Processing Trade, Firm Productivity, and Tariff Reductions: Evidence from Chinese Products*

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Abstract

This paper explores how processing trade, jointly with output and input tariff reductions, can improve firm productivity. Output tariff reductions generate productivity gains via competition, whereas input tariff reductions do so by saving firm's cost. More importantly, processing firms enjoy extra gains from processing trade. Using highly disaggregated Chinese product-level trade data and firm-level production data from 2000–2006, after constructing firm-level tariffs based on product information and controlling for possible endogeneity, I find that a 10% output tariff decrease generates a 10% increase in firm productivity gains, which is around twice higher than the productivity gains from cutting input tariffs. The logarithm of productivity of processing firms, on average, is .05 higher than those of non-processing firms.

JEL: F1, L1, O1, O2

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1 Introduction

This paper investigates the influence of processing trade and tariff reductions on Chinese firm productivity. Although the impact of tariff reductions on firm productivity has been widely explored in the literature, relatively little research has focused on the role of processing trade, as a type of trade liberalization on intermediate goods.

Processing trade is a popular trade pattern in many developing countries (especially China, Mexico, and Vietnam). A domestic firm first obtains raw materials or intermediate inputs abroad and after some processing domestically it then exports the value-added final goods. To encourage processing trade, governments usually offer tariff reductions or even tariff exemptions on the processing of intermediate goods. In contrast to output tariff reductions, which could foster firm productivity by inducing tougher import competition, input tariff reductions could generate firm productivity via a variety of cost-saving behavior like learning effects (Amiti and Konings, 2007). In addition, processing trade can introduce high-quality imported intermediate inputs (Helpern *et al.,* 2010). In addition, processing trade also provides more varieties choices to domestic firms as in the love-of-variety story of Krugman (1979). As a result, processing firms usually enjoy more productivity gains than those of non-processing firms. In addition, FIEs have higher productivity possibly due to their superior international technology spillover (Keller and Yeaple, 2009) or less financial constraints (Feenstra *et al.*, 2010).

In the past decade, China's foreign trade has grown dramatically. China has now replaced Germany as the largest exporter in the world. Indeed, the processing exports regime jointly with foreign invested enterprises (FIEs) has become the driving force of China growing exports. China's processing exports has accounted for more than half of its total trade exports since 1995. Simultaneously, the share of total exports by FIEs has also increased dramatically, from around 20% in 1992 to around 60% in 2006. China's foreign direct investment as a share of GDP once climbed to 6% in 1994 before plateauing at 3% (Naughton, 2006). In addition, China obeyed to its World Trade Organization (WTO) commitment after 2001 and has cut tariffs from 18.53% in 2001 to 8.87% in 2006. Finally, China's average annual increase in total factor productivity (TFP) in the last decade has been around 2.7% by estimating a gross output production function (Brandt *et al.*, 2009).

Using highly disaggregated Chinese firm-level production data and product-level trade data, in this paper I unravel the three channels of raising productivity gains from trade liberalization: the import competition effect via output tariff reduction; the cost-saving effect via input tariffs reduction; and the additional productivity gains from processing trade. I then explore the processing firm's heterogeneity on productivity gains across firm types. To the best of my knowledge, this paper is one of the few studies to show the gains from processing trade. These results are found to be robust by using a variety of methodological assessments.

Firstly, I measure firm productivity in two ways. I first calculate firm's TFP by using the Olley and Pakes (1996) approach with some necessary modifications and extensions to fit with China's reality. In this way, I am able to control for the simultaneity bias and selection bias caused by the usual OLS estimates on the Solow residual associated with TFP. Note that one of the important assumptions of the Olley–Pakes approach is that capital is more actively responsive to unobserved productivity. However, one might worry that China is a labor-abundant country and thereby labor costs are relatively low. When facing a productivity shock, China's firms are more likely to adjust their labor input to re-optimize their production behavior. This is consistent with the idea suggested by Blomström and Kokko (1996) that labor embodies more productivity improvements than capital does. Therefore, I adopt the Blundell and Bond (1998) system GMM approach as an alternative way to measure firm's TFP.

Secondly, in this paper China's processing trade is broken down into several specific types, including processing trade with assembly and processing trade with imported materials. I delve into each type to explore the effects of tariff reductions and the particular type of processing trade on firm productivity gains. In addition, the effects differ according to a firm's ownership. FIEs are found to have high productivity whereas state-owned enterprises (SOEs) have low productivity possibly due to the misallocation of factor endowments in China (Hsieh and Klenow, 2009). Interestingly, I also find that FIEs involved in processing trade have lower productivity than those not involved.

Thirdly, I use highly disaggregated micro-level data to perform my estimations. Researchers are usually suspicious of the quality of China's aggregated-level data. Holz (2004) stressed the bias of using China's aggregated data because of the mismatch between disaggregated and aggregated statistical data. Often owing to using Chinese firm productivity data, findings on China's TFP growth are mixed and somewhat controversial. For example, Young (2003) found that China's TFP growth rate was modest and perhaps even negative in the post-Mao era. To avoid the possible aggregations bias caused by using firm productivity data, in this paper I use firm-level production data to obtain a firm's capital, labor, and material intermediate inputs and thereby calculate a firm's TFP. More importantly, based on the information about a firm's product-level import value, I am able to construct a firm-level tariff index to precisely measure a firm's exposure to foreign trade, which is much more accurate than using an industry-level tariff as in many previous studies.

Finally, I adopt the instrumental variable (IV) approach to control for the possible reverse causality of firm productivity growth on import tariffs. After controlling for this endogeneity, I still find robust evidence that a 10% decrease in output (input) tariffs leads to a 9.7%(5.9%) increase in firm productivity gains. In addition, compared to non-processing firms, processing firms enjoy significantly additional productivity gains.

This paper joins the growing literature on the nexus between trade liberalization and productivity. To measure productivity, papers such as Trefler (2004) emphasize labor productivity, although most studies have concentrated on TFP. In the early stage, researchers usually rely on industry-level data to measure TFP. These include, among others, Tybout *et al.* (1991), Levinsohn (1993), Harrison (1994), and Head and Ries (1999). More recent studies, such as Pavcnik (2002) and Amiti and Konings (2007), consider firm productivity by using firm-level data. In line with these works, I am able to take a step forward to explore the nexus between trade liberalization and productivity by using Chinese product-level data.

There have been many studies on trade liberalization and productivity that cover both developed and developing countries. The studies testing data on developed countries, among others, include Bernard and Jensen (2004) for the United States and Trefler (2004) for Canada. But more evidence has been found in developing countries, such as Bustos (2009) for Argentina, Schor (2004) for Brazil, Tybout *et al.* (1991) and Pavcnik (2002) for Chile, Fernandes for Columbia (2007), Harrison (1994) for Cote d'Ivoire, Krishna and Mitra (1998) and Topalova and Khandelwal (2010) for India, Amiti and Konings (2007) for Indonesia, Iscan (1998) for Mexico and Levinsohn (2003) for Turkey.[1]

Relatively few studies have assessed trade liberalization and firm performance for China despite it being the largest developing economy in the world. Jefferson *et al.* (1996) was a pioneering work on China's firm productivity TFP. Koopman *et al.* (2008) investigated how much of Chinese exports really are made in China by modifying the formula of "vertical specification" proposed by Hummels *et*

[1] Some other research like Van Biesebroeck (2005), De Loecker (2007), and Park *et al.* (2010) also explore the nexus between export growth and productiivty improvement.

al. (2001), and reconstructed the input–output tables to assess domestic value-added products. Lu *et al.* (2010) found that Chinese exporters are less productive than non-exporters among foreign affiliates. A recent study by Brandt *et al.* (2009) documented that China's productivity growth is among the highest in the world during 1998-2006 by using the firm-level production dataset which is the same as the present paper.[2] However, very few studies, if any, have systematically explored the impact of trade liberalization on firm productivity in China by using micro-level data. Thus, this paper provides novel evidence to fill in the gaps in the research.

Like almost all other previous works, the measures of various non-tariff barriers are excluded from this analysis because of data unavailability. However, such a limitation does not affect the results in this paper since my aim is not to explore the complete effect of trade liberalization. Instead, my main interests are to explore how processing trade, the new element of trade liberalization in China, as well as output tariff and input tariff reductions affect firm productivity.

The rest of the paper is organized as follows. Section 2 introduces the econometric method. Section 3 describes data used in this paper. The main estimation results and sensitivity analysis are discussed in Section 4. Finally, Section 5 concludes.

2 The Econometric Methodology

In this section, I first introduce how to precisely measure TFP, followed by an empirical investigation of the effect of trade liberalization on productivity.

2.1 Measures of TFP

The literature on TFP usually suggests using a Cobb–Douglas production function to introduce technology improvement.[3] Following Amiti and Konings (2007), I consider a form as follows:

$$Y_{it} = \pi_{it}(\tau_{it}) M_{it}^{\beta_m} K_{it}^{\beta_k} L_{it}^{\beta_l}, \tag{1}$$

where Y_{it}, M_{it}, K_{it}, L_{it} is firm i's output, materials, capital, and labor at year t, respectively. Firm i's productivity, π_{it}, is affected by tariffs that it faced, τ_{it}, in year t. To measure firm's TFP, one needs

[2] In addition, Feenstra *et al.* (2010) ascertained that Chinese firms' credit constraints affect its exports. Fernandes and Tang (2010) instead explore Chinese firms' different ownship and control rights accoss pure-assembly firms and import-and-assembly firms.

[3] An alternative specification would be to use a trans-log production function, which also leads to similar estimation results.

to estimate (1) by taking a log function first:

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_k \ln K_{it} + \beta_l \ln L_{it} + \epsilon_{it}, \tag{2}$$

Traditionally, TFP is measured by the estimated Solow residual between the true data on output and its fitted value, $\ln \hat{Y}_{it}$. That is:

$$TFP_{it} = \ln Y_{it} - \ln \hat{Y}_{it}. \tag{3}$$

However, this approach suffers from two problems: simultaneity bias and selection bias. As first suggested by Marschak and Andrews (1944), at least some parts of TFP changes could be observed by the firm early enough for it to change its input decision to maximize profit. Thus, the firm's TFP could have reverse endogeneity in its input factors. The lack of such a consideration would make the firm's maximized choice biased. In addition, the firm's dynamic behavior also introduces selection bias. With international competition, firms with low productivity would die and exit the market, whereas those with high productivity remain (Krugman, 1979, Melitz, 2003). In a panel dataset, the firms observed are those that have already survived. By contrast, firms with low productivity that collapsed and exited the market are excluded from the dataset. This means that the samples covered in the regression are not randomly selected, which in turn causes estimation bias.

Olley and Pakes (1996) provided an econometric methodology to deal with both the simultaneity bias and selection bias in measured TFP. Since then, many researchers such as De Loecker (2007), Amiti and Konings (2007), and Keller and Yeaple (2009) among others have modified and tailored their approaches to calculating TFP. Here, I adopt the Olley–Pakes approach to estimating and calculating a firm's TFP with some extensions.

Firstly and most importantly, I use deflated prices at firm productivity level to measure TFP. Previous works such as Felipe *et al.* (2004) stressed the estimation bias of using monetary terms to measure output when estimating the production function. In that way, one actually estimates an accounting identity.[4] Hence, I first adopt different price deflators for inputs and outputs. Data on input deflators and output deflators are directly from Brandt *et al.* (2009) in which the output deflators are constructed using "reference price" information from *China's Statistical Yearbooks* whereas input

[4] To gain a precise measure of TFP, ideally one should rely on product-specific prices to calculate the "*physical productivity*" (Foster *et al.* 2007). However, as many other studies, the prices of all of a firm's products are unavailable in my data. As a compromise, I use the industrial price to deflate the firm's output.

deflators are constructed based on output deflators and China's national input-output table (2002).[5]

Secondly, I take China's WTO accession in 2001 into account since such a positive demand shock would push Chinese firms to expand their economic scales, which in turn can exaggerate the simultaneous bias of their measured TFP.

Thirdly, it is essential to construct the real investment variable when using the Olley-Pakes (1996) approach. As usual, I adopt the perpetual inventory method to investigate the law of motion for real capital and real investment. Different from assigning an arbitrary number for the depreciation ratio, I use the exact firm's real depreciation provided by the Chinese firm-level data set.

Finally, I also consider firm's processing behavior in the TFP realization by constructing two dummies variables–an export dummy (one denotes export and zero otherwise) and an import dummy (one denotes import and zero otherwise). The idea is that both exporting behavior and importing behavior of a processing firm may affect its production maximization problem. The detailed estimation procedure can be checked out from Appendix A.

As discussed above, the augmented Olley–Pakes approach assumes that capital responded to the unobserved productivity shock with a Markov process whereas other input factors do so without any dynamic effects. However, labor may be correlated with unobserved productivity shock as well (Ackerberg *et al.*, 2006). This consideration may fit with China's case more closely given that China is a labor abundant country. When facing an unobserved productivity shock, firms might prefer adjusting their labor to re-optimize their production behavior rather than capital. I then use the Blundell–Bond (1998) system GMM approach to capture the dynamic effects of other input factors. By assuming that the unobserved productivity shock depends on firm's previous period realizations, the system GMM approach models TFP to be affected by all types of a firm's inputs in both current and past realizations.[6] In particular, this model has a dynamic representation as follows:

$$\begin{aligned} \ln y_{it} &= \gamma_1 \ln L_{it} + \gamma_2 \ln L_{i,t-1} + \gamma_3 \ln K_{it} + \gamma_4 \ln K_{i,t-1} + \gamma_5 \ln M_{it} \\ &\quad + \gamma_6 \ln M_{i,t-1} + \gamma_7 \ln y_{i,t-1} + \varsigma_i + \zeta_t + \omega_{it}, \end{aligned} \tag{4}$$

[5] Such data can be accessed from http://www.econ.kuleuven.be/public/N07057/CHINA/appendix/.

[6] Note that first-difference GMM introduced by Arellano and Bond (1991) also allows a firm's output to depend on its past realization. However, such an approach would lose the instruments for the factor inputs because the lag of output and factor inputs are correlated with past error shocks and the autoregressive error term. By contrast, by assuming that the first difference of instrumented variables is uncorrelated with the fixed effects, the system GMM approach can introduce more instruments and thereby dramatically improve efficiency.

where ς_i is firm i's fixed effect and ζ_t is year-specific fixed effect. The idiosyncratic term ω_{it} is serially un-correlated if there is no measurement error.[7] One can obtain consistent estimates of the coefficients in (12) by using a system GMM approach. The idea is that labor and material inputs are not taken as exogenously given. Instead they are allowed to be changed over time as capital grows. Although the system GMM approach still faces a technical challenge to control for the selection bias when a firm exits, it is still worthwhile using it to estimate a firm's TFP as a robustness check.

2.2 Estimation Framework

In this section, I consider an empirical framework as follows:

$$TFP_{it}^{OP} = \alpha_0 + \alpha_1 OT_{it} + \alpha_2 IT_{it} + \alpha_3 PE_{it} + \boldsymbol{\theta}\mathbf{X}_{it} + \varpi_i + \eta_t + \mu_{it,} \tag{5}$$

where TFP_{it}^{OP} is firm i's Olley-Pakes type TFP in year t whereas OT_{it} (IT_{it}) denotes firm i's weighted tariff on its final (input) goods in year t[8]. PE_{it} is a dummy of a processing firm to measure whether or not firm i is involved in processing trade in year t.[9] Here α_1 measures the import competition effect from output tariff reductions and thereby is expected to be negative. α_2 measures the cost-saving effect from input tariff reductions. The declining input tariffs serve as cost reduction for importing firms which in turn would help them improve their productivity. In addition, α_3 measures the possible gains from processing trade. $\mathbf{X}_{it}$ denotes other control variables for firm i in year t such as its markup, firm productivity markup, Herfindahl index, logarithm of firm's capital-labor ratio, and its type of ownership. Traditional wisdom believes that SOEs have a relatively low economic efficiency and thereby lower productivity. By contrast, FIEs have higher productivity due in part to their superior international technology spillover (Keller and Yeaple, 2009) or less financial constraints (Feenstra *et al.*, 2010). Therefore, I construct two dummies to measure the roles of SOEs and FIEs.

Furthermore, if firms in less concentrated sectors have weaker monopolistic power to charge a higher markup, they would exert every effort to improve their efficiency and thereby chances of survival. To ascertain that tariff reductions do not just pick up the residual competition effect in initially lesser concentrated industries, I include the three following control variables with a one-year lag to isolate

[7] As discussed by Blundell and Bond (1998), even if there is a transient measurement error in some of the series (*i.e.*, ω_{it}~$MA(1)$), the system GMM approach can still reach consistent estimates of the coefficients in (6).

[8] I will carefully introduce how to construct such a weight.

[9] As introduced before, there are many types of processing trade. Here, a processing firm is defined as a firm that involves *any* type of processing of imports/exports.

any possible side effects: (1) a firm's markup, defined as the firm's sales over its sales minus profits as in Nickell (1996) and Keller and Yeaple (2009); (2) firm productivity markup, which is identical to a firm's markup except in each Harmonized System (HS) two-digit sector; and (3) a Herfindahl concentration index, which is the sum of the squared market share at the HS two-digit level.

Finally, I add logarithm of a firm's capital/labor ratio, into my estimations to control for the effect of firm's size on TFP realization. The error term is divided into three components: (1) firm-specific fixed effects ϖ_i to control for time-invariant factors such as a firm's location; (2) year-specific fixed effects η_t to control for firm-invariant factors such as Chinese *RMB* appreciation; and (3) an idiosyncratic effect μ_{ijt} with normal distribution $\mu_{ijt} \sim N(0, \sigma_{ij}^2)$ to control for other unspecified factors.

3 Data

To investigate the impact of trade liberalization on firm productivity, in this paper I rely on the following three highly disaggregated large panel dataset: tariffs data, firm-level production data, and product-level trade data.

3.1 Firm-Level Production Data

The sample used in this paper comes from a rich firm-level panel dataset that covers around $162,885$ firms in 2000 to $301,961$ firms in 2006. The data are collected and maintained by China's National Bureau of Statistics in an annual survey of manufacturing enterprises. It contains complete information on the three major accounting statements (*i.e.*, balance sheet, profit & loss account, and cash flow statement). Briefly, it covers two types of manufacturing firms – all SOEs and non-SOEs whose annual sales are more than five million *RMB* (or equivalently, $ 750 thousand).[10] The dataset includes more than 100 financial variables listed in the main accounting statements of all these firms.[11]

Although this dataset contains rich information, some samples are noisy and thereby misleading, largely because of mis-reporting by some firms.[12] Following Jefferson *et al.* (2008), I clean the sample and omit outliers by using the following criteria. First, observations whose key financial variables (such

[10] Indeed, aggregated data on the industrial sector in the annual *China's Statistical Yearbook* by the Natural Bureau of Statistics are compiled from this dataset.

[11] Holz (2004) offers careful scrutiny on the possible measurement problems when using Chinese data, especially at the aggregated level.

[12] For example, information on some family-based firms, which usually have no formal accounting system in place, is based on a unit of one Yuan, whereas the official requirement is a unit of 1000 *RMB*.

as total assets, net value of fixed assets, sales, and gross value of firm productivity output) are missing were dropped. Secondly, the number of employees hired for a firm had to be no less than 10 people.[13]

Following Cai and Liu (2009) and Feenstra *et al.* (2010), I delete observations according to the basic rules of Generally Accepted Accounting Principles if any of the following are true: (1) liquid assets are higher than total assets; (2) total fixed assets are larger than total assets; (3) the net value of fixed assets is larger than total assets; (4) the firm's identification number is missing; or (5) there is an invalid established time (*e.g.*, the opening month is later than December or earlier than January).

3.2 Product-Level Trade Data

The extremely disaggregated product-level trade data was obtained from China's General Administration of Customs. It records a variety of useful information for each trading firm's product list including their trading price, quantity and thereby value at the HS eight-digit level. The number of trade transactions in each year is reported in the first row of Panel A in Table 1. Equally importantly, this rich dataset not only includes both import and export data but also breaks down to many specific types of processing trade.

[Insert Table 1 Here]

China's processing trade has accounted for more than 50% of total trade volume since 1995. Although it covers around 16 specific types of processing trade in China according to the reports by the General Administration of Customs, two of them are more important: processing exports with assembly and processing exports with imported materials.[14] For the first type, a domestic Chinese firm obtains raw materials and parts from its foreign trading partners *without* payment. However, after some domestic processes, the firm has to sell its products to a designated firm. By contrast, for processing exports with imported materials, a domestic Chinese firm imports raw materials from abroad. With some domestic processes, it can then sell its final goods elsewhere abroad. The first type was more popular in the 1980s since most Chinese firms lacked the capital to be able to import. The second type has become more popular in China since the 1990s.

[13] Levinsohn and Petrin (2003) suggest covering all Chilean plants with at least 10 workers. Here, we follow their criterion.

[14] Other types of processing trade include, among others, foreign aid (code: 12), compensation trade (13), goods on consignment (16), good on lease (17), border trade (19), contracting projects (20), outward processing (22), barter trade (30), customs warehouse trade (33), and entrepôt trade by bonded area (34).

Table 2 reports a simple statistical summary for Chinese product-level trade data by shipment and year. Overall, when focusing on highly disaggregated HS eight-digit level, around 40% of the 17,170,641 observations are ordinary trade, whose exports account for 24% of China's total exports during 2000–2006. This suggests that the average trade volume of ordinary trade is less than that of processing trade. Within the remaining 60% of observations of processing trade, around 9%, which account for 11% of China's total export shares, are processing assembly (code: 14).

China has not separately reported processing exports with imported materials after its accession to the WTO in 2001 in this dataset. This type is classified into other types of processing trade (code: 99), which account for more than 55% of total trade volume. However, even though processing with imported materials only have two-year observations, it still accounts for another 10% of total trade volume. To precisely measure the difference between the two, I focus on their differences in these two-year observations (*i.e.*, 2000 and 2001). Finally, Table 2 shows that China's total trade volume has increased over the years with the exception of 2006, largely because of the RMB revaluation in 2005 (Yu, 2009).

[Insert Table 2 Here]

3.3 Measures of Tariffs

Tariffs data can be accessed directly from the WTO.[15] China's tariffs data are available at the HS six-digit disaggregated level for the period 2000–2007.[16] Given that the product-level trade data are at the HS eight-digit level. I first merge the tariff dataset into the product-level trade data. Since my interest is to measure the average effect of trade liberalization on firm productivity, I use average *Ad Valorem* duty to measure trade liberalization.

Table 3 reports the clustered HS two-digit *Ad Valorem* duty (v) from 2000-2006. Of the 15 clustered categories, textiles and garments (code: 50–63) have the highest average import tariffs followed by footwear and headgear (64–67). By contrast, mineral products (25–27) and machinery and electrical products (84–85) have relatively low import tariffs.

[Insert Table 3 Here]

[15] source of the data: http://tariffdata.wto.org/ReportersAndProducts.aspx.

[16] There are no data from 2000, but data from 1996 and 1997 are available. As reported in *Customs Import & Export Tariff of the P.R. C.* (various years), China did not experience dramatic tariff reductions between 1997 and 2000, I hence have used the 1997 tariffs to serve as a proxy of those in 2000.

Since the main interest of this paper is to explore the effect of tariffs on firm productivity, it is important to properly measure the tariff level faced by firms given that each might import multiple products. To consider how important of a product for a firm, ideally one would use the domestic value of each product produced by a firm. Unfortunately, I do not have such data. However, according to Melitz (2003), a high productivity firm is not only able to sell its products domestically but also exports them. If so, a product would be sold domestically if it is sold aboard. By assuming that a product is sold domestically and abroad at the same proportion, I use each product's export value to construct a weighted output tariff index (OT_{ijt}) for firm i in industry j at year t as follows:

$$OT_{ijt} = \sum\nolimits_k \left(\frac{X_{ijt}^k}{\sum_k X_{ijt}^k}\right)\upsilon_{jt}^k,$$

where the ratio in the parenthesis measures the weight of product k based on its export value (X).[17]

By clustering the HS two-digit industries into the 15 categories as above, I then also report a firm's average duty in Table 3. One can observe that both industry-level and firm-level tariffs have declined over the years. Within each category, the average firm-level duty is smaller than the average product-level duty. The economic rationale behind this observation is that firms have high weights on products with low tariffs. One possible reason is that, when facing tougher import competition for a product (*i.e.*, a lower import tariff), firms exert every best to improve its quality, which in turn results in a higher unit price and higher value. As a result, the weight increases and thereby the value of their products.[18]

In addition, I also construct an industrial input tariff index as follows:

$$IT_{jt} = \frac{1}{K} \sum_{\substack{k\in\Theta \\ k\notin\Theta\cap\Lambda}} \upsilon_{jt}^k,$$

where K is number of products in industry j, Θ is the set of importing goods, and Λ is the set of exporting goods. To calculate the input tariffs, one possible way is to use information from input-output table (Amiti and Konings, 2007). Ideally, this approach requires that the input-output coefficients for all industries must vary by year. However, China does not compile its annual input-output tables. The

[17] However, a caveat exists: due to data restriction, for those products only sold in domestically, I am not able to calculate their weights by this approach.

[18] Note that firm-level average duties in industries such as animals (01–05), vegetables (06–15), and food (16–24) are much lower than product-level average duties. However, my estimations do not cover these agricultural sectors given that firm-level production datasets only cover manufacturing firms.

most recent available one is year 2002. To detour this empirical challenge, I consider an alternative way to construct the input tariff. Specifically, if good k in industry j is importable (*i.e.*, $k \in \Theta$) but not exportable (*i.e.*, $k \notin \Theta \cap \Lambda$), then such a good is classified as intermediate good and hence the tariff imposed on such a good is counted as input tariff. This idea, once again, is follow the result of Melitz (2003) that the exporting goods must also be sold domestically.

3.4 Data Manipulation and Measures

As introduced above, firm-level production data is crucial to measure firm's TFP whereas product-level trade transaction data is non-substitutable to identify a processing firm. However, researchers immediately face practical difficulties when combining the two data sets. Although they share a common variable (*i.e.*, the firm's identification number), the coding system in each is different. In particular, the firm's codes in the product-level trade data are at an 10-digit level, whereas those in the firm-level production data are at a nine-digit level with no common elements inside. Without a common variable, the two separate data sets cannot work together.

To fix this problem, I rely on two other common variables to identify firms: zip code and the last seven digits of a firm's phone number.[19] The rationale is that firms should have different and unique phone numbers within a postal district. Although the method seems straightforward, there remain some subtle technical and practical difficulties. Appendix B describes the detailed technique and procedure for measuring such dataset.

Table 1 clearly demonstrates that each firm trades multiple products with their trading partners. Noteworthy, more than 60 million *monthly* transaction during 2000-2006 are traded by only $654,352$ firms. By using both zip code and phone number to identify firms, I then omit observations if any of the following are true of the data: (1) missing zip code or phone number; (2) invalid zip code (*i.e.*, number less than 100,000); or (3) invalid seven-digit phone number (*i.e.*, number less than 1,000,000). After this rigorous filter, there are 218,024 valid firms remaining between 2000 and 2006, which account for 34% of the 640,352 trading firms in the sample. Turning to the firm-level production dataset, after deleting observations with invalid zip codes or phone numbers, this number reduces to 973,207. Following the same filtering process as before, I then obtain 433,273 firms over the same period, which

[19] An alternative way is to use firm's Chinese name as the identifier. In this way, however, more than 85% observations would be lost since the Chinese characters for a particular firm are not exactly identical in the two datasets.

account for 44.5% of the 973,207 production firms in the sample.

I then merge the dataset of both the product-level trade data and firm-level production data. I obtain 31,393 common trading firms together, which accounts for only around 15% of the valid firms in the product-level trade dataset and around 8% of the valid firms in firm-level production dataset. This observation indicates two important phenomena about China's exporting distribution.

First, exporting firms in the sample, on average, export more than those out of the sample. The remaining 8% of large firms (4.8% exporting firms and 3.2% importing firms[20]), implies that more than 90% of large firms do not trade internationally. Such an exporting proportion might have an underestimation bias because of missing information on the two identifiers in the sample. Feenstra *et al.* (2010) found that around 27% of all large (or "above scale") firms exported in 2000–2007. By dropping observations in 2007, I find that the proportion of large exporting firms is stable (around 24% over 2000–2006). However, although my sample includes only around 21% of large exporting firms[21], their total export volumes still account for more than 45% of total exports for all large exporting firms in China.

Secondly, most trading firms in China are small. As suggested by data from the General Administration of Customs, during 2000–2006 there were 218,024 trading firms but only 31,393 of them were large. That is, more than 85% of trading firms were below the "scale level" (*i.e.*, annual sales of less than 5 million RMB or around $730,000).[22]

Finally, Table 1 also offers information on merging a firm's entry and exit during 2000–2006. Clearly, more firms entered than exited before the *RMB* revaluations in 2005 and a reverse trend occurred after that.

3.5 Statistical Summary

Table 4 summarizes the estimates of the Olley–Pakes input elasticity of Chinese plants at the HS two-digit level. I first cluster the 97 HS two-digit industries into 15 categories and calculate their estimated probabilities and input elasticities. The estimated firm's survival probability in the next year varies from .977 to .996 with a mean of .994, which suggests that firm exits were less severe in the sample

[20] Note that a firm could be involved with processing trade with both exporting and importing behavior. Here, exporting firms simply work with a firm with exporting activities, if any. Similarly, importing firms merely indicate a firm with any importing activities.

[21] That is, 4.8%/24%=21%.

[22] Note that the firm-level production dataset also includes small and medium-sized SOEs.

during this period.[23]

[Insert Table 4 Here]

Table 4 then presents the difference of the estimated coefficients for labor, materials, and capital by using both the Olley–Pakes methodology and the system GMM approach. The last row of Table 4 suggests that, on average, the Olley–Pakes approach has a higher elasticity of capital ($\alpha_k^{OP} = .117, \alpha_k^{GMM} = .001$), whereas the system GMM approach has a higher elasticity of labor ($\alpha_l^{OP} = .052, \alpha_l^{GMM} = .240$). Summarizing all the estimated elasticities, the implied scale elasticities are .989 by using the Olley–Pakes approach,[24] which is close to the constant returns-to-scale elasticities.[25] Turning to the comparison between the OLS and Olley–Pakes approaches, the estimates suggest that the usual OLS approach has a downward bias ($TFP^{OLS} = .958; TFP^{OP} = 1.188$) largely because of the lack of control for simultaneity bias and selection bias.

Finally, for a cross-country comparison of Olley–Pakes estimates, my estimation results suggest that the intermediate inputs (*i.e.*, materials) for Chinese firms are more important than those for American firms estimated by Keller and Yeaple (2009), or for Indonesian firms estimated by Amiti and Konings (2007), but the elasticity of capital input is less important than its counterparts in the US or Indonesia. This implies that processing trade indeed plays a significant role in China's productivity growth, which will be explored in detail shortly.

Table 5 reports the statistical summary of some key variables for estimations. By using product's export share within a firm ($X_{ijt}^k / \sum_k X_{ijt}^k$) as the product's duty weight, firm's output tariff has a mean of 4.44. By way of comparison, the average industrial input tariff is relatively small with the mean of 2.19. As introduced above, FIEs are associated with high productivity and SOEs with low productivity *ceteris paribus*. The firm-level production dataset offers information on a firm's ownership type. I then construct a dummy for foreign-invested firms (FIE_{it}) if the firm has any investment which obtained from other countries (regimes). Given the fact that many inflow foreign investments are from Hong

[23] Note that here firm exits mean a firm either stopped trading and exited the market or simply had an annual sales figure that was lower than the "large scale" amount (*i.e.*, 5 million sales per year) and dropped from the dataset. Owing to the restriction of the dataset, I am not able to distinguish the difference between the two.

[24] Calculated as $.052 + .820 + .117 = .989$ by using the Olley-Pakes approach.

[25] Note that here I use the industrial deflator as a proxy of a firm's price. Indeed, it is even possible that Chinese firms might exhibit the increasing returns-to-scales property in the new century if using the firm's actual prices to calculate the "physical" productivity. This is a future research topic provided that such data are available.

Kong/Macao/Taiwan (H/M/T), I therefore take such investment into account when constructing the dummy.[26] As shown in the bottom module of Table 5, around two-thirds of trading firms are classified as FIEs by the broad definition. At first glance, these ratios are much higher than their counterparts (around 10%) reported in other studies. For example, Feenstra *et al.* (2010) found around 10% of FIEs within the whole "above scale" firms for 2000–2007. However, this is simply because firms covered in the present paper are "above scale" trading firms only. Those non-trading "above scale" firms have been excluded accordingly.

Similarly, the dummy for SOEs is one if a firm has any investment from the government and its operation scales are larger than the "above scale" threshold, and zero otherwise.[27] To avoid missing the role of small and medium-sized firms, I also include SOEs with annual sales lower than 5 million RMB to construct a broad definition of SOEs as well. Around 2% of large trading firms in the sample are SOEs.

[Insert Table 5 Here]

4 Empirical Results

4.1 Benchmark Results

As shown in Figure 1, an avereage of firm-level weighted output tariffs across all firms in each year have declined over 2000–2006.[28] Simultaneously, a firm's TFP has exhibited an increasing trend over this period. This observation implies that there is a negative correlation between tariff reductions and firm productivity. Hence, I explore such a nexus between the two in this section.

[Insert Figure 1 Here]

[26] Specifically, FIEs include the following firms: foreign-invested joint-stock corporations (code: 310), foreign-invested joint venture enterprises (320), fully FIEs (330), foreign-invested limited corporations (340), H/M/T joint-stock corporations (210), H/M/T joint venture enterprises (220), fully H/M/T-invested enterprises (230), and H/M/T-invested limited corporations (240).

[27] By the official definition reported in the *China City Statistical Yearbook* (2006), SOEs include firms such as domestic SOEs (code: 110); state-owned joint venture enterprises (141); state-owned and collective joint venture enterprises (143), but exclude state-owned limited corporations (151).

[28] The increasing reverse trend in 2006 is possibly due to Reminbi (RMB) appreciation in late 2005. With a stronger RMB, Chinese firms face softer import competition and have less incentives to improve their quality. In this way, the firm may end up with a higher weight.

Table 6 reports the benchmark pooling OLS estimation results for this unbalanced panel for 31,393 firms from 2000–2006.[29] As shown in Column (1), the effect of a firm's import tariffs on its TFP is significantly negative, which is consistent with the message obtained from Figure 1 and suggests that tariff reductions foster a firm's efficiency by inducing tougher import competition. Similarly, the negative and significant coefficient of industrial input tariffs also suggests a cost-saving promotion effect of input tariffs cut on firm's productivity. More importantly, the sign of the dummy of processing firm is significantly positive, which suggests that processing firms enjoy additional productivity gains compared to non-processing firms.

Column (1) also controls for some other factors that might affect firm productivity. I first include the logarithm of firm's capital-labor ratio as a proxy of firm's size. If larger firms are more likely to exhibit the property of increasing returns-to-scale, then such firms can have higher productivity, *ceteris paribus*. The estimated positive sign of firm's capital-labor ratio ascertains such a conjecture. As stated above, I include firm's markup, industrial markup, and the Herfindahl industrial index to control for the possible impact of market structure *status quo ante*. To avoid the possible simultaneity effect between such variables and TFP, such three variables are lagged with one period in the estimations. Particularly, the negative coefficient of the Herfindahl index suggests that firms in more concentrated sectors have lower productivity.

Previous works like Lin *et al.* (2004) also suggest that SOEs have relatively low productivity compared with non-SOEs because of their low efficiency and impotent incentive systems. Therefore, I include a dummy of SOEs as a control variable. It turns out that the coefficients of SOEs are all significantly negative. Such a finding is broadly consistent with Jefferson *et al.* (2000), who found that Chinese SOEs have a relatively low TFP compared with private firms in China.

Finally, it is somehow controversial among researchers to select a cutoff stock share to identify whether or not a firm is a FIE. To avoid such possible confusion, here I simply use a dummy to identify firms receiving some foreign investment. In particular, FIEs are defined as firms receiving foreign investment including money from H/M/T. Clearly, Column (1) shows that FIEs have higher productivity.

[Insert Table 6 Here]

[29] The total size of my sample for estimation is 101,292 since some observations have missing TFP values.

If both processing firms and FIEs have higher productivity, it is worthwhile asking whether those FIEs involved in processing trade have higher productivity. Therefore, I include two more interaction terms between FIEs/SOEs and processing firms. The interaction terms between SOEs and processing firms are all statistically insignificant. Interestingly, those between FIEs and processing firms are significantly negative in all columns, which suggest that non-processing FIEs have higher productivity than processing FIEs, which is broadly consistent with the findings in Lu *et al.* (2010). The economic rationale is as follows. Most FIEs have high productivity *status quo ante*. Only those with lower productivity are more eager to involve with processing activity to enjoy additional productivity gains.

It may be easily to understood that both tariff reductions in final goods (*i.e.*, output tariffs) and intermediate goods (*i.e.*, input tariffs) lead to firm productivity gains. However, one may worry that the positive coefficient of dummy of processing firm could be picking up the differences across industries due to differences in shares of processing trade. To address this concern, Columns (2)-(4) include industrial fixed effects in the estimations and still find robust results for the three key parameters: processing dummy, output tariffs, and input tariffs.

However, previous works like Bernard *et al.* (2003) suggest that firm's markup is highly endogenous with firm's productivity. To see whether the key variable, processing dummy, together with output tariff and input tariff, are sensitive with the inclusion of firm markup, I drop the variable of firm markup in Column (3) but still find robust results. In addition, one may have a concern that the Herfindahl index and firm markup at the industry level is likely to be highly correlated, to check how serious of this possible multicollinearity, I drop variable of industrial markup but keep the Herfindahl index in Column (4). The estimation results again show that all the coefficients are insensitive for such checks. Nevertheless, in all OLS estimations, a firm's tariffs are shown to significantly negatively correlate to its TFP, whereas processing firms have higher productivity.

Finally, I add an additional interaction term between FIEs and its logarithm of capital-labor ratio to see whether TFP is higher for foreign-invested firms with higher capital-labor ratios. The estimated coefficient for this interaction term is negative but significant, whish suggests that TFP is lower for foreign-invested firms with higher capital-labor ratio.

Columns (5)–(6) report the estimation results with firm-specific and year-specific fixed effects. As mentioned above, some time-invariant factors such as a firm's location can affect firm productivity but are not explicitly controlled in the OLS estimates in Columns (1)-(4). Firms on the eastern coast usually have higher productivity since they are closer to the sea and thereby have lower transport costs when involved with foreign trade. Similarly, the ignorance of other time-variant but firm-insensitive factors such as RMB appreciation can bias the OLS estimates. The firm-specific and time-specific fixed effects can efficiently control for such factors. It turns out that the estimated coefficients for the two variables, firm's output tariff and processing dummy, again have anticipated and significant signs. In addition, their economic magnitudes are close to their counterparts obtained by the OLS estimates in Columns (1)-(4). However, the coefficients of industrial input tariffs in Columns (5)-(6) are insignificant. I suspect that this is due to the lack of control for the endogeneity between firm's productivity and output tariffs, which I will investigate shortly.

It is also worthwhile to stress that some firms do not have their own production activity but only export goods that collected from other domestic firms or import goods abroad and then sell to other domestic companies. To make the estimates precise, I shall exclude such pure trading companies from my sample. To do that, I first identify such trading firms from both production-level and trade-level data sets by using their names. In particular, if a firm's name include any Chinese characters of "trading company" or "importing & exporting company", such observations would be dropped from the sample.[30] It turns out that not many pure trading firms are included in my *merged* data set. After this filter, the estimation results without pure trading firms are reported in Column (7) of Table 6. Clearly, the results are highly close to Column (6) with trading firms. In particular, the coefficient of processing firms still has anticipated sign and statistically significant.

4.2 Estimates by Industry

In my sample, firm productivity is shown to be significantly heterogeneous across different industries. In particular, wood products (HS code: 44-49) have average highest TFP whereas industries such as machinery (HS code: 84-85) have average lowest TFP. By deleting the two outliers with the highest and lowest industrial productivity, Figure 2 clearly demonstrates that, overall, industries with low output tariffs have high productivity. However, as shown in Table 3, the variation of a firm's weighted output tariff by industry is sizable. For instance, textiles and garments (HS code: 50–63) have much higher tariffs than those in the machinery and electrical industries (HS code: 84 & 85). Therefore, I further explore the heterogeneous effects of tariff reductions on firm productivity by industry.

[30] In China, pure trading companies are required to register with a name contained Chinese characters of "trading company" or "importing & exporting company".

[Insert Figure 2 Here]

With inclusive of year-specific fixed effects, Columns (1) and (2) of Table 7 first report the industrial-specific fixed-effects and firm-specific fixed-effects estimation results by excluding the two categories with the highest and lowest industrial productivity (*i.e.*, wood and machinery). The estimated coefficients are fairly close to their counterparts in Columns (4) and (6) of Table 6. In Columns (3)-(4) I include wood industries only and find that the coefficient of the processing dummy still has the anticipated sign, though insignificant. In contrast, the estimated coefficients of the output tariff and input tariff are, once again, significantly negative.

The rest of Table 7 investigates the textiles and garments industry, the one with the highest output tariffs, and the machinery industry, the one with the lowest output tariffs. The coefficients of output tariffs have the same sign as previous estimates. Turning to the economic magnitude, the coefficients of a firm's output tariff in the machinery and in the textiles and garment industry are quite close to the average industrial level reported in Columns (1)-(2). Finally, Columns (7)-(8) also suggest that processing firms have higher productivity than non-processing firms.

[Insert Table 7 Here]

4.3 Alternative Measures of Productivity

To enrich the understanding of the nexus between a firm's efficiency and tariff reductions, TFP is re-measured by the system GMM approach. In this way, labor and intermediate inputs as well as capital are allowed to have a dynamic impact on the unobserved productivity shock. By covering all industries in the sample, the OLS and fixed-effect estimates in Columns (1) and (2) of Table 8 reveal similar findings to their counterparts in Tables 6 and 7 in which TFP is measured by using the Olley–Pakes approach. In particular, processing firms are shown to have higher productivity than non-processing firms.

However, it may not be very much appropriate to directly include processing assembly into estimations. The idea is that firms which involve with processing assembly do not make any choice themselves of materials. They only simply receive those free material from foreign clients. If this is true, neither the Olley-Pakes approach nor the system GMM work very well since both of these methods assume that a firm makes its input choices with the objective of maximizing profits. In this way, intermediate inputs like materials are a variable input that the firm can adjust to its entire productivity shock. To avoid this possible drawback, I therefore drop firms with processing assembly from the sample and run the OLS estimations in Column (3) and fixed-effect estimations in Column (4) again. The estimation results are shown be close to the benchmark results in Columns (1)-(2) of Table 8.

If a firm can enjoy additional productivity gains from processing trade, we should expect that processing with imported material (PWIM), as one of the most important types of processing trade, would exhibit this feature as well. The positive coefficient of the processing dummy shown in Columns (5) ascertains this conjecture. With firm-specific fixed effects, the PWIM dummy in Column (6) is still positive but insignificant due in part to the missing observations of PWIM after year 2001 in the dataset. Turning to other variables, in all the estimations in Table 8, FIEs are, once again, shown to have higher productivity than non-FIEs whereas SOEs have lower productivity than non-SOEs.

Finally, it is possible that, during the period investigated, some firms previously involved with processing trade might no longer obtain raw materials abroad but purchase intermediate goods only from domestic market. Similarly, it is also possible that some non-processing firms switch to processing trade. Appendix Table A suggests that, on average, a processing (non-processing) firm this year has a probability of 24.2% (11.3%) to switch to a non-processing (processing) firm in the next period. Although I have captured these possible switching behaviors by choosing a *time-variant* dummy of processing trade, it is still worthwhile exploring the specific feature of non-switching firms only. Column (7), therefore, reports the OLS estimates for the non-switching firms (*i.e.*, processing dummy here means that a firm has *always* been a processing firm) during this period. It turns out that tariff reductions are shown to significantly boost firm productivity. By contrast, the coefficient of processing dummy is negative but insignificant. I suspect that this unexpected result is due to the lack of consideration of endogeneity.

[Insert Table 8 Here]

4.4 Endogeneity

Although tariff reductions are regulated by the GATT/WTO agreements, they are still, to some extent, endogenous since firms in low productivity sectors would lobby the government for protection (Grossman and Helpman, 1994), which maintains the related internationally negotiated tariffs at a relatively high level. One needs to control for such a reverse causality to obtain accurate estimated effects of tariff reductions on TFP. The IV estimation is a powerful econometric method that can address this problem.

It is usually a challenging task to find a good instrument for firm's output tariffs.[31] Following Amiti and Konings (2007), here I adopt a firm's weighted output tariffs in 1996 as an instrument. In particular, I construct the IV as:

$$OT_{ijt}^{1996} = \sum_k \left(\frac{X_{ijt}^k}{\sum_k X_{ijt}^k}\right) \upsilon_{kj}^{1996},$$

where υ_k^{1996} is product k's tariff in 1996 and the export value weight $X_{it}^k / \sum_k X_{it}^k$ measures the extent of importance of product k for firm i at year t. Therefore, the weighted output tariff in 1996 measures how important those tariffs were on the products that firms produce today. The economic rationale is as follows. It is generally difficult for the government to rid an industry with a high tariff of its high protection *status quo ante*, possibly because of the domestic pressure from special interest groups. Hence, it is reasonable to expect that, compared with other sectors, industries with high tariffs five years before China's accession to the WTO still have relatively high tariffs now. Moreover, an identical line of tariffs on products would have had different effects across firms since a firm might produce multiple goods.

Several tests were performed to verify the quality of the instrument. First, Columns (1)–(3) of Table 9 were checked to see whether such an exclusive instrument was "relevant". That is, whether it is correlated with the endogenous regressor (*i.e.*, the current firm's weighted output tariffs). In my econometric model, the error term is assumed to be heteroskedastic: $\epsilon_{ijt} \sim N(0, \sigma_{ij}^2)$. Therefore, the usual Anderson (1984) canonical correlation likelihood ratio test is invalid since it only works under the homoskedastic assumption of the error term. Instead, I use the Kleibergen–Paap (2006) Wald statistic to check whether the excluded instrument correlates with the endogenous regressors. The null hypothesis that the model is under-identified is rejected at the 1% significance level.

Second, I test whether or not the instrument is weakly correlated with the firm's current tariffs. If so, then the estimates will perform poorly in the IV estimate. The Kleibergen–Paap (2006) F-statistics provide strong evidence to reject the null hypothesis that the first stage is weakly identified at a highly significant level.[32] Third, both the Anderson and Rubin (1949) statistic (which is an LM test) and

[31] Here the industrial input tariff is still taken as exogenous in the sense that firms have already enjoyed the tariff reductions on thier intermediate inputs and hence have no incentive to lobby for a high input tariff.

[32] Note that the Cragg and Donald (1993) F-statistic is no longer valid since it only works under the *i.i.d.* assumption.

the Stock and Wright S Statistic (which is a GMM distance test) reject the null hypothesis that the coefficient of the endogenous regressor is equal to zero. In short, these statistical tests provide sufficient evidence that the instrument performs well and, therefore, the specification is well justified.

Columns (1)–(3) of Table 9 present the IV estimates by using Olley–Pakes TFP as the regressand. After controlling for the endogeneity of output tariffs, the coefficient of a firm's output tariff is significantly negative and its economic magnitude is relatively larger than its counterparts in Table 6. This ascertains that output tariff reductions lead to productivity improvement. Without controlling for the reverse causality, the estimated coefficient of output tariffs could be underestimated since low efficient firms could lobby government for protection. In Columns (2)-(3), by dropping (keeping) firm's markup but including (excluding) the interaction term of FIE and logarithm of firm's capital-labor ratio in the estimations, I still find similar results as those in Column (1). Importantly, I find that the three key variables (*i.e.*, processing dummy, output tariffs, and input tariffs) are robust in term of their signs and magnitudes.

In Columns (4)–(6) I control for firm-specific and year-specific fixed-effects IV estimates. The coefficients for almost all variables remain stable across the three specifications. The estimation results suggest that, after controlling for the endogeneity issue, processing firms enjoy extra gains from trade. On average, the logarithm of processing firms is .052 higher than that of non-processing firms. Moreover, output and input tariffs reduction are shown to lead to productivity gains, respectively. In particular, a 10% decrease in a firm's output tariff (industrial input tariff) leads to a 9.7% (5.9%) increase in a firm's logarithm of TFP. Put another way, the productivity gains from output tariff reductions is around twice larger than the productivity gains from cutting input tariffs.

[Insert Table 9 Here]

This finding is particularly interesting when we make an international comparison. By using Indonesian firm-level data, Amiti and Konings (2007) find that firm productivity gains from input tariff reductions are around twice larger than those of output tariff reductions instead. The main reason that Chinese firms enjoy more productivity gains from reducing output tariffs is that processing exports in China account for around a half of total exports. Given that intermediate goods for processing exports are essentially duty free, the impact of reduction on input tariffs must be relatively small. However, processing trade itself can generate additional gains from trade from other channels like quality upgrading (Helpern *et al.,* 2010).

4.5 Further Estimates of Processing Trade

To explore the competition effect of tariff reductions on a firm's TFP, I take a step forward to check the heterogeneous competition effects across different types of processing trade. As introduced above, within the 16 types of processing trade in China today, processing assembly and processing with imported materials are the most important. In contrast to other types, processing assembly are totally duty-free. Once the firm accesses assembly abroad, it immediately enjoys free duty. By contrast, processing with imported materials imports materials from abroad and has to pay import duty. However, after the value-added products are exported, the processing firm can receive an import duty rebate from the authorities. Compared with non-processing trade, this type of processing trade still enjoys the privilege of free duty. However, compared with processing trade with assembly, it has a higher demand on a firm's cash flow since it requires the firm to pay import duty initially, even though it eventually has this outlay returned. In this sense, processing firms with imported materials have relatively lower import costs than non-processing firms but relatively higher import costs than firms with processing assembly.

If this is correct, by constructing a dummy of processing with imported materials (*i.e.*, one if a firm is involved with processing with imported materials and zero otherwise), the dummy $PWIM_{it}$ should have a higher coefficient than that of the processing dummy (PE_{it}) estimated before. As shown in Columns (1) and (2) of Table 10, the coefficient of assembly dummy is .057 in the IV estimate and .054 in the fixed-effects IV estimate, which are slightly higher than their counterparts: .053 in Columns (3) and .052 in Column (6) of Table 9. Finally, I exclude assembly from the sample and find that the processing dummy in Columns (3)-(4) are also larger than their counterparts in Table 9. One can easily find an even larger effect by dropping both assembly and PWIM from the sample as shown in Columns (5)-(6), which suggests that firms involved with other types of processing trade can still enjoy a significantly gains from trade, though such types of processing trade only account for a small proportion of China's processing exports value.

[Insert Table 10 Here]

4.6 More Robustness Checks

Although the weighted output tariff is helpful to tailor the heterogenous effect of an identical tariff line on firm productivity, it still faces the problem that imports will tend to be lower for the products with highest tariffs. To avoid this empirical challenge, I also consider a following non-weighted average tariff (OT_{jt}) in industry j:

$$OT_{jt} = \frac{1}{K} \sum\nolimits_{k \in J,} \upsilon_{jt}^{k}$$

for robustness checks later. As shown in Table 5, the mean of industrial non-weighted output tariff is 4.57, which is quite close to the mean of firm's weighted output tariff (4.44).

Table 11 reports the estimation results using the industrial non-weighted output tariff. In Columns (1)-(2), in addition to year-specific fixed effects, I perform the industry-specific and firm-specific fixed effects with all observations in the sample, respectively, and find similar results as in Table 6. In particular, processing firms have higher productivity than non-processing firms whereas industrial output tariffs reduction leads to high firm productivity. Such findings keep robust even by dropping processing firms with assembly in Column (3). In Column (4), I particularly investigate the effect of processing firms with imported materials (PWIM). The PWIM dummy, once again, is shown to be significantly positive. Equally importantly, both industrial output tariffs and industrial input tariffs have anticipated negative signs. Finally, Column (5) drops the switching processing firms and find that the continuing processing firms have higher productivity than its counterpart. In short, all the estimation results in Table 11 are consistent with the findings in previous tables.

[Insert Table 11 Here]

5 Concluding Remarks

The paper is one of the first to explore the role of processing trade on Chinese firm productivity gains. In many developing countries, trade liberalization includes both output and input tariff reductions and processing behavior. In contrast to tariff reductions, which could generate productivity gains via the international competition effect or the cost-saving effect, processing exports can enjoy additional gains from trade. Using highly disaggregated Chinese data on trade, tariffs, and firm-level production, I find that a 9.7% output tariff decrease generates a 10% increase in firm productivity gains, which is almost twice higher than the productivity gains from cutting input tariffs. Moreover, firms benefit additional productivity gains from processing trade.

This paper enriches our understanding of Chinese firms productivity. Possibly because of poor data quality and restricted methodologies, previous works reported mixed findings on China's TFP improvement. By combining the most reliable firm-level production data and production-level trade data, I could properly measure and precisely calculate a firm's TFP. The augmented Olley–Pakes empirical methodology was applied to deal with the usual two problems of estimating TFP: simultaneity bias and selection bias. Equally importantly, the system GMM approach was adopted to correct for the possible overestimation of capital elasticity by using this approach.

The paper also has policy implications. If tariff reductions can generate productivity gains for both processing and non-processing firms, free trade would be beneficial to domestic firms, even if it intensified a firm's international competition. Although today's tariffs have been maintained at a relatively low level after many rounds of GATT/WTO negotiations, a variety of non-tariff barriers are still prevalent all over the world. In this sense, a further step of trade liberalization is necessary for producers as well as consumers.

References

[1] Ackerberg., Daniel, Kevin Caves, and Garth Frazer (2006), "Structural Identification of Production Functions," UCLA mimeo.

[2] Anderson, T.W. (1984), *Introduction to Multivariate Statistical Analysis*, 2nd ed. New York: John Wiley & Sons.

[3] Anderson, T. W., and H. Rubin.(1949), "Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations," *Annals of Mathematical Statistics* 20, pp. 46-63.

[4] Arellano, Manuel and Stepen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies* 58, pp. 277-97.

[5] Amiti, Mary, and Jozef Konings (2007), "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review* 93, pp. 1611-1638.

[6] Arnold, Jens Metthias (2005), "Productivity Estimation at the Plant Level: A Practical Guide," mimeo.„ Bocconi University.

[7] Bernard, Andrew, Jonathan Eaton, Bradford Jensen, and Sameul Kortum (2003), "Plants and Productivity in International Trade," *American Economic Review* 93 (5), pp. 1628-1690.

[8] Bernard, Andrew, and Bradford Jensen (2004), "Why Some Firms Export?" *Review of Economics and Statistics* 86(2), pp.561-569.

[9] Blomström, Magnus and Ari Kokko (1996), "The Impact of Foreign Investment on Host Countries: A Review of the Empirical Evidence," World Bank Policy Research Working Paper, No. 1745.

[10] Blundell, Richard and Stepen Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics* 87, pp. 11-143.

[11] Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang (2009), "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing," NBER Working Paper, No. 15152.

[12] Bustos, Paula (2010), "Trade Liberalization, Exports and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinean Firms," *American Economic Review*, forthcoming.

[13] Cai, Hongbin and Qiao Liu (2009), "Does Competition Encourage Unethical Behavior? The Case of Corporate Profit Hiding in China", *Economic Journal* 119, pp.764-795.

[14] Cragg, J.G. and S.G. Donald (1993), "Testing Identfiability and Specification in Instrumental Variables Models," *Econometric Theory* 9, pp. 222-240.

[15] De Loecker, Jan (2007), "Do Exports Generate Higher Productivity? Evidence from Slovenia," *Journal of International Economics* 73(1), pp. 69-98.

[16] Feenstra, Robert, Li, Zhiyuan and Miaojie Yu (2010), "Export and Credit Constraints under Private Information: Theory and Empirical Investigation from China", miemo, University of California, Davis.

[17] Felipe, Jesus, Hasan, Rana, and J.S.L, McCombie (2004), "Correcting for Biases When Estimating Production Functions: An Illusion of the Laws of Algebra?" CAMA Working Paper Series, No. 14, Australia National University.

[18] Fernandes, Ana (2007), "Trade Policy, Trde Volumes and Plant-Level Productivity in Columbina Manufacturing Industries," *Journal of International Economics* 71, pp. 52-71.

[19] Fernandes, Ana and Heiwai Tang (2010), "The Determinants of Vertical Integration Trade in Export Processing: Theory and Evidence from China," miemo, Tufts University.

[20] Foster, Lucia, Haltiwanger, John and Syverson, Chad (2007), "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" mimeo, University of Chicago.

[21] Grossman, Gene and Elhanan Helpman (1994), "Protection for Sales," *American Economic Review* 84(4), pp. 833-50.

[22] Harrison, Ann (1994), "Productivity, Imperfect Competition and Trade Reform," *Journal of International Economics* 36, pp. 53-73.

[23] Head, Keith, and John Ries (1999), "Rationalization Effects of Tariff Reduction," *Journal of International Economics* 47(2), pp. 295-320.

[24] Halpern, Laszlo, Miklos Koren, and Adam Szeidl (2010), "Imported Inputs and Productivity," University of California, Berkeley, Mimeo.

[25] Holz, Carsten (2004), "China's Statistical System in Transition: Challenges, Data Problems, and Institutional Innovations," *Review of Income and Wealth* 50(3), pp. 381-409.

[26] Hummels, David, Jun Ishii, and Kei-Mu Yi (2001), "The Nature and Growth of Vertical Specification in World Trade," *Journal of International Economics* 54, pp. 75-96.

[27] Hsieh, Chang-Tai and Peter J. Klenow (2009), "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economic*s, CXXIV(4), pp. 1403-48.

[28] Iscan, B. Talan (1998), "Trade Liberalization and Productivity: A Panel Study of the Mexican. Manufacturing Industry" J*journal of Development Studies* 34 (5), pp. 123-148.

[29] Jefferson, Gary, Rawski, Thomas, and Yuxin Zheng (1996), "Chinese Industrial Productivity: Trends, Measurement Issues, and Recent Developments," *Journal of Comparative Economics* 23(2), pp. 146-180.

[30] Jefferson, Gary, Rawski, Thomas, Wang Li, and Zheng Yuxin (2000), "Ownership, Productivity Change, and Financial Performance in Chinese Industry," *Journal of Comparative Economics* 28(4), pp. 786-813.

[31] Keller Wolfgang and Stephen R. Yeaple (2009), "Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States," *Review of Economics and Statistics* 91(4), pp. 821-831.

[32] Kleibergen, Frank and Richard Paap (2006), "Generalized Reduced Rank Tests Using the Singular Value Decomposition," *Journal of Econometrics* 133(1), pp. 97-126.

[33] Koopman, Robert, Zhi Wang, and Shang-Jin Wei (2008), "How Much of Chinese Exports Is Really Made in China? Assessing Domestic Value-Added When Processing Trade is Pervasive," NBER Working Paper No.14109.

[34] Krishna, Pravin and Devashish Mitra (1999), "Trade Liberalization, Market Discipline and Productivity Growth: New Evidence from India," *Journal of Development Economics* 56(2), pp. 447-62.

[35] Krugman, Paul (1979), "Increasing Returns, Monopolistic Competition, and International Trade," *Journal of International Economics* 9(4), pp. 469-79.

[36] Levinsohn, James (1993), "Testing the Imports-as-Market-Discipline Hypothesis," *Journal of International Economics* 35(1), pp. 1-22.

[37] Levinsohn, James and Amil Petrin (2003), "Estimating Production Functions Using Inputs to Control for Unobservable," *Review of Economic Studies* 70(2), pp. 317-341.

[38] Lin, Justin, Fang Cai, and Zhou Li (2004), *The China Miracle: Development Strategy and Economic Reform*, Chinese University of Hong Kong.

[39] Lu, Jiangyong, Yi Lu, and Zhigang Tao (2010), "Exporting Behavior of Foreign Afflicates: Theory and Evidence", *Journal of International Economics* 81(2), pp. 197-205.

[40] Marschak, Jacob and Andrews, William (1944), "Random Simultaneous Equations and the Theory of Production," *Econometrica* 12(4), pp. 143-205.

[41] Melitz, Marc (2003), "The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity," *Econometrica* 71(6), pp. 1695-1725.

[42] Naughton, Barry (2006), *The Chinese Economy: Transition and Growth*, MIT press, Cambridge.

[43] Nickell, S. (1996), "Competition and Corporate Performance," *Journal of Political Economy* 104, pp. 724-746.

[44] Olley, Steven and Ariel Pakes (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica* 64(6), pp. 1263-1297.

[45] Park, Albert Xinzheng, Shi, Dean Yang, and Yuan Jiang (2010), "Exporting and firm performance: Chinese Exporters and the Asian Financial Crisis", *Review of Economics and Statistics*, forthcoming.

[46] Pavcnik, Nina (2002), "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants, " *Review of Economic Studies* 69(1), pp. 245-276.

[47] Schor, Adriana (2004), "Heterogenous Productivity Response to Tariff Reduction: Evidence from Brazilian Manufacturing Firms," *Journal of Development Economics* 75(2), pp. 373-96.

[48] Trefler, Daniel (2004), "The Long and Short of the Canada-U.S. Free Trade Agreement," *American Economics Review* 94(3): 870-895.

[49] Tybout, James, Jaime de Melo, and Vittorio Corbo (1991), "The Effects of Trade Reforms on Scale and Technical Efficiency: New Evidence from Chile," *Journal of International Economics* 31(3), 231-250.

[50] Tybout, James (2003), "Plant and Firm-Level Evidence on "New" Trade Theories," In *Handbook of International Trade*, ed. James Harrigan and Kwao Choi, pp. 388-415. New York: Blackwell Publishing Ltd.

[51] Topalova, Petia, and Amit Khandelwal (2010), "Trade Liberalization and Firm Productivity: The Case of India," *Review of Economics and Statistics*, forthcoming.

[52] Van Biesebroeck, Johannes (2005), "Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms," *Journal of International Economics* 67(2), pp. 373-391.

[53] Young, Alwyn (2003), "Gold into Base Metals: Productivity Growth in the People's Republic of China during the Reform Period," *Journal of Political Economy* 111(6), pp. 1220-1261.

[54] Yu, Miaojie (2009), "Revaluation of the Chinese Yuan and triad trade: A gravity assessment," *Journal of Asian Economics* 20, pp. 655-668.

Table 1: Basic Summary of Data Sets

#. of Obs.[a]	2000	2001	2002	2003	2004	2005	2006
			Product-Level Trade Data				
Transactions	10,586,696	12,667,685	14,032,675	18,069,404	21,402,355	24,889,639	16,685,377
Trading Firms[b]	74,225	76,235	68,130	61,017	99,707	118,765	142,273
Valid Firms[c]	21,869	17,485	12,625	15,241	40,143	55,168	55,493
			Firm-Level Production Data				
Firms	162,885	171,256	181,557	196,222	276,474	271,835	301,961
Valid Firms[d]	43,239	35,374	37,037	53,843	86,477	72,626	104,677

Notes: (a) The source of HS eight-digit monthly multi-product level trade data is China's General Administration of Customs. The firm-level annual accounting data are from China's National Bureau of Statistics. The HS six-digit disaggregated annual tariffs data are from the WTO. (b) Number of firms indicates number of trading firms ever reported by the General Administration of Customs. (c) Trading firms refers to the number of trading firms with a valid zip code and telephone information. (d) Valid firms refers to the number of firms with a valid zip code and telephone information reported in the firm's accounting dataset.

Table 2: Chinese Highly Disaggregated Product-Level Trade by Shipment and by Year

# of Obs. (HS 8-Digit)			Year					Total
Type	2000	2001	2002	2003	2004	2005	2006	(Percent)
10	348,634	534,180	679,058	1,042,585	1,369,341	1,512,498	1,289,312	6,775,608
	(2.03%)	(3.11%)	(3.95)	(6.07%)	(7.97%)	(8.80%)	(7.51%)	(39.46%)
14	138,380	188,227	194,673	219,349	293,621	297,851	218,479	1,550,580
	(0.81%)	(1.09%)	(1.13%)	(1.27%)	(1.71%)	(1.74%)	(1.27%)	(9.03%)
15	762,254	881,097	–	–	–	–	–	1,643,351
	(4.44%)	(5.13%)						(9.57%)
99	139,600	146,614	1,048,472	1,320,835	1,615,786	1,631,738	1,298,057	7,201,102
	(0.81%)	(0.85%)	(6.11%)	(7.69%)	(9.41%)	(9.50%)	(7.56%)	(41.94%)
Total	1,388,868	1,750,118	1,922,203	2,582,769	3,278,748	3,442,087	2,805,848	17,170,641
(%)	(8.09%)	(10.19%)	(11.19%)	(15.04%)	(19.10%)	(20.05%)	(16.34%)	(100%)

Total Trading Value								Total
Type	2000	2001	2002	2003	2004	2005	2006	(Percent)
10	1.81e+10	2.57e+10	2.62e+10	4.10e+10	5.68e+10	6.45e+10	3.83e+10	2.71e+11
	(1.58%)	(2.24%)	(2.28%)	(3.57%)	(4.95%)	(5.62%)	(3.33%)	(23.61%)
14	6.54e+09	8.77e+09	8.32e+09	9.79e+09	2.77e+10	4.45e+10	1.87e+10	1.24e+11
	(0.57%)	(0.76%)	(0.72%)	(0.85%)	(2.41%)	(3.87%)	(1.63%)	(10.84%)
15	5.32e+10	6.17e+10	–	–	–	–	–	1.15e+11
	(4.63%)	(5.37%)						(10.01%)
99	4.35e+09	5.09e+09	7.79e+10	1.19e+11	1.59e+11	1.74e+11	9.76e+10	6.37e+11
	(0.37%)	(0.44%)	(6.79%)	(10.36%)	(13.85%)	(15.18%)	(8.51%)	(55.53%)
Total	8.22e+10	1.01e+11	1.12e+11	1.70e+11	2.43e+11	2.83e+11	1.55e+11	1.15e+12
(%)	(7.16%)	(8.82%)	(9.80%)	(14.79%)	(21.23%)	(24.69%)	(13.48%)	(100%)

Notes: Types of shipment: 10 denotes ordinary trade; 14 denotes processing exports with assembly; 15 denotes processing exports with imported materials; and 99 denotes other types of processing trade.

Table 3: Average Tariffs Clustered by HS 2-digit Industries (%)

Category	Type	2000	2001	2002	2003	2004	2005	2006
(01-05)	Product Duty	22.33	18.24	14.99	13.45	12.21	10.80	11.14
	Output Duty	.71	.24	.31	.21	.21	.41	.42
(06-15)	Product Duty	16.66	15.16	11.42	10.99	9.93	9.43	9.52
	Output Duty	1.39	.99	.70	.72	.59	.62	.59
(16-24)	Product Duty	20.23	16.49	14.26	13.42	12.65	11.76	10.32
	Output Duty	2.29	2.25	1.19	.95	1.13	1.16	1.01
(25-27)	Product Duty	12.25	11.58	7.96	7.65	7.12	6.93	7.00
	Output Duty	4.35	3.97	3.72	3.16	2.37	2.88	2.26
(28-38)	Product Duty	15.16	13.81	9.64	8.84	8.08	7.69	7.64
	Output Duty	4.60	4.10	3.19	3.10	2.76	2.92	2.83
(39-40)	Product Duty	17.53	16.10	11.69	10.36	9.39	8.89	8.96
	Output Duty	4.66	4.62	3.77	3.51	2.87	3.13	3.88
(41-43)	Product Duty	22.42	19.38	15.93	14.61	12.82	12.11	11.75
	Output Duty	9.20	8.01	7.00	6.12	5.27	5.77	6.11
(44-49)	Product Duty	18.34	16.31	12.04	10.46	9.13	8.22	8.49
	Output Duty	6.54	5.63	4.74	4.13	3.44	3.41	3.65
(50-63)	Product Duty	26.79	21.81	17.92	15.69	13.66	12.50	12.47
	Output Duty	13.20	10.47	9.68	8.55	7.64	7.02	7.53
(64-67)	Product Duty	22.88	21.51	18.05	17.10	15.99	15.76	15.26
	Output Duty	16.09	17.02	15.02	14.10	14.65	14.25	14.29
(68-71)	Product Duty	18.98	17.97	14.01	12.87	11.37	10.98	10.69
	Output Duty	9.55	9.34	6.85	6.73	5.66	5.41	5.72
(72-83)	Product Duty	14.56	13.48	10.12	9.38	8.79	8.65	8.80
	Output Duty	5.20	4.79	4.11	3.95	3.57	3.59	3.79
(84-85)	Product Duty	13.59	12.71	7.63	6.61	6.10	5.85	5.84
	Output Duty	4.21	3.94	3.26	3.02	2.89	2.72	2.68
(86-89)	Product Duty	19.71	17.43	15.80	13.66	12.63	12.61	11.78
	Output Duty	7.07	8.42	5.79	6.05	6.84	5.56	4.96
(90-97)	Product Duty	19.12	16.34	12.74	11.39	9.95	9.07	8.97
	Output Duty	7.49	6.71	5.42	4.73	4.35	3.76	4.01
Average	Product Duty	18.53	16.24	12.09	10.66	9.48	8.97	8.87
	Output Duty	6.74	5.97	5.11	4.67	4.21	4.06	4.28

Sources: Author's own calculation.

Table 4: Estimates of Olley-Pakes Input Elasticity of Chinese Firms

HS 2-digit	Log of	Labor		Materials		Capital	
	TFP(OP)	OP	GMM	OP	GMM	OP	GMM
Animal Products	1.126	.056**	.053	.888**	.970**	.048**	-.022
(01-05)		(3.32)	(.87)	(55.36)	(17.71)	(1.80)	(-.43)
Vegetable Products (06-15)	1.286	.007	.031**	.891**	.571**	.052**	.019
		(.49)	(8.55)	(68.05)	(9.82)	(5.49)	(.46)
Foodstuffs (16-24)	1.529	.036**	-.020	.874**	.595**	.044	.027
		(2.23)	(-.25)	(68.48)	(10.73)	(1.07)	(.46)
Mineral Products (25-27)	.686	.035*	.241**	.872**	.671**	.099**	.089
		(1.70)	(3.78)	(51.00)	(15.51)	(2.69)	(1.57)
Chemicals & Allied	1.453	.014**	.127**	.831**	.488**	.103**	.071
Industries (28-38)		(1.98)	(1.95)	(121.70)	(10.99)	(7.79)	(1.48)
Plastics / Rubbers (39-40)	1.765	.064**	.321**	.796**	.298**	.103**	-.003
		(8.49)	(6.98)	(107.17)	(4.54)	(5.59)	(-.08)
Raw Hides, Skins, Leather	1.505	.102**	.125*	.810**	.738**	.090**	.043
& Furs (41-43)		(7.76)	(1.85)	(65.53)	(11.55)	(3.36)	(.66)
Wood Products	2.374	.039**	.041	.855**	.266**	.012	.118**
(44-49)		(4.29)	(.46)	(97.11)	(6.83)	(.47)	(2.99)
Textiles (50-63)	1.983	.085**	.157**	.810**	.653**	.066**	.043*
		(19.50)	(4.81)	(192.59)	(22.96)	(10.38)	(1.95)
Footwear / Headgear (64-67)	1.629	.072**	.138	.864**	.703**	.033**	-.108**
		(5.93)	(1.62)	(73.17)	(10.77)	(5.43)	(-2.38)
Stone / Glass (68-71)	1.663	.104**	.233**	.785**	.448**	.103**	.063
		(9.14)	(3.56)	(67.02)	(11.58)	(8.19)	(1.16)
Metals (72-83)	1.167	.045**	.191**	.832**	.400**	.109**	.084**
		(6.30)	(4.22)	(131.73)	(11.67)	(16.23)	(2.72)
Machinery/Electrical (84-85)	.480	.065**	.056	.825**	.548**	.150**	.175**
		(13.36)	(1.15)	(206.22)	(13.43)	(10.83)	(4.97)
Transportation (86-89)	1.368	.042**	.147*	.883**	.426**	.043**	.068
		(2.80)	(1.70)	(69.58)	(8.81)	(3.47)	(1.08)
Miscellaneous (90-98)	1.683	.083**	.195**	.796**	.276**	.098**	.007
		(10.32)	(3.58)	(110.01)	(8.15)	(10.70)	(.22)
All industries	1.259	.052**	.240**	.820**	.486**	.117**	.001
		(30.75)	(17.05)	(493.33)	(44.54)	(27.08)	(.11)

Notes: Numbers in parentheses are robust t-values, *(**) indicates significance at 5(1)% level.

Table 5: Summary Statistics (2000-2006)

Variables	Mean	Std. Dev.	Min	Max
Year	2003	1.88	2000	2006
Firm's Log TFP (Olley-Pakes)	1.34	.348	-1.50	11.8
Firm's Log TFP (System-GMM)	2.45	.397	-.159	10.7
Dummy of Processing Firm (PE_{it})	.406	.491	0	1
Firm's Weighted Output Tariff $(OT_{ijt})^a$	4.44	7.07	0	65
Industrial Simple Output Tariff $(OT_{jt})^b$	2.19	4.17	0	43.5
Industrial Input Tariff $(IT_{jt})^c$	4.57	5.88	0	42.1
IV (OT_{ijt}^{1996})	29.8	.149	0	80
Firm's Markup in Pervious Year	1.04	.586	-128	47.3
Industrial Markup in Pervious Year	1.05	.010	.968	1.28
Herfindahl Index in Pervious Year	.015	.027	0	.825
$\ln(K/L)_{it}$	3.66	1.39	-5.66	10.5
SOEs Dummy	.017	.129	0	1
FIEs Dummy (FIE_{it})	.665	.471	0	1
$FIE_{it} \times PE_{ij}$	.159	.365	0	1
$SOE_{it} \times PE_{ij}$	.005	.067	0	1
$FIE_{it} \times \ln(K/L)_{it}$	2.39	2.12	-5.66	9.73

Notes: (a) Firm's weighted duty at product level is the product of the weight of each product and its duty at HS 6-digit level: $OT_{ijt} = \sum_k (X_{ijt}^k / \sum_k X_{ijt}^k)\upsilon_{jt}^k$ where X_{ijt}^k is the export of product k of firm i in industry j in year t. (b) Industrial simple tariff is defined as $(\sum_{k\in J,} \upsilon_{jt}^k)/K$ where K is number of total products in industry j. (c) Industrial input tariff is defined as $\frac{1}{K} \sum\limits_{k\in\Theta, k\notin\Theta\cap\Lambda} \upsilon_{jt}^k$ as interpreted in the text.

Table 6: Benchmark Estimates

Regressand: $\ln TFP_{it}^{OP}$	OLS				Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output Tariffs (OT_{ijt})	-.581**	-.500**	-.505**	-.503**	-.499**	-.511**	-.511**
	(-26.20)	(-19.85)	(-2.05)	(-19.95)	(-12.86)	(-13.22)	(-13.23)
Ind. Input Tariffs (IT_{jt})	-.382**	-.309**	-.305**	-.324**	.078	.067	.067
	(-7.86)	(-6.33)	(-6.24)	(-6.63)	(.93)	(.80)	(.80)
PE_{it}	.021**	.020**	.020**	.019**	.045**	.044**	.044**
	(3.14)	(3.00)	(2.94)	(2.85)	(3.6)	(3.53)	(3.53)
$\ln(K/L)_{it}$	.012**	.010**	.014**	.013**	.012**	.009**	.009**
	(10.02)	(7.99)	(6.79)	(6.15)	(7.09)	(3.11)	(3.08)
FIE_{it}	.060**	.055**	.072**	.071**	.063**	.047**	.047**
	(16.90)	(15.48)	(7.86)	(7.71)	(11.28)	(3.31)	(3.30)
SOE_{it}	-.019	-.026*	-.031**	-.031**	.013	.016	.017
	(-1.28)	(-1.72)	(-2.01)	(-2.00)	(.61)	(.74)	(.77)
$markup_{it-1}$	.049**	.048*	–	.047*	.188**	.190**	.190**
	(1.97)	(1.95)		(1.94)	(15.8)	(15.91)	(15.92)
ind_markup_{it-1}	-.637**	-1.378**	-1.349**	–	1.052**	–	–
	(-4.42)	(-9.07)	(-8.91)		(3.64)		
$H\,\mathrm{erf}_{it-1}$	-.208**	.002	-.021	-.024	-.307**	-.326**	-.326**
	(-3.25)	(.03)	(-.34)	(-.37)	(-3.12)	(-3.32)	(-3.31)
$FIE_{it} \times PE_{it}$	-.039**	-.041**	-.042**	-.041**	-.050**	-.049**	-.049**
	(-5.18)	(-5.35)	(-5.52)	(-5.4)	(-3.63)	(-3.52)	(-3.52)
$SOE_{it} \times PE_{it}$	-.005	.005	.004	.006	-.016	-.017	-.015
	(-.20)	(.20)	(.16)	(.23)	(-.33)	(-.34)	(-.32)
$FIE_{it} \times (\ln K/L)_{it}$	–	–	-.005*	-.004*	–	.004	.004
			(-1.89)	(-1.77)		(1.23)	(1.26)
Industrial Fixed Effects	No	Yes	Yes	Yes	No	No	No
Firm Fixed Effects	No	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes	Yes
Observations	54,937	54,937	54,937	54,937	54,937	54,937	54,916
Prob.>F	.000	.000	.000	.000	.000	.000	.000
Root MSE	.334	.331	.331	.331	.303	.303	.303
R-squared	.025	.047	.044	.045	.046	.046	.046

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *(**) indicates significance at the 10(5) percent level. The estimation in Column (7) excludes pure trading companies.

Table 7: Estimates by Industry

Industries Covered	All Industries w/o Woods & Machinery		Woods Only		Textile Only		Machinery Only	
Regressand:	OLS	FE	OLS	FE	OLS	FE	OLS	FE
$\ln TFP_{it}^{OP}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Output Tariffs	-.453**	-.462**	-.867**	-.657**	-.470**	-.404**	-.540**	-.426**
	(-15.84)	(-11.2)	(-10.57)	(-5.67)	(-9.76)	(-5.28)	(-7.99)	(-4.80)
Ind. Input Tariffs	-.298**	-.013	-1.027**	-.798**	-.385**	-.031	.408**	.575**
	(-5.50)	(-.16)	(-6.78)	(-4.14)	(-4.06)	(-.26)	(2.46)	(3.16)
PE_{it}	.015*	.039**	.002	.055	-.010	.024	.046**	.067**
	(1.94)	(2.93)	(.07)	(1.56)	(-.69)	(1.10)	(2.69)	(2.74)
$\ln(K/L)_{it}$	.013**	.011**	-.011	-.010	.008*	.010*	.026**	.024**
	(5.64)	(3.40)	(-1.37)	(-1.00)	(1.93)	(1.74)	(5.20)	(3.53)
FIE_{it}	.072**	.054**	-.073**	-.077*	.092**	.081**	.156**	.138**
	(7.09)	(3.5)	(-2.03)	(-1.84)	(5.16)	(3.00)	(5.81)	(4.23)
SOE_{it}	-.043**	.018	-.003	.082	-.045	.032	.022	.092**
	(-2.31)	(.74)	(-.04)	(.96)	(-1.20)	(.59)	(.71)	(2.56)
$markup_{it-1}$	.037*	.167**	.444**	.516**	.029*	.065**	.218*	.428**
	(1.82)	(13.32)	(5.37)	(9.33)	(1.86)	(2.82)	(1.85)	(13.83)
ind_markup_{it-1}	-1.150**	1.335**	-2.671**	-.452	-1.032**	2.115**	-2.085**	.330
	(-6.99)	(4.46)	(-5.56)	(-.62)	(-2.97)	(3.26)	(-3.39)	(.45)
$H\,\mathrm{erf}_{it-1}$	-.065	-.498**	.059	.257	.554**	.038	.653*	.877**
	(-.95)	(-4.9)	(.29)	(.93)	(2.68)	(.15)	(1.74)	(2.66)
$FIE_{it} \times PE_{it}$	-.034**	-.041**	-.021	-.067*	-.018	-.036	-.072**	-.076**
	(-4.05)	(-2.77)	(-.66)	(-1.76)	(-1.14)	(-1.49)	(-3.53)	(-2.84)
$SOE_{it} \times PE_{it}$	-.001	-.054	.086	-.002	.003	-.036	-.019	-.065
	(-.04)	(-1.02)	(1.01)	(-.01)	(.04)	(-.39)	(-.41)	(-.89)
$FIE_{it} \times \ln(K/L)_{it}$	-.006**	.002	.029**	.034**	-.014**	-.008	-.019**	-.014*
	(-2.24)	(.48)	(2.8)	(3.14)	(-2.74)	(-1.16)	(-2.82)	(-1.78)
Ind. Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	42,958	42,958	4,386	4,368	10,052	10,052	7,593	7,593
Root MSE	.327	.309	.368	.357	.303	.301	.321	.309
Prob.>F	.000	.000	.000	.000	.000	.000	.000	.000
R-squared	.045	.046	.072	.090	.025	.050	.052	.071

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *(**) indicates significance at the 10(5) percent level.

Table 8: Alternative Estimates on Productivity

Regressand: $\ln TFP_{it}^{GMM}$	All Industry		w/o Assembly		PWIM Only		No
Method:	OLS	FE	OLS	FE	OLS	FE	Switchers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output Tariffs (OT_{ijt})	-.587**	-.639**	-.597**	-.624**	-.531**	-.628**	-.530**
	(-20.20)	(-14.26)	(-20.04)	(-13.76)	(-18.32)	(-14.01)	(-14.43)
Ind. Input Tariffs (IT_{jt})	-.392**	-.004	-.273**	.154	-.364**	-.112	-.409**
	(-7.44)	(-.04)	(-4.73)	(1.54)	(-6.94)	(-1.19)	(-6.21)
PE_{it}	.019**	.041**	.038**	.074**	-.100**	.017	-.011
	(2.33)	(2.80)	(4.28)	(4.65)	(-4.63)	(.33)	(-.70)
$\ln(K/L)_{it}$	.059**	.056**	.058**	.055**	.0598**	.056**	.045**
	(24.13)	(15.93)	(23.68)	(15.53)	(24.30)	(16.02)	(16.09)
FIE_{it}	.083**	.064**	.075**	.054**	.052**	.033**	.097**
	(7.69)	(3.92)	(6.87)	(3.30)	(4.95)	(2.11)	(7.51)
SOE_{it}	-.087**	-.060**	-.086**	-.062**	-.075**	-.044**	-.118**
	(-4.79)	(-2.34)	(-4.76)	(-2.44)	(-4.69)	(-1.94)	(-5.68)
$markup_{it-1}$	.054*	.205**	.055*	.216**	.055*	.211**	.030*
	(1.87)	(14.90)	(1.85)	(15.41)	(1.88)	(15.31)	(1.62)
ind_markup_{it-1}	-1.598**	1.097**	-1.641**	.886**	-1.145**	1.076**	-1.601**
	(-9.30)	(3.29)	(-9.27)	(2.65)	(-6.56)	(3.23)	(-7.41)
$H\,\mathrm{erf}_{it-1}$	-.018	-.386**	-.008	-.328**	.011	-.350**	-.006
	(-.23)	(-3.39)	(-.10)	(-2.87)	(.15)	(-3.09)	(-.06)
$FIE_{it} \times PE_{it}$	-.075**	-.086**	-.086**	-.105**	-.024	.021	-.067**
	(-8.17)	(-5.39)	(-8.84)	(-6.08)	(-1.04)	(.42)	(-4.19)
$SOE_{it} \times PE_{it}$	.038	.052	.067**	.103*	.085	.118	.139**
	(1.12)	(.91)	(1.99)	(1.71)	(1.56)	(.99)	(2.71)
$FIE_{it} \times \ln(K/L)_{it}$	-.009**	-.001	-.007**	.001	-.007**	.001	-.011**
	(-3.04)	(-.15)	(-2.34)	(.22)	(-2.39)	(.21)	(-3.12)
Ind. Fixed Effects	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No
Observations	54,937	54,937	51,768	51,768	54,937	54,937	33,963
Root MSE	.371	.350	.369	.350	.371	.350	.362
Prob.>F	.000	.000	.000	.000	.000	.000	.000
R-squared	.094	.090	.093	.088	.093	.088	.075

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *(**) indicates significance at the 10(5) percent level.

Table 9: IV Estimates

Regressand: $\ln TFP_{it}^{OP}$	(1)	(2)	(3)	(4)	(5)	(6)
Output Tariffs (OT_{ijt})	-1.063**	-1.077**	-.991**	-1.009**	-.921**	-.969**
	(-15.58)	(-15.93)	(-10.16)	(-10.39)	(-9.39)	(-9.82)
Ind. Input Tariffs (IT_{jt})	-.932**	-.937**	-.847**	-.854**	-.577**	-.593**
	(-14.48)	(-14.61)	(-10.34)	(-10.45)	(-5.24)	(-5.35)
PE_{it}	.024**	.023**	.020**	.020**	.053**	.052**
	(3.06)	(3.03)	(2.57)	(2.55)	(3.86)	(3.78)
$\ln(K/L)_{it}$	.008**	.009**	.006**	.009**	.011**	.009**
	(5.26)	(3.76)	(4.06)	(3.84)	(5.60)	(2.69)
FIE_{it}	.053**	.055**	.046**	.058**	.056**	.048**
	(13.43)	(5.29)	(11.85)	(5.64)	(9.20)	(3.12)
SOE_{it}	-.016	-.018	-.021	-.025	.019	.014
	(-.94)	(-1.07)	(-1.25)	(-1.48)	(.75)	(.55)
$markup_{it-1}$	.058*	–	.057*	–	.175**	–
	(1.71)		(1.70)		(13.76)	
$H\,\mathrm{erf}_{it-1}$	.121	.085	.072	.032	.036	.013
	(1.58)	(1.21)	(.88)	(.44)	(.29)	(.10)
$FIE_{it} \times PE_{it}$	-.036**	-.038**	-.033**	-.034**	-.045**	-.051**
	(-4.14)	(-4.32)	(-3.76)	(-3.96)	(-3.03)	(-3.38)
$SOE_{it} \times PE_{it}$	-.011	-.013	.001	-.001	-.028	-.041
	(-.34)	(-.41)	(.04)	(-.02)	(-.51)	(-.74)
$FIE_{it} \times \ln(K/L)_{it}$	–	.000	–	-.003	–	.003
		(-.17)		(-1.13)		(.81)
Ind. specific Fixed Effects	Yes	Yes	Yes	Yes	No	No
Firm specific Fixed Effects	No	No	No	No	Yes	Yes
Year specific Fixed Effects	No	No	No	No	Yes	Yes
R-squared	.03	.03	.04	.04	.05	.06
	First-Stage Regression					
τ_{it}^{1996} (IV in the First-stage)	.177**	.177**	.147**	.147**	.080**	.080**
	(73.95)	(73.75)	(52.28)	(52.17)	(13.01)	(13.01)
Kleibergen-Paap Wald rk F statistic	5,468†	5439†	2734†	2722†	169.2†	169.3†
Kleibergen-Paap rk LM statistic	4,136†	4127†	2180†	2174†	168.7†	168.8†
Anderson-Rubin χ^2 Statistic	243.8†	255.1†	104.0†	109.0†	4.31†	4.36†
Stock-Wright LM S Statistic	241.9†	253.5†	103.6†	108.6†	4.30†	4.36†

Notes: There are 40,620 observations in each column. Robust t-values in parentheses. *(**) is 10(5) % significance. † is p-value less than 0.01.

Table 10: IV Estimates by Processing Types

Regressand: TFP_{it}^{OP}	PWIM Only		w/o Assembly		w/o Assembly or PWIM	
	(1)	(2)	(3)	(4)	(5)	(6)
Output Tariffs (OT_{ijt})	-.752**	-.865**	-.836**	-.824**	-.815**	-.818**
	(-5.00)	(-6.81)	(-8.49)	(-7.96)	(-7.92)	(-7.86)
Ind. Input Tariffs (IT_{jt})	-.566**	-.611**	-.482**	-.395**	-.447**	-.306**
	(-4.78)	(-5.45)	(-5.37)	(-3.44)	(-4.50)	(-2.49)
PE_{it}	–	–	.043**	.066**	.044**	.072**
			(5.45)	(4.43)	(5.19)	(4.57)
$PWIM_{it}$	.057**	.054**	–	–	–	–
	(3.68)	(2.76)				
$\ln(K/L)_{it}$	.029**	.031**	.009**	.007**	.009**	.007**
	(4.58)	(4.25)	(4.14)	(2.11)	(3.94)	(2.06)
FIE_{it}	.094**	.101**	.046**	.032**	.047**	.038**
	(3.36)	(3.19)	(4.56)	(2.1)	(4.59)	(2.50)
SOE_{it}	-.049	-.050	.014	.018	.015	.024
	(-1.38)	(-1.58)	(.81)	(.72)	(.87)	(.97)
$markup_{it-1}$	.003	-.004	.057*	.190**	.071	.192**
	(.18)	(-.71)	(1.64)	(14.59)	(1.35)	(14.4)
ind_markup_{it-1}	-1.377**	-.969*	-.162	.524	-.052	.676**
	(-1.92)	(-1.73)	(-.78)	(1.59)	(-.24)	(2.03)
$H\,\mathrm{erf}_{it-1}$	-.522	-.185	.057	.071	-.010	-.003
	(-1.32)	(-.96)	(.67)	(.56)	(-.13)	(-.02)
$FIE_{it} \times PWIM_{it}$	-.042**	-.047**	-.045**	–	–	–
	(-2.21)	(-2.09)	(-4.99)			
$FIE_{it} \times PE_{it}$	–	–	–	-.060**	-.045**	-.069**
				(-3.68)	(-4.77)	(-4.07)
$SOE_{it} \times PWIM_{it}$	.104*	.107**	–	–	–	–
	(1.68)	(1.98)	–	–	–	–
$SOE_{it} \times PE_{it}$	–	–	.027	.008	.026	.008
	–	–	(.83)	(.13)	(.66)	(.12)
$FIE_{it} \times (\ln K/L)_{it}$	-.015**	-.015**	.000	.007	.000	.005
	(-2.02)	(-1.93)	(.13)	(1.67)	(.02)	(1.26)
Industry Fixed Effects	Yes	No	Yes	No	Yes	No
Firm Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	6,775	6,777	37,915	37,915	36,278	36,278
R-squared	.02	.02	.08	.05	.08	.06

Notes: Robust t-values corrected for firm clustering in parentheses. *(**): significance 10(5) percent.

Table 11: Further Estimates using Industry Output Tariffs

Regressand: $\ln TFP_{it}^{OP}$	All Sample		Without Assembly	PWIM only	Without Switchers
	(1)	(2)	(3)	(4)	(5)
Industry Output Tariffs	-.639**	-.847**	-.358**	-.637**	-.631**
	(-18.15)	(-16.24)	(-14.08)	(-18.13)	(-13.49)
Industry Input Tariffs	-.201**	-.121	.070	-.201**	-.217**
	(-3.90)	(-1.39)	(1.30)	(-3.96)	(-3.58)
PE_{it}	.035**	.041**	.044**	–	.032**
	(5.41)	(3.28)	(6.51)		(2.64)
$PWIM_{it}$	–	–	–	.032*	–
				(1.65)	
$\ln(K/L)_{it}$	.012**	.007**	.013**	.013**	.004*
	(5.99)	(2.42)	(6.87)	(6.54)	(1.80)
FIE_{it}	.068**	.052**	.058**	.057**	.065**
	(7.56)	(3.66)	(6.44)	(6.53)	(5.95)
SOE_{it}	.010	.006	.013	.013	-.007
	(.69)	(.28)	(.86)	(1.03)	(-.42)
$markup_{it-1}$	–	–	.048**	.049**	.027*
			(1.96)	(2.04)	(1.89)
ind_markup_{it-1}	-1.49	.796**	-1.21	-.177	-.253**
	(-.91)	(2.73)	(-.71)	(-1.08)	(-1.22)
$H\,\mathrm{erf}_{it-1}$	-.018	-.367**	.002	.006	.026
	(-.30)	(-3.71)	(.03)	(.10)	(.33)
$FIE_{it} \times PE_{it}$	-.044**	-.056**	-.052**	–	-.040**
	(-6.06)	(-4.05)	(-6.74)		(-3.09)
$FIE_{it} \times PWIM_{it}$	–	–	–	-.037**	–
				(-1.93)	
$SOE_{it} \times PE_{it}$	.000	-.026	.021	–	.040
	(.02)	(-.52)	(.83)		(1.18)
$SOE_{it} \times PWIM_{it}$	–	–	–	.041	–
				(.96)	
$FIE_{it} \times \ln(K/L)_{it}$	-.002	.004	-.000	-.002	-.002
	(-1.18)	(.99)	(-.11)	(-.95)	(-.88)
Industry-specific Fixed Effects	Yes	No	Yes	Yes	Yes
Firm-specific Fixed Effects	No	Yes	No	No	No
Year-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	54,937	54,937	51,768	54,937	33,963
Prob.>F	.000	.000	.000	.000	.000
Root MSE	.330	.304	.329	.329	.316
R-squared	.077	.056	.077	.054	.053

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *(**) indicates significance at the 10(5) percent level.

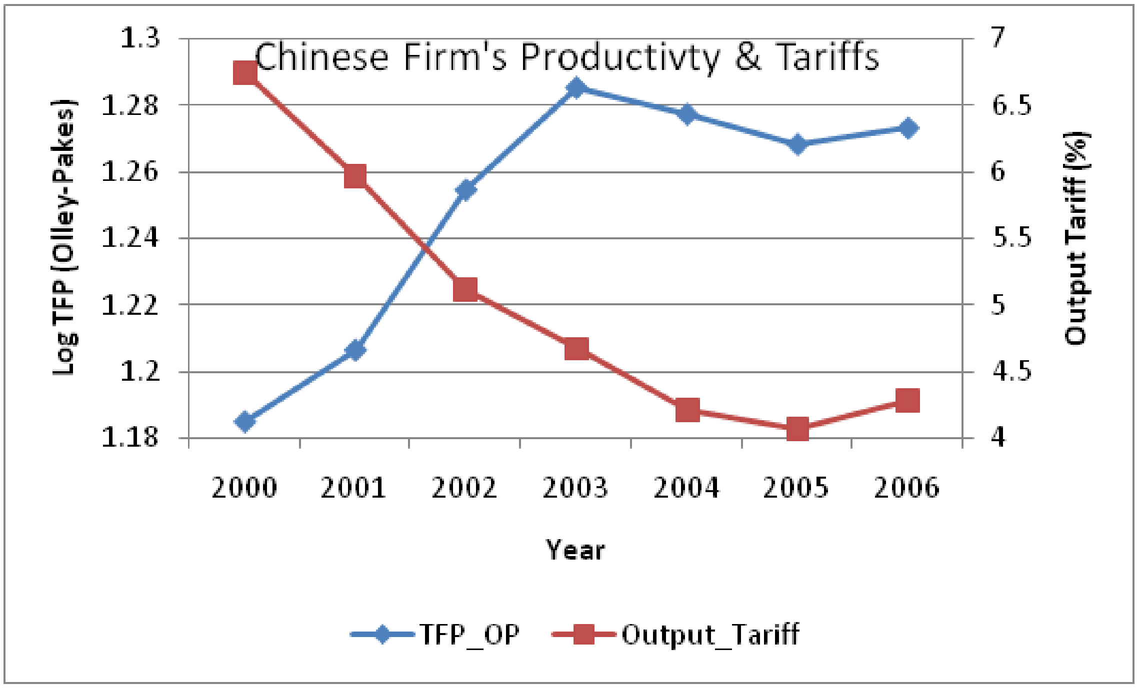

Figure 1: Firm's Logarithm of TFP and Weighted Output Tariffs (2000-2006)

Notes: Productivity and output tariffs are measured as an average of log TFP and weighted output tariffs levels taken across all firms in each year in the sample.

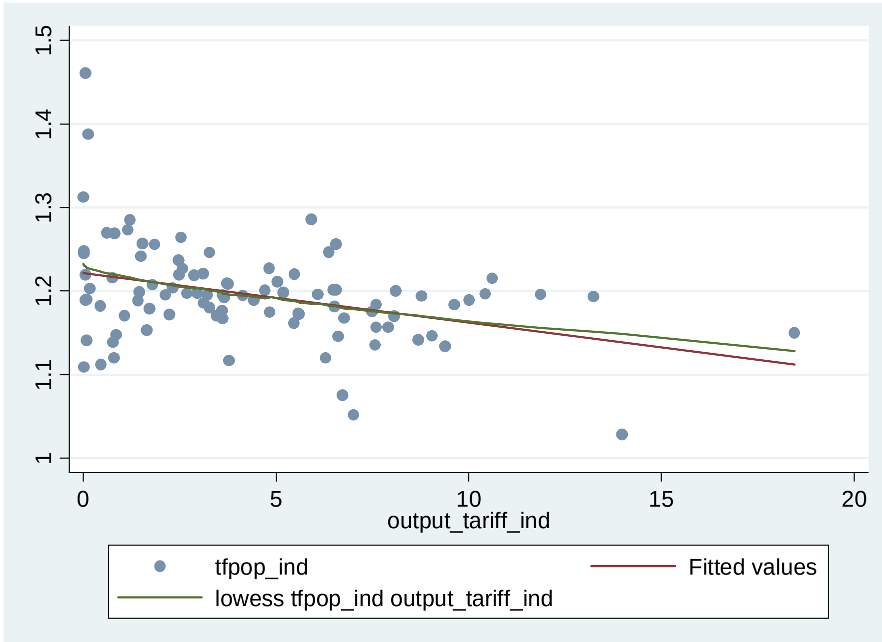

Figure 2: Chinese Firm's Productivity and Weighted Output Tariffs (2000-2006)

Sources: Author's own calculation from the sample. Productivity and output tariffs are measured as an average of log TFP and output tariffs levels taken across all firms in HS 2-digit level industries and all sample years. Thus, one plot in the figures denotes an industry at HS 2-digit level across all sample years.

6 Appendix

6.1 Appendix A: Measuring TFP

Econometricians have tried hard to address the empirical challenge of measuring TFP, but were unsuccessful until the pioneering work by Olley and Pakes (1996). In the beginning, researchers used two-way (*i.e.*, firm-specific and year-specific) fixed effects estimations to mitigate simultaneity bias. Although the fixed effect approach controls for some unobserved productivity shocks, it does not offer much help in dealing with reverse endogeneity and remains unsatisfactory. Similarly, to mitigate selection bias, one might estimate a balanced panel by dropping those observations that disappeared during the period of investigation. The problem is that a substantial part of information contained in the dataset is wasted, and the firm's dynamic behavior is completely unknown.

Fortunately, the Olley–Pakes methodology makes a significant contribution in addressing these two empirical challenges. By assuming that the expectation of future realization of the unobserved productivity shock, υ_{it}, relies on its contemporaneous value, the firm i's investment is modeled as an increasing function of both unobserved productivity and log capital, $k_{it} \equiv \ln K_{it}$. Following previous works, such as van Biesebroeck (2005) and Amiti and Konings (2007), the Olley–Pakes approach was revised by adding the firm's export decision as an extra argument of the investment function since most firms' export decisions are determined in the previous period (Tybout, 2003):

$$I_{it} = \tilde{I}(\ln K_{it}, \upsilon_{it}, EF_{it}, IF_{it}), \tag{6}$$

where EF_{it} (IF_{it}) is a dummy to measure whether firm i exports (imports) in year t. Therefore, the inverse function of (6) is $\upsilon_{it} = \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it}, IF_{it})$.[33] The unobserved productivity also depends on log capital and the firm's export decisions. Accordingly, the estimation specification (2) can now be written as:

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_l \ln L_{it} + g(\ln K_{it}, I_{it}, EF_{it}, IF_{it}) + \epsilon_{it}, \tag{7}$$

where $g(\ln K_{it}, I_{it}, EF_{it})$ is defined as $\beta_k \ln K_{it} + \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it})$. Following Olley and Pakes (1996) and Amiti and Konings (2007), fourth-order polynomials are used in log-capital, log-investment, firm's export dummy, and import dummy to approximate $g(\cdot)$.[34] In addition, since my firm dataset is from 2000 to 2006, I include a WTO dummy (*i.e.*, one for a year after 2001 and zero for before) to characterize the function $g(\cdot)$ as follows:

$$g(k_{it}, I_{it}, EF_{it}, IF_{it}, WTO_t) = (1 + WTO_t + EF_{it} + IF_{it}) \sum_{h=0}^{4} \sum_{q=0}^{4} \delta_{hq} k_{it}^h I_{it}^q. \tag{8}$$

After finding the estimated coefficients $\hat{\beta}_m$ and $\hat{\beta}_l$, I calculate the residual R_{it} which is defined as $R_{it} \equiv \ln Y_{it} - \hat{\beta}_m \ln M_{it} - \hat{\beta}_l \ln L_{it}$.

The next step is to obtain an unbiased estimated coefficient of β_k. To correct the selection bias as mentioned above, Amiti and Konings (2007) suggested estimating the probability of a survival indicator on a high-order polynomial in log-capital and log-investment. One can then accurately estimate the following specification:

$$R_{it} = \beta_k \ln K_{it} + \tilde{I}^{-1}(g_{i,t-1} - \beta_k \ln K_{i,t-1}, \hat{pr}_{i,t-1}) + \epsilon_{it}, \tag{9}$$

where $\hat{pr}_i$ denotes the fitted value for the probability of the firm 's exit in the next year. Since the specific "true" functional form of the inverse function $\tilde{I}^{-1}(\cdot)$ is unknown, it is appropriate to use

[33] Olley and Pakes (1996) show that the investment demand function is monotonically increasing in the productivity shock υ_{ik}, by making some mild assumptions about the firm's production technology.

[34] Using higher order polynomials to approximate $g(\cdot)$ does not change the estimation results.

fourth-order polynomials in $g_{i,t-1}$ and $\ln K_{i,t-1}$ to approximate that. In addition, (9) also requires the estimated coefficients of the log-capital in the first and second term to be identical. Therefore, non-linear least squares seem to be the most desirable econometric technique (Pavcnik, 2002; Arnold, 2005). Finally, the Olley–Pakes type of TFP for each firm i in industry j is obtained once the estimated coefficient $\hat{\beta}_k$ is obtained:

$$TFP_{ijt}^{OP} = \ln Y_{it} - \hat{\beta}_m \ln M_{it} - \hat{\beta}_k \ln K_{it} - \hat{\beta}_l \ln L_{it}. \tag{10}$$

6.2 Appendix B: Merging production-level trade data and firm-level production data

Although the adoption of using both zip code and phone number as identifiers seems to be a good way to merge these two dataset, there remains one subtle technical difficulty when using phone number as a common variable: the phone numbers in the product-level trade data include both area phone codes and a hyphen, whereas those in the firm-level production data do not.

Therefore, I use the last seven digits of the phone number to serve a proxy for firm identification for two reasons: (1) during 2000–2006, some large Chinese cities changed their phone number digits from seven to eight, which usually added one more digit at the start of the number. Therefore, sticking to the last seven digits of the number would not confuse the firm's identification; and (2) in the original dataset, phone number is defined as a string of characters with the phone zip code. However, it is inappropriate to de-string such characters to numerals since a hyphen bar is used to connect the zip code and phone number. Using the last seven-digit substring solves this problem neatly.[35]

[35] In practice, we still can see some problems. For example, some firms mistakenly include their zip code after their phone number as the number reported, or the seven-digit phone number might be reduced to six digits if the second digit is a zero. Hence, we omitted such observations to avoid confusion. These omissions only accounted for 1% of the sample and should not affect our results.

Appendix Table A: Transition Probability for Processing Firms

	Processing Firms in the Next Year		
Processing Firms this year	0	1	Total
0	88.75%	11.25%	100%
1	24.23%	75.77%	100%
Total	61.00%	39.00%	100%

Notes: 0 means non-processing firms, 1 means processing firms.