Firm Quality, Productivity, and Capability Among Chinese Exporters

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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 product quality, productivity, and export market capability. The empirical results indicate substantial firm heterogeneity in both the quality and productivity dimensions with quality being a more important determinant of the differences in export market capability. Our measure of firm export capability is very useful in summarizing differences between firms based on the length of time they export to a destination and the number of destination markets they participate in. Firms that are long-term exporters in a destination have a higher capability index, on average, than firms that do not export to the destination. Firms that export to many destinations have higher average capability.

1 Introduction

The growth of Chinese manufactured exports is one of the most significant changes in world trade patterns in the last decade. Between 1998 and 2007, the real value of Chinese manufactured exports grew at 32 percent per year. In the initial years of export expansion, Chinese manufacturers exploited the advantages provided by low labor costs and competed in world markets by charging low prices. Over the last decade, export composition has shifted from traditional unskilled labor intensive products (textiles, garments, and toys) toward products that are more intensive in the use of skilled labor and capital and that increasingly overlap with products manufactured in developed countries (See Brandt, Rawski, and Sutton (2008), Schott (2008), and Amiti and Freund (forthcoming)). The underlying causes and implications of this shift in product composition are less clear. Sutton has emphasized the importance of Chinese firms shifting their investments toward "building capability" in order to maintain their market position against expanding low-cost competitors like Vietnam and India and to compete with the high-quality products manufactured in developed countries. This investment process should lead to both upgrading in product quality and productivity improvement and is seen by Rodrik (2006) as an important hurdle if Chinese manufacturers are to sustain the export success they have had in the last decade. In contrast, Branstetter and Lardy (2008) have argued that the underlying change in the Chinese production structure has been minor with much of it reflecting foreign-owned firms using China as a low-cost manufacturing base. A better understanding of the firm-level process of "capability building" is key to understanding the past and likely future success of Chinese exporting firms.

The recognition that firms are heterogenous in their underlying profit determinants and that this has implications for the sorting of firms into export markets is pervasive in the recent trade literature. Building on earlier work by Melitz (2003), several recent papers have developed heterogeneous firm models to simultaneously explain bilateral trade flow patterns and unit value prices arising from differences in firm efficiency or product quality. Baldwin and Harrigan (2009), Johnson (2009), Khandelwal (forthcoming), and Crozet, Head, and Mayer (2010) all recognize that firms differ in both productivity and product quality and that this affects pricing and market participation decisions. They find evidence consistent with quality heterogeneity across producers.

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 $2000-2006$ to measure differences in firm product quality, productivity, and export market capability. Our data set combines information on firm-level balance sheet and production data from the Annual Survey of Manufacturing with detailed records on the value and quantity of firm-level exports by destination market contained in the Chinese Monthly Customs Transactions. We develop an empirical model of export demand, pricing, and market participation by destination market that allows us to measure firm-level quality and productivity indexes The measure of firm quality relies on differences across firms in export market shares, controlling for firm prices, in the destination markets. The measure of productivity relies on differences in firm export prices, controlling for firm costs and markups, across destinations. Both factors play a role in determining the firm's profits in each export market and thus the decision to export. We then use these measures to construct an index of firm-level export market capability that varies by destination market.

The empirical results indicate substantial firm heterogeneity in both the quality and productivity dimensions. Estimates of firm quality and productivity differ across firms based on their ownership type and geographic location. Privately-owned firms are relatively high quality but low cost producers when compared with either foreign-owned firms or firms headquartered in Hong Kong, Taiwan, or Macau and this gives them relatively high indexes of capability in most export markets. Although both firm quality and productivity contribute to export capability, the across-firm distribution of capability is more heavily affected by differences in firm quality. We find that our measure of firm export capability is very useful in summarizing differences between firms based on the length of time they export to a destination and the number of destination markets they participate in. Firms that are long-term exporters in a destination have a higher capability index, on average, than firms that do not export to the destination. Firms that export to many destinations have higher average capability than firms that export to one or a small number of markets.

2 Theoretical Model of Export Revenue

2.1 Demand

We begin with a demand model that can be used to estimate a firm's product quality. Denote i as an individual firm variety, that is, a single detailed 6-digit product produced by a specific firm. We will use the term "variety" to refer to a combination of firm and product. Second, g is defined as the product category that variety i belongs to. The utility that consumer c in destination market d, year t receives from the variety is given by the utility function:

$$u_{ci}^{dt} = \delta_i^{dt} + \zeta_{cg}^{dt} + (1-\sigma)\epsilon_{ci}^{dt} \tag{1}$$

where $0 \leqslant \sigma < 1$. This specification allows for a variety-specific component δ_i^{dt}, a product-group component ζ_{cg}^{dt}, and a transitory component ϵ_{ci}^{dt}. Berry (1994) shows that, if ϵ is assumed to be a Type I extreme value random variable then we can aggregate over consumers and express the market share for variety i in market dt. Define the inclusive value of each group g as $D_g^{dt} = \sum_{i \in g} exp(\delta_i^{dt}/(1-\sigma))$. The market share of variety i in destination market dt can then be written as $s_i^{dt} = \frac{exp(\delta_i^{dt}/(1-\sigma))}{D_g^{dt}} \frac{(D_g^{dt})^{1-\sigma}}{\sum_k (D_k^{dt})^{1-\sigma}}$. If we normalize this market share by a single product category $g=0$ where $D_0^{dt}=1$, the normalized logarithmic market share takes a simple form:

$$ln(s_i^{dt}) - ln(s_0^{dt}) = \delta_i^{dt} + \sigma ln(s_{ig}^{dt}) \tag{2}$$

where s_{ig}^{dt} is variety i's market share within group g in market dt.

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

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

This equation says that there is a firm component ξ_f or "brand-name" effect to the utility derived from variety i. This brand-name effect will be unique to each firm and constant across all markets in which it operates. It could reflect differences in the quality of the firm's product, size of its distribution network, or stock of customers that are familiar with firm f. Holding price fixed, an increase in ξ_f will raise the market share for this variety in all markets. We will refer to ξ_f as **firm quality.** The term u_i^{dt} captures market level shocks to demand for variety i. The variable I_f^{dt-1} will be a discrete indicator equal to one if the firm exported to this market d in the previous year. The coefficient ρ will be a measure of the gain in market share that experienced exporters have in a market.[1] The utility and market share of the product will be declining in the price of the good, where $\tilde{p}_i^{dt}$ is the price paid by consumers for variety i in the destination market. To convert this price into the price received by the producing firm we incorporate ad valorem trade costs between China and each destination market $\ln \tilde{p}_i^{dt} = \ln p_i^{dt} + \ln(1 + \tau^{dt})$. In this case τ^{dt} captures all exchange rate effects and tariffs between China and each market.

Substituting equation (3) and destination-specific price into the normalized market share equation gives the demand equation:

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

[1] 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 and thus market shares tend to increase over time. It 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.

where $\tilde{\tau}^{dt} = -\alpha^d ln(1+\tau^{dt})$. This demand equation can be estimated using data on the market shares of varieties in different destination markets. The demand model contains a destination-specific price parameter α^d, market-specific effects $\tilde{\tau}^{dt}$, an experience effect in demand ρ, and a firm-specific quality component ξ_f.

2.2 Cost and Pricing

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

$$\ln c_i^{dt} = \gamma_d + \gamma_g + \gamma I_f^{dt-1} + \gamma_w lnw_f^t + c_f + v_i^{dt} \tag{5}$$

where γ_d and γ_g are destination and product-specific cost factors, γI_f^{dt-1} is a cost effect for experienced exporters in market d, w_f^t is a set of observable firm-specific variable input prices and fixed factors, c_f is a firm-level unobserved cost component, and v_i^{dt} are cost shocks that the firm observes prior to setting its price. The firm cost component captures two forces: c_f is inversely related to underlying firm productivity but it likely to be positively correlated with firm quality ξ_f since, on average, it is more costly to produce higher quality/brand-name products. To simplify discussion we will simply refer to c_f as **firm productivity** but we recognize that it could also include the cost of producing higher quality products. 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:

$$\ln p_i^{dt} = \ln(\frac{\alpha_d}{\alpha_d - (1-\sigma)}) + \gamma_d + \gamma_g + \gamma I_f^{dt-1} + \gamma_w lnw_f^t + c_f + v_i^{dt} \tag{6}$$

This pricing equation shows that the price of variety i in market dt will depend on the destination-specific demand parameter α_d and all the marginal determinants in equation (5). In particular, this pricing equation shows that c_f will be a firm-level component of the export price. If product quality is expensive to produce and varies across firms then firms with high prices will have high c_f. Our empirical model will allow for an unconstrained correlation between c_f and ξ_f.

2.3 Revenue and Capability

Using the demand and pricing equations, we can express the expected revenue of variety i in market dt. Define the destination specific markup $\mu_d = \frac{\alpha_d}{\alpha_d-(1-\sigma)}$, the firm component of marginal cost as $c_f^t = \gamma_w lnw_f^t + c_f$, and the aggregate demand shifter for group g as $\Phi_g^{dt} = \frac{(D_g^{dt})^{-\sigma}}{\sum_k (D_k^{dt})^{1-\sigma}} M^{dt}$ 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 two components, one of which depends only on market and group-level parameters and variables and one of which incorporates all firm-level variables:

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

where

$$\begin{aligned} \ln \bar{\Phi}_g^{dt} &= \ln \Phi_g^{dt} + (\frac{\tilde{\tau}^{dt}}{1-\sigma})\mu_d^{(1-\frac{\alpha_d}{1-\sigma})} + (\frac{(1-\sigma-\alpha_d)(\gamma_d+\gamma_g)}{1-\sigma}) \\ \ln \bar{r^d}(\xi_f, c_f^t) &= \frac{1}{1-\sigma}(\xi_f + (1-\sigma-\alpha_d)c_f^t) + \ln E_{u,v}[exp(\frac{u_i^{dt} + (1-\sigma-\alpha_d)v_i^{dt}}{1-\sigma})] \end{aligned} \tag{8}$$

In this equation $\ln\bar{\Phi}_g^{dt}$ captures all factors that affect the revenue of group g products in market dt, including the market size and overall competition, tariff, exchange rate effects, markup, and destination-specific and product-specific cost. The second term, $\ln\ \bar{r^d}(\xi_f, c_f^t)$, includes all the firm-specific factors that affect the revenue of variety i in the market. It is not a function of the variety-level shocks u_i^{dt} and v_i^{dt} because of the expectation operator. Expressing the log of the expectation over u and v as a constant C_{uv}, we can express the firm-level contribution to the log revenue of variety i as:

$$ln\bar{r^d}(\xi_f, c_f^t) = \frac{1}{1-\sigma}[\xi_f + (1-\sigma-\alpha_d)c_f^t] + C_{uv} \tag{9}$$

This term captures all the firm-level factors that generate differences in sales in a market. In addition to the firm's input prices this includes both the firm's quality ξ_f and productivity c_f. This notation indicates that the function $\ln\bar{r^d}$ varies with the destination market because of the parameter α_d.

We will define $ln\bar{r^d}(\xi_f, c_f^t)$ as a measure of **firm capability**.[2] It summarizes how firm-level factors determine the firm's sales in market dt. A larger value of ξ_f, reflecting higher utility and demand for the firm's product,will imply a larger value of $ln\bar{r^d}(\xi_f, c_f^t)$. Since the term $(1 - \sigma - \alpha_d)$ is negative, a higher value of c_f^t will imply a lower level of capability. A larger value of σ implies more elastic demand for the varieties and this will magnify the differences in ξ_f and c_f^t across firms. The component c_f^t contains the firm-level productivity measure c_f. If variation in c_f across firms only reflects productivity differences then high c_f would imply lower capability. However, as explained above, c_f can also include the cost of producing higher quality products, so in this case $corr(c_f, \xi_f) > 0$ and thus, as we compare across firms, higher quality firms will have higher capability if their larger market share, due to ξ_f, outweighs the increase in cost captured by c_f. The equation also indicates that the firm capability will vary by destination market because the cost component is scaled by the parameters $(1 - \sigma - \alpha_d)$, and α_d is destination specific. In a destination with more elastic demand (larger α_d), the cost differences across firms are more important as a source of revenue differences.

2.4 Exporting Decision

This model of demand and cost also implies a set of destination countries for each firm. The final component of our model will explain the firm's mix of destination countries. If firm f has product lines G_f, its profit in destination market dt is: $\pi(\xi_f, c_f^t; G_f, \bar{\Phi}^{dt}) = \frac{\mu_d - 1}{\mu_d}\bar{r^d}(\xi_f, c_f^t)\sum_{g \in G_f}\bar{\Phi}_g^{dt}$. The firm's decision to export to a specific market dt is based on a comparison of the profits earned by supplying the market with the costs of operating in the market. If the firm f sells in the market d in the current year t it needs to incur a fixed cost ϕ_f^{dt} which we model as a draw from a normal distribution. If the firm has not sold in the market in the previous year, then it must also pay a constant entry cost

[2] This definition of firm capability is similar to the one introduced by Sutton (2005). He defined capability as the ratio of firm quality and the unit cost of production, while our index also depends on the demand elasticity in the destination market.

ϕ_s. Define I_f^{dt-1} as the discrete export indicator which 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. Since the fixed cost is stochastic we can define the probability that the firm exports as

$$P(I_f^{dt}=1) = \Pr ob(\phi_f^{dt} \leqslant \pi(\xi_f, c_f^t; G_f, \bar{\Phi}^{dt}) - \phi_s(1 - I_f^{dt-1}) + \beta \Delta EV(\xi_f, c_f^t, G_f, \bar{\Phi}^{dt}))$$

where the rhs of the expression is the current plus expected future payoff from exporting to this market.[3] Following the framework of Roberts and Tybout (1997), we will treat this payoff as a latent variable. In our case it is a function of the two factors entering the firm's capability ξ_f and c_f^t, the destination-specific markup μ_d, the aggregate desirability of the product in this destination, and the firm's prior period export experience I_f^{dt-1}. This will lead to an approximation to the policy function for the firm's export participation decision:

$$P(I_f^{dt}=1) = \Phi[\xi_f, c_f^t, \sum_{g \in G_f} \bar{\Phi}_g^{dt}, \mu_d, I_f^{dt-1}; \psi] \tag{10}$$

where ψ is the parameter vector to be estimated.

An alternative to this estimating model are the structural models developed by Das, Roberts, and Tybout (2007), and Aw, Roberts, and Xu (forthcoming). These papers calculate the long-run firm value and estimate the distribution of fixed costs and entry costs in dollars. The model used here expresses the export participation decision as a function of firm and market-level variables that shift the long-run profits for exporting. This does not allow us to estimate the magnitude of the entry cost or long-run firm value but does provide a consistent framework for analyzing the determinants of the export decision. In this case, modeling the participation decision in equation (10) will help to

[3] More precisely, the integrated value function is $EV(\xi_f, c_f^t; G_f, \bar{\Phi}^{dt}, I_f^{dt}) = \int_{\bar{\Phi}', c_f'} E_{\phi_f} \max[\pi(\xi_f', c_f'; G_f, \bar{\Phi}') - \phi_s(1 - I_f^{dt}) - \phi_f + \beta \Delta EV(\xi_f', c_f'; G_f, \bar{\Phi}'), 0] dF(\bar{\Phi}', c_f' | \bar{\Phi}^{dt}, c_f^t)$
where the expected increment to future profits from exporting in period t is: $\Delta EV(\xi_f, c_f^{t+1}; G_f, \bar{\Phi}^{dt+1}) = EV(\xi_f, c_f^{t+1}; G_f, \bar{\Phi}^{dt+1} | I_f^{dt}=1) - EV(\xi_f, c_f^{t+1}; G_f, \bar{\Phi}^{dt+1} | I_f^{dt}=0)$

estimate the pattern of firm capabilities because capability will now be estimated using information on the market share, pricing, and participation decision of the firms. As explained in the econometric section below, this will be particularly useful for the firms that infrequently export.

Overall, the model we have developed in this section provides a unified framework for explaining firm-level pricing, sales, and market participation patterns for Chinese exporting firms in an industry. It can be estimated with our firm-level data on export prices, quantities, production costs, and destination markets. It provides a way to infer unobservable firm product quality and productivity components and combines them into a natural index of firm capability. 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 (10). In the demand equation we estimate destination-specific parameters α_d, the across-nest substitution parameter σ, and destination-year trade barriers $\tilde{\tau}^{dt}$. Using the pricing equation we recover how prices depend on firm-level observed characteristics γ_w and destination-specific cost differences γ_d. In this equation, we include each firm's physical capital stock and log wage rate in W_f^t. To allow for possible correlation between u_i^{dt} and v_i^{dt}, we assume that they are jointly normally distributed with mean zero and covariance Σ. Finally, to control for the endogenous choice of destination markets we model each firm's export participation decision (10).

Importantly, we are interested in the empirical distribution of unobserved firm quality ξ_f and cost c_f beccause these are the crucial building blocks of $\bar{r}^d(\xi_f, c_f^t)$, our firm-level capability index at each destination. If our only interest is in the demand and pricing equation coefficients α_d, σ, $\tilde{\tau}^{dt}$, γ_w, γ_d, γ_g and if, in addition, the transitory shocks u_i^{dt}

and v_i^{dt} are uncorrelated with each other, then the identification and estimation of our demand and pricing equations (4) and (6) are straightforward. They follow standard fixed-effect panel data models where the within estimator provides consistent estimates. Note that in this case the unbalanced panel resulting from export participation does not introduce an additional selection problem since it depends on the same set of firm fixed effects.

However, there are two concerns that prevent us from adopting such a simple estimation strategy. First, the independence assumption between u_i^{dt} and p_i^{dt} could be problematic for several reasons. Firm-time specific unobserved quality u_i^{dt} and cost differences v_i^{dt} can be positively correlated, even after controlling for persistent firm-level differences in ξ_f and c_f. 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. Second, one of our primary research interests is to measure the firm's capability distribution at the micro-level. This depends crucially on the joint distribution of the unobservables ξ_f and c_f. In this sense, while a standard fixed effect approach treats these unobservables as nuisance parameters to be differenced out, we want to treat them as firm-specific parameters. It's also worth noting that, compared with standard panel data sets with one firm observation per time period, we have many more firm-level observations that are informative about firm-specific invariant unobservable: we observe each firm's discrete export choice in each destination-year dt as well as prices and sales for each product group g, destination d and year t.

Our estimation strategy follows Arellano and Bonhomme (2009) by using an *average likelihood function* 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 we have a non-negligible dimension for the number of markets dt that a firm participates in (i.e. the firm exports to multiple destinations over multiple time periods with various product groups), we estimate the firm-level ξ_f and c_f using individual firm $f\prime s$ price, quantity, and cost data, conditional on the common parameters. On the other hand, when a firm rarely exports we rely heavily on the discrete export participation decision and this requires placing more structure on the estimates of ξ_f and c_f. In this case we use the random-effect approach for these firms, where their contribution to the likelihood function is weighted by a specified distribution for firm unobservables. As we will describe in detail below, Arellano and Bonhomme (2009) show that a pragmatic use of the Bayesian MCMC method provides a powerful and flexible way of evaluating the likelihood function and generating the posterior distribution of the model parameters, including the individual heterogeneity terms. In this setup, additional observable firm characteristics can be allowed to correlate with firm quality and productivity. We assume a prior distribution for (ξ_f, c_f) that is bivariate normal where its mean b is specified as as a function of time-invariant firm characteristics $Z_f : b = [Z_f\bar{b}_\xi, Z_f\bar{b}_c]$. In our case we will use a constant and the firm's ownership type and geographic location to model b. This will allow the joint distribution of our estimates of firm quality and productivity to shift with these characteristics. 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). In our case, the observed firm cost shifters lnw_f^t, which include factor prices and capital stocks, can be treated as instruments that are correlated with price, but uncorrelated with the demand shocks u_i^{dt}. Jointly estimating the demand and pricing equations while allowing for arbitrary correlation between u_i^{dt} and v_i^{dt} provides consistent estimates of the demand elasticity parameters α_d and σ.

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 W_f^t and export market participation dummies I_f^{dt}. Conditional on $I_f^{dt} = 1$, we also observe prices p_i^{dt}, market shares $lnsh_i^{dt}$, and sales revenue r_i^{dt} for each product firm f produces. We denote the full set of data for firm f as D_f.

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

$$l(D_f|\Theta) = \int l(D_f|\Theta; \xi, c) w_f(\xi, c) d\xi dc \tag{11}$$

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 possibly exogenous covariates Z_f. Then equation (11) defines an integrated likelihood for a random-effect estimator of Θ. Alternatively, consider a pair of $\hat{\xi_f}(\Theta), \hat{c_f}(\Theta)$ which maximize $\log l(D_f|\Theta, \xi, c)$. If the weighting function $w_f(\xi, c)$ assigns all probability mass to $\hat{\xi_f}(\Theta), \hat{c_f}(\Theta)$, then we have fixed-effects maximum likelihood estimator. As we show in detail below, our Hierarchical Bayesian estimator accommodates these two cases in a flexible way by using bias-reducing weights (or priors in the Bayesian sense) $w_f^B(\xi, c)$ suggested in Arellano and Bonhomme (2009).

There are two important pieces to the average likelihood function for firm f. First, the bias-reducing weights $w_f^B(\xi, c)$ proposed by Arellano and Bonhomme (2009) coincide with a first-stage prior for the firm-specific parameters (ξ, c) in a Hierarchical Bayesian setup. We assume a bivariate normal distribution for the prior of (ξ_f, c_f) where its mean

b and variance-covariance W are specified as:

$$\begin{aligned} b &= [Z_f\bar{b}_\xi, Z_f\bar{b}_c] \\ W &= [\sigma_\xi, \sigma_c, \sigma_{\xi c}] \end{aligned} \tag{12}$$

Following standard practice, b and W themselves are assumed to be random parameters which have a proper but diffuse prior. Their updating will obviously be driven by information from sampled individual effects $(\xi_f, c_f), f = 1, 2, .., N$ given the data. The time-invariant covariates Z_f that shift the mean of the prior distribution include a constant, the firm's ownership type, and geographic location.

Second, the likelihood for firm f conditional on both the common parameters and firm specific unobservables is defined as:

$$\begin{aligned} L(D_f|\Theta;\xi,c) = \prod_{dt}[\phi(ln(s_i^{dt}) - ln(s_0^{dt}) - \xi - \alpha^d \ln p_i^{dt} - \tilde{\tau}^{dt} - \sigma ln(s_{ig}^{dt}),& \\ lnp_i^{dt} - c - \gamma_w lnw_f^t - \gamma_d - \gamma_g; \Sigma)]^{I_f^{dt}}& \\ \Phi[ln\bar{r}^d(\xi, c, lnw_f^t), ln(\sum_{g\in G_f} \bar{\Phi}_g^{dt}), \mu_d, I_f^{dt-1}; \psi]^{I_f^{dt}}& \\ (1 - \Phi[ln\bar{r}^d(\xi, c, lnw_f^t), ln(\sum_{g\in G_f} \bar{\Phi}_g^{dt}), \mu_d, I_f^{dt-1}; \psi])^{(1-I_f^{dt})}& \end{aligned}$$

The first line 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 and only an outline of the procedure will be discussed here. 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. 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 quality and productivity components can be sampled firm-by-firm. This latter step allows us to construct the joint distribution of firm quality and productivity.

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 measures of product quality for each firm.

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 will study the behavior of firms in the footwear industry. In this industry we are able to identify 1108 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 711 to 970 firms across years.

Table 1 - Number of Firms in the Sample

Year	Number of Firms	Number of Exporting Firms	Export Rate
2002	711	428	0.60
2003	796	505	0.63
2004	970	695	0.72
2005	947	707	0.74
2006	922	655	0.71

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. The number of exporting firms varies from 428 to 707 and the export rate varies from 0.60 to 0.74 over time. Among the exporting firms, the destination markets vary in popularity. Table 2 reports the fraction of exporting firms in our sample that export to each destination between 2002 – 2006. The US and Canada have been the most popular destination, with approximately half of the exporting firms in our sample exporting to these countries in any year. This is followed by Japan/Korea and Rest of Asia, where more than 40 percent of the exporting firms sell. Approximately 30 percent of the exporting firms sell in the Non-EU countries of Europe, Africa, and Latin America. Australia and New Zealand are the least popular destination market, with 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. It will be important to model and control for the different profitability across destination markets.

Table 2 - Proportion of Exporting Firms By Destination

	Year				
Destination	2002	2003	2004	2005	2006
US/Canada	.507	.542	.482	.509	.551
Japan/Korea	.463	.422	.419	.401	.412
Australia/NZ	.220	.240	.201	.205	.208
Rest of Asia	.360	.426	.441	.429	.447
Non EU Europe	.273	.285	.305	.322	.334
Latin America	.301	.267	.302	.314	.336
Africa	.252	.307	.299	.355	.352

Table 3 focuses on the differences in the export participation patterns across firms. For a single year, 2005, it reports the export market participation rates of Chinese firms based on their ownership structures. We compare state-owned or listed firms, privately-owned firms, firms owned by companies headquartered in Hong Kong, Macau, or Taiwan, and foreign-owned firms.[4] The first row of the table gives the proportion of firms that export. The state-owned firms are the least export oriented (64.3 percent of them export), followed by the HK/Macau/Taiwan owned firms (68.5 percent), foreign-owned firms (72.7 percent) and the privately-owned firms are the most export oriented (83.0 percent). The remaining rows of the table give the proportion of the total firms that

[4]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.

sell in each destination. Focusing on the richer destination countries, US/Canada, Japan/Korea, and Australia/NZ, we see that the state-owned firms export at the lowest rate while the other three ownership categories have similar rates of export participation. In contrast, in the poorer destinations, Africa, Latin America, Non-EU Euorpe,and the Asian countries outside of Japan and Korea, the participation rate for private firms is substantially higher than for the other two groups. With the exception of Latin America, the state-owned firms also export to the poorer destinations at a higher rate than they do to the richer countries. These data features indicate that the capability of a given group of firms may vary substantially across markets. In general, a model with one dimension of firm heterogeneity, such as differences in productivity, will have difficulty explaining this pattern of specialization. In our model, firms differ in two dimensions, quality and productivity, and, as shown in equation (9), the relative importance of cost efficiency differences depends on each destination's demand elasticities

Table 3 - Export Market Participation by Ownership Type

	Ownership Structure			
	State	Private	HK/TW/MK	Foreign
Proportion that Export	.643	.830	.685	.727
Proportion that Export to:				
US/Canada	.214	.356	.476	.357
Japan/Korea	.196	.307	.268	.338
Australia/NZ	.125	.137	.173	.159
Rest of Asia	.268	.477	.244	.224
Non-EU Europe	.214	.307	.173	.231
Latin America	.107	.325	.205	.185
Africa	.250	.386	.193	.198

Table 4 investigates the individual firm's pricing decision. The question we are interested in is whether or not a firm charges different prices across different destination markets. We can examine the magnitude of across-destination variation in prices by estimating a reduced-form regression of the log of the firm's export price on year, product, and destination dummies, while controlling for firm effects. The first column of Table 4 reports the destination coefficients (relative to the US/Canada) from a regression without firm fixed effects. It's apparent that there are systematic differences in the mean export price across destinations. Mean prices vary from a low of 7.3 percent below the US price for Africa to more than 8.0 percent above the US price in Non EU Europe and Australia. In the second column we control for firm fixed effects and thus compare the prices across destinations using within-firm variation in the data. We observe that the destination variation is reduced. The mean price to Africa is now 6.4 percent less than the US while the mean price to Australia is now 4.0 percent above, but the across-country differences do not disappear and are statistically significant. There are several possible explanations for this pattern, including, as suggested by Manova and Zhang (2010), each firm selling different quality products in each destination. Alternatively, in our model we allow demand elasticities and markups to vary across markets which, as shown in the pricing equation (6), will lead to price variation across destinations after controlling for firm effects. We make this modeling choice because it is directly estimable and testable using our data on firm sales, production, and prices. Finally, the fixed effect regression also shows that there is considerable price heterogeneity across firms. The fraction of total price variation that is attributable to the across-firm dimension is .81. It will be very important to account for firm-level sources of price heterogeneity in the data and our model will do this with the firm-level quality and productivity components.

Table 4 - Log Price Regressions

Destination	Without Firm FE	With Firm FE
intercept (US/Canada)	1.053 (.026)	1.039 (.018)
Japan/Korea	.055 (.018)	.043 (.012)
Australia/NZ	.080 (.022)	.040 (.014)
Rest of Asia	-.009 (.018)	-.018 (.011)
Non-EU Europe	.082 (.019)	.016 (.013)
Africa	-.073 (.019)	-.064 (.012)
Latin America	-.008 (.019)	-.015 (.012)
Proportion across firm		.811

All regressions include year and product dummies

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5 Empirical Results

5.1 Demand Estimates

The empirical model includes the demand equation (4), pricing equation (6), and export market participation (10). Table 5 reports estimates of the demand curve parameters, which include the destination-specific price parameters α_d and the within-group substitution parameter σ. together these provide a destination-specific demand elasticity, $\alpha_d/(1-\sigma)$, and markup, $\alpha_d/(\alpha_d-(1-\sigma))$ which are reported in the columns. The three panels of the table correspond to different estimators, specifically OLS, Fixed Effects, and the Hierarchical Bayes estimator. Comparing across the panels we see that the price parameter α_d increases in absolute value as we move from OLS to FE to HB which is consistent with the expected bias due to the endogeneity of prices in the first two estimators. The increase in the magnitude of α_d implies an increase in the demand elasticity and a reduction in the markup as we move across the panels. Focusing on the HB estimator we see that the within-group subsidization parameter is .803 which implies a fairly high degree of substitution among products in the same six-digit category. The demand elasticities using the HB estimator are fairly large and vary from -7.35 to -10.75 across destination countries, reflecting that Chinese exporters face reasonably elastic demand in their destination markets. It is important to note that the demand elasticities are highest in the low-income destination, Africa, Latin America, and the Rest of Asia, where they vary between -9.17 and -10.75. The higher-income destinations, U.S., Australia-New Zealand, Japan-Korea, and non-EU Europe, have demand elasticities that vary between -6.89 and -7.84. This implies lower markups in the low-income destinations although, given the magnitude of the demand elasticities, the markups only vary between 10 and 17 percent across destinations. Finally, one additional parameter estimated in the demand model is the coefficient on the lagged participation variable. It is not reported in the table with the other demand parameters but is equal to 0.12 with a standard error of (0.026). It indicates a substantial premium in market share for experienced exporters which likely reflects the fact that export sales may build up gradually after a firm enters a new destination.

Table 5 - Demand Curve Parameter Estimates

	OLS		Fixed Effects		Hierarchical Bayesian		
Destination	α_d	elasticity	α_d	elasticity	α_d	elasticity	markup
US/Canada	0.31	-1.86	0.40	-2.37	1.44	-7.35	1.15
Japan/Korea	0.38	-2.27	0.49	-2.90	1.56	-7.94	1.14
Australia/NZ	0.25	-1.45	0.37	-2.19	1.36	-6.89	1.17
Rest of Asia	0.81	-4.78	0.92	-5.44	1.97	-10.01	1.11
Non-EU Europe	0.21	-1.22	0.46	-2.72	1.47	-7.47	1.15
Africa	0.93	-5.22	1.05	-6.21	2.12	-10.75	1.10
Latin America	0.63	-3.75	0.76	-4.50	1.81	-9.17	1.12
σ	0.831		0.804		0.803		

5.2 Pricing Equation Estimates

Table 6 reports parameter estimates of the pricing equation (6) which include the marginal cost coefficients. These include coefficients on the firm's capital stock and wage rate, which are shifters of the firm's marginal cost function, as well as product and destination dummy variables. The coefficient on the wage rate is positive, as expected, and statistically significant. The coefficient on the firm's capital stock is also positive, which is not consistent with it being a shifter of the short-run marginal cost function. Because we do not use any data on the cost of the firm's variable inputs, but instead estimate the cost function parameters from the pricing equation, this coefficient will capture any systematic difference in prices with firm size. It is important to emphasize that the estimation has already controlled for firm-specific factors in cost (c_f) and demand (ξ_f) so the capital stock variable is measuring the effect of variation in firm size over time which is likely to capture factors related to the firm's investment path and not just short-run substitution between fixed and variable inputs. The destination-specific coefficients capture the term $\ln(\frac{\alpha_d}{\alpha_d-(1-\sigma)}) + \gamma_d$ in equation (6). The variation across destination countries indicates that the lower income countries, Africa, Latin American, and the rest of Asia, 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-side parameters, α_d and σ, in explaining the pricing differences by constructing $\ln(\frac{\alpha_d}{\alpha_d-(1-\sigma)})$ from the demand estimates and comparing it with the country coefficients in Table 5. These implied estimates of the contribution of the markup to pricing are reported in the last column of Table 6. These do not fully capture the level or movement of the destination dummies in the pricing equation. This implies that there other destination-specific factors that are determining the level of export prices than just the markup estimated from the demand parameters. This could reflect destination-specific marginal cost shifters. Understanding the source of the differences requires further work

Table 6 - Pricing Equation Parameter Estimates

	Parameter	Standard Error	Implied log markup from demand equation $\ln(\frac{\alpha_d}{\alpha_d-(1-\sigma)})$
$ln(capitalstock)_{ft}$	0.034	0.006	
$ln(wage)_{ft}$	0.027	0.015	
Past Exporter Dummy I_f^{dt-1}	0.020		
Product Group Dummies (γ_g)			
Leather Shoes	0.507	0.010	
Textile Shoes	0.041	0.011	
Destination Dummies(γ_d)			
US/Canada	0.657	0.081	0.146
Japan/Korea	0.702	0.082	0.135
Australia/NZ	0.691	0.081	0.157
Rest of Asia	0.636	0.082	0.105
Non EU Europe	0.684	0.082	0.144
Africa	0.596	0.081	0.098
Latin America	0.653	0.082	0.115

5.3 Market Participation Estimates

The third equation in our empirical model is the probability of exporting. The parameter estimates for this equation are reported in Table 7. The parameter estimates show that the two firm components ξ_f and c_f are both significant determinants of the export decision. Product quality enters positively implying that firms with high product quality are more likely to export to a destination. This is consistent with high priced firms producing higher quality products and having larger market shares in the destinations. The cost variable c_f is multiplied by $(1 - \sigma - \alpha_d) < 0$, so the positive coefficient in the regression implies that high cost firms have a lower probability of entering. Even though ξ_f and c_f are positively correlated, once we control for firm quality, firms with low productivity will be less likely to export. The capital stock, a measure of firm size, has a significant positive in the decision and high wages enter negatively. 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.

Table 7 - Export Market Participation

Dependent Variable	Parameter Estimate	Standard Deviation
ξ_f	0.473	0.022
$(1 - \sigma - \alpha_d)c_f$	0.402	0.026
$ln(capitalstock)_{ft}$	0.026	0.008
$ln(wage)_{ft}$	-0.019	0.027
Past Participation I_f^{dt-1}	1.635	0.022

Model includes destination*year dummies

5.4 Firm Quality, Productivity, and Capability

The three equation model and estimation method we implemented produces estimates of the firm-specific demand and cost factors, ξ_f, c_f. It is important to emphasize that all three equations, including the export participation equation are helpful in identifying the joint distribution of firm components ξ_f and c_f. Specifically, firms with low values of these parameters will not export as frequently or to as many destinations as firms with higher values. In addition our framework models the joint distribution of these components as functions of observable firm characteristics, including geographic location and ownership type. The parameters on these characteristics are reported in Table 8 and these describe how the mean of the posterior distribution of ξ_f, c_f across firms shifts with the firm observables. Each of the parameters measures a shift in location or ownership type relative to a firm in the north. On the demand side, firms located on the east coast have significantly higher firm quality than in other regions while the southern regions are significantly lower. There are also substantial differences in the firm quality based on the type of ownership. The privately-owned firms, firms owned by overseas Chinese firms, and firms owned by foreign producers all have significantly higher firm quality than the state-owned firms. In this dimension the privately-owned Chinese firms actually have the highest firm quality

On the cost side, there are significantly lower costs in all regions compared to the north with the largest cost advantages enjoyed by firms in the two southern regions. It is interesting to note that even though firms in the east coastal region have a higher demand side factor they still have lower costs than the base category firms indicating that firms in these regions will have substantial export market advantages relative to firms in either the north or west regions. The comparison with firms in the southern regions is less clear because, while they have lower product quality than the east coast firms, they have significant cost advantages. The variation in c_f resulting from differences in firm ownership indicates that the privately-owned, foreign-owned, and firms owned by Hong Kong, Taiwan, or Macau firms all have significantly higher costs, which is consistent with the higher quality component estimated on the demand side. Together the parameters in Table 7 indicate significant variation in both firm-level cost and quality across different categories of ownership and geographic location

Table 8 - Hierarchical Parameters

	Demand ξ		Cost c	
Firm Characteristic Z_f	Estimate b_ξ	S.E	Estimate b_c	S.E
East Coastal	0.13	0.09	-0.30	0.05
Mid-South	-0.44	0.08	-0.55	0.07
Southeast Coastal	-0.19	0.10	-0.55	0.05
West	0.06	0.16	-0.03	0.09
State Owned/Listed	-1.25	0.15	-0.22	0.10
Private	-0.31	0.12	0.12	0.08
HK/Taiwan/Macau	-0.60	0.12	0.27	0.08
Foreign	-0.55	0.12	0.25	0.08

* The base category is a northern firm.

The empirical model produces estimates of firm quality ξ_f and productivity c_f for each of the 1108 firms in our sample. Figure 1 provides kernel density estimates of the quality and productivity measures. It is clear from the picture that the dispersion in firm quality is much larger than in firm productivity. This implies that heterogeneity in firm quality will be more important than productivity differences in generating differences in export market capability. The values of ξ_f and c_f are positively correlated across firms with a simple correlation of .850. This implies that high-cost firms are generally high-quality firms so that some of the variation in c_f simply reflects the higher cost of producing high-quality products. To further understand this correlation we regress c_f on a polynomial in ξ_f and assess the fit of the regression. The estimated regression (standard errors in parentheses)is:

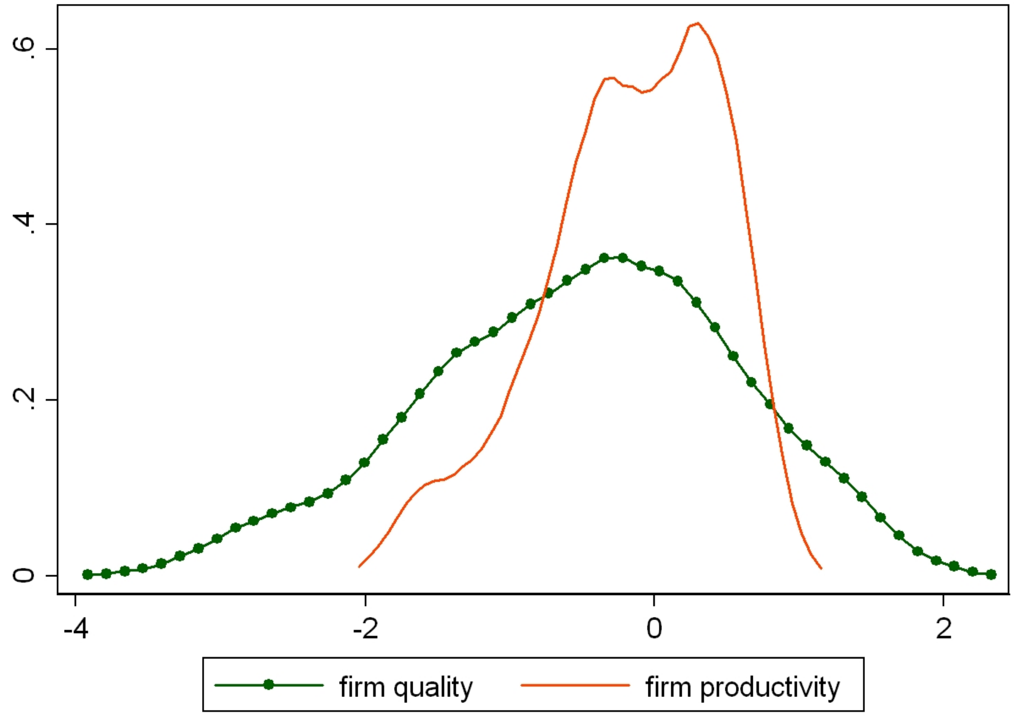
$$c_f = \underset{(0.014)}{0.135} + \underset{(0.014)}{0.439}\xi_f - \underset{(0.012)}{0.069}\xi_f^2 - \underset{(0.005)}{0.009}\xi_f^3, R^2 = .736, \hat{\sigma} = .316.$$

which indicates that about 74 percent of the sample variation in c_f is explained by variation in firm quality. To a large extent in our sample the high-quality firms will be high-cost firms.

The quality and productivity indexes can be combined to construct a measure of firm capability using equation (9). In particular this index of capability will vary across destination markets because of variation in the demand parameter α_d and across firm locations and ownership categories because of variation in the parameters underlying the joint distribution of (ξ_f, c_f).[5] The impact of cost differences across firms on their capability will vary by destination because of the interaction term between α_d and c_f in this equation. Table 9 reports the mean level of firm capability across these three

[5]When constructing the measure of firm capability we did not include the terms that depend on the firm's wage rate or capital stock because they had no effect on the across-firm distribution of capability. The capability measures with and without the wage and capital stock data have a simple correlation that is greater than .988 in every destination market. The across-firm distribution of capability is determined by the values of ξ_f and c_f.

Figure 1: Density of Quality and Productivity



dimensions (the mean level of capability across all firms and destinations is -.236)

Table 9 - Average Firm Capability $\ln \overline{r^d}(\xi_f, c_f)$

	Destination Market (demand elasticity)			
	US/Canada (-7.35)	Japan/Korea (-7.94)	Latin America (-9.17)	Africa (-10.75)
Firm Ownership Type				
State-owned	-.551	-.496	-.384	-.236
Private	-.006	.020	.072	.141
HK/TWN/MC	-.469	-.453	-.421	-.361
Foreign	-.403	-.396	-.381	-.361
Firm Geographic Location				
North	-.825	-.842	-.879	-.925
East Coastal	-.230	-.215	-.184	-.143
Mid-south	-.531	-.487	-.391	-.281
SE Coast	-.292	-.252	-.169	-.062
West	-.537	-.541	-.548	-.567

We report results for four destination regions for Chinese exporters, two wealthy destinations with lower demand elasticities, US/Canada and Japan/Korea, and two poorer regions with higher demand elasticities, Latin America and Africa. The other three destination regions fall between these two extremes. The top panel of the table shows how the mean capability of the firms differs with the ownership type. Across all destination markets the privately-owned firms have the highest average capability. The HK/Taiwan firms and the foreign owned firms have substantially lower average capability in all destinations than the privately-owned firms. This reflects the pattern in table 8 where these two groups had lower quality but higher cost than the privately-owned firms. The state-owned firms provide an interesting contrast. In Table 9 they are the group with the lowest capability in the high-income destinations but they do much better, relative to the HK/Taiwan and foreign firms, in the Latin American and African markets. This reflects the fact that, while they have the lowest firm quality in Table 8, they also have lower cost. This combination of low quality and low cost becomes more attractive in the countries with more elastic demand. As seen in equation (9), cost differences play a larger role in generating differences in capability when demand is more elastic. This illustrates that different combinations of firm demand and cost components will lead to variation in the ranking of firm capability in different destinations.

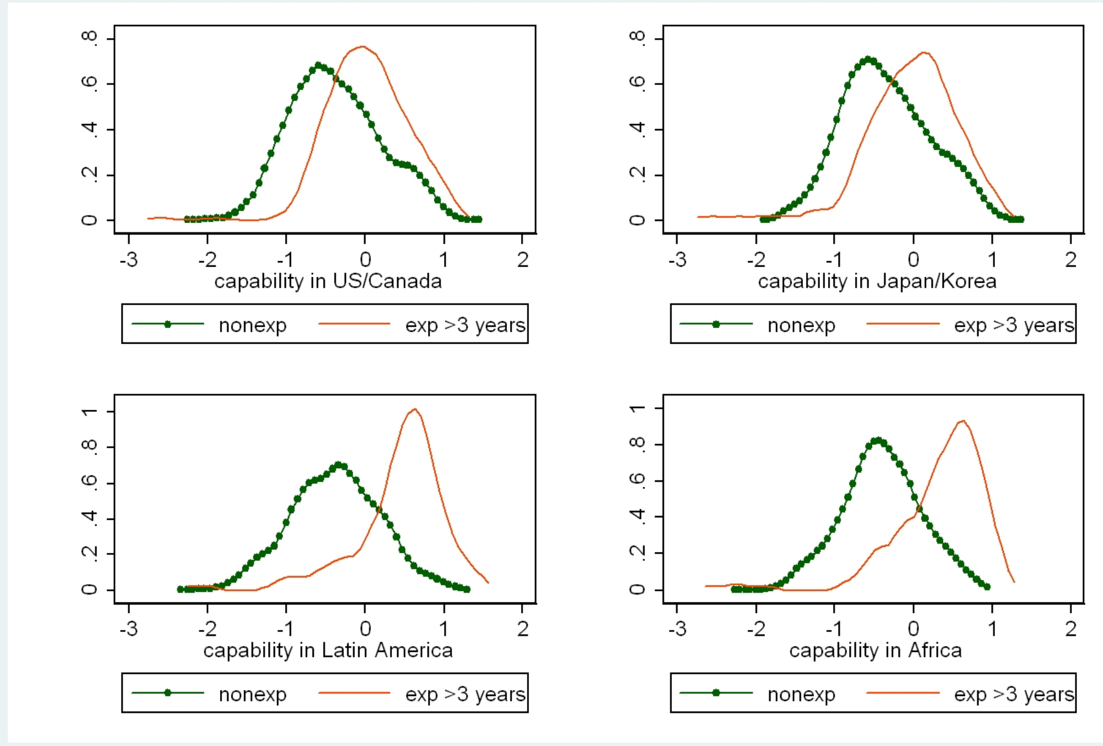
The lower half of Table 9 reports mean capability across firms from different regions of the country. The northern firms have the lowest capability in all destination markets, followed by the western firms, reflecting their relatively high costs and low quality parameters in Table 8. The firms located in the east coast and southeast coast have the highest relative capabilities across all destinations. The reflects that fact that they have a combination of relatively high quality and relatively low cost across the geographic categories in Table 8. Firms in the mid-south region do not rank as highly in export capability because while they have relatively low cost, they also have low firm quality.

5.5 Capability and Export Patterns

The results reported in Table 9 show how the mean capability measure varies across the whole set of sample firms based on ownership types, geographic regions, and destinations but does not relate the variables to the actual export patterns. In this section we compare the distribution of firm capabilities in each destination, distinguishing each firm based on the length of time in our sample that it exports to the destination. In order to highlight the role of firm capability we contrast the group of firms that never export to a destination with the group that export either four or five years. Figure 2 graphs the kernel density for nonexporters and long-term exporters in each of four destinations. The upper left panel is for the U.S./Canada market and it is clear that the distribution of firm capability 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 capability in that market than the firms that choose not to export to the U.S. The corresponding mean and standard deviation of the distribution for all seven destinations are reported in Table 10. The mean (standard deviation) of capability among the nonexporters to the U.S. is -.375 (.57) while the same numbers for the long-term exporters are .019 (.52). 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. As was the case with the U.S. market, the distribution of firm capability for the long-term exporters in each destination is shifted to the right relative to the nonexporters.

Comparing across destinations in Figure 2 and Table 10, the distribution of firm capability for the nonexporters is roughly similar. The mean varies from -0.345 to -0.478 across destinations and the standard deviation is between 0.5 and 0.58 in all markets. In contrast, the capability of the long-term exporters differs substantially across the

Figure 2: Density of Firm Capability by Destination Market



destinations. The mean capability of the long-term exporters varies from a low of -0.261 in the Rest of Asia market to .0.438 in Africa. In particular the long-term exporters have much higher capability in the three markets with the lowest export participation rates, NonEU Europe, Africa and Latin America. Alternatively, the destinations with higher export participation rates, such as the U.S and Japan, have more low capability firms among the group of long-term exporters. The one exception to this pattern is Australia/NZ which has both low export rates (see Table 2), probably because of its small size, but still a weaker set of exporting firms.

Table 10 - Mean (Standard Deviation) of Firm Capability

Destination	Non Exporters	Long-Term Exporters
US/Canada	-0.375 (0.57)	0.019 (0.52)
Japan-Korea	-0.345 (0.55)	-0.029 (0.58)
Aust-NZ	-0.397 (0.58)	-0.040 (0.65)
Rest of Asia	-0.444 (0.50)	-0.261 (0.66)
Non EU Europe	-0.478 (0.50)	0.297 (0.60)
Africa	-0.382 (0.56)	0.438 (0.57)
Latin America	-0.409 (0.50)	0.317 (0.60)

The final summary measure of the capability distribution compares the average of each firm's capability across all markets with the total number of markets the firm exports to. Figure 3 provides kernel density estimates for three groups of firms: ones that export to only one destination, ones that export to three or four destinations, and ones that export to six or seven destinations. It is clear from the figure that the firms that export to more destinations have a more favorable level of average capability. The contrast is particularly strong for the firms that export to only one destination. The corresponding means for the three distributions increase from -0.587 to -0.061 to 0.149 as the number of destination markets increases. It is also possible to summarize the separate roles of ξ_f and c_f in determining the number of markets that each firm exports to. We estimate a poisson regression of the number of export destinations for each firm, a count variable from 1 to 7, on the firm's quality and cost indexes. The estimated regression results are:

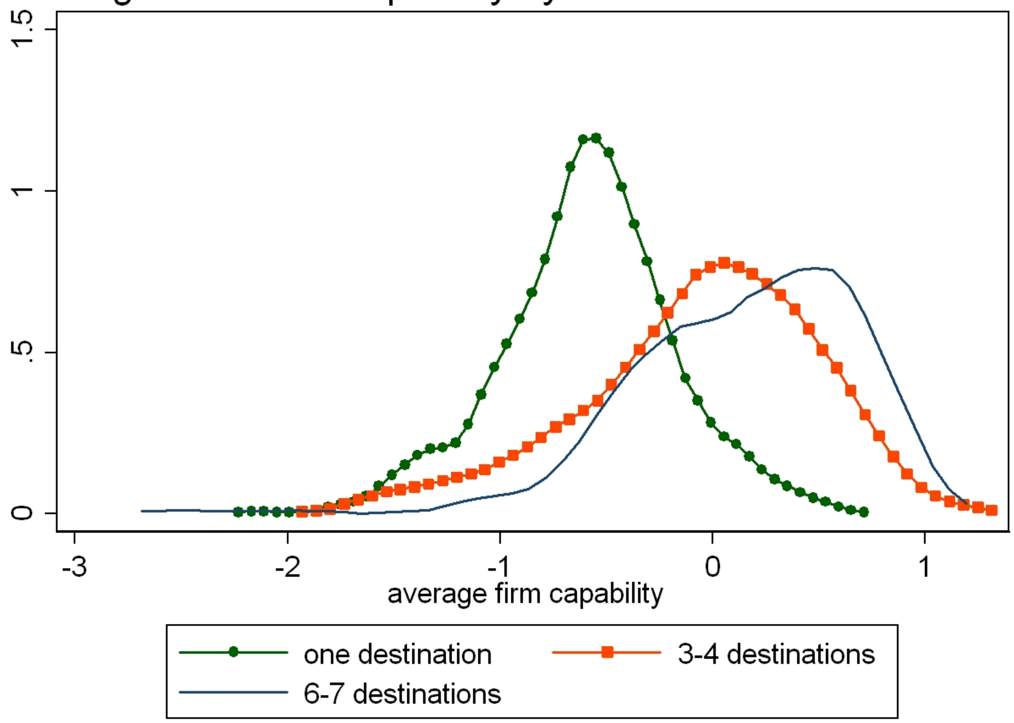
$$numdest_f = \underset{(.018)}{1.197} + \underset{(0.032)}{0.629}\xi_f - \underset{(0.056)}{0.789}c_f, R^2 = .093$$

This regression indicates that firm quality is positively correlated with the number of export destinations for the firm while higher costs are negatively correlated

6 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

Figure 3: Firm Capability by Number of Destinations



export market participation. The model allows us to measure firm-level quality and productivity indexes and provides a way to combine them into a measure of a firm's capability in each of seven regional export destinations. The measure of firm quality relies on differences across firms in export market shares, controlling for firm prices, in the destination markets. The measure of productivity relies on differences in firm export prices, controlling for firm costs and markups, across destinations. Both factors play a role in determining the firm's profits in each export market and thus the decision to export. The model allows demand elasticities and markups to vary across destinations and we show that the relative importance of quality versus productivity in generating differences in firm capability in an export destination depends on the demand parameters. In markets with more elastic demand, productivity differences across firms are magnified and become more important in determining firm capability than in markets with more inelastic demand.

To estimate the model we use panel data from 2002-2006 for a group of 1108 Chinese firms that export footwear. The econometric model utilizes some recent insights by Arellano and Bonhomme (2009) that allow us to nest fixed effects and random effects models while allowing a very flexible joint distribution for the firm-level quality and productivity indexes. The empirical results indicate very elastic demand in the destination markets with more elastic demand in lower-income export destinations. The export participation equation indicates a significant role for both firm quality and productivity as determinants.

The estimates of firm quality and productivity differ across firms based on their ownership type and geographic location. Privately-owned firms are relatively high quality but low cost producers when compared with either foreign-owned firms or firms headquartered in Hong Kong, Taiwan, or Macau and this gives them relatively high indexes of capability in most export markets. Although both firm quality and productivity contribute to export capability, the across-firm distribution of capability is more heavily affected by differences in firm quality. We find that our measure of firm export capability is very useful in summarizing differences between firms based on the length of time they export to a destination and the number of destination markets they have. Firms that are long-term exporters in a destination have a higher capability index, on average, than firms that do not export to the destination. Firms that export to many destinations have higher average capability than firms that export to one or a small number of markets.

Overall, this paper represents a first step in our research agenda to study how underlying firm heterogeneity on both the demand and production sides influences the long-run performance of Chinese manufacturing exporters. This paper demonstrates that indexes of firm quality and productivity can be retrieved from micro data on firm production and export transactions and that the indexes are useful in summarizing differences in firm export patterns across destination markets. The next step in our research project is to use the model estimates to study counterfactual changes in export market conditions. In particular, we will use data from the EU countries, which we did not use in the estimation of the model, to measure how the EU quota on Chinese footwear exports affected the mix of high and low capability firms in those countries and then simulate how removing the quota would alter this mix.

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A Appendix - Sampling Procedure

Define the set of common demand parameters as $\alpha = (\alpha_d, \tilde{\tau}^{dt}, \sigma)$, the set of common cost parameters as $\gamma = (\gamma_w, \gamma_d)$, and the common parameters describing the demand and pricing shocks as Σ. At the start of simulation round s there are previous draws α^{s-1}, γ^{s-1}, and Σ^{s-1}, and draws for each of the firm quality and productivity shocks: $(\xi_f^{s-1}, c_f^{s-1}), f = 1, 2, .., N$. 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 Σ^{s-1}. We can then draw α^s using the demand equation:

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

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

$$ln p_i^{dt} - c_f^{s-1} - ln(\frac{\alpha_d^s}{\alpha_d^s - (1-\sigma^s)}) = \gamma_d + \gamma_w ln W_f^t + v_i^{dt}$$

$$\frac{ln(s_i^{dt}) - ln(s_0^{dt}) - \xi_f^{s-1} - \tilde{\tau}_{dt}^s - \sigma^s ln(s_{ig}^{dt})}{-\alpha_d^s} - c_f^{s-1} - ln(\frac{\alpha_d^s}{\alpha_d^s - (1-\sigma^s)})$$
$$= \gamma_d + \gamma_w ln W_f^t - \frac{1}{\alpha_d^s} u_i^{dt} + v_i^{dt}$$

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

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

4. Given $\alpha^s, \gamma^s, \xi^{s-1}, c^{s-1}$ and Σ^s, calculate the market popularity measure using the revenue equations (7) and (8):

$$\begin{aligned} ln\bar{\Phi}_g^{dt} &= ln(\sum_{i\in g} r_i^{dt}) - \sum_{i\in g}((\frac{\xi_f^{s-1} + (1-\sigma^s - \alpha_d^s)(c_f^{s-1} + \gamma_d^s + \gamma_w^s lnW_f^t)}{1-\sigma^s}) \\ &\quad + \ln E_{u,v}^s[exp(\frac{u_i^{dt} + (1-\sigma^s-\alpha_d^s)\nu_i^{dt}}{1-\sigma^s})]) \end{aligned}$$

where $E_{u,v}^s$ depends on Σ^s.

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

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

$F[.]$ is a flexible polynomial of firm demand/cost heterogeneity and market popularity.

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

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

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 (ξ_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

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

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 $(\xi_f^s, c_f^s), f = 1, 2, .., N$.