Demand, Cost, and Profitability Across Chinese Exporting Firms

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Abstract

In this paper we use micro data on both trade and production for a sample of large Chinese manufacturing firms in the footwear industry from 2002-2006 to estimate an empirical model of export demand, pricing, and market participation by destination market. We use the model to construct indexes of firm-level demand, cost, and export market profitability. The empirical results indicate substantial firm heterogeneity in both the demand and cost dimensions with demand being a more important determinant of the across-firm differences in export market profitability. Our measure of the firm-specific component of export profitability is very useful in distinguishing between firms based on the length of time they export to a destination. Firms that are long-term exporters in a destination have a higher profitability index, on average, than firms that do not export to the destination. We use the estimates to analyze the reallocation resulting from removal of the quota on Chinese footwear exports to the EU and find that it led to a rapid restructuring of export supply sources in favor of firms with high demand and low cost indexes.

1 Introduction

A large empirical literature spanning industrial organization, international trade, macro, and productivity analysis has developed to study the relationship between underlying firm characteristics and firm decisions to enter or exit markets and make pricing, output, or investment decisions. As a unifying framework much of this literature relies on the theoretical models of firm heterogeneity and market selection developed by Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995) and Melitz (2003).[1] These models recognize a single dimension of firm heterogeneity, usually termed productivity, that persists over time and helps determine the firm's long-run profits from participating in a market and short-run pricing, output, or investment decisions. Treating firms as heterogenous in a single productivity variable is a simplification, but it has worked well in empirical studies with business-level micro data sets that contain information on firm sales and input expenditures. Recently, more detailed data on firm-level output and input quantities and prices has become available for some countries and industries and this has encouraged the development of empirical models that allow for both cost side and demand side dimensions to firm heterogeneity. Foster, Haltiwanger, and Syverson (2008) use data on output price and quantity for plants in eleven U.S. manufacturing industries to construct physical productivity and demand indexes for each plant and then show that these measures are correlated with plant entry and exit patterns. Specifically, they find that differences in demand are more important than differences in productivity in explaining patterns of plant survival but, more generally, highlight the fact that the underlying productivity and demand conditions should affect firm decisions on pricing, quantities, and market participation.[2]

[1] An early example of the empirical studies in each of these areas is: Dunne, Roberts, and Samuelson (1988) on plant growth and exit, Bernard and Jensen (1999) on the characteristics of firms that export, Davis, Haltiwanger and Schuh (1998) on job creation and destruction over the business cycle, and Baily, Hulten and Campbell (1992) on aggregate productivity movements.

[2] Eslava, Haltiwanger, Kugler, and Kugler (2004) use plant-level input and output prices for Colombian manufacturing plants to estimate demand curves and production functions at the plant level and then analyze patterns in the residuals including their persistence over time and how they are related to

One field in which the insights on the importance of firm hetergeneity in profits have been widely incorporated in both theoretical and empirical work is international trade. Eaton and Kortum (2002), Melitz (2003), and Bernard, Eaton, Jensen, and Kortum (2003) have developed theoretical models which embody heterogenous firms and use them to analyze aggregate patterns of trade. More recently, Baldwin and Harrigan (2009), Johnson (2009), Hallak and Sivadasan (2009), Khandelwal (forthcoming), and Crozet, Head, and Mayer (2010) have extended these earlier models, which have one dimension of heterogeneity, to allow for differences in two dimensions, productivity and product quality, and relate this to both trade flow and pricing patterns across countries.[3] Manova and Zhang (forthcoming) utilize data on export and import prices and quantities for Chinese exporting firms to estimate reduced form regressions of pricing and conclude that their results are consistent with variation in product quality across firms. In an empirical study using French firm-level data, Eaton, Kortum, and Kramarz (2008) study the patterns of trade across a large number of destination markets and emphasize the essential role played by firm heterogeneity in costs and demand. In their study, accounting for firm heterogeneity in efficiency results in substantial improvements in the ability to predict which firms enter which destination markets and, to a lesser degree, the volume of sales in the destination. They conclude that "any theory ignoring features of the firm that are universal across markets misses much."

In this paper we develop a structural model to estimate both demand-side and cost-side dimensions of firm heterogeneity using micro panel data on the prices and quantities of exported goods and firm costs. We use it to analyze demand and cost heterogeneity for a sample of 1106 large Chinese exporting firms in the footwear industry from $2002-2006$. This project differs from Foster, Haltiwanger, and Syverson (2008) by incorporating the

reallocations of activity across firms in response to economic reforms.

[3] A large empirical literature beginning with Roberts and Tybout (1997), Clerides, Lach, and Tybout (1998), Bernard and Jensen (1999), and Aw, Chung, and Roberts (2000) has used micro data to document the significant differences in size, productivity, and other firm-level factors that are correlated with a firm's participation in international markets. See Wagner (2007) for a survey of the empirical literature on exporting and firm characteristics.

firm-level demand and cost parameters into equations that describe the firm's discrete decisions on which export markets to serve as well as the firm's continuous decisions on pricing and market shares. We exploit the fact that, in the export context, we have multiple observations on many of the firms because they export to multiple destination markets and this helps to identify the distribution of firm-level demand and cost parameters. This project also differs from the recent trade literature that emphasizes multiple dimensions of firm heterogeneity because we estimate the firm-level demand and cost components along with the structural parameters of demand, marginal cost, and export profits. The trade literature has focused more on characterizing cross-section correlations in the trade flow and price data but has not attempted to measure the individual firm-level heterogeneity components.

The measure of firm demand heterogeneity that we construct in our empirical model relies on differences across firms in export market shares, controlling for firm prices, in the destination markets. The measure of cost heterogeneity relies on differences in firm export prices, controlling for observable firm costs and markups, across destinations. Both factors play a role in determining the firm's profits in each export market and thus the decision to export. We then use these measures to construct an index of firm-level export market profitability that varies by destination market. The econometric methodology we utilize is a paractical application of a Hierarchical Bayesian method that relies on MCMC and Gibb's sampling for implementation. This allows us to both include a large number of parameters, two for each of our 1106 firms, and to incorporate the parameters in nonlinear equations, such as the probability of exporting, in a very tractable way.

We use the model to analyze export patterns among China's footwear producers, one of the important industries contributing to China's rapid export growth.[4] Our data set

[4] One question of interest in the literature on China's export growth is the extent to which their success has reflected their advantage as a low-cost manufacturing base or a more dynamic process of firm investment in building what Sutton (2005) terms "capability." This latter includes the ability to produce higher quality products which can compete with goods produced in developed countries. See

combines information on firm-level balance sheet and production data from the *Annual Survey of Manufacturing* with detailed records on the value and quantity of firm-level exports by destination market contained in the *Chinese Monthly Customs Transactions.* This allows us to measure firm-level export prices and market shares. The empirical results indicate substantial firm heterogeneity in both the demand and cost dimensions with demand being a more important determinant of the across-firm differences in export market profitability. Our measure of the firm-specific component of export profitability is very useful in distinguishing between firms based on the length of time they export to a destination. Firms that are long-term exporters in a destination have a higher profitability index, on average, than firms that do not export to the destination. We use the estimates to analyze the reallocation resulting from removal of the quota on Chinese footwear exports to the EU and find that it led to a rapid restructuring of export supply sources in favor of firms with high demand and low cost indexes.

The next section of the paper develops the theoretical model of export demand, pricing, and market participation. The third section develops the estimation methodology, the fourth section describes the Chinese firm-level data and summary statistics. The fifth section presents the structural parameter estimates and the final section analyzes the changes in the composition of exporting firms in response to removal of the EU quota on Chinese footwear imports.

2 Theoretical Model of Export Revenue

2.1 Demand

We begin with a demand model that can be used to estimate an index of firm demand. Denote i as an individual firm variety, that is, a 6-digit product produced by a specific firm. We will use the term "variety" to refer to a combination of firm and product. A firm can produce and export multiple products and thus have multiple varieties. Let

Rodrik (2006), Schott (2008), and Branstetter and Lardy (2008) for discussion.

k represent a broader product group, such as a 4-digit product category, that includes variety i. The utility that an importer c in destination market d, year t receives from the variety i is given by the utility function:

$$u_{ci}^{dt} = \delta_i^{dt} + \epsilon_{ci}^{dt}. \tag{1}$$

This specification allows for a variety-specific component δ_i^{dt} that varies by destination market and year and a transitory component ϵ_{ci}^{dt} that captures all heterogeneity in preferences across importers.[5] Berry (1994) shows that, if ϵ is assumed to be a Type I extreme value random variable then we can aggregate over importers and express the market share for variety i in market dt. Define the inclusive value of all varieties in the market as $V^{dt} = \sum_j \exp(\delta_j^{dt})$. The market share for variety i in market dt can be written in the logit form $s_i^{dt} = \exp(\delta_i^{dt})/V^{dt}$. If we normalize this market share by a single variety where $\delta_0^{dt} = 0$ the normalized logarithmic market share takes the simple form:

$$ln(s_i^{dt}) - ln(s_0^{dt}) = \delta_i^{dt}. \tag{2}$$

We will model the variety-specific term δ_i^{dt} as a combination of firm, product group, destination market, and variety components. Specifically, if variety i in product group k is produced by firm f, then

$$\delta_i^{dt} = \xi_f + \rho I_f^{dt-1} + \xi_k - \alpha^d \ln \tilde{p}_i^{dt} + u_i^{dt} \tag{3}$$

This equation says that there is a firm component ξ_f or "brand-name" effect to the utility derived from variety i. This brand-name effect will be unique to each firm and constant across all markets in which it operates and all products it sells. It could reflect differences in the stock of customers that are familiar with firm f, size of its distribution network, or

[5] We think of the consumers in the destination market as wholesalers, retailers, or trading companies that buy from the Chinese producers and resell to households. The wholesalers demand for Chinese exports will depend on the household demand in their own country but, since we do not have household-level data, we do not attempt to model this household demand. Instead, we capture all the effects of consumer income, tastes, competing suppliers in the destination and market power in the wholesale/retail sector in the modeling of the destination-specific utility component δ_i^{dt}.

quality of the firm's product. Holding price fixed, an increase in ξ_f will raise the market share for this variety in all markets. Since the ξ_f captures all firm-level factors that systematically affect the utility that importers receive from variety i, we will refer to it as a **firm demand component.**[6] The variable I_f^{dt-1} will be a discrete indicator equal to one if the firm exported to market d in the previous year. This term is included to capture the fact that it takes a while for a firm to build up contacts and sales in a new market. Even with an established product, initial sales may be low in a market until consumers learn about the product's availability.[7] The coefficient ρ will be a measure of the gain in market share that experienced exporters have in a market.[8] There is also a product group utility shifter ξ_k that will lead to higher utility for some product groups in all markets, holding price fixed. The utility and market share of the variety will be declining in the price of the variety where $\tilde{p}_i^{dt}$ is the price paid by the importers for variety i in the destination market. To convert this price into the FOB price, p_i^{dt}, set by the producing firm we incorporate ad valorem trade costs between China and each destination market $\ln \tilde{p}_i^{dt} = \ln p_i^{dt} + \ln(1 + \tau^{dt})$. In this case τ^{dt} captures all exchange rate effects, tariffs, and shipping costs between China and each destination market in each year. The final term u_i^{dt} captures market level shocks to the demand for variety i. Substituting equation (3) and destination-specific price into the normalized market

[6] The demand model we use relies on horizontal differentiation across varieties and is not one where firm's products can be ranked by quality. For this reason, we do not refer to ξ_f as an index of firm "quality" but rather use the broader term "firm demand component" because it will capture any factor that generates larger market shares for the firm's varieties, holding price fixed.

[7] Using transactions-level data for Colombian exports to the U.S., Eaton, Eslava, Krizan, Kugler, and Tybout (2011) study the process of buyer-seller matching and the gradual accumulation of customers by successful exporting firms. They show that a model of exporter search and learning can describe the patterns of growth following export market entry.

[8] The variable will also control for the fact that the initial sales reported by a new exporter in our data may not reflect a full year of operation for the firm in the market and thus be artificially low. More detailed indicators could be constructed with sufficiently long time-series data for each firm. For example, the number of years they have been present in the market, or a series of discrete variables distinguishing the firm's age in the market could be incorporated. In our data we have a fairly short time-series of participation so we will only distinguish previously existing firms in the market from new firms.

share equation gives the demand equation for variety i:

$$ln(s_i^{dt}) - ln(s_0^{dt}) = \xi_f + \rho I_f^{dt-1} + \xi_k - \alpha^d \ln p_i^{dt} + \tilde{\tau}^{dt} + u_i^{dt} \tag{4}$$

where $\tilde{\tau}^{dt} = -\alpha^d ln(1+\tau^{dt})$. The parameter α_d, which captures the market share response to a change in the FOB price, is allowed to vary across destination markets to reflect the country-specific differences in the consumer tastes, income, and the structure of the domestic retail sector.

This demand equation can be estimated using data on the market shares of varieties in different destination markets. Overall, the demand model contains a destination-specific price parameter α^d, destination market/year effects $\tilde{\tau}^{dt}$, an experience effect in demand ρ, product group effects ξ_k, and a firm-specific demand shifter ξ_f. One goal of the empirical model developed below will be to estimate the parameters of equation (4) including the firm-specific demand factor ξ_f.

2.2 Cost and Pricing

To incorporate heterogeneity arising from the production side of the firm's activities we model log marginal cost of variety i in market dt as:

$$\ln c_i^{dt} = \gamma_{dt} + \gamma_k + \gamma_w lnw_f^t + h(\xi_f) + \omega_f + v_i^{dt} \tag{5}$$

where γ_{dt} and γ_k are destination/year and product-group cost factors, and w_f^t is a set of observable firm-specific variable input prices and fixed factors. The specification includes two additional sources of firm-level shocks. The function $h(\xi_f)$ is included to control for the fact that firms that have higher demand or more desirable products will likely have higher costs if the extra demand is the result of higher quality or investments to build a customer base. The second firm-level shock ω_f is included to capture differences in productivity or efficiency among producers. Finally v_i^{dt} are cost shocks at the variety level and the firm is assumed to observe these prior to setting the price for variety i. For estimation purposes we will combine the firm costs resulting from ξ_f with the productivity term into a single **firm cost component** that we will represent as $c_f = h(\xi_f) + \omega_f$.

Assuming monopolistically competitive markets, a profit-maximizing firm facing the demand curve in equation (4) will charge a price for variety i in market dt given by:[9]

$$\ln p_i^{dt} = \ln(\frac{\alpha_d}{\alpha_d - 1}) + \gamma_{dt} + \gamma_k + \gamma_w lnw_f^t + c_f + v_i^{dt} \tag{6}$$

This pricing equation shows that the price of variety i in market dt will depend on the destination-specific demand parameter α_d and all the marginal cost determinants in equation (5). In particular, this pricing equation shows that c_f will be a firm-level component of the export price. A second goal of our empirical model is to estimate the parameters of the pricing equation (6) including the firm cost component c_f while allowing for an unconstrained correlation between c_f and ξ_f.

2.3 Export Revenue and Profitability

Using the demand and pricing equations, (4) and (6), we can express the expected revenue of variety i in market dt. Define the destination specific markup as $\mu_d = \frac{\alpha_d}{\alpha_d - 1}$ and the aggregate demand shifter in market dt as $\Phi^{dt} = M^{dt}/V^{dt}$ where M^{dt} is the total market size. Using these definitions we can express the logarithm of the expected revenue for variety i as the sum of three components, one of which depends only on market-level parameters and variables, one which incorporates all product-group variables, and one which incorporates all firm-level variables:

$$\ln r_i^{dt} = \ln \bar{\Phi}^{dt} + \ln r_k^d + \ln r^{dt}(\xi_f, c_f) \tag{7}$$

[9] If we assume firms compete by taking into account the impact of their prices on the inclusive value V^{dt}, then the markup term becomes $ln(\frac{\alpha_d(1-s_i^{dt})}{\alpha_d(1-s_i^{dt})-1})$. Because virtually all of our exporting firms have small market shares (as described in the data section), we ignore the effect of the firm's price on the inclusive value.

where

$$\begin{aligned}
\ln \bar{\Phi}^{dt} &= \ln \Phi^{dt} + \tilde{\tau}^{dt} + (1-\alpha_d)(\ln \mu_d + \gamma_{dt}) \\
\ln r_k^d &= \xi_k + (1-\alpha_d)\gamma_k \\
\ln r^{dt}(\xi_f, c_f) &= \xi_f + (1-\alpha_d)\left(\gamma_w lnw_f^t + c_f\right) + C_{uv}
\end{aligned} \tag{8}$$

In this equation $\ln\bar{\Phi}^{dt}$ captures all market-level factors that affect product revenue, including the market size and overall competition, tariff, exchange rate effects, markup, and destination-specific cost. The second term $\ln r_k^d$ captures all product group effects in both demand and cost.

The final term, $\ln r^{dt}(\xi_f, c_f)$, combines all the firm-specific factors that affect the export revenue of variety i in the market: the firm demand component ξ_f, the firm cost component c_f , and the observable firm-level marginal cost shifters $\gamma_w lnw_f^t$. The expectation over the variety-specific demand and cost shocks u_i^{dt} and v_i^{dt} is denoted by $C_{uv} = \ln E_{u,v}[exp(u_i^{dt} + (1-\alpha_d)v_i^{dt})]$, which is a constant across all firms.[10] A larger value of ξ_f, reflecting higher demand for the firm's variety, will imply a larger value of $\ln r^{dt}(\xi_f, c_f)$. Since the term $(1-\alpha_d)$ is negative, a higher value of c_f will imply a lower level of export revenue for the firm in this destination market. If variation in c_f across firms only reflects productivity differences, then high c_f would imply lower export revenue. However, as explained above, c_f can also include the cost of producing higher demand, so in this case $corr(c_f, \xi_f) > 0$ and thus, as we compare across firms, higher-demand firms will have higher export revenue if their larger market share, due to ξ_f, outweighs the increase in cost captured by c_f. Finally, the firm export revenue will vary by destination market because the marginal cost terms are scaled by $(1-\alpha_d)$ and α_d is destination specific. In a destination with more elastic demand (larger α_d), the cost differences across firms are more important as a source of export revenue differences.

[10] The term $\ln r^{dt}(\xi_f, c_f)$ is similar to the measure of firm capability introduced by Sutton (2005). He defined capability as the ratio of firm quality and the unit cost of production, while our index also depends on the demand elasticity in the destination market.

Given the functional form assumptions on demand and marginal cost, we can use the revenue equation for variety i, (7), to express the total expected profits that firm f will earn in market dt. If the firm sells a set of varieties, or product line, denoted by K_f, its profit in destination market dt is the sum of revenues over all its varieties scaled by the demand elasticity or, if expressed in logs:

$$\ln \pi^{dt}(\xi_f, c_f; w_f^t, K_f) = \ln \left[\frac{1}{\alpha_d}\right] + \ln \bar{\Phi}^{dt} + \ln \left[\sum_{k \in K_f} r_k^d\right] + \ln r^{dt}(\xi_f, c_f). \tag{9}$$

As shown by this equation, the firm component of export revenue enters directly into the firm's profits in the market and will be a useful summary statistic of the role of firm demand and cost factors in generating differences in the profitability of exporting firms in a destination market. For this reason we will refer to $\ln r^{dt}(\xi_f, c_f)$ as the **firm profit component.**[11]

2.4 Exporting Decision

This model of demand, cost, and profits also implies a set of destination countries for each firm's exports. The firm's decision to export to market dt is based on a comparison of the profits earned by supplying the market with the costs of operating in the market. If firm f sells in market d in the current year t we assume that it needs to incur a fixed cost ϕ_f^{dt} which we model as an independent draw from a normal distribution that is the same across all markets. If the firm has not sold in the market in the previous year, then it must also pay a constant entry cost ϕ_s. Define I_f^{dt-1} as the discrete export indicator that equals one if the firm exported to market d in year $t-1$ and zero if it did not. The

[11] Several other papers have characterized a firm's market participation decision when firm heterogeneity arises from both demand and cost factors. In a model in which firms produce differentiated goods and consumers value variety, Foster, Haltiwanger, and Syverson (2008) develop a "firm profitability index" that is the difference between a firm's demand shifter and its marginal cost. They show that this is correlated with patterns of firm survival. In a model with vertical quality differentiation, Sutton (2007) studies how firm survival depends on its "capability" which is a combination of firm quality and productivity. Katayama, Lu, and Tybout (2009) use firm-level revenue and cost data to estimate indexes of marginal cost and product appeal which they relate to consumer and producer surplus.

firm will choose to export to this market if the current plus expected future payoff is greater than the fixed cost it must pay to operate. Since the fixed cost is stochastic we can define the probability that the firm exports to a particular market as the probability that the fixed cost is less than the profits that would be earned by exporting:

$$P(I_f^{dt}=1)=\Pr(\phi_f^{dt}\leq \pi^{dt}(\xi_f,c_f,w_f^t,K_f)-\phi_s(1-I_f^{dt-1})+\beta\Delta EV(\xi_f,c_f,w_f^t,K_f,I_f^{dt})) \tag{10}$$

where the term after the inequality sign is the current plus expected future payoff from exporting to this market.[12] The third goal of our empirical model is to estimate the firm's market participation condition and, in particular, determine the role of the firm specific demand and cost components ξ_f and c_f in the export decision. Following the framework of Roberts and Tybout (1997), we will treat the payoff in equation (10) as a latent variable. In our case it is a function of the two firm factors ξ_f and c_f, the observable marginal cost shifters w_f^t, the firm's product mix $\sum_{k\in K_f} r_k^d$, the aggregate desirability of the product in this destination $\bar{\Phi}^{dt}$, and the firm's prior period export experience I_f^{dt-1}. This will lead to a probit approximation to the policy function for the firm's export participation decision:

$$P(I_f^{dt}=1)=G[\xi_f,c_f,w_f^t,\sum_{k\in K_f} r_k^d,\bar{\Phi}^{dt},I_f^{dt-1};\psi] \tag{11}$$

where G is the normal cdf and ψ is the parameter vector to be estimated.

Alternatives to this estimating model are the structural models developed by Das, Roberts, and Tybout (2007), and Aw, Roberts, and Xu (2011). These papers calculate the long-run firm value and estimate the distribution of fixed costs and entry costs in

[12] More precisely, the integrated value function also depends on the evolution of the aggregate demand conditions $\bar{\Phi}^{dt}$. It is $EV(\xi_f,c_f,w_f^t,K_f,I_f^{dt},\bar{\Phi}^{dt})=\int\limits_{\bar{\Phi}',w_f'} E_{\phi_f}\max[(\pi(\xi_f,c_f,w_f',K_f,\bar{\Phi}')-\phi_s(1-I_f^{dt})-\phi_f+\beta\Delta EV(\xi_f,c_f,w_f',K_f,I_f^{dt},\bar{\Phi}'),0]dF(\bar{\Phi}',w_f')$
where the expected increment to future profits from exporting in period t is: $\Delta EV(\xi_f,c_f,w_f',K_f,I_f^{dt},\bar{\Phi}')=EV(\xi_f,c_f,w_f',K_f,I_f^{dt},\bar{\Phi}'|I_f^{dt}=1)-EV(\xi_f,c_f,w_f',K_f,I_f^{dt},\bar{\Phi}'|I_f^{dt}=0)$

dollars. The model used here expresses the export participation decision as a function of firm and market-level variables that shift the long-run profits for exporting, in particular the firm demand and cost components ξ_f and c_f . This does not allow us to estimate the magnitude of the entry cost or long-run firm value but does provide a consistent framework for analyzing the determinants of the export decision. In this case, modeling the participation decision in equation (11) will help to identify the firm demand and cost parameters and, as explained in the econometric section below, this will be particularly useful for the firms that infrequently export.

Overall, the model developed in this section provides a unified framework for explaining a combination of continuous (firm-level sales, pricing) and discrete (market participation) decisions for Chinese exporting firms in an industry. It recognizes that unobserved heterogeneity, in the form of firm-level demand and cost components, generate linkages between all the equations describing firm decisions and that the endogenous participation decision underlies the observed firm data on export prices and sales in each market. The model can be estimated with firm-level data on export prices, quantities, production costs, and destination markets. It will allow us to infer the unobserved firm-level demand and cost components and combine them into a natural index of the firm's ability to generate export market profits. In the next section we discuss the econometric methods that we use to estimate the model.

3 Estimation

3.1 Empirical Model and Identification

Our empirical model consists of three key structural equations: demand (4), pricing (6), and export market participation (11). Importantly, there are unobserved firm effects ξ_f and c_f that link these three decisions entering both linearly and nonlinearly in different equations. We are interested in estimating the empirical distribution of these effects because these are the crucial building blocks of $r^{dt}(\xi_f, c_f)$, our firm-level index of export market sales or profits in each destination. The export data also has the feature that we observe many of the firms selling in multiple destination markets with multiple products and this will be useful in identifying the distribution of firm effects. In the demand equation we estimate destination-specific parameters α_d and destination-year trade barriers $\tilde{\tau}^{dt}$. Using the pricing equation we recover how prices depend on firm-level observed characteristics (log wages and capital stocks) with the parameters γ_w, destination-specific cost differences γ_d, and product group cost differences γ_k. To allow for possible correlation between the variety-level demand and cost shocks, u_i^{dt} and v_i^{dt}, we assume that they are jointly normally distributed with mean zero and covariance Σ. Finally, to control for the endogenous choice of destination markets we model each firm's export participation decision in each market.

Our estimation strategy utilizes the framework of *average likelihood function* laid out in Arellano and Bonhomme (2009) to nest the random-effect approach (where parametric assumptions on the distribution of individual effects are made) and the fixed-effect approach (where the distribution of individual effects is flexible). Intuitively, when a firm exports to multiple destinations over multiple time periods with many varieties then we have a substantial number of price and quantity observations for the firm. We could estimate the firm-level ξ_f and c_f using individual firm price, quantity, and cost data, conditional on the common parameters, which is conceptually close to fixed-effect approach. On the other hand, when a firm rarely exports we rely heavily on the discrete export participation decision and this requires placing more structure on the estimates of ξ_f and c_f. In this case we let firm unobservables' contribution to the likelihood function weighted by a specified distribution. This is essentially the random-effect approach. In either case, observations of the same firm's discrete or/and continous choices across multiple destinations, years, and varieties facilitate a large T that is important to address incidental parameter concerns. Overall, the average likelihood function framework fits very closely with the structure of our model and data.

If our only interest is in the demand and pricing equation coefficients that are common across all firms: $\alpha_d, \tilde{\tau}^{dt}, \xi_{k,}\rho, \gamma_w, \gamma_{dt}, \gamma_k$, and if the transitory demand and cost shocks u_i^{dt} and v_i^{dt} are uncorrelated with each other, then the demand and pricing equations (4) and (6) could be estimated with standard fixed-effect within estimators. However, this ignores the fact that the firm effects enter nonlinearly in the participation decision and does not exploit the information from non-exporting behavior that is present in the data.[13] Second , use of the within estimator does not remove the need to address the endogeneity of prices. Firm-time specific unobserved demand shocks u_i^{dt} are likely to be positively correlated with the marginal cost shocks v_i^{dt} even after controlling for persistent firm-level differences in ξ_f and c_f. This leads to endogeneity of the product price which biases the price coefficients α_d in the demand equation toward zero when using the within estimator. In addition, as a practical aspect of the export transaction data, there could also be non-trivial measurement error in reported transaction prices, in which case u_i^{dt} and p_i^{dt} are correlated by definition. The within estimator is inconsistent and known to perform poorly in these scenarios.

As we will describe in detail below, Arellano and Bonhomme (2010) show that a pragmatic use of the Bayesian MCMC method provides a powerful and flexible way of evaluating the likelihood function and generating the posterior distribution of the model parameters, including the individual firm heterogeneity terms. The computational advantages of MCMC result because we do not need to integrate out firm-level effects in order to evaluate the likelihood function of the common parameters, we can sample common and firm-specific parameters sequentially, and we can streamline the sampling of common parameters with the use of Bayesian regression.

[13] Melitz, Helpman, and Rubenstein (2008) develop a model of trade flows between countries that recognizes that many country pairs have no trade. Empirically, they find that, by studying only the country pairs with positive trade flows, estimates of the underlying trade determinants, such as transport costs, are substantially biased. The biases are traced to the failure to control for the firm-level decision to export.

3.2 Estimation Details

Before we move into the details of our estimation procedures, we first summarize the data we observe. For each firm, we observe a sequence of cost shifterslnw_f^t and export market participation dummies I_f^{dt}. Conditional on $I_f^{dt} = 1$, we also observe prices lnp_i^{dt}, market shares $\ln s_i^{dt}$, and sales revenue r_i^{dt} for each variety sold by firm f. We denote the full set of data for firm f as D_f.

Denote the set of demand, cost, and participation parameters that are common for all firms as $\Theta = (\alpha_d, \tilde{\tau}^{dt}, \rho, \xi_k, \gamma_w, \gamma_{dt}, \gamma_k, \Sigma, \psi)$. Following Arellano and Bonhomme (2009), denote the joint distribution of firm f's unobserved quality ξ_f and cost c_f as a weighting function $w_f(\xi, c)$. An average likelihood function for D_f can then be defined as:

$$l(D_f|\Theta) = \int l(D_f|\Theta; \xi, c) w_f(\xi, c) d\xi dc \tag{12}$$

To see how this setup nests both random-effects and fixed-effects models, first allow the weighting function $w_f(\xi, c)$ to depend on a pre-specified distribution with parameters of the mean $\bar{b}$, variance W, and optional exogenous covariates Z_f. Then equation (12) defines an integrated likelihood for a random-effect estimator of Θ. Alternatively, consider a pair of $\hat{\xi_f}(\Theta), \hat{c_f}(\Theta)$ which maximize $\log l(D_f|\Theta, \xi, c)$. If the weighting function $w_f(\xi, c)$ assigns all probability mass to $\hat{\xi_f}(\Theta), \hat{c_f}(\Theta)$, then we have fixed-effects maximum likelihood estimator.

There are two important pieces to the average likelihood function for firm f. First, the likelihood for firm f conditional on both the common parameters and firm-specific unobservables is defined as:

$$\begin{aligned} & l(D_f|\Theta; \xi, c) = \\ & \prod_{dt} [g(ln(s_i^{dt}/s_0^{dt}) - \xi - \rho I_f^{dt-1} - \xi_k + \alpha^d \ln p_i^{dt} - \tilde{\tau}^{dt}, lnp_i^{dt} - \gamma_{dt} - \gamma_k - \gamma_w lnw_f^t - c; \Sigma)]^{I_f^{dt}} \\ & G[\xi, c, w_f^t, \sum_{k \in K_f} r_k^d, \bar{\Phi}^{dt}, I_f^{dt-1}; \psi]^{I_f^{dt}} (1 - G[\xi, c, w_f^t, \sum_{k \in K_f} r_k^d, \bar{\Phi}^{dt}, I_f^{dt-1}; \psi])^{(1-I_f^{dt})} \end{aligned} \tag{13}$$

where g and G are the standard normal pdf and cdf, respectively. The first line of the firm likelihood reflects the contribution of the market share and price data using the demand and pricing equations, (4) and (6). The second line is the contribution of the discrete decision to export to market dt. This likelihood function provides us with guidance on blocks of parameters to be sampled. It indicates that the demand and pricing equation parameters, the participation equation parameters, and firm specific unobservables can be sampled sequentially. Thus we use the Gibbs sampler to further simplify the computational burden of the Markov Chain Monte Carlo method. The details of the Gibbs sampler are described in the appendix. The basic idea is to sequentially use the demand equation to sample the demand parameters, the pricing equation to sample the cost parameters, and the errors in both equations to sample the correlation structure of the demand and pricing shocks. To further tackle the classical simultaneity bias arising from the correlation between u_i^{dt} and p_i^{dt}, our estimation procedure is then augmented with a Bayesian instrumental variables approach as in Rossi, Allenby, and McCulloch (2005, Chapter 7). In our case, the observed firm cost shifters lnw_f^t, which include factor prices and capital stocks, can be treated as instruments that are correlated with price, but uncorrelated with the demand shocks u_i^{dt}. Jointly estimating the demand and pricing equations while allowing for arbitrary correlation between u_i^{dt} and v_i^{dt} provides consistent estimates of the demand elasticity parameters α_d. Next the export revenue in each market provides information on the aggregate demand parameters in the markets which are then used to construct latent firm profit and sample the parameters of the export participation equation. Finally, given values of all the common demand, cost, and export profit parameters the firm-specific demand and cost components can be sampled firm-by-firm and their joint distribution estimated.

The second component of the average likelihood are the weights $w_f(\xi, c)$ and these coincide with a first-stage prior for the firm-specific parameters (ξ, c) in a Hierarchical Bayesian setup. We assume a bivariate normal distribution for the prior of (ξ_f, c_f) where its mean b and variance-covariance W are specified as:

$$\begin{aligned} b &= [b_\xi, b_c] \\ W &= [\sigma_\xi, \sigma_c, \sigma_{\xi c}] \end{aligned} \tag{14}$$

Following standard practice, b and W themselves are assumed to be random parameters which have a proper but diffuse prior (see Rossi, Allenby, and McCulloch 2005, Chapter 5). The updating of b and W will be driven by information from the sampled firm effects $(\xi_f, c_f), f = 1, 2, .., N$ given the data. Note that when dt is large, the effect of prior distribution (weights) becomes negligible compared to that of the likelihood of firm.

4 Chinese Firm-Level Production and Trade Data

4.1 Data Sources

We will use the empirical model developed above to study the determinants of trade by Chinese firms operating in the footwear industry. The data we use in this paper is drawn from two large panel data sets of Chinese manufacturing firms. The first is the *Chinese Monthly Customs Transactions* from $2002 - 2006$ which contains the value and quantity of all Chinese footwear exporting transactions at the 6-digit product level. This allows us to construct a unit value price of exports for every firm-product-destination combination which makes it feasible to estimate demand models and construct a measure of each firm's demand component.

We supplement the trade data with information on manufacturing firms from the *Annual Survey of Manufacturing*, an extensive survey of Chinese manufacturing firms conducted each year by the Chinese National Bureau of Statistics. This survey is weighted toward medium and large firms, including all Chinese manufacturing firms that have total annual sales (including both domestic and export sales) of more than 5 million RMB (approximately $600,000). This survey is the primary source used to construct many of the aggregate statistics published in the *Chinese Statistical Yearbooks*. It provides detailed information on ownership, production, and the balance sheet of the manufacturing firms surveyed. It includes domestically-owned firms, foreign-owned firms, and joint-venture firms operating in China as long as they are above the sales threshold. This data is important in our research to provide measures of total firm production, observable cost shifters including capital stocks and wage rates, and detailed ownership information. In China, these two data sources are collected by different agencies and do not use a common firm identification number. They do, however, each report the Chinese name, address, phone number, zip code, and some other identifying variables for each firm. We have been engaged in a project to match the firm-level observations across these two data sets using these identifying variables.

In this paper we study the export behavior of firms in the footwear industry. We chose this industry for study because it is a major export industry in China, accounting for more than 70% of the footwear imports in the large markets in North America and Japan, has a large number of exporting firms, more than 2500 exporters were present in 2002, and was subject to a quota in the countries of the European Union during the first part of our sample period. We will use our estimated model to examine the inefficiency resulting from the EU quota. In this industry there are 18 distinct 6-digit products and they can grouped into three 4-digit product classes: textile footwear, rubber footwear, and leather footwear. In this industry we are able to identify 1106 unique firms in both the custom's and production data sets. Table 1 reports the number of these firms that are present in each of the sample years. This varies from 709 to 968 firms across years.

Table 1 - Number of Firms in the Sample

Year	Number of Firms	Number of Exporting Firms	Export Rate
2002	709	435	0.61
2003	794	522	0.66
2004	968	718	0.74
2005	945	711	0.75
2006	920	657	0.71

The key demand variable is the market share of each firm/six-digit product in a destination. To construct these market shares we divide the firm's exports to the destination by the total imports of footwear to the destination. The market shares for the Chinese firms in our sample are very small, more than 99% of the sample observations are below .004 and the maximum market share in any destination is .034. Given the few observations with larger market shares justifies our assumption of monopolistic competition in the firm's pricing decision.

4.2 Empirical Patterns for Export Participation and Prices

In this subsection we summarize some of the empirical patterns of export market participation and export pricing for Chinese firms that produce footwear and discuss factors in the model that will help capture them. The second and third columns of Table 1 summarize the number and proportion of sample firms that export in each of the years. To be in the sample it is required that a firm export to at least one destination in one year. The number of exporting firms varies from 435 to 718 and the export rate varies from 0.61 to 0.75 over time.

Among the exporting firms, the destination markets vary in popularity. Table 2 reports the fraction of exporting firms in our sample that export to each destination between 2002−2006. The U.S. and Canada have been the most popular destination, with approximately half of the exporting firms in our sample exporting to these countries in any year. This is followed by Japan/Korea and Rest of Asia, where more than 40 percent of the exporting firms sell. Approximately 30 percent of the exporting firms sell in the Non-EU countries of Europe, Africa, and Latin America. Australia and New Zealand are the least popular destination market, with just over 20 percent of the Chinese exporters selling there. These numbers suggest that export profits will vary by destination market. Market size, tariffs, transportation costs, and degree of competition are all country-level factors that could contribute to differences in the profitability of destination markets and result in different export rates. They are captured in the theoretical model through the terms in $\ln \bar{\Phi}^{dt}$ in equation (8) and the participation decision in each market will depend on the interaction of these country-level factors and the firm-level distribution of profitability.

Table 2 - Proportion of Exporting Firms By Destination

Destination	2002	2003	2004	2005	2006	Average
US/Canada	.514	.540	.487	.509	.549	.520
Japan/Korea	.459	.420	.413	.400	.412	.421
Australia/NZ	.220	.236	.206	.207	.205	.215
Non EU Europe	.331	.354	.351	.386	.407	.366
Rest of Asia	.356	.420	.438	.428	.447	.418
Latin America	.303	.258	.299	.314	.333	.301
Africa	.251	.297	.294	.354	.352	.310

Table 3 focuses on the export intensity and participation of firms that differ in their ownership structure and geographic locations. For a single year, 2005, the table reports the share of firms that export in different ownership and location categories, the average number of destinations, and average export sales. The first column gives the proportion of firms that export disaggregated by four ownership categories.[14] The state-owned firms are the least export oriented, with a participation rate of .67, followed by the HK/Macau/Taiwan owned firms, .69, foreign-owned firms, .73 and the privately-owned Chinese firms are the most export oriented, with a participation rate of .84. The second column gives the average number of destinations, for the firms in each ownership group, where the destinations are the seven aggregated regions. On average, the state-owned firms sell in 2.19 of the seven destinations, while the other ownership groups export to more destinations: 2.37 for foreign firms, 2.58 for HK/Taiwan owned firms, and 2.84 for private firms. The final column reports the export sales of the median firm in the ownership group. There are clear size differences across the ownership categories with private firms being the largest exporters, followed by the HK and foreign firms at approximately half the size, and the state-owned firms are much smaller. Overall there is a clear patterns that the privately-owned firms are the most heavily exposed to the

[14] The state- listed firms are government-owned firms that have listed a fraction of their shares for sale. We combine them with the state-owned firms and together the two groups account for 5.9 percent of the sample firms in 2005. The privately-owned firms are 34.7 percent, HK/Macau/Taiwan owned firms are 26.8 percent, and foreign-owned firms are 32.5 percent of the total firms in our sample in 2005.

export market with higher export rates, number of destinations and sales. The state-owned firms are the least exposed and the other two categories are in the middle. The bottom half of the table reports the same statistics if the firms are grouped by three geographic regions: east coast, southeast coast, and the rest of the country. Here we see, not surprisingly,that the coastal regions have higher export rates, .71 and .78, higher average number of destinations, and higher median sales than the non-coastal firms. This pattern suggests that it is important to account for differences in the ownership structure and location of the firms when accounting for their demand and pricing patterns. The model predicts that firm participation and sales will depend on the firm demand and cost components ξ and c. After estimating the empirical model we will compare the estimated firm components across ownership and geographic location categories to see how closely they reflect these differences in export probability and sales.

Table 3 -Export Propensity by Firm Ownership and Region - 2005

	Proportion that Export	Av. Number Destinations	Median Export Sales (thousand $)
Ownership Type			
State Owned	0.67	2.19	91.2
Private	0.84	2.84	810.2
HK/TWN/MK	0.69	2.58	363.9
Foreign	0.73	2.37	362.8
Geographic Location			
East Coastal	0.78	2.65	569.3
Southeast Coastal	0.71	2.83	263.2
Rest	0.68	1.82	179.0

Table 4 investigates the individual firm's price and quantity decision to highlight the important dimension of heterogeneity in the data. The table reports the R^2 from OLS regressions of log price and log quantity on combinations of product, destination, year, and firm dummies in explaining price and quantity variation. The one-way regressions show that the product dimension accounts for 32.9 percent of the sample variation in log price and 10.6 percent in log quantity. By itself, the destination dimension accounts for just over 1 percent of the sample variation in prices and just under 5 percent in quantity and the time dimension accounts for virtually no variation in prices or quantities. Most importantly, the firm dimension accounts for the vast majority of the sample variation: 75.1 percent of the price variation and 43.4 percent of the quantity. Adding characteristics sequentially, beginning with the product dimestions, we see that destination and year contribute little additional explanatory power in the price and quantity regressions. In contrast the firm dimension continues to contribute substantial explanatory power for both variables. Overall, the table simply illustrates that most of the micro-level price and quantity variation is accounted by across-firm differences, some by differences in the type of product (leather vs. rubber vs. plastic shoes), and very little by time and destination. This reinforces the focus of our empirical model on characterizing the extent of firm heterogeneity in demand and cost conditions.

Table 4 - Sources of Price and Quantity Heterogeneity

R^2 from OLS regressions		
Categories of Controls	log price	log quantity
Four-Digit Product (3 categories)	.329	.106
Destination (7 areas)	.013	.049
Year (5 years)	.002	.002
Firm (1106 firms)	.751	.434
Product, Destination	.334	.143
Product, Destination, Year	.338	.144
Product, Destination, Year, Firm	.815	.480

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5 Empirical Results

5.1 Demand Estimates

The empirical model includes the demand equation (4), pricing equation (6), and export market participation (11). Table 5 reports estimates of the demand cuve parameters, which include the destination-specific price parameters α_d, group demand shifters ξ_k, and dummy variable for prior sales in the markets ρI_f^{dt-1}.[15] The demand elasticity in each market is $-\alpha_d$ and the markup, the ratio of price to marginal cost, is $\alpha_d/(\alpha_d - 1)$. The three panels of the table correspond to different estimators of the demand curve, OLS, firm Fixed Effects (FE), and the Hierarchical Bayes (HB) estimator we developed above. Comparing across the panels we see that the price parameter α_d increases as we move from OLS to FE to HB which is consistent with the expected bias due to the endogeneity of prices in the first two estimators. The increase in the magnitude of α_d implies an increase in the demand elasticity and a reduction in the markup as we move across the panels. Focusing on the HB estimator we see that the demand elasticities vary from -2.049 to -2.764 across destination countries. The demand elasticities are highest in the low-income destination, Africa, Latin America, and the Rest of Asia, where they vary between -2.596 and -2.764. This implies lower markups in these destinations with the ratio of price to marginal cost varying from 1.567 to 1.627. The higher-income destinations, U.S., Australia-New Zealand, Japan-Korea, and non-EU Europe, have demand elasticities that vary between -2.049 and -2.438 and markups that all exceed 1.695. The table also reports estimates for the effect of past sales on the market share and, as expected, this is a significant positive effect. It indicates a substantial premium in market share for experienced exporters which likely reflects the fact that export sales build up gradually as the firm expands its customer base over time. Finally, the two product group coefficients imply that consumers get higher utility from leather shoes and lower utilty from textile shoes, relative to rubber shoes.

[15] When estimating the demand curve we define the market share of variety i in market dt as the sales of variety i divided by the total imports of footwear from all supplying countries in market dt. We normalize this market share by s_0^{dt} the market share of a single product, waterproof footwear, aggregated over all Chinese suppliers. In effect, we are treating the category of waterproof footwear as being produced by a single Chinese firm and the utility of this product is normalized to 0 in market dt. In the demand function the price of this normalizing good varies across markets but will be absorbed in the destination-year dummies included in the empirical demand function.

Table 5 - Demand Curve Parameter Estimates
(standard error in parentheses)

Parameter	OLS	Fixed Effects	Hierarchical Bayesian	$\frac{p}{c} = (\frac{\alpha_d}{\alpha_d - 1})$
α_d - US/Canada	0.599 (.056)	0.706 (.068)	2.386 (.182)	1.722
α_d - Japan/Korea	0.664 (.069)	0.706 (.082)	2.438 (.188)	1.695
α_d - Australia/NZ	0.311 (.096)	0.496 (.095)	2.121 (.192)	1.892
α_d - Non-EU Europe	0.244 (.079)	0.340 (.083)	2.049 (.189)	1.953
α_d - Rest of Asia	0.839 (.063)	0.948 (.071)	2.596 (.184)	1.627
α_d - Africa	0.988 (.074)	1.081 (.078)	2.764 (.187)	1.567
α_d - Latin America	0.853 (.074)	1.010 (.079)	2.641 (.188)	1.609
history - ρI_f^{dt-1}	0.919 (.043)	0.791 (.044)	0.787 (.045)	
ξ_g - leather	-1.051 (.054)	-0.568 (.053)	0.227 (.107)	
ξ_g - textile	-0.967 (.054)	-0.624 (.055)	-0.638 (.056)	

The model includes a full set of destination*year dummies

5.2 Pricing Equation Estimates

Table 6 reports parameter estimates of the pricing equation (6). These include coefficients on the firm's capital stock and wage rate, which are shifters of the firm's marginal cost function, as well as product and destination dummy variables. The coefficient on the wage rate is positive, as expected, but not statistically significant. The coefficient on the firm's capital stock is also positive, which is not consistent with it being a shifter of the short-run marginal cost function. Because we do not use any data on the cost of the firm's variable inputs, but instead estimate the cost function parameters from the pricing equation, this coefficient will capture any systematic difference in prices with firm size. It is important to emphasize that the estimation has already controlled for firm-specific factors in cost (c_f) and demand (ξ_f) so the capital stock variable is measuring the effect of variation in firm size over time which is likely to capture factors related to the firm's investment path and not just short-run substitution between fixed and variable inputs. The destination dummy variable coefficients reported in the table are the average over the destination-year coefficients in the regression and will capture both country-specific demand parameters and time varying cost parameters, $\tilde{\gamma}_d = \ln(\frac{\alpha_d}{\alpha_d - 1}) + (1/T)\left[\sum_t \gamma_{dt}\right]$, as seen from equation (6). The variation across destination countries indicates that the lower income countries, Rest of Asia, Africa, and Latin American, also have the lowest export prices, reflecting a pattern that was also seen in the demand elasticity and markup estimates. We can learn about the importance of the demand elasticity parameters, α_d, in explaining the pricing differences by constructing $\ln(\frac{\alpha_d}{\alpha_d - 1})$ from the demand estimates and comparing it with the average destination coefficients in Table 6. If the two are very similar in levels and ranking of the countries this would imply that the demand elasticity differences, not cost differences, are responsible for the difference in price levels across countries. These implied estimates of the contribution of the markup to pricing are reported in the last column of Table 6. A comparison of columns 1 and 3 shows that the top four countries in each list (SU, Japan, Austrailia, Non EU Europe) and the bottom three countries (Rest of Asia, Africa, and latin America) are the same, suggesting that there is little role for marginal cost differences across destinations to explain the level of export prices.

Table 6 - Pricing Equation Parameter Estimates

	Parameter Estimate	Standard Error	$\ln(\frac{\alpha_d}{\alpha_d - 1})$
$ln(capitalstock)_{ft}$	0.039	0.007	
$ln(wage)_{ft}$	0.004	0.011	
Product Group Dummies (γ_k)			
Leather Shoes	0.489	0.011	
Textile Shoes	-0.039	0.013	
Average Destination Coef ($\tilde{\gamma}_d$)			
US/Canada	0.523		0.543
Japan/Korea	0.577		0.528
Australia/NZ	0.556		0.638
Non EU Europe	0.546		0.669
Rest of Asia	0.499		0.486
Africa	0.452		0.449
Latin America	0.504		0.476
The model includes a full set of destination*year dummies			

5.3 Market Participation Estimates

The third equation in our empirical model is the probability of exporting, equation (11), and the parameter estimates are reported in Table 7. The participation decision for a firm depends on the firm demand and cost components, ξ_f and c_f, and both are found to be significant determinants of the export decision. The demand factor enters positively implying that firms with desirable products are more likely to export to a destination. This is consistent with high-price firms producing higher quality products and having larger market shares in the destinations. The cost variable c_f is multiplied by $(1 - \alpha_d) < 0$, so the positive coefficient in the regression implies that high cost firms have a lower probability of entering. Even though ξ_f and c_f are positively correlated, once we control for the firm demand component, firms with high production costs will be less likely to export. The capital stock, a measure of firm size, has a significant positive effect in the decision and wages enter negatively, as expected if they are cost shifters. The firm's product mix, measured as the combination of the product coefficients ξ_k and γ_k in demand and cost equations, and defined in equation (8), is also highly significant as a determinant of the export decision. Firms producing products with high appeal or low cost have higher probabilities of exporting. Finally, as seen in every empirical study of exporting, past participation in the destination market raises the probability of exporting to that destination in the current period. Overall, an important point to be taken from modeling the participation decision is that the firm-level demand and cost factors are both important determinants of entry and, given that the coefficient estimates in Table

7 are not equal for the two terms, each play a different role in the export decision.

Table 7 - Export Market Participation Equation

Dependent Variable	Parameter Estimate	Standard Error
firm demand shock ξ_f	0.323	0.016
firm cost shock $(1-\alpha_d)c_f$	0.228	0.018
$ln(capitalstock)_{ft}$	0.025	0.009
$ln(wage)_{ft}$	0.032	0.030
product mix $\sum_{k \in K_f} r_k^d$	0.324	0.041
past participation I_f^{dt-1}	1.584	0.023
The model includes a full set of destination/year dummies		

5.4 Firm Demand, Cost, and Profitability

Our empirical model and estimation method produce estimates of the firm-specific demand and cost factors, ξ_f and c_f. It is important to emphasize that all three equations, including the export participation equation, are helpful in identifying the joint distribution of firm components ξ_f and c_f. Specifically, firms with low (high) values of ξ_f (c_f) will not export as frequently or to as many destinations as firms with higher (lower) values. The parameters of the posterior distribution of firm components are reported in Table 8. since we include a full set of destination-year dummies in the market share and pricing equations, the posterior means of ξ_f and c_f are both estimated to be very close to zero. The posterior variances are 2.948 for the demand components and 0.438 for the cost component, implying that producer heterogeneity is much more substantial on the demand side than on the cost side. The across firm hetergeneity in market shares is leading to substantial variation in the estimated ξ_f across firms while the heterogeneity in prices leads to a much smaller degree of dispersion in c_f.

Table 8 - Posterior Distribution of Hierarchical Parameters

	Demand ξ		Cost c	
	Estimate	Standard Dev	Estimate	Standard Dev
$mean$	-0.010	0.075	-0.002	0.029
var	2.948	0.316	0.438	0.022
$cov(\xi, c)$	0.778	0.092		

The disperson in demand-side factors will be larger than the cost-side factors and this

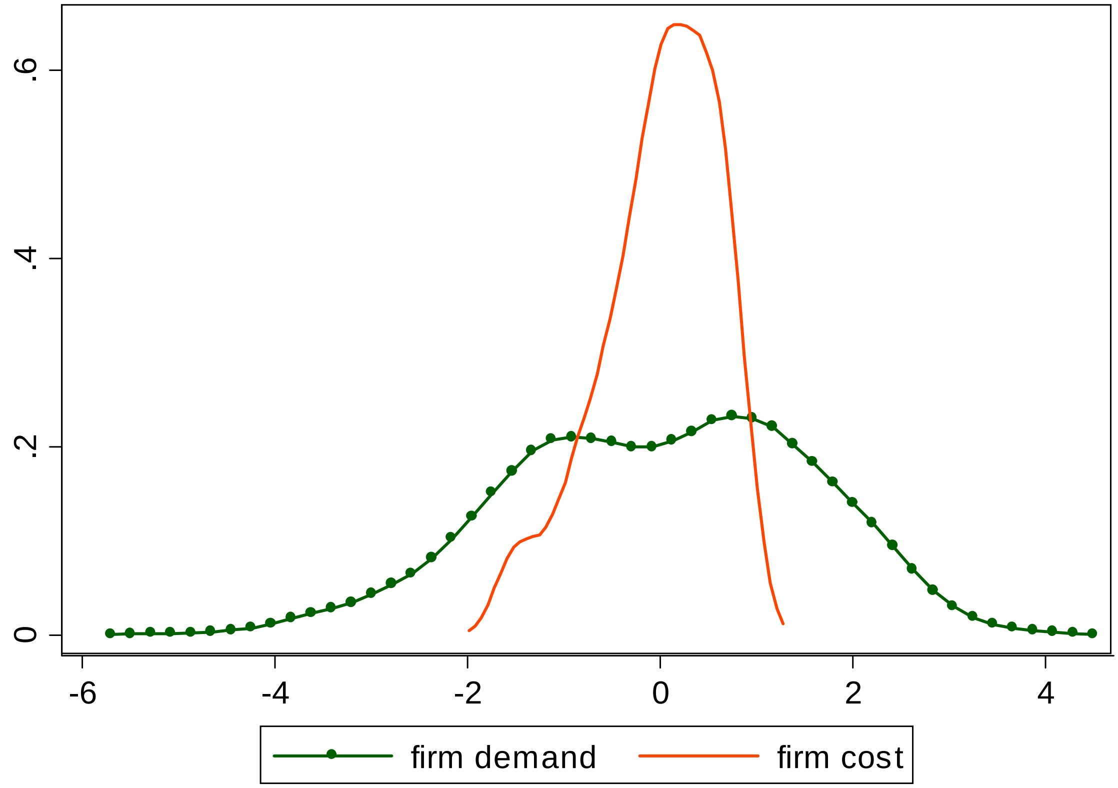


Figure 1: Density of Demand and Cost Components

can be clearly seen in Figure 1, which presents kernel density estimates of the distributions of ξ_f and c_f over the 1106 firms in our sample. This implies that heterogeneity in firm demand will be more important than firm-level cost heterogeneity in generating differences in export market sales and profits.

The final parameter reported in Table 8 is the covariance of the posterior distribution which equals .778. Firms with relatively high demand components also have higher costs which is consistent with the firm making costly investments that raise maginal cost, such as improving product quality or building a stock of customers, in order to increase demand. As explained in the theory section, the estimate of c_f includes both any firm-level costs $h(\xi_f)$ to produce higher demand as well as pure productivity differences across firms ω_f. To further understand the correlation between c_f and ξ_f we regress c_f on a polynomial in ξ_f and assess the fit of the regression. The estimated regression (standard errors in parentheses) is:

$$c_f = \underset{(0.017)}{0.048} + \underset{(0.013)}{0.263}\xi_f - \underset{(0.005)}{0.019}\xi_f^2 + \underset{(0.002)}{0.002}\xi_f^3 + \hat{\omega_f}, R^2 = .515. \tag{15}$$

which indicates that half of the sample variation in c_f is explained by variation in the firm demand component, leaving the remaining half of the cost variation to be explained as productivity differences. To a large extent in our sample the firms with high-product demand will have higher costs

.In Table 9 we summarize how the estimated firm components vary across groups of firms with different ownership and geographic location. The table reports coefficients from OLS regressions of the estimated firm components on a set of ownership and location dummy variables. The intercept is the mean component for state-owned firms in the non-coastal regions and the other coefficients are deviations from this for different ownership and location categories. It is important to emphasize that information on the ownership type or location has not been used in the estimation of the firm components but the table shows that the estimated components vary systematically across these groups of firms. The mean of the demand component ξ_f is 1.008 for private firms, .552 for foreign and .417 for firms owned by HK/TWN/MAC firms (all are relative to the state-owned firms). This implies that the private firms will, on average, have the highest demand for their products and the state-owned the lowest. The last two rows of the table report deviations for firms in the two coastal regions and we see that firms in the east coastal region will have higher demand and the southeast coastal firms have lower demand than the base group. On the cost side, all three groups of firms have higher costs than the state-owned firms but the cost differentials are not as large as the demand differentials. The same is true of the difference between the geographic locations. All have higher costs than the state firms in the non-coastal areas.

The demand and cost components both contribute to across-firm differences in sales and profits as seen in equations (7) and (9). We combine them into an index of the contribution of the firm components to profitability, $\ln r^{dt}(\xi_f, c_f)$, using equation (8).[16] This firm profitability index will also vary across destination markets because of variation in the demand parameter α_d. Because ξ_f and c_f are positively correlated and $1-\alpha_d < 0$, the profit index for any destination has less dispersion than the sum of the individual components. In the last two columns of Table 9 we report regression coefficients using the value of $\ln r^{dt}(\xi_f, c_f)$ averaged over the seven destination markets as the dependent variable. The regression coefficients show that, on average, the export profitability index will be highest for private firms and firms in the east coastal region. This will help to explain the high export rate and high level of sales seen in Table 3 for these categories of firms. The coefficients in Table 9 also imply that foreign-owned firms, on average, have high profitability indexes than the state-owned firms. Finally there is no difference in the average profitability index beween state-owned firms and those owned by HK/TWN/MAC firms.

Table 9 - Average ξ_f , c_f, $\ln r^{dt}(\xi_f, c_f)$ with Ownership and Location

	Demand ξ_f		Cost c_f		Profits $\ln r^{dt}(\xi_f, c_f)$	
	Coef	Std Dev	Coef	Std Dev	Coef	Std Dev
Intercept *	-0.738	0.204	-0.121	0.082	-0.565	0.142
Ownership Dummies						
Private	1.008	0.192	0.152	0.077	0.791	0.134
HK/TWN/MAC	0.417	0.198	0.289	0.080	0.005	0.137
Foreign	0.552	0.202	0.276	0.077	0.158	0.133
Location Dummies						
East Coastal	0.272	0.142	-0.063	0.057	0.361	0.099
Southeast Coastal	-0.411	0.168	-0.282	0.068	-0.009	0.117

* Represents a state-owned firm outside the coastal regions.

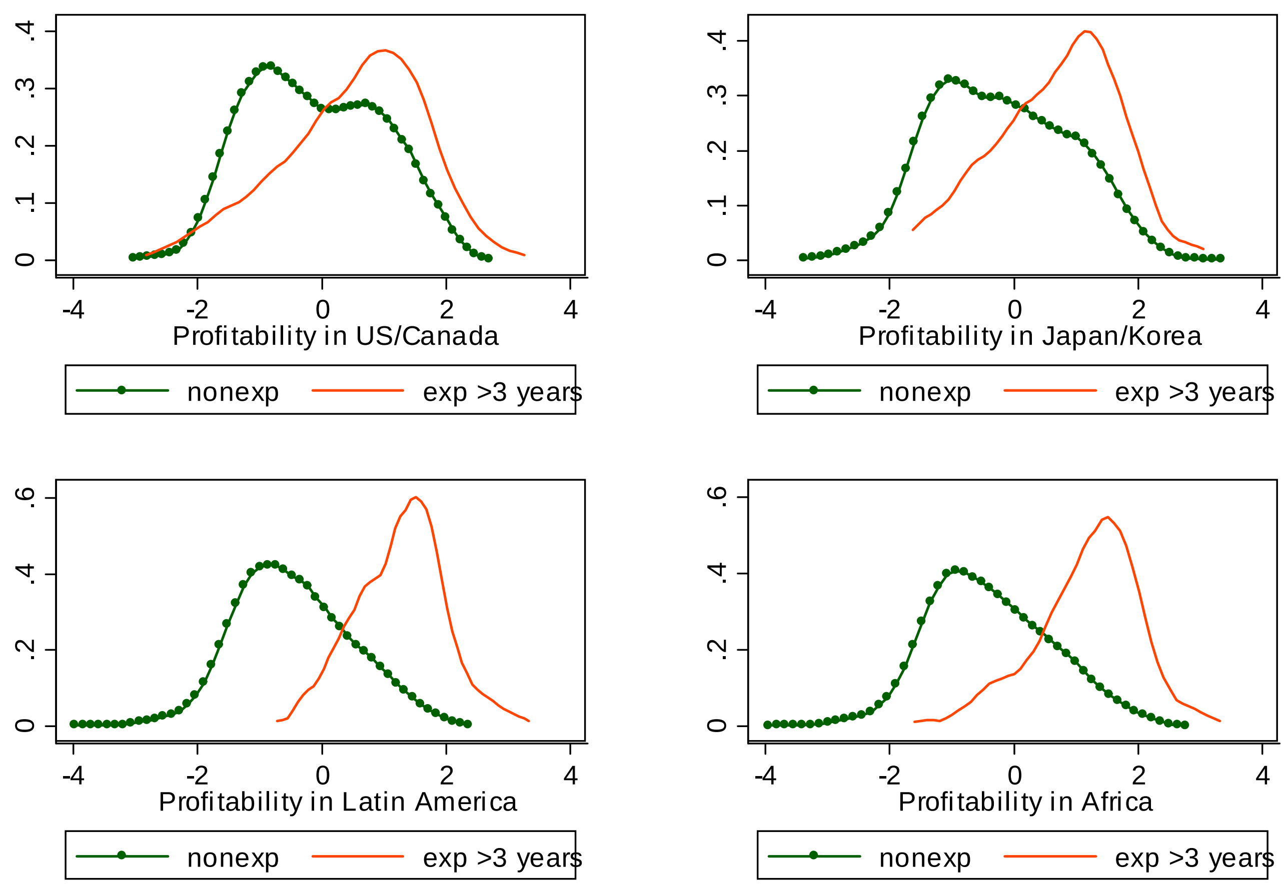
[16] When constructing the measure of firm profitability we did not include the terms that depend on the firm's wage rate or capital stock because they had no effect on the across-firm distribution of profitability. The profitability measures with and without the wage and capital stock data have a simple correlation that is greater than .99 in every destination market. The across-firm distribution of profitability is determined by the values of ξ_f and c_f.

5.5 Profitability and Export Patterns

The results reported in Table 9 show how the mean profitability measure varies across the whole set of sample firms based on ownership types and geographic regions but does not relate the variables to the actual export patterns. In this section we compare the distribution of firm profitability in each destination, distinguishing each firm based on the length of time in our sample that it exports to the destination. In order to highlight the role of firm profitability we contrast the group of firms that never export to a destination with the group that export either four or five years. Figure 2 graphs the kernel density for nonexporters and long-term exporters in each of four destinations. The upper left panel is for the U.S./Canada market and it is clear that the distribution of firm profitability among the long-term exporters is shifted further to the right indicating that the long-term exporters to the U.S. have a higher average level of profitability in that market than the firms that choose not to export to the U.S. The corresponding mean and standard deviation of the distribution for all seven destinations are reported in Table 10. The mean (standard deviation) of firm profitability among the nonexporters to the U.S. is -.092 (1.046) while the same numbers for the long-term exporters are .497 (1.111). The other three destination markets in Figure 2, which include one other rich country market with a relatively low demand elasticity, Japan/Korea, and two of the destination markets with higher demand elasticities, Latin America and Africa, all show the same pattern with the distribution of firm profitability for the long-term exporters being shifted to the right relative to the nonexporters.

Comparing across destinations in Table 10, a strong pattern is evident. The destinations in the first three rows, U.S., Japan, and Australia, are similar in that the mean profitability for the non-exporters varies from -.092 to -.186 and the mean for the long-term exports from .497 to .683. This leads to a difference in the mean of the two groups, reported in column 3, that varies from .589 to .869 for the three destinations. The remaining four destinations are very different from this and, in particular, show

Figure 2: Density of Firm Profitability by Destination Market



much a much sharper contrast between the profitability of long-term exporters and non-exporters. For the last four destinations in table 10, the mean for the non-exporters varies from -.375 to -.542 while for the long-term exporters it varies from 1.084 to 1.256. This leads to a gap in the mean profitability of the two groups that varies from 1.554 to 1.705 across the four countries. While similar across the four countries, the gap between the two groups is twice as large as the gap for the first three countries.

To a large extent, the profitability gap between long-term exporters and non exporters in Table 10 reflects the overall desirability of the export destination. The less desirable the destination, the larger the profit gap between long term and non exporters. The final column reports the number of firm/year observations in our sample in each destination market as a measure of the desirability of each market. Two of the most desirable markets, the U.S. and Japan, are in the group of destinations with a small difference in profitability and a relatively low mean productivity for the long-term exporters. Three of the least desirable markets, non EU Europe, Africa, and Latin America are in the group of destinations where the gap is large and the long-term exporters have relatively high productivity. The two outliers are Australia, which has the smallest number of exporters but a firm profitability distribution that looks like the U.S. and Japan, and the rest of Asia, which is a popular export destination but has a firm profitability distribution that looks like the less desirable destinations of Africa and Latin America.

Table 10 - Mean (Standard Deviation) of Firm Profitability

Destination	Non Exporters	Long-Term Exporters	(LT-NE)	Firm-Year Obs
US/Canada	–0.092 (1.046)	0.497 (1.111)	0.589	1579
Japan/Korea	-0.186 (1.092)	0.683 (0.955)	0.869	1271
Australia/NZ	-0.178 (1.144)	0.538 (0.979)	0.716	649
Non EU Europe	-0.477 (1.051)	1.190 (0.755)	1.667	1124
Rest of Asia	-0.542 (0.911)	1.084 (0.813)	1.626	1287
Africa	-0.449 (0.925)	1.256 (0.696)	1.705	958
Latin America	-0.375 (0.979)	1.179 (0.809)	1.554	924

6 Analyzing the EU Quota Restriction on Chinese Footwear Exports

One feature of the environment faced by the Chinese footwear exporters was a quota on total footwear imports in the European Union that was in place during the beginning of our sample and then removed at the end of the sample. We have not used the data on exports to the EU in estimating the structural parameters and constructing the firm demand and cost indexes. In this section we analyze the mix of firms that export to the EU and summarize how this compares during and after the quota period.

Restrictions on Chinese footwear exports to the EU countries date back to the 1990's. During the the first three years of our data, 2002-2004, there was an EU quota on total Chinese footwear imports. The quota applied to all three product categories and substantially constrained total exports from China. The quota was adjusted upward between 10 and 20 percent each year following China's entry into the WTO in late 2001. In 2005 it was removed and this expiration date was widely known ahead of time. As a consequence, part of the response of Chinese exporters was already observed in 2004. The quota was monitored by the EU commission. It was directly allocated across importing firms with 75 percent of the allocation given to "traditional importers," firms that could prove they imported the covered products from China in previous years. The remaining 25 percent of the allocation was given to "non-traditional importers," basically new importing firms, but they were constrained to a maximum of 5,000 pairs of shoes per importer. In effect, the quota limited the ability of new importing firms to gain access to Chinese footwear exports. In addition, when the total application by the importers exceeded the aggregate quota, as is the case for our sample years, applications were met on a pro rata basis, calculated in accordance with each applicant's share of the total imports in previous years.

These quota restrictions impacted the export decision of Chinese footwear producer's in important ways. First, given the preferential treatment in quota allocation to "traditional importers," there was a lack of presence of "non-traditional" importers. Removal of the quota is likely to result in the entry of firms that did not previously export to the EU. Furthermore, the quota may also constrain the traditional importers' choice of which Chinese export firm to buy from. If it takes time for traditional importers to switch their Chinese suppliers then any disruption in their import quantity in one year would adversely affect their quota allocation in the next year. This suggests that traditional importers may not have been completely unconstrained in their choice of Chinese firm to buy from and, more generally, that the export history of a Chinese supplier in the EU may have played a more important role than in other non-restricted markets. Overall, the quota is likely to have discouraged the entry of new exporting firms to the EU and slowed the reallocation of market share towards high ξ and low c firms among incumbent Chinese producers. Second, from the perspective of Chinese producers,the binding quota restriction implied a constrained profit maximization problem. The shadow cost of the quota restriction translates into a per unit trade cost incurred by producers. In addition to lowering the overall profitability of Chinese exporters in the EU market, the per-unit trade cost also has a composition effect that favors firms with a higher unit price (and higher demand because of positive correlation between ξ and c) in the quota regime.

Next we document the large increase in aggregate exports to the EU by Chinese firms in our sample and quantify the firm adjustment in both the extensive and intensive margins using the demand and cost indexes we constructed with data from the non-EU markets. Table 11 shows the total exports to the EU by the 1106 firms in our sample for the years 2002-2006. For comparison, the total exports of these same firms to the U.S./Canada and Japan/Korea are presented. It is clear from the table that there was a gradual increase in exports to the EU for all three categories of footwear that were under EU quota constraints from 2002-2003 followed by a substantial increase in 2004 and 2005. In contrast, the magnitude of this expansion was not present in either the

U.S. or Japanese export markets.[17]

Table 11 - Quantity of Footwear Exports by Sample Firms (millions of pair)

	2002	2003	2004	2005	2006	Growth Rate 2002-2006
Plastic Footwear[a]						
EU	9.8	17.0	25.3	34.1	39.0	297%
Japan/Korea	13.5	15.6	18.8	19.9	21.8	61%
US/Canada	14.3	24.2	37.8	34.3	42.6	197%
Leather Footwear[b]						
EU	1.71	2.23	4.08	11.2	7.31	327%
Japan/Korea	6.82	7.92	6.57	5.44	5.06	-26%
US/Canada	8.19	8.57	10.1	14.1	12.3	50%
Textile Footwear[c]						
EU	2.66	6.84	12.7	17.1	23.6	787%
Japan/Korea	22.7	23.1	25.6	28.6	29.4	29%
US/Canada	17.0	17.1	23.1	24.5	31.9	87%

[a]product 640299 only, [b] 640391 and 640399, [c] 640411 and 640419

The changes in the quota constraint were accompanied by firm adjustment on both the extensive and intensive margins. The top panel of Table 12 summarizes the export participation rate for our sample of firms in the EU, US, and Japanese markets. The participation rate in the EU market rose from .28 to .36 to .46 over the sample period, while it remained virtually unchanged at approximately .45 in the US and .39 in Japan. Relaxing the quota was accompanied by net entry of Chinese exporting firms into the EU market. The lower panel of the table shows the average size (in thousands of pairs of shoes) of continuing firms in the three markets in each year. In each destination there is a substantial increase in the size of the exporting firms from 2002-2005, followed by a drop in 2006. Across the three destinations the proportional increase over the whole period was larger in the EU (141 percent) than in the US (39 percent) or Japan (31 percent). There is a significant increase in the average size of the Chinese firms sales in the EU market as the quota was relaxed.

[17]There was another change in policy that affected leather footwear imports to the EU in 2006. An anti-dumping tariff was placed on Chinese leather footwear exports and this contributed to the observed decline in export quantity of this product in 2006.

Table 12: Source of Export Expansion by Year, Destination

	2002	2003	2004	2005	2006
Extensive Margin (Prop. firms exporting to destination)					
EU	.28	.36	.38	.46	.46
US/Canada	.42	.45	.42	.45	.46
Japan/Korea	.37	.39	.38	.39	.38
[a]Intensive Margin of Long-Term Exporters					
EU	54.0	89.7	139.1	161.0	130.1
US/Canada	74.2	96.5	132.6	128.1	103.6
Japan/Korea	85.4	93.1	116.2	115.9	112.1
[a]Median quantity, thousands of pairs					

Table 12 implies that there is reallocation of market shares among the set of firms that are selling to the EU market. The next question we address is whether this reallocation is related to the underlying firm demand and cost indexes.[18] In Table 13 we will first examine reallocation on the extensive margin resulting from the entry and exit of the exporting firms from the EU market then, in table 14, we will summarize reallocation on the intensive margin reflecting changes in the size of continuing exporters.

In the top half of Table 13, we group the 1106 firms in our sample into 5 equal-sized bins ranked from low ξ_f to high ξ_f.[19] In the first column we report the export rate to the EU in each bin in 2003, which is within the quota-constrained period. The last column reports the same numbers for 2005, which is the first year after the quota is lifted. The middle two columns report the entry rate and the exit rate from the EU market.[20] When the quota was in place there was an increase in the export rate, from .127 to .425, as the firm demand index increased. That indicates that firms with high demand for their exports in other destinations were more likely to be exporting to the EU during the quota period. The remaining columns of the table show a very dramatic shift in the mix

[18]It is not possible to construct the index of firm profitability for the firms in the EU market because we do not have an estimate of the demand parameter α_d in this destination market. We will instead focus on the separate comparisons of demand and cost.

[19]There are 221 firms per bin with the exception of the smallest bin which has 222.

[20]The entry rate is the number of new EU exporters observed in 2005 relative to the number of firms not exporting to the EU in 2003. The exit rate is the number of firms that leave the EU market by 2005 relative to the total number of EU exporters in 2003.

of exporting firms as the quota is removed and the shift is closely correlated with the demand index. The entry rate of firms into the EU market market increases from .150 to .598 across the five bins and the exit rate decreases from .678 to .128 as the demand index rises. Firms in the highest quintile of the distribution of ξ_f were much more likely to enter the EU market and much less likely to exit than firms from the lower quintiles. With one exception, the entry and exit rates are monotonic across the size classes. Basically, this is saying that firms that were large exporters in markets outside of the EU are the ones that enter the EU market while firms with relatively low sales in other markets are the ones that exit from the EU market after the quota is lifted. In 2005 we observe that the export rate is higher for all five categories than it was in 2003, reflecting the overall expansion of exports to the EU when the quota was lifted, but the largest increases in export market participation came among the firms with the highest demand indexes. For example, for the firms in the highest quintile of the distribution, the export rate rose from .425 to .715. Overall, as the quota was relaxed the composition of the firms in the EU market shifts toward the exporters who have higher demand indexes.

Table 13: Adjustment in the Number of Firms Exporting to the EU

ξ_f bins (low to high)	2003 Export Rate	Entry Rate	Exit Rate	2005 Export Rate
1	.127	.150	.678	.172
2	.181	.110	.425	.195
3	.253	.255	.250	.380.
4	.330	.378	.315	.480
5	.425	.598	.128	.715
ω_f bins (high to low)				
1	.226	.193	.480	.267
2	.271	.236	.283	.367
3	.276	.256	.262	.389
4	.290	.306	.313	.416
5	.253	.382	.143	.502
All firms	.263	.274	.292	.388

The bottom half of Table 13 makes the same comparison across groups of firms based on their cost index. Here we use the measure of $\hat{\omega}_f$ from the regression in equation

(15) as the cost index in order to control for the difference in firm costs that result from differences in the demand index. Firms with large values of $\hat{\omega}_f$ have high marginal costs, after controlling for the costs associated with producing ξ_f. To make the comparison with the top half of the table straightforward, the bins are sorted from high cost to low cost, so as we move down the categories firm export profits should increase. The first significant pattern observed is that the 2003 export rate does not vary systematically across the cost bins. In particular, the low cost firms (category 5) have the second-lowest export rate among the five categories and the overall variation across categories is fairly small, varying between .226 and .290. This is different than what we observed for the differences in demand indexes in 2003. However, the entry and exit patterns between 2003 and 2005 do reflect a systematic change in the mix of firms toward lower-cost producers. The entry rate into the EU market increases monotonically from .193 to .382 as we move from the high-cost to low-cost bins. The exit rate decreases from .480 to .143, although not monotonically, as we move from high to low-cost firms. Both of these turnover patterns contribute to a change in the mix of firms exporting to the EU in favor of lower-cost producers after the quota is relaxed. The composition effect results in a doubling of the export rate for the lowest cost producers, from .253 to .502, but only a four percentage point change, from .226 to .267, for the highest cost producers. In 2005, unlike 2003, we now observe that firms with lower costs have a higher propensity to export and the magnitude of the differences across cost bins are much more substantial than when the quota was in place. Overall, removing the quota resulted in systematic changes in the extensive margin in favor of firms with high demand indexes and low cost indexes. The mix of firms present in 2005 is substantially different than the mix of firms exporting to the EU in 2003.

Finally, we examine the adjustment on the intensive margin by summarizing the percentage change in quantity sold from 2003 to 2005 for the continuing firms in each demand and cost category. In the top half of Table 14, we report the suvival rate, the proportion of EU exporters in 2003 that remain in the market in 2005, for each fo the five ξ categories and the growth rate of their export quantity from 2003 to 2005. The growth rate applies to the set of firms that were present in both years. The firms in low ξ categories experienced relatively low survival rates and, more interestingly, the survivors experienced an overall reduction in the quantity of footwear exported to the EU. This reduction occurred despite the overall lower trade barrier faced by Chinese exporters. The quantity of footwear sold by the continuing firms declined by 20.4 and 12.5 percent, respectively, for the two lowest demand categories. The firms in the three higher ξ categories experienced higher survival rates and fast growth, particularly the firms in the top two categories. When combined with the high continuation rate for these firms in the export market, this expansion by firms with high demand indexes makes a significant contribution to the overall increase in total footwear exports to the EU. If we examine the total change in the quantity of footwear shipped to the EU by the firms in our sample between 2003-2005, we see that the continuing firms account for 57 percent of the total increase, and virtually of this comes from firms in the top two demand categories, while net entry accounts for the remaining 43 percent. Both the intensive and extensive margins show substantial change when the quota was removed.

Table 14: Quantity Adjustment by Continuing Exporters

ξ_f bins (low to high)	Survival Rate	Percentage Change in Quantity Sold
1	.321	-20.41
2	.575	-12.50
3	.750	24.31
4	.685	101.90
5	.873	125.90
ω_f bins (high to low)		
1	.520	7.98
2	.717	135.60
3	.738	197.42
4	.688	7.98
5	.857	47.62

In the bottom of Table 14, we report the same comparison based on cost index $\hat{\omega}$.

Focusing on the output growth rate for the surviving firms, we see that expansion of the intensive margin is not systematically related to the firm cost index. While firms in the highest cost category had low growth, the second and third highest cost categories expanded the fastest, 135 and 197 percent, respectively. This is not consistent with the pattern we documented for the extensive entry margin in Table 13, where new entrants were concentrated in the low-cost categories.

Overall, we find that the quota in the EU market substantially affected the composition of firms selling in the market. Removing the quota resulted in a rapid shift in the composition of firms toward ones with higher demand ξ indexes and lower cost $\hat{\omega}$ indexes. At the same time the growth in the quantity of exports by continuing exporters was dramatically higher for firms with higher demand indexes but, surprisingly, this was not true for firm firms with the lowest cost indexes.

7 Summary and Conclusion

In this paper we utilize micro data on the export prices, quantities, and destinations of Chinese footwear producers to estimate a structural model of demand, pricing, and export market participation. The model allows us to measure firm-level demand and cost parameters and provides a way to combine them into a measure of a firm's profitability in each of seven regional export destinations. Estimation of the heterogeneity in firm demand parameters relies on across-firm differences in export market shares, controlling for firm prices, in the destination markets. The measure of cost heterogeneity relies on differences in firm export prices, controlling for firm costs and markups, across destinations. Both factors play a role in determining the firm's profits in each export market and thus the decision to export. The model allows demand elasticities and markups to vary across destinations and we show that the relative importance of demand versus cost in generating differences in firm profitability in an export destination depends on the elasticity of demand in the destination. In markets with more elastic demand, cost differences across firms are magnified and become more important in determining firm profitability than in markets with more inelastic demand.

To estimate the model we use panel data from 2002-2006 for a group of 1106 Chinese firms that export footwear. The econometric methodology we utilize is a practical application of a Hierarchical Bayesian method that relies on MCMC and Gibb's sampling for implementation. This allows us to both include a large number of parameters, two for each of our 1106 firms, and to incorporate the parameters consistently in both the linear and nonlinear equations in our model in a very tractable way. The empirical results indicate substantial firm heterogeneity in both the demand and cost dimensions with demand being a more important determinant of the across-firm differences in export market profitability. We find that our measure of firm export profits is very useful in summarizing differences between firms based on the length of time they export to a destination. Firms that are long-term exporters in a destination have a higher profitability index, on average, than firms that do not export to the destination. Finally, we use our firm indexes to study the reallocation of export sales across Chinese producers in response to the removal of the quota on Chinese exports of footwear to the EU. We find that removal of the quota led to a substantial change in the mix of firms that exported to the EU with the shift in composition toward firms with higher demand and lower cost indexes.

Overall, this paper represents a first step in our research agenda to study how underlying firm heterogeneity on both the demand and production sides influences the long-run performance of Chinese manufacturing exporters. This paper demonstrates that firm parameters from both the demand and cost side of the firm's activities can be retrieved from micro data on firm production and export transactions and that the firm parameters are useful in summarizing differences in firm export patterns across destination markets.

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A Appendix - Sampling Procedure

Define the set of common demand parameters as $\alpha = (\alpha_d, \tilde{\tau}^{dt}, \rho, \xi_k)$, the set of common cost parameters as $\gamma = (\gamma_w, \gamma_{dt}, \gamma_k)$, and the common parameters describing the demand and pricing shocks as Σ. At the start of simulation round s there are previous draws α^{s-1}, γ^{s-1}, and Σ^{s-1}, and draws for each of the firm quality and productivity shocks: (ξ_f^{s-1}, c_f^{s-1}), $f = 1, 2, .., N$. To update the parameters in simulation s we perform the following steps.

1. Conditional on $\alpha^{s-1}, \gamma^{s-1}$ and c_f^{s-1}, the pricing equation (6) directly implies v_i^{dt} and the distribution of $u_i^{dt}|v_i^{dt}$ is well defined given Σ^{s-1}. We can then draw α^s using the demand equation:

$$ln(s_i^{dt}) - ln(s_0^{dt}) - \xi_f^{s-1} = \xi_k + \rho I_f^{dt-1} - \alpha_d lnp_i^{dt} + \tilde{\tau}^{dt} + u_i^{dt}|v_i^{dt}$$

2. Conditional on α^s, we draw the cost parameters γ^s using both the pricing and demand equations:

$$\begin{aligned} lnp_i^{dt} - c_f^{s-1} - ln(\frac{\alpha_d^s}{\alpha_d^s - 1}) &= \gamma_{dt} + \gamma_k + \gamma_w lnw_f^t + v_i^{dt} \\ \frac{ln(s_i^{dt}) - ln(s_0^{dt}) - \xi_f^{s-1} - \tilde{\tau}_{dt}^s}{-\alpha_d^s} - c_f^{s-1} - ln(\frac{\alpha_d^s}{\alpha_d^s - 1}) &= \gamma_{dt} + \gamma_k + \gamma_w lnw_f^t - \frac{1}{\alpha_d^s} u_i^{dt} + v_i^{dt} \end{aligned}$$

   Note these two equations share the same set of right hand side variables and can be analyzed using standard Bayes regression.

3. Conditional on $\alpha^s, \gamma^s, \xi^{s-1}, c^{s-1}$, draw Σ^s using the demand and pricing residuals $\hat{u}_i^{dt}, \hat{v}_i^{dt}$.

4. Given $\alpha^s, \gamma^s, \xi^{s-1}, c^{s-1}$ and Σ^s, calculate the product group effect $r_k^d(\xi_k^s, \gamma_k^s, \alpha_d^s)$ defined in (8).

5. Define the latent payoff if firm f exports to market dt as

$$\pi_f^{dt}(\alpha^s, \gamma^s, \xi^{s-1}, c^{s-1}, \Sigma^s) = F[ln\bar{r}^d(\xi_f^{s-1}, c_f^{s-1}, \gamma_d^s + \gamma_w^s lnW_f^t), ln(\sum_{k \in K_f} \bar{r}_k^d), \bar{\Phi}^{dt}; \psi]$$

where $F[.]$ is a flexible polynomial of firm demand/cost heterogeneity, product group effects, and market-time effects.

6. Conditional on $\alpha^s, \gamma^s, \xi^{s-1}, c^{s-1}$ and Σ^s, draw ψ^s using:

$$\prod_{f,d,t} G[\pi_f^{dt}]^{I_f^{dt}}(1 - G[\pi_f^{dt}])^{(1-I_f^{dt})}$$

where I_f^{dt} is the firm's observed discrete export participation decision in market dt. Evaluating this likelihood is in general costly and of poor numerical performance but McColloch and Rossi (1994) provide an efficient algorithm that avoids direct evaluation of this function using *data augmentation* techniques.

7. The next step involves updating the draws of the individual firm quality and productivity parameters $(\xi_f^s, c_f^s), f = 1, 2, .., N$ given the updated values of the common parameters. The key distinction here is to use a Metropolis-Hasting algorithm and accept/reject these draws *firm by firm*. These draws are generated from a conditional density

$$p(\xi_f^s, c_f^s | D_f; \alpha^s, \gamma^s, \Sigma^s, \psi^s) \propto f(D_f | \alpha^s, \gamma^s, \Sigma^s, \psi^s; \xi, c) w_f^{s-1}(\xi, c)$$

The prior (weights) $w_f^{s-1}(\xi, c)$ is based on the last round hyper-parameters b^{s-1}, W^{s-1} and thus incorporate information from the data.

8. Finally, draw b^s, W^s using newly accepted draws of $(\xi_f^s, c_f^s), f = 1, 2, .., N$.