**Supplementary material: Data and Code**

# 1 Data

## 1.1 Production data

The Annual Survey of Manufacturing is an extensive survey of Chinese Manufacturing firms collected every year by the Chinese National Bureau of Statistics. This survey contains all state-owned industrial firms and non-state-owned firms with sales above 5 million RMB (roughly 0.9 million dollars). Aggregates for employment, sales, capital and exports for these firms match almost perfectly the totals reported annually in China's Statistical Yearbook.(Brandt et al. 2017)
The data contains standard information on firm-level production and is comparable to the Longitudinal Research Database (LRD) maintained by the U.S. Bureau of the Census or to the widely used census data for Colombia and Chile.(Brandt et al. 2014) For this paper, I use data from 2000-2006 for three reasons.

1. The data file for 2009 misses important variables, such as revenue, wages, material input, and fixed assets. The data files for 2010 and 2011 that we obtained had incorrect information for employment.

2. The data file from 2008 doesn't contain intermediate input.

3. The data file for the Chinese Monthly Customs Transaction only starts at 2000.

Because my ultimate goal is to carry out a productivity estimation exercise, it is impossible to estimate without intermediate inputs. In addition, I need the demand side variation to separate unobserved demand shocks from physical productivity. Therefore, I need to compile the Annual Survey of Manufacturing data with the Chinese Monthly Customs Transaction which contains detailed information of destination.

The estimation of the production function requires information on plant-level revenues, value added(thinking about it), input use: labor as measured by full time equivalent production workers, raw materials and a measure of the capital stock. I follow Brandt et al.(2014) to construct the latter and mainly use the stata code provided on their website.[1] Fixed assets are reported in three ways in AMS:

1. Original fixed asset($fa^o$): sum of past investments at historical price.

2. Net fixed asset: Original fixed asset-fixed depreciation

3. Total fixed asset($fa$): Net fixed asset+construction materials and ongoing construction

Therefore, the basic idea is to construct a category by province annual growth rate of capital accumulation and use the price index of each year to back out the real capital stock from the birth year to the first year each firm appeared in my database. And later on, use the nominal capital accumulation in my database and price index of the year to calculate the real capital stock. The basic step is as follows:

1. Construct an average growth rate($g_s$) of nominal capital stock between 1993 and 1998 at category level for each province. (Use information from 1993 annual enterprise survey)

2. Denote the birth year of a firm as b. For firms open before 1978, assume their initial capital stock is the same as 1978.(Before 1978, China underwent a huge revolution and the damage to manufacturing industry was detrimental.)

3. initial nominal capital stock:$nk_b = fa_a/(1+g_s)^{a-b}$

4. Initial real capital stock:$rk_b = nk_b * 100/p_b$, $p_b$ is an investment price index at firm's birth year.

5. Nominal capital law of motion before year a:$nk_{t+1} = nk_t * (1+g_s)$

6. Real capital law of motion:$rk_{t+1} = rk_t * (1-\delta) + nk_t * g_s * 100/p_{t+1}$

[1] https://feb.kuleuven.be/public/u0044468//CHINA/appendix/

7. Get $rk_a$ by the law of motion above.

8. For years after year a: $rk_{t+1} = rk_t * (1 - \delta) + (fa^o_{t+1} - fa^o_t) * 100/p_{t+1}$

I adopted the investment price index from Brandt et al(2014) as we are studying the similar period and using the same dataset. In addition, I follow their calibration of $\delta = 0.09$.(Later would examine through sensitivity analysis) In the Stata Code of Brandt et al(2014), there are a few points to mention:

1. They use firms enter before 1993 to calculate $g_s$ in order for the dataset to be more comparable.

2. When using the AMS, they assume there is no capital accumulation(nominal investment) if the dataset reports a decrease in $fa^o$ in two consecutive years.

3. Since it is an unbalanced data set, if a firm appears only in 2000 and 2006,then the capital growth rate in the time gap is calculated using a local interpolation.

There are several concerns using the AMS.

1. The problem with above-scale sample selection: Though the data contains all state-owned firms. The footwear industry is mainly private-owned. Therefore, the data cannot be used to study exit behavior and there might be potential selection bias. As for small firms, they will be particularly productive in order to be contained in the sample.

2. the Chinese AMS is not an establishment-level dataset and the basic unit is legal unit. Subsidiaries that are not legal units, so-called "industrial activity units (plants) are not included in the survey. However, for footwear industries, nearly 97% of the firms contain only one "industrial activity unit". Therefore, it is a quasi-plant level dataset.

## 1.2 Custom Data

I use the Chinese Monthly Customs Transactions from 2000-2006 at the 6-digit product level. The dataset allows me to construct a unit value price of exports for every firm-product-destination combination. The dataset also contains mainly three types of trade regimes. Processing trade firms can import duty-free raw materials, components and capital equipment but cannot sell to domestic market.

Below is a picture for illustration I take from Yu (2015)

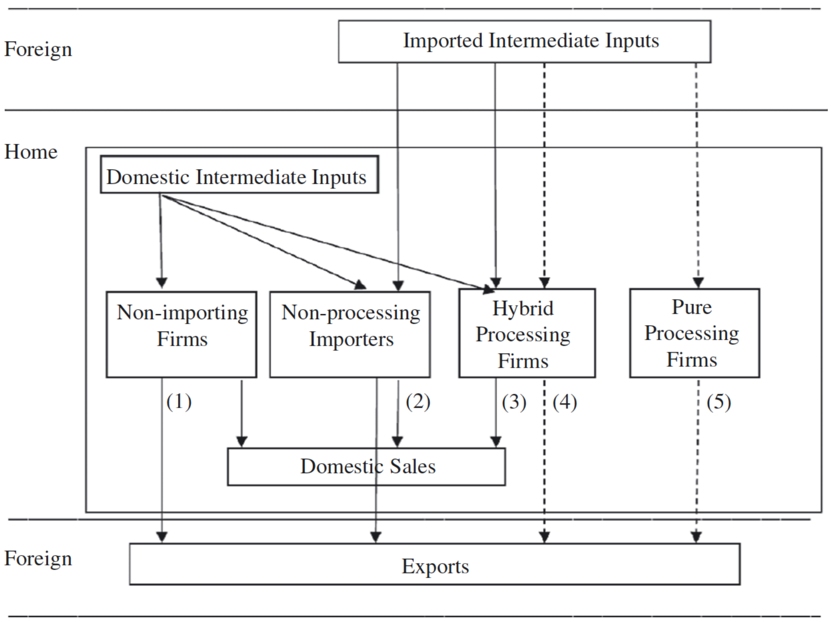



Fig. 3. *Four Types of Chinese Firms*
*Note*. Dotted lines denote firms' processing imports/exports; solid lines represent firms' non-processing imports/exports.

1. Ordinary trade: include export which doesn't use any imported materials

2. Processing with imported materials: a Chinese corporation purchases raw materials and components (either from the ultimate foreign purchaser or a third party). Therefore it has to make foreign currency payments. The ownership of those imported commodities remains that of the Chinese enterprise. The Chinese enterprise exports the finished products to any foreign customer after processing and assembling.

3. Processing with supplied materials (Assembly):raw materials and components are supplied by a foreign company and processed by a Chinese enterprise on a consignment basis. Ownership of raw materials and components remains that of the foreign customer. The Chinese company does not have to make foreign

exchange payments, and is paid through charging a processing fee. Finished products are owned and distributed by the foreign customer.

In that context it does not matter if the materials and components were imported or supplied. The amount of imported materials and components used in the manufacture of the finished products is free from tariffs and import-related taxes. However, if the finished products are intended to be sold on the Chinese market, Chinese customs will levy duties and interest on deferred payments subject to valid approval documents for sale on the Chinese market issued by the relevant authorities.
The major problem of linking trade data with firm level data is the fact that:

- There is no identifier to link the two dataset.
    1. Use firm name and geographic information to construct a mapping between the two datasets.
    2. Use identification ID to link different years together within each dataset.
- Inconsistency in industry classification.(Having think of a good way to categorize the sports shoes.)
- Firms report large exports cannot be found in custom dataset:
    1. Prior to 2004, many private firms could only export through third parties (trade intermediaries). Even after 2004, private firms can act as "indirect" exporters and authorize intermediaries to sell for them abroad.
    2. Parent companies with many subsidiaries will choose some of the subsidiaries to register with the Chinese Customs.

## 1.3 Trade protection Data

A large proportion of the sales in the footwear industry is exported to the world. In addition, the footwear industry is highly tariffed by countries like Italy and Brazil. Therefore, there is potentially a lot of variation in the demand side.

I will first use the tariff data as a measurement of trade protection in each country. I export all tariff data available on WITS TRAINs database from 2000-2006 for all footwear HS-6 level products. The following are four types of tariff data collected by Trains and I am using the volume adjusted effectively applied tariff as my measurement of the tariff that exporters are facing.

1. Most-Favored Nation Tariffs:MFN tariffs are what countries promise to impose on imports from other members of the WTO, unless the country is part of a preferential trade agreement.

2. Preferential Tariffs: Preferential trade agreement, under which they promise to give another country's products lower tariffs than their MFN rate.

3. Bound Tariffs: specific commitments made by individual WTO member governments. The bound tariff is the maximum MFN tariff level for a given commodity line. When countries join the WTO or when WTO members negotiate tariff levels with each other during trade rounds, they make agreements about bound tariff rates, rather than actually applied rates.

4. effectively applied tariff: WITS uses the concept of effectively applied tariff which is defined as the lowest available tariff.

Next, I will consider adding in non-tariff measures in the TRAINS database if the variation is not enough.

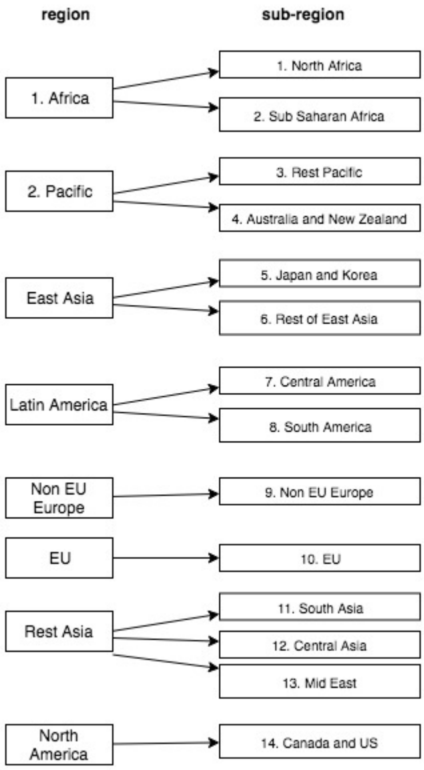
# 2 Price Deflators

To make nominal variables comparable over time, I need a price deflator to express values in constant year prices. Here I choose year 2004 as the reference year. I use the output deflator benchmark calculated in Brandt et al.(2014). This benchmark deflator uses the additional information reported in the survey from 2000-2003. In surveys from 2000-2003, the firms were asked to report the output both in nominal and real price and such could be used as a firm level price index. Later, they calculate a weighted average of such price-index using the current price output as weights to get the segment average price.For 2004-2006, they use the 2-digit ex-factory price index from China Statistical Yearbook to extend the more detailed deflator.

This I also follow the Brandt et al.(2014) which constructs using the output deflators and input shares calculated from the 2002 National Input–Output (IO) table. Most of the sectors defined in the IO table are less detailed than the industry definition used in the firm-level data and they constructed a concordance table linking the IO sectors to the four-digit industries. We first calculate an aggregate output price index for each IO sector as an un-weighted average of underlying industry prices. They then obtain the input deflator for each IO sector by calculating a input-share weighted average of these output deflators.

# 3 Market definition and aggregate demand shifter

Here I will follow the definition of market and aggregate demand shifter from Roberts et al. (2017). In my empirical analysis, there are nine regions in which each has a different demand elasticity and 14 subregions are defined as follows:




Therefore, the general environment can be think of as at each region, the wholesaler is purchasing footwear products from all over the world. The aggregate demand shifter is defined using the total import of footwear category at that destination in each period. Here I use the measure from WITS UN COMTRADE dataset and the group is predefined as above. Essentially I am relying on this aggregate demand shifter to identify the demand elasticity parameters. If there is no substantial difference among them, then it is hard to identify the parameters. I will compare my estimates using these two method. I will follow De Loecker (2011) to compute the aggregate demand shifter in domestic market as industry weighted deflated revenue. And $q_t^{domestic} = \sum_i ms_{it} R_{it}^d / P_t^d$

Since I am applying the same PPI or Wholesale Price Index in each destination market, it is important to check whether the various measures moves in similar patterns. However, one thing to notice is the across market PPI comparison. I hope the destination fixed effect is going to absorb this difference.

# 4 Code

The Estimation is as follows:

1. Run first stage to get $\phi_{it}$ by either doing a polynomial or a local kernel estimation on $(x_1{=}k_{it}, l_{it}, m_{it})$ and $(x_2{=}n_{it}, qr_{it}, \sum_d q^d_{st}, D)$ and thus we can have an estimation of $\phi_{it}$

2. Start with an initial guess of $\beta_1$ and $\beta_2$, corresponding to $x_1$ and $x_2$ and back out productivity $\omega_{it}$ and $\omega_{it-1}$.

3. Use another polynomial to non-parametric estimation by regressing $\omega_{it}$ and $\omega_{it-1}$ and $qr_{it-1}$ to back out the innovation term $\nu_{it}$.

4. This is the residual that enters the moment equation and we can use it to construct sample analogues.

5. I want to separately estimate the elasticity of demand because if I jointly estimate both, the problem will suffer from curse of dimensionality.

First, I didn't correct for the unobserved demand side variations and use a control function approach followed by ACF(2015). There is a Stata code called prodest and the standard error is bootstrapped.
Second, I follow DeLoecker(2011) and the original LP code is adjusted by including the additional demand variables capturing quota protection ($qr_{it}$).
Third, due to the problem of dimensionality, I didn't estimate the destination fixed effect. I use Julia to run the GMM estimation and generate 500 boostrap samples to do inference of my estimates.

# 5 Discussion about Gross output production function and value-added production function

## 5.1 Definitions

The data consists of firms i=1,...,I over period t=1,...,T. Firm i's output, capital, labor and intermediate inputs are given by $(Q_{it}, K_{it}, L_{it}, M_{it})$ and they log values will be denoted in lowercase by $(q_{it}, k_{it}, l_{it}, m_{it})$. We assume that firms operate in a monopolistic competition in each destination market but are price takers in the intermediate input market. We let $P_{it}^d$ denote the output price of firm i in destination d at time t and $p_{mt}$ be the price if intermediate inputs faced by the firm. Let $\mathcal{I}_{it}$ denote the "information set" of the firm in period t, it consists of all information the firm can use to solve its period t decision problem. If the choice of a generic input is a function of $\mathcal{I}_{it-1}$, then we say it is a predetermined input in period t, as it was effectively chosen at (or before) $t - 1$. If an input's optimal period t choices are affected by lagged values of that same input, then we say the input is **dynamic**. If an input is predetermined, dynamic, or both, we say it is **non-flexible**. If an input is chosen in this period and its choice does not depend on lagged values, so it is neither predetermined nor dynamic, then we say it is **flexible**.

## 5.2 Assumptions

**Assumption 1.** The relationship between output and the inputs takes the form

$$Q_{it} = F(K_{it}, L_{it}, M_{it})e^{\omega_{it}+\epsilon_{it}}$$

The production function F is differentiable at all (k, l, m) $\in R_{++}^3$ and strictly concave in m. $\omega_{it}$ is the part of productivity that is known to the firm before making its period t decisions, whereas $\epsilon_{it}$ is an ex-post productivity shock realized only after the period decisions are made.

**Assumption 2.** $\omega_{it} \in \mathcal{I}_{it}$ is known to the firm at the time of making its period t decisions, whereas $\epsilon_{it}$ is not. I assume $P_\epsilon(\epsilon_{it}|\mathcal{I}_{it}) = P_\epsilon(\epsilon_{it})$.

Furthermore $\omega_{it}$ is Markovian so that its distribution can be written as $P_\omega(\omega_{it}|I_{it-1}) = P_\omega(\omega_{it}|\omega_{it-1}, qr_{it-1})$. The function $g(\omega_{it-1}, qr_{it-1}) = \mathbb{E}[\omega_{it}|\omega_{it-1}, qr_{it-1}]$ is continuous. If we express $\omega_{it} = g(\omega_{it-1}, qr_{it-1}) + \nu_{it}$, by construction $\nu_{it}$ satisfies $\mathbb{E}[\nu_{it}|\mathcal{I}_{it-1}] = 0$. $\nu_{it}$ can be interpreted as the unanticipated at period t-1, "innovation" to the firm's persistent productivity $\omega_{it}$ in period t. We normalize $\mathbb{E}[\epsilon_{it}|\mathcal{I}_{it}] = 0$, without loss of generality. Given this normalization, it follows that $\mathbb{E}[\epsilon_{it}|k_{it}, l_{it}, m_{it}] = 0$.

This assumption by itself corrects for potential selection bias when firms choose export destination. Because this is a non-parametric specification and such nest decision making models where the destination choice depend on firm's previous productivity and export status.

**Assumption 3.** Intermediate inputs $m_{it}$ and $l_{it}$ are flexible inputs, i.e., it is chosen at time t independently of the amount of m and l the firm employed in the previous period. We treat capital $k_{it}$ predetermined, i.e., as chosen in the previous period (hence $k_{it} \in \mathcal{I}_{it}$).

The following assumption formalizes the environment in which firms operate.

**Assumption 4.** Firms are price takers in the labor and intermediate input market, with $p_{mt}$ and $p_{lt}$ denoting the common intermediate input price and labor input price. And they are engaged in monopolistic competition in which prices are $P^d_{it}$.

## 5.3 Firm's problem

$$max_{M_{it},L_{it}} P(Q_t)\mathbb{E}[F(k_{it}, l_{it}, m_{it})e^{\omega_{it}+\epsilon_{it}}|\mathcal{I}_{it}] - p_{mt}M_{it} - p_{lt}L_{it}$$

$Q_t$ is the aggregate output in the segment and the FOC for $M_{it}$ becomes:

$$(\frac{\partial P_{it}}{\partial Q_t}\frac{\partial Q_t}{\partial Q_{it}} + \frac{\partial P_{it}}{\partial Q_{it}})\frac{\partial}{\partial M_{it}}F(k_{it}, l_{it}, m_{it}))e^{\omega_{it}}F(k_{it}, l_{it}, m_{it}))e^{\omega_{it}} + P_{it}(Q_t)\frac{\partial}{\partial M_{it}}F(k_{it}, l_{it}, m_{it}))e^{\omega_{it}} = p_{mt}$$

Because here we assume monopolistic competition, $\frac{\partial Q_t}{\partial Q_{it}} = 0$ and from assumption 2, $\mathbb{E}[\epsilon_{it}|\mathcal{I}_{it}] = 0$. The equation above can be simplifies as follows:

$$(\eta_{it} + 1)\frac{\partial}{\partial M_{it}}F(k_{it}, l_{it}, m_{it})e^{\omega_{it}} = p_{mt}$$

Where $\eta_{it}$ is the elasticity faced by firm i. Therefore it implies the input demand function is

$$m_{it} = \mathbb{M}_t(k_{it}, l_{it}, \omega_{it}, X_{demand})$$

Here I use $X_{demand}$ to denote the observable demand shifters which will affect $\eta_{it}$.

## 5.4 Using a static input

The material demand function can be defined as follows.

$$m_{it} = m_t(k_{it}, l_{it}, \omega_{it}, qr_{it}, \sum_d q_t^d, D, n_{it}) \tag{1}$$

Here I assume firms are engaged in monopolistic competition in each region. Firms are price takers in the input market. Therefore, input demand is affected by the firms productivity, capital stock, labor usage and the demand(aggregate demand shifter in each region and the country and region specific fixed effect, the segment and time effect). Since the markup is constant and is correlated with productivity, there is a monotone relationship between productivity and material input conditional on other factors.Therefore I can rely on a function to proxy for productivity:

$$\omega_{it} = h_t(k_{it}, m_{it}, l_{it}, qr_{it}, \sum_d q_t^d, D, n_{it}) \tag{2}$$

I follow the concern of Ackerberg, Caves, and Frazer (2015) as there is not enough variation to affect labor and material input separately. Therefore, I don't identify any coefficient in the first stage. The first stage is designed to separate the observed demand shock and unobserved productivity from the unobserved idiosyncratic demand and production shock.

$$\tilde{r_{it}} = \phi_t(k_{it}, l_{it}, m_{it}, qr_{it}, \sum_d q_t^d, D, n_{it}) + \epsilon_{it} \tag{3}$$

### 5.5 Comparison with Value added production function

Value added is defined as follows:

$$P_{it}Q_{it} - p_{mt}M_{it}$$

and is a common alternative empirical approach which requires less parameters to estimate and is immune to the identification problem of gross output production which I will discuss in the following subsection. However, one thing to notice is the fact that value added production function holds capital and labor fixed while the gross output production function controls for capital, labor and intermediate inputs. Therefore, the value added production function will possibly ignore any potential substitutions between intermediate inputs and capital and labor and yield very different results of productivity estimation. For a more complete discussion, one can refer to Gandhi et al. (2017) for both theoretical and empirical evidence.

## 6 Invertibility conditions

To proof the invertiblity condition of LP method in an imperfect competition setup, it is key to prove that higher productivity firms are not able to charge higher markups. If we have CES demand and monopolistic competition, the mark up is constant across all the firms regardless of its productivity, thus the monotonicity assumption is satisfied. However, one has to worry about whether more productive firms can choose to export to countries with higher mark up and thus breaks the monotonicity condition.

$$f_{L\omega} f_{mL} > f_{LL} f_{m\omega}$$

This second equation is sufficient to guarantee the invertibility.

$$f_{L\omega}f_{mL} - f_{LL}f_{m\omega} > \frac{1}{\eta}((f_{LL}f_m f_\omega + f_L^2 f_{m\omega}) - (f_{L\omega}f_L f_m + f_L f_\omega f_{mL}))$$

# 7 A behavioral model for export

Here I want to build up a model to study the underline mechanism of learning through exporting. Is it a learning about the demand and word of mouth effect or is it a learning by doing and a decrease in marginal cost. In each destination market (d), I will use the demand as before but allow the individual demand shifter to depend on the past experience in the market.

$$Z_{it}^d = (1-\delta)Z_{it-1}^d + (1-\delta)R_{it-1}^d \tag{4}$$

For a firm i, it is going to decide how much to sell to each of the 9 different regions both on a intensive and extensive margin. In each of the market

# 8 Additional empirical results and findings

## 8.1 Differentials for exporters and non-exporters by year

The following two tables present the difference between exporters and non-exporters in different years by using an OLS regression and $Exp2$ as a measure of export status for each year. Across all years, exporting firms hire more workers, pay more wages and their performance are sometimes better in total sales.

$$x_{it} = \alpha + \beta exp_{it} + \gamma l_{it} + \sum_s \delta_s D_s + \sum_p \delta_p D_p + \epsilon_{it} \tag{5}$$

**Table 1: Differentials for exporters and non-exporters by year (All Firms)**

| Year | Employee | Domestic sales | Total sales | Capital p/w | Average wage | No. of firms |
|---|---|---|---|---|---|---|
| 2000 | 0.880*** | -1.465*** | 0.150** | -0.050 | 0.184*** | 1467 |
| 2001 | 0.812*** | -1.510*** | 0.084 | 0.074 | 0.146*** | 1877 |
| 2002 | 0.745*** | -1.476*** | -0.011 | -0.062 | 0.137*** | 2221 |
| 2003 | 0.862*** | -1.631*** | -0.058 | -0.136** | 0.148*** | 1965 |
| 2004 | 0.690*** | -2.105*** | -0.052 | -0.113 | 0.056*** | 3111 |
| 2005 | 0.733*** | -1.367*** | -0.032 | -0.115 | 0.051* | 3499 |
| 2006 | 0.673*** | -1.326*** | -0.07 | -0.113 | 0.057** | 3302 |

*** means significant at 1%.
** means significant at 5%.
* means significant at 10%.

**Table 2: Differentials for exporters and non-exporters by year (Small Firms)**

| Year | Employee | Domestic sales | Total sales | Capital p/w | Average wage | No. of firms |
|---|---|---|---|---|---|---|
| 2000 | 0.464*** | -1.430*** | 0.243*** | 0.023 | 0.225*** | 1035 |
| 2001 | 0.467*** | -1.447*** | 0.167** | 0.138* | 0.194*** | 1388 |
| 2002 | 0.406*** | -1.444*** | 0.024 | 0.002 | 0.142*** | 1677 |
| 2003 | 0.421*** | -1.476*** | 0.021 | -0.086 | 0.202*** | 1430 |
| 2004 | 0.335*** | -2.001*** | -0.001 | -0.091 | 0.077*** | 2428 |
| 2005 | 0.384*** | -1.306*** | 0.046** | -0.043 | 0.065** | 2692 |
| 2006 | 0.354*** | -1.238*** | 0.012 | -0.056 | 0.075*** | 2482 |

*** means sigfinicant at 1%.
** means sigfinicant at 5%.
* means sigfinicant at 10%.

## 8.2 Production function coefficients and demand parameters

The importance of controlling for simultaneity and selection bias in estimating productivity has been extensively discussed in Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2015) and others. Productivity and input usage are often correlated, simply running an OLS regression would potentially lead to overestimates of coefficients of labor and intermediary inputs as long as the cost advantage would be partly passed through to output prices. While firms will higher capital level are less likely to exit, the selection bias suggests the coefficient of capital would be underestimated. (Olley and Pakes (1996))

$$\hat{r_{it}} = \beta^k_{ols} k_{it} + \beta^l_{ols} l_{it} + \beta^m_{ols} m_{it} + \epsilon_{it}$$

As one can see in Table 3, the OLS estimates use a deflated revenue by a price deflator in Chinese domestic market. Without controlling for simultaneity bias, I simply estimate the above equation. The proxy is estimated using the prodest package in

Stata which taken into account the concerns of Ackerberg, Caves, and Frazer (2015) and jointly estimate the labor coefficient with capital and material in the second stage. I use a third order polynomial in the first stage and a bootstrapped sample of 500. For the proxy method, I still use a common price deflator common across firms. The result after controlling for the simultaneity bias is consistent with theory. Both the coefficient for labor and material are getting smaller due to the positive relationship between input demand and productivity. The coefficient on capital gets smaller too. Since I am using a above-scale sample, firms who disappear from my sample may not necessarily exit the market. This could potentially breaking down the negative relation between capital and productivity.

The third column is which I add the demand system to control for unobserved prices. Keeping the results comparable with column 2, I use a third order polynomial in the first stage and also bootstrap for 500 times. As one can see, the labor and material coefficient significantly increases. Since both prices and input demand would respond to a demand shock, the effect of omitted price effect on production function estimates becomes vague. As expected, the change in capital coefficient is not large as capital is assume predetermined.

When a firm exports to different markets, I use the inverse of total region as a proxy for the actually quantity proportion sold in each region. Fearing such proxy may introduce bias, I run the estimation with demand on a subsample where each firm serves one region. As one can expect, the subsample are only firms either sell in domestic market or in the intermediary market. Thus the estimation should be similar to the proxy one as the price deflator for the domestic market is the same as in proxy. However, with the additional intermediary market, the estimates moves in direction similar to column 3. Indicating that, adding the demand system would correct for an underestimation of labor coefficient due to unobserved price effect.

In Table 4 I show the full set of demand parameters I estimate using a GMM method. As I mentioned in section 4, adding the full set of country and subregion fixed effect would lead to a very inaccurate result as I would otherwise estimate 130

**Table 3: Production function estimates**

| | OLS | Proxy | With Demand | Single Market |
|---|---|---|---|---|
| Capital | 0.026 | 0.020 | 0.030 | 0.027 |
| | (0.003) | (0.000) | (0.270) | |
| Labor | 0.120 | 0.114 | 0.795 | 0.148 |
| | (0.009) | (0.000) | (0.200) | |
| Material | 0.845 | 0.839 | 1.020 | 0.833 |
| | (0.012) | (0.000) | (0.390) | |
| No. of obs | 17,442 | 17,442 | 17,442 | 9,630 |

For both proxy and with demand, the standard errors are bootstrapped.
The bootstrapped sample is 500

parameters. I follow De Loecker (2011) to include them as part of the productivity estimate in $\omega_{it}$ and focus on the change in productivity in which the time invariant fixed effect would cancel out. Therefore, my productivity are not directly comparable to usual estimates as it includes destination fixed effect. However, the within firm productivity dynamics and the difference between exporters and non-exporters are still informative as fixed effects are assumed to be time invariant when I additionally control for time fixed effect. Moreover, I still control for $qr_{it}$ which would pick up firm's response towards demand shocks. As one can see, between 2000-2006, there are three distinct time period. From 2000 to 2001 is the pre-WTO period. Between 2002-2005, the tariff in almost all region decrease, leading to a decrease in average protection exposure measured by $qr_{it}$. At 2006, due to the tariff increase in East Asia and Pacific region, the protection exposure goes up. Therefore, I add three time dummies to control for the time trend. The time trend is in practice very sensitive to initial value and the estimates can be very volatile. Since the time trend would also determine the productivity dynamics across years, I would like to minimize its bias on the actual productivity dynamics. Therefore, I am setting the initial guess to 0 for the three time dummies. In addition, I control for the segment but their actual differences are very small.

In Table 4, the first column is my estimates of the demand parameters. Compared with column 6, which is the estimates of demand in Roberts et al. (2017), most of their estimates fall into the confidence interval of my estimates but my elasticities are smaller in magnitude. Their estimates are very informative benchmark because

**Table 4: Region specific demand estimators**

| Parameters | $\beta$ Include | Not Include | 90% Confidence Interval Include | Elasticity Include | Elasticity Range Include | Elasticity Reference | Elasticity Reference2 Demand only |
|---|---|---|---|---|---|---|---|
| No. of Destination ($N_{it}$) | 10.232 | | [ 1.060, 20.870 ] | | | | |
| Region1-Africa | 0.624 | 0.252 | [ 0.450, 0.870 ] | -1.601 | [-1.149,-2.222] | -3.186(0.334) | -3.286(0.687) |
| Region2-East Asia and Pacific | 0.129 | -2.232 | [-0.120, 1.070 ] | -7.751 | [-0.935,-$\infty$] | -2.850(0.326) | -2.140 (1.474) |
| Region3-Latin America | 0.809 | -0.816 | [ 0.440, 1.220 ] | -1.236 | [-0.820,-2.273] | -2.889(0.335) | -2.941(0.654) |
| Region4-Non EU Europe | 0.427 | 0.945 | [ 0.000, 0.590 ] | -2.343 | [-1.695,-$\infty$] | -2.297(0.325) | -1.157(0.699) |
| Region5-EU | 0.626 | -0.251 | [ 0.380, 0.960 ] | - 1.599 | [-1.042, -2.632] | | |
| Region6-Rest of Asia | 0.510 | 0.991 | [ 0.330, 0.940 ] | -1.960 | [-1.064,-3.030] | -2.943(0.326) | -2.949(0.644) |
| Region7-North America | 0.791 | -3.336 | [ 0.020, 1.210 ] | -1.264 | [-0.826,-50.000] | -2.720 (0.319) | -1.735(0.845) |
| Region8a-China Domestic | 0.582 | -1.639 | [ 0.320, 1.160 ] | -1.718 | [-0.862,-3.125] | | |
| Region8b-China Intermediary | 0.615 | 0.011 | [ 0.400, 1.430 ] | - 1.627 | [-0.699,-2.500] | | |
| qr (tariff protection) | -1.784 | | [-41.58, 93.96 ] | | | | |
| dgyear1(2000-2001) | -1.137 | | [-2.750, 0.060 ] | | | | |
| dgyear2(2002-2005) | 0.440 | | [-0.530, 2.590 ] | | | | |
| dgyear3(2006) | 0.546 | | [-1.660, 1.110 ] | | | | |
| Texile | -0.069 | | [-0.820, 0.510 ] | | | | |
| Rubber | 0.083 | | [-1.020, 0.600 ] | | | | |
| Plastic | -0.995 | | [-1.800, -0.110] | | | | |

The confidence interval for demand parameters are bootstrapped. The bootstrap sample is 500. I report the confidence interval instead of the standard error is because the test statistics may not follow a standard normal or student's t-distribution.
The standard error for elasticity estimates are in parentheses for column 6 and 7

I study the same industry as theirs in a similar time period and follows similar market definitions. However, their paper use a subsample of the firms I studied (firms engaged in ordinary trade only), therefore the elasticity estimated would be different if the products sold by ordinary and processing trade are systematically different. Mine therefore can be regarded as an average elasticity across all the products. We do discover similar trends that low income regions like Africa and Rest of Asia have higher price elasticity than high income regions like North America and EU. I need to point out that my estimates could suffer from endogenous selection bias as firms self select into different regions to serve. As one can see in column 7, Roberts et al. (2017) also lists the estimates only using the demand equation. For most of the elasticity estimates, it becomes smaller in magnitude and noisier, which is similar to my estimates. They also get a insignificant estimates for the elasticity in East Asia and Pacific market. Therefore, correcting for the possible selection bias is what I would do in a follow up revise when I fully model the exporting behavior of firms. Since I follow De Loecker (2011) to not seek to estimate the country and subregion fixed effect but simply control them in the first stage. In column 2, I report the demand estimates in which I only control for time and segment fixed effect but not the subregion and country ones. As one can see, some of the coefficients become negative, indicating a positive price quantity relation. For Latin America and Non-EU Europe, the estimates get much bigger, which is typically observed in the literature. Therefore, even through I don't estimate them directly, to control for such demand shocks would lead to a more accurate demand elasticity estimates.

Firms with an additional destination would have a significantly higher revenue which is consistent with empirical result. A 1 % increase in number of destination would lead to a 10.23% percent increase in the total revenue. The time effect is not significant according to my bootstrap result. This is partly because when constructing the price deflator, part of the time trend has been taken into account. In addition, the aggregate demand also picks up time trend which are common across same region. Therefore, in my estimates of TFP, the time effect would be set as zero. The segment effect is also very small and most of them are insignificant. Since the default is firms producing leather shoes, the results indicates that firms producing plastic shoes would earn 99.5% less revenue than firms producing leather shoes, which is in fact very large.

### 8.2.1 TFP distribution across time

I further plot the distribution across years. As one can see the pattern is persistent across year. Since my estimates also contains country and subregion fixed effect, the results may potentially be contaminated. I hope my region level aggregate demand shifter would pick up some region level difference.

Figure 1: TFP distribution using different measure at different time