Exporting and Productivity Dynamics in the Chinese Footwear Industry

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Abstract

This paper studies whether exporters are of higher productivity in the footwear industry in China and whether trade liberalization leads to within-firm productivity increases. I construct a demand system with the production function to deliver valid physical productivity estimates following De Loecker (2011). After purging out the price effect, I find pure exporters have higher physical productivity than non-exporters in the footwear industry. However, the pure processing trade firms, which imported duty-free intermediate input from abroad but are forced to reexport all its final products, have substantially lower productivity than other exporters and lower productivity gains from trade liberalization.

Keywords: Production function, trade protection, export market selection

JEL codes: F14, D43, L25

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1 Introduction

A seemingly robust result that characterizes exporters is that exporters are of higher measured productivity than non-exporters.[1] In addition, opening up to trade, often measured by tariff reduction, would increase measured productivity. These are often cited as an argument for active export promotion in many developing countries. My paper seeks to empirically test the two empirical regularities of exporters in China.

Though the literature has documented the superior performance of exporters, the empirical findings characterizing China's exporting firms are a bit puzzling. Lu (2010) documents that China's exporters are significantly less productive and sell less in the domestic market than non-exporters, especially in labor-intensive industries. Unlike the US firms, the exporting firms in the labor-intensive industry in China have a U-shape exporting intensity. In addition, most paper use revenue-based productivity measures that contains price effect. Foster et al. (2008) raised a major problem of using revenue in firm-level survey data to calculate productivity that it is impossible to distinguish the quantity-productivity from the output price effect. A valid estimate of productivity would benefit my paper in analyzing the relationship between trade liberalization and firm-level productivity because the productivity estimates would be biased if exporters and non-exporters face systematically different demand shocks.

Production function and productivity estimation are tools used extensively to study the relationship between trade openness and firm or industry performance. Due to the revenue data's non-separable quantity and price information, I construct a CES demand model alongside a control function approach to control price effect and the simultaneity bias from physical productivity measure following De Loecker (2011). Even though I can not observe the price of each product, I use observable demand shifters from variations in trade protections as valid instruments and identify the productivity effects.

For the empirical analysis, I focus on the footwear industry in China between 2000 and 2006. The footwear industry of China is a labor-intensive industry

[1]Melitz (2003) builds a theoretical model that firms who self-select into the export market should have higher productivity. Such findings have been supported by Bernard and Jensen (1999) for the US, Van Biesebroeck (2005) for sub-Saharan Africa. Studies by Aw,Chung and Roberts (2000) for Korean and De Loecker (2007) for Slovenia find that exporters also generate higher productivity upon entering the export market.

and is the world's largest exporter. Understanding its productivity evolution is meaningful. In addition, China entered the WTO in 2001. The sample period is ideal for studying the effect of trade liberalization on firms' performance. Third, the footwear industry is highly exposed to export and different demand shocks. Therefore, it helps to construct a set of plausibly exogenous demand shifters.

The empirical fact discovered by Lu (2010) can be partly explained by the export-promoting policy and the prevalence of processing trade in China. Processing trade firms typically import all or part of the intermediate input and re-exports finished products after processing or assembling. In an effort to stimulate export, the final product using imported input would be exempted from input tariff as long as it is not sold in the domestic market. Therefore, if a firm chooses to re-export all its products, it becomes a pure processing trade company. I find that when controlling for the price effect, firms with high physical productivity enter into the exporting market. However, due to processing trade policies, low productivity firms enter the market to become processing trade companies and export as well. However, when using revenue-based productivity measures, the processing trade firms are falsely measured high productivity due to the price effect in their exporting countries.

From the estimated physical productivity measures, I next examine the productivity dynamics due to trade liberalization. Pure exporters witness a significant increase in productivity because output tariff reductions and the pro-competition effect enhance the firm selection. The input tariff reduction allows firms to employ cheaper and better intermediate inputs and boost firm-level productivity. In addition, there are sizable gains from exporting for pure exporters. However, the processing trade firms benefit less from trade liberalization and exporting. By selecting the less productive firms into exporting, my findings suggest that the processing trade policy is less efficient in promoting the footwear industry's overall productivity.

Literature Review: My paper can be seen as broadly contributing to the following strand of literature.

The well-known simultaneity and selection bias caused by unobserved productivity in estimating production function can be addressed using a control function approach following the insights of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015). Typically, the annual firm survey data will report the total revenue and expenditure in labor, capital, and intermediate goods. Many papers are using such data to estimate productivity in various countries. However, when a country is opening up to trade, the impact of liberalization on demand and price will be confounded with its impact on productivity, which might generate invalid welfare implications. To solve the problem raised by Foster et al. (2008), I follow De Loecker (2011) to construct a demand system in the standard production function approach to back out the relation between price and quantity when only revenue is observed on a firm level.

Studies by Klette and Griliches (1996), Katayama, Lu, and Tybout (2009) point out problems using revenue data to obtain true efficiency measures. However, its importance in practice has only been checked when quantity data is available. De Loecker (2011) proposes a novel method to recover the relationship between price and quantity when quantity data is missing, but its applicability in different contexts has not been explored. Apart from the theoretical attractiveness of adding a demand model, the estimation procedure relies on demand shifters highly correlated with price. In addition, to identify the different price effect across export destinations, the variations in demand shifters across nations is also demanding. My paper applies the gist of De Loecker (2011) and intends to understand the empirical importance of separating the price effect when studying trade liberalization in China.

Third, processing trade is an important type of trade in developing countries and often receives special tariff treatment. Understanding the productivity dynamics of such firms is of policy relevance. My finding is consistent with existing literature that evaluates the processing trade in China. Yu (2015) uses the revenue-based productivity measure, and a selection model shows that low productivity firms self-select into processing trade in order to enjoy this special tariff treatment. With the existence of a large number of processing trade firms, he further documents that the effect of input tariff cut is weaker for processing trade companies since they had already been exempted from input tariff. Dai et al. (2014) use matched microdata of Chinese manufacturing firms in 2000-2006 to show that after teasing out the processing trade firms, the productivity of exporters is higher than non-exporters.

The remainder of this paper is organized as follows. Section 2 will describe the background information of Chinese exporters and the footwear industry, the three primary datasets I use, and perform some preliminary analysis. Section 3 will discuss the production function and the demand system I use to estimate productivity. Section 4 introduces the empirical strategies. The main results are presented in section 5. Section 6 concludes.

2 Background on footwear market and data

In this section, I will first provide some background information about the footwear industry in China and the trade regime which is also common in developing countries and the tariff treatment of exporting firms in China. Furthermore, I will describe my three main dataset and use them to present the distinct exporting patterns of Chinese exporters.

2.1 Footwear market, processing trade and special tariff treatment

Processing trade is defined as "business activities in which the operating enterprise imports all or part of the raw or ancillary materials, spare parts, components, and packaging materials, and re-exports finished products after processing or assembling these materials/parts". The footwear industry, like many processing trade industry in China is subjected to special tariff treatment. Began in the early 1980s, government encourages Chinese firms to import all or part of the intermediate inputs and re-export final valued-added goods after local processing. For processing trade firm, the imported material is duty-free but due to this cost advantage, the firm cannot sell the final product in domestic market. I take Figure 1 from Yu (2015) as an illustration.

Owing to this special tariff treatment, there are mainly three kinds of firms. First, firms don't use any duty free imported input in any of its product at all. This first type can either be an non-exporter or an exporter. If it is an exporter, it is engaged in ordinary trade since it uses domestic inputs or imported inputs with tariff. Second, firms enjoy special tariff treatment in all its products and only export. This type is also called pure processing trade firms. Third, a hybrid firm which participate in both ordinary and processing trade.

As a part of its negotiated WTO entry, the average output tariff gradually reduced from 43.2% in 1992 to 15.3% in 2001 when China entered the WTO. (Brandt

Figure 1: Trade Regime Illustration from Yu (2015)

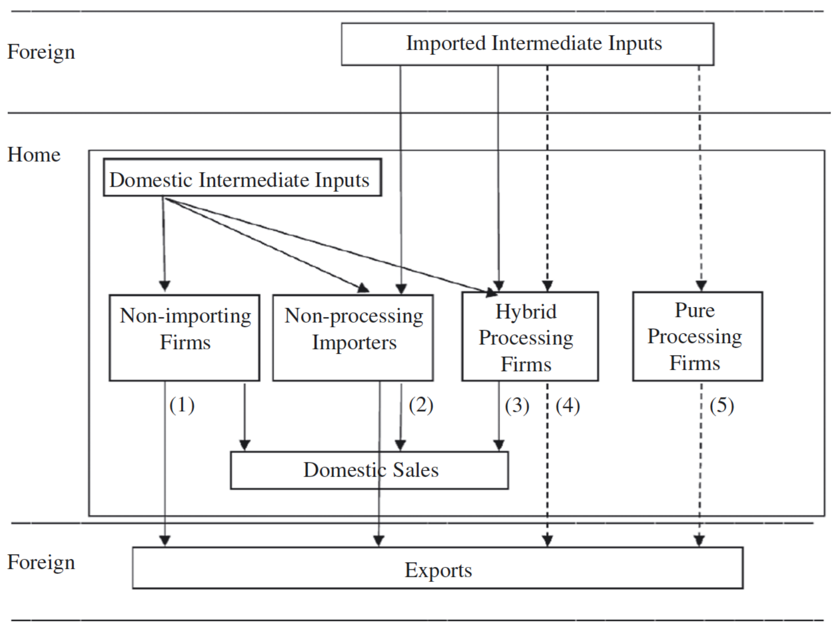
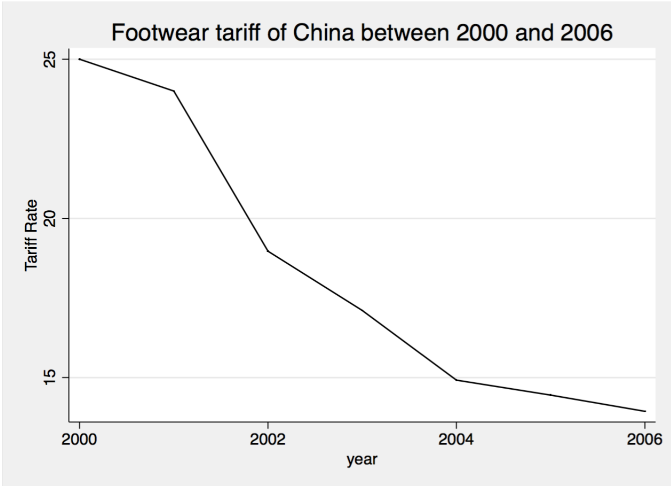


Fig. 3. *Four Types of Chinese Firms*
Note. Dotted lines denote firms' processing imports/exports; solid lines represent firms' non-processing imports/exports.

et al., 2017) The same is happening in the footwear industry as well. As one can see in Figure 2, the output tariff kept decreasing during the sample period. The reduction had a downward pressure on output prices in the domestic market. Research on the impact of tariff reduction on firm performance show that firms benefit not only from pro-competitive environment but also a reduction on input tariff, which gives them access to better intermediate inputs. However, the effect of tariff reduction on imported input would be different from those suggested in existing literature because firms engaging in processing trade are not fully affected by the reduction in import tariff.

To investigate the effect of trade liberalization on firms productivity, I rely on the following three panel data set: the production data, the custom data and the tariff data.

Figure 2: Output Tariff of Footwear Industry of China



Note: The output tariff is calculated using the effectively applied tariff for the footwear industry. (HS-2 digit level with code 64)

2.2 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). My sample covers firms active in the Chinese footwear industry during the period 2000-2006. [2] I adopt the method of constructing real capital, output and input deflator from Brandt et al. (2014) and mainly use the Stata code provided on their website.[3]

There are several well documented concerns using the AMS. First, the sample is subjected to the above-scale sample selection. Though the data contains all

[2]It is due to data availability issue. Details about reasons I choose the time period can be found in supplementary materials.

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

state-owned firms, the footwear industry is mainly private-owned. Therefore, the data cannot be used to study exit behavior. There might also be potential selection bias as small firms appearing in the sample will be particularly productive. Second, 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.

Follow the literature by Brandt et al. (2017), I exclude firms with employees less than 8 people. As I am focusing on the footwear industry, I select firms with CIC code 18 (texile industry), 19 (Leather industry), 29 (Rubber industry) and 30 (Plastic industry). I exclude from my sample firms which are not footwear firms based on their main products provided in the dataset. I also exclude from my sample firms with negative or missing capital, sales and intermediate input information. In addition, I exclude firms with abnormal intermediate input to sales ratio. I delete samples whenever the ratio is smaller than 0.2 or larger than 2 and further delete 334 observations. In Table 1 presents the summary statistics of the key variables I use for production function estimation.

From Table 1, the average revenue is overall increasing during the sample period while the employment level declines. In addition, the average revenue per worker also increases, which can be regarded as a crude measure for productivity, also increased overtime. However, revenue also contains the information of price variation. In the last column, I list the output price index of China. Since it also increases during the sample period, it is hard to tell the dynamics of physical productivity.

Table 1: Summary Statistics of Production Data

Year	Revenue	Capital	Employment	Intermediate inputs	Rev p/w	Price index	No. of Firms
2000	9.955	8.025	5.627	9.752	4.312	0.984	1467
2001	9.842	8.195	5.509	9.651	4.310	0.977	1877
2002	9.870	8.227	5.465	9.683	4.389	0.985	2221
2003	9.992	8.277	5.529	9.761	4.445	0.983	1965
2004	9.893	7.967	5.430	9.605	4.463	1.000	3111
2005	10.019	8.121	5.423	9.696	4.622	1.027	3499
2006	10.217	8.273	5.484	9.897	4.775	1.044	3302

numbers are in log-term. Revenue, Capital and Intermediate inputs are originally measured in 1000 RMB

2.3 Custom Data

I use the Chinese Monthly Customs Transactions from 2000-2006. This is a dataset at the HS 6-digit product level. The dataset contains the price and quantity information of each product for every firm-product-destination combination. The dataset also contains mainly three types of trade regimes for each transaction as I briefly discuss in section 2.1. I collect data with HS-id beginning with 64, indicating the product is traded is in footwear industry. In addition, I exclude all trading company transactions as I cannot match them with ASM dataset.[4] In order to fully investigate the exporting behavior of firms, I match the custom data with the ASM production data to obtain information of exporting destination, trade regime and revenue in each destination.

The major problem of linking trade data with firm level data is that there is no common identifier of the two dataset. Therefore, I use firm name and geographic information to construct a mapping between the two datasets and later use identification ID to link different years together within each dataset.[5] However, such could only provide a lower bound of firms' exporting revenue. 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. Because of this, I cannot identify then in the Custom dataset even though they should be defined as exporters. Therefore, I consider two measures of exporting status. $Exp1 = 1$ is exporters I successfully matched in the Chinese Monthly Customs Transactions dataset. These firms can be regarded as developing export networks on their own. Alternatively, I use export delivery value in the Annual Survey of Manufacturing to construct a second measure of exporting status. $Exp2 = 1$ are firms with a positive export delivery value in addition to firms which I have already defined as exporters in *Exp1*. If a firm has a positive export delivery value but cannot be matched in the Customs Transactions dataset, it is defined as using trading companies to export.

Table 2 summarize the number of firms in my sample and number of exporters based on different measures. In 2004, the Annual Survey of Manufacturing didn't collect export delivery value, so I am using the average export delivery value of

[4]Trading companies(intermediaries) are potentially useful as they provide information about the countries Chinese trading companies are in contact with. But due to the huge data volume, I ignore them in this version of my paper.

[5]detailed information can be found in the appendix of Yu (2015).

that firm in neighboring years as a proxy for the value of that year. As one can see in Table 2, nearly half of the exporting firms were using intermediaries to export in that time. Not including them in the exporting group will lead to an overestimation of firm's domestic sales. So for the rest of the paper analysis, I will define exporters as $Exp2 = 1$ and use *Exp1* to distinguish firms using intermediaries to trade.

Table 2: Number of Firms in the Sample and Export Rate

Year	No. of firms	No. of EXP1	Export Rate 1	No. of EXP2	Export Rate 2
2000	1467	533	36.33%	930	63.39%
2001	1877	605	32.23%	1139	60.68%
2002	2221	711	32.01%	1374	61.86%
2003	1965	668	33.99%	1215	61.83%
2004	3111	982	31.57%	1866	59.98%
2005	3499	1092	31.21%	2117	60.50%
2006	3302	1115	33.77%	2001	60.60%

The export rate is defined as the percentage number of firms exporting in a given period using different measures.

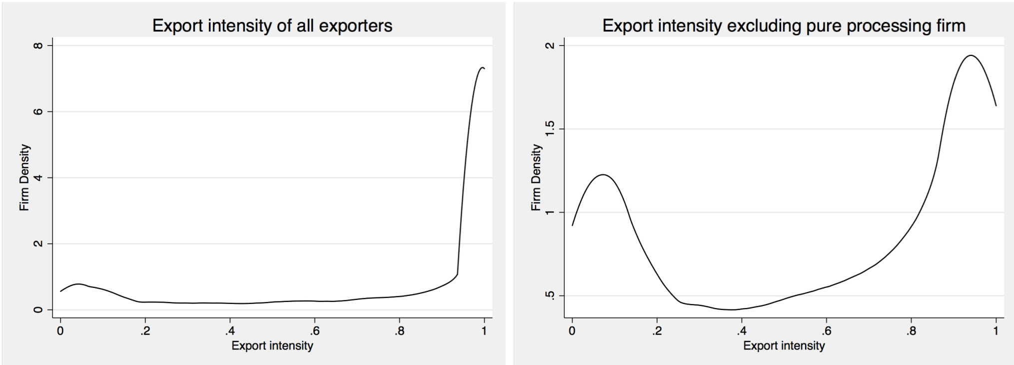
2.4 Trade Data

Trade and tariff data are available on WITS in TRAINS and UN COMTRADE database from 2000-2006 for all footwear at a HS 6-digit disaggregated level. I use the volume adjusted effectively applied tariff as my measurement of the tariff that exporters are facing. In addition, I consider a HS-2 level tariff as a measure of the competitive environment of the footwear industry in a country. The net import value of total footwear product can be found in UN COMTRADE dataset and is used to construct aggregate demand.

2.5 Exporting patterns of Chinese exporters in the footwear industry

Guided by Melitz (2003), exporters are firms initially perform well in the domestic market and due to the opening up, they self selection into exporting market. A direct prediction of the model is that a large proportion of exporters should have a small exporting intensity. Such theory is supported by empirical facts using US and OECD data shown in the Table 2 of Lu (2010). Lu (2010) documented an exporting pattern among Chinese exporters, the exporter intensity is U-shaped, with a large proportion of firms exporting more than 90% of their total production. As one can see in Figure 3 , the U-shaped exporting intensity pattern also applied to the footwear industry in my paper. This observation can partly be explained by the fact that pure processing trade companies are not allowed to sell in domestic market. After excluding the pure processing trade companies, the export intensity of exporters are still U-shaped.

Figure 3: Export Intensity in the Footwear Industry



Note: Export intensity is defined as the proportion of foreign sales of exporters. Left one is the export intensity of all exporters, the right one exclude pure processing trade firms.

According to Yu (2015), low-productivity firms self-select into processing trade possibly to enjoy the special tariff treatment. Therefore, it would potentially lead to a different relationship between productivity and export due to this selection. Before I analysis the performance of pure processing trade firms in detail, I first present in Table 3 the share of numbers and export values of pure processing trade firms in the footwear industry. As one can see, nearly half of the exporting firms are pure processing firms and the share in term of export values is more than half except for 2003. Even though the proportion of pure processing firms is getting smaller over time, the export value of incumbent pure processing firms is getting bigger.

Table 3: Share of number of firms and export value, by processing status

Year	No. of exporting firms	No. of Pure processing firms	No. of other exporting firms	No. of firm share	Export share
2000	930	481	449	51.72%	56.65%
2001	1139	575	564	50.48%	57.92%
2002	1374	685	689	49.85%	56.40%
2003	1215	670	545	55.14%	35.63%
2004	1866	748	1118	40.09%	60.84%
2005	2117	890	1227	42.04%	61.39%
2006	2001	850	1151	42.48%	60.94%

The export share is calculated using the export value of pure processing trade firms in a year divided by the total value exported of exporting firms of that year. Here the number of exporting firms are defined using dexp2.

2.6 How exceptional are exporters?

In order to examine the true productivity exporters and non-exporters, I first perform a preliminary analysis to show whether there are systemic difference between the exporters and non-exporters in the footwear industry of China between 2000-2006. Compared with previous analysis done in the developed economies, the industry is more labor intensive and China was a transition economy. Therefore, the patterns may be different. Following Bernard and Jensen (1999) and De Loecker (2007), I run the following OLS regression:

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

x_{it} refers to the characteristics and performance of firm i at time t. I also include in the firm characteristics, the sales performance of domestic market due to the unique exporting patterns. exp_{it} is a dummy variable indicating whether a firm exports at time t. l_{it} is the log labor of a firm aims to control for the firm size. In addition, I control for category (S) and state(p) fixed effects.

According to Table 4, exporting firms are significantly larger and have higher wages. In addition, the result is robust among different subgroups or using different export status measures. Such finding is consistent with Bernard and Jensen (1999) for the USA, Bernard and Wagner (1997) and De Loecker (2007) and the magnitude is also comparable. When using a more conservative export status measure, exporters uses significant more capital especially for small firms. If I switch to $Exp2$, the difference is no longer significant. The interesting finding comes from domestic performance. Even if I use the conservative measure $Exp1$, exporters' sale in the domestic market are only 8.5% higher than non-exporters. While, their sales as total is 18.7% higher. When I deduct the sales of intermediaries from domestic sales, exporting firms were doing significantly worse in the domestic market.

The last column compares pure processing trade firms with other exporters. Since they don't sell in domestic market, their domestic performance is left as blank. Compared to other exporters, there is no significant difference in employees and wages. However, pure processing firms earn less revenue and use less capital, implying their performance is worse than other exporters. The result[6] confirms that there is a substantial difference between the exporters and

[6]Details of differentials in performances between exporters and non-exporters across time can

non-exporters in terms of firm size and performance. In addition, the systematic performance difference between the exporters and non-exporters in the domestic market called into question of using a common domestic output price deflator to deflate total revenue. Therefore, the question of whether the exporters are truly exceptional in terms of physical productivity is still not clear.

Table 4: Characteristics Differentials for Exporters and Non-exporters

	Exp1		Exp2		Pure processing trade
x_{it}	All Firms	Small Firms	All Firms	Small Firms	All Firms
Employee	0.911***	0.421***	0.741***	0.385***	-0.045
Domestic sales	0.081***	0.067	-1.559***	-1.481***	-
Total sales	0.180***	0.160***	-0.011	0.056*	-0.207***
Capital per worker	0.263***	0.329***	-0.079	-0.021	-0.353***
Average wage	0.174***	0.171***	0.100***	0.124***	0.004
Number of firms	17,442	13,132	17,442	13,132	10,642

x_{it} are log values with appropriate price deflators. The table is presenting β estimates.
Small firms are firms with less than 520 employees.
*** means significant at 1%. ** means significant at 5%. * means significant at 10%.

3 Model

I start out with a model of single product firms with standard Cobb-Douglas production function. In each period, each firm makes export decision. Since firm level quantity data are not observed, to single out the productivity response to trade policies, I introduce a demand system at each destination market into the production framework to purge out the price effect.

Environment:

All firms are located in the home market and produce products belong to one of the four segments (denoted by s): textile, leather, rubber and plastic. In each period, each firm makes export decision of where and how much to export to each of the destination including the home country (denoted by d). This assumption departs from previous exporting models where domestic market is typically assumed as a default choice when firms are self selected into export market. (Aw, Roberts & Xu (2011), Roberts et al. (2017)) Firms are assumed to participate in monopolistic competition in each destination market, which can be rationalized by a wholesaler or retailer at each destination market deciding among different products to import as suggested by Roberts et al.(2017).[7]

be found in appendix section 8.1

[7]This assumption allows me to find the empirical measure of market and related aggregate demand and price index.

Firm side:

Standard Cobb-Douglas production function where a firm i produces a unit of output Q_{it} at time t using labor (L_{it}),intermediate input (M_{it}) and capital (K_{it}). In addition, firm level production also depends on unobserved productivity shock ω_{it} and iid idiosyncratic shock u_{it}:

$$Q_{it} = L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} exp(\omega_{it} + u_{it}) \tag{1}$$

$$Q_{it}^d = Q_{it} C_{it}^d$$

C_{it}^d is Firm i's choice of where and how much to export.

Since every firm is producing one product, $Q_{jt}^d = Q_{it}^d$ and I will use Q_{it}^d for the following analysis.

Since physical quantity (Q_{it}) is typically not observed in most datasets, researchers rely on the measured revenue (R_{it}) and a detailed producer price index (P_t) to eliminate price effect.

$$R_{it}/P_t = L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} exp(\omega_{it} + u_{it})$$

This could potentially bring up two issues. First, firm level input demand is correlated with output price and hence invalidates the estimation of production function coefficients. Second, since trade liberalization would also impact prices, the productivity estimates using a deflated revenue approach would also contain price and demand variations. Therefore, I follow the insight of De Loecker (2011) to construct a demand system to purge out the demand effect.

Demand side:

Following the traditional trade literature, I consider a standard horizontal product differentiation demand system where I allow for different substitution pattern at each destination market(d).

$$max\ U(\{Q_{jt}^d\}_{j=1}^{J^d}) = [\sum_{j=1}^{J^d} {V_{jt}^d}^{1/\eta^d} {Q_{jt}^d}^{(\eta^d-1)/\eta^d)}]^{(\eta^d)/\eta^d-1)}$$

$$\text{s.t. } \sum_j \tilde{P}_{jt}^d Q_{jt}^d = R_t^d$$

Q_{jt}^d the the quantity demanded of good j at time t in destination d. Since each firm is producing one product, I will use Q_{jt}^d for the rest of the paper. Here I assume the elasticity of substitution (η^d) is the same within a given destination.

V_{jt}^d is a product specific demand shifter. $\hat{P_{jt}^d}$ is the price of product j at market d in time t and R_t^d is the total expenditure a representative consumer (the wholesaler) spends on importing foreign footwear products.Solve for this equation, the demand function is:

$$Q_{it}^d = \frac{R_t^d V_{it}^d}{\tilde{P_{it}^d}^{\eta^d} \sum_J (\tilde{P_{it}^d})^{(1-\eta^d)} V_{it}^d} = Q_t^d (\frac{\tilde{P_{it}^d}}{P_t^d})^{-\eta^d} V_{it}^d$$

Q_t^d is the destination specific aggregate level demand shifter which is equal to R_t^d / P_t^d. P_t^d is the price index which is equal to $(\sum_J (\tilde{P_{it}^d})^{(1-\eta^d)} V_{it}^d)^{(1/(1-\eta^d))}$.
I further take log and derive the demand equation for each destination:

$$q_{it}^d = q_t^d - \eta^d (\tilde{p_{it}^d} - p_t^d) + \xi_{it}^d$$

Here $\xi_{it}^d = ln(V_{it}^d)$ and represents the unobserved demand shocks. All lower case variables are logarithm of upper case variables defined before. To convert the price ($\tilde{p_{it}^d}$) firm charges in the destination market to the price (p_{it}^d) firm actually receive in its revenue, I use an ad valorem trade cost as in Roberts et al. (2017) between the home country and each destination, where $\hat{\tau_t^d}$ takes into account shipping cost, possible tariff and exchange rate effects. In addition, I denote $\tau_t^d = -ln(1 + \hat{\tau_t^d})$ for simplicity.

$$\tilde{p_{it}^d} = p_{it}^d + ln(1 + \hat{\tau_t^d})$$

Therefore, the demand equation which reveal the relationship between price and quantity firm i at time t becomes:

$$q_{it}^d = q_t^d - \eta^d (p_{it}^d - \tau_t^d) + \eta^d p_t^d + \xi_{it}^d$$

The revenue of a firm in each destination can be written as:

$$ln(R_{it}^d) = r_{it}^d = \frac{\eta^d - 1}{\eta^d} q_{it}^d + \frac{1}{\eta^d} (q_t^d + \xi_{it}^d) + p_t^d + \tau_t^d$$

Here I deflate the log revenue by the price index of destination d at time $\tilde{r}_{it}^d = r_{it}^d - p_t^d$ and rewrite the relationship among revenue at each destination, which I can observed in data, quantity and demand shifters which are typically not available to researchers.

$$\tilde{r}_{it}^d = \frac{\eta^d - 1}{\eta^d} q_{it}^d + \frac{1}{\eta^d}(q_t^d + \xi_{it}^d) + \tau_t^d$$

Because information used for production function and productivity estimation are only available at firm level. I have to aggregate information in each destination market into my production function framework by summing up the deflated log revenue across all destination a firm sells to in period t:

$$\sum_{d_i} \tilde{r}_{it}^d = \sum_{d_i} \frac{\eta^d - 1}{\eta^d} q_{it}^d + \sum_{d_i} \frac{1}{\eta^d}(q_t^d + \xi_{it}^d) + \sum_{d_i} \tau_t^d$$

Combining the equations above:

$$\tilde{r}_{it} = q_{it} \sum_{d_i} \frac{\eta^d - 1}{\eta^d} + \sum_{d_i} \frac{\eta^d - 1}{\eta^d} c_{it}^d + \sum_{d_i} \frac{1}{\eta^d}(q_t^d + \xi_{it}^d) + \sum_{d_i} \tau_t^d$$

Here $c_{it}^d = ln(C_{it}^d)$ and $\tilde{r}_{it} = \sum_d \tilde{r}_{it}^d$.
Plug in equation (1), the regression equation of interest is:

$$\tilde{r}_{it} = \sum_{d} \frac{\eta^d - 1}{\eta^d} c_{it}^d + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \sum_{d_i} \beta^d q_t^d + \omega_{it}^* + \xi_{it}^* + u_{it}^* \tag{2}$$

$\beta_h = \alpha_h \sum_d \frac{\eta^d - 1}{\eta^d}$ where $h = \{l, m, k\}$, $\beta^d = \frac{1}{\eta^d}$, $\omega_{it}^* = \omega_{it} \sum_{d_i} \frac{\eta^d - 1}{\eta^d}$ and $\xi_{it}^* = \sum_{d_i} \frac{1}{\eta^d} \xi_{it}^d + \sum_{d_i} \tau_t^d$, $u_{it}^* = u_{it} \sum_d \frac{\eta^d - 1}{\eta^d}$.

The coefficients of labor, material and capital are reduced form parameters which also include demand elasticity in each destination. Therefore, the parameters and productivity would typically be scaled up even if we assume no demand heterogeneity. In fact, as firms are exporting to different destination, the revenue could also be affected by the destination demand elasticity η_d and the aggregate demand shifter q_t^d.

4 Estimation and identification

In this section I will discuss the estimation procedure of Equation (2)

$$\tilde{r}_{it} = \sum_{d} \frac{\eta^d - 1}{\eta^d} c_{it}^d + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \sum_{d_i} \beta^d q_t^d + \omega_{it}^* + \xi_{it}^* + u_{it}^*$$

The ultimate goal is to recover the unobserved productivity ω_{it} from the unobserved demand shock ξ_{it}.[8] The firm level unobserved demand should be affected by variation in inputs, the aggregate level demand in each destination market and also trade protection in different market. Since firms in my data export to different countries, the protection rates varies across firms and acts as a firm-specific residual demand shock. Owning to this, I can decompose the unobserved demand shock into four parts following De Locker (2011).

$$\xi_{it} = \xi_{dest} + \xi_s + \xi_t + \tau q r_{it} + \tilde{\xi}_{it} \tag{3}$$

The first three parts take into account the destination, segment and time fixed affect which I use to control for unobserved demand shocks. A potential worry is the systematic difference in technology across destinations. This worry will be eliminated as I will focus on the productivity change across time for an given firm therefore the time invariant productivity difference across destination will be canceled out. In addition, the estimates can be regarded as a conservative measure containing both productivity change and firm's reaction to destinations while I am still able to purge out the price effect.

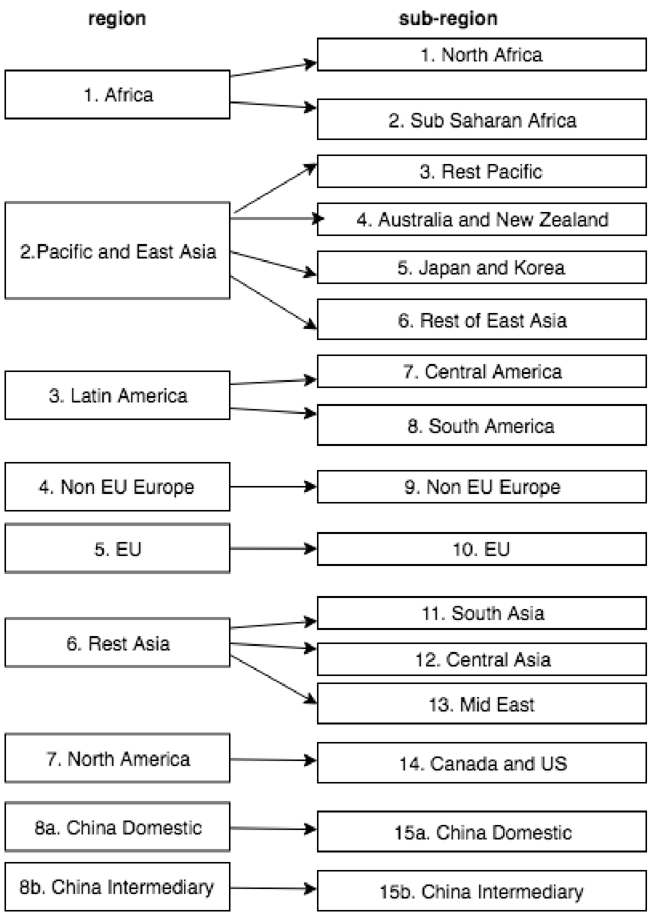
Apart from the domestic market, other market is defined as the import footwear market in each region.[9] Figure 4 is a illustrative graph about the three layer of destinations that I define. The region level is where I define my market and I assume that different regions have different demand elasticity (η_d). The subregion level is where I have different fixed-effect to control for subregional demand differences. Because I can also observe firm's exporting countries, I additionally control for country level fixed effect. The demand elasticity is assumed to be region specific and time invariant, which is a strong assumption. Therefore, I hope to capture the rest difference with the set of time fixed effects. As I mentioned in section 2, nearly half of the exporters are using trading intermediaries to export. I construct a intermediary market to separate its revenue from domestic sales. First, firms using trading companies are different from non-exporters. Second, they face different demand shocks.

Since I don't know the exact quantity of C^d_{it} in each market especially firm's domestic market and intermediary market, I apply the method by De Loecker

[8] the asterisk are used to keep track of the effect of demand elasticity which can be regarded as a scale parameter common across firms exported to the same set of destinations.

[9] For a more detailed discussion about market definition, please refer to appendix section 3

Figure 4: Illustrative Graph about Relation among Region, Subregion and Country



(2011) to use $1/N_{it}$ as a proxy for the unobserved C_{it}^d where N_{it} is the total number of regions a firm sells to, arguing that the tariff protection measure will pick up changes in C_{it}^d due to demand change. Due to the existence of pure processing trade firms, there are firms in my sample which do not sell in domestic market. Table 5 presents the number of destinations including domestic market a firm sell to and the popularity of the destination. Here the destination is defined on a region level.

Except for domestic market and intermediary market, the North America, East Asia and Pacific and EU are top choices for exporters. Distant region like Africa, Latin America account for a smaller proportion. The pattern is similar to Roberts et al. (2017) but different in magnitude as they look at exporters engaged in ordinary trade. One thing to notice is that the proportion is sensitive to

Table 5: Proportion of Firms by Region

Destination	2000	2001	2002	2003	2004	2005	2006
Region1-Africa	0.100	0.093	0.093	0.115	0.129	0.135	0.157
Region2-East Asia and Pacific	0.296	0.250	0.251	0.265	0.241	0.228	0.270
Region3-Latin America	0.124	0.118	0.124	0.125	0.112	0.109	0.127
Region4-Non EU Europe	0.136	0.120	0.123	0.142	0.121	0.125	0.152
Region5-EU	0.177	0.170	0.167	0.185	0.186	0.191	0.219
Region6-Rest of Asia	0.121	0.108	0.110	0.138	0.135	0.130	0.144
Region7-North America	0.252	0.228	0.216	0.234	0.198	0.192	0.214
Region8a-China Domestic	0.672	0.694	0.692	0.659	0.760	0.649	0.651
Region8b-China Intermediary	0.593	0.570	0.581	0.580	0.542	0.566	0.566

region definition. Since I rely on the regional aggregate demand to identify demand elasticities, combining the East Asian and Pacific market together can give me meaningful estimates. That is the reason I am combining these two regions together.

4.1 Constructing firm specific tariff protection

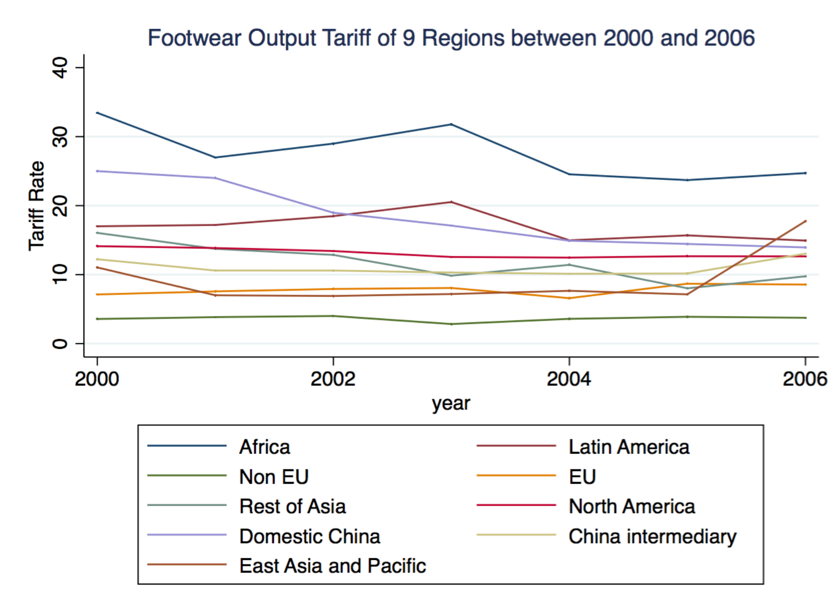
The fourth part in Equation (3) is a composite variable measuring the trade environment a firm is exposed to. The trade protection is measured by tariff level and consists of two parts:

$$qr_t^d = \sum_f a_{ft}^d tarrif_{ft}^d$$

$$qr_{it} = \sum_d \frac{W_{it}^d}{W_{it}} qr_t^d$$

$tarrif_{ft}^d$ is a market's (m) tariff to a partner country (f) at time t in the footwear industry. a_{ft}^d is the weight of country f in market d's total footwear import at time t. Therefore I consider qr_t^d as a measure of market level openness to trade. A higher qr_t^m means higher tariff barrier and thus a less opened market. I will use the volume adjusted effectively applied tariff which is available in TRAINS at the region level for the total footwear to measure qr_t^d. The protection level faced by exporters using intermediaries is a weighted sum of all markets except the domestic market and I use Chinese export share to a specific market in the footwear industry as a weight. The second term measures a firm's specific exposure to export environment where $\frac{W_t^d}{W_{it}}$ takes into account a weighted sum of export.(For the weights I consider both a simple average and a revenue weights.) Finally I

Figure 5: Tariff Protection in Nine Regions across Time



Note: Nine regions are defined in Figure 4. The output tariff is also measure at a HS-2 digit level with code 64.

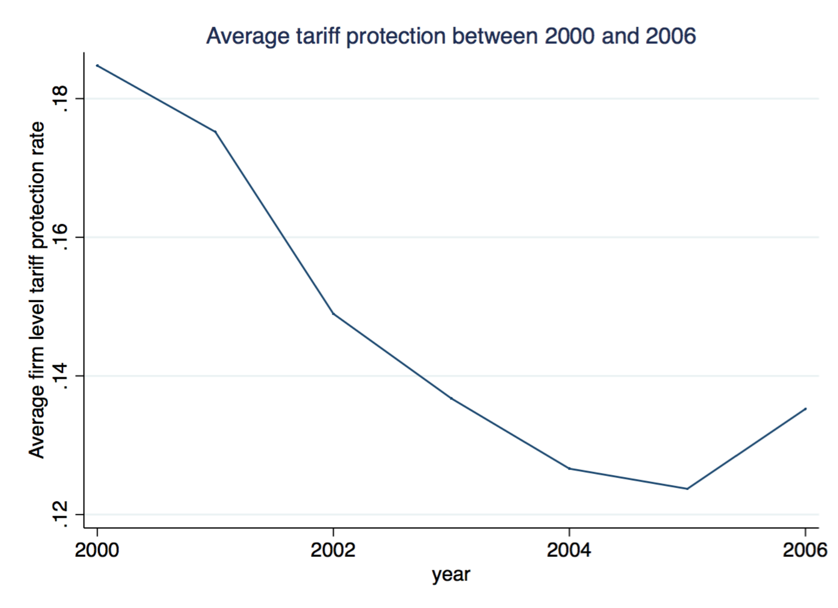
use revenue in each region as the weight because it yields a most reasonable estimates and in addition control for firm's intensive margin decision in allocating final goods when facing different demand shocks.

As we can see from the Figure 5 and Figure 6, firms face highest protection level in African market and lowest protection in Non-EU European market. On average firms face less protection until 2005 and the protection level slightly increases because of the sharp increase in tariff in East Asia and Pacific market.

4.2 Aggregate demand and price index in each destination market

From my definition of market, the empirical measure of price index is the import price index (IPI) at each destination market I collect from CEIC dataset. I use a weighted average of representative countries in each region and make sure the price index follows similar trends. For the Chinese domestic market, I use the

Figure 6: Firm Exposure to Tariff Protection across Time qr_{it}



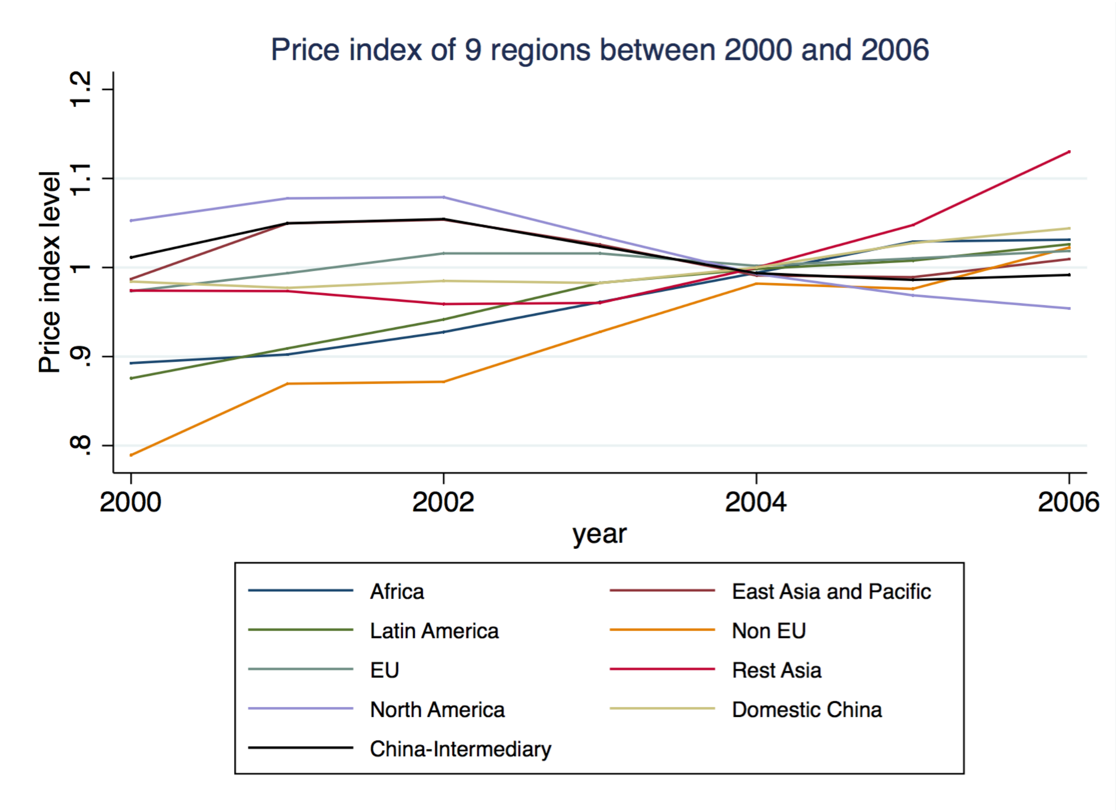
Note: The firm level tariff protection is a weighted average of regional tariff protection where the weight is sales in each region at a particular year.

output deflator calculated in Brandt et al.(2014).[10] Similar to the trade protection level of intermediary market, the price index of the intermediary market is a weighted average of price index in all foreign regions where the weight is Chinese footwear export share in that region. As one can see from the Figure 7, price levels across market are hard to compare because the price index is relative to a base year of the same region. Therefore, it provides across time difference within a region. I would use the regional fixed effect to control for the price difference across regions.

The empirical measure of aggregate demand shifter is the total import of footwear category at each region in each period. The aggregate demand for domestic market is constructed using the total production plus net import in the footwear industry. I use the measure from WITS UN COMTRADE dataset and the group is predefined as in Figure 4. 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 those parameters. The aggregate demand for Chinese intermediary market is defined as a weighted average of all its trading partners' aggregate demand with the same weights as before. In Figure 8 I present the aggregate demand shifters across time. As we

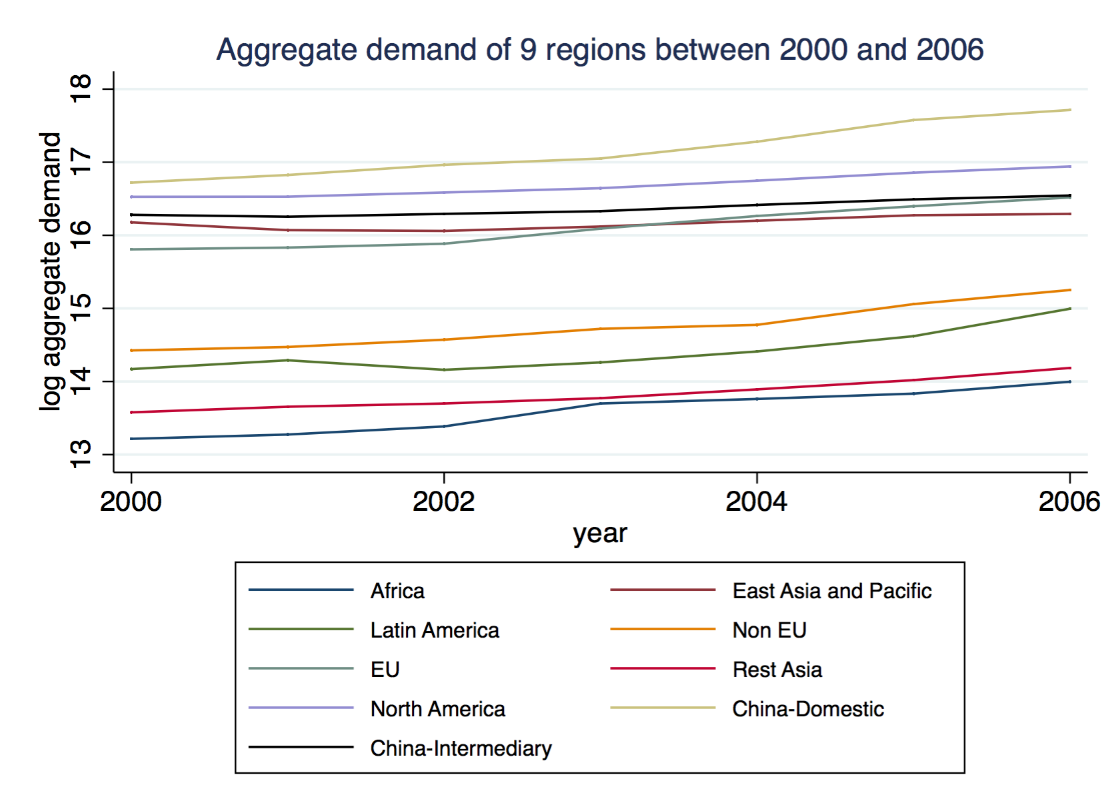
[10] Details of how I construct a price index at each region can be found in supplementary materials section 2

Figure 7: Price Index across Time p_t^d



Note: Price index is an average of Import Price Index in the footwear industry of representative countries in each region. The base year in each country is 2004 and therefore the figure reflects price level compared with price level in 2004.

Figure 8: Aggregate demand shifter across time q_t^d



Note: The aggregate demand shifter is the deflated total import value of footwear industry in each region in each year. The unit is 1000 usd.

can see, China's domestic market has the highest demand, followed by the North America market. Africa market has the lowest aggregate demand. There are substantial differences in aggregate demand and thus would benefit identification of region level price elasticities estimates. In addition, the aggregate demand can be regarded as exogenous as each firm's share is negligible in each region.
Therefore, the main estimation equation of interest is:

$$\tilde{r_{it}} = \beta_{nd} n_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \sum_d \beta^d q_t^d + \omega_{it}^* + \sum_{d \in D(i)} \delta_d D_{id} + \sum_g \delta_g D_{ig} + \sum_t \delta_t D_{it} + \tau q r_{it} + \epsilon_{it} \tag{4}$$

$n_{it} = -ln(N_{it})$ and N_{it} is the number of destinations a firm sell to. $D(i)$ represents the set of subregions and countries. $G(i)$ represent the set of segments.(Leather, textile, rubber and plastic) and $T(i)$ represents the set of time, which are all dummy variables. q_t^d is set to zero when a firm is not observed selling to region d at time t. ϵ_{it} captures all the production and demand side idiosyncratic shocks.

The protection variation (qr_{it}) will affect a firm in two ways. First it will affect the residual demand in the same period. Second it will affect a firm's future productivity through firms' reaction to increased competition by eliminating inefficiencies. Similar to De Loecker (2014), I also add a dummy variable to indicate a firm's exporting experience, allowing the model to detect learning from exporting. Therefore, the law of motion of productivity becomes as follows:

$$\omega_{it} = g_t(\omega_{it-1}, qr_{it-1}, dexp2_{it-1}) + \nu_{it} \tag{5}$$

In practice, I fit a second order polynomial similar to the existing literature.

Given the assumption that a region's tariff change cannot be influenced by an individual firm. I rely on the following moment conditions to identify τ, which measures firm's instantaneous response to tariff change:

$$E(\nu_{it}|qr_{it}) = 0 \tag{6}$$

In addition, the following moment condition holds by construction.

$$E(\nu_{it}|qr_{it-1}) = 0 \tag{7}$$

4.3 Using a static input

To overcome the problem of zero investment in the dataset, I follow the method of Levinsohn and Petrin (2003) by using a static input demand condition to control for unobserved productivity. Following the concern of Ackerberg, Caves, and Frazer (2015) as there is not enough variation to affect labor and material input separately, I don't identify any coefficient in the first stage. Empirically, I use a third order polynomial to get an estimates of $\hat{\phi}_t$ which separates the observed demand shock and unobserved productivity from the unobserved idiosyncratic demand and production shock.[11] In the second stage, I use the law of motion defined in equation (9) and the moment condition in equation (10) to identify parameter of interest.

I follow De Locker (2011) to include subregion and country fixed effect in the nonparametric regression of ω_{it+1} on ω_{it} and qr_{it} $dexp2_{it}$ due to a practical reason.

[11] For more detailed assumption, the input demand equation and the monotonicity condition, one can refer to supplementary material, section 5 and 6

Because I would be solving a non-linear GMM, the estimates would suffer from a curse of dimensionality and would yield very inaccurate estimates. Therefore, in the empirical analysis, I will mainly focus on the changes in productivity for an individual firm due to export and tariff reduction.

$$\omega_{it+1} = \hat{\phi_{t+1}} - \beta_{nd} n_{it} - \beta_l l_{it+1} - \beta_m m_{it+1} - \beta_k k_{it+1} - \sum_d \beta^d q^d_{t+1} - \tau q r_{it+1} - \sum_g \delta_g D_{ig} - \sum_d \delta_t D_{it} \tag{8}$$

$$\nu_{it+1} = \omega_{it+1} - g_{t+1}(\omega_{it}, qr_{it}, dexp2_{it}) \tag{9}$$

Finally, the GMM conditions I am using to identify the parameters are:

$$E = \left\{ \nu_{it+1}(\beta_k, \beta_l, \beta_m, \beta^d, \tau, \delta) \begin{pmatrix} k_{it+1} \\ m_{it} \\ l_{it} \\ q^d_t \\ qr_{it+1} \\ D \end{pmatrix} \right\} = 0 \tag{10}$$

I will follow this two-step approach and use the bootstrap to get right inference. The parameter τ is identified as the tariff is assumed to be exogenous. The parameters β^d are identified under the assumption that the shocks to productivity is not correlated with lagged total output in each destination market.

5 Main Results

In this section I first present my TFP estimates which controls for price effect and compare it with the revenue deflated estimates. Second, I will show effect of tariff reduction on productivity dynamics through my estimates.

5.1 TFP measures and TFP dynamics

As stressed by Bernard et al. (2003), if the markup is positively correlated with physical productivity, then the revenue-based productivity would work well. From my estimates, the markups are measured by the inverse of elasticities in each region (η^d). The markups are not clearly ranked among the regions, therefore it is hard to tell the relationship between markup and true efficiency. For the main result part, I would use the following equation to estimate the productivity residual and plug in the estimates of production function and demand coefficient.[12]

$$\hat{\omega_{it}} = (\hat{\phi_t} - \hat{\beta_l} l_{it} - \hat{\beta_m} m_{it} - \hat{\beta_k} k_{it} - \sum_d \hat{\beta^d} q_t^d - \hat{\tau} qr_{it} - \hat{\delta_g} D_{ig} - \hat{\delta_t} D_{it}) / (\sum_{d_i} \frac{\hat{\eta^d} - 1}{\hat{\eta^d}})$$

While the usual deflated revenue-based productivity is calculated using the Stata package prodest with the following equation

$$\hat{\omega_{it}^{st}} = \hat{\phi_t^{st}} - \hat{\beta_l^{st}} l_{it} - \hat{\beta_m^{st}} m_{it} - \hat{\beta_k^{st}} k_{it}$$

To get the estimated productivity, I plug in the estimates I get from Table 7 and Table 8. I set the parameter to zero if its 90% confidence interval contains zero. Therefore, in the estimates, the coefficient on capital, price elasticity in East Asia and Pacific region, the tariff protection, time fixed effect and the fixed effect of Textile and rubber segments are set to zero.

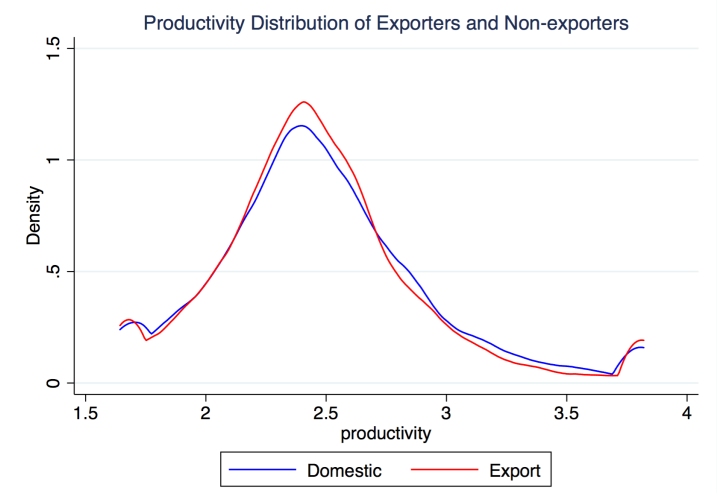
As one can see, due to a dimensionality problem I discussed in section 4, my productivity estimates which controls for price effect contains country and subregion fixed effect. Therefore, there is no direct comparison between my productivity estimates and the revenue-based productivity estimates. However, looking at the productivity distribution within each measure across different groups can still be informative.

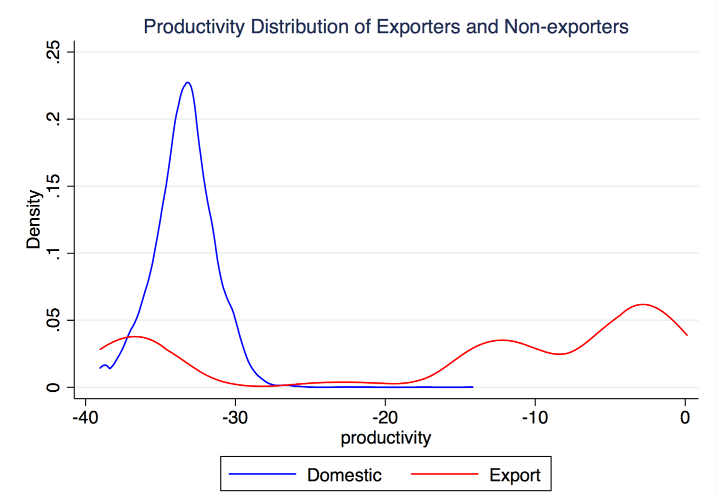
Figure 9 shows the productivity distribution using two measures. Since the productivity is very spread, I present a winsorized productivity distribution to better present the difference across groups. On the top is the revenue-based TPF measure using a common price deflator in my paper is the output price deflator of domestic footwear market. At the bottom is the TFP distribution I in addition control for price effects. I plot three types of groups, exports are those I can find directly in the custom dataset, indicating they establish relationship with foreign buyers to trade. The red line represents firms which use trading companies to trade. Therefore, they don't have to pay additional effort and cost to establish a relationship with foreign buyers or go through registration procedures to export. The black line represents firms which only serves the domestic market.

As one can see, if I use a common deflator, it is impossible to tell the produc-

[12] Details of estimates of production function and elasticities can be found in appendix section 8.2

Figure 9: TFP Distribution for Exporters and Non-exporters Using Two Measures





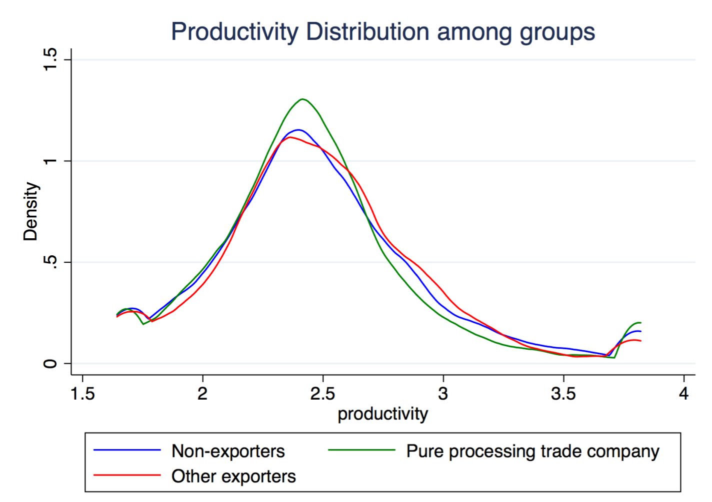
Note: On the top is the revenue-based TPF measure using a common price deflator (output price deflator of domestic footwear market). At the bottom is the TFP distribution I in addition control for price effects. The distribution is winsored to modify the top 2.5% and bottom 2.5% extreme value tivity difference between exporters and non-exporters. However, if I in addition control for price effect, productivity of exporters are more dispersed. There are two direct implications from the productivity estimates when additionally control for price effect. First, compared with non-exporters, the productivity of exporters are in general higher. The empirical finding is partly in line with theoretical model predictions (Melitz, 2003) as exporters who need to pay extra fixed cost to enter a foreign market should have the higher productivity. Second, there is an overlap in productivity between the exporters and non-exporters in the footwear industry.As I briefly mentioned in Section 2, the exporting behavior of Chinese footwear manufacturers would in addition be affected by the special tariff treatment. According to Yu (2015), he built up a model of firms self select into processing trade and verify empirically in China low productivity firms self-select into processing trade. Thus the overlap could be potentially be explained by the existence of processing trade firms.

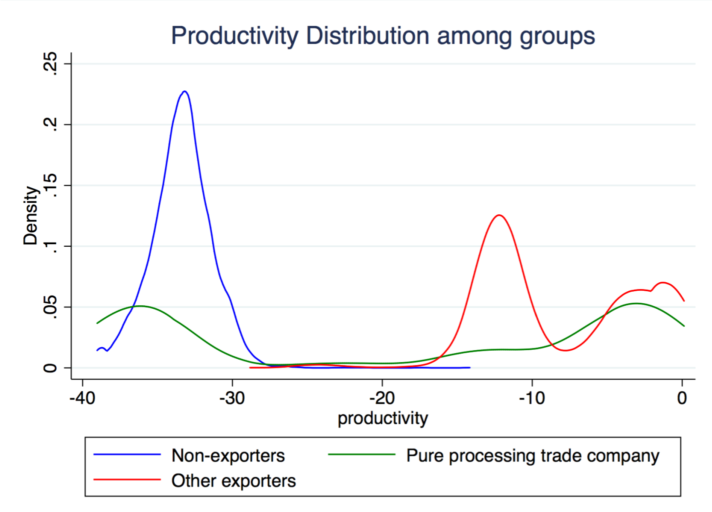
Therefore, I also compare the productivity of those pure processing firms with other firms based on whether they have sales in domestic market, given that a pure processing trade company cannot sell in domestic market. In Figure 10 I further split the exporters to pure processing trade firms and other exporters.
The graph using my new measure shows that the productivity of pure processing firms are very dispersed. Compared with other exporters, the average productivity of the processing trade firms is lower which is consistent with finding by Yu (2015). Except for the fact the pure processing trade firms don't serve the domestic market while 85% of other firms serve the domestic market, the destination of both types are similar.

To test whether the estimates controlling for price effect is robust, I also plot the production distribution between exporters and non-exporters across years. The distribution pattern is very similar to Figure 9. In addition, I also split the exporters by whether it uses intermediary to export. Firms using trading companies don't need to physically enter a foreign market and thus avoid some of the fixed cost, therefore they are different from firms directly export. Among exporters using intermediary, other exporters and non-exporters group, exporters using intermediary have a substantially lower productivity than other exporters while they are still in general more productive than non-exporters. The distribution pattern is very similar across years.[13].

[13]Details can be found in appendix section 8.3

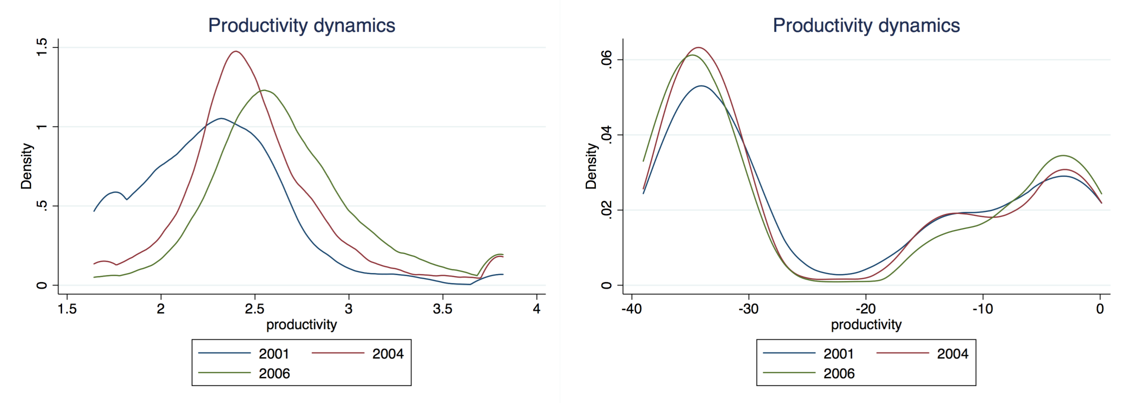
Figure 10: TFP Distributions among Groups Using Two Measures





Note: On the top is the revenue-based TPF measure using a common price deflator. At the bottom is the TFP distribution I in addition control for price effects. The distribution is winsored to modify the top 2.5% and bottom 2.5% extreme value

Figure 11: Productivity Dynamics across Time Using Different Measures



Note: On the left is the revenue-based TPF measure using a common price deflator. On the right is the TFP distribution I in addition control for price effects. The distribution is winsored to modify the top 2.5% and bottom 2.5% extreme value

Next, I will illustrate the industry level and firm level TFP dynamics. Both Figure 5 and Figure 6 indicate firms faces a less protected environment in the global market until 2006. Even in 2006, except for East Asia and Pacific region, most regions still saw a decrease in output tariff. How is the environment affecting the aggregate level physical productivity of the footwear industry as a whole? I pick three preventative years on Figure 11. There is a noticeable shift of the industry TFP distribution to the right if using a revenue-based TFP. However, one may fear the increase would potentially due to the demand effect since in Figure 8, the aggregate demand shifter for all regions rises. When I control for such demand effect, the industry level TFP are very close. Since it is very hard to tell the difference across time, I in addition follow Olley and Pakes (1996) to calculate a weighted industry level productivity by using the following equation, where I use the firm's employment share to calculate s_{it}:

$$\omega_t = \sum s_{it}\omega_{it}$$

The growth rate of aggregate TFP using the two measures seems to fluctuate and most of the time works in opposite directions. With the footwear industry opening up gradually, the selection effect would allocate resources to more profitable firms and thus increase the aggregate productivity. It seems the empirics are at odds with the theory. I further conduct a static decomposition following Olley and Pakes (1996) to check whether such tariff reduction would allocate resources to more productive firms by checking the covariance between employment share and productivity. It moves in the same direction with the weighted productivity. Therefore, it suggests that tariff reduction is not pushing resources to allocate to more productive firms from my estimates. This pattern is also very consistent among the three groups: non-exporters, pure processing trade firms and firms who export by themselves.

Table 6: Aggregate TFP Dynamics

Year	weighted ave TFP2	Growth Rate	unweighted ave TFP2	weighted ave TFP1	Growth Rate	unweighted ave TFP1
2000	-13.193		-19.955	4.161		5.885
2001	-14.659	-0.111	-21.649	3.206	-0.229	2.954
2002	-14.109	0.037	-21.511	2.538	-0.208	2.355
2003	-13.533	0.041	-21.799	2.525	-0.005	2.445
2004	-14.798	-0.093	-22.282	2.960	0.172	2.751
2005	-15.309	-0.035	-23.025	3.042	0.028	3.084
2006	-14.971	0.022	-22.318	2.773	-0.088	2.803

5.2 The effect of trade liberalization on firms' productivity

Brandt et al. (2017) document that during China's accession to WTO, the productivity of incumbents are more responsive to output tariff cut while new entrants are more responsive to input tariff cut. Yu (2015) studying the same period with a focus on processing trade, further documents that the effect of input tariff cut on productivity is weaker for processing trade companies. The consensus is that tariff protection would promote firm level productivity. While China is experiences a decrease in output tariff, for exporters in the footwear industry in China, the reduction of tariff is prevalent across the world and this less protected environment further promote export. Therefore, firms would not only benefit from the input tariff reduction or a pro-competitive environment in home country, but also learning from exporting when opening up to trade. Therefore, I plan to explore the role of different mechanism in a non-parametric estimation.

A standard method to study this problem is a two-stage approach in which productivity is first estimated and then the impact of trade liberalization on productivity is estimated by running the following equation:

$$\hat{\omega}^{st} = c + \lambda q r_{it} + \epsilon_{it} \tag{11}$$

Therefore, in order to get a consistent estimator of λ, protection should be exogenous to the error term. If I use a revenue-deflated productivity estimates, the estimates itself contains price effect. Therefore, the strong assumption is protection is only affecting price through productivity, which is at odd with the pro-competitive mechanism. In addition, as pointed out by De Loecker (2011), such equation just allow for instantaneous respond of tariff reduction to productivity but ignore the productivity evolution of a firm, which would underestimate the impact.

Therefore, I am going to estimate the impact of tariff reduction on the productivity change by estimating a polynomial specification of firm's productivity evolution function.

$$\Delta\omega_{it} = \alpha_0 + \alpha_1\omega_{it-1} + \alpha_2\omega_{it-1}^2 + \alpha_3 qr_{it-1} + \alpha_4 dexp2_{it-1} + \alpha_5\omega_{it-1} * qr_{it-1} + \nu_{it}$$

As one can see, the τ I estimated in Table 8 by adding a demand system is supposed to capture the price change to protection variation and α_3 in the equation above is supposed to capture the productivity response to tariff reduction. I use the difference instead of a level effect because my productivity estimates contains destination fixed effect. If the destination stay fixed during the sample period, it would be canceled out. α_4 is designed to capture the learning by exporting effect.

Table 7: Impact of Tariff Reduction

TFP measure	TFP1	TFP2	TFP2	TFP2
α_1	-1.011	0.318	0.066	0.475
	(0.006)	(0.036)	(0.010)	(0.072)
α_2	0.000	0.008	0.001	0.010
	(0.000)	(0.001)	(0.000)	(0.001)
α_3	-3.752	-36.844	-7.992	-28.788
	(2.275)	(4.862)	(2.167)	(6.135)
α_4	-0.120	1.704	0.384	3.287
	(0.316)	(0.270)	(0.050)	(0.841)

Standard errors are in parentheses
All standard errors are clustered at firm level

Column 1 of Table 7 uses the revenue-based TFP measure. α_1 is the persistence parameter. α_3 which indicates a firm's productivity react to tariff reduction is negative but not significant and there is no learning from exporting. The second column is where I correct for the price effect. If last period's TFP increases, then the difference between the two period would increase. In addition, this method also presents significant productivity increase due to tariff reduction. If the tariff increase by 1%, then the tariff difference will be decreasing by 0.368. Compared with De Loecker (2011), it seems to be a very large number. However, the difference is a level difference instead of a percentage difference as my productivity estimates are negative and I cannot take log. Therefore, the sign rather than the magnitude is more meaningful. In addition, my estimates show there is significant learning by exporting. If a firm export in the previous period, his productivity difference will increase by 1.704.

My productivity estimates contains destination fixed effect. Once a firm switch to a new region, the productivity estimates should also include the change in fixed effects between the two destinations. Even though I control for some of the destination fixed effect through aggregate demand and protection exposure, firms may still match on unobserved demand heterogeneity. Therefore, in column 3 I run a subsample of firms which didn't switch during my sample period and therefore the fixed effects are canceled out across time. As one can see, the magnitude of the impact of tariff reduction is smaller, but it is still negative and significant. In addition, the subsample is still able to detect significant learning from exporting. In column 4, I present the effect on pure processing trade companies. Compared with the full sample, the impact of tariff reduction is smaller which is consistent with findings of Yu (2015) and there is also learning by exporting.

The tariff reduction is in fact exhibits time patterns which could be reflected from the protection exposure. Therefore, I additionally run the protection impact across time to see whether it would match the protection exposure trend. As one can see, α_3 changes with time and is initially smaller than year 2004, 2005 and 2006 when the tariff sharply decreases. Even though the protection seems to pick up in 2006, I assume the tariff reduction would impact productivity with a lag and thus will not affect the productivity evolution. Such pattern cannot be detect using a revenue-deflated productivity estimates.

6 Conclusion

In this paper, I test the method proposed by De Loecker (2011) to overcome the problem of not observing physical quantity in estimating physical productivity for the China footwear industry during the period of 2000-2006. By adding a demand system at each of the nine regions I previously defined, I am able to derive a relation between quantity and price and thus purge out the price effect from revenue-based productivity estimator. With my new estimates, I am able to iden-

Table 8: Impact of Tariff Reduction across Year

Year	2001	2002	2003	2004	2005	2006
α_1	0.338**	0.200	0.179	-0.182	0.801***	0.106
	(0.171)	(0.134)	(0.188)	(0.183)	(0.186)	(0.220)
α_2	0.0103***	0.0102***	0.0121***	0.00128	0.00175	0.00973***
	(0.00249)	(0.00230)	(0.00248)	(0.00193)	(0.00153)	(0.00188)
α_3	-31.24***	-11.22	-21.36	-42.67***	-54.26***	-46.47***
	(11.71)	(9.109)	(15.26)	(14.77)	(16.70)	(17.70)
α_4	2.397	-1.293	-5.460*	0.0488	7.660***	-2.028
	(3.047)	(2.823)	(3.277)	(3.153)	(1.972)	(2.464)
No. of observation	1,332	1,703	1,502	1,583	2,917	3,241

Standard errors are in parentheses
All standard errors are clustered at firm level

tify that exporters on average have higher productivity than non-exporters in the footwear industry. In addition, during the period of opening up and worldwide tariff reduction in the footwear industry, there is significant productivity increase from tariff reduction within firm and exporters witness increase in their productivity once entering the export market.

Due to the existence of processing trade, some Chinese exporters don't serve domestic market in my sample at all. This observation is different from most export models as they typically assume the domestic market as the default option when firms self-select into exporting market. The different selection mechanism would yield different implications on productivity. Therefore, I also evaluate the performance of pure processing trade firms. Compared with other exporters, they are less affected by tariff reduction. In addition, there also exist significant productivity increase when these firms enter the export market. Compared with revenue-based TFP measures, my estimates purge out price effect which is essential in the context of export and I show that these two TFP measures yield very different results both in the productivity distribution and evolution.

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