-0.0014	-0.0014
	(0.0020)	(0.0020)	(0.0021)	(0.0022)	(0.0024)
Sum of Signal Coefficients	0.0931	0.1379	0.1588	0.1701	0.1785
N	163,652	163,652	152,921	142,421	131,275
R^2	0.872	0.872	0.870	0.869	0.864
adj. R^2	0.796	0.797	0.796	0.795	0.791

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 500 bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All six columns contain fkt and idt fixed effects along with dummies for the first month in the year in which an export spell occurs. Columns 3 through 5 also control for the signal revealed by that particular firm in that market if they were active 3, 4, or 5 years prior to the most recent entry. $\ln(\text{Quantity})_{fkdt}$ is the number of units sold in the first year of an export spell. The signal variables are constructed from Equation 1.21 and 1.28. Signal_{kdt-a} is defined as the average signal revealed in the year $t-a$. Results are from estimating Equation 2.28. I only include the first-year sales of an export spell and exclude all spells which are left-censored.

Table 4.3: Intensive Margin with More Distant Signals - Duration

	IHS(Duration)$_{fkdt}$				
	(1)	(2)	(3)	(4)	(5)
Signal$_{kdt-1}$	0.0083***	0.0070***	0.0045	0.0031	0.0018
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0030)
	[0.0026-0.0033]	[0.0025-0.0033]	[0.0026-0.0032]	[0.0026-0.0033]	[0.0027-0.0034]
Signal$_{kdt-2}$		0.0055	0.0038	0.0038	0.0028
		(0.0029)	(0.0029)	(0.0030)	(0.0030)
		[0.0025-0.0033]	[0.0026-0.0034]	[0.0025-0.0033]	[0.0027-0.0035]
Signal$_{kdt-3}$			0.0031	0.0040	0.0023
			(0.0029)	(0.0029)	(0.0031)
			[0.0026-0.0033]	[0.0025-0.0034]	[0.0027-0.0036]
Signal$_{kdt-4}$				-0.0005	0.0059
				(0.0030)	(0.0032)
				[0.0026-0.0038]	[0.0026-0.0041]
Signal$_{kdt-5}$					0.0033
					(0.0032)
					[0.0027-0.0036]
ln(Sales)$_{fkdt}$	0.1313***	0.1311***	0.1299***	0.1294***	0.1300***
	(0.0025)	(0.0025)	(0.0025)	(0.0024)	(0.0024)
Tariff$_{HS4dt}$	-0.0003	-0.0003	-0.0003	-0.0006	-0.0008
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Sum of Signal Coefficients	0.0083	0.0125	0.0114	0.0104	0.0161
N	163,652	163,652	152,921	142,421	131,275
R^2	0.676	0.676	0.677	0.678	0.677
adj. R^2	0.486	0.486	0.492	0.499	0.502

Standard errors in parentheses are clustered by country-sector (HS 2-digit) and are the mean of 100 bootstrap replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All six columns contain fkt and idt fixed effects. Columns 3 through 5 also control for the signal revealed by that particular firm in that market if they were active 3, 4, or 5 years prior to the most recent entry. IHS(Duration)$_{fkdt}$ is the inverse hyperbolic sine of the duration of the spell. The signal variables are constructed from Equation 1.21 and 1.28. Signal$^{t-1}_{kdt-a}$ is defined as the average signal revealed in the year $t-a$. Results aree from estimating Equation 2.28.

4.2 Comparative Statics

Marginal costs are decreasing in the productivity shifter of each variety and in the overall measure of varieties used (at a decreasing rate):

$$\frac{\partial C_i}{\partial a_{ij}} = \underbrace{\frac{1}{\phi}}_{>0} \underbrace{\left(\frac{1}{1-\eta}\right)}_{<0} \underbrace{\left(\int_0^{M_i} p_j^{1-\eta} a_{ij} dj\right)^{\frac{\eta}{1-\eta}}}_{>0} \underbrace{p_j^{1-\eta}}_{>0} < 0 \tag{4.26}$$

$$\frac{\partial C_i}{\partial M_i} = \underbrace{\frac{1}{\phi}}_{>0} \underbrace{\left(\frac{1}{1-\eta}\right)}_{<0} \underbrace{\left(\int_0^{M_i} p_j^{1-\eta} a_{ij} dj\right)^{\frac{\eta}{1-\eta}}}_{>0} \underbrace{p_j^{1-\eta} a_{ij}}_{>0} < 0 \tag{4.27}$$

$$\frac{\partial^2 C_i}{\partial M_i^2} = \underbrace{\frac{1}{\phi}}_{>0} \underbrace{\frac{\eta}{(1-\eta)^2}}_{>0} \underbrace{\left(\int_0^{M_i} p_j^{1-\eta} a_{ij} dj\right)^{\frac{2\eta-1}{1-\eta}}}_{>0} \underbrace{(p_j^{1-\eta} a_{ij})^2}_{>0} > 0 \tag{4.28}$$