

The ABCs of Firm Heterogeneity: The Effects of Demand and Cost Differences on Exporting ^{*}

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Abstract

We develop a novel methodology for disentangling the demand and cost drivers of firm heterogeneity. Our specific focus is on export status differences, and we utilize a new data set containing firm-product information on prices and quantities sold in the domestic and each export market. Our methodology allows us to jointly estimate firm-level productivity and markups in every market while imposing no functional form restrictions on demand. We find that i) exporters have thicker domestic markets than non-exporters; ii) this advantage translates to foreign markets; and iii) while all firms face a trade-off between lowering costs and enhancing demands, export firms achieve demand increases with much less loss in productivity.

Keywords: Exporting, Demand, Markups, Productivity

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1 Introduction

It has been known for some time that, within an industry, firms are heterogeneous along a number of dimensions: output level, survival time, and export status to name some of the most studied. Moreover, these differences are persistent and thus have aggregate effects. We know, in particular, that large firms, as measured by output level, are more likely to continue to be large, have higher average survival rates, and are more likely to export regularly than are smaller firms. The persistence of these differences is indicative of some (set of) scarce resource(s) that underlie firm heterogeneity. Researchers have proposed various alternatives. Some have suggested that the scarce resource is entrepreneurial ability (see [Lucas \(1978\)](#), [Boyd and Prescott \(1987\)](#)). Others have suggested that some innovation that reduces production costs – productivity – is the scarce resource (see [Hopenhayn \(1992\)](#) and [Ericson and Pakes \(1995\)](#)). Still others have suggested that some firm-specific (and irreproducible) demand characteristics are at the heart of the observed heterogeneity (see [Bai, Krishna, and Ma \(2017\)](#) and [Ruhl and Willis \(2017\)](#)). In fact, it may be that there are different combinations of resources that are responsible for different dimensions of firm heterogeneity.

Numerous authors have investigated empirically the source(s) of firm heterogeneity (see [Syverson \(2011\)](#) for a review of the productivity estimation literature). A clear consensus has emerged that cost heterogeneity, due to “productivity” differences, is an important determinant of overall firm-level heterogeneity. Equally clear from this research, however, is that, we can only obtain an accurate picture of the importance of productivity differences if we also account for any demand-side heterogeneity. [Foster, Haltiwanger, and Syverson \(2008\)](#), for instance, show that a failure to account for demand heterogeneity can lead to significant biases in estimates of firms’ cost heterogeneity. These biases lead to mis-estimations of size distributions and survival probabilities. Indeed, Foster and her co-authors show that survival probabilities are largely driven by demand heterogeneity, not cost heterogeneity.

One challenge in incorporating demand heterogeneity in empirical studies is that a firm’s demand typically varies by market. This is problematic not only from a data perspective – one requires market-by-market data on firm performance – but also from an estimation perspective. Unless all firms operate in all markets, the estimation procedure must account for the selection of firms into markets. This challenge exists whether one is interested in firms that produce non-traded or traded goods but is likely especially relevant in the latter case and in particular when studying variation in export status. Domestic and foreign markets often have markedly different demand characteristics and the selection of markets into which export firms sell typ-

ically varies considerably across firms. At the same time, an export market is a reasonably well-defined entity, in a way that domestic sub-markets may not be, and one for which customs data on prices and quantities is available. These facts make exporting behavior a potentially fruitful, if challenging, avenue for understanding the ways that demand and productivity / costs differences contribute to firm heterogeneity. For this reason, we focus this paper on export status heterogeneity; however, the methodology and findings are likely relevant to other aspects of firm heterogeneity.

Studies on export status to date have not been able to address completely the problems of demand heterogeneity and market selection.¹ The reason is that researchers have not had the data to distinguish price and quantity sold in *each market* a firm serves. Those studies that employ manufacturing survey data sets have, at best, information on firms' domestic and foreign sales (sometimes prices and quantities) but foreign sales are not broken down by market. Usually these studies can only measure an exporter's average performance over all the markets the firm chooses to serve. With export firms self-selecting into different foreign markets and facing different demands domestically than abroad, these averages may conceal a host of important differences between exporters and non-exporters. Similarly, studies that employ customs data have no information on non-exporters (other than that they do not export) or on the domestic sales of exporters. Out of necessity, then, research based on these type of data can only focus on how well various types of export firm heterogeneities explain cross-firm differences in observed exporting outcomes – export prices, quantities, and destinations – but not on what makes exporters and non-exporters different. In both cases, we obtain an incomplete picture of firms' demand heterogeneity and, as a consequence, of firms' cost heterogeneity and of the drivers of export status.

This paper advances our understanding of the drivers of firm heterogeneity by providing both a new estimation strategy and a new data set that, together, allow us to properly account for the impact of demand and cost heterogeneity. Our application is to the question of export status heterogeneity and, in particular, to the question of what makes successful exporters fundamentally different than non-exporters. The data we have is a new firm, product, market, year-level data set for Chilean firms. It is constructed by combining Chile's Annual Manufacturing Survey (ENIA) with its Customs Database for the years 2002-2009. This data set provides information on each firm's dollar and quantity sales in all markets, including dollar and quantity sales in the

¹That being said, these studies indicate that productivity differences provide at best only a partial explanation for differences in firm exporting decisions. Market-specific forces have been highlighted as an important other factor (see e.g., [Das, Roberts, and Tybout \(2007\)](#), [Eaton, Kortum, and Kramarz \(2011\)](#), [Albornoz, Fanelli, and Hallak \(2016\)](#), and [Roberts et al. \(2018\)](#)).

domestic market. The latter proves to be particularly important because the domestic market is the only one in which all firms sell. We will use this feature to address the market selection problem. In addition, our data set provides data on the standard plant-level output and input variables available in manufacturing surveys.

To use these data to their full potential, we develop a new estimation methodology that allows us to jointly estimate firm-level production functions and productivities, and markups at the firm-, time-, product-, and market-level. Our procedure requires no assumptions on the structure of demand facing firms in each market and therefore allows for a nonparametric estimation of market power (markups) for each product across each market at any time. The estimation procedure builds on the framework in [Gandhi, Navarro, and Rivers \(2017\)](#) and exploits our detailed destination-specific data on firm-level prices and quantities. Key to our estimation procedure is the fact that we can write the first-order conditions for intermediate inputs in terms of domestic prices. This allows us to derive expressions that depend only on domestic markups and not on demand in other destinations. Because all firms in our sample sell in the domestic market, this technique avoids the selection problems associated with firms choosing to export to different foreign markets. It also avoids the dimensionality problem that would arise in a control function approach when the number of foreign destinations is large.

Using the productivity and markup estimates, and our data, we calculate firms' marginal cost curves and (local) nonparametric values for the elasticities and slopes of the individual firm (residual) demand curves. We obtain these demand estimates for the domestic market and every foreign market to which a firm exports. By embedding these slope / elasticity estimates in either linear or iso-elastic local demand approximations, we show that it is possible to construct a domestic profitability index for each firm-product-market triplet and that this index is informative about the export / no export decision. Further, by examining the differences in the components of our index for exporters and non-exporters, we uncover the cost-side and demand-side fundamentals that make exporters different than non-exporters.

Our analysis yields several new results that, together, both highlight the importance of measuring firm-market demand heterogeneity and allow us to identify, and quantify the importance of, the fundamental drivers of export status. As to the former, we find that export firms charge a significantly lower markup in foreign markets than they do in the domestic market. Specifically, within firm, product, and year, markups are 20% lower in the firm's main foreign destination than in the domestic market. This difference is crucial. When we calculate average markups not accounting for markup differences across markets, as is typically done in the literature, we find that exporters have only a 2% higher average markup than non-exporters. This mis-estimation

suggests, incorrectly, that demand differences are not especially important. In fact, we estimate that, in the domestic market, exporters have an 11% higher markup relative to non-exporters.

As to the latter, we find that, while productivity and demand heterogeneity both play roles in determining export status, demand heterogeneity is the key driver. Further, we find that among the array of possible demand differences between exporters and non-exporters, the most significant is that exporters have “thicker” domestic markets. In essence, exporters have products that attract significantly more domestic customers at any price than do non-exporters. This “market thickness” is the key driver of domestic profitability differences between exporters and non-exporters. In addition, we find that foreign market thickness across exporting firms is highly correlated with domestic market thickness – the rank correlation between the two measures is roughly 0.4 – and that this drives export status.

While demand-side heterogeneity plays a significant role in explaining export status, productivity still matters. Its role, however, is more subtle. The reason is, in part, that high productivity (low cost) firms tend to have demand curves that are shifted down. In particular, we find that the estimated willingness-to-pay for a firm’s product (the vertical shift of the firm demand curve) and the firm’s production cost are highly correlated, with high willingness-to-pay associated with high cost (lower productivity) within the firm.² This correlation tends to mask the role that productivity plays. Exporters are not unconditionally more productive than non-exporters but, comparing exporters and non-exporters with similar demands, we find that exporters are more productive. Similarly, comparing exporters and non-exporters with similar productivity, the exporters have larger demands. In essence, we find that exporters face a better trade-off between improving productivity and improving demand.

Finally, and not surprisingly for an analysis of export status, there remains a caveat to the above results. It takes the form of a non-trivial set of exporters that are indistinguishable, in terms of productivity and domestic demand, from non-exporters. A distinguishing feature of these firms is that they have abnormally high foreign demand, relative to other exporters, in the markets they serve. This foreign market advantage comes from having a significantly higher willingness-to-pay by consumers in the foreign market – the foreign demand curves are shifted up significantly – as well as thicker foreign market demand.

Within the large literature that estimates the sources of firm heterogeneity, our work is particularly related to [Foster, Haltiwanger, and Syverson \(2008\)](#), who demonstrate that a failure

²This correlation suggests that firms face a trade-off between reducing production costs and expanding their markets. [Roberts et al. \(2018\)](#) and [Jaumandreu and Yin \(2018\)](#) find a similar negative correlation between demand and cost heterogeneity using data from China. The trade-off between investing in cost reduction versus demand promotion is studied in [Cavenaile and Roldan \(2016\)](#).

to account for demand heterogeneity results in biased productivity estimates. For a selection of arguably homogeneous goods (corrugated boxes, white bread, carbon black, to name a few), Foster and her co-authors show that high productivity firms produce more output and charge lower prices than do low productivity firms. As a result, failure to account for demand heterogeneity shrinks the role of cost heterogeneity. In our context, we demonstrate that a failure to account for market-by-market demand heterogeneity results in a serious underestimation of the importance of demand differences in explaining export status.

In the context of studying firms' export decisions, our work is related to [De Loecker and Warzynski \(2012\)](#) and [De Loecker et al. \(2016\)](#) who jointly estimate supply and demand firm heterogeneity. [De Loecker and Warzynski \(2012\)](#) do not have firm-level price data. They focus on estimating markups only and “*..are not concerned with obtaining productivity estimates.*” (page 2465). As we do, they find that exporters charge higher markups than non-exporters and argue that this fact should explain at least part of the measured productivity differences between the two groups. By contrast, we can jointly estimate firm-level demand and productivity heterogeneity. Moreover, we can allow demand heterogeneity to vary by market. We show that demand heterogeneity explains the majority of the profitability differences between exporters and non-exporters, with the caveat that, after controlling for demand differences, exporters are more productive than non-exporters. [De Loecker et al. \(2016\)](#) have output price data and impose some structure to proxy for firm-level input prices in order to estimate demand and cost heterogeneity. Again, they do not have market specific price and sales data and, as a result, their firm-level demand measure is some average across the markets to which the firm sells. Perhaps for these reasons, rather than focusing on the structural differences between exporters and non-exporters as we do, [De Loecker et al. \(2016\)](#) focus on the effects of a trade liberalization on equilibrium costs and markups.

Still in the same context, [Roberts et al. \(2018\)](#) study Chinese exporters of apparel and investigate the extent to which firm-level heterogeneity in production cost, demand, and export cost determine export performance. Our study confirms their finding that demand and production cost heterogeneity are highly correlated, with high cost firms having high (shifted) demand curves. In contrast to [Roberts et al. \(2018\)](#), we are able to analyze the differences between exporting and non-exporting firms and to deal with issues related to firm selection into foreign markets. Also, having firm-level output and input data, including input prices, we can estimate firms' physical quantity production functions and distinguish between firms' cost and technical efficiency.³

³There is a large literature that studies demand and exporting using less detailed data than we use in this

Our paper also contributes to a growing literature that uses product-level data on prices and quantities of outputs to jointly estimate firm-level markups and productivities. For an early study, see [Roberts and Supina \(1996\)](#), and for more recent work see [De Loecker et al. \(2016\)](#), [Forlani et al. \(2016\)](#), [Garcia-Marin and Voigtländer \(2017\)](#), and [Lamorgese, Linarello, and Warzynski \(2018\)](#). What differentiates our paper is that we develop a new methodology and combine it with a correspondingly detailed dataset in order to estimate markups separately for each destination in which a firm sells.⁴

The rest of the paper is organized as follows. The next section discusses our new data and presents their summary statistics. Section 3 describes the model of firm production we use, and Section 4 presents the estimation strategy that will connect model and data. Section 5 presents the results, and the last section concludes.

2 Data

In order to construct the data for our analysis, we combine two very detailed datasets on manufacturing firms in Chile. The first comes from Chile's Annual Manufacturing Survey (ENIA), which covers all manufacturing plants in the country with at least 10 employees. While a standard version of this dataset has been used extensively in the literature (see [Pavcnik \(2002\)](#) for an early user of these data), we utilize a version with much richer information, as it relates to output and inputs. In terms of plant-level input variables, the survey provides data on employment (hours and workers), wages, and plant investment in physical capital. We use these investment

paper. [Kahandelwal \(2010\)](#) and [Johnson \(2012\)](#) estimate demand systems using product-level trade data; [Hallak and Sivadasan \(2013\)](#), [Baldwin and Harrigan \(2011\)](#), [Kugler and Verhoogen \(2012\)](#), and [Manova and Zhang \(2012\)](#) show reduced form evidence on firm-level export prices suggesting that quality (demand) variation is a feature of trade data. [Gervais \(2015\)](#) finds that firm-level demand residuals are important for explaining patterns of firm exporting. [Crozet, Head, and Mayer \(2012\)](#) study the extent to which an observed measure of quality can explain variation in the export performances of Champagne producers. In common with our work, all these papers conclude that demand matters for exporting performances. Unlike all these papers, we structurally estimate demand and supply heterogeneity across exporters and non-exporters in the domestic market, the only market in which they operate together. [Hottman, Redding, and Weinstein \(2016\)](#) use detailed domestic sales data to decompose firm size heterogeneity into demand and cost heterogeneity. Like us, they find that demand is the most important component. Unlike us, they do not have production data and thus cannot distinguish between the fundamental drivers of cost heterogeneity. Moreover, they do not focus on the selection of firms into different markets, nor do they study firms' export decisions.

⁴[Georgiev \(2018\)](#) uses similar data to ours for Bulgaria, but only looks at differences between domestic and foreign destinations, grouping all foreign destinations together. [Caselli, Chatterjee, and Woodland \(2017\)](#) estimate markups separately by destination using data from Mexico. Both of these papers apply a version of the control function approach of [De Loecker et al. \(2016\)](#) applied to multiple markets. However, as we mention above, and discuss more below, it is not clear how these papers address the dimensionality problem that arises in such an approach.

data to compute a measure of the plant's capital stock using the perpetual inventory method.

A key advantage of these data for our purposes is that, in addition to providing value output measures (revenues), the Manufacturing Survey data contain plant-level domestic and export sales as well as the total physical quantity sold for each 3-digit Central Product Classification (CPC) good produced in the plant. When combined with Customs data, this allows us to compute prices for each product sold by the firm, both for domestic and foreign sales. Another valuable feature of our data is that it has data on both expenditures and quantities of intermediate inputs, which we use to construct a firm-specific price index for intermediates.⁵

In order to allocate plants' foreign sales to specific foreign countries, we link the Chilean Annual Manufacturing Survey to Chile's Customs Database, where all Chilean export transactions are recorded. These data also measure sales of each product (in both dollars and quantities) to each foreign destination. Export revenues (and therefore the computed prices) are free on board (FOB) in that they are net of transportation and other trade costs.

The customs data identify the Chilean exporter at the firm level, not at the plant level, and thus this merge is done at the level of the firm-product-year. The key characteristic of the resulting merged dataset is that, for the years 2002 - 2009, it contains information at the firm, product, and year level on both dollar sales and quantity sold to the Chilean domestic market and to every foreign market the firm sells to. Appendix A describes the construction of the dataset.

A few points about these data are worth highlighting. First, the 3-digit Central Product Classification, the level at which we measure products, covers 305 products in all sectors of the economy and 186 manufactured products. To illustrate, within the beverage industry, the data distinguish between four products: spirits, liqueurs, and other spirituous beverages (CPC 241); wines (CPC 242); malt liquors and malt (CPC 243); and soft drinks, and bottled waters (CPC 244). Second, as we will discuss more fully in the methodology section, we estimate production functions at the 3-digit ISIC industry level, allowing for the fact that some firms are multi-product firms.⁶ Given the data demands imposed by our estimation procedure, our analysis covers 9 industries. Table 1 shows summary statistics on these industries. We chose these industries based on the total number of observations available, the fraction of firms that

⁵We construct our firm-specific price index as follows. For each firm we identify the top 3-digit CPC intermediate input used (in terms of total expenditures) across all time periods. Next we take the median price of this input for each firm to create a firm-specific price. Then we divide this firm-specific price by the median of these prices for firms in the same industry that produce the same output product to create the index. We also employ a standard industry-level intermediate input price deflator to control for aggregate price movements over time.

⁶In order to focus on the main products produced, in our empirical analysis we focus on products for which there are at least 40 firm-year observations.

export, and the uniformity of the measure of physical units across firms in these industries.⁷

3 Model

Each observation in our dataset consists of a firm f , selling a product j , to a destination n , in a year t . Firms are allowed to produce multiple products, and we let J_{ft} denote the number of products produced by firm f in period t . Firms sell the output they produce to the domestic market and potentially to a subset of foreign markets. For each observation we observe a vector of quantities and a vector of revenues corresponding to the output of each product sold to each destination, including the domestic market: Q_{fjtn}, R_{fjtn} . We can then construct a measure of prices, $P_{fjtn} = \frac{R_{fjtn}}{Q_{fjtn}}$, from these data.

The total quantity produced of product j by firm f in period t is denoted by $Q_{fjt} = \sum_n Q_{fjtn}$. Within each industry, the product-specific production function (in logs) is given by:

$$q_{fjt} = f_{jt}(k_{fjt}, l_{fjt}, m_{fjt}) + \omega_{fjt},$$

where lower-case letters denotes logs, q denotes the quantity of output produced, k denotes capital, l denotes labor, m denotes intermediate / materials inputs, and ω is a persistent (Hicks-neutral) productivity shock that is known to the firm when making its period t decisions. The observed quantity of output is given by

$$y_{fjt} = q_{fjt} + \varepsilon_{fjt},$$

where ε is an ex-post shock to output capturing measurement error. Productivity ω is assumed to follow a first-order Markov process:

$$\omega_{fjt} = h(\omega_{fjt-1}) + \eta_{fjt}. \quad (1)$$

Let $X \in \{K, L, M\}$ denote a generic input of the firm. For firms that produce multiple products, the researcher only observes the total inputs used by the firm:

$$X_{ft} = \sum_{J_{ft}} X_{fjt}.$$

⁷In many cases quantities are measured in a standard unit such as litres or kilograms. However, for some products, quantities are measured simply in “units”.

Capital and labor are assumed to be chosen a period ahead in period $t - 1$. Intermediate inputs are chosen flexibly at period t to minimize costs.

For each product produced by a firm, the firm chooses an allocation of quantities to each market that it serves in that period, Q_{fjtn} , such that it maximizes profits.⁸ This static maximization problem implies a series of first-order conditions which equate marginal revenue in each market with marginal cost.⁹ Since firms are assumed to use the same production function to produce output, regardless of the destination, this implies that the marginal costs are equal across markets (destinations). As a result, firms will equate marginal revenues across markets, which implies that the ratio of prices for any two markets (1 and 2, say) is equal to the ratio of the markups,

$$\frac{P_{fjt1}}{P_{fjt2}} = \frac{\mu_{fjt1}}{\mu_{fjt2}}, \quad (2)$$

where μ_{fjtn} denotes the markup over marginal cost for firm f , product j , in period t , for destination n .

4 Estimation

Following [De Loecker et al. \(2016\)](#), we estimate a production function whose parameters vary at the industry, but not firm, level using data on single-product firms only. The advantage of this approach is that, for these firms, we do not need to make any assumptions about how the firm allocates inputs to different products. For the estimation of marginal costs, markups, and productivity, all of which vary at the product level, we use both single-product and multi-product firms. Our estimation strategy is based on the approach developed by [Gandhi, Navarro, and Rivers \(2017\)](#), henceforth GNR. We extend the methodology both by allowing for multi-product firms and by incorporating data on output prices in order to recover estimates of markups.

4.1 Single-product firms

The first stage of the estimation procedure in GNR is based on the firm's profit maximization problem with respect to choice of intermediate inputs (the variable inputs). Because we want to

⁸Note that we are abstracting away from the choice of which markets to participate in as this is not needed for estimation, although the extensive margin decisions of exporting could be added to the model (see e.g., [Roberts et al. \(2018\)](#)).

⁹Recall that our prices are free on board prices that net out the costs of transporting the products to the final destination market, and therefore our marginal costs reflect the marginal cost of production only.

be agnostic about the form of demand, we derive our first stage estimates here from the firm's cost minimization problem instead.

Specifically, if we let P_t^M denote the price of intermediate inputs, then the firm minimizes expenditures on intermediate inputs subject to the production constraint:

$$\begin{aligned} & \min_{M_{ft}} P_t^M M_{ft} \\ \text{s.t. } & F(K_{ft}, L_{ft}, M_{ft}) e^{\omega_{ft}} \geq Q_{ft}. \end{aligned}$$

This yields the following first order condition

$$P_t^M = \lambda_{ft} \left(\frac{\partial Q_{ft}}{\partial M_{ft}} \right),$$

where λ_{ft} is the Lagrange multiplier and represents the (short-run) marginal cost. This expression can be re-arranged to derive an equation relating the observed share of intermediate input expenditures in total quantity of output, the elasticity of output with respect to intermediate inputs ξ_{ft}^M , and the marginal cost:

$$\frac{P_t^M M_{ft}}{Q_{ft}} = \xi_{ft}^M \times \lambda_{ft}.$$

Adding the ex-post shocks ε , we have

$$\frac{P_t^M M_{ft}}{Y_{ft}} = \xi_{ft}^M \times \lambda_{ft} \times e^{-\varepsilon_{ft}}.$$

Letting $n = D$ denote the domestic market, we can divide both sides of the equation above by the price charged *in the domestic market*, and take logs to obtain

$$\ln \left(\frac{P_t^M M_{ft}}{P_{ftD} Y_{ft}} \right) \equiv s_{ftD} = \ln \xi_{ft}^M - \ln (\mu_{ftD}) - \varepsilon_{ft}, \quad (3)$$

where the LHS is total expenditures on intermediate inputs divided by the total quantity of output valued at the *domestic* price and $\mu_{ftD} = \frac{P_{ftD}}{\lambda_{ft}}$ is the domestic markup. Notice that we could have divided by the price charged in any of the markets served by firm f in period t . The markup on the right hand side would then correspond to whichever destination's price was used. The domestic price is a good choice here because all firms serve the domestic market and, therefore, the domestic market price is observed for all firms.

Next, we can write domestic quantity demanded as a general function of domestic price P_{ftD} , demand shifters z_{ftD} , and an unobserved demand shock χ_{ftD} :

$$Q_{ftD} = Q(P_{ftD}, z_{ftD}, \chi_{ftD}).$$

We allow for the demand shock χ_{ftD} to enter flexibly, as opposed to a standard multiplicative demand shock, as we want to allow for firm-specific heterogeneity in markups. This implies that domestic markups can be written as a function of domestic prices and demand shifters

$$\mu_{ftD} = \mu(P_{ftD}, z_{ftD}, \chi_{ftD}).$$

Because the demand shock is unobserved, then under the assumption that the quantity demanded is monotone in χ , we can write $\chi_{ftD} = Q^{-1}(P_{ftD}, z_{ftD}, Q_{ftD})$. This implies that the markup can be written as

$$\mu_{ftD} = \tilde{\mu}(P_{ftD}, z_{ftD}, Q_{ftD}).$$

As a result, equation (3) can be written as

$$s_{ftD} = \ln \xi^M(k_{ft}, l_{ft}, m_{ft}) - \ln \tilde{\mu}(P_{ftD}, z_{ftD}, Q_{ftD}) - \varepsilon_{ft}. \quad (4)$$

By regressing the modified shares s_{ftD} on inputs, domestic price, domestic quantity, and demand shifters (such as advertising expenditures), we recover a combined function of the (log) output elasticity of intermediate inputs and the (log) markup, as well as the ex-post shock ε . Since quantity is measured with error, we use lagged inputs, as instruments in the first stage.¹⁰

The second stage of the estimation procedure is also based on GNR. The difference is that we are estimating the contribution of intermediate inputs to production in the second stage instead of the first stage. In the baseline setup of perfect competition in GNR, there are no markups to estimate and the output elasticity of intermediate inputs is recovered directly in the first stage.

¹⁰An alternative to our first-stage regression is to apply the method of [De Loecker and Warzynski \(2012\)](#) and [De Loecker et al. \(2016\)](#), which regresses output quantities on a number of covariates including output price and market shares in the first stage. However, applying this approach in our setting would require data on prices and market shares in each market served by the firm, which would lead to a curse of dimensionality. Moreover, while market shares could likely be measured for the domestic market, it is not clear that given existing datasets one could measure market shares in foreign markets, due to a lack of data on imports from other destinations. The derivation of our first-stage regression from the firm's cost minimization problem allows us to express everything in terms of just the domestic market.

A problem that must be addressed in the second stage estimation is one of units. In the standard methods of estimating a “revenue production function” using deflated revenues as the output measure, the output of different products are all measured in the same units (value). When using quantities of output directly, one now has to account for the fact that different products might be measured in different units (for example, kilograms versus litres). In order to control for this, we can re-write the production function as

$$y_{fjt} = f(k_{ft}, l_{ft}, m_{ft}) + \phi_j + \omega_{ft} + \varepsilon_{ft},$$

where ϕ_j is a unit adjustment factor for product j . This implies that we can form

$$\tilde{\omega}_{ft} = \omega_{ft} + \phi_j = y_{fjt} - f(k_{ft}, l_{ft}, m_{ft}) - \varepsilon_{ft}.$$

Imposing the Markovian structure on ω in equation (1) gives us

$$\tilde{\omega}_{ft} = h(\tilde{\omega}_{ft-1} - \phi_j) + \eta_{ft} + \phi_j.$$

Combining these two equations gives us:

$$y_{fjt} = f(k_{ft}, l_{ft}, m_{ft}) + \hat{\varepsilon}_{ft} + h(y_{fjt-1} - f(k_{ft-1}, l_{ft-1}, m_{ft-1}) - \hat{\varepsilon}_{ft-1} - \phi_j) + \phi_j + \eta_{ft} \quad (5)$$

Recall that we have already estimated ε_{ft} and ε_{ft-1} in the first stage. Since the innovation to productivity is, by construction, mean independent of the firm’s information set in period $t - 1$, denoted \mathcal{I}_{ft-1} , we have the following conditional moment restriction:

$$E[\eta_{ft} | \mathcal{I}_{ft-1}] = 0,$$

where \mathcal{I}_{ft-1} includes all lags of inputs, all lags of output prices, as well as current capital and labor (which are assumed to be pre-determined). We can then form a GMM criterion function using moments in η_{ft} to identify h and f .

Because $(k_{ft}, l_{ft}, y_{ft-1}, k_{ft-1}, l_{ft-1}, m_{ft-1}) \in \mathcal{I}_{ft-1}$, these variables can be used to instrument for themselves. We then use product fixed effects to control for the ϕ_j ’s. This leaves m_{ft} which is determined in period t and correlated with the contemporaneous innovation to productivity η . Previous work by GNR shows that, without additional sources of variation, the output elasticity of intermediate inputs cannot be identified using a second-stage procedure like the one we are proposing. Fortunately, the observed output prices in our data provide a source of

identifying variation, both across firms and over time. We focus on domestic prices since they are available for each firm, and to avoid issues of aggregating prices across different markets.

Conditional on the total quantity sold, domestic output prices will vary due to domestic demand shocks χ . In addition, variation in the number and identity of destination markets, as well as their corresponding demand shocks, will provide further variation, as they determine the quantity sold domestically versus to foreign markets. Overall, firms that can charge higher prices (for a given quantity) will want to produce more, and thus will demand more intermediate inputs. To alleviate concerns that contemporaneous demand shocks might be correlated with contemporaneous productivity shocks, we use lagged output prices as instruments (see [Doraszelski and Jaumandreu \(2013\)](#)). Since these demand shocks are transmitted to the optimal choice of intermediate inputs, we also use twice-lagged intermediate inputs m_{ft-2} as an over-identifying restriction (recall that m_{ft-1} is already included as a control variable).

From our second-stage estimates we recover an estimate of the output elasticity of intermediate inputs: $\xi^M = \frac{\partial f(k_{ft}, l_{ft}, m_{ft})}{\partial m_{ft}}$. We then combine this estimate with our first-stage estimates to back out a measure of the domestic markup

$$\begin{aligned} \widehat{\ln \mu_{ftD}} &= -s_{ftD} - \widehat{\varepsilon}_{ft} + \widehat{\ln \xi_{ft}} \\ &= - \left(\ln \xi^M(k_{ft}, l_{ft}, m_{ft}) - \widehat{\ln \tilde{\mu}}(P_{ftD}, z_{ftD}, Q_{ftD}) \right) + \widehat{\ln \xi_{ft}}. \end{aligned}$$

Once we have an estimate of the domestic markup, we can use relationships in equation (2) implied by profit maximization, combined with the observed data on prices to each destination, to recover estimates of markups for each export destination n as

$$\mu_{fjtn} = \mu_{fjtD} \left(\frac{P_{fjtn}}{P_{fjtD}} \right).$$

4.2 Multi-product firms

For multi-product firms, a well-known challenge is that the researcher does not observe how firms allocate inputs to the production of each product. Rather one only observes the total amount of each input used to produce all products. There are two main solutions to this problem proposed in the literature. [De Loecker et al. \(2016\)](#) use an iterative procedure in which they assume that productivity for a firm is the same across all products and then, using this restriction, back out the input allocations. An alternative approach is to assume that inputs are allocated proportionally to the revenue shares of each product ([Foster, Haltiwanger, and Syverson \(2008\)](#)). For simplicity, and since a prior draft of [De Loecker et al. \(2016\)](#) notes that this

alternative approach generates allocations that are highly correlated with those derived from their iterative approach, we assume that inputs are allocated proportionally to revenue shares, which are measurable directly from the data.¹¹ Letting $\rho_{fjt} = \frac{R_{fjt}}{R_{ft}}$ denote the revenue share of product j for firm f in period t , for all inputs X , we have that $X_{fjt} = \rho_{fjt} * X_{ft}$. We can then form a share analogous to the one used in the first stage in equation (4) for single-product firms:

$$s_{fjtD} \equiv \ln \left(\frac{P_t^M M_{fjt}}{P_{fjtD} Y_{fjt}} \right),$$

where P_{fjtD} and Y_{fjt} are the domestic price and total quantity of product j for firm f in period t . This yields the following first-stage equation for multi-product firms:

$$s_{fjtD} = \ln \xi(k_{fjt}, l_{fjt}, m_{fjt}) - \ln \tilde{\mu}(P_{fjtD}, z_{fjtD}, Q_{fjtD}) - \varepsilon_{fjt}. \quad (6)$$

This equation for multi-product firms can be estimated in the same way as the version for single-product firms in equation (4), with the only difference being that the arguments depend on both firm and product. Using the estimates of the production function already obtained, we can construct the output elasticity of intermediate inputs $\xi^M = \frac{\partial f(k_{fjt}, l_{fjt}, m_{fjt})}{\partial m_{fjt}}$. Using this we can recover an estimate of the domestic markup μ_{fjtD} from the estimates of equation (6). Finally, we can then recover all of the foreign destination markups in the same fashion as for the single product firms, using the relationships in equation (2).

4.3 Intermediate input prices

A final issue to address is that, in most datasets, intermediate inputs are measured as total expenditures as opposed to quantities. As noted previously in the literature (see e.g., [Ornaghi \(2006\)](#), [Katayama, Lu, and Tybout \(2009\)](#), [Grieco, Li, and Zhang \(2016\)](#), [De Loecker et al. \(2016\)](#)) using expenditures instead of quantities in the estimation of the production function can lead to biased estimate of the production function parameters and productivity. A primary concern is that firms that produce output of varying qualities use intermediate inputs of similarly varying qualities: apparel firms using different quality textiles, for instance (see e.g., [Kugler and Verhoogen \(2012\)](#)).

¹¹In our data we also observe a measure of total variable costs, separately for each product produced by the firm. Another alternative would be to allocate inputs to products according to each product's variable cost share. This is the approach used in [Garcia-Marin and Voigtländer \(2017\)](#). Since in our data these cost shares have a correlation with revenue shares of 0.99, this is likely to generate very similar results.

When output is also measured in values (revenues), to the extent that input quality differences are transmitted to output quality differences, the biases from not measuring the quantities of output and inputs may net each other out (see [De Loecker and Goldberg \(2014\)](#)). However, when the production function is estimated using quantities of output, as is the case in this paper, that is no longer the case.

Various solutions to this issue have been proposed in the literature. [Grieco, Li, and Zhang \(2016\)](#) use first-order conditions for labor and intermediate inputs to recover the unobserved intermediate input prices (and therefore also the quantities). In order to derive these first-order conditions, they impose a parametric CES specification for output demand. [De Loecker et al. \(2016\)](#) propose a control function approach to address the issue. The idea is that, after controlling for market share, there should be a monotone mapping from a product’s input to output prices. This approach is less appealing in our case given that we have product prices in every market the firm sells to, and we do not have firms’ market shares in all foreign markets.

As discussed in [Section 2](#), an additional benefit of the richness of our data is that it allows us to construct a firm-specific intermediate input price deflator directly. We deflate intermediate input expenditures directly using this firm-specific price index, which allows us to recover quantities directly from the data.¹² In [Section 5](#) below, we show how controlling for heterogeneous intermediate input prices affects our estimates. In order to show how our intermediate input prices relate to output prices, in [Table 2](#) we report estimates of a regression of (log) domestic output price on (log) intermediate input price, controlling for product-year fixed effects.¹³ The estimates indicate that a 1% increase in the intermediate input price is associated with a 0.28% increase in the output price, consistent with the notion that higher quality intermediate inputs are used to product higher quality outputs.

4.4 The estimates

For each industry, we estimate a Cobb-Douglas specification of the production function. While we could estimate a higher-order approximation such as a translog, doing so places additional demands on the data. In addition, the Cobb-Douglas specification allows us to derive a closed-

¹²In our data we also observe wages separately from hours worked. In our application we choose to use the wage bill (instead of hours) as our measure of labor input, under the assumption that wage variation captures differences in the efficiency of workers (see [Griliches and Mairesse \(1998\)](#) and [Fox and Smeets \(2011\)](#)). This contrasts with [De Loecker et al. \(2016\)](#) who estimate a single control function which they use to deflate all inputs.

¹³Very similar results are obtained using an average (across destinations) output price.

form expression for the marginal cost function which will aid in interpreting the results below.¹⁴

In Table 3, we report the estimated production function elasticities. As a comparison, we report estimates both with and without correcting for input price variation. The table shows that there is some evidence that failing to control for input prices is negatively affecting the estimates. Several of the estimated capital and labor elasticities are quite small, and in a few cases negative. Additionally, the intermediate input elasticity is estimated to be above one for two industries. These problems are resolved once we control for observed variation in input prices.

Overall, the estimates are quite reasonable. We find roughly constant returns to scale in most industries, with mild decreasing returns in industry 153 (grain mill products, starches, and animal feeds) and 155 (beverages), and evidence of increasing returns to scale in industry 222 (printing and service activities related to printing). In what follows, we use estimates based on the specification that controls for intermediate input price variation.

Table 4 reports median and mean firm-level markups by industry. The numbers in this table are obtained by calculating a revenue-weighted average markup over products, markets, and years for each firm, and then computing the median and mean across firms. Focusing on the results controlling for variation in intermediate input prices, the averages, across industries, of the median and mean markups are 1.49 and 1.85, respectively. These markup estimates are similar to what other papers in the literature have found. For example, [De Loecker et al. \(2016\)](#) obtain industry-average median and mean markups of 1.34 and 2.70. [Roberts et al. \(2018\)](#) estimate markups that vary only across destination which range between 1.44 and 1.72.

5 What makes exporters different?

In this section we detail the key findings on exporters and non-exporters based on our joint estimates of productivities and markups. We begin by presenting a comparison both of the distributions of estimated productivities for exporters and non-exporters and of estimates of the values of domestic markups for each type of firm. We also examine the estimated values of cross-country markups for exporters. Next, to understand at a structural level – note that markup estimates are equilibrium outcomes – what makes exporters different, we present estimates for the implied firm-level marginal cost functions. We also construct demand function approximations using both linear and CES specifications and information from prices, quanti-

¹⁴See also [De Loecker and Warzynski \(2012\)](#) and [Garcia-Marin and Voigtländer \(2018\)](#) who find that Cobb-Douglas and translog specifications generate similar results.

ties sold, and the estimated markups. Together, these demand and cost estimates allow us to identify the key structural features that make exporters and non-exporters different.

5.1 Productivity and markups

Since our main focus is on examining differences across firms and destinations, and not across products, in what follows we report results using the main product produced by the firm, defined as the product that generates the most revenue for the firm.¹⁵ The distributions of estimated productivities for exporters and non-exporters, after netting out year and product effects, are presented in Figure 1. Strikingly, the distributions are essentially the same, with no evidence that exporters are more productive than non-exporters. The second to last column in Table 5 shows that, after controlling for product and year effects, the productivity of the average exporter is 3.6% larger than that of the average non-exporter, but this difference is not statistically significant. This result contrasts with those of other studies (see [Bernard et al. \(2012\)](#) for a survey) that find that exporters have a significant productivity advantage over non-exporters. Part of the estimated productivity advantage of exporters found in these studies is likely attributable to not properly controlling for markups. Furthermore, in a context in which both demand and productivity heterogeneity are operating together, they need to be evaluated jointly. We revisit this point in Section 5.2.4.

Figure 2 plots the distribution of the estimated values of firms' domestic markups, again after netting out year and product effects.¹⁶ The dashed line in the figure represents exporters while the solid line represents non-exporters. While there is significant overlap between the markup distributions in Figure 2, the figure shows clearly that exporters tend to charge higher markups than non-exporters in the domestic market. The first column in Table 5 confirms that exporters charge, on average, a 11% higher domestic markup than non-exporters.

Looking just at exporters, we can also compare markups across markets for a given firm, product, year. The second column of Table 5 compares the value of an export firm's domestic markup to the average value of its foreign markups. There we see that a firm selling the same product both at home and abroad charges a 9% lower markup abroad, on average. The third column of Table 5 compares the markup charged in the domestic market to that charged in the firm's main foreign market, defined here as the foreign market that accounts for the largest share

¹⁵Results using all products are very similar and available upon request. For recent work focused the multi-product nature of firms see e.g., [De Loecker et al. \(2016\)](#), [Grieco and McDevitt \(2016\)](#), [Dhyne et al. \(2017\)](#), and [Garcia-Marin and Voigtländer \(2017\)](#).

¹⁶We construct estimates of the value of marginal cost for each firm-product-time observation using the markup estimates and our data on prices.

of the firm's dollar sales. In this case, markups are about 20% lower in the main foreign market than in the domestic market. Table 6 investigates how foreign markups are related to country characteristics, in particular to gravity variables. Again, controlling for firm-product-time fixed effects, we find that markups are higher in export destinations that are richer and farther away and in countries that speak Spanish.

The fact that markups differ significantly across destination, and, in particular, between foreign and domestic markets, suggests that inferences about demand heterogeneity based on average markups may be quite misleading. We highlight this fact in Table 7 that reports estimates from a regression of average markups (across all destinations, including the domestic market) on a dummy for exporting. Recall that exporters have 11% higher domestic markups compared to non-exporters. When we look at firms' average markups, we find a difference of only 2.4% in markups between exporters and non-exporters, a drop of almost 80%! This significantly lower average is driven by the fact that foreign markups are, on average, lower than domestic markups. By using only an average markup as a measure of firm heterogeneity, ones conflates the true underlying differences across firms with differences across the destinations that these firms serve. In our case, the bias in markups introduced by selection into foreign markets results in a significant underestimation of the importance of demand-side heterogeneity.

Our collection of results so far suggest that demand-side features likely play a significant role in determining firms' export decisions.¹⁷ However, given that the markup estimates are equilibrium values and, as such, depend not just on underlying demand and cost parameters but also on firm pricing decisions, the results at this point are no more than suggestive. To illustrate the problem, note that a firm with a low estimated value of domestic markup need not be a low demand / low productivity firm. Instead, this firm may simply be one that sells a large amount of output while facing a variable elasticity demand function, and uses expensive inputs.

To get a deeper understanding of the sources of heterogeneity that make export firms different, we need some way to get at structural demand and cost function parameters using our markup and production function estimates. We develop a methodology for doing this in the next subsection. On the demand side, our methodology focuses on domestic markups / market power as the main source of demand-side heterogeneity. We take this focus for several reasons. First, in contrast to each of the foreign destinations, every firm in our data sells domestically. Therefore, we can compute a measure of market power in the domestic market for all firms and

¹⁷Note that the notion that demand heterogeneity is a driver of exporting would also be consistent with the management strategy literature that suggests that product differentiation plays a key role in creating a successful business. Porter (1980), for instance, defines "overall cost leadership" and "differentiation" as two generic strategies firms can pursue.

use this measure to compare across exporters and non-exporters. Second, the set of observed foreign markups is selected. It is likely that firms export to those destinations with stronger demand for their products. Finally, to the extent that market power varies systematically between destinations, which our estimates in Tables 5 and 6 above suggest, then averaging across markets combines differences across firms with differences across destinations. We avoid this problem by focusing primarily on the domestic market.

5.2 The structure behind exporters

Our methodology for uncovering what makes exporters different involves the development of a profitability index, based on structural demand-side and cost-side parameters. To construct this index, we first need to generate cost function estimates, which we do using our estimates of the production function parameters and productivity. We also need to compute domestic demand function parameters from the price and quantity data and from our estimates of domestic markups. We turn first to the cost function estimates.

5.2.1 Firms' marginal cost curves

From the structure imposed for the production function estimation, we have that the firm's marginal cost curve is given by:¹⁸

$$MC_i = \left[\frac{P_i^{M\gamma}}{e^{\omega_i}} \right]^{\frac{1}{\gamma}} \left[\frac{1}{K_i^\alpha L_i^\beta} \right]^{1/\gamma} \frac{1}{\gamma} q_i^T \left(\frac{1-\gamma}{\gamma} \right) \quad (7)$$

where q_i^T denotes the total quantity produced by the firm. As usual, firms' marginal cost curves will differ to the extent that they have different productivities or face different input prices, according to the ratio $\left[\frac{P_i^{M\gamma}}{e^{\omega_i}} \right]$.¹⁹

In estimating the production functions and productivities, we assume that firms' capital and labor are pre-determined. Maintaining these assumptions, the levels of these inputs will affect both the levels and slopes of firms' marginal cost curves. Specifically, all else equal, larger amounts of capital and labor make marginal costs lower and the marginal cost curve flatter at any level of output. By contrast, allowing for long enough time periods such that capital and labor are chosen optimally for any level of output, then with constant returns to scale, marginal

¹⁸For simplicity, we drop the time subscript below and let the subscript i denote a firm-time combination.

¹⁹This input-price weighted productivity measure is the analogue of the marginal cost component of the profitability index in Foster, Haltiwanger, and Syverson (2008) when capital and labor are pre-determined. And as we show below, it will be the source of cost-side heterogeneity in our profit index.

cost curves will differ across firms only by the scaled productivity metric of $[\frac{P_i^{M\gamma}}{e^{\omega_i}}]$.²⁰ In what follows we will study both scenarios.

5.2.2 Firms' demand curves

Turning to firm demand functions, we can use our estimates of markups to calculate the slope of the demand function at the equilibrium point. We denote this slope parameter as $b_{in} = (\mu_{in} - 1)/\mu_{in} * (P_{in}/Q_{in})$. It gives the estimate of the slope of the firm's demand curve for a given product, in a given market and time period, at the equilibrium price and quantity. Importantly, this parameter estimate does not rely on any assumptions on the functional form of the demand function, and it is not "estimated" by pooling observations across firms, markets, or years. Instead, it is a nonparametric measure of the slope of the demand for any given firm-product-market-year combination.

Our markup estimates are also informative of another feature of the firm's demand function. In particular, along with quantity data, they can tell us the relationship between equilibrium markups and quantity sold in a market. Table 8 reports these results, showing that markups are systematically and negatively related to quantity sold. While the numbers reported are admittedly just correlations, this finding is, nonetheless, robust to using variation across firms, markets, and time as the source of identification. For instance, in a specification with product-firm-market fixed effects, i.e., using time variation as the source of identification, a 1% increase in quantity sold is related to 0.3% smaller markups. Specifications that use variation across firms produce smaller estimates. This is expected as firms with more market power will sell more in a given market, which pushes up the correlation between markups and quantities. These results are, at the very least, suggestive of an underlying demand structure that allows demand elasticities to vary as equilibrium prices and quantities vary.²¹

As we discuss in Appendix B, a specification that allows for both stable preferences across time / markets and elasticities that vary with equilibrium prices and quantities is a linear (individual) consumer demand system with varying numbers of consumers. For this reason, we choose to approximate the firm's demand function with a linear demand function through the

²⁰In this case $MC_i = \theta[\frac{P_i^{M\gamma}}{e^{\omega_i}}]P^K^\alpha P^L^\beta$, where P^K and P^L are the rental rate of capital and wage rate, respectively, and θ is a parameter that depends on the capital, labor, and intermediate input shares in production (α, β, γ).

²¹Our findings here suggest that CES demand is probably not a good representation of preferences. This has implications for a number of literatures (for instance, see [Haltiwanger, Kulick, and Syverson \(2018\)](#) in the context of the literature on resource misallocation).

observed price-quantity point and with slope given by b_{in} above.²² Using the linearity, we can estimate consumers’ “willingness-to-pay” (the location parameter of the demand approximation) for the firm’s product in a given market and time period. Notably, this linear approximation is able to re-produce the observed negative relationship between equilibrium quantities and markups observed in the data while maintaining stable utility parameters.²³

Formally, we assume that firm-product demand is approximated by the linear demand function:

$$p_{in} = a_{in} - b_{in}q_{in} - \eta Q_{-in}, \quad (8)$$

where q_{in} is firm i ’s output in market n and Q_{-in} is the total output of firm i ’s competitors in market n (following [Melitz and Ottaviano \(2008\)](#)). Given the observed data on prices and quantities and the measures of b_{in} constructed from the estimated markups, we estimate the location parameter of the firm demand curve as $a_{in}^0 = a_{in} - \eta Q_{-in}$. The parameter a^0 gives our measure of the “willingness-to-pay” for a firm’s product in a given market. The slope parameter b provides a measure of market thickness: smaller values of b correspond to flatter demand curves and thus thicker market demand.²⁴

5.2.3 Exporters vs. non-exporters: the structure of demand, cost, and profitability

With our estimates of the structure of firm-level demand and costs in place, we can begin to examine what makes exporters different than non-exporters. Figures 3-5 show, separately for exporters and non-exporters, the estimated heterogeneity in the domestic demand location parameter (a_{id}^0), the slope of domestic demand (b_{id}), and the input-price weighted productivity ($[\frac{P_i^{M\gamma}}{e^{\omega_i}}]$). Visually, these figures indicate that exporters have slightly larger domestic demand location parameters than non-exporters, although the two distributions show significant overlap. As in the results reported in Figure 1, exporters and non-exporters have very similar distributions of input-price weighted productivities. Strikingly, the distribution of values of the slope of

²²It is worth emphasizing again that we do not impose a linear demand system when estimating demand heterogeneity. The slope estimates in our linear approximation are obtained from an unrestricted demand system. The linear approximation to this demand system is utilized here purely for the purpose of developing a profitability index of exporter status and for diagnostics on this index.

²³The negative correlation between equilibrium markups and quantities is an across product and time correlation. It can be captured by joint variations across products and time in the slope of the marginal cost curve and in b_{in} , the latter arising from variations in the number of customers demanding any particular product i at time t .

²⁴While this linear demand approximation has features in common with [Melitz and Ottaviano \(2008\)](#), it is different in that it allows for demand heterogeneity – different slope and intercept parameters – across varieties within the same product class. This heterogeneity is the result of different numbers of consumers demanding different varieties and not underlying utility parameter variation across varieties. In this way, the model has features analogous to the customer accumulation literature (see [Arkolakis \(2010\)](#) and [Gourio and Rudanko \(2014\)](#)).

domestic demand for exporters is significantly left-shifted relative to the one for non-exporters. Table 9 reports the results of a regression of these three sources of heterogeneity on an exporter dummy variable.²⁵ For completeness, it also reports the result of a regression of productivity on an exporter dummy variable. In all cases we include product-year fixed effects so that the estimates are identified off variation across firms. On average, exporters have 10% larger domestic demand location parameters and about 80% smaller demand slopes (167 log-points) when compared to non-exporters. As discussed in a previous section, both productivity and input-price weighted productivities are statistically the same for exporters and non-exporters.²⁶

Since profitability must be the ultimate criterion that drives firm decisions, we construct a profitability index for exporters and non-exporters using our estimated demand and cost parameters.²⁷ To make it possible, ultimately, to separately identify demand and cost impacts (and their interactions), the profitability index we construct is an approximation to the maximized value of profits, resulting from utilizing a linear approximation to the firm's marginal cost curve. Later in the paper we show that our main results hold under an alternative specification using the actual marginal cost curve.

To be precise, we assume that firm i 's upward-sloping marginal cost curve is approximated by the linear function $MC = c_i q_i^T$, where q_i^T denotes the total quantity produced by the firm (summing across all destinations). This approximation imposes the Cobb-Douglas restriction that the marginal cost curve passes through the origin and rules out negative marginal cost values that might arise in alternative linear approximations. Under this approximation, and with our linear demand approximation, we have that firm i 's profit maximizing output (in market n), q_{in} , is given by the condition:

$$a_{in}^0 - 2b_{in}q_{in} = c_i q_i^T = c_i q_{in} + c_i q_{i-n}^T \quad (9)$$

or

$$q_{in} = \frac{a_{in}^0 - c_i q_{i-n}^T}{2b_{in} + c_i}, \quad (10)$$

where q_{i-n}^T denotes the total quantity sold by the firm to all markets other than n . Given our

²⁵We obtain similar results for regressions against the number of export destinations.

²⁶This finding is similar to that of [Rivers \(2010\)](#) who also uses a gross output production function and models pricing behavior. A difference here is that we have data directly on the prices charged by firms and do not have to assume an explicit model for demand.

²⁷[Foster, Haltiwanger, and Syverson \(2008\)](#) make the same point in the context of determining firm exit *within* markets.

Cobb-Douglas specification, the value of c_i is given by $c_i = c_i^0 [\frac{q_i^T}{K_i^\alpha L_i^\beta}]^{(1/\gamma)} q_i^{T(-2)}$, with $c_i^0 = (1/\gamma) [\frac{P_i^{M\gamma}}{e^{\omega_i}}]^{1/\gamma}$. Note that the firm-specific component of the term c_i^0 depends only on the input-price weighted productivity of the firm. Substituting in for c_i , we have a solution for q_{in} as a function of demand and cost parameters and scale (the values of K_i , L_i , q_i^T , and q_{i-n}^T):

$$q_{in} = \frac{a_{in}^0 - c_i q_{i-n}^T}{2b_{in} + c_i^0 [\frac{q_i^T}{K_i^\alpha L_i^\beta}]^{(1/\gamma)} q_i^{T(-2)}}. \quad (11)$$

Profits for firm i in market n are then given by:

$$\Pi_{in} = 0.5 \left[\frac{(a_{in}^0 - c_i q_{i-n}^T)^2}{2b_{in} + c_i^0 [\frac{q_i^T}{K_i^\alpha L_i^\beta}]^{(1/\gamma)} q_i^{T(-2)}} \right] \quad (12)$$

Note that, with the exception of scale, our profit index is a function only of estimated demand and cost parameters. Since scale should normally be thought of as an equilibrium object, we address this in multiple ways, as described in the next paragraphs. In all cases, the ultimate goal is to examine how variation in the fundamental demand and cost parameters a^0 , b , and c^0 affect firm profitability.²⁸

As a first experiment, we set q_i^T equal to the median quantity sold of that product by non-exporters, \bar{q}^T , and set K_i and L_i to the median capital stock and labor force of non-exporters, \bar{K} and \bar{L} . This set of assumptions models the following thought experiment: Suppose that all firms only sold domestically – were all non-exporters – and had scale associated with the median non-exporter. From a profitability standpoint, and within the universe of estimated domestic market parameters, what would make the firms that are, in fact, exporters look different than those that are non-exporters? We can answer this question by noting that, under the thought experiment, the profitability index for the domestic market is:²⁹

$$\Pi_i^{Idx} = 0.5 \left[\frac{(a_i^0)^2}{2b_i + c_i^0 \bar{r}} \right] \quad (13)$$

where $\bar{r} = [\frac{\bar{q}^T}{\bar{K}^\alpha \bar{L}^\beta}]^{(1/\gamma)} \bar{q}^{T(-2)}$. This index captures how heterogeneity in the fundamental demand and cost parameters drive profit heterogeneity for a firm with marginal cost evaluated at the median quantity, producing at the median capital and labor intensity, were that firm selling on the domestic market only. Our estimating procedure and the structure we propose in this section give us estimates of the three key sources of firm heterogeneity: a^0 , b , and c^0 . Figure 6

²⁸Recall that, for reasons discussed earlier, we focus primarily on demand estimates from the domestic market.

²⁹Because all firms sell only in the domestic market, q_{i-n}^T in expression (12) is equal to zero.

shows the distribution of the above domestic profitability index, after controlling for product-year fixed effects. The dashed line shows the distribution for exporters while the solid line shows the distribution for non-exporters. What we see is that, when evaluated at the scale of the median non-exporting firm, the distributions of profitability for exporters' and non-exporters' overlap significantly but exporters are more profitable than non-exporters. The second to last column in Table 9 shows that exporters are, on average, 58 log-points more profitable than non-exporters, were they to operate at the same relatively small scale.

The next thought experiment still keeps scale as pre-determined but replaces \bar{q}^T , \bar{K} , and \bar{L} with the corresponding median values for exporters. Doing so implies values that are 12, 10, and 8 times larger, respectively, than the median values for non-exporting firms. This highlights the substantial size differences between exporters and non-exporters. We then conduct the same thought experiment as before. Figure 7 confirms that the larger scale allows exporters to leverage their demand advantage, and their profit distribution stochastically dominates the one for non-exporters. Since the main distinction between exporters and non-exporters is that the former have flatter demands, i.e., can sell more units without having to drop prices too much, the larger capacity magnifies the profit advantage of exporters. The last column in Table 9 shows that exporters are, on average, 127 log-points more profitable than non-exporters.

An obvious alternative to either of the above thought experiments is one that assumes that the observed inputs and output levels are optimally chosen and to evaluate, in this context, the profitability of exporters and non-exporters. Given that exporters and non-exporters differ primarily in terms of demand parameters, one should expect in this case that differences in profitability must be ultimately associated to demand differences, even if working through scale. Indeed, the profitability index under this thought experiment captures not only the direct effects of demand parameters and productivity on profits, as previously, but also the indirect effects via scale. Given that our production functions are estimated to be roughly constant returns to scale, we have that profits under the thought experiment are given by:

$$\Pi_i^{Idx} = \frac{(a_i^0 - MC_i)^2}{4b_i}, \quad (14)$$

where MC_i is the marginal cost value estimated in Section 4. Figure 8 reports this profitability index for exporting and non-exporting firms and confirms that exporters are significantly more profitable. Because this index is scale independent, we use it to place a number on the difference in profitability between exporters and non-exporters: exporters are, on average, 199 log-points more profitable than non-exporters.

5.2.4 Disaggregating profits: demand vs cost

All of the analysis so far indicates that market thickness is of first-order importance in determining scale and export status. While the distributions of willingness-to-pay and productivity are very similar between exporters and non-exporters, the distribution of market thickness is very different. These differences result in exporting firms having a significantly higher profitability index than non-exporting firms.

This being said, one should be cautious in ruling out a role for willingness-to-pay and productivity in determining profitability. If willingness-to-pay and productivity are negatively correlated – for example, if firm investments in higher willingness-to-pay come at the expense of investments in higher productivity – then this negative correlation and the large impact of market thickness on profitability may mask more subtle roles played by each of these variables. In order to investigate this possibility, we study the roles that a^0 and c^0 play in our profitability index once normalized by the market thickness variable, b . In particular, we rewrite equation (13) as:

$$\Pi_i^{Idx} = 0.5 \left[\frac{\frac{(a_i^0)^2}{b_i}}{\left(2 + \frac{c_i^0}{b_i} \bar{r}\right)} \right] \quad (15)$$

Under this normalization, heterogeneity in the profitability of a firm depends on the two components of interest: normalized willingness-to-pay, $\frac{(a_i^0)^2}{b_i}$ and normalized productivity, $\frac{c_i^0}{b_i}$.

Figure 9 plots these two components based on export status. We find that there is a strong positive correlation between normalized cost-side and demand-side heterogeneity. Indeed, controlling for product-time effects, the correlation (in logs) between a^0 and c^0 is 0.874.³⁰ This correlation is indicative of the aforementioned trade-off between investments in productivity enhancements and enhancements in willingness-to-pay. We also find that exporters are shifted both down (lower costs / higher productivity) and to the right (higher willingness-to-pay) relative to non-exporters. In essence, we have that, conditional on willingness-to-pay, exporters have higher productivity than non-exporters; conditional on costs, exporters have higher domestic willingness-to-pay. These results are displayed in a regression format in Table 10.

This result highlights the importance of controlling for demand heterogeneity when examining cost/productivity differences across firms, in particular by export status. Indeed, if we

³⁰This finding is in keeping with that of Roberts et al. (2018) that finds a correlation between the firm-specific demand and cost parameters for Chinese footwear exporters of 0.709. This strong correlation drives the correlation of log prices and log marginal costs in their model.

regress the measure of normalized cost-heterogeneity against a dummy for export status, without controlling for demand heterogeneity, the results suggest that exporters have significantly higher costs than non-exporters (see column 1). However, once we condition on the measure of normalized demand-side heterogeneity as well (column 3), we see that exporters in fact have lower costs. Similarly, failing to control for cost-heterogeneity when examining the relationship between demand and exporting leads to an upward bias in the estimate, driven by the positive correlation between costs and demand.

To summarize, we find that export firms are larger and more profitable in the domestic market, in part, because they have thicker markets – flatter domestic demand curves– which lead to larger scale. At the same time, productivity and willingness-to-pay still matter for profitability and export status. In the case of these two factors, though, there is no one-size-fits-all pattern to distinguish exporters from non-exporters. What exporters have in this case is a more favorable trade-off between promoting willingness-to-pay in the domestic market and enhancing productivity: enhancing willingness-to-pay comes with a smaller loss in productivity enhancement. These factors combine to give exporters a higher domestic profitability index than non-exporters.

5.2.5 From domestic profitability to exporting

The question yet to be addressed in all of the above is why domestic profitability is a good predictor of export status. That is, why is higher domestic profitability a good indicator of higher profitability in foreign markets?³¹ An obvious explanation for this outcome is that domestic demand characteristics carry over into foreign markets. In this section, we investigate the extent to which this is true. Specifically, we use our metric of normalized demand-side heterogeneity $\frac{(a_i^0)^2}{b_i}$ to ask whether high domestic demand is correlated with high foreign demand.

Column 1 in Table 11 reports results from a regression of the (log) foreign demand indices of a firm on its domestic counterpart, controlling for product-time-foreign destination fixed effects. Column 2 shows the results of the same regression using only observations from the firm’s main foreign market (based on the share of the firm’s sales in dollars). In both cases, foreign demand is found to be strongly correlated with firms’ domestic demand. Figures 10 and 11 display the correlation between firms’ domestic and foreign demand-side heterogeneity.

³¹It is worth noting that there is a large literature on Home Bias, i.e., large domestic demand and increasing returns to scale in production leading to low marginal cost and thus exporting (see [Linder \(1961\)](#) for an early articulation of this hypothesis and [Krugman \(1980\)](#) for its formalization). This is not what is happening here, as we find roughly constant returns to scale in most industries.

In Figure 10 foreign demand is measured as the average $\frac{(a_i^0)^2}{b_i}$ across the destinations the firm sells to and, in Figure 11, it is measured as $\frac{(a_i^0)^2}{b_i}$ of the firm's main foreign market. In the first case the rank correlation between domestic and foreign demand-side heterogeneity equals 0.51 while in the second it equals 0.43. Exporters with high domestic demand indices tend to have high foreign demand indices as well.

Foreign demand indices vary systematically across destinations as well. Table 12 shows estimates for gravity regressions with the demand index within firm, product, and time being the dependent variable. We find that the firm has higher estimated willingness-to-pay in countries with high income per-capita, and has flatter demand curves in larger countries. In farther away countries, the firm tends to have slightly higher demand location parameters and significantly steeper demands.

5.2.6 The exceptions to the rule

Although we find that exporters tend to have a higher domestic profitability index than non-exporters, it would be surprising if there were complete separation: the lowest exporter profitability index higher than the highest non-exporter profitability index. In fact, we do find exporting firms that are not particularly exceptional relative to non-exporting firms, either in terms of cost or demand. One can see this in the overlapping left tails of the series in any of the figures reporting the profitability indices (Figure 8, for instance). A natural question, given the evidence above, is whether these firms that are apparently unexceptional domestically have disproportionately high foreign profitability. If they do, what is the source of this higher profitability: high foreign willingness-to-pay, thick foreign markets, or both?

In order to examine this issue, we separate our sample of exporters into two groups, based on whether their domestic profit index is above or below the median profitability among exporters. We then regress the (log) profit index in each foreign market on the (log) domestic profit index interacted with an indicator for below median domestic profitability (controlling for product-time fixed effects). We compute the predicted values from this regression and plot them in Figure 12 against the domestic profit index.

For both groups of firms, we find that foreign and domestic profits are positively correlated with each other. On average, a 1% increase in domestic profitability is associated with a 0.47% increase in foreign market profitability. However, the relationship is about 50% weaker for firms with lower domestic profitability. In other words, exporting firms with especially low domestic profitability have unexpectedly high foreign profitability. These results are consistent

with the hypothesis that firms that are unexceptional domestically and yet manage to sell in foreign markets do so because they have particularly strong demand in these foreign markets.

To study the source of the *relatively* high foreign demand these unremarkable exporters have, we run regressions of the difference between the firms' foreign and domestic demand location parameters and slopes on a constant and a dummy variable indicating whether the firm is below the median value in domestic profitability. Table 13 reports the estimates. The unremarkable exporters tend to have both larger foreign demand location parameters (higher willingness-to-pay) and flatter foreign demand slopes (thicker markets), relative to their corresponding domestic values. Table 14 shows that these firms tend to sell to larger and richer countries and to countries that are farther away from Chile and do not speak Spanish. The confidentiality of our data does not allow us to find out details about these unremarkable exporters, but we were able to identify that these exporters are over-represented in the beverage category. One explanation that suggests itself, in this instance, is that at least some of these exporters sell higher-priced Chilean wines that have greater demand in richer foreign countries than in Chile.

5.2.7 Robustness: Do the linear approximations matter?

In many of the above results, the profitability index, and related components, utilize linear approximations to the firm-level demand function and marginal cost. As a robustness check on whether the linear approximations are driving some of our findings, we re-derive the profitability index assuming an iso-elastic demand approximation and using the firms estimated marginal cost curve. See Appendix C for the details of this derivation.

We start by approximating the firms' demand function using an iso-elastic function of the form $p_{in} = \kappa_{in} q_{in}^{-\rho_{in}}$. Just like with linear demand, ρ_{in} is derived from the markup estimates and κ_{in} can be obtained using our data on p_{in} and q_{in} . However, in this case, the observed decline in equilibrium markups with quantity must be driven by changes over firms, time, and market in the parameter ρ_{in} . In other words, it does not arise endogenously as firms expand output, as the firm's optimal markup does not change with quantity.

Figures 13 and 14 show, separately for exporters and non-exporters, the estimated heterogeneity in the κ and ρ parameters for the domestic market. Visually, these figures indicate that exporters have slightly less elastic domestic demands (larger ρ) than non-exporters, although the two distributions show significant overlap. The distribution of values of the κ parameter, however, for exporters is shifted to the right relative to the one for non-exporters. It is worth noting that, with the iso-elastic demand function, the κ parameter is the one capturing the market thickness effect, just like the demand slope parameter in the linear demand case. Therefore,

both with linear and CES demand approximations the message is the same: exporters have thicker domestic demands than non-exporters.

Using the iso-elastic approximation to demand and the estimated marginal cost curve in equation (7), we have that firms' domestic profit index is:

$$\Pi_i^{Idx-CES} = \kappa_i \left[\frac{(1 - \rho_i) \kappa_i}{\bar{\psi}_i \delta} \right]^{\frac{1 - \rho_i}{\rho_i + \delta - 1}} - \bar{\psi}_i \left[\frac{(1 - \rho_i) \kappa_i}{\bar{\psi}_i \delta} \right]^{\frac{\delta}{\rho_i + \delta - 1}} \quad (16)$$

where $\bar{\psi}_i = P_i^M \left[\frac{1}{K_i^\alpha L_i^\beta e^{\omega_i}} \right]^{\frac{1}{\gamma}}$, and $\delta = \frac{1}{\gamma}$.

Figures 15, 16, and 17 show the profitability indices for exporters and non-exporters under small (median non-exporting firm), large (median exporting firm), and equilibrium scales, respectively. In all cases exporters are significantly more profitable than non-exporters. Overall, these results confirm that the linear approximations do not drive our main findings.

6 Discussion

A firm is characterized by its marginal cost and demand functions. Given that a firm's demand function varies by market, including markets in which the firm does not operate, it is not surprising that economists know more about firm heterogeneity on the production side than on the demand side. Even then, however, lack of information on demand heterogeneity may lead to incorrect estimates of firms' cost heterogeneity. This is particularly important when comparing exporters and non-exporters since the distinguishing factor between these firms is the markets in which they sell. This paper solves this problem by jointly estimating demand and costs in the domestic market and all foreign markets in which firms participate. What we find is that estimating individual firm and market-specific demand heterogeneity matters. Foreign markets are significantly more competitive for Chilean firms than the Chilean domestic market, and by not taking this into account one would under-estimate exporters' markup advantage by 80%. When properly accounting for demand heterogeneity, we find that, while both demand and cost heterogeneity matter, the former plays the dominant role in determining the firm's export status. Moreover, we find that the specific demand characteristic that matters is the ability to sell large amounts without having to significantly lower prices, i.e., having flat demand curves or thick markets. This characteristic not only matters for domestic profitability but it also tends to carry over in foreign markets.

In essence, what our findings show is that it is product characteristics that are the key determinant of export success. This result has important policy implications. Typically, policies

aimed at promoting exports target firm-level productivity enhancement. Our results show that such policies are unlikely to promote exporting if the extra units produced significantly reduce the price charged by the firm. As selling in foreign markets is known to require significant fixed costs, our finding that foreign market thickness is an important driver of export success, although new, should not come as a big surprise.

While a study of the reasons why exporters have thicker markets is beyond the scope of this paper, the measure of advertising expenditures in our data provides a possible path for future research. Exporters spend 79% more in advertising as a share of sales compared to non-exporters, even controlling for firm size. This suggests that exporters have larger returns from advertising, perhaps because of spill-over effects on foreign markets. Moreover, advertising expenditure is strongly positively correlated with our measure of demand heterogeneity $\frac{(a_i^0)^2}{b_i}$, and has a similarly strong relationship with both components of demand heterogeneity. This may be evidence that advertising affects demand through both “prestige” (via a^0) and “information” (via b) effects.³²

³²See [Stigler \(1961\)](#); [Butters \(1977\)](#) and [Becker and Murphy \(1993\)](#) for theoretical discussions of the informative and prestige effects of advertising, respectively. For an empirical investigation of these two effects see [Akerberg \(2001\)](#).

A Appendix: Data construction

The first dataset we use comes from Chile’s annual industrial survey *Encuesta Nacional Industrial Anual* (ENIA) from the period 2002-2009. This survey is conducted by Chile’s *Instituto Nacional de Estadísticas* (National Institute of Statistics–INE) and covers all manufacturing plants with 10 or more workers. For each product produced by each plant-year pair, separate data on the value (revenues) and quantity is reported, in addition to the unit of quantity measurement (e.g., litres, kilograms). Each product is classified by the 5-digit Central Product Classification (CPC) code.³³ This dataset also contains a measure of the total quantity of exports for each product produced.

The second dataset is collected by Chile’s *Servicio Nacional de Aduanas* (National Customs Service) and covers all Chilean export transactions from the period 2002-2009. Each observation relates to a separate export transaction and contains information on the identity of the exporting firm, the 8-digit Harmonized System product classification of the product, the destination country, the free-on-board (FOB) value, the quantity, and the unit of quantity measurement. We use a crosswalk to aggregate products from the HS-8 classification to CPC-5.

In order to merge these two datasets, we aggregate the ENIA data across plants within a firm to create observations at the firm-product-year level. We then aggregate the Customs data to the firm-product-year level. In addition, in order to obtain a consistent measure of output between ENIA and Customs, we aggregate both datasets to the 3-digit CPC level.

Our production function estimation is performed separately for all products within each 3-digit industry code (ISIC). In some cases, products within the same industry are measured in different units, and thus the quantities are not directly comparable. In order to deal with this, we construct an equivalent measure of quantities using the following procedure. First, for each 5-digit CPC product, we compute an average price across all firms and years. Second, within each 3-digit CPC product, we select a numeraire product (the one with the highest sales). Third, for each 5-digit CPC product, we multiply the quantity by the ratio of the average numeraire price to the average price for that product, to translate quantities into units of the numeraire product. These adjusted quantities are then summed at the firm-year-3-digit CPC level to form our quantity measure.

In order to focus on the main products produced by a firm, we drop products with fewer than 40 observations (firm-time pairs). To minimize the impact of outliers, we drop observations with an overall output price (a weighted average across all markets) or a domestic price that is

³³The raw data collected by INE are at the 7-digit level, but the data we were provided are at the 5-digit level.

in the top or bottom 2.5% of the distribution for the corresponding product.

B Appendix: Utility maximization framework

In this Appendix, we develop a microstructure from which one can derive a linear, heterogeneous demand model with stable utility function parameters. This model is related to that of [Melitz and Ottaviano \(2008\)](#) in that it posits a linear demand structure. It is unlike the [Melitz and Ottaviano \(2008\)](#) model in that it allows for heterogeneous demand across product varieties within the same product category. This feature is required in order to capture the variation in demand slopes that we observe across products in the same product category. We derive our results for a 2 good, 2 variety setting, although it should be obvious how to extend this model to more varieties.

To proceed, consider an economy with 2 goods: X a composite good with price normalized to 1 and Y a differentiated good with varieties Y_1 and Y_2 . Variety Y_1 is produced by a single firm – firm 1 – and variety 2 is produced by a single firm, firm 2. Each firm produces its respective variety with constant marginal cost, $c_1 = c_2 = c$. There are 2 types of consumers in the economy, type 1 and type 2. A type 1 consumer prefers Y_1 and X to Y_2 in the sense that there is no price for Y_2 above c such that the type 1 consumer would rather buy Y_2 than either X or Y_1 , for any price of Y_1 . A type 2 consumer is the opposite and prefers X and Y_2 to Y_1 . There are n_1 type 1 consumers and $n_2 > n_1$ type 2 consumers. The utility function for a type 1 consumer is given by:

$$U_1 = x + ay_1 - .5by_1^2 \quad (17)$$

with lower case letter giving individual consumption levels of the various goods. The utility for a type 2 consumer is symmetric:

$$U_2 = x + ay_2 - .5by_2^2 \quad (18)$$

All consumers have identical income levels of m and the total number of consumers is $N = n_1 + n_2$.

Under this specification, the inverse demand function for a representative type 1 consumer is:

$$p_1 = a - by_1. \quad (19)$$

For a representative type 2 consumer, the demand function is:

$$p_2 = a - by_2. \quad (20)$$

Market demand for Y_1 is then given by:

$$p_1 = a - \frac{b}{n_1}Y_1 \quad (21)$$

and for Y_2 by:

$$p_2 = a - \frac{b}{n_2}Y_2. \quad (22)$$

Since $n_2 > n_1$ the slope of the market demand curve for Y_2 is flatter than the slope of the market demand curve for Y_1 . Further, of aggregate income $M = mN$, a fraction n_1/N is spent by type 1 consumers on X and Y_1 and a fraction n_2/N is spent by type 2 consumers on X and Y_2 .

How does this aggregate? Consider a representative consumer with income M who allocates it among X , Y_1 , and Y_2 . Let this consumers preferences be given by then utility function

$$U = (U^1)^{n_1/N} (U^2)^{1-n_1/N} \quad (23)$$

with U^1 and U^2 defined respectively by:

$$U^1 = x + ay_1 - .5\frac{b}{n_1}y_1^2 \quad (24)$$

and

$$U^2 = x + ay_2 - .5\frac{b}{n_2}y_2^2. \quad (25)$$

This representative consumer spends a fraction n_1/N of M on X and Y_1 and a fraction n_2/N on X and Y_2 , just as in the disaggregated case. For any prices above c , the quantity demanded of X , Y_1 and Y_2 will also be the same as in the disaggregated case. This idea easily extends to the N goods case.

C Appendix: Iso-elastic demand system

Consider a firm producing variety i and selling in market n facing demand given by the function

$$p_{in} = \kappa_{in} q_{in}^{-\rho_{in}} \quad (26)$$

where $\kappa_{in} > 0$ is a product-destination specific demand shifter and $0 < \rho_{in} < 1$. Suppose that the firm's total cost function is given by the expression

$$tC_i = \bar{\psi}_i q_i^\delta \quad (27)$$

where $\bar{\psi}_i > 0$ is a firm-specific cost parameter and $\delta > 1$. Then, the firm's profit maximizing level of q_{in} is given by the condition

$$(1 - \rho_{in})\kappa_{in}q_{in}^{-\rho_{in}} = \bar{\psi}_i \delta q_i^{\delta-1} \quad (28)$$

so that the profit maximizing output level is

$$q_{in} = [(1 - \rho_{in})\kappa_{in}/\delta\bar{\psi}_i]^{1/(\rho_{in}+\delta-1)}. \quad (29)$$

The maximized value of profits is given by the expression

$$\pi_{in} = \kappa_{in}[(1 - \rho_{in})\kappa_{in}/\bar{\psi}_i]^{(1-\rho_{in})/(\rho_{in}+\delta-1)} - \bar{\psi}_i[(1 - \rho_{in})\kappa_{in}/\delta\bar{\psi}_i]^{\delta/(\rho_{in}+\delta-1)}. \quad (30)$$

This is the expression given in equation (16) of the text.

In the above expression, if each individual consumer c in country n has an identical CES individual demand function $q_{in}^c = \zeta_{in} p_{in}^{-\varepsilon}$ and there are M_n such individuals, then it is straightforward to show that the value of κ_{in} is $(\zeta_{in} M_n)^{1/\varepsilon}$. In this sense, κ_i is the appropriate measure of market thickness for a given product i .

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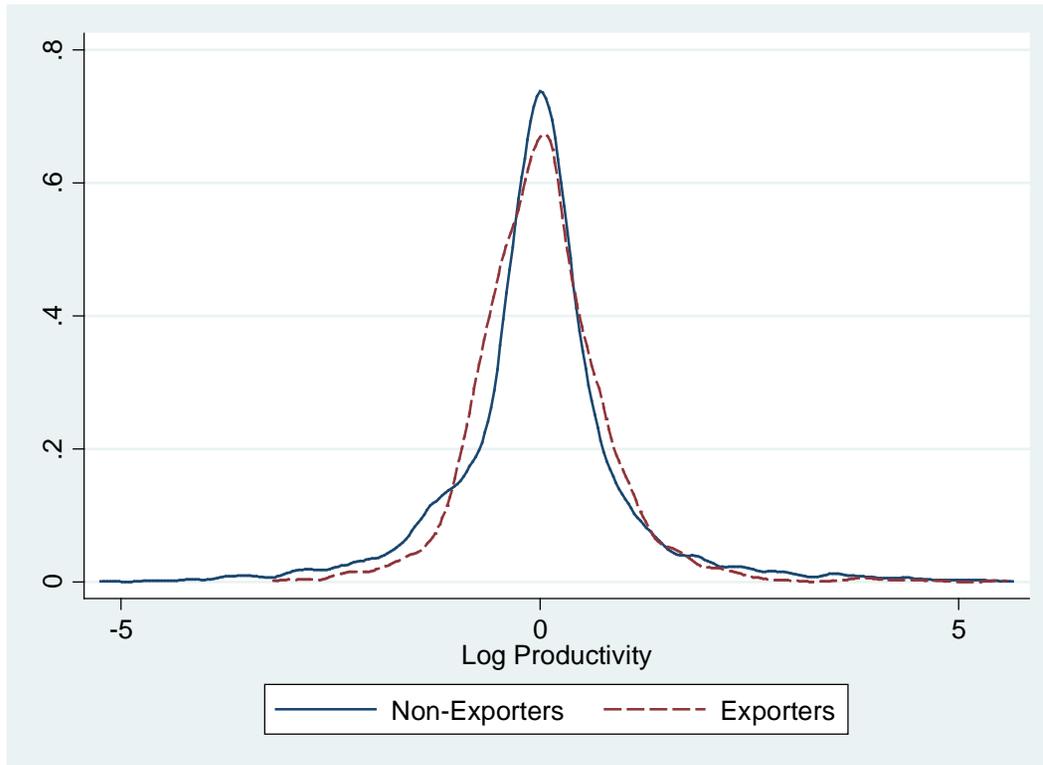
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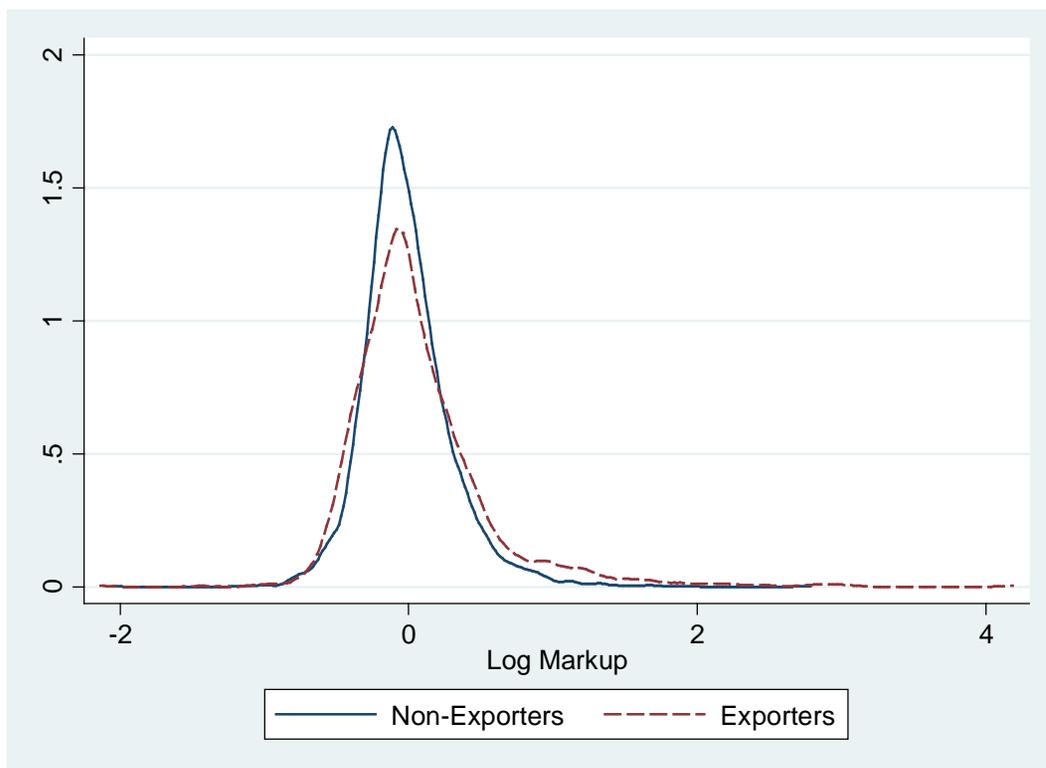
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Figure 1: Distribution of Productivity



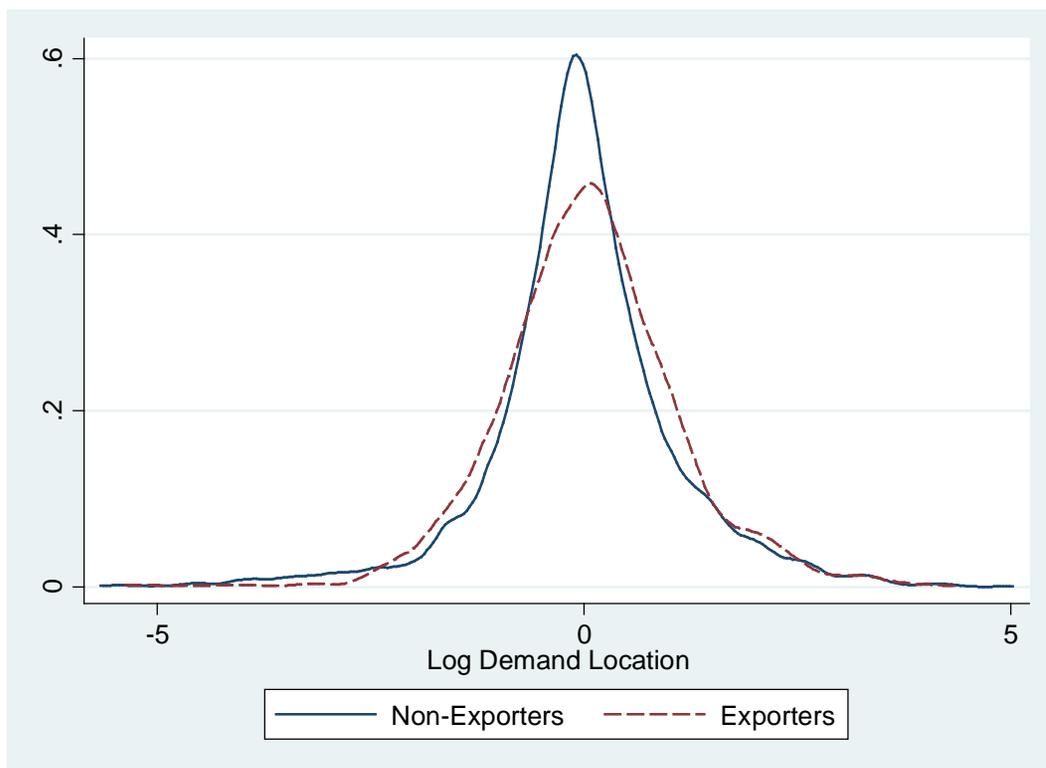
Notes: In this figure we plot the distribution of (log) productivity, separately for exporters and non-exporters. Productivity is measured at the firm-product-year level and is net of product-year fixed effects. The left panel uses observations from all products. The right panel uses only observations from a firm's main product.

Figure 2: Distribution of Domestic Markup



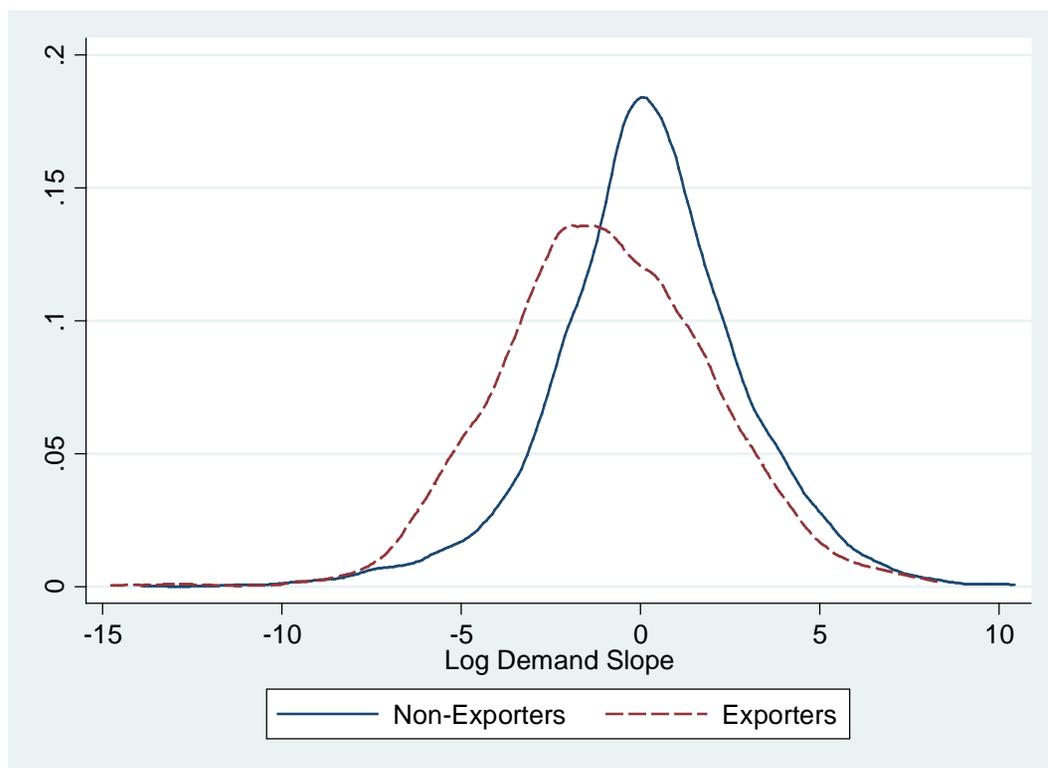
Notes: In this figure we plot the distribution of the (log) domestic markup, separately for exporters and non-exporters. The firm-product-year domestic markups are net of product-year fixed effects. The left panel uses observations from all products. The right panel uses only observations from a firm's main product.

Figure 3: Distribution of Domestic Demand Location Parameter



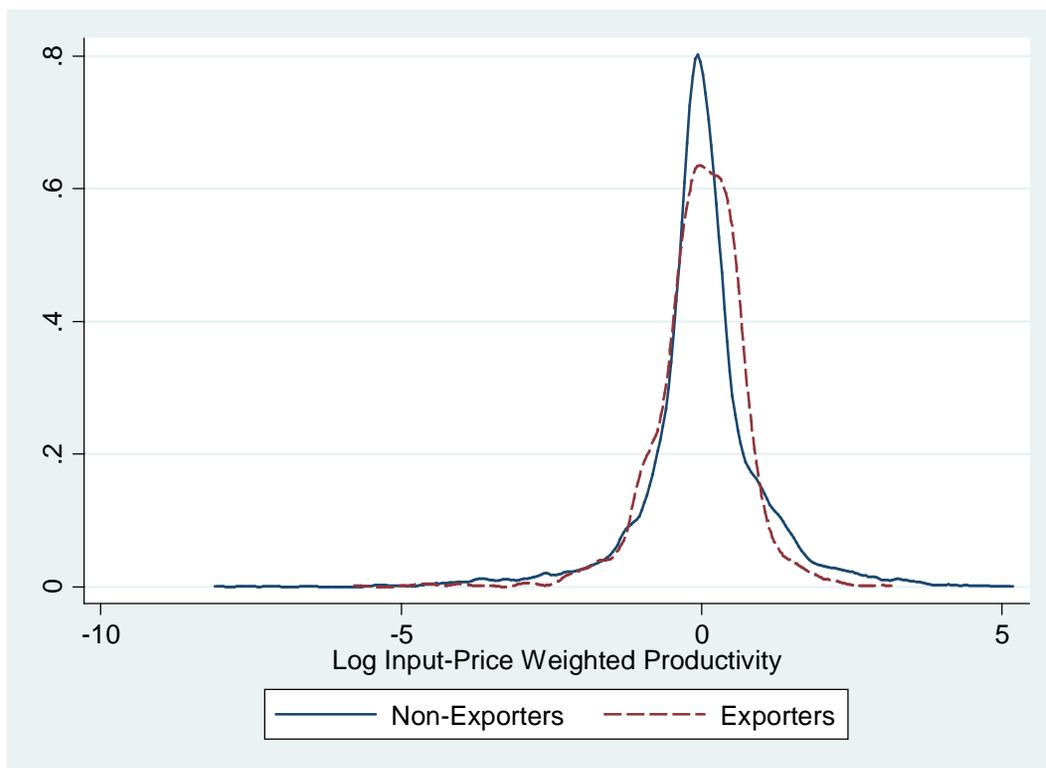
Notes: In this figure we plot the distribution of the (log) domestic demand location parameter (a^0), separately for exporters and non-exporters. This parameter is measured at the firm-product-year level and is net of product-year fixed effects.

Figure 4: Distribution of Domestic Demand Slope



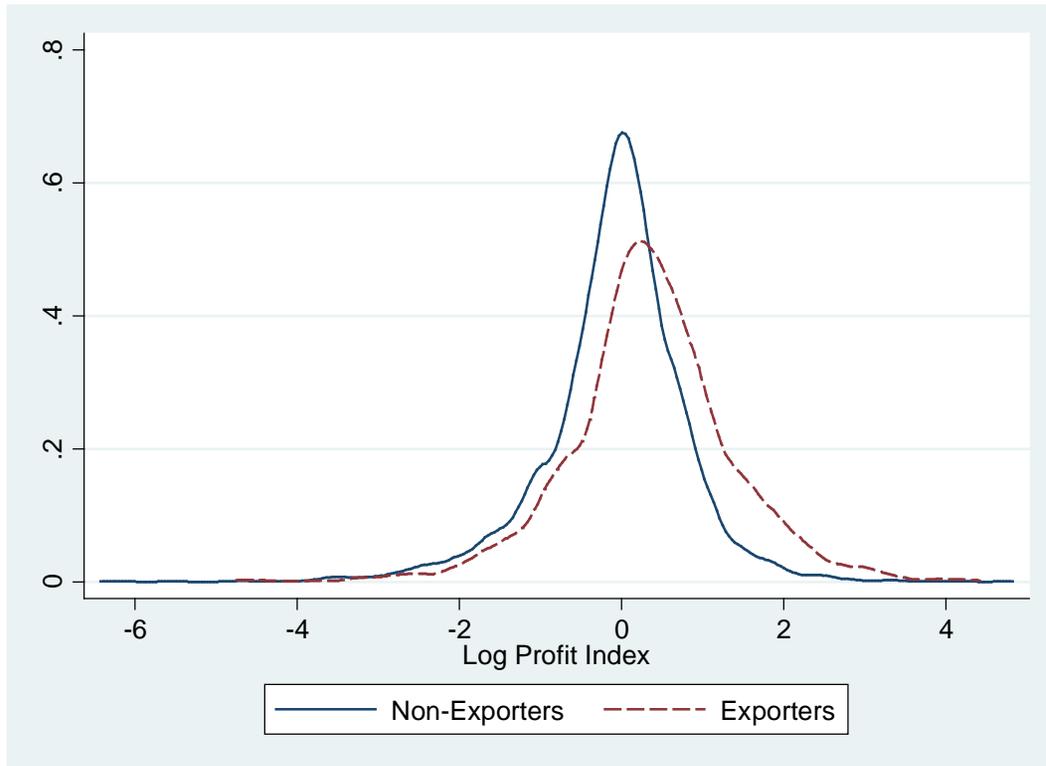
Notes: In this figure we plot the distribution of the (log) domestic demand slope (b), separately for exporters and non-exporters. The slope is measured at the firm-product-year level and is net of product-year fixed effects.

Figure 5: Distribution of Input-Price Weighted Productivity



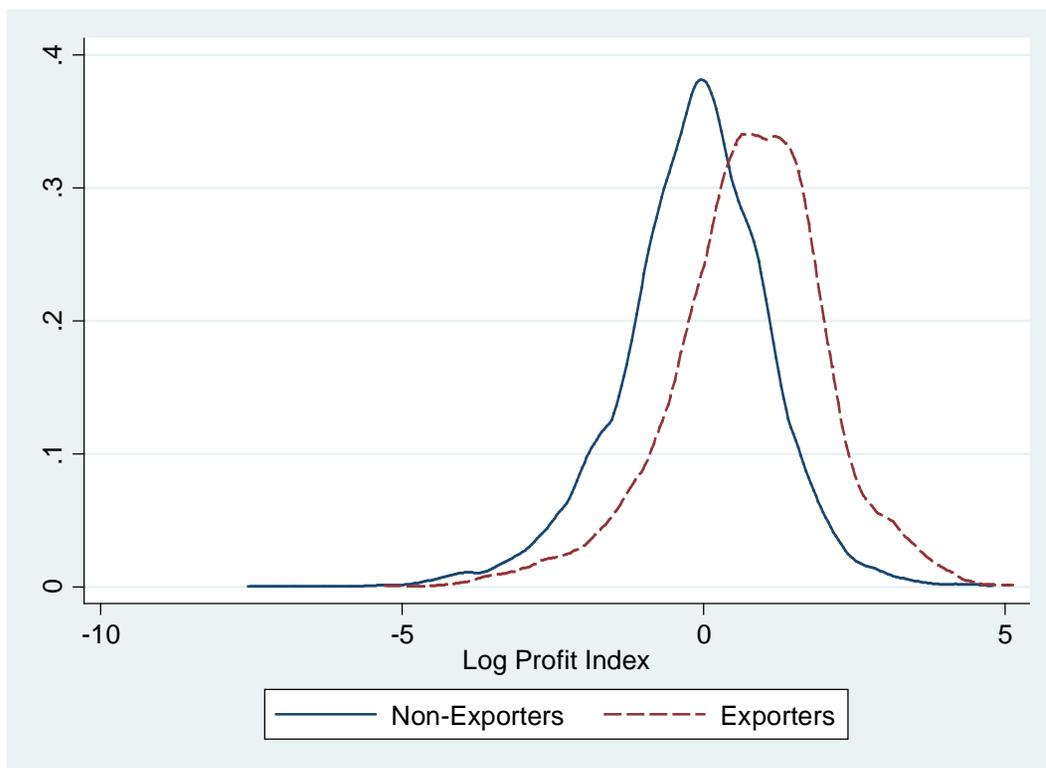
Notes: In this figure we plot the distribution of the (log) cost-side heterogeneity $\left(\frac{(P^M)^Y}{e^\omega}\right)$, separately for exporters and non-exporters. It is measured at the firm-product-year level and is net of product-year fixed effects.

Figure 6: Distribution of Domestic Profitability Index: Scale of Non-Exporters



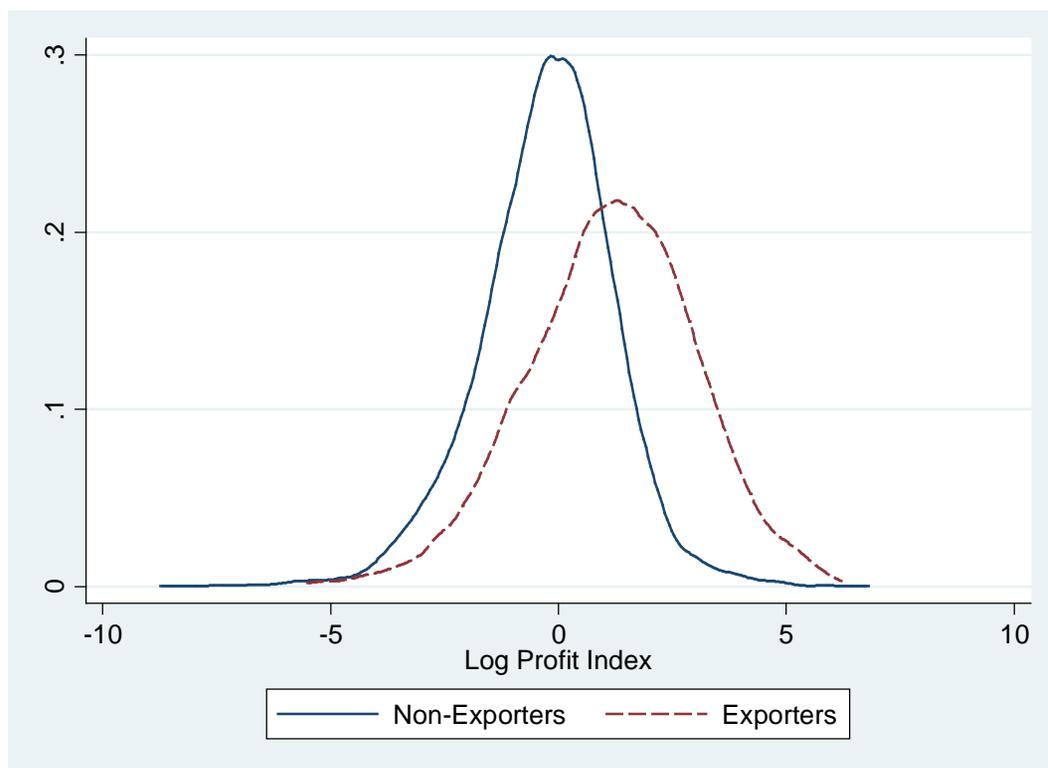
Notes: In this figure we plot the distribution of the (log) domestic profitability index, separately for exporters and non-exporters. The index is measured at the firm-product-year level, and is computed by fixing capital and labor at values corresponding to the median values for a non-exporting firm.

Figure 7: Distribution of Domestic Profitability Index: Scale of Exporters



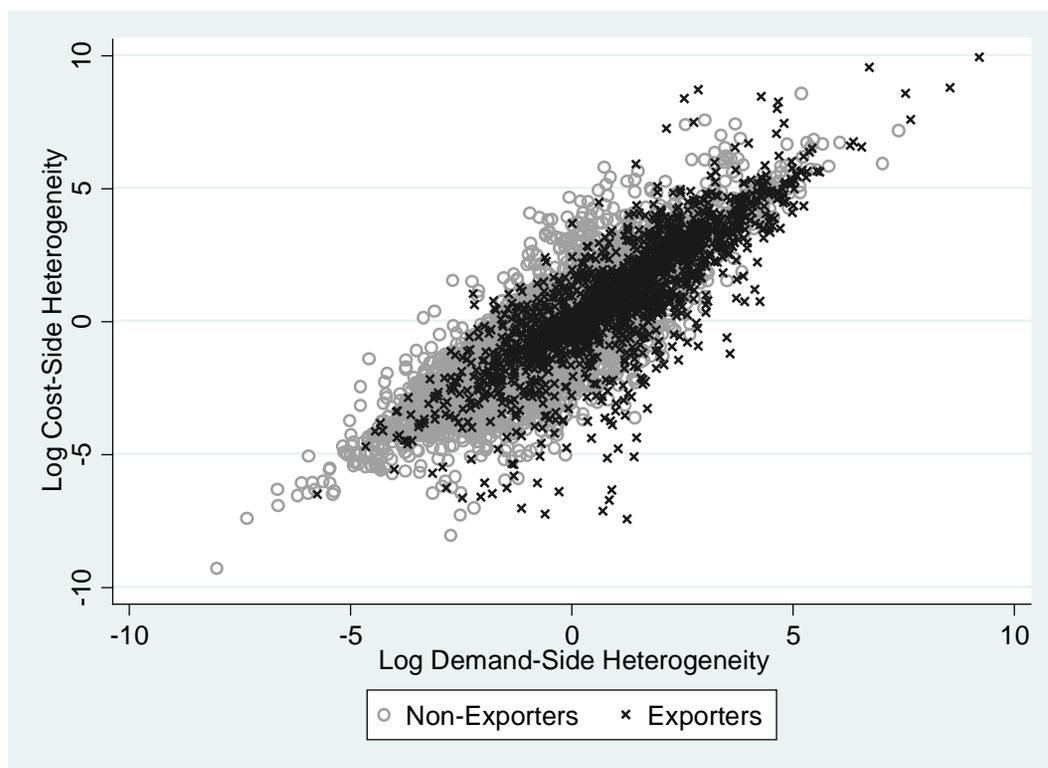
Notes: In this figure we plot the distribution of the (log) domestic profitability index, separately for exporters and non-exporters. The index is measured at the firm-product-year level, and is computed by fixing capital and labor at values corresponding to the median values for an exporting firm.

Figure 8: Distribution of Domestic Profitability Index: Long-Run Measure



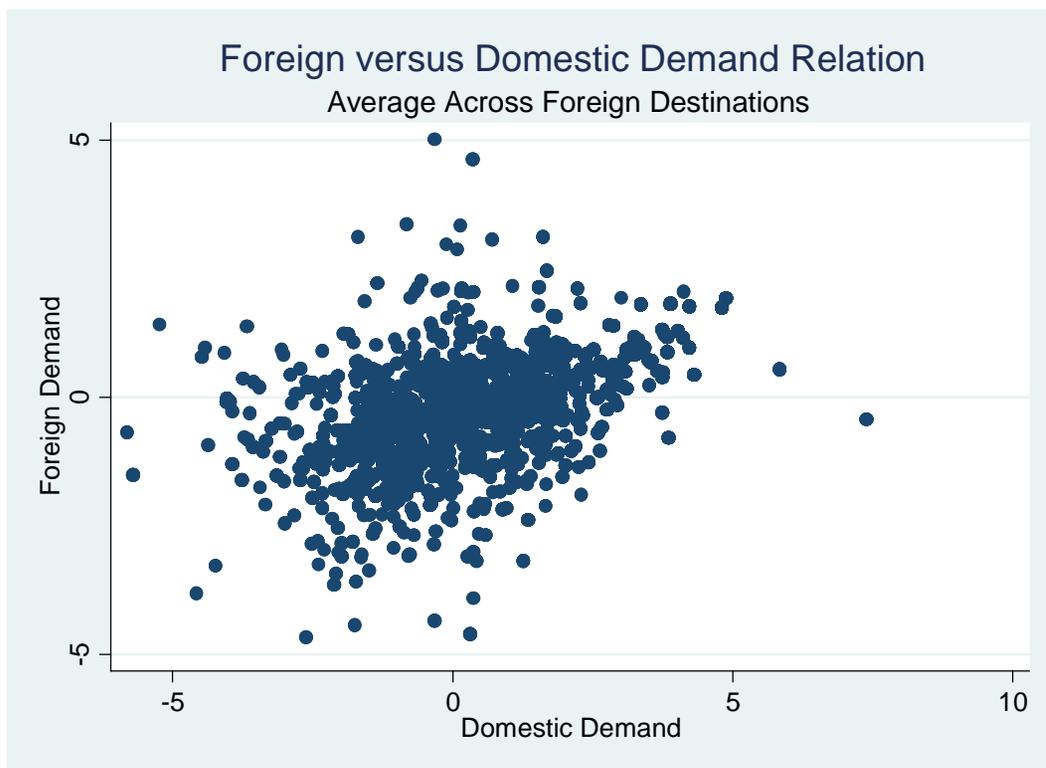
Notes: In this figure we plot the distribution of the (log) domestic profitability index, separately for exporters and non-exporters. The index is the long-run version in equation (14) with constant marginal costs. It is computed at the firm-product-year level and is net of product-year fixed effects.

Figure 9: Relationship between Domestic Demand and Cost Heterogeneity in Profitability



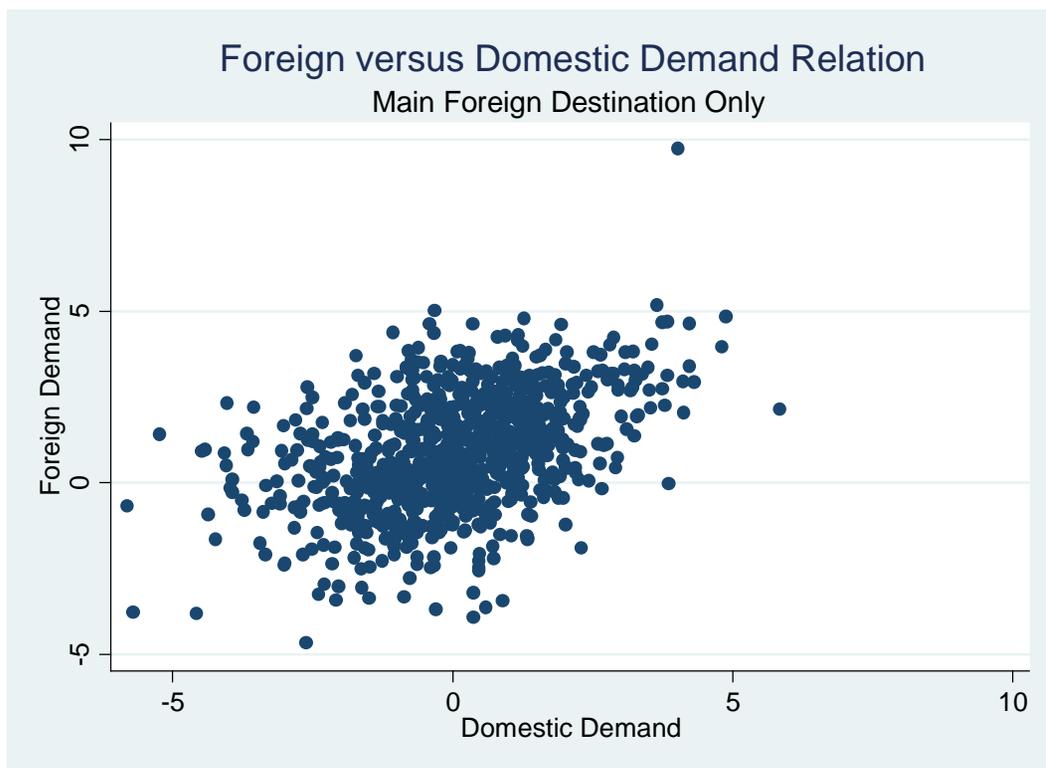
Notes: In this figure we plot (in logs) the measure of cost-side ($\frac{c^0}{b}$) heterogeneity in profitability against the demand-side heterogeneity ($\frac{(a^0)^2}{b}$), separately for exporters and non-exporters. Both measures are computed at the firm-product-year level and are net of product-year fixed effects.

Figure 10: Relationship Between Foreign and Domestic Demand—Averaging Across Foreign Destinations



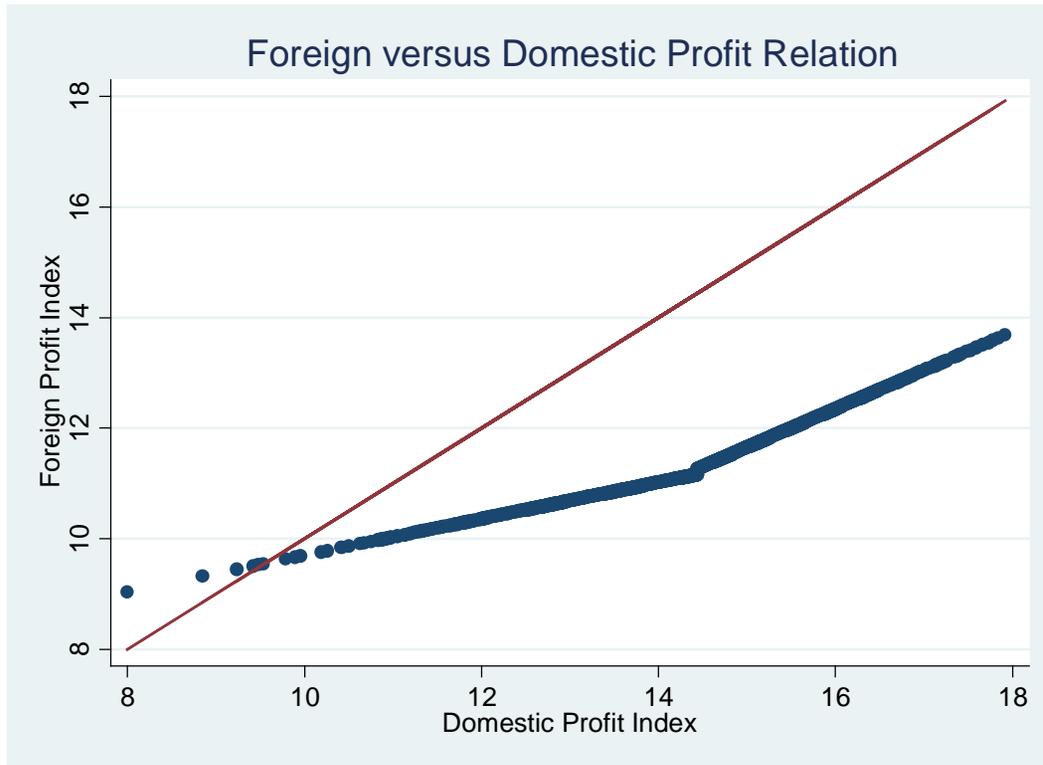
Notes: In this figure we plot the (log) measure of demand-side heterogeneity $\left(\frac{a^0}{b}\right)^2$ averaged across all foreign destinations against the domestic counterpart. The observations vary at the firm-product-year level and are all net of product-market-year fixed effects. The rank correlation between the domestic and average foreign demand-side heterogeneity is 0.51.

Figure 11: Relationship Between Foreign and Domestic Demand—Main Foreign Destination Only



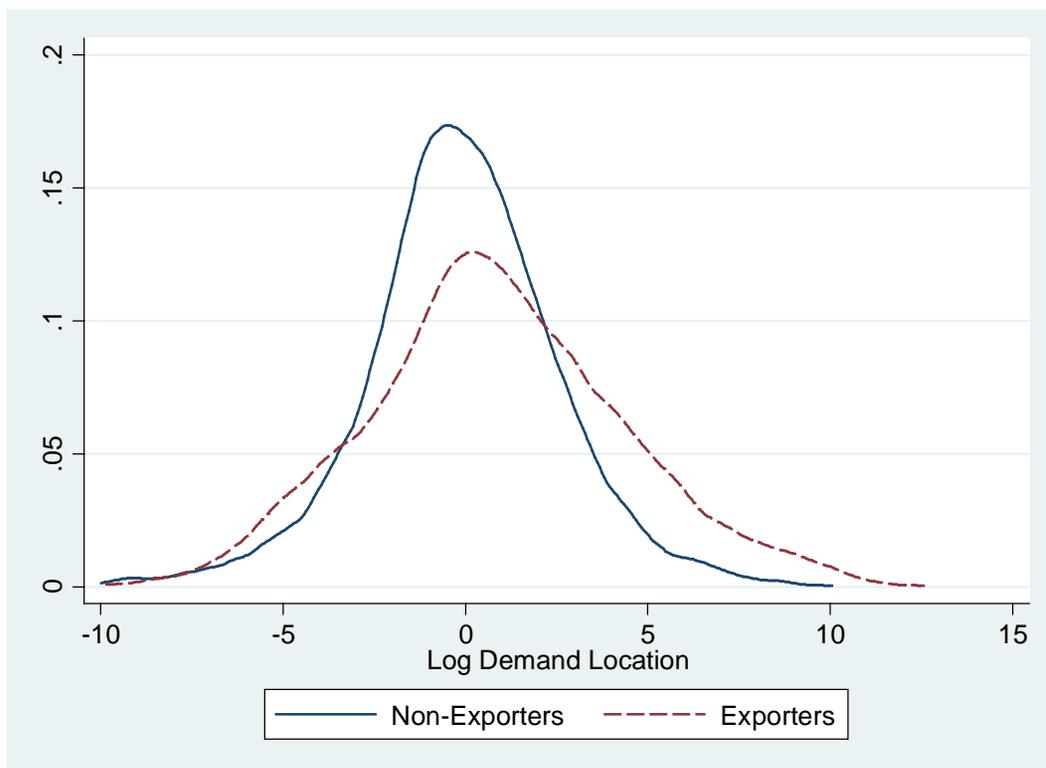
Notes: In this figure we plot the (log) measure of demand-side heterogeneity $\left(\frac{a^0}{b}\right)^2$ for the main foreign destination (largest share of revenues) against the domestic counterpart. The observations vary at the firm-product-year level and are all net of product-market-year fixed effects. The rank correlation between the domestic and foreign demand-side heterogeneity is 0.43.

Figure 12: Relationship between Foreign and Domestic Profit Indices



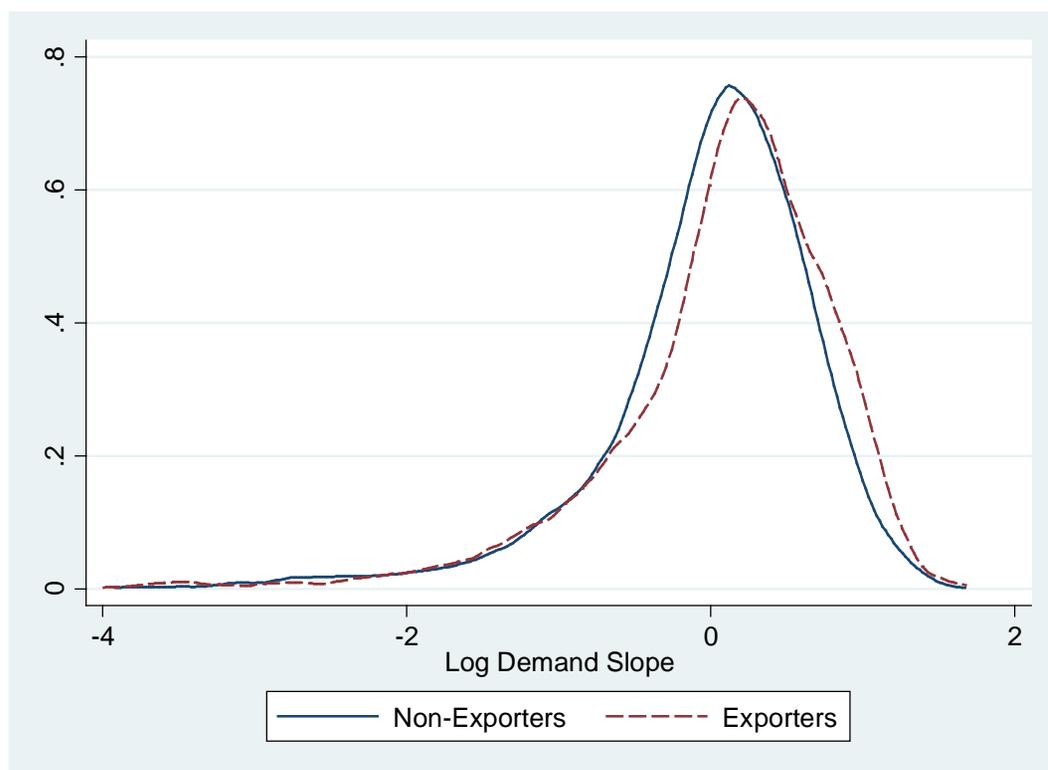
Notes: This figure plots the predicted values from a regression of the foreign profitability index on the domestic profitability index, a dummy for whether the domestic profitability is below the median, and their interaction (controlling for product-year fixed effects).

Figure 13: Distribution of Domestic Demand Location Parameter: CES Demand (κ)



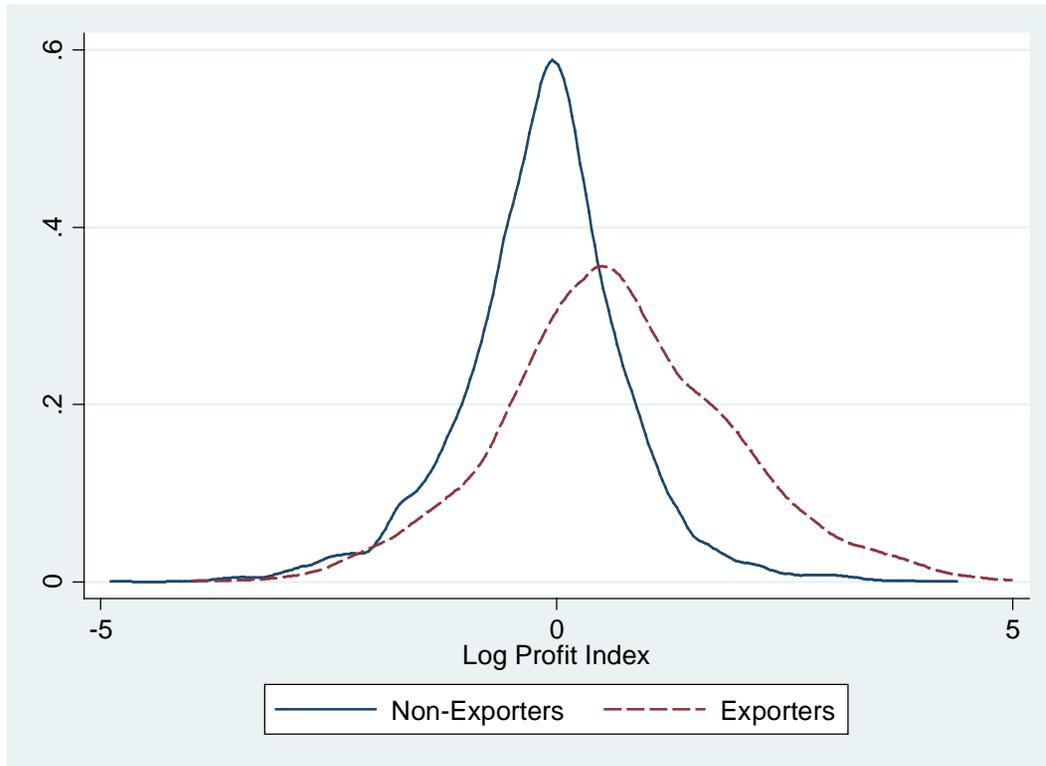
Notes: In this figure we plot the distribution of the (log) domestic demand location parameter (κ), based on a CES approximation to demand, separately for exporters and non-exporters. The parameter is measured at the firm-product-year level and is net of product-year fixed effects.

Figure 14: Distribution of Domestic Demand Slope: CES Demand (ρ)



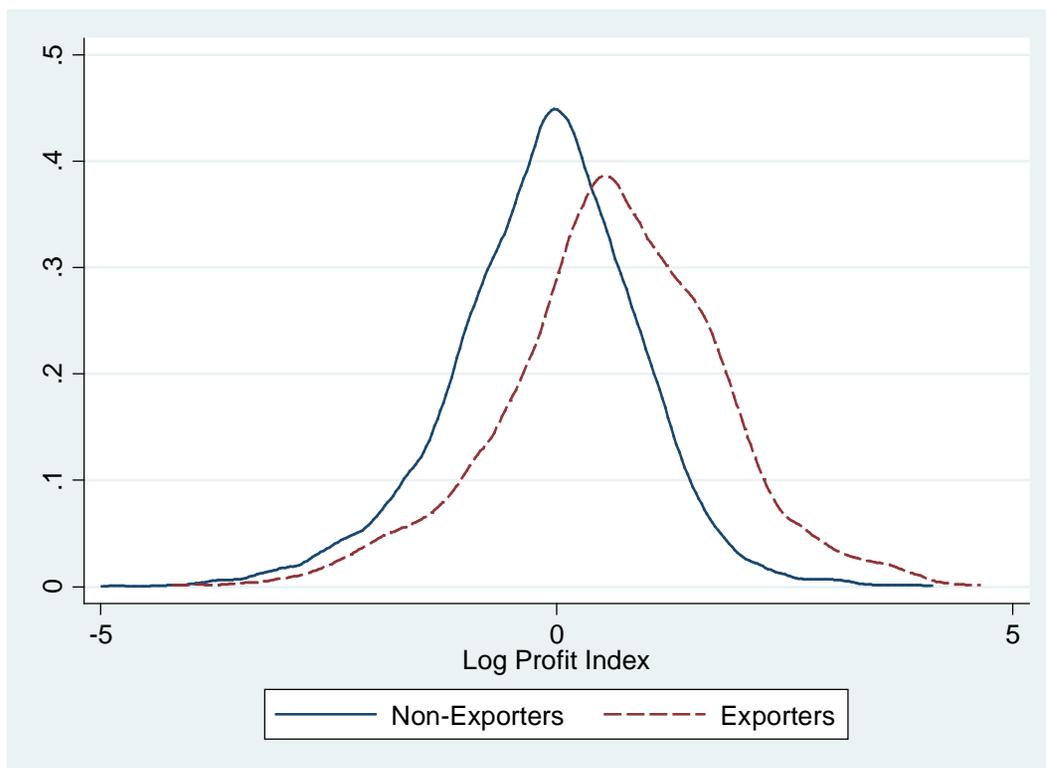
Notes: In this figure we plot the distribution of the (log) domestic demand slope (ρ), based on a CES approximation to demand, separately for exporters and non-exporters. The slope is measured at the firm-product-year level and is net of product-year fixed effects.

Figure 15: Distribution of Domestic Profitability Index: Scale of Non-Exporters: CES Demand



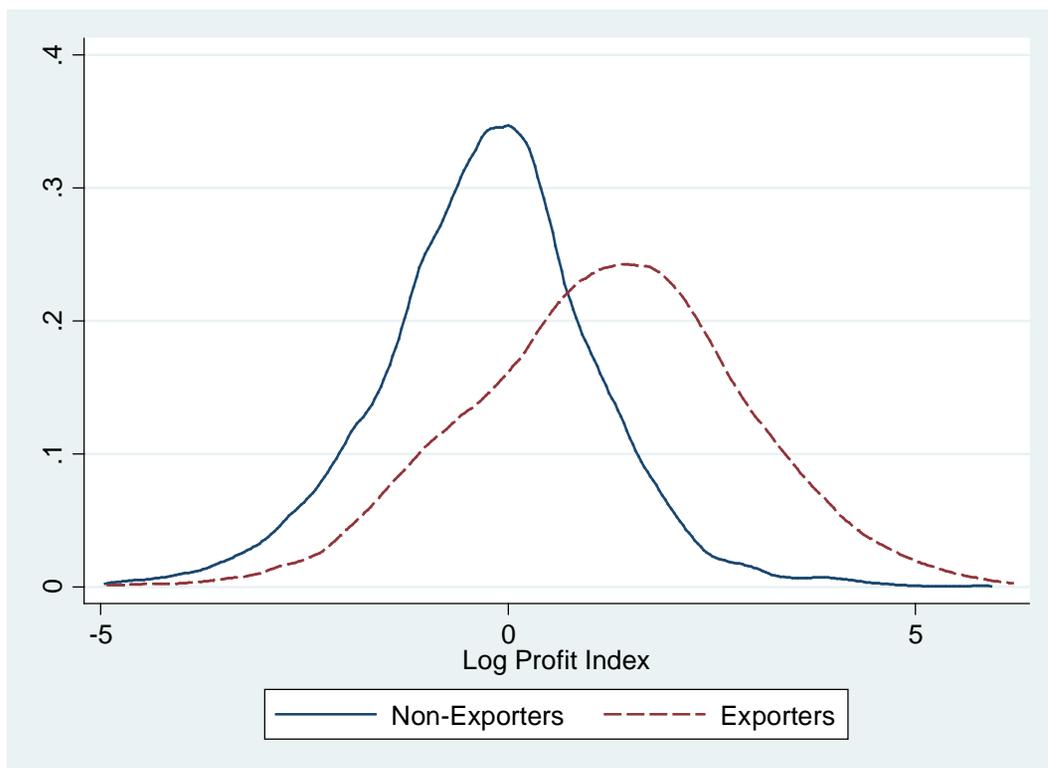
Notes: In this figure we plot the distribution of the (log) domestic profitability index, separately for exporters and non-exporters. The index is measured at the firm-product-year level, and is computed by fixing capital and labor at values corresponding to the median values for a non-exporting firm. It is computed at the firm-product-year level and is net of product-year fixed effects.

Figure 16: Distribution of Domestic Profitability Index: Scale of Exporters: CES Demand



Notes: In this figure we plot the distribution of the (log) domestic profitability index, separately for exporters and non-exporters. The index is measured at the firm-product-year level, and is computed by fixing capital and labor at values corresponding to the median values for an exporting firm. It is computed at the firm-product-year level and is net of product-year fixed effects.

Figure 17: Distribution of Domestic Profitability Index: Long-Run Measure: CES Demand



Notes: In this figure we plot the distribution of the (log) domestic profitability index, separately for exporters and non-exporters. The index is a long-run version of equation (16) using the firm's observed levels of capital and labor. It is computed at the firm-product-year level and is net of product-year fixed effects.

Table 1: Descriptive Statistics

ISIC 3 Industry Code	Industry Description	Percentage of Manufacturing Sales	Percentage of Exporting Firms	Number of Firms	Number of Products
151	Production, processing and preservation of meat, fish, fruit, vegetables, oils and fats	14%	46%	389	8
153	Manufacture of grain mill products, starches and starch products, and prepared animal feeds	4%	20%	113	3
154	Manufacture of other food products	5%	5%	627	9
155	Manufacture of beverages	7%	69%	168	3
181	Manufacture of wearing apparel, except fur apparel	1%	25%	272	3
201	Sawmilling and planing of wood	4%	32%	203	6
221	Publishing	1%	11%	183	6
222	Printing and service activities related to printing	1%	13%	146	6
242	Manufacture of other chemical products	5%	60%	171	9
281	Manufacture of structural metal products, tanks, reservoirs and steam generators	1%	13%	245	10
361	Manufacture of furniture	1%	19%	226	7
Total		43%	--	2,475	70
Average		4%	28%	275	6

Table 2: Relationship between Output and Input Prices

Dependent Variable: (Log) Domestic Output Price	
(Log) Intermediate Input Price	0.278*** (0.02)
Product-Year FE	Yes
r ²	0.86
N	14068

Notes: This table reports estimates of a regression of log domestic output price on the log of the intermediate input price index, controlling for product-year fixed effects. Very similar results are obtained using an average (across destinations) output price. Standard errors are reported in parentheses below the point estimates.

Table 3: Production Function Estimates

No Intermediate Input Prices					Intermediate Input Prices				
ISIC 3 Industry	Labor Elasticity	Capital Elasticity	Intermediate Input Elasticity	Returns to Scale	ISIC 3 Industry	Labor Elasticity	Capital Elasticity	Intermediate Input Elasticity	Returns to Scale
151	0.2455	0.1026	0.7053	1.0534	151	0.1296	0.1872	0.6941	1.0109
153	0.0535	0.0654	0.7752	0.8941	153	0.0460	0.0690	0.8025	0.9174
154	0.4339	0.0760	0.5415	1.0514	154	0.3677	0.0873	0.5792	1.0343
155	0.0295	0.0526	0.8579	0.9400	155	0.3063	0.0565	0.6996	1.0624
181	0.1732	0.0133	0.7743	0.9608	181	0.2850	0.1951	0.4552	0.9353
201	0.0845	0.1001	0.8384	1.0230	201	0.2263	0.0802	0.7521	1.0586
221	0.4063	-0.0418	0.6365	1.0010	221	0.4104	0.1671	0.4500	1.0275
222	-0.0509	0.4925	0.7932	1.2348	222	0.2107	0.5532	0.5058	1.2697
242	0.1142	0.0693	0.7754	0.9589	242	0.4667	0.0777	0.5038	1.0482
281	-0.4154	0.0072	1.6552	1.2470	281	0.0623	0.1408	0.9103	1.1134
361	-0.0015	0.0882	1.0430	1.1297	361	0.1111	0.1520	0.7450	1.0081

Notes: The left panel shows estimates not using information on intermediate input prices. The right panel reports estimates using intermediate input prices.

Table 4: Summary Statistics—Median and Mean Firm-Level Markups

No Intermediate Input Prices			Intermediate Input Prices		
ISIC 3 Industry	Median Markup	Mean Markup	ISIC 3 Industry	Median Markup	Mean Markup
151	1.490	2.279	151	1.426	2.120
153	1.219	1.385	153	1.224	1.359
154	1.259	1.353	154	1.331	1.432
155	2.392	3.434	155	1.902	2.661
181	2.156	2.611	181	1.236	1.473
201	1.779	2.042	201	1.619	1.861
221	1.917	2.044	221	1.360	1.407
222	2.107	2.276	222	1.412	1.492
242	1.997	3.747	242	1.330	2.502
281	3.454	4.105	281	1.882	2.188
361	2.420	2.668	361	1.729	1.908
Industry Average	2.018	2.540	Industry Average	1.496	1.855

Notes: For each firm we compute a revenue-weighted markup (across markets, products, and years). In this table, we report the median and mean of this distribution. The left panel shows estimates not using information on intermediate input prices. The right panel reports estimates using intermediate input prices.

Table 5: Markups, Productivity, and Marginal Cost

	Dependent Variable:				
	Log(Domestic Markup)	Log(Markup)	Log(Markup)	Log(Productivity)	Log(Marginal Cost)
Dummy (Exporter)	0.110*** (0.01)			0.036 (0.03)	-0.062* (0.03)
Dummy (Foreign Market)		-0.094*** (0.02)			
Dummy (Main Foreign Market)			-0.223*** (0.04)		
Product-Year FE	Yes	No	No	Yes	Yes
Product-Firm-Year FE	No	Yes	Yes	No	No
r ²	0.21	0.73	0.64	0.1	0.89
N	11054	27680	12550	11054	11054

Notes: Columns 1, 4, and 5 are based on observations that vary at the firm-product-year level. The numbers are estimates from regressions of (log) domestic markup, productivity, and marginal cost on a dummy variable for whether the observation corresponds to a product that is being exported by a given firm in a given year. The regressions in these three columns contain product-year fixed effects. Columns 2 and 3 are based on observations that vary at the firm-product-year-destination level. The numbers in column 2 and 3 are estimates from a regression of (log) markup on a dummy variable for whether the observation corresponds to a foreign destination. The estimates in column 2 are based on all observations, whereas the estimates in column 3 are based on only observations corresponding to the domestic market or the main foreign destination. The regressions in these two columns contain product-firm-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 6: Markups within Firms and Markets—Gravity

Dependent Variable: Log(Foreign Markup)	
Log(GDP)	0.005 (0.00)
Log(GDP per capita)	0.051*** (0.00)
Log(Distance)	0.020* (0.01)
Common Language	0.037** (0.01)
Product-Firm-Year FE	Yes
r ²	0.83
N	15722

Notes: The numbers reported are estimates from a regression of (log) foreign markups, at the firm-product-year-destination level, on a set of gravity variables—the log of gross domestic product (GDP), the log of gross domestic product per capita, the log of the distance between Chile and the export destination, and an indicator for whether the main language in the destination country is Spanish. The regression includes product-firm-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 7: Markups and Aggregation

Dependent Variable:

	Log(Average Markup)	Log(Domestic Markup)
Dummy (Exporter)	0.024*	0.110***
	-0.01	-0.01
Product-Year FE	Yes	Yes
r2	0.18	0.21
N	11054	11054

Notes: These numbers are estimates from regressions of (log) domestic and average markups on a dummy variable for whether the observation corresponds to a product that is being exported by a given firm in a given year, as well as product-year fixed effects. The average markup is computed as a quantity-weighted average markup across all destinations, including the domestic market. The estimates are based on observations that vary at the firm-product-year level. Standard errors are reported in parentheses below the point estimates.

Table 8: Markups and Quantity

	Dependent Variable:					Log(Domestic Markup)
	Log(Markup)					
Log(Quantity)	-0.118*** (0.00)	-0.115*** (0.00)	-0.301*** (0.00)	-0.124*** (0.00)	-0.078*** (0.00)	
Log(Total Quantity)						-0.032*** (0.00)
Fixed-Effects	Product	Product- Time	Product- Market-Firm	Product- Market-Time	Product- Firm-Time	Product-Time
r ²	0.22	0.27	0.76	0.49	0.75	0.23
N	27680	27680	27680	27680	27680	11054

Notes: The numbers reported are estimates from regressions of (log) markups, at the firm-product-year-destination level, on (log) quantity, with different sets of fixed effects. The last column shows results of a regression of (log) domestic markups on (log) total quantity. Standard errors are reported in parentheses below the point estimates.

Table 9: Exporter Premium on Domestic Demand and Cost Parameters and on Profitability

	Dependent Variable:				Profit Index (Domestic Scale)	Profit Index (Exporter Scale)
	Demand Location	Demand Slope	Cost-Side Heterogeneity	Productivity		
Exporter	0.095** (0.03)	-1.670*** (0.09)	-0.066 (0.05)	0.036 (0.03)	0.581*** (0.03)	1.272*** (0.04)
Product-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
r ²	0.87	0.83	0.84	0.1	0.43	0.32
N	11052	10033	11054	11054	10897	10469

Notes: The numbers reported are estimates from regressions of the (log) domestic profitability index, and its components—demand location, demand slope, slope of marginal cost, and productivity—on a dummy for whether a firm exports a given product in a given year. All regressions include product-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 10: Relationship between Exporting and Domestic Demand and Cost Heterogeneity

	Dependent Variable			
	Cost	Demand	Cost	Demand
Exporter	1.575*** (0.06)	1.803*** (0.05)	-0.34*** (0.04)	0.759*** (0.03)
Demand			1.065*** (0.01)	
Cost				0.664*** (0.00)
Product-Year FE	Yes	Yes	Yes	Yes
r2	0.63	0.31	0.8	0.89
N	10033	10033	10033	10033

Notes: The numbers reported are estimates from regressions of the measures of (log) normalized demand heterogeneity and (log) normalized cost heterogeneity against a binary indicator for exporting and product-year fixed effects. The normalized cost heterogeneity is measured by $(\frac{c^0}{b})$, and the normalized demand heterogeneity is measured by $(\frac{(\alpha^0)^2}{b})$. Standard errors are reported in parentheses below the point estimates.

Table 11: Relationship between Foreign and Domestic Demand Heterogeneity within Firm and Product

	Dependent Variable:	
	<u>Log(Foreign Demand Heterogeneity)</u>	
	All Markets	Main Foreign Only
Domestic Counterpart	0.372*** (0.01)	0.575*** (0.04)
Product-Market-Year FE	Yes	Yes
r2	0.58	0.81
N	12669	976

Notes: The numbers reported are estimates from regressions of the (log) foreign demand heterogeneity on the (log) domestic demand heterogeneity. Demand heterogeneity is measured by $(\frac{a^0}{b})^2$. All regressions include product-foreign market-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 12: Demand Location and Slope within Firms across Foreign Destinations—Gravity

	Dependent Variable:	
	Log(Foreign Demand Location)	Log(Foreign Demand Slope)
Log(GDP)	-0.001 (0.00)	-0.368*** (0.01)
Log(GDP per capita)	0.063*** (0.01)	-0.04 (0.02)
Log(Distance)	0.026* (0.01)	0.215*** (0.04)
Common Language	0.023 (0.02)	-0.13 (0.07)
Product-Firm-Year FE	Yes	Yes
r ²	0.83	0.68
N	14664	12556

Notes: The numbers reported are estimates from regressions of (log) foreign demand location parameters and slopes, at the firm-product-year-destination level, on a set of gravity variables—log of gross domestic product (GDP), log of gross domestic product per capita, log of the distance between Chile and the export destination, and an indicator for whether the main language in the destination country is Spanish. The regressions include product-firm-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 13: The Foreign Demand of Unremarkable Exporters

	Dependent Variable:	
	<u>Log Difference Between Foreign and Domestic</u>	
	Demand Location	Demand Slope
Below Median Domestic Profitability	0.544*** (0.03)	-0.333*** (0.08)
Constant	-0.057*** (0.02)	5.053*** (0.05)
Product-Market-Year FE	Yes	Yes
r2	0.36	0.42
N	15518	12669

Notes: The numbers reported are estimates from regressions of (log) foreign demand location parameters and slopes, at the firm-product-year-destination level, on a dummy variable indicating whether the firm is below or above the median value of domestic profitability. The regressions include product-destination-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 14: Characteristics of Export Destinations for Unremarkable Exporters

	Dependent Variable:			
	Log(GDP)	Log(GDP per capita)	Log(Distance)	Common Language
Below Median Domestic Profitability	0.556*** (0.04)	0.264*** (0.02)	0.080*** (0.01)	-0.047*** (0.01)
Product-Year FE	Yes	Yes	Yes	Yes
r2	0.10	0.10	0.23	0.22
N	15722	15722	15982	15982

Notes: The numbers reported are estimates from regressions of a set of gravity variables—log of gross domestic product (GDP), log of gross domestic product per capita, log of the distance between Chile and the export destination, and an indicator for whether the main language in the destination country is Spanish—on a dummy variable indicating whether the firm is below or above the median value of domestic profitability. The data vary at the firm-product-year-destination level. The regressions include product-year fixed effects. Standard errors are reported in parentheses below the point estimates.