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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 more dispersed. The firm-specific demand and cost components are very useful in explaining differences in the extensive margin of trade, the length of time a firm exports to a destination, and the number and mix of destinations, as well as the export prices, while cost is more important in explaining the quantity of firm exports on the intensive margin. 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.

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# 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 determines the firm's long-run profits from participating in a market and short-run pricing, output, or investment decisions. Treating firms as heterogeneous 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]

In this paper we develop the role of firm demand and cost heterogeneity in explaining

[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] Gervais (2011) also uses U.S. manufacturing sector production data to estimate firm-level demand and productivity components and then shows that these help to explain patterns of firm exporting. 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 reallocations of activity across firms in response to economic reforms.

the export decisions of Chinese manufacturing firms.[3] The success of Chinese manufacturing exports is one of the most significant phenomena in world trade in the last decade, however, debates remain about the underlying causes at the individual producer level. Have Chinese firms invested in "capability building" to improve their product appeal (See Brandt, Rawski, and Sutton (2008) and Schott (2008)) or have they succeeded primarily because of low labor and input costs that allow them to serve as a manufacturing base for foreign-owned firms (Branstetter and Lardy (2008))? Given escalating domestic wages and input prices, which give limited room for further cost reduction by Chinese firms, the separate roles of demand and cost heterogeneity are key to their likely future success against expanding low-cost competitors like Vietnam and India. This distinction between demand and cost-side heterogeneity has been formally modeled by Sutton (2007) who shows that low wage countries can offset low labor productivity but, because of the need to purchase some tradeable material inputs, they cannot fully offset low product quality. In the short run this generates a floor on product quality which surviving firms must exceed and, in the long run, strengthens incentives to invest in improving demand side factors and is potentially an important force contributing to the development of countries like China and India.

We take a first step toward studying the role of these factors in Chinese export market expansion by developing a structural model of demand, cost, and dynamic export participation that can be used to measure the extent of firm-level cost and demand heterogeneity. We estimate the model using micro data on prices and quantities of exported goods and firm costs for a panel of 1106 large Chinese exporting firms in the footwear industry from $2002-2006$. In our data set, the firm-level export price, quantity, and destination patterns indicate a potentially important role for two dimensions of firm heterogeneity that persist across destinations. Firms that export to many destinations also export to more difficult destinations and have higher average export quantities in each destination. This is consistent with persistent firm-level demand heterogeneity. These same firms also have higher average export prices which suggests

[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.

that the demand differences are costly to produce or maintain and is not consistent with low cost being the sole determinant of export success. The only way to distinguish the role of cost and demand heterogeneity is to specify a structural model which includes distinct demand and cost components at the firm level.

In the econometric model we develop, the measure of firm demand heterogeneity 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 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 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 unobservables, two for each of our 1106 firms, and to incorporate them in nonlinear equations, such as the probability of exporting, in a very tractable way.

The empirical results indicate substantial firm heterogeneity in both the demand and cost dimensions with both factors affecting the choice of export destinations, price, and quantity of sales. On the extensive margin, the demand and cost factors are both important explanatory factors in the length of time the firm exports to a destination, the number of destinations, and the mix of destinations. On the intensive margin we find that both the demand and cost factors are approximately equally important in explaining export price variation across firms and destinations but that efficiency differences are much more important in explaining variation in the quantity of exports across firms and destinations. After controlling for demand differences across firms, export quantities are much larger for firms with low costs. 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.

Accounting for firm-level heterogeneity has been particularly important in the recent empirical literature attempting to explain trade volume differences between countries.[4] In an empirical study using French firm-level data, Eaton, Kortum, and Kramarz (2011) find that 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." The model we develop incorporates firm-level heterogeneity that is universal across all a firm's markets. Other recent empirical papers have relied on data on prices of exported goods to draw inferences about the magnitude of firm heterogeneity in product quality and productivity as distinct sources of trade advantage. A number of papers have used firm-level micro data to analyze price and quantity correlations and find higher prices for exporting firms (Hallak and Sivadasan (2009) and Kugler and Verhoogen (forthcoming)) or firms that export to more markets (Manova and Zhang (forthcoming)) or firms that ship greater distances (Baldwin and Harrigan (2011) and argue this is consistent with higher quality products being exported. Johnson (2009) and Khandelwal (2010) estimate structural models of demand using product-level data on prices and trade flows between countries and find evidence consistent with quality variation at the country level. Crozet, Head, and Mayer (forthcoming) exploit firm level data on prices, exports, and direct quality measures for Champagne producers and find quality is positively correlated with price, quantity and the number of destination markets the firm sells in. They also show that it is important to correct for the endogenous selection of destination markets when estimating the effect of quality on export variables. In this paper we specify and jointly estimate structural demand, cost, and market participation equations for a set of seven destination markets for each firm. This project differs from these empirical trade papers, as well as the work by Foster, Haltiwanger, and Syverson (2008) and Gervais (2011) that uses domestic firm prices, by integrating the unobserved firm-level demand and cost components 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

[4] 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.

firms because they export to multiple destination markets and this helps to both identify the distribution of firm-level demand and cost components and control for the endogenous selection of which markets to sell in. Our framework allows us to tie together the pricing, output, and participation decisions with a consistent set of firm-level demand and cost components.

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 a Firm's 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 $k$ 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 $\delta_i^{dt}$ that varies by destination market and year and a transitory component $\epsilon_{ci}^{dt}$ that captures all heterogeneity in preferences across importers.[5] Berry (1994) shows that, if $\epsilon$ 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

[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 modelling of the destination-specific utility component $\delta_i^{dt}$.

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 $\delta_i^{dt}$ 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 $\xi_f$ 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 quality of the firm's product. Holding price fixed, an increase in $\xi_f$ will raise the market share for this variety in all markets. Since the $\xi_f$ 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 $\rho$ 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 $\xi_k$ that will lead to higher utility for

[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 $\xi_f$ 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.

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 $\tau_{dt}$ 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 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 $\alpha_d$, 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 $\alpha_d$, destination market/year effects $\tilde{\tau}_{dt}$, an experience effect in demand $\rho$, product group effects $\xi_k$, and a firm-specific demand shifter $\xi_f$. One goal of the empirical model developed below will be to estimate the parameters of equation (4) including the firm-specific demand factor $\xi_f$.

## 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:

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

where $\gamma_{dt}$ and $\gamma_k$ 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 unobservables. 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 unobservable $\omega_f$ 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 $\xi_f$ 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]

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

This pricing equation shows that the price of variety $i$ in market $dt$ will depend on the destination-specific demand parameter $\alpha_d$ 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 $\xi_f$.

### 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

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

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 $\xi_f$, the firm cost component $c_f$, and the observable firm-level marginal cost shifters $\gamma_w ln w_f^t$. 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. A larger value of $\xi_f$, 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 $\xi_f$, 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 $\alpha_d$ is destination specific. In a destination with more elastic demand (larger $\alpha_d$), the cost differences across firms are more important as a source of export revenue differences.

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:

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

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.**[10]

## 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 $\phi_f^{dt}$ 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 $\phi_s$. 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 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. To describe each firm's export participation decision, we summarize their individual state variables into $s_f = \{\xi_f, c_f, w_f, K_f\}$ and previous export status $I_f^{dt-1}$. Assuming the the firm forms a rational perception of the sequence of aggregate state variables $\bar{\Phi}^{dt}$ we define the value function of the firm that chooses to export to destination $dt$ as $V_e^{dt}(s_f, I_f^{dt-1}; \bar{\Phi}^{dt})$ and the value of the

[10] 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. 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. Sutton (2007) introduces a measure of firm capability, defined as the pair of firm quality and labor productivity, which is similar to our $\ln r^{dt}(\xi_f, c_f)$. In his framework the two arguments of firm capability are not isomorphic because there is a lower threshold on firm quality which a firm must exceed to be viable. In our setting the two terms contribute differently to firm profit and participation across destination markets because the cost component is weighted by the demand elasticity in the destination market.

firm not exporting as $V_n^{dt}(s_f; \bar{\Phi}^{dt})$. These values can be defined recursively as:

$$\begin{aligned} V_e^{dt}(s_f, I_f^{dt-1}; \bar{\Phi}^{dt}) &= \bar{\pi}^{dt}(s_f, I_f^{dt-1})\bar{\Phi}^{dt} - (1 - I_f^{dt-1})\phi^S \\ &\quad + \beta E_\phi[max(V_e^{dt+1}(s_f, 1; \bar{\Phi}^{dt+1}) - \phi_f^{dt+1}(s_f; \bar{\Phi}^{dt+1}))] \\ V_n^{dt}(s_f; \bar{\Phi}^{dt}) &= \beta E_\phi[max(V_e^{dt+1}(s_f, 0; \bar{\Phi}^{dt+1}) - \phi_S^{dt} - \phi_f^{dt+1}(s_f; \bar{\Phi}^{dt+1}))] \end{aligned}$$

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 net benefits of exporting:

$$p_e^{dt}(s_f, I_f^{dt-1}; \bar{\Phi}^{dt}) = \Pr[\phi_f^{dt} \leq V_e^{dt}(s_f, I_f^{dt-1}; \bar{\Phi}^{dt}) - V_n^{dt}(s_f; \bar{\Phi}^{dt})] \tag{10}$$

The third goal of our empirical model is to estimate the firm's market participation decision $p_e^{dt}(s_f, I_f^{dt-1}; \bar{\Phi}^{dt})$ and, in particular, determine the role of the firm specific demand and cost components $\xi_f$ and $c_f$ in the export decision. In our model it is a function of the two firm factors $\xi_f$ and $c_f$, the observable marginal cost shifters $w_f$, 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 $I_f^{dt-1}$. If the fixed cost is normally distributed, this leads to a probit approximation to the policy function for the firm's export participation decision:

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

where $G$ is the normal cdf and $\psi$ is the parameter vector to be estimated.[11]

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 for a set of destination countries. 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

[11] Das, Roberts, and Tybout (2007), and Aw, Roberts, and Xu (2011) have estimated structural models of the firm's discrete export decision using equation 10. They calculate the long-run firm values $V_e$ and $V_n$ and estimate the distribution of fixed costs and entry costs. Using the insights of Hotz and Miller (1993), it is possible to invert the choice probabilities in equation 11 and retrieve the value functions. We do not pursue this avenue in this paper because we do not have any need for these objects and equation 11 is sufficient for our goal of estimating the distributions of $\xi_f$ and $c_f$.

estimated with firm-level data on export prices, quantities, production costs, and destination markets.[12] 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 $\xi_f$ 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 $\alpha_d$ 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 $\gamma_w$, destination-specific cost differences $\gamma_d$, and product group cost differences $\gamma_k$. 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 $\Sigma$. 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 (2011) 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

[12] If we used only the price and quantity data from markets that the firm chose to export to and ignored the endogenous market participation decisions would likely result in upward biased estimates of the distribution of $\xi_f$ and downward biased estimates of the distribution of $c_f$.

of price and quantity observations for the firm. We could estimate the firm-level $\xi_f$ and $c_f$ using individual firm price, quantity, and cost data, conditional on the common parameters, which is conceptually close to a 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 $\xi_f$ and $c_f$. In this case we let firm unobservables' contribution to the likelihood function be weighted by a specified distribution. This is essentially the random-effect approach. In either case, observations of the same firm's discrete and/or 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 $\xi_f$ and $c_f$. This leads to endogeneity of the product price which biases the price coefficients $\alpha_d$ 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 (2011) 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

[13] Helpman, Melitz, 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.

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.

### 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 shifters $lnw_f^t$ 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 (2011), denote the joint distribution of firm $f$'s unobserved quality $\xi_f$ 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 $\Theta$. 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 a 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:

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

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 $\alpha_d$. 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 $(\xi, c)$ in a Hierarchical Bayesian setup.

We assume a bivariate normal distribution for the prior of $(\xi_f, c_f)$ 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 the 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. The market share of variety $i$ in market $dt$ is defined as the sales of variety $i$ divided by the total imports of footwear from all supplying countries in market $dt$. 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.[14]

### 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 $2002-2006$. US/Canada is 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.

[14] When estimating the demand curve we normalize this market share by $s_0^{dt}$ the market share of a single product, waterproof footwear, aggregated over all suppliers to market $dt$. In effect, we treat the category of waterproof footwear as being produced by a single firm and the utility of this product is normalized to zero 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 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 |
| Rest of Asia | .356 | .420 | .438 | .428 | .447 | .418 |
| Non EU Europe | .331 | .354 | .351 | .386 | .407 | .366 |
| Africa | .251 | .297 | .294 | .354 | .352 | .310 |
| Latin America | .303 | .258 | .299 | .314 | .333 | .301 |
| Australia/NZ | .220 | .236 | .206 | .207 | .205 | .215 |

Table 3 provides evidence that the number of destinations a firm exports to and the popularity of the destination are related. The first column of the table reports the proportion of firms that sell in only one destination market (.376) through all seven destinations (.094). More than half of the firms sell in only one or two markets and the remainder are approximately evenly divided across three to seven destinations. The remainder of the table gives the proportion of firms exporting to $n = 1, ...7$ destinations, conditional on exporting to one of the destinations. The destinations are ordered from most to least popular in terms of overall export rate. The table shows a clear correlation between number of destinations and the popularity of the destination. Firms that export to the most popular destinations, US/Canada and Japan/Korea, are most likely to export to only one destination and there is a U-shaped relationship in the frequency distribution of number of destinations. These firms are less likely to export to three or four destinations and then more likely to sell in five to seven. Conditional on selling in any of the other five destinations, the probability of exporting to $n$ destinations increases monotonically as $n$ increases from 1 to 7. The firms that export to the least popular destinations, Africa, Latin American, and Australia/NZ, are most likely to export to a large number of destinations. This pattern is consistent with underlying sources of firm heterogeneity that persist across all the firm's destination markets. Firms with demand and cost components that allow them to be profitable in difficult markets, that is ones with low aggregate demand or high transport and entry costs, will also tend to be profitable in easier markets and export to a larger total number of markets. Firm-level demand and cost components play a major role in the empirical model developed here. If firm-level heterogeneity was the only determinant of export profits then Table 3 should have all zero elements above the diagonal. The fact that

this hierarchical ranking does not hold perfectly is evidence that there is a role for firm-market level factors to play a role. These forces are captured by the firm-market shocks in the demand and pricing equation and the fixed cost in the participation equation.[15]

Table 3 - Frequency Distribution of Total Number of Destinations

| Number of Destinations $n$ | | Conditional on Exporting to: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (overall frequency) | US/Can | Jap/Kor | Rest Asia | non EU | Africa | Lat Am | Aust/NZ |
| 1 | (.376) | .203 | .299 | .072 | .055 | .046 | .032 | .061 |
| 2 | (.156) | .156 | .107 | .119 | .092 | .082 | .061 | .073 |
| 3 | (.107) | .109 | .091 | .128 | .111 | .108 | .098 | .099 |
| 4 | (.089) | .099 | .084 | .134 | .143 | .132 | .139 | .112 |
| 5 | (.088) | .124 | .110 | .166 | .154 | .171 | .188 | .124 |
| 6 | (.090) | .145 | .131 | .185 | .205 | .211 | .229 | .201 |
| 7 | (.094) | .164 | .179 | .196 | .240 | .250 | .254 | .331 |

While Table 3 provides evidence that firm-level factors help determine the extensive margin of trade, we also find evidence that the intensive margin of trade is affected. Table 4 investigates the individual firm's price and quantity decision to highlight the important dimension of firm 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

[15] Eaton, Kortum, and Kramarz (2011) provide evidence that French firms export to a hierarchy of countries. They show that if the export decision to each destination was independent there would be a substantially weaker pattern in the set of destination markets by the exporting firms. Firm-level factors that persist across markets is an important factor that could generate the dependence in the set of destination markets.

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 Variation

| $R^2$ 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 |

We also find that the extensive margin and the intensive margin are correlated in a way that is consistent with firm-level heterogeneity that persists across markets. Table 5 reports coefficients from regressions of log price and log quantity on dummy variables for the number of destination markets. All coefficients are relative to firms with only one destination and the regressions include a full set of product, year, destination dummies. The first column of the table shows that firms that export to two destinations have prices, on average, that are 6.7 percent lower than firms that export to one destination. After that, firms that export to 3 or more destinations have prices that are between 9.9 and 17.4 percent higher than single destination firms. The second column shows that the average firm export quantity to each market also rises as the number of destinations increases. Firms that export to two destinations have an average quantity of sales in each market that is 38 percent higher than single destination firms. The firms that export to three or more markets have an average quantity of sales that is between 7.3 and 67.9 percent higher than the base group. This increase in the average quantity of exports is monotonic in the number of destinations for three or more destinations. Overall, Table 5 shows that the intensive margin, the average quantity of sales in each market, is increasing with the number of destinations the firm exports to. The price is also higher for firms that export to more markets. This is consistent with underlying firm differences in

demand, firms with high demand components export to more markets and sell more, but also with higher costs, and thus higher prices for these firms. It is not consistent with low-cost and low-price being the sole determinant of export participation and price, but the only way to sort out demand versus cost differences is to estimate a model with distinct firm cost and demand components.

Table 5 - Price, Quantity, Number of Destinations

| Coefficients (standard errors in parentheses) | | |
|---|---|---|
| Number of destinations | log price | log quantity |
| 2 | -.067 (.028) | .380 (.091) |
| 3 | .099 (.029) | .073 (.093) |
| 4 | .174 (.027) | .080 (.087) |
| 5 | .108 (.025) | .168 (.082) |
| 6 | .160 (.024) | .402 (.077) |
| 7 | .107 (.022) | .679 (.072) |
| Regressions include a full set of year,product,destination dummies | | |

The last data evidence regarding firm heterogeneity we examine relates export patterns in both the extensive and intensive margin to some potentially important observable firm characteristics: ownership structure and geographic location. For a single year, 2005, Table 6 reports the share of firms that export, the average number of destinations, and average export sales for different ownership and location categories. The first column gives the proportion of firms that export disaggregated by four ownership categories.[16] 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

[16] 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.

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 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 $\xi$ 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 6 -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 |

Overall, the empirical patterns summarized in Tables 3-6 suggest that firm-level differences in profitability that persist across destination markets is a likely contributor to the export decisions on both the extensive and intensive margins for Chinese footwear exporters. However, it is not possible to infer the relative importance of demand-side versus cost-side heterogeneity based on this evidence and so we next turn to estimates of the structural parameters.

# 5 Empirical Results

## 5.1 Demand Estimates

Table 7 reports estimates of the demand cuve parameters, equation (4) which include the destination-specific price parameters $\alpha_d$, group demand shifters $\xi_k$, and dummy variable for prior sales in the markets $\rho I_f^{dt-1}$. 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 $\alpha_d$ 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 $\alpha_d$ 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 -2.319 to -3.032 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 -2.866 and -3.032. This implies lower markups in these destinations with the ratio of price to marginal cost varying from 1.492 to 1.536. The higher-income destinations, US/Canada, Australia/NZ, Japan/Korea, and non-EU Europe, have demand elasticities that vary between -2.319 and -2.709 and markups that all exceed 1.585. 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.

Table 7 - Demand Curve Parameter Estimates
(standard error in parentheses)

| Parameter | OLS | Fixed Effects | Hierarchical Bayesian | $\frac{p}{c} = (\frac{\alpha_d}{\alpha_d - 1})$ |
|---|---|---|---|---|
| $\alpha_d$ - US/Canada | 0.621 (.055) | 0.762 (.066) | 2.653 (.278) | 1.605 |
| $\alpha_d$ - Japan/Korea | 0.659 (.068) | 0.732 (.080) | 2.709 (.282) | 1.585 |
| $\alpha_d$ - Australia/NZ | 0.307 (.093) | 0.527 (.092) | 2.386 (.281) | 1.722 |
| $\alpha_d$ - Non-EU Europe | 0.328 (.070) | 0.397 (.074) | 2.319 (.282) | 1.758 |
| $\alpha_d$ - Rest of Asia | 0.834 (.061) | 0.989 (.069) | 2.866 (.279) | 1.536 |
| $\alpha_d$ - Africa | 0.987 (.074) | 1.117 (.077) | 3.032 (.282) | 1.492 |
| $\alpha_d$ - Latin America | 0.856 (.075) | 1.050 (.078) | 2.908 (.281) | 1.524 |
| history - $\rho I_f^{dt-1}$ | 0.971 (.042) | 0.823 (.044) | 0.785 (.044) | |
| $\xi_g$ - leather | -1.032 (.052) | -0.546 (.051) | 0.361 (.149) | |
| $\xi_g$ - textile | -0.972 (.052) | -0.649 (.055) | -0.650 (.059) | |
| The model includes a full set of destination*year dummies | | | | |

## 5.2 Pricing Equation Estimates

Table 8 reports parameter estimates of the pricing equation (6). These include coefficients on the firm's capital stock and local 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 ($\xi_f$) 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 regions indicates that the lower

income regions, 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, $\alpha_d$, 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 8. 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 8. A comparison of columns 1 and 3 shows that the estimates are very similar which indicates that there is little role for marginal cost differences across destinations to explain the level of export prices.

Table 8 - Pricing Equation Parameter Estimates

| | Parameter Estimate | Standard Error | $\ln(\frac{\alpha_d}{\alpha_d - 1})$ |
|---|---|---|---|
| $ln(capitalstock)_{ft}$ | 0.038 | 0.007 | |
| $ln(wage)_{ft}$ | 0.022 | 0.025 | |
| Product Group Dummies ($\gamma_k$) | | | |
| Leather Shoes | 0.484 | 0.011 | |
| Textile Shoes | -0.041 | 0.013 | |
| Average Destination Coef ($\tilde{\gamma}_d$) | | | |
| US/Canada | 0.479 | | 0.473 |
| Japan/Korea | 0.533 | | 0.461 |
| Australia/NZ | 0.511 | | 0.543 |
| Non EU Europe | 0.502 | | 0.564 |
| Rest of Asia | 0.454 | | 0.429 |
| Africa | 0.408 | | 0.400 |
| Latin America | 0.459 | | 0.421 |
| 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 9. The participation decision for a firm depends on the firm demand and cost components, $\xi_f$ 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 $\xi_f$ 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 $\xi_k$ and $\gamma_k$ 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 8 are not equal for the two terms, each play a different role in the export decision.

Table 9 - Export Market Participation Equation

| Dependent Variable | Parameter Estimate | Standard Error |
|---|---|---|
| firm demand shock $\xi_f$ | 0.327 | 0.016 |
| firm cost shock $(1-\alpha_d)c_f$ | 0.240 | 0.019 |
| $ln(capitalstock)_{ft}$ | 0.023 | 0.009 |
| $ln(wage)_{ft}$ | -0.121 | 0.065 |
| product mix $\sum_{k \in K_f} r_k^d$ | 0.273 | 0.049 |
| past participation $I_f^{dt-1}$ | 1.586 | 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, $\xi_f$ 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 $\xi_f$ and $c_f$. Specifically, firms with low (high) values of $\xi_f$ ($c_f$) 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 10. Since we include a full set of destination-year dummies in the market share and pricing equations, the posterior means of $\xi_f$ and $c_f$ are both estimated to be very close to zero. The posterior variances are 3.439 for the demand components and 0.436 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 $\xi_f$ across firms while the heterogeneity in prices leads to a much smaller degree of dispersion in $c_f$.

Table 10 - Posterior Distribution of Hierarchical Parameters

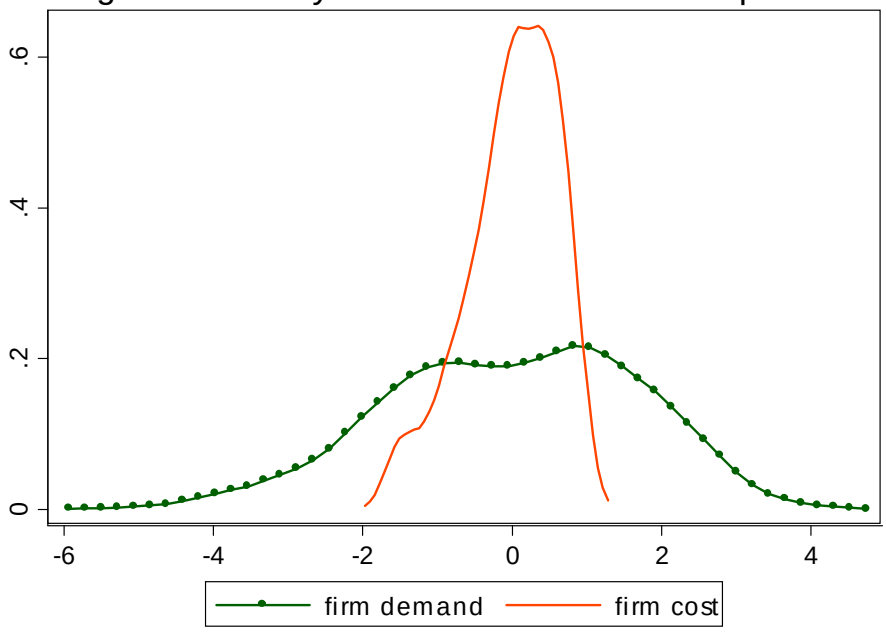
| | Demand $\xi$ | | Cost $c$ | |
|---|---|---|---|---|
| | Estimate | Standard Dev | Estimate | Standard Dev |
| *mean* | -0.001 | 0.081 | 0.001 | 0.029 |
| *var* | 3.439 | 0.541 | 0.436 | 0.022 |
| $cov(\xi, c)$ | 0.898 | 0.129 | | |

The disperson in demand-side factors will be larger than the cost-side factors and this can be clearly seen in Figure 1, which presents kernel density estimates of the posterior means of $\xi_f$ and $c_f$ over the 1106 firms in our sample. This implies that heterogeneity in both firm demand and firm cost will contribute to across-firm differences in export market sales and profits, although the relative importance of the two factors will vary by destination with differences in $\alpha_d$ as seen in equation (8).

The final parameter reported in Table 10 is the $Cov(\xi, c)$ which equals .898. 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 firm-level coststo produce higher demand $h(\xi_f)$ as well as a pure productivity component $\omega_f$. To further understand the correlation between $c_f$ and $\xi_f$ we regress $c_f$ on a polynomial in $\xi_f$ and assess the fit of the regression. The estimated regression (standard errors in parentheses) is:

$$c_f = \underset{(0.015)}{0.047} + \underset{(0.012)}{0.262}\xi_f - \underset{(0.004)}{0.016}\xi_f^2 + \underset{(0.001)}{0.001}\xi_f^3 + \omega_f, R^2 = .585. \tag{15}$$

Figure 1: Density of Demand and Cost Components

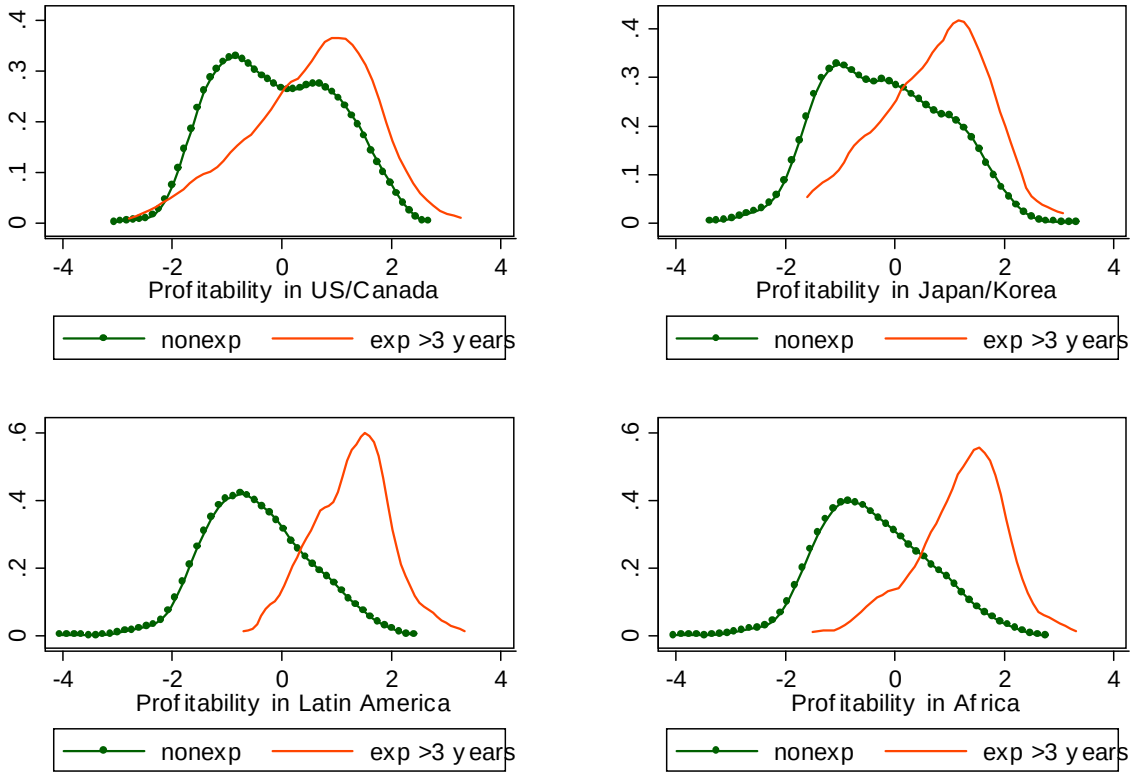



which indicates that almost 60 percent of the sample variation in $c_f$ is explained by variation in the firm demand component, leaving the remainder to be explained as productivity differences. To a large extent in our sample the firms with high-product demand will have higher costs.

Given estimates of $\xi_f$, $c_f$, and $\omega_f$ we can now examine their distinct contributions to the export patterns we observe for the Chinese firms. One dimension of successful export market performance is long-term presence in the destination and this depends on firm profitability in the market. Using the demand and cost components, we construct the the distribution of firm profitability in each destination and compare firms based on the length of time in our sample that they export to the destination. Using equation (8), we construct the index $\ln r^{dt}(\xi_f, c_f)$ from, that captures the joint contribution of $\xi_f$ and $c_f$ to firm profits in the destination.[17] 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

[17] When constructuring $\ln r^{dt}(\xi_f, c_f)$ we did not include the terms that depend on the wage rate or capital stock because they had no effect on the across-firm distribution of profitability. The profitability measures with and without these variables have a simple correlation greater than .99 in every destination market. The across-firm distribution of profitability is determined by the values of $\xi_f$ and $c_f$.

## Figure 2: Density of Firm Profitability by Destination Market




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 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. The same difference in distributions holds for the three destinations not graphed.

In addition to duration in a market, two other dimensions of successful firm export performance are exporting to many destinations and exporting to destinations which are more difficult

and thus have lower overall export rates. In Table 3 we found that the firm export patterns in these two dimensions are correlated. Table 11 shows that the estimated firm demand and cost components contribute to these two dimensions of export performance. In the top half of Table 11 we group the 1106 firms in our sample in five equal-sized bins, ranked from low to high values of $\xi_f$.[18] The bottom half of the table does the same thing but now the bins divide firms into high and low values of cost. As the cost measure we use the estimates of $\omega_f$ from equation (15) in order to remove the effect of heterogeneity in cost that arises from differences in $\xi_f$. Firms with high values of $\omega_f$ have high marginal costs, after controlling for the costs associated with producing $\xi_f$. 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. By construction $\omega_f$ and $\xi_f$ are uncorrelated. The columns are sorted by the overall export rate to the destination.

The first row of the table shows that the 20 percent of firms with the lowest values of $\xi_f$ have export rates that vary from a high of .541 in the U.S. market to a low of .099 in the Australian market. On average, these firms export to 1.76 of the seven total destinations. Focusing on the demand heterogeneity, it is clear that as we move from the low to high $\xi_f$ bins, the export rate increases. However, this upward trend is fairly weak for the two most popular destinations US/Canada and Japan/Korea but is very strong for the less popular destinations. In the two most popular destinations, large differences in $\xi_f$ do not substantially affect the probability of export while, in the other 5 destinations, export participation depends a great deal on the level of the firm's demand component. For example, in the Japan market the probability of exporting equals .432 for the lowest demand group and increases 20 percentage points as $\xi_f$ increases, while the same figures for the Rest of Asia market are .270 and a 50 percentage point increase. As $\xi_f$ increases, the average number of destination markets also rises. Firms in the top quintile of the distribution export, on average, to 4.37 of the seven destinations. The top half of the table confirms that firm's with a high demand component export to more countries and to the less popular destinations.

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

Table 11 - Destination Export Rates By Demand and Cost Category

| | Destination Market | | | | | | | Av. Num |
|---|---|---|---|---|---|---|---|---|
| $\xi_f$ Bins | US/Can | Jap/Kor | Rest Asia | Non-EU Eur | Africa | Latin Am | Austr/NZ | Dest. |
| 1 - low | .541 | .432 | .270 | .122 | .149 | .153 | .099 | 1.76 |
| 2 | .538 | .466 | .290 | .204 | .235 | .258 | .244 | 2.23 |
| 3 | .561 | .525 | .471 | .466 | .389 | .403 | .330 | 3.14 |
| 4 | .579 | .633 | .588 | .488 | .466 | .425 | .321 | 3.50 |
| 5 - high | .652 | .575 | .778 | .683 | .643 | .615 | .425 | 4.37 |
| $\omega_f$ Bins | | | | | | | | |
| 1- high | .584 | .484 | .240 | .204 | .122 | .176 | .244 | 2.05 |
| 2 | .561 | .529 | .348 | .298 | .258 | .299 | .271 | 2.57 |
| 3 | .538 | .479 | .507 | .398 | .389 | .335 | .290 | 2.94 |
| 4 | .602 | .548 | .575 | .462 | .406 | .471 | .312 | 3.43 |
| 5 - low | .586 | .590 | .725 | .599 | .644 | .572 | .302 | 4.02 |

The bottom half of Table 11 provides similar evidence for cost heterogeneity and a very similar pattern is seen. Differences in $\omega_f$ do not lead to large differences in the export rate for the US/Canada and Japan/Korea markets. In the U.S., the export rates vary from .538 to .602 and in Japan from .479 to .590 and neither increases monotonically across bins with reductions in $\omega_f$. For the next four destinations, export rates increase substantially as costs fall, mirroring the changes seen with the demand component. The export probability for the lowest-cost firms is 40 to 50 percentage points higher than for the high-cost firms. The one deviation from this pattern is the Australian market. Here cost differences play a more modest role than demand differences. The export rate varies from .244 to .312 across cost bins but from .099 to .425 across demand bins. The table clearly demonstrates that both cost and demand components are important in generating the patterns of export market participation for the firms. Firms with high demand and low cost components are more likely to export, export to more destinations, and are more likely to export to less popular destinations. The across-firm differences in demand and cost components are particularly important in explaining the firm export decisions in the less popular destinations.

We can also examine the contribution of $\omega_f$ and $\xi_f$ to differences in the intensive margin of trade across firms. In Tables 4 and 5 we presented evidence suggesting that firm components were important in explaining price and quantity variation in the data and that factors that

made firms more likely to export could also be contributing to larger sales and higher prices when they did export. Table 12 shows how export quantity and price vary across firms with different $\omega_f$ and $\xi_f$. Each column is a regression of either log quantity or log price on a set of dummy variables distinguishing the quintiles of the distribution of $\xi_f$ (top half of the table) or $\omega_f$ (lower half of the table). The omitted category are firms in the lowest demand and highest cost quintile. Also included in all regressions are product, year, and destination dummies. The first column shows that average firm export quantity rises as we move from low to high demand firms. Firms in the quintile with the highest demand components have export quantities that are 134.5 percent higher than the exports of firms in the lowest demand quintile. The lower part of the column shows that firms in the lowest cost quintile have export quantities that are 339.4 percent higher than firms in the highest cost quintile. While there are significant differences in export quantity across firms in both the demand and cost dimensions, the variation between the highest and lowest quintiles is much more substantial from efficiency differences across firms than from demand-side differences. This reflects, at least partly, the role of the demand elasticity term $(1-\alpha_d)$ which acts to scale up the effect of cost differences across firms as seen in the term $\ln r^{dt}(\xi_f, c_f)$ in equation (8). The importance of cost differences is further supported by examining the goodness of fit of the regressions as we drop either the demand or cost side factors. Dropping the dummies for $\omega$ in column 2 we see that the $R^2$ drops from .363 to .178. While dropping the dummies for $\xi$ in column 3 only lowers the $R^2$ to .335. Accounting for cost heterogeneity is very important in explaining differences in the intensive margin across firms.

A similar set of regressions for price variation is given in the last three columns of the table. In column 4, we see that firms in the highest demand quintile have average export prices that are 131 percent higher than firms in the lowest demand quintile. Firms in the lowest cost quintile have prices that are 105.9 percent lower than the highest cost firms. In both cases, demand and cost side heterogeneity is translated into export prices but the difference in magnitudes is not as extreme as we observed with the quantity regressions. Comparing the deterioration in $R^2$ as we drop either the $\xi$ or $\omega$ dummies we observe that both sets have a similar impact on the model fit. The $R^2$ drops from .745 to .584 and .555 as we drop the $\omega$ and $\xi$ variables, respectively. Overall, the results from Tables 11 and 12 indicate the both the

extensive and intensive margins of exporting firms are affected by firm-level cost and demand components. While both components are roughly equally important in explaining export participation and pricing patterns, the cost component is more important than the demand component in explaining differences in export quantities across exporters.

Table 12 - Price and Quantity by Demand and Cost Category

| $\xi_f$ Bins | log q | | | log p | | |
|---|---|---|---|---|---|---|
| 2-low | 0.359 (.074) | 0.773 (.083) | | 0.478 (.016) | 0.354 (.021) | |
| 3 | 0.575 (.069) | 0.988 (.077) | | 0.773 (.015) | 0.651 (.019) | |
| 4 | 0.760 (.069) | 1.289 (.077) | | 1.039 (.015) | 0.887 (.019) | |
| 5-high | 1.345 (.071) | 1.478 (.077) | | 1.310 (.016) | 1.306 (.019) | |
| $\omega_f$ Bins | | | | | | |
| 4 - high | 1.052 (.068) | | 1.393 (.067) | -0.250 (.015) | | 0.058 (.019) |
| 3 | 1.645 (.067) | | 2.112 (.065) | -0.444 (.015) | | -0.028 (.018) |
| 2 | 2.358 (.065) | | 2.723 (.064) | -0.667 (.014) | | -0.321 (.018) |
| 1-low | 3.394 (.065) | | 3.511 (.065) | -1.059 (.014) | | -0.898 (.018) |
| intercept | 8.103 (.085) | 9.573 (.087) | 8.470 (.073) | 0.527 (.019) | | 1.021 (.021) |
| $R^2$ | .363 | .178 | .335 | .745 | .584 | .555 |

Base group is low-demand, high-cost firms. All regressions contain destination, year, product dummies

As a final step in assessing the role of firm heterogeneity we summarize how the estimated firm components vary with some important observable firm characteristics including ownership type and geographic location. Table 6 showed there were differences in export patterns across ownership categories and firm location. Table 13 reports coefficients from OLS regressions of the estimated firm components on a set of ownership and location dummy variables and dummy variables for whether or not the firm advertises, receives goverment subsidies, and the percent of the workforce that is unionized.[19] 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 no information on these characteristics has been used in the estimation of the firm components but the table shows that the estimated components vary systematically across firms. The mean of the demand component $\xi_f$ is 1.067 for private firms, .609 for foreign and .597 for firms owned by HK/TWN/MAC firms (all are relative to the state-owned firms). This implies that

[19] Unionization is a proxy for the how formal the employment relationship between workers and firm is. It is not a measure of bargaining power between the two groups.

the private firms will, on average, have the highest demand for their products and the state-owned the lowest. The location dummies indicate that firms in the East Coastal region will have higher demand and the Southeast Coastal firms have lower demand than the base group. The remaining coefficients indicate that the demand component will be larger for firms that advertise, receive government subsidies, and are less unionized. On the cost side, the private firms will have the lowest cost components while the other two groups of firms have higher costs than the state-owned firm These cost differentials are not as large as the demand differentials. Both coastal regions will have lower costs than the inland firms. The coefficients on the final three characteristics have signs that are the opposite of their effect on demand. This means that if a factor is correlated with higher demand coefficient they will also be correlated with a lower cost coefficient, implying that across these firms, the demand and cost differences will reinforce each other leading to larger differences in profits across firms in these dimensions. In particular firms that advertise will have higher demand and lower cost factors than firms that do not advertise.

Table 13 - Variation in $\xi_f$ and $c_f$ with Firm Characteristics

| | Demand $\xi_f$ | | Cost $c_f$ | |
|---|---|---|---|---|
| | Coef | Std Dev | Coef | Std Dev |
| Intercept * | | | | |
| Ownership Dummies | | | | |
| Private | 1.067 | 0.242 | -0.101 | 0.056 |
| HK/TWN/MAC | 0.597 | 0.246 | 0.167 | 0.056 |
| Foreign | 0.609 | 0.238 | 0.139 | 0.054 |
| Location Dummies | | | | |
| East Coastal | 0.166 | 0.173 | -0.135 | 0.039 |
| Southeast Coastal | -0.528 | 0.205 | -0.086 | 0.047 |
| Other Characteristics | | | | |
| Advertising Dummy | 0.563 | 0.126 | -0.062 | 0.029 |
| Govt Subsidy Dummy | 0.249 | 0.116 | -0.047 | 0.026 |
| Percent Unionized | -0.182 | 0.099 | 0.075 | 0.023 |
| Demand $\xi_f$ | | | 0.298 | 0.008 |

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

To summarize, in this section we provide estimates of structural demand and pricing equations and related export participation equations for Chinese exporting firms across seven des-

tination markets. Our econometric methodology provides a way to estimate unobserved firm-level demand and cost components and we have found them to be very important in explaining patterns of firm export behavior including the number of export destinations, the mix of destinations in terms of overall popularity, and the duration of export presence in a destination. The firm-level demand component has larger variance across firms than the cost component but both play a very significant role in generating differences in firm profitability in each market. The cost component is particularly important in accounting for differences in export quantities across firms and both components are of approximately equal importance in explaining across-firm export price differences. In the next section we study the response of the 1106 firms in our sample to the removal of the EU quota on footwear exports from China and ask whether the firm demand and cost heterogeneity play a role in explaining the subsequent entry, exit, and growth patterns

# 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. 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. We have not used the data on exports to the EU in estimating the structural parameters and constructing the firm demand and cost indexes and this section provides some validation that the estimates are capturing useful dimensions of firm profit heterogeneity.

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 commis-

sion. 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 $\xi$ 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 $\xi$ 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 14 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 US/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.[20]

Table 14 - 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 13 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

[20]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.

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.

Table 15: 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 |
| Intensive Margin of Long-Term Exporters[a] | | | | | |
| 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 15 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.[21] In Table 16 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 17, we will summarize reallocation on the intensive margin reflecting changes in the size of continuing exporters.

In the top half of Table 16, we group the 1106 firms in our sample into 5 equal-sized bins ranked from low $\xi_f$ to high $\xi_f$. 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.[22] When the quota was in place there was an increase in the export rate, from .122 to .421, as the firm demand index increased. That indicates that firms with high demand for their exports in other destinations were more

[21]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 $\alpha_d$ in this destination market. We will instead focus on the separate comparisons of demand and cost.

[22]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.

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 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 .149 to .601 across the five bins and the exit rate decreases from .667 to .118 as the demand index rises. Firms in the highest quintile of the distribution of $\xi_f$ 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 .421 to .719. 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 16: Adjustment in the Number of Firms Exporting to the EU

| $\xi_f$ bins | 2003 Export Rate | Entry Rate | Exit Rate | 2005 Export Rate |
|---|---|---|---|---|
| 1 - low | .122 | .149 | .667 | .172 |
| 2 | .190 | .117 | .405 | .208 |
| 3 | .249 | .271 | .273 | .38. |
| 4 | .335 | .347 | .324 | .457 |
| 5 - high | .421 | .601 | .118 | .719 |
| $\omega_f$ bins | | | | |
| 1 - high | .226 | .164 | .500 | .240 |
| 2 | .253 | .261 | .304 | .371 |
| 3 | .281 | .226 | .226 | .380 |
| 4 | .294 | .314 | .338 | .416 |
| 5 - low | .262 | .411 | .121 | .534 |
| All firms | .263 | .274 | .292 | .388 |

The bottom half of Table 16 makes the same comparison across groups of firms based on their cost index $\omega_f$. 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 lowest export rate among the five categories and the overall variation across categories is fairly small, varying between .226 and .294. 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 from .164 to .411 and the exit rate decreases from .500 to .121 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 .262 to .534, but only a 1.4 percentage point change, from .226 to .240, 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 17, we report the suvival rate, the proportion of EU exporters in 2003 that remain in the market in 2005, for each of the five $\xi$ 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 $\xi$ 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 20.1 and 21.7 percent, respectively, for the two lowest demand categories. The firms in the three higher $\xi$ 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 17 - Quantity Adjustment by Continuing Exporters

| $\xi_f$ bins | Survival Rate | Percentage Change in Quantity Sold |
|---|---|---|
| 1 - low | .333 | -20.11 |
| 2 | .595 | -21.70 |
| 3 | .727 | 44.04 |
| 4 | .676 | 66.49 |
| 5 - high | .882 | 147.97 |
| $\omega_f$ bins | | |
| 1 - high | .500 | -15.41 |
| 2 | .696 | 151.20 |
| 3 | .774 | 196.28 |
| 4 | .662 | 3.32 |
| 5 - low | .879 | 54.37 |

In the bottom of Table 17 we report the same comparison based on cost index $\omega$. 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 negative growth of -15.4 percent, the second and third highest cost categories expanded the fastest, 151 and 196 percent, respectively. This is not consistent with the pattern we documented for the extensive entry margin in Table 16, 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 $\xi$ indexes and lower cost $\omega$ 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 profit 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, 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 unobserved firm components, 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 export price, quantity, and destination patterns across firms indicate a potentially important role for unobserved firm components that persist across destinations. Firms that export to many destinations also export to more difficult destinations and have higher average export quantities in each destination. This is consistent with persistent firm-level demand heterogeneity. These same firms also have higher average export prices which suggests that the demand differences are costly to produce or maintain and is not consistent with low cost being the sole determinant of export success. The empirical results indicate substantial firm heterogeneity in both the demand and cost dimensions with both factors affecting the choice of export destinations, price, and quantity of sales. On the extensive margin, the demand and cost factors are both important explanatory factors in the length of time the firm exports

to a destination, the number of destinations, and the mix of destinations. On the intensive margin we find that both the demand and cost factors are approximately equally important in explaining export price variation across firms and destinations but that efficiency differences are much more important in explaining variation in the quantity of exports across firms and destinations. After controlling for demand differences across firms, export quantities are much larger for firms with low costs. 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 toward understanding 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. The source of heterogeneity is potentially very important in understanding the ability of Chinese firms to compete in the future with other low-cost supplying countries. If there is limited scope for future cost improvements by Chinese producers then the role of the demand component, both how it differs across firms and how it impacts profitability in a destination, will be critical to continued export expansion. The next step is to expand the framework we have developed here to allow these firm demand and cost components to vary over time and be altered by the firm's investments in R&D or physical capital so that firm export success or failure becomes a result of firm decisions to affect its productivity or demand for its products.

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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 $\Sigma$. At the start of simulation round $s$ there are previous draws $\alpha^{s-1}$, $\gamma^{s-1}$, and $\Sigma^{s-1}$, and draws for each of the firm quality and productivity shocks: $(\xi_f^{s-1}, c_f^{s-1}), f = 1, 2, .., N$. 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 $\Sigma^{s-1}$. We can then draw $\alpha^s$ using the demand equation:

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

2. Conditional on $\alpha^s$, we draw the cost parameters $\gamma^s$ 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 $\Sigma^s$ 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 $\Sigma^s$, 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 $\Sigma^s$, draw $\psi^s$ 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 $(\xi_f^s, c_f^s), f = 1, 2, .., N$.