The ABCs of Firm Heterogeneity when Firms Sort into Markets: The Case of Exporters *

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Abstract

We develop a novel methodology for disentangling the demand and cost drivers of firm heterogeneity when firms sort themselves into different markets, and we apply it to export status differences. Our methodology results in joint estimates of firm-level productivity and of markups in every market, without imposing functional form restrictions on demand. We find that exporters, relative to non-exporters i) have flatter domestic demand curves – thicker domestic markets and ii) have higher demand conditional on productivity. Finally, iii) these demand advantages translate to foreign markets, thereby leading to export status differences.

Keywords: Markups, Productivity, Demand, Exporting

JEL codes: L11, D22, D24, F14

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1 Introduction

Economists have known for some time that, within an industry, firms are heterogeneous along a number of dimensions: output level, survival time, and export status being among the most studied. We also know that these differences are persistent. Specifically, we know that large firms 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 and that have aggregate economic implications. Researchers have proposed various alternatives for the key resource. Some have suggested that it 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, the evidence points to there being no single resource, but rather some combination of resources, that are responsible for the various dimensions of firm heterogeneity.[1]

Whatever are the resources responsible for firm heterogeneity within an industry, these resources must translate into some combination of cost and demand advantages for some firms relative to others. In trying to understand the landscape of heterogeneous cost and demand advantages or disadvantages, demand heterogeneity poses particular challenges for empirical researchers. The reason is that, unlike productivity, a firm's demand is almost guaranteed to vary from market to market. This variation is problematic from a data perspective – it requires market-by-market data on firm performance – and also from an estimation perspective: unless all firms operate in all markets, the estimation procedure must account for the selection of firms into markets. Even having surmounted this challenge to obtain estimates of cost and demand heterogeneity, with multiple sources of heterogeneity the researcher still faces the challenge of uncovering how these interact to affect firm size, survival, export status, or other relavant outcomes.

In this paper, we propose methodologies for confronting both of these challenges. We first

[1]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 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.

develop an estimation approach that jointly estimates markup and productivity/marginal cost heterogeneity across firms while accounting for firm selection into markets. We apply this methodology to detailed data on manufacturing firms in Chile.[2] Next, using our estimates of the *equilibrium* levels of cost and markups, we create a theoretical framework that maps them into two fundamental firm-product-market-time-level demand characteristics – willingness-to-pay (a) and market thickness (b), and a firm-product-time-level marginal cost characteristic (c). This is the A, B, C's of firm heterogeneity. This theoretical framework is crucial if the goal is to study the fundamental sources of firm heterogeneity and not only the differences in endogenous objects such as marginal costs, markups, firm survival, and firm size.

Although our methodologies should be applicable to the various dimensions of firm heterogeneity, the specific dimension to which we apply these methodologies is export status. One reason is that, in contrast to domestic sub-markets, an export market is a reasonably well-defined entity for which data on prices and quantities are available from Customs records. In addition, while not all firms within an industry export, they do sell domestically. The estimation procedure we develop exploits this feature of the data to generate estimates free of selection problems.

Our estimation procedure works by jointly estimating production functions and productivities at the firm-, time- and product-level, and markups at the firm-, time-, product- and market-level. It requires no parametric assumptions on the structure of demand facing firms in each market, allowing for a nonparametric estimation of market power (markups) for each product across each market at any time. The procedure builds on the framework in Gandhi, Navarro, and Rivers (2020) and exploits our detailed destination-specific data on firm-level prices and quantities. The methodology in Gandhi, Navarro, and Rivers (2020) is based on a transformation of the firm's first-order condition. We show that this approach can be extended to jointly estimate productivity and markups. Key to our estimation procedure is the fact that we can write the first-order condition for intermediate inputs in terms of the firm's domestic price only. 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

[2] Our dataset is a new firm, product, market, year-level dataset for Chilean firms. It is constructed by combining Chile's Annual Manufacturing Survey (ENIA) with Chile's Customs Database for the years 2002-2009. It provides information on each firm's dollar and quantity sales in all markets, including dollar and quantity sales in the domestic market. In addition, it has information on the standard plant-level output and input variables available in manufacturing surveys.

the number of foreign destinations is large. Finally, another advantage of our methodology is that it allows for unobserved heterogeneity in demand (Bond et al. (2021)).

Using the productivity and markup estimates, and our data, we can then recover 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 for every foreign market to which a firm exports. The methodology we develop for interpreting how these multiple dimensions of demand and cost heterogeneity impact export status first embeds the slope / elasticity estimates in either linear or iso-elastic local demand approximations. Next, using these approximations, we construct an index for each firm-product-market-time combination that captures how demand and cost heterogeneity combine to determine firm profitability. We show that this profitability index is not only informative about the firm's export / no export decision but, by examining the differences in the components of this index for exporters and non-exporters, it allows us to uncover the cost-side, c, and demand-side, a and b, fundamentals that make exporters different than non-exporters.

What we find is that, while both productivity and demand heterogeneity play important roles in determining export status, in many ways demand heterogeneity plays the more significant role of the two.[3] Especially significant is that exporters have "thicker" domestic markets; i.e., exporters face less steeply sloped demand curves in the domestic market. In essence, exporters have products that can attract significantly more domestic customers for any price reduction than do non-exporters. This "market thickness" is the key driver of both domestic profitability and size differences between exporters and non-exporters. The basic reason is that even a small cost / productivity advantage for export firms gets translated into a large profitability difference because the extra units produced can be sold with only a small price reduction. We also find that foreign market demand thickness across exporting firms is highly correlated with domestic market demand thickness – the rank correlation between the two measures is roughly 0.4 – suggesting that this contributes to determine export status. As in the domestic market, less steeply sloped foreign demands allow firms to translate even small cost differences into large foreign profitability differences.

We also find that demand differences across firms come at a cost. In particular, firms with demands that feature high estimated willingness-to-pay (the vertical shift of the firm demand curve) also have high estimated production costs.[4] This correlation between costs and demand

[3]Foster, Haltiwanger, and Syverson (2008) show that survival probabilities are also largely driven by demand heterogeneity, not cost heterogeneity. Foster, Haltiwanger, and Syverson (2016) document the relative importance of demand heterogeneity in explaining the dynamics of the size gaps between new and established firms.

[4]While we do not take a stand on the sources of the correlation between demand and cost heterogeneity we find

tends to mask the role that productivity plays in determining export status. A key contribution of our methodology is that it allows us to look at productivity differences across exporters and non-exporters while controlling for any demand differences. What we find is that, when comparing exporters and non-exporters with similar demands, exporters are, indeed, more productive. Similarly, comparing exporters and non-exporters with similar productivity, exporters have larger demands. In short, exporters have better demand-cost combinations than non-exporters but are not necessarily better in one particular dimension. Indeed, we find that there is considerable overlap in the *unconditional* productivity distributions for exporters and non-exporters. Studies that estimate revenue production functions will also tend to mask this crucial demand-cost difference between exporters and non-exporters because the estimated revenue productivity combines both demand and cost heterogeneity into a single measure that cannot be disaggregated. All of this simply highlights the need for caution in interpreting results when there are multiple dimensions of heterogeneity.

Our analysis also yields several results that, together, highlight the importance of measuring firm-market demand heterogeneity. In particular, we find that export firms charge a significantly lower markup in foreign markets than they do in the domestic market.[5] Specifically, within firm, product, and year, markups are on average 15% lower in foreign destinations 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.[6]

Finally, while our analysis does not explicitly model the dynamics of export status choice, our results provide a useful starting point for such modeling. Typically, models of export status choice assume productivity heterogeneity and some form of heterogeneity in either foreign demands or foreign selling costs. Our results indicate that there is some firm-specific product characteristic that i) translates into thicker domestic markets (less steeply sloped demand curves) and ii) carries over to foreign markets to yield thicker foreign markets. Further, we find

in the data, potential mechanisms include high demand products being high quality and costing more to produce, and firms facing a trade-off between investing in reducing costs and improving demand. Note that Roberts et al. (2018) and Jaumandreu and Yin (2018) find a similar correlation in Chinese data.

[5]See also Bughin (1996), Moreno and Rodríguez (2004), Georgiev (2018), and Jaumandreu and Yin (2018) who find evidence that foreign markups are lower than domestic markups.

[6]It is worth noting that our results are consistent with the “shipping the good apples out” story first proposed by Alchian and Allen (1964). We find that exporters have demand curves for their products that are shifted up when compared to non-exporters. This is consistent with the firms producing high quality products being the ones that export.

that demand and productivity are not independent draws. Rather, firms face a trade-off between enhanced demand and enhanced productivity/lower cost. What characterizes successful export firms is that they achieve better demand-cost outcomes than do non-exporters. This ability defines a key source of firm heterogeneity. We expect this to be true when looking at many other dimensions of firm heterogeneity (outside of exporting behavior) as well.

To date, studies on export status have not been able to address completely the problems of demand heterogeneity and market selection.[7] 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 datasets 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. As we show above, 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. 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 this 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 their connection to export status.

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 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 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 estimated 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.[8] Like Foster, Haltiwanger, and

[7] That being said, the existing literature does show that productivity differences provide at best only a partial explanation for differences in firm exporting decisions, and that market-specific forces are important (see e.g., Das, Roberts, and Tybout (2007), Eaton, Kortum, and Kramarz (2011), Albornoz, Fanelli, and Hallak (2016), and Roberts et al. (2018)).

[8] More recently, Hottman, Redding, and Weinstein (2016) used detailed domestic sales data to decompose firm

Syverson (2008), we also show that, unless properly controlled for, demand heterogeneity can mask the important role played by productivity heterogeneity.

In the context of studying firms' export heterogeneity, 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 jointly estimate and analyze 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. Rather than focusing on the underlying demand and cost 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.[9]

size heterogeneity into demand and cost heterogeneity. Like us, they find that demand plays a key role. Unlike us, they do not deal with the selection of firms into different markets, nor do they study firms' export decisions.

[9]There is a large literature that studies demand / quality and exporting using less detailed data than we use in this 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

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.[10]

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 use the combination of 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 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 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

quality can explain variation in the export performances of Champagne producers. Iacovone and Javorcik (2012) show that Mexican manufacturers raise their domestic prices before they start exporting to the US, and suggest that this may be evidence of a correlation between domestic demand increases and exporting. In common with our work, all these papers conclude that demand matters for exporting performances. Unlike all these papers, we estimate demand and supply heterogeneity across exporters and non-exporters in the domestic market, the only market in which they operate together.

[10] 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.

sales as well as the total physical quantity sold for each 3-digit Central Product Classification (CPC) good produced in the plant.[11] When combined with Customs data, this allows us to compute prices for each product sold by the firm, both for domestic and foreign sales.

In order to allocate plants' foreign sales to specific foreign countries, the Chilean Annual Manufacturing Survey is linked to Chile's Customs Database, where all Chilean export transactions are recorded. These data 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.[12]

The resulting merged dataset is an unbalanced panel covering the years 2002 - 2009.[13] 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 couple of 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). This level of aggregation is higher than the one used in some papers in the literature. For instance, De Loecker et al. (2016) use Indian data with product information on around 1,400 product codes. As we discuss in Section 4, we have performed robustness analyzes confirming that the product level of our data does not drive our findings. Finally, we estimate production functions at the 3-digit ISIC industry level, allowing for the fact that some firms are multi-

[11] For confidentiality reasons, we observe only an (internally consistent) anonymized product code. This prevents us from matching the codes to the product names. We do, however, observe the true industry code for each firm.

[12] Aggregating plants into firms can potentially hide important data variation, in particular if firms produce a product in one plant for the foreign market and in another plant for the domestic market. Fortunately, multi-plant firms are not particularly common in our data (see also e.g., Pavcnik (2002)). In particular, less than 3% of firm-product-year observations correspond to multi-plant firms that produced the same product in more than one plant. All the results of the paper are robust to dropping these observations from the analysis.

[13] As documented in Olley and Pakes (1996), balancing the panel can lead to selection biases due to firm exit. However, as also shown in the original Olley and Pakes (1996) paper, as well as in subsequent work (e.g., Griliches and Mairesse (1998) and Levinsohn and Petrin (2003)) selection due to attrition has little effect empirically as long as one works with the unbalanced panel. Because of this, we work with the unbalanced panel and abstract away from selection due to exit.

product firms.[14]

Second, because of the data demands imposed by our estimation procedure, we limit our sample to products for which there are at least 40 firm-year observations, which trims some more marginal products. As discussed in the estimation section, we have performed robustness analyzes showing that this restriction does not drive our results. We further restrict our analysis to 10 industries that feature large numbers of observations and high fractions of firms that export. Moreover, a key feature of these 10 industries is a more standard (and uniform) measure of physical quantities of output across firms (e.g., standard units such as litres or kilograms, as opposed to “units” or “boxes”). The 10 industries in our analysis account for 43% of manufacturing output and include a total of 2,749 firms, 21% of which export. Table 1 shows summary statistics on our sample, and Appendix A provides more details.

3 Model

Each observation in our dataset consists of a firm f, selling a product j, to a destination n, in 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 have information on a vector of quantities and a vector of revenues corresponding to the output of each product sold to each destination in a given year, 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:

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

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

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

[14] This is a more disaggregated level than the ones often used in the literature. For example, De Loecker et al. (2016), estimate production functions at the level of 2-digit NIC sectors.

where ε is an ex-post shock to output capturing measurement error.[15] Productivity ω is assumed to follow a first-order Markov process:

$$\omega_{fjt} = h\left(\omega_{fjt-1}\right) + \eta_{fjt}. \tag{1}$$

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:

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

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.[16] This static maximization problem implies a series of first-order conditions which equate marginal revenue from products sold to each market with marginal cost.[17]

For firms that sell a product in multiple markets, the researcher does not observe the input allocation to goods sold in each market. Thus, one must assume that firms use the same production function to produce output, regardless of the destination where the product is sold.[18] This implies that 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,

$$\frac{P_{fjt1}}{P_{fjt2}} = \frac{\mu_{fjt1}}{\mu_{fjt2}}, \tag{2}$$

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

[15]We follow the standard practice in the literature of assuming the absence of measurement error in inputs. See, e.g., Kim, Petrin, and Song (2016) and Collard-Wexler and De Loecker (2016) for recent work that seeks to relax this assumption.

[16]Note 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)).

[17]Recall that the price under firms' control is the "producer price" and, thus, optimization involves firms equating marginal revenues to the marginal cost of production. In fact, we observe revenues, and thus prices, free on board (FOB) reflecting what the firms effectively receive for their products, net of the costs of getting the products to final consumers in the domestic or foreign markets.

[18]See e.g., Roberts et al. (2018) and Jaumandreu and Yin (2018).

nation n.

4 Estimation

Our estimation strategy is based on the approach developed by Gandhi, Navarro, and Rivers (2020), henceforth GNR, which we extend by allowing for multi-product firms and by incorporating data on output prices in order to recover estimates of markups. Before we detail our estimation methodology, it is useful to present the intuition behind it. The estimation proceeds in two stages. In a first stage, we jointly recover the output elasticity of intermediate inputs and the domestic markup from production data. The residual of this regression, the ex-post shock to output, ε, together with a standard Markov assumption on productivity, ω, allows us to estimate the production function in a second stage. Using estimates from the first two stages we can solve for productivity and separate the output elasticity of intermedate inputs from the domestic markup. Finally, we use price data, our marginal cost estimates, and the first-order conditions (equation 2) to recover markups for each foreign export destination served by the firm. The next sections detail the estimation procedure, and Appendix B outlines the steps of the estimation algoritm.

4.1 Single-product firms

We estimate production functions separately for each industry using data on single-product firms only (see De Loecker et al. (2016)).[19] The advantage of using only single-product firms for this step 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.

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

[19] As a result, the parameters of the model are industry specific (e.g., the production function and Markov process). Also, because the production function will be the same for both single and multi-product firms in a given industry, as in De Loecker et al. (2016), we rule out physical synergies in production. That being said, this approach does allow for some forms of economies of scope through such things as correlated productivity shocks across products, shared input prices, and shared fixed costs / overheads. See De Loecker et al. (2016) for a detailed discussion.

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

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

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

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

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 write the demand function for firm f's product in the domestic market as a general function of domestic price P_{ftD}, demand shifters z_{ftD}, and an unobserved domestic demand shock χ_{ftD}:

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

Note that, in addition to capturing any demand shifters that are unobserved to the researcher, the demand shock χ_{ftD} enters the specification flexibly in order to permit for firm-specific heterogeneity in markups.[20] Doing so means that, even though our demand specification does not depend explicitly on any competitors' strategic variables, our framework is still flexible enough to capture many well-known models of imperfect competition. This includes models with strategic interactions such as the nested CES model with Cournot competition in Atkeson and Burstein (2008) as well as the logit demand model with Nash Bertrand competition in Berry (1994). For more details, see Appendix C.

Given this demand specification, it is straightforward to show that the price elasticity of demand in the domestic market can be written as a function of price and the demand shifters. Under profit maximization, the optimal domestic markup can be written as a function of this elasticity (via the Lerner Index) and thus written as a function of domestic prices and demand shifters:

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

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

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

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

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

By regressing the modified shares s_{ftD} on inputs, domestic price, domestic quantity, and demand shifters (lagged advertising expenditures and product/time dummies), 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 this first stage.[21]

[20] See Doraszelski and Jaumandreu (2020) for a discussion of the importance of controlling for unobserved demand heterogeneity in the context of the production function approach to markup estimation.

[21] An 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

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.

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 re-write the production function as

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

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

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

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

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

Combining these two equations, and defining $\tilde{y}_{ft} \equiv y_{ft} - \varepsilon_{ft}$, gives us:

$$\tilde{y}_{ft} = f\left(k_{ft}, l_{ft}, m_{ft}\right) + h\left(\tilde{y}_{ft-1} - f\left(k_{ft-1}, l_{ft-1}, m_{ft-1}\right) - \phi_j\right) + \phi_j + \eta_{ft} \tag{5}$$

Recall that we have already recovered 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:

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

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 potentially be measured for the domestic market, it is not clear that given existing datasets one could measure market shares in foreign markets, since this would require data on world-wide imports into every destination. 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.

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). Then, we can form a GMM criterion function using moments in η_{ft} to identify the functions h and f.

Because $(k_{ft}, l_{ft}, y_{ft-1}, k_{ft-}, l_{ft-1}, m_{ft-1}) \in \mathcal{I}_{ft-1}$, these variables can be used to instrument for themselves. We 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 under the assumption that the demand shocks are correlated over time (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: $\xi^M_{ft} = \frac{\partial f\left(k_{ft}, l_{ft}, m_{ft}\right)}{\partial m_{ft}}$. We then combine this estimate with our first-stage estimates using equation (4) to back out a measure of the domestic markup

$$\ln \mu_{ftD} = -s_{ftD} - \varepsilon_{ft} + \ln \xi^M_{ft}.$$

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

$$\mu_{ftn} = \mu_{ftD} \left(\frac{P_{ftn}}{P_{ftD}} \right).$$

4.2 Multi-product firms

For multi-product firms, a well-known challenge is that we do not observe the allocation of inputs across products within a given firm. Rather we only observe 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)).[22] 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.[23]

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:

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

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 from the estimation using single-product firms, we can construct the output elasticity of intermediate inputs $\xi_{fjt}^M = \frac{\partial f\left(k_{fjt}, l_{fjt}, m_{fjt}\right)}{\partial m_{fjt}}$. 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

[22] In 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). As a robustness check we have re-estimated all of our results using variable cost shares to allocate inputs, and we find that the results are quantitatively very similar.

[23] A third approach would be to place assumptions on demand and back out input share allocations from the demand parameters and price and quantity data (e.g., Orr (2022)). However, since one of our main objectives is to study the role of demand heterogeneity, we want to avoid placing additional assumptions/structure on demand.

markups in the same fashion as for the single product firms, using the relationships in equation (2).

4.3 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-form expression for the marginal cost function which will aid in interpreting the results below.[24]

In our first specification we use firms' wage bills (instead of hours) as the measure of labor input. This assumes that wage variation captures differences in the efficiency of workers (see Griliches and Mairesse (1998) and Fox and Smeets (2011)). Following the same logic, we use expenditures in intermediate inputs as our measure of materials input.

The left panel in Table 2 reports the estimated production function elasticities. The estimates are reasonable, although the capital and labor elasticities are on the low side, including a few negative point estimates, and one materials elasticity above 1.

A useful feature of our data is that they report firms' expenditures on and quantity used of intermediate inputs. This allows us to deflate intermediate input expenditures directly using firm-specific input prices and to recover input quantities directly from the data. As noted 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 estimates of the production function parameters and productivity. The 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)). 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 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.

[24]It is worth noting that De Loecker and Warzynski (2012) and Garcia-Marin and Voigtländer (2019) find that Cobb-Douglas and translog specifications generate similar results.

(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 our focus on the selection of firms into markets. On one side we have product prices in every market the firm sells to; on the other we do not have firms' market shares in their foreign markets. An additional potential disadvantage of this approach is that it imposes a single control function to deflate intermediate inputs, labor, and capital.

Appendix A discusses the construction of the input price indices we use in the analysis. The right panel in Table 2 shows production function estimates when we deflate intermediate input expenditures with firm-specific input prices. While the results are not dramatically different, we do find that controlling for intermediate input prices does improve the estimates as it resolves the low/negative elasticity estimates for capital and labor and the high materials elasticity estimate. In what follows we use estimates based on the specification that controls for intermediate input price variation. We find roughly constant returns to scale in most industries, with slight decreasing returns in industry 153 (grain mill products, starches, and animal feeds) and 181 (wearing apparel, except fur apparel), and evidence of increasing returns to scale in industry 222 (printing and service activities related to printing) and 281 (structural metal products).

Table 3 reports median and mean firm-level markups by industry. The numbers in this table are obtained by calculating a weighted average markup over products, markets, and years for each firm, and then computing the median and mean across firms. Focusing on the results that use firm-level variation in intermediate input prices, the averages, across industries, of the median and mean markups are 1.47 and 1.65, 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. For the rest of the analysis we use the estimates that control for input prices. We should note, however, that all the qualitative results of the paper hold even when the production functions are estimated using input expenditures.

Before concluding this section, we discuss a couple of robustness checks. The first investigates whether the 3-digit aggregation of our output data influences our estimates and, ultimately, our main findings. To check for this possibility, we identified the roughly 50% of firms in our working sample that produce only a single 5-digit CPC product. For these firms, unobserved heterogeneity due to working at the 3-digit level is not a concern. The estimation procedure applied to these firms finds similar parameter estimates.[25] Moreover, we carried out the analyses in the entire paper using this sub-sample of firms, and the main results of the paper hold for this sample of firms as well. The second check relaxes the restriction that products must have at least 40 firm-year observations. Again, we find that this restriction does not affect any of the main findings of the paper. Finally, we used all firms to estimate the production functions (allocating inputs using revenue shares), instead of single-product firms only. The estimates and the main findings of the paper are similar in this case to what we obtain with our preferred specification.[26]

5 What makes exporters different?

In this section we detail our findings based on our joint estimates of productivities, marginal costs, and markups. We begin by presenting and discussing four key features of our estimates: i) the distributions of estimated productivities and marginal costs for exporters and non-exporters, ii) the estimated domestic market markups for exporters and non-exporters, iii) the estimated foreign market markups for exporters and iv) the relation between estimated markups and market quantities sold. To preview our results, we find that the distributions of estimated productivities and marginal costs are very similar for exporters and non-exporters, domestic markups are significantly larger for export firms, foreign markups are significantly smaller than the firm's domestic markup, and markups decline with output.

Because firms are heterogeneous in multiple dimensions, it would be inappropriate to draw conclusions on export status based on any one of the above results in isolation. For instance, it would be erroneous to conclude, a priori, that productivity plays no role in export status based solely on the fact that exporters and non-exporters share similar estimated productivity distributions. Further, the described features of markups and marginal cost estimates are statements about equilibrium outcomes and so cannot be used directly to make statements about the demand or cost features associated with export status. To address these issues, the second part of this section is devoted to developing a methodology that maps our estimates into key features of the demand and cost fundamentals for firms. We then show how these features interact and relate to export status. An important result of this part of the analysis is that demand and cost heterogeneity do indeed *jointly* relate to export statuts. In particular, in spite of the fact that the *unconditional* distributions of estimated productivities for exporters and non-exporters are very

[25] This estimation is still carried out at the 3-digit level but only using firms that produce a single 5-digit product.
[26] These results are available upon request.

similar, we find that exporters are clearly more productive than non-exporters *conditional on demand*.

5.1 Productivity, equilibrium marginal cost and markups

Since our main focus is on examining differences across firms and destinations, and not across products within a firm, in what follows we report results utilizing the main product produced by the firm, defined as the product that generates the most revenue for the firm.[27] In this case, and looking across all firms in the sample, we find that the distributions of estimated productivities for exporters and non-exporters, after netting out product-year effects, are very similar (see Figure 1). Taken on their own, we find no evidence in the overall distributions to argue that exporters are unequivocally more productive than non-exporters. To this point, the first column in Table 4 shows that, after controlling for product-year effects, the productivity of the average exporter is 5.0% larger than that of the average non-exporter, but this difference is not statistically significant. Similarly, Column 2 in the same table shows that exporters have, in equilibrium, a 4.6% marginal cost advantage when compared to the average non-exporter, although this effect is also not statistically significant. Figure 1 shows the distribution of marginal cost values for exporters and non-exporters and shows significant overlap.

The lack of a strong correlation between estimated productivity and export status contrasts with other studies (see Bernard et al. (2012) for a survey) that find that exporters have a significant productivity advantage over non-exporters.[28] More important than our evidence on the average exporter premium, however, is our evidence that the TFPQ distributions for exporters and non-exporters show significant overlap. This indicates the presence of a second source of firm heterogeneity. Unlike most of the literature, here we study the joint relationship between demand and productivity heterogeneity and export status, and therefore these two sources of heterogeneity, and the correlation between them, should be estimated and evaluated jointly before any conclusion is reached. We return to this point in Section 5.2.5 where we show that productivity differences between exporters and non-exporters are operative and are

[27] Results using all products are similar and available upon request. For recent work focused on the multi-product nature of firms see e.g., De Loecker et al. (2016), Grieco and McDevitt (2016), Dhyne et al. (2017), Garcia-Marin and Voigtländer (2017), and Orr (2022).

[28] It should be noted, however, that direct evidence on the TFPQ exporter premium with firm-level price data is scarce. For example, while there are a few papers that use Chilean data to estimate TFPQ in the context of exporting (Garcia-Marin and Voigtländer (2017), Linarello (2018), Lamorgese, Linarello, and Warzynski (2018), and Garcia-Marin and Voigtländer (2019)), none of these papers report the TFPQ exporter premium. Moreover, to our knowledge, our estimate of the TFPQ premium is the first one in the literature using firm-level prices while controlling for the selection of firms into markets.

more correlated to export status than is revealed by the unconditional distribution of estimated productivities.

Unlike the productivity distributions, the distributions of estimated domestic market markups vary significantly between export firms and non-export firms. Figure 1 plots these distributions, again after netting out product-year effects. The dashed line in the figure represents exporters while the solid line represents non-exporters. While there is significant overlap between the markup distributions, the figure shows clearly that exporters tend to charge higher markups than non-exporters in the domestic market. The third column in Table 4 confirms that exporters charge, on average, a 11% higher domestic markup than non-exporters.

Next, looking solely at firms that export, we find that markups in foreign markets are very different than those in the domestic market. These results are reported in Table 5. The first column of this table 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 15% lower markup abroad, on average.[29] The second column 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.[30]

The fact that markups differ significantly across destinations, and, in particular, between foreign and domestic markets, makes it likely that inferences about demand heterogeneity based on average markups will be quite misleading. We highlight this fact in column 4 of Table 4 that reports estimates from a regression of average markups (across all destinations, including the domestic market) on a dummy for exporting. Recall that exporters charge 11% higher domestic markups compared to non-exporters *in the same market*. When we look at firms' average markups, we find a difference of only 2.7% 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.[31] By using only an average markup as a mea-

[29]As a robustness check, we compare the markup charged in the domestic market to that charged in the firm's main foreign market, defined as the foreign market that accounts for the largest share of the firm's dollar sales. In this case, the result is even stronger with markups being more than 25% lower in the main foreign market than in the domestic market, illustrating that the lower average markup abroad is not driven by fringe export markets.

[30]One should be careful when drawing conclusions on the reasons why equilibrium markups are lower abroad than at home. As is standard in the literature, markups are estimated using producer prices (FOB) so that differences between domestic and foreign markups may reflect a variety of factors from differences in the state of competition to differences in distribution and trading costs across markets. Of course, this is not the case when comparing markups across firms in the domestic market.

[31]Using a different approach that allows them to estimate markup averages for groups of firms, Doraszelski and Jaumandreu (2019) find that average markups for exporters are not systematically different than for non-exporters

sure of firm demand heterogeneity, one 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. The fact that markups differ significantly even across foreign destinations implies that a one-size-fits-all approach to firms' selection into markets like, for example, using an exporter dummy in the estimation procedure, cannot capture this market composition effect.

Finally, because it is informative about the structure of firm-level demands and demand heterogeneity, we examine the relation between equilibrium markups and quantity sold in a market. Table 6 reports these results, showing that markups are systematically and negatively related to quantity sold. This is the case whether looking across firms in a given market – a specification with product-time-market fixed effects – where a 1% increase in quantity sold is associated with a 0.13% smaller markup or looking within a firm across markets – a specification with product-firm-time fixed effects – where a 1% increase in quantity sold is associated with a 0.07% smaller markup. This result is inconsistent with firms having homogeneous CES demands, even when there is strategic interaction like, for instance, in Atkeson and Burstein (2008). It is also different than what De Loecker et al. (2016) find using data on Indian firms. We should highlight, however, that both De Loecker et al. (2016) and we find that equilibrium marginal costs and prices decrease with quantity. The difference is that, in our case, prices decrease by more than marginal costs as quantity sold goes up.[32]

The joint facts that equilibrium markups decrease with quantity sold and that exporters, who tend to sell larger quantities, charge higher markups in the domestic market can only be made consistent if exporters and non-exporters face different demand functions. A model with supply-side heterogeneity only cannot explain these two sets of observations. The last column in Table 6 shows the relationship between the domestic markup and quantity sold, interacted with export status. The results confirm that markups and quantity sold are negatively correlated for both exporting and non-exporting firms but, controlling for quantity sold, exporters charge higher markups than non-exporters.

While the results so far are informative on ways that exporters and non-exporters are similar and different – seemingly not so different on the cost side but somehow quite different on

and suggest that this might be driven by foreign markups being lower on average than domestic markups. Our results, which allow us to estimate firm-level markups separately by market, are consistent with this conjecture.

[32] The negative correlation between markups and quantity sold in a market also holds when we use the subsample of firms that produce a single 5-digit product. This suggests that unobserved product heterogeneity does not drive this relationship.

the demand side – they cannot, by themselves, reveal the demand and cost fundamentals that are associated with export status. With the exception of the productivity estimates, all other results presented thus far are on equilibrium entities. To understand the fundamental sources of heterogeneity that make exporters different and how these fundamentals interact to determine different equilibrium outcomes for exporters, we need to get estimates of the underlying demand and cost function parameters. We can do this using our markup and production function estimates and, in the next subsection, we develop a methodology for doing it. On the demand side, our methodology focuses on *domestic* markups / market power as the main source of demand-side heterogeneity. By focusing on domestic market demand heterogeneity, we avoid selection bias issues due to firms selecting into markets – all firms in the data sell domestically – and minimize demand variation that may come from differences in selling costs and/or differences in competition across markets. In this way, we obtain as clean an estimate as possible on demand variation between firms that export and those that do not. We can also then check to see the extent to which domestic demand characteristics for export firms carry over to their foreign markets.

5.2 Cost and demand differences between exporters and non-exporters

This section develops a methodology that uses the results from the production function estimates and data on prices and quantities to construct firm-product-market-time demand curves and firm-product-time marginal cost curves. The methodology starts by recovering firms' marginal cost functions from our estimates of the production function parameters and productivity. Next, it computes domestic demand function parameters from the price and quantity data and from our estimates of domestic markups.

We then use the demand and cost curves to study firm-level heterogeneity in export status. Here, as in the previous section, we focus on firms' main product. Thus the marginal cost curve and demand parameters that we recover are those for each firm's main product. 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:[33]

[33] For simplicity, we let the subscript i denote a firm-product-time combination.

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

where q_i^T denotes the total quantity produced by the firm and α, β, and γ denote the output elasticities of labor, capital, and intermediate inputs, respectively. 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 $[\frac{P_i^{M\gamma}}{e^{\omega_i}}]$.[34]

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.

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 / price sensitivity of the demand for each firm-product-market-year combination.

In addition to slope, a second parameter often used to characterize demand functions is a location parameter. To obtain some estimate of this location parameter, while at the same time maintaining the flexibility of our demand estimation process, we utilize our (flexibly estimated) slope parameter and the equilibrium price and quantity point to construct a linear approximation to the individual firm demand function. The intercept of this approximation gives our estimate of the demand's location parameter. Formally, we assume that firm-product demand is approximated by the linear demand function:

$$p_{in} = a_{in} - b_{in} q_{in} - \eta Q_{-in}, \tag{8}$$

[34]This 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.

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 compute the location parameter of the firm demand curve as $a_{in}^0 = a_{in} - \eta Q_{-in}$. We refer to a^0 as 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.[35]

Summarizing demand heterogeneity with this two-parameter structure provides several benefits. First, as will become clear below, it allows us to obtain a closed-form solution for the connection between firm demand and cost heterogeneity and firm profits. This will prove useful for understanding the demand and cost features associated with exporter status.[36] Equally important, with both demand and cost heterogeneity, the linear approximation is able to reproduce the negative relationship between equilibrium quantities and markups observed in the data while, at the same time, maintaining stable preference parameters.[37] Appendix D develops a microstructure from which one can derive this heterogeneous demand system with stable utility function parameters.

5.2.3 Exporters vs. non-exporters: demand and cost heterogeneity

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. Figure 2 shows, 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

[35]While 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. As we show in Appendix D, this heterogeneity can be derived from different numbers of consumers demanding different varieties, as opposed to imposing different underlying utility parameters across varieties. In this way, the model has features analogous to the customer accumulation literature (see Arkolakis (2010); Gourio and Rudanko (2014); Foster, Haltiwanger, and Syverson (2016)), and to the finding in Bernard et al. (2022) that firms are heterogeneous in the cost of building customer relationships.

[36]Appendix E shows that the use of this linear approximation does not drive our findings and shows results using an iso-leastic heterogeneous demand approximation.

[37]The negative correlation between equilibrium markups and quantities can be captured by joint variations across firms, markets, and time in the slope of the marginal cost curve and in the slope of the market demand curve, with variation in the latter arising from variations in the number of customers demanding the firm's product in a given market at time t. Depending on the joint variation in these two elements, our specification is flexible enough to permit either decreasing or increasing markups with quantity.

($[\frac{P_i^{M\gamma}}{e^{\omega_i}}]$).[38] In all cases, the graphs report the estimates after netting out product-time effects.[39] 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 the values of the slope of domestic demand for exporters is significantly left-shifted relative to the one for non-exporters. Table 7 reports the results of regressions of these three sources of heterogeneity on an exporter dummy variable.[40] 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 (165 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.[41]

5.2.4 A profitability index

In the case of unidimensional firm heterogeneity, productivity, a scalar variable, provides the relevant summary measure for both firm profitability and export status. For our model of multidimensional firm heterogeneity, we seek to define an analogous scalar measure that is informative of both export status and the ways that demand and cost heterogeneity relate to this status. The measure we define is an index associated with firm profitability: the profitability index. Profit is a natural choice given it is a scalar variable that incorporates all aspects of firm heterogeneity and is presumably crucial in firms' decisions, including the exporting decision.[42] The profitability index is defined for each firm i's main product and each market n in which i

[38] As is common in this literature, we obtain a small set of markup estimates slightly below one. This happens in less than 9% of the observations–as a comparison, De Loecker et al. (2016) obtain that "The firm-level markups are below one for only about 8% of the sample..." Because demand curves (and profit functions) are not well-defined in these cases, in the results reported in this section of the paper we replace these cases with values slightly above one (markups equal to 1.01). As a robustness check, we drop these observations from the analysis and find very similar results.

[39] In all of our figures we control for product-market-time interacted fixed effects (equivalent to product-time fixed effects for the domestic market results), allowing us to focus on variation driven by heterogeneity across firms.

[40] We obtain similar results for regressions against the number of export destinations.

[41] This 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.

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

sells that product.

Specifically, the profitability index for firm i selling in market n is the expression for the maximized value of profit for i in n when i) i's market n demand function is approximated by a linear demand function defined by our estimates a_{in}^0 and b_{in}, and ii) i's marginal cost curve is approximated by a linear, upward-sloping marginal cost curve, $MC = c_i q_i^T$, where q_i^T denotes the total quantity produced by the firm (summing across all destinations). Note that this structure imposes the Cobb-Douglas restriction that the marginal cost curve passes through the origin.[43] Being defined by linear approximations to the underlying (non-linear) demand and cost curves, the profitability index is a synthetic construct, an index number, and not an expression for a firm's actual profitability. We use these approximations because they allow for a closed form solution for profits that is decomposable and so can show the ways that exporters and non-exporters are different.[44] In this way, and informed by our demand and cost estimates, the profitability index provides us with a scalar measure that is informative about the ways that exporters and non-exporters are different and how demand and cost heterogeneity interact to produce these differences.

To construct the profitability index, we start by noting that, under the restrictions discussed in the previous paragraph, the profit maximizing output (in market n) for firm i, q_{in}, is given by the condition:

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

or

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

where q_{i-n}^T denotes the total quantity sold by the firm to all markets other than n. To be consistent with our Cobb-Douglas assumption, 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):

[43] It also rules out negative marginal cost values that might arise in alternative linearizations of a firm's upward-sloping marginal cost curve.

[44] Appendix E shows that the main results of the paper do not rely on using these linear approximations and hold when we compare profits computed using the actual marginal cost curve and iso-elastic demand curves.

$$q_{in} = \frac{a^0_{in} - c_i q^T_{i-n}}{2b_{in} + c^0_i[\frac{q^T_i}{K^\alpha_i L^\beta_i}]^{(1/\gamma)} q_i^{T(-2)}}. \tag{11}$$

Profits are then given by:

$$\Pi_{in} = 0.5[\frac{(a^0_{in} - c_i q^T_{i-n})^2}{2b_{in} + c^0_i[\frac{q^T_i}{K^\alpha_i L^\beta_i}]^{(1/\gamma)} q_i^{T(-2)}}] \tag{12}$$

It is this expression that is assigned to each firm, i, in the data as its profitability index. Note that, with the exception of the scale terms, our profitability index is a function only of estimated demand and cost parameters. Controlling for scale, variation in the demand and cost parameter estimates, a^0, b, and c^0, across exporters and non-exporters induce variations in the profitability index. This variation provides insights into the ways that exporters and non-exporters are different and how demand and cost fundamentals interact to create profitability differences.[45] The appropriate way to control for scale is the one remaining issue.

In determining how demand and cost fundamentals relate to export status, we need to be careful not to contaminate our analysis with (potentially) endogenous scale effects, especially the values of K and L. That is, we want to avoid concluding that export firms are different because they have more K and L. Rather, we want to ask what domestic market demand and cost features make the profitability index for firms that export different than that for firms that do not export and so can potentially explain export status (and the observed larger scale). Our first approach to addressing this question is to choose scale parameters so that q^T_i is equal to the median quantity sold of the product by non-exporters, $\bar{q}^T$, and K_i and L_i are equal 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:[46]

$$\Pi^{Idx}_i = 0.5[\frac{(a^0_i)^2}{2b_i + c^0_i \bar{r}}] \tag{13}$$

[45] Recall that, for reasons discussed earlier, we focus primarily on demand estimates from the domestic market.
[46] Because all firms sell only in the domestic market, q^T_{i-n} in expression (12) is equal to zero.

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 profitability heterogeneity for a firm with marginal cost evaluated at the median quantity, producing at the median capital and labor intensity, were that firm selling in the domestic market only. The first graph in Figure 3 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 7 shows that exporters are, on average, 66 log-points more profitable than non-exporters, were they to operate at the same relatively small scale.

An alternative to the above thought experiment still keeps scale as fixed but replaces $\bar{q}^T$, $\bar{K}$, and $\bar{L}$ with the corresponding median values for exporters. Doing so implies values that are roughly an order of magnitude larger than the median values for non-exporting firms. This highlights the substantial size differences between exporters and non-exporters. The second graph in Figure 3 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 7 shows that, in this case, exporters are substantially more profitable (124 log-points) than non-exporters, on average.

As a final way to approach this issue of scale, we note that our estimates indicate that the production functions are roughly constant returns to scale, i.e., each firm's long run marginal cost curve is constant. In this case, any cost difference across firms in the long run is driven solely by differences in productivity (and input prices). This suggests an alternative specification for the profitability index that is scale free. This alternative index approximates firm i's marginal cost curve with its associated constant long run marginal cost curve. Profits under this thought experiment are given by:

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

where MC_i is the equilibrium marginal cost value estimated in Section 4. The last graph in Figure 3 reports this profitability index for exporting and non-exporting firms and confirms that exporters are significantly more profitable. On average, exporters are 210 log-points more profitable than non-exporters.

5.2.5 Further disaggregating profits between demand and cost

All of the analysis so far indicates that domestic market thickness – the slope of the firm's domestic market demand curve – is of first-order importance in determining scale and export status. While the distributions of willingness-to-pay and productivity are 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, i.e., high willingness-to-pay products have high production costs – for example, because of quality differences not captured by input prices or because 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:

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

Under this normalization, heterogeneity in the profitability of a firm depends on the two components of interest: normalized willingness-to-pay, $\frac{\left(a_i^0\right)^2}{b_i}$ and normalized productivity, $\frac{c_i^0}{b_i}$. These components highlight that the effect of a shift in demand or in the marginal cost curve on profits depends on the slope of demand. If in order to sell an extra unit the firm needs to significantly drop its price, the higher demand and the lower cost will not have much of an effect on profits.

Figure 4 plots these two components based on export status. We find that there is indeed a strong positive correlation between normalized cost-side and demand-side heterogeneity. Controlling for product-time effects, the correlation (in logs) between a^0 and c^0 is 0.842.[47] We also find that exporters are shifted both down (lower costs / higher productivity) and to the right

[47] This 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.

(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. This relation is indicative of the fact that exporters have higher domestic markups than do non-exporters. These results are displayed in a regression format in Table 8.

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 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 of Table 8). 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 and this is associated with the fact that they have thicker markets – flatter domestic demand curves. At the same time, productivity and willingness-to-pay are still related to 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 demand-cost configuration than do non-exporters. These factors combine to give exporters a higher domestic profitability index than non-exporters.

5.2.6 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?[48] 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 $\frac{\left(a_i^0\right)^2}{b_i}$ to ask whether high domestic demand is correlated with high foreign demand.

Table 9 reports results from a regression of the (log) foreign demand index of a firm on

[48] It 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.

its domestic counterpart, controlling for product-time-foreign destination fixed effects. Foreign demand is found to be strongly correlated with firms' domestic demand. Figure 5 displays the correlation between firms' domestic and foreign demand-side heterogeneity, where foreign demand is measured as the average $\frac{\left(a_i^0\right)^2}{b_i}$ across the destinations the firm sells to. The rank correlation between domestic and foreign demand-side heterogeneity equals 0.42, further illustrating that exporters with high domestic demand indices tend to have high foreign demand indices as well.

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 (see e.g., Foster, Haltiwanger, and Syverson (2008)). 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. Markups in foreign markets are significantly lower than in the domestic market, and by not taking this into account, one would underestimate exporters' markup advantage by 80%. When properly accounting for demand heterogeneity, we find that while both demand and cost heterogeneity matter, the former is the dominant firm-specific feature related to export status. Moreover, we find that the specific demand feature 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 short, what our findings show is that successful export firms are those that provide products with significant (domestic) demand advantages at a still reasonable cost (productivity). This result has important policy implications. Typically, policies aimed at promoting exports target firm-level productivity enhancement or market access costs. Our results indicate that doing so, without considering the demand advantages the product enjoys, are likely to have limited success. As selling in foreign markets is known to require significant fixed costs, our finding that foreign and domestic market thickness are related and matter for export success, although new, should not be a surprise, and further supports the notion that market access policies should be targeted at firms with significant domestic demand advantages. Finally, our results also have implications for analyses of trade liberalization policies. Typically, this discussion has focused on the fact that these policies create efficiency gains by reallocating output towards more productive firms. Our results indicate that a trade liberalization is also likely to reallocate output towards firms with higher markups created by demand effects / market power.

Our findings also have important implications for models of firm-level export decisions. Specifically, static, firm-level trade models since Melitz (2003) have traditionally posited that productivity distinguished exporters (high productivity) from non-exporters (low productivity). Subsequent models, some of them on exporting dynamics, posited differences in market entry cost and foreign demand heterogeneity as additional factors. Our work shows that demand heterogeneity, captured by differences in domestic demand, is a key characteristic distinguishing exporters and non-exporters. In this sense, there is a firm-product characteristic at the demand level that makes exporters different. In addition, we show that the interaction between demand and productivity heterogeneity is nuanced and paints a new picture of the fundamental differences between exporters and non-exporters.

While a study of the reasons that 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 77% 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 spillover effects on foreign markets. Moreover, advertising expenditure is strongly positively correlated with our measure of demand heterogeneity $\frac{\left(a_i^0\right)^2}{b_i}$, 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.[49]

[49]See 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 Ackerberg (2001).

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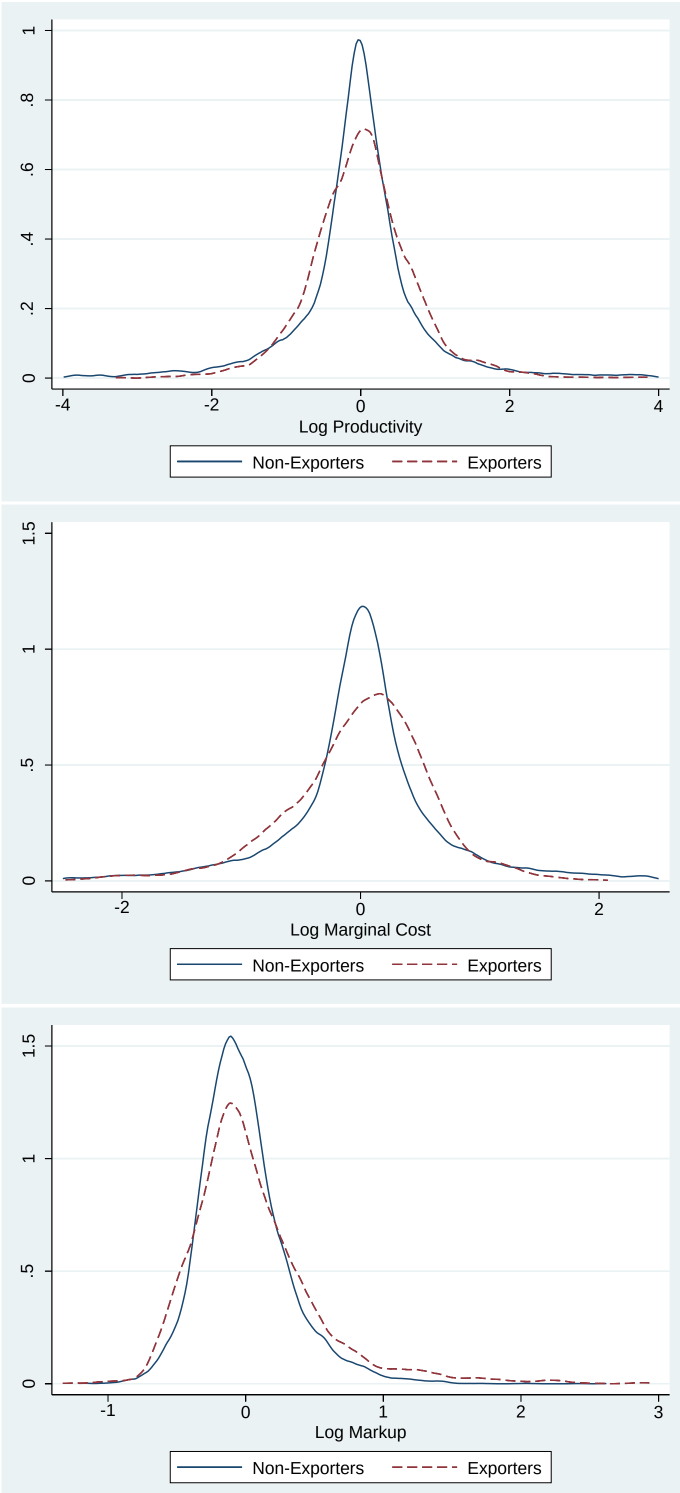
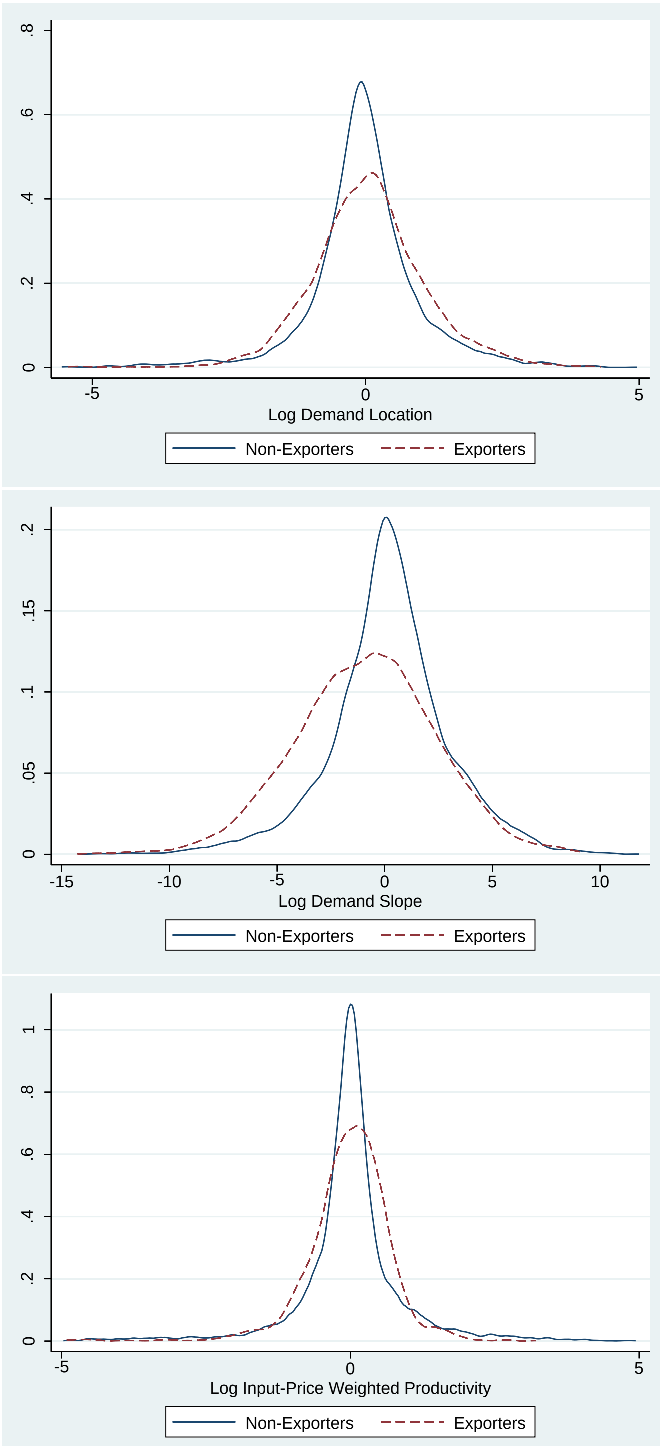
Figure 1: Distribution of Productivity, Marginal Cost, and Domestic Markup



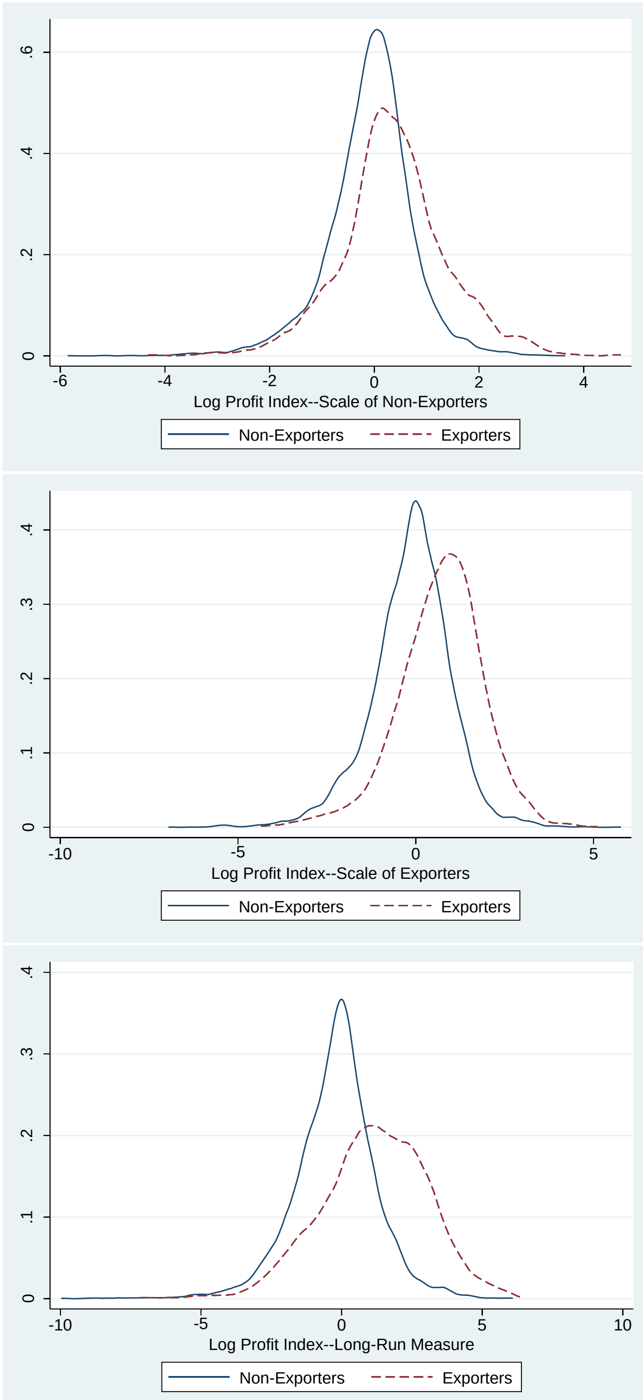
Notes: In this figure we plot the distributions of (log) productivity, (log) marginal cost, and (log) domestic markup, separately for exporters and non-exporters. All are measured at the firm-product-year level and are net of product-year fixed effects.

Figure 2: Distribution of Domestic Demand Location Parameter, Domestic Demand Slope, and Input-Price Weighted Productivity



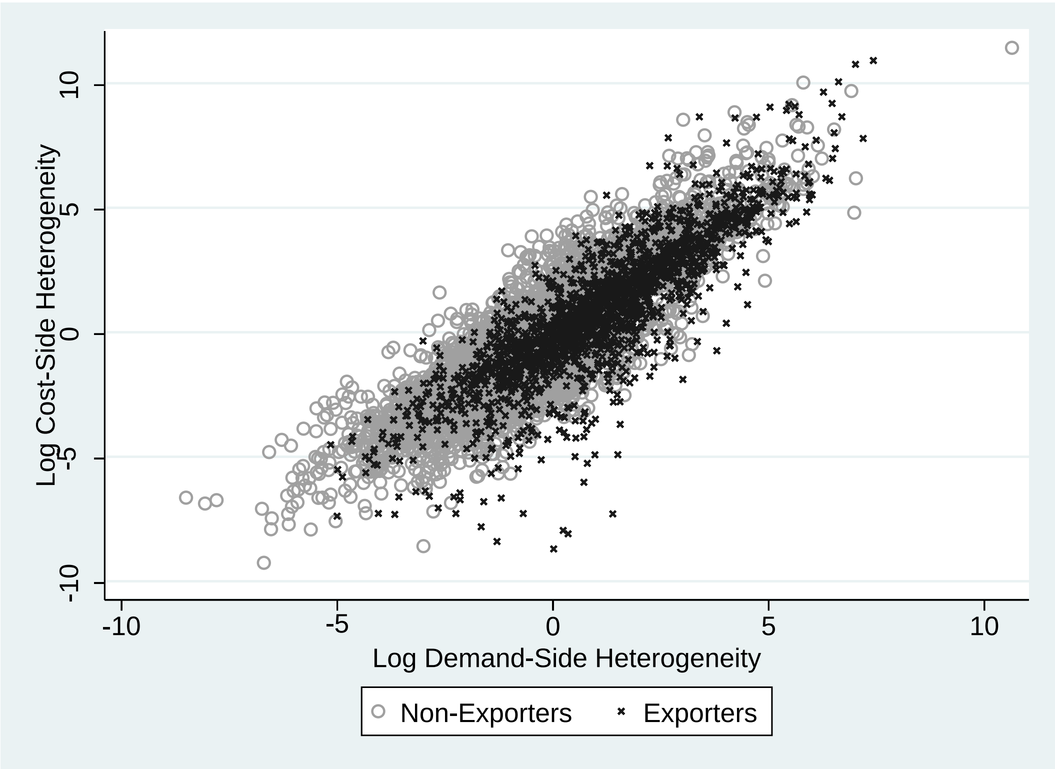
Notes: In this figure we plot the distributions of the (log) domestic demand location parameter (a^0), (log) domestic demand slope (b), and (log) cost-side heterogeneity $\left(\frac{(P^M)^{\gamma}}{e^{\omega}}\right)$, separately for exporters and non-exporters. All are measured at the firm-product-year level and are net of product-year fixed effects.

Figure 3: Distribution of Domestic Profitability Index



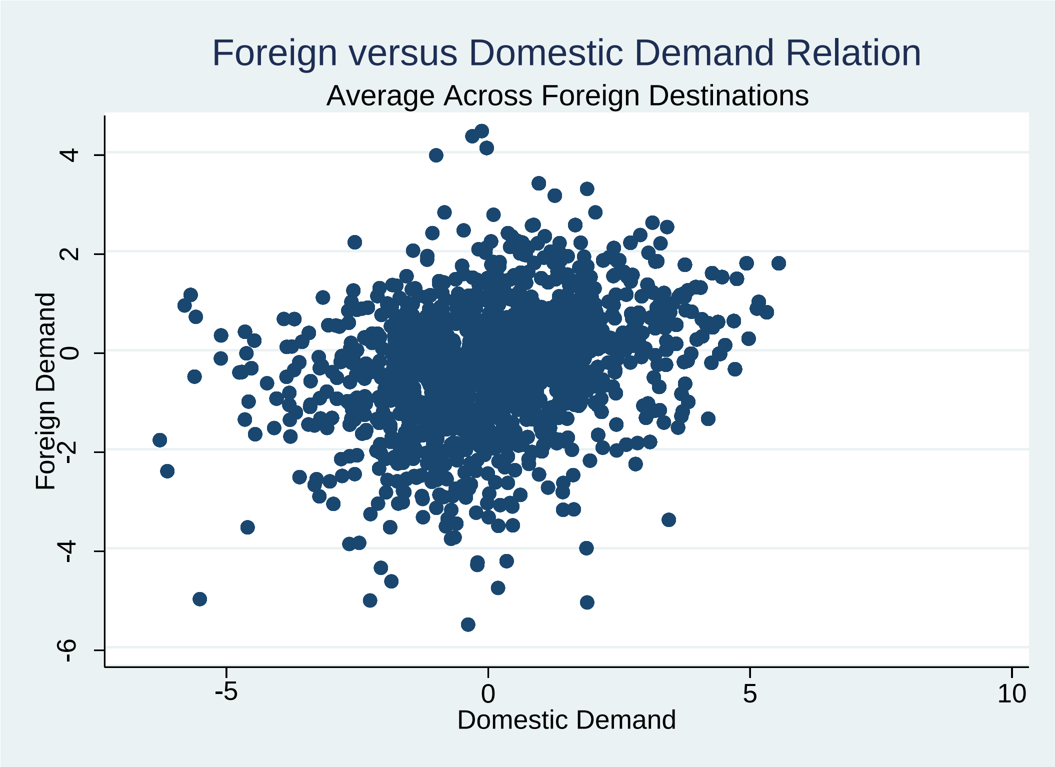
Notes: In this figure we plot the distribution of the three versions of the (log) domestic profitability index, separately for exporters and non-exporters. The first two are computed by fixing capital and labor at values corresponding to the median for non-exporting and exporting firms, respectively. The third is the long-run version in equation (14) with constant marginal costs. All of the profitability index measures are at the firm-product-year level and are net of product-year fixed effects.

Figure 4: 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 5: Relationship between Foreign and Domestic Demand



Notes: In this figure we plot the (log) measure of demand-side heterogeneity ($\frac{(a^0)^2}{b}$) 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 0.42.

Table 1: Descriptive Statistics

ISIC 3 Industry Code	Industry Description	Percentage of Manufacturing Sales	Exporting Firms (%)	Number of Firms	Number of Products	Number of Products Exported	Single Product Firms (%)	Nobs (Firm-Product-Time)	Nobs (Firm-Time)
151	Production, processing and preservation of meat, fish, fruit, vegetables, oils and fats	14%	37%	394	8	8	65%	1938	1558
153	Manufacture of grain mill products, starches and starch products, and prepared animal feeds	4%	11%	117	3	3	26%	894	542
154	Manufacture of other food products	5%	3%	816	9	7	90%	4074	3749
155	Manufacture of beverages	7%	60%	169	3	3	90%	667	631
181	Manufacture of wearing apparel, except fur apparel	1%	12%	274	3	1	91%	1126	1074
201	Sawmilling and planing of wood	4%	22%	210	6	6	64%	1148	864
221	Publishing	1%	5%	184	6	5	42%	1195	627
222	Printing and service activities related to printing	1%	9%	143	6	5	40%	932	436
242	Manufacture of other chemical products	5%	41%	196	9	9	53%	1248	882
281	Manufacture of structural metal products, tanks, reservoirs and steam generators	1%	8%	246	10	6	67%	1179	921
Total		**43%**	**--**	**2,749**	**63**	**53**	**--**	**14,401**	**11,284**
Average		**4%**	**21%**	**275**	**6**	**5**	**63%**	**1,440**	**1,128**

Table 2: Production Function Estimates

Intermediate Input Expenditures					Firm-level Deflated Intermediate Input Quantities				
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	0.25	0.08	0.72	1.05	151	0.19	0.16	0.66	1.01
153	0.07	0.06	0.80	0.92	153	0.13	0.09	0.71	0.93
154	0.35	0.07	0.64	1.07	154	0.20	0.06	0.79	1.05
155	0.01	0.08	0.86	0.95	155	0.26	0.05	0.75	1.06
181	0.12	0.00	0.84	0.96	181	0.14	0.15	0.64	0.93
201	0.11	0.12	0.77	0.99	201	0.28	0.09	0.67	1.04
221	0.37	-0.05	0.71	1.03	221	0.40	0.14	0.47	1.01
222	0.16	0.46	0.67	1.28	222	0.35	0.47	0.47	1.30
242	0.09	0.10	0.77	0.96	242	0.43	0.07	0.53	1.04
281	-0.40	0.00	1.66	1.26	281	0.18	0.14	0.81	1.13

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

Table 3: Summary Statistics—Median and Mean Firm-Level Markups

Intermediate Input Expenditures

ISIC 3 Industry	Median Markup	Mean Markup
151	1.389	1.624
153	1.228	1.337
154	1.477	1.564
155	2.063	2.479
181	2.265	2.666
201	1.540	1.728
221	2.056	2.202
222	1.849	1.982
242	1.945	2.586
281	3.425	3.970
Industry Average	1.924	2.214

Firm-level Deflated Intermediate Input Quantities

ISIC 3 Industry	Median Markup	Mean Markup
151	1.260	1.390
153	1.081	1.155
154	1.800	1.918
155	1.777	2.007
181	1.709	1.985
201	1.341	1.541
221	1.372	1.466
222	1.367	1.412
242	1.324	1.745
281	1.644	1.908
Industry Average	1.468	1.653

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 4: Markups, Productivity, and Marginal Cost

	Dependent Variable:			
	Log(Productivity)	Log(Marginal Cost)	Log(Domestic Markup)	Log(Average Markup)
Dummy (Exporter)	0.050	-0.046	0.113***	0.027*
	(0.03)	(0.03)	(0.01)	(0.01)
Product-Year FE	Yes	Yes	Yes	Yes
r2	0.09	0.89	0.24	0.24
N	11284	11284	11284	11284

Notes: Observations 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 include product-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 5: Markups within Firms and Markets

	Dependent Variable:	
	Log(Markup)	Log(Foreign Markup)
Dummy (Foreign Market)	-0.154***	
	(0.02)	
Log(GDP)		0.005*
		(0.00)
Log(GDP per capita)		0.055***
		(0.00)
Log(Distance)		0.023**
		(0.01)
Common Language		0.043***
		(0.01)
Product-Firm-Year FE	Yes	Yes
r2	0.72	0.83
N	28849	16840

Notes: Column 1 reports estimates from a regression of (log) markups, at the firm-product-year-destination level, on a dummy variable for whether the observation corresponds to a foreign destination. Column 2 reports 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. All the regressions include product-firm-year fixed effects. Standard errors are reported in parentheses below the point estimates.

Table 6: Markups and Quantity

	Dependent Variable:			
	Log(Markup)			Log(Domestic Markup)
Log(Quantity)	-0.316***	-0.133***	-0.074***	
	(0.00)	(0.00)	(0.00)	
Log(Domestic Quantity)				-0.057***
				(0.00)
Exporter Dummy				0.717***
				(0.05)
Log(Domestic Quantity)*Exporter Dummy				-0.034***
				(0.00)
Fixed-Effects	Product-Market-Firm	Product-Market-Time	Product-Firm-Time	Product-Time
r2	0.77	0.49	0.74	0.31
N	28849	28849	28849	11284

Notes: The numbers reported in the first three columns are estimates from regressions of (log) markups, at the firm-product-year-destination level, on (log) quantity (sold to the corresponding market), with different sets of fixed effects. The last column shows results of a regression of (log) domestic markups on (log) domestic quantity, and exporter dummy, and an interaction term. Standard errors are reported in parentheses below the point estimates.

Table 7: Exporter Premium on Domestic Demand and Cost Parameters and on Profitability

	Dependent Variable:					
	Demand Intercept	Demand Slope	Cost-Side Heterogeneity	Productivity	Profit Index (Domestic Scale)	Profit Index (Exporter Scale)
Exporter	0.101***	-1.590***	-0.098*	0.050	0.659***	1.240***
	(0.03)	(0.09)	(0.05)	(0.03)	(0.03)	(0.03)
Product-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.86	0.78	0.84	0.09	0.41	0.41
N	11284	11284	11284	11284	11284	11284

Notes: The numbers reported are estimates from regressions of the (log) domestic profitability index, and its components—demand intercept, 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 8: Relationship between Exporting and Domestic Demand and Cost Heterogeneity

	Dependent Variable:			
	Cost	Demand	Cost	Demand
Exporter	1.492***	1.793***	-0.510***	0.803***
	(0.06)	(0.05)	(0.03)	(0.03)
Demand			1.117***	
			(0.01)	
Cost				0.663***
				0.00
Product-Year FE	Yes	Yes	Yes	Yes
r2	0.52	0.40	0.88	0.84
N	11284	11284	11284	11284

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 $(\frac{(a^0)^2}{b})$. Standard errors are reported in parentheses below the point estimates.

Table 9: Relationship between Foreign and Domestic Demand Heterogeneity within Firm and Product

	Dependent Variable: Log(Foreign Demand Heterogeneity)
Domestic Counterpart	0.301***
	(0.01)
Product-Market-Time FE	Yes
r2	0.57
N	17565

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

The ABCs of Firm Heterogeneity when Firms Sort into Markets: The Case of Exporters

Bernardo S. Blum, Sebastian Claro, Ignatius Horstmann, and David A. Rivers

Online Appendix

A Appendix: Data construction

The data used in this paper come from a merged ENIA-Customs dataset for the period 2002-2009 created by the Chilean Instituto Nacional de Estadisticas specifically for this research. The Encuesta Nacional Industrial Anual (ENIA) is an annual industrial survey conducted by Chile's *Instituto Nacional de Estadisticas* (National Institute of Statistics–INE) and covers all manufacturing plants with 10 or more workers. For each product produced by each plant-year pair, the data report value (revenues) and quantity produced and sold by the plant, in addition to the unit of quantity measurement (e.g., litres, kilograms). Each product is classified by a 5-digit Central Product Classification (CPC5) code, version 1. Also, these data contain a measure of the total quantity of each product exported by a plant-year pair. The Chilean Customs data are collected by the Chilean Customs Office and cover all Chilean export transactions. The data put together for this project contains an identifier for the exporting firm, the 5-digit CPC product classification of the exported good, the destination country, the free-on-board (FOB) value, the exported quantity, and the measurement unit. Because the Customs data identify the exporting *firm*, not the plant, the merge between the ENIA and the Customs data is done at the firm level. Finally, for confidentiality reasons, the data report an anonymized versions of the 5-digit Central Product Classification (CPC5), although they report the real ISIC 3-digit industry the firm belongs to.

Match quality and aggregation

A key feature of the data is the match between the ENIA and the Customs datasets. At the firm level, the export values reported in ENIA and in Customs match quite closely. Export values in the two datsets have a correlation coefficient of 0.96. Moreover, the export value reported in ENIA accounts for 99% of the export value reported by the same firms in Customs. At the firm-product (5-digit CPC) level, we identified quite a few cases in which ENIA reports exports of a given product in a given year by a firm, but the Customs data do not report such an export. Instead, in most cases the Customs data report that the same firm exported a different product during the same year. Recall that the match of firm-level export values is extremely good. This implies that the source of these mismatches is mis-classification of the exported product in either of the two datasets. Note that this can happen because while firms self-report their product categories in ENIA, Customs reports the classification assigned by the Customs agent that processed the export transaction. Because of this, we aggregate products to the CPC 3-digit level. At the firm-year-CPC3 level, these mis-matches become extremely rare. In particular, they account for only 4% of the value of exports.

When aggregating from CPC5 to CPC3, we construct an equivalent measure of quantities using the following procedure. First, for each CPC5 product, we compute the average product price across all firms in each year. Then, within each CPC3 product, we select a numeraire product (the CPC5 product that has the highest average sales across years). Next, for each CPC5 product, we multiply the quantity produced by the ratio of the average numeraire price to the average price for that product. What this does is to use the average relative price between the two goods to translate the quantity of a given CPC5 product into an equivalent quantity of the numeraire product. These adjusted quantities are then summed at the firm-year-CPC3 product level to form our measure of quantity. To illustrate the intuition behind this procedure, suppose that a firm produces *Sparkling wine of fresh grapes* and *Wine of fresh grapes*, two CPC5 products belonging to the same CPC3 group (*Wines*). Our procedure computes the average prices of each CPC5 category in the economy, and "converts" *Sparkling wine of fresh grapes* into the equivalent of *Wine of fresh grapes* using this price ratio.

More precisely, let (f, j, k, t) index firms, CPC3 products, CPC5 products, and year, respectively. Thus, q_{fjkt} represents the quantity produced by firm f in year t of CPC5 product k which is part of CPC3 group j. The "equivalent units" measure of quantity expressed in terms of numeraire product N is given by $\tilde{q}_{fjkt} = q_{fjkt}\frac{p_{jkt}}{p_{jNt}}$, where $p_{jkt} = \frac{\sum_{\Omega_{jkt}} r_{fjkt}}{\sum_{\Omega_{jkt}} q_{fjkt}}$ is a quantity-weighted average price across firms and Ω_{jkt} is the set of firms producing product jk in period t. Then, we define the "equivalent units" price as $\tilde{p}_{fjkt} = \frac{r_{fjkt}}{\tilde{q}_{fjkt}}$, where r_{fjkt} denotes revenues.

Within each firm-year pair, we aggregate across CPC5 products to the CPC3 level: $\tilde{q}_{fjt} = \sum_{\Omega_{fjt}} \tilde{q}_{fjkt}$, where Ω_{fjt} is the set of CPC5 products within CPC3 group j produced by firm f in period t. It is easy to show that the implied CPC3 price $\tilde{p}_{fjt}$ is a quantity-weighted average of the CPC5 prices: $\tilde{p}_{fjt} = \frac{\sum_{\Omega_{fjt}} r_{fjkt}}{\sum_{\Omega_{fjt}} \tilde{q}_{fjkt}} = \frac{\sum_{\Omega_{fjt}} \tilde{p}_{fjkt}\tilde{q}_{fjkt}}{\sum_{\Omega_{fjt}} \tilde{q}_{fjkt}}$. A similar aggregation procedure is performed in the Customs data, so that the final dataset has information of exported values and quantities for each firm-destination-CPC3-year quartet.

Intermediate input prices

As discussed in the text, a valuable feature of our ENIA data is that they contain information on both expenditures on and quantities used of intermediate inputs for each firm-year. This section describes how we use these data to construct firm-level measures of prices paid for intermediates.

Even though firms in our sample use, on average, 7.5 CPC5 different products (and 6 CPC3 categories) as inputs, expenditures on inputs are highly concentrated. The average firm spends 68% of their input expenditures on its main CPC5 input and 73% on its main CPC3 input category. In light of this, our main firm-level input price index is constructed using information on the firm's top CPC3 intermediate input (in terms of total expenditures across all time periods). In particular, because we are primarily interested in cross-firm variation in input prices, we calculate the median price paid for the top CPC3 input by the firm over time and, then, we normalize this price by the median price paid for the same input by all firms producing the same output. Finally, we use the industry-level intermediate input price deflator to allow for input price movements over time.

We have explored using several other measures of firm input prices, including constructing the index described above using the firm's main CPC5 input (instead of the main CPC3 input). We have also computed firm-specific input price indices based on the prices paid for all inputs the firm uses. In this case, we first normalize the median price paid by the firm for each input by the median price paid for the same input by all firms producing the same output (as above). Then, we compute firm-level revenue-weighted averages of these relative prices. Finally, we use the industry-level intermediate input price deflator to allow for input price movements over time.

Irrespective of the way the input price index is computed, we find a positive correlation between firms' input and output prices. For example, regressions of (log) domestic output price on (log) intermediate input price, controlling for product-year fixed effects show an elasticity of output price with respect to input price of around 0.3 (we obtain similar numbers when we use the average output price charged by the firm across destinations). This is consistent with the notion that higher quality intermediate inputs are used to produce higher quality outputs, but it also reveals a pass-through that is far less than complete. These results are not reported in the paper to conserve space but are available upon request.

The way input price indices are computed does not affect the main results of the paper. The results reported in the main text use the input price index based on the firm's main CPC3 input. We find that the indices using all inputs are noisier due to the fact that some marginal inputs are used by very few firms. As a result, the median price paid by all firms for that input can be quite volatile, which creates noise. Nevertheless, all the main results of the paper hold irrespective of the input price index used.

Variable construction, working sample, and summary statistics

The variables used in the estimation procedure are constructed in the following way. From ENIA we have CPC3-level total sales for each firm-product-year pair. From Customs, we have the total value of exports by destination, also by firm-CPC3-year trio. These two variables are converted into US Dollars using the yearly average exchange rate. The value of domestic sales for each firm-product-year trio is given by the difference between total and export sales.

The Customs data report exports at the firm-product-year-destination level. This is the measure of exports we use. The same data report export quantities as well, but we cannot directly use these data because ENIA and Customs often measure quantities in different physical units (e.g., kilograms vs. litres). Instead, we use the fact that the ENIA data report firms' total quantity sold and the share of this quantity exported, by product and year. We combine these two variables to obtain the quantity exported by firm, product, and year. From Customs, we compute the share of firm-product-year export quantity sold to each foreign market. We use these shares to allocate, across foreign markets, the firm-product-year total export quantity reported in the ENIA data. Finally, unit prices by firm-product-year-market are obtained by dividing sales by quantities.

As discussed in the text, our working sample includes 10 industries that feature large numbers of observations, high fractions of firms that export, and use a more standard (and uniform) measure of physical quantities of output across firms (e.g., standard units such as litres or kilograms, as opposed to "units" or "boxes"). Within these industries, we limit our analysis to products with at least 40 firm-year observations, due to the data demands imposed by our estimation procedure. This trims some marginal products and affects about 6% of the observations. Finally, we trim the top and bottom 5% tails of the intermediate input price distribution, as well as the top and bottom 2.5% tails of the overall and domestic output price distribution. We also trim observations with intermediate input shares close to zero or above 1. This affects about 2% of the observations.

Our final working sample consists of 14,401 firm-product-time observations and 11,284 firm-year observations corresponding to the main product of each firm. Table 1 in the text reports summary statistics at the industry level. Table A1 below reports summary statistics at the firm-year level.

B Appendix: Estimation algorithm

SINGLE-PRODUCT FIRMS

First Stage:

1. Regress the modified shares s_{ftD} on inputs, domestic price, domestic quantity, and demand shifters $(k_{ft}, l_{ft}, m_{ft}, P_{ftD}, z_{ftD}, Q_{ftD})$, instrumenting for domestic quantity using lagged inputs (k_{ft-1}, l_{ft-1}) following equation (4). Obtain an estimate of ε_{ft} and the combined term $\ln \xi^M (k_{ft}, l_{ft}, m_{ft}) - \ln \tilde{\mu} (P_{ftD}, z_{ftD}, Q_{ftD})$, where ξ^M is the output elasticity of intermediate inputs.

Second Stage:

1. Form $\tilde{y}_{ft} = y_{ft} - \varepsilon_{ft}$.

2. For a guess of the parameters of the production function, the Markov process for productivity, and the product fixed effects (ϕ_j), solve for η_{ft} using equation (5). In our estimates we employ a Cobb-Douglas production function and an AR(1) process for productivity, which gives us:

$$\begin{aligned}\eta_{ft} \;\; = & \;\; \tilde{y}_{ft} - \alpha k_{ft} - \beta l_{ft} - \gamma m_{ft} \\ & -\rho_0 - \rho_1 \left(\tilde{y}_{ft-1} - \alpha k_{ft-1} - \beta l_{ft-1} - \gamma m_{ft-1} - \phi_j\right) - \phi_j .\end{aligned}$$

3. Form moments between η_{ft} and instruments to estimate $(\alpha, \beta, \gamma, \rho_0, \rho_1, \phi_j)$ via GMM.[50]

Compile Estimates:

1. Use the estimates to solve for productivity, domestic markups, marginal costs, and foreign markups.

   (a) Productivity

$$\hat{\omega}_{ft} = y_{ft} - \hat{\alpha} k_{ft} - \hat{\beta} l_{ft} - \hat{\gamma} m_{ft} - \hat{\phi}_j - \hat{\varepsilon}_{ft}$$

[50] Alternatively, given the AR(1) structure for productivity, one could solve for $\tilde{\omega}_{ft}$ and $\tilde{\omega}_{ft-1}$ as a function of (α, β, γ) and regress $\tilde{\omega}_{ft}$ on $\tilde{\omega}_{ft-1}$ controlling for product-specific fixed effects. The residual from this regression, η_{ft}, could then be interacted with instruments to estimate (α, β, γ). This is what we do in practice, using $k_{ft}, l_{ft,} m_{ft-2}, p_{ftD}$ as instruments.

(b) Domestic markup

$$\ln \hat{\mu}_{ftD} = -s_{ftD} - \hat{\varepsilon}_{ft} + \ln \hat{\gamma}$$

(c) Marginal cost

$$\ln \hat{mc}_{ft} = \ln P_{ftD} - \ln \hat{\mu}_{ftD}$$

(d) Foreign markups (for all foreign destinations n)

$$\hat{\mu}_{ftn} = \hat{\mu}_{ftD} \frac{P_{ftn}}{P_{ftD}}$$

MULTI-PRODUCT FIRMS

First Stage:

1. Regress the modified (product-specific) shares s_{fjtD} on inputs, domestic price, domestic quantity, and demand shifters $(k_{fjt}, l_{fjt}, m_{fjt}, P_{fjtD}, z_{fjtD}, Q_{fjtD})$, instrumenting for domestic quantity using lagged inputs (k_{fjt-1}, l_{fjt-1}) following equation (4). Obtain an estimate of ε_{fjt} and the combined term $\ln \xi^M (k_{fjt}, l_{fjt}, m_{fjt}) - \ln \tilde{\mu} (P_{fjtD}, z_{fjtD}, Q_{fjtD})$, where ξ^M is the output elasticity of intermediate inputs.

Second Stage (not needed):

Compile Estimates:

1. Use the estimates to solve for productivity, domestic markups, marginal costs, and foreign markups.

   (a) Productivity

   $$\hat{\omega}_{fjt} = y_{fjt} - \hat{\alpha} k_{fjt} - \hat{\beta} l_{fjt} - \hat{\gamma} m_{fjt} - \hat{\phi}_j - \hat{\varepsilon}_{fjt}$$

   (b) Domestic markup

   $$\ln \hat{\mu}_{fjtD} = -s_{fjtD} - \hat{\varepsilon}_{fjt} + \ln \hat{\gamma}$$

   (c) Marginal cost

   $$\ln \hat{mc}_{fjt} = \ln P_{fjtD} - \ln \hat{\mu}_{fjtD}$$

   (d) Foreign markups (for all foreign destinations n)

   $$\hat{\mu}_{fjtn} = \hat{\mu}_{fjtD} \frac{P_{fjtn}}{P_{fjtD}}$$

C Appendix: Generality of demand structure in estimation procedure

The purpose of this appendix is to show that, although our demand specification in Section 3 does not explicitly depend on competitors' strategic variables, it is still able to capture a large set of models of imperfect competition (and demand-side assumptions) used in the literature. Recall that the modeling assumption used in the estimation procedure is that the optimal markup charged by firm f in a market μ_f and its quantity demanded Q_f can be written as a function of the firm's own price P_f, observed demand shifters z_f, and an unobserved demand shock χ_f. Note that χ_f can incorporate multiple sources of heterogeneity (for example multiple unobserved demand shifters). The only restriction is that their joint impact on demand can be written as a single sufficient statistic χ_f. For example, in the standard logit demand model (see Berry (1994)), any relevant demand characteristics that are not observed will be subsumed within the unobserved product characteristics (often denoted by ξ).

To illustrate how this specification can capture well-known models of imperfect competition, consider the nested CES structure with Cournot competition in Atkeson and Burstein (2008). In this case, $\mu_f = \frac{\varepsilon_f}{\varepsilon_f - 1}$, where $\varepsilon_f = \left(s_f \frac{1}{\theta} + (1 - s_f) \frac{1}{\gamma} \right)^{-1}$, and quantity demanded is given by $Q_f = \left(\frac{P_f}{P_s} \right)^{-\gamma} \left(\frac{P_s}{P} \right) Y$. θ and γ are parameters and P_s, P, and Y are aggregate components. The former are subsumed in the flexible specification while the latter are captured by product-time fixed effects. Besides these variables and the firm's own price, the model has one additional variable of relevance: the firm's market share, s_f. This firm-specific shifter is captured in our specification by χ_f. Hence, although this model features strategic interactions between firms, in that firms respond to the prices of other firms, the impact of these strategic interactions is fully captured in a sufficient statistic, s_f. Of course our framework can also handle models of imperfect competition without strategic interactions including monopolistic competition under various demand structures (e.g., linear demand as in Melitz and Ottaviano (2008), logit demand as in Roberts et al. (2018), and CES demand as in Melitz (2003)).

The assumption of a sufficient statistic that captures the state of competitor behavior is common in analytical models of imperfect competition. It serves the purpose of reducing a complex optimization problem to a simple, univariate one. In standard CES-variety models of monopolistic competition, the sufficient statistic is common to all firms – the aggregate price index is the sufficient statistic. In the homogeneous goods Cournot model, as another example, the sum of competitors' outputs is the firm-specific sufficient statistic. Where the sufficient statistic is common across all firms, it is an unobserved aggregate component (part of aggregate fixed effects) in our estimation procedure. Where the sufficient statistic is firm specific, as in Atkeson and Burstein (2008), it becomes an unobserved, firm-specific shifter.

While our assumptions are consistent with a wide variety of models used in the literature, not all models fit our assumptions. Models in which the pricing decisions of firms have differential effects on their competitors do not admit this sufficient statistic representation. For example, quality differentiation (vertical) and spatial models feature individual firm demands that depend on the prices of "neighboring" products. In these cases firm demand (and markups) will depend on the neighboring prices that different firms face.

D 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 is straightforward 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. For simplicity, assume 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:

$$U_1 = x + ay_1 - .5by_1^2 \tag{16}$$

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

$$U_2 = x + ay_2 - .5by_2^2 \tag{17}$$

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:

$$p_1 = a - by_1. \tag{18}$$

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

$$p_2 = a - by_2. \tag{19}$$

Market demand for Y_1 is then given by:

$$p_1 = a - \frac{b}{n_1}Y_1 \tag{20}$$

and for Y_2 by:

$$p_2 = a - \frac{b}{n_2}Y_2. \tag{21}$$

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 consumer's preferences be given by the utility function:

$$U = (U^1)^{n_1/N}(U^2)^{1-n_1/N} \tag{22}$$

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

$$U^1 = x + ay_1 - .5\frac{b}{n_1}y_1^2 \tag{23}$$

and

$$U^2 = x + ay_2 - .5\frac{b}{n_2}y_2^2. \tag{24}$$

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.

E Appendix: Do the linear approximations matter?

Many of the results in Section 5, the profitability index and related components, utilize linear approximations to the firm-level demand function and marginal cost curve. As a check on whether the linear approximations are driving our findings, we re-derive the profitability index assuming an iso-elastic heterogeneous demand approximation and using the firms' estimated marginal cost curve.

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 completely by changes over firms, time, and market in the parameter ρ_{in}. In contrast to the linear approximation, here markups will not change with output changes driven by cost changes and changes in the number of customers.[51]

Figure E1 shows, 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 b in the linear demand case. To see this, suppose that 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. 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:

[51] In Appendix D above we show that heterogeneity in market thickness for the linear approximation (b) can be micro-founded under stable preference parameters as stemming from differences in the number of customers demanding different products.

$$\Pi_i^{Idx-CES} = \kappa_i[\frac{(1-\rho_i)\kappa_i}{\bar{\psi}_i \delta}]^{\frac{1-\rho_i}{\rho_i+\delta-1}} - \bar{\psi}_i[\frac{(1-\rho_i)\kappa_i}{\bar{\psi}_i \delta}]^{\frac{\delta}{\rho_i+\delta-1}} \tag{25}$$

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

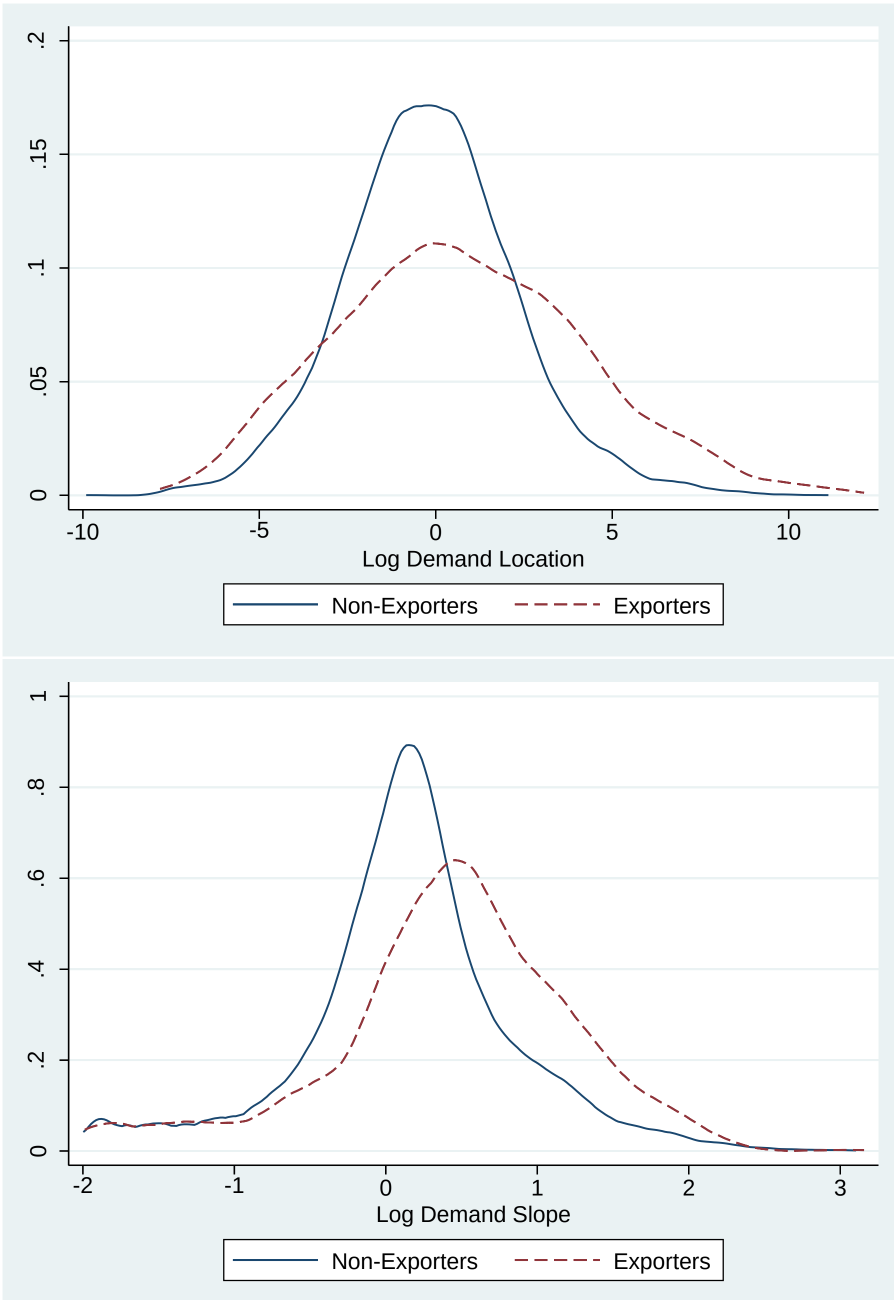
Figure E2 shows the profitability indices for exporters and non-exporters under small (median non-exporting firm), large (median exporting firm), and equilibrium scales, respectively. In all cases exporters are significantly more profitable than non-exporters. Overall, these results confirm that the linear approximations do not drive our main findings.

Table A1: Additional Descriptive Statistics

ISIC 3 Industry Code	Number of Products			Number of Export Destinations (Cond. on Exporting)			Total Revenues			Domestic Revenues			Percentage of Revenues from Exports (Cond. on Exporting)		
	Mean	St. Dev.	Median	Mean	St. Dev.	Median	Mean	St. Dev.	Median	Mean	St. Dev.	Median	Mean	St. Dev.	Median
151	1.24	0.55	1.00	9.59	8.81	7.00	9,308	23,500	1,456	6,250	18,400	989	52.0%	33.4%	58.0%
153	1.65	0.48	2.00	4.83	4.04	3.00	6,740	14,900	2,848	6,644	14,600	2,814	14.4%	21.8%	5.8%
154	1.09	0.39	1.00	11.15	11.15	7.00	1,897	19,800	232	1,675	17,000	232	12.9%	18.0%	4.4%
155	1.06	0.28	1.00	25.56	19.64	21.00	13,100	37,000	2,294	9,199	31,300	743	59.0%	28.4%	65.1%
181	1.05	0.25	1.00	2.37	1.49	2.00	1,346	3,147	335	1,312	3,066	334	8.1%	17.6%	1.4%
201	1.33	0.60	1.00	5.30	7.90	3.00	5,865	30,900	576	3,269	12,800	566	34.2%	26.7%	29.0%
221	1.91	1.20	1.00	4.65	2.87	5.00	1,713	4,458	301	1,690	4,375	301	2.9%	3.7%	1.9%
222	2.14	1.36	2.00	8.11	6.15	6.50	1,892	4,464	435	1,776	3,951	435	11.5%	9.8%	11.0%
242	1.41	0.77	1.00	5.77	4.91	4.00	8,584	20,700	1,993	7,953	19,800	1,872	11.2%	18.1%	3.7%
281	1.28	0.63	1.00	2.45	1.50	2.00	1,561	3,409	485	1,524	3,258	485	9.7%	12.4%	6.5%

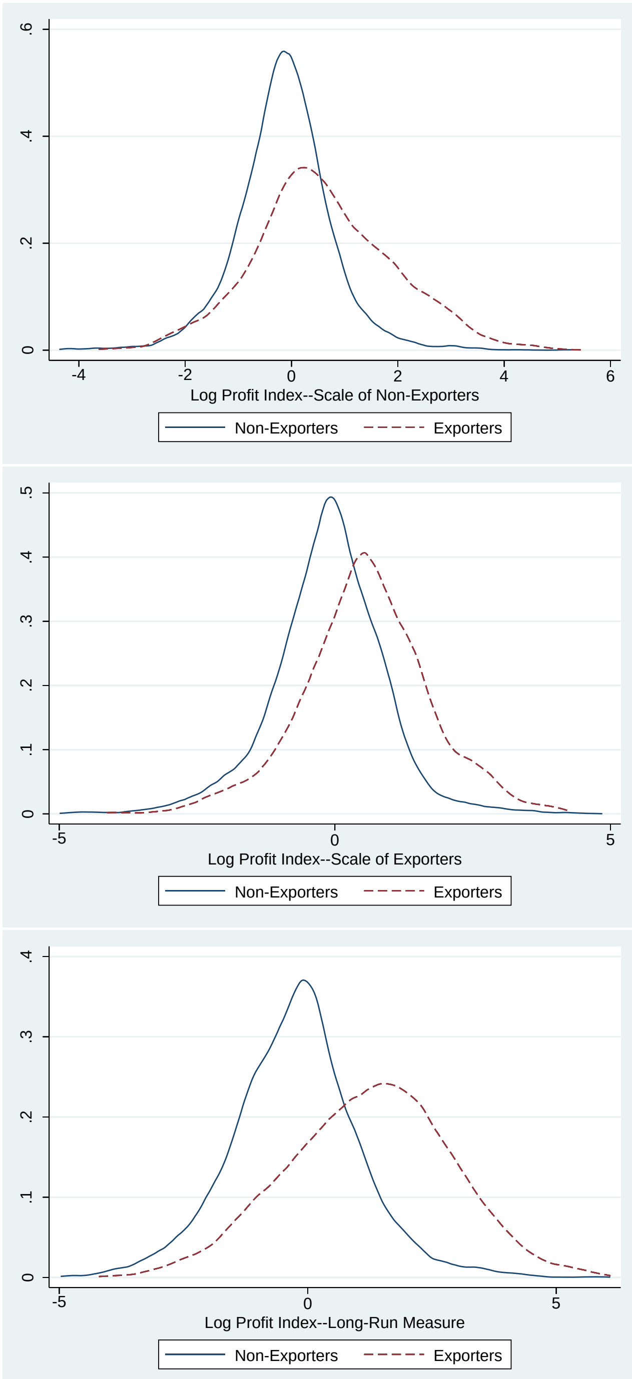
Notes: This table reports summary statistics across firm-time observations within each industry. Revenue figures are reported in millions of Chilean pesos. See Table 1 for the industry descriptions.

Figure E1: Distribution of Domestic Demand Parameters CES: Location (κ) and Slope (ρ)



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

Figure E2: Distribution of Domestic Profitability Index: CES Demand



Notes: In this figure we plot the distribution of the (log) domestic profitability index, separately for exporters and non-exporters, for three versions of the profitability index. The first is computed by fixing capital and labor at values corresponding to the median values for a non-exporting firm. The second is computed by fixing capital and labor at values corresponding to the median values for an exporting firm. The third is a long-run version of equation (25) using the firm's observed levels of capital and labor. All of the profitability index measures are at the firm-product-year level and are net of product-year effects.