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

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Abstract

This paper explores how processing trade, jointly with tariff reduction, can improve a firm's productivity. Tariff reductions generate productivity gain via competition, whereas processing export does so via spillovers. Using mostly 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 found that a 10% tariff decrease generates a 12% increase in a firm's productivity gain. In addition, processing firms enjoy significant productivity gains via spillovers, with heterogeneity across firms divided according to ownership. These findings are robust to various econometric methods, disaggregated specifications, and measures.

JEL: F1, L1, O1, O2

Keywords: Processing Trade, Productivity, Firm's Heterogeneity, Chinese Plants

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1 Introduction

This paper investigates the influence of processing trade and tariff reductions on Chinese firms' productivity. Although the impact of tariff reductions on a firm's 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 tariff reductions, which could foster a firm's productivity by inducing tougher import competition, processing trade can introduce international knowledge spillovers and other learning effects on domestic firms. As a result, processing firms usually enjoy more productivity gains than those of non-processing firms. The spillover effects can differ according a firm's ownership. In particular, foreign-invested enterprises (FIEs) are associated with high productivity since they enjoy international spillovers. By contrast, state-owned enterprises (SOEs) usually have low productivity since they are less efficient.

In the past decade, China's foreign trade has grown very fast. China has now replaced Germany as the largest exporter in the world. Indeed, the processing export regime jointly with FIEs has become the driving force of China growing exports. Within its total trade volume, China's processing trade has accounted for more than half 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 past two decades has been around 4%, although this pace seems to have slowed down over time (Zheng et al., 2008).

Using the most disaggregated Chinese firm-level production data and product-level trade data, in this paper I unravel the two channels of raising productivity gains from trade liberalization for processing firms: the import competition effect via tariff reductions and the learning effect via processing trade. In addition, I explore the processing firm's heterogeneity on productivity gain across firm types. To the best of my knowledge, this paper is one of the few studies to show that China's tariff reductions generate productivity gains via increased competition, whereas processing export does so via spillovers. These results are found to be robust by using a variety of methodological assessments.

Firstly, I measure a firm's productivity in two ways. I first calculate the 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 aggressively 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 a 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 a firm's productivity gains. More importantly, the spillover effect differs according to a firm's ownership. FIEs are associated with high productivity since they enjoy international spillovers. By contrast, SOEs usually have low productivity since they are less efficient. Interestingly, I find that FIEs involved in processing trade have lower productivity than those not involved.

Thirdly, I mostly use 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 industrial 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 drawback of using industrial 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 industrial-level tariff as in many previous studies.

Finally, I adopt the instrumental variable (IV) approach to control for the possible reverse causality of a firm's productivity growth on import tariffs. After controlling for this endogeneity, I still find robust evidence that a 10% decrease in tariffs leads to a 12% increase in a firm's productivity gain. In addition, processing firms enjoy significantly additional productivity gain via spillover effects.

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, de Melo, and Corbo (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 firms' 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 plant(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 et al. (2006) for the United States and Trefler (2004) for Canada. But more evidence has been found in developing countries, such as Bustos (2009) for Argentina, Scholr (2004) for Brazil, Tybout, de Melo, and Corbo (1991) and Pavcnik (2002) for Chile, Harrison (1994) for Cote d'Ivoire, Krishna and Mitra (1998) for India, Amiti and Konings (2007) for Indonesia, De Loecker (2007) for Slovenia, Iscan (2008) for Mexico, and Levinsohn (1993) for Turkey.

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 industrial 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, Ishii, and Yi (2001), and reconstructed the input–output tables to assess domestic value-added products. Lu et al. (2009) found that Chinese exporters are less productive than non-exporters among foreign affiliates. Li and Yu (2009) ascertained that Chinese firms' credit constraints and their productivities jointly affect exports. Park *et al.* (2010) found that Chinese firms whose export destinations experience weaker currency depreciation have faster export growth. However, very few studies, if any, have systematically explored the impact of trade liberalization on a firm's productivity in China by using micro-level data. Thus, this paper provides novel evidence to fill in the gaps in the research.

This paper also enriches our understanding of the trade sources of productivity gains. As concisely summarized by Amiti and Konings (2007), there generally exist three sources: (1) Competition effects. With less trade barriers, domestic firms face more import competition and have to cut their markup and reduce their market shares. As a result, firms have to make every effort to increase their productivity to survive (Helpman and Krugman, 1985). (2) Spillovers effects. The more exposure to foreign trade, the more likely firms are to enjoy international knowledge spillover. This could be through the incremental inflow of foreign direct investment (Keller and Yeaple, 2009), processing trade to import more high quality intermediate goods, or learning by exporting (De Loecker, 2007). (3) Reallocation effects. By efficiently reallocating input endowments, a firm's productivity can significantly increase. Recently, Hsieh and Klenow (2009) argued that China would enjoy an additional quarter of TFP gains if its capital and labor were reallocated efficiently. However, their estimations are based on aggregated data, and the heterogeneous effects across and within industries still deserve further exploration. In this paper, I focus on the first two channels of productivity growth, but leave the last one for future 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 tariff reductions affect a firm's productivity.

The rest of the paper is organized as follows. Section 2 introduces my econometric method. Section 3 describes the 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.[1] 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 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.

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

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 Locker (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, I use an industrially deflated price to measure TFP. Previous works such as Felipe, Hasan, and McCombie (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.[2] 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. Similarly, following Amiti and Konings (2007), I also include a firm's export behavior in calculating TFP by constructing a binary variable (one denotes export and zero otherwise). The detailed procedure for the estimation of TFP is provided in Appendix A.

As discussed above, the augmented Olley–Pakes approach assumes that capital is more aggressively responsive to an unobserved productivity shock than labor. However, this assumption might not fit very well with China since it is a labor-abundant country. Firms might prefer to adjust their labor to re-optimize their production behavior rather than capital. I then use the Blundell–Bond (1998) system GMM approach to handle this potential empirical challenge. 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.[3] In particular,

[2] To gain a precise measure of TFP, ideally one should rely on product-specific prices to calculate the "*physical productivity*" (Foster, Haltiwanger, and Syverson, 2005). 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.

[3] 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

this model has a dynamic representation as follows:

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

where ς_i is firm i's fixed effect and ζ_t is year-specific fixed effect. The idiosyncratic term ω_{it} is serially uncorrelated if there is no measurement error.[4]One can obtain consistent estimates of the coefficients in (12) by using a system GMM approach (Blundell and Bond, 1998). 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:

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

where TFP_{it}^{OP} is firm i's Olley-Pakes type TFP in year t whereas τ_{it} denotes firm i's product value-weighted tariff in year t. PE_{it} is a dummy of a processing firm to measure whether or not firm i is involved in processing trade (either import or export) in year t.[5] Here α_1 measures the import competition effect among firms and thereby is expected to be negative. By contrast, α_2 measures the learning effects such as technological spillovers via processing trade and thereby is anticipated to be positive. $\mathbf{X}_{it}$ denotes other control

the fixed effects, the system GMM approach can introduce more instruments and thereby dramatically improve efficiency.

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

[5] 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.

variables for firm i in year t such as its markup, the industrial markup, Herfindahl index, capital utilization, 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 possibly because of their superior international technology spillover (Keller and Yeaple, 2009) or lower financial constraints (Li and Yu, 2009). 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 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) industrial 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 the extent of a firm's capital utilization, defined as its logarithm of the capital/labor ratio, into my estimations to control for the possible endowment effect 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 real 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 completely investigate the impact of trade liberalization on a firm's productivity, in this paper I rely on the following three highly disaggregated large panel datasets: disaggregated 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 $162,885$ in 2000 to $301,961$ 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*.[6] The dataset includes more than 100 financial variables listed in the main accounting statements of all these firms.[7]

Although this dataset contains rich information, some samples are noisy and thereby misleading, largely because of misreporting by some firms.[8] Following Jefferson *et al.* (2008), I clean the sample and omit outliers by using the following criteria. First, observations whose key financial variables (such as total assets, net value of fixed assets, sales, and gross value of industrial output) are missing were dropped. Secondly, the number of employees hired for a firm had to be no less than 10 people.[9]

Following Cai and Liu (2009) and Li and Yu (2009), 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).

[6] 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.

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

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

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

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 export with assembly and processing export with imported materials. 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.

Table 2 reports a simple statistical summary for Chinese product-level trade data by shipment and year. Overall, when focusing on the most 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 export with assembly (code: 14).

China has not separately reported processing export with imported materials in this dataset after its accession to the WTO in 2001. 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 trade with imported materials only has 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 Disaggregated Tariffs Data

Tariffs data can be accessed directly from the WTO.[10] China's tariffs data are available at the HS six-digit disaggregated level for the period 2000–2007.[11] For each commodity the following variables are available: number of ad valorem (AV) duty and non-AV duty; average, minimum, and maximum AV duties; percentage of duty free; and even the bound duty. 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 a firm's productivity, I use average AV duty to measure trade liberalization.

Table 3 reports the clustered HS two-digit AV duty (υ) 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.

[10] http://tariffdata.wto.org/ReportersAndProducts.aspx

[11] There are no data from 2000, but data from 1996 and 1997 are available. Since China did not experience dramatic tariff reductions between 1997 and 2000, I have used the 1997 tariffs to serve as a proxy of those in 2000.

[Insert Table 3 Here]

Since the main interest of this paper is to explore the effect of tariffs on a firm's productivity, it is important to properly measure the tariff level faced by firms given that each might import multiple products. Here, I construct a product weighted tariff index (τ_{ijt}) for firm i in industry j at year t as follows:

$$\tau_{ijt} = \sum_k \left(\frac{m_{ijt}^k}{\sum_k m_{ijt}^k}\right) \upsilon_{jt}^k,$$

where the ratio in the parenthesis measures the weight of product k based on its trading value (m). 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. Within each category, the average firm's duty is smaller than the average product duty. The economic rationale behind this observation is that firms produce more products with lower tariffs. One possible reason is that, when facing tougher import competition, firms attempt to improve quality and thereby the value of their products.[12]Nevertheless, both industry-level and firm-level tariffs have declined over the years.

3.4 Data Manipulation and Measures

It is of great help for researchers to understand Chinese firms' production and trading behavior with these three datasets at hand. However, researchers immediately face practical difficulties when combining product-level trade data with firm-level production data. Although these two datasets share a common variable (*i.e.*, the firm's identification number), the coding system in each is *completely* different. In particular, the firm's codes in the product-level trade data are at an 11-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 datasets cannot work together. To fix this problem, I rely on

[12] 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.

other common variables to identify firms. Appendix B describes the detailed practical technique and procedure of measuring such data sets.[13]

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. 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 without valid common merging variables, this number reduces to 973,207. Following the same filtering process as before, I then obtain 433,273 firms over the same period, which account for 44.5% of the 973,207 production firms in the sample.

I then merge the datasets 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[14]), implies that more than 90% of large firms do not trade internationally. Such a proportion might have an underestimation bias because of missing information on the two identifiers in the sample. Li and Yu (2009) found that around 27% of all large (or "above scale") firms exported in 200$\hat{0}$–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[15], their total export volumes still account for more than 45% of total exports for all large exporting firms in

[13]Interested Readers can contact me for this appendix.

[14]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.

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

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).[16]

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 0.977 to 0.996 with a mean of 0.994, which suggests that firm exits were less severe in the sample during this period.[17]

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.[18] 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,[19] which is close to the constant returns-to-scales elasticities.[20] Turning to the comparison

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

[17] 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.

[18] Here, I use the original book value of fixed assets to estimate TFP. However, using the net value of fixed assets (after depreciation) does not change my results.

[19] Calculated as $.052 + .582 + .117 = .989$ by using the Olley-Pakes approach.

[20] Note that here I use the industrial deflator as a proxy of a firm's price. Indeed, it is even possible that

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. Its upper module presents HS eight-digit product-level information. Of the $16,262,159$ monthly observations, the product's duty weight, which is defined as $m_{ijt}^{k}/\sum_{k} m_{ijt}^{k}$, has a mean of .006 and thereby the average firm's weighted duty is .072. The tariffs slightly decline to .067 when clustered at the firm-year level as shown in the bottom module of Table 5.

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 type. I first construct a dummy for foreign-invested firms ($Foreign_{it}$) if the firm has any investment abroad. A caveat here is that the dummy excludes investment from Hong Kong, Macao, and Taiwan (H/M/T) since they are classified as 'out of border' investment rather than foreign investment. However, as emphasized by Feenstra and Hanson (2004), China's re-export from Hong Kong has a special place within China's foreign trade. Therefore, I consider, as a robustness check, a broad classification of FIEs (FIE_{it}) if a firm receives any investment from Hong Kong/Macao/Taiwan (H/M/T)-

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.

owned firms.[21] As shown in the bottom module of Table 5, around one-third of trading firms are classified as FIEs by the narrow definition but around two-thirds 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, Li and Yu (2009) 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 states and its operation scales are larger than the "above scale" threshold, and zero otherwise.[22] 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.

4 Empirical Results

4.1 Benchmark Results

As shown in Figure 1, a firm's tariffs have declined over 2000–2006. 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 a firm's productivity. Hence, I explore such a nexus between the two in this section.

[Insert Figure 1 Here]

[21] 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 (code: 210), H/M/T joint venture enterprises (220), fully H/M/T-invested enterprises (230), and H/M/T-invested limited corporations (340).

[22] 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).

Table 6 reports the benchmark pooling OLS estimation results for this unbalanced panel for 31,393 firms from 2000–2006.[23] Column (1) includes the two essential variables as regressors: a firm's weighted tariffs (τ_{it}) and the dummy of processing firms (PE_{it}). The effect of a firm's import tariffs on its TFP is significantly negative, which suggests that tariff reductions significantly foster a firm's efficiency by inducing tougher import competition. The significantly positive coefficient of the dummy of processing firms ($\hat{\alpha}_2$=.015) creates an impression that processing firms are associated with high productivity.

Classical trade theory predicts that labor-abundant countries export labor-intensive products. If this is true, firms in labor-abundant industries (or firms with a relatively rich labor endowment) would export more. Coincidentally, firms with high productivity are associated with more exports (Bernard et al., 2006). Hence, it seems reasonable to expect that a Chinese firm's capital utilization, measured as its logarithm of the capital/labor ratio, is negatively correlated to a firm's productivity. Therefore, I include a firm's capital utilization in Column (2) to control for such a possible correlation. Column (2) also controls for other factors that might affect a firm's import competition due to its industrial market structure *status quo ante*, and still finds that tariff reductions lead to productivity gains.

Previous work also suggests that SOEs have relatively low productivity compared with non-SOEs because of their low efficiency and impotent incentive systems (Wu, 2005). Therefore, I add a dummy of SOEs as a control variable after the first column. 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 professionals in China 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 isolate a firm receiving foreign investment from one not.

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

In particular, I consider two different definitions of a FIE dummy. In a narrow category, FIEs are defined as firms receiving foreign investment except that from H/M/T. By contrast, a broad definition of the FIE dummy includes investment from H/M/T. Column (2) shows that FIEs are positively associated with high productivity. More importantly, the estimates in Columns (3) and (4) show that, including foreign investment from H/M/T, FIEs are associated with more productivity growth, in terms of economic magnitude.

[Insert Table 6 Here]

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 in Column (3). Interestingly, the interaction term between FIEs and processing firms is significantly negative, whereas that between SOEs and processing firms is significantly positive, which suggests that non-processing FIEs have higher productivity than processing FIEs, and that the reverse holds for non-processing SOEs. The economic rationale is as follows. Since SOEs usually have lower efficiency, they would like to work with processing trade to gain technological spillovers effects. As a result, processing SOEs have higher productivity than non-processing SOEs. By contrast, most FIEs have high productivity status quo ante. Only those with lower productivity are more eager to involve with processing activity and gain additional spillovers from trade. Finally, I add an additional interaction term between FIEs and its log capital/labor ratio to see whether FIEs are more capital-abundant than non-FIEs. The estimated coefficient for this interaction term is negative but insignificant. Nevertheless, a firm's tariffs are shown to significantly negatively correlate to its TFP, whereas processing firms have higher productivity.

Columns (5)–(7) are the two-way fixed effects estimations. As mentioned above, some time-invariant factors such as a firm's location can affect a firm's 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 tariff and processing dummy, again have anticipated signs. In addition, their economic magnitudes are close to their counterparts obtained by the OLS estimates in Columns (1)–(4).

4.2 Estimates by Industry

In my sample, a firm's productivity is shown to be significantly heterogeneous across different industries. In particular, industries such as tobacco and cereals (HS code: 24 & 10) have a much higher TFP than industries such as ceramic products and arms (HS code: 69 & 93). By deleting the two outliers with the highest and lowest industrial productivities, Figure 2 clearly demonstrates that, overall, industries with low import tariffs have high productivity. However, as shown in Table 3, the variation of a firm's weighted 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 a firm's productivity by industry.

[Insert Figure 2 Here]

Columns (1) and (2) first report the OLS and fixed effect estimation results by excluding the two outliers with the highest and lowest industrial productivities. The estimated coefficients are very close to their counterparts in Columns (4) and (7) of Table 6. Since high-tech industries (i.e., telecommunication) are usually expected to have high productivity, I omit the other industries and run regressions on Columns (3) and (4). The estimation results suggest that tariff reductions again significantly foster a firm's productivity. More importantly, their economic magnitude is much higher than their counterparts in Columns (1) and (2), which cover all industries. However, processing firms in high-tech industries are also positively, although insignificantly, associated with a firm's productivity.

The rest of Table 7 investigates the textiles and garments industry, the one with the highest tariffs, and the machinery industry, the one with the lowest tariffs. Each estimated coefficient has the same sign as previous estimates. Turning to the economic magnitude, the coefficients of a firm's tariff in the machinery industry are much higher than those in the textiles and garments industry, which suggest that firms in the former benefit much more from tariff reductions. One possible reason is these firms face far tougher import competition given China has a huge intra-industry trade in machinery, as reported by China's General Administration of Customs.

[Insert Table 7 Here]

4.3 Specifications of Periodic Differences

To reduce the estimation bias caused by unobserved firm heterogeneity, the estimates in Tables 6 and 7 control for the firm-specific and year-specific fixed effects by adopting the firm's annual data. However, some unobserved factors would still change according to the firm and year. One possible example is that taxation reduction policies in special economic zones vary by year, affecting the productivity of firms based in these zones. The regular two-way fixed effects estimation seems unable to fully control for this omitted variable problem.

To address this empirical challenge, I consider alternative econometric specifications by taking periodic differences. In Column (1) of Table 8, I take the first difference for both the firm's tariff and processing firms as well as the dummy of FIEs and SOEs. It turns out that both tariffs and the processing dummy still have anticipated coefficients, although insignificantly for the processing dummy. I suspect that this insignificance is because of the above naive specification. Column (2) offers a complete specification and finds that the processing dummy is significantly positive. Similarly, estimates of the second and third periodic differences have the same qualitative finding.

The only surprising finding is that the coefficients of FIEs and the interaction term with processing firms changes their signs in all periodic specifications. However, these signs are all insignificant in the conventional statistical sense.

[Insert Table 8 Here]

4.4 Alternative Measures on 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, the role of capital will not be overemphasized in China. By covering all industries in the sample, the OLS and fixed effect estimates in Columns (1) and (2) of Table 9 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.

If processing trade can boost a firm's productivity via spillovers, we should expect that assembly, 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 (3) and (4) ascertains this conjecture. However, 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. 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 (5), 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. Again, tariff reductions are shown to significantly boost a firm's productivity and processing firms have higher productivity.

Thus far, all estimates reveal that processing firms have higher productivity than non-processing firms because of spillovers effects. However, it is interesting to ask whether processing firms, compared with non-processing firms, gain more from tariff reductions because of the import competition effects. Therefore, I include an interaction term between the firm's tariffs and processing dummy in the last column of Table 9. After controlling for the two-way fixed effects, such an interaction term is shown to have a significantly negative effect. This clearly suggests that, in addition to the spillovers, processing firms benefit from import competition.

Turning to other variables, in all the estimations in Table 9, FIEs are shown to have higher productivity than non-FIEs, but the interaction term with processing firms are significantly negative again. In addition, the positive sign of the log capital/labor ratio suggests that capital-abundant non-FIEs tend to have high productivity. By contrast, the estimated negative interaction term between a firm's endowment and dummy FIE variable suggests that capital-abundant FIEs are associated with low productivity.

[Insert Table 9 Here]

4.5 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.[24]

It is usually a challenging task to find a good instrument for tariffs. Following Amiti

[24] The IV approach is a good way to control for endogeneity issues. Wooldridge (2002) provides a careful scrutiny of this topic.

and Konings (2007), here I adopt a firm's import weighted tariffs in 1996 as an instrument. In particular, I construct the IV as:

$$\tau_{it}^{1996} = \sum\nolimits_k (\frac{m_{it}^k}{\sum_k m_{it}^k}) \upsilon_k^{1996},$$

where υ_k^{1996} is product k's tariff in 1996 and the import value weight $m_{it}^k / \sum_k m_{it}^k$ measures the extent of importance of product k for firm i at year t. Therefore, the weighted 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 10 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 tariffs). In my econometric model, the error term is assumed to be heteroscedastic: $\epsilon_{ijt} \sim N(0, \sigma_{ij}^2)$. Therefore, the usual Anderson (1984) canonical correlation likelihood ratio test is invalid since it only works under the assumption. 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.[25] Third, both the Anderson and

[25] Note that the Cragg and Donald (1993) F-statistic is no longer valid since it only works under the

Rubin (1949) statistic (which is an LM test) and 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 10 present the IV estimates by using Olley–Pakes TFP as the regressand. In Column (1), FIEs exclude firms that have investments from H/M/T. After controlling for the endogeneity of import tariffs, the coefficient of a firm's tariff is significantly negative and its economic magnitude is much larger than its counterparts in Table 6. This ascertains that tariff reductions lead to productivity growth. Without controlling for the reverse causality, the estimated tariff coefficient could be underestimated since low efficient firms could lobby government for protection. I then adopt a broad category of FIEs in Column (2) to include firms with investment from H/M/T as well as their interaction term with the capital/labor ratio, but still find similar evidence to that in Column (1).

Turning to other control variables, in all the IV estimates the industrial Herfindahl index is negative, although insignificantly. Aside from this, both the firm's markup and industrial markup show a positive sign, although it is insignificant for the former. This finding, to some extent, is different from the traditional wisdom that firms with higher markups status quo ante have a stronger monopolistic power and thereby should be less efficient. These unexpected results for such control variables might be because of the lack of controlling for fixed effects.

Therefore, I control for the two-way fixed effects IV estimates in Columns (4)–(6). The coefficients for almost all variables remain stable across the three specifications. The only exception is that now the firm's markup is positively significant. One possible reason for this interesting correlation is that some other fundamental factors might now affect both the firm's markup and productivity. However, this is not the main interest of this paper,

i.i.d. assumption.

and deserves further detailed exploration. The bottom line here is that, after controlling for the market structure, tariff production leads to productivity gain, whereas processing firms enjoy extra benefit from spillovers. In particular, a 10% decrease in a firm's tariff leads to a 12% increase in a firm's log of TFP after controlling for the reverse causality.

[Insert Table 10 Here]

4.6 Further Estimates of Processing Trade

To completely 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,[26]processing exports with assembly and processing exports with imported materials are the most important. In contrast to other types, processing exports with assembly are totally duty-free. Once the firm accesses assembly abroad, it immediately enjoys free duty. By contrast, processing trade 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 assembly (*i.e.*, one if a firm is involved with processing assembly and zero otherwise), the assembly dummy (ASM_{it}) should have a higher coefficient than that of the processing dummy (PE_{it}) estimated be-

[26] 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).

fore. As shown in Columns (1) and (2) of Table 11, the coefficient of assembly dummy is .034 in the IV estimate and .039 in the fixed effects IV estimate, which are both higher than their counterparts (.028) in Columns (3) and (6) of Table 10. Similarly, by constructing a dummy for processing dummy with imported materials ($PEIM_{it}$) in Columns (3) and (4), the coefficients in both the IV and fixed effects IV estimates are higher than their counterparts in Table 10. Finally, by putting these two important processing types together, the estimates in Columns (5) and (6) still find a similar finding: firms involved with these types of processing trade have higher productivity.

[Insert Table 11 Here]

Finally, since most processing firms enjoy (at least nearly) duty-free once involved in processing activities, the ongoing tariff reductions should have limited effects on boosting productivity gain via inducing import competition. In particular, the productivity of processing firms is expected to increase *less* than those of non-processing firms via tariff reductions. The reason is that firms would be free of duty charge *immediately* they become involved in processing trade. Tariff reductions in the period, therefore, have only a limited effect on inducing tougher import competition. If this is correct, I should include the interaction term between the firm's tariff and processing dummy in the regressions.

The first three columns of Table 12 report the estimation results after including this interaction term. At first, it seems that the benchmark OLS and fixed effect estimations do not support the prediction since the coefficient of the interaction term is still negative and significant. I suspect that this is because of the lack of control for the reverse causality of the firm's tariff. Once the endogeneity is controlled, Column (3) shows that the coefficient of the interaction term $\tau_{it} \times PE_{it}$ becomes significantly positive. However, the total effect of tariff reductions on a processing firm's productivity is still negative ($-1.448+1.124 < 0$), which implies that it still benefits from ongoing tariff reductions via the competition effect. The reason for this is that some processing firms only just started to become involved with processing trade during the period 2000–2006.

My last robustness check is to investigate both the competition effects and spillover effects across different processing types. As shown in Columns (4)–(6) of Table 12, when splitting the sample into types of processing trade, the coefficients of the interaction term $\tau_{it} \times PE_{it}$ for either type (*i.e.,* processing assembly, processing export with imported materials, or both) is insignificant, although the coefficient has an anticipated positive sign for samples with both assembly and imported materials. In any case, all the estimates suggest that tariff reductions boost a firm's productivity, whereas processing firms are associated with higher productivity.

[Insert Table 12 Here]

5 Concluding Remarks

The paper is one of the first to explore the role of processing trade on a firm's productivity gain. In many developing countries, trade liberalization includes both tariff reductions and processing behavior. In contrast to tariff reductions, which could generate productivity gain via the international competition effect, processing export can raise a firm's productivity via technological spillovers from abroad. Using the most disaggregated Chinese data on trade, tariffs, and firm-level production, I found that, on average, Chinese firms enjoy productivity gains from tariff reductions. Moreover, processing firms benefit from additional international spillovers.

This paper enriches our understanding of Chinese firms' TFP. 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. Overall, I found that Chinese firms exhibit increasing returns-to-scales and their TFPs are significantly increased.

The paper also has rich policy implications. First, since processing behavior can significantly increase a firm's productivity via technological spillovers, governments in developing countries such as China might retain an export-oriented development strategy in line with its own comparative advantage (Lin, 2009; Yao and Yu, 2010). Second, 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] Anderson, T.W. (1984), *Introduction to Multivariate Statistical Analysis*, 2nd ed. New York: John Wiley & Sons.

[2] 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.

[3] 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.

[4] Amiti, Mary, and Jozef Konings (2007), "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review* 97 (5), pp. 1611-1638.

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

[6] Bernard, Andrew, and Bradford Jensen (1999), "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics* 47, pp.1-25.

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

[8] 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.

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

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

[11] 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.

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

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

[14] Feenstra, Robert and Gordon Hanson (2004), "Intermediaries in Entrepôt Trade: Hong Kong Re-Exports of Chinese Goods," *Journal of Economics & Management Strategy* 13(1), pp.3-35.

[15] 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.

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

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

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

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

[20] Helpman, Elhanan, and Paul Krugman (1985), *Market Structure and Foreign Trade: Increasing Returns, Imperfect Competition, and the International Economy*. Cambridge, MA: MIT Press.

[21] 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.

[22] 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.

[23] 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.

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

[25] 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.

[26] 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.

[27] Jefferson, Gary, Rawski, Thomas, and Yifan Zhang (2008), "Productivity Growth and Convergence across China's Industrial Economy," *China Economic Quarterly* (in Chinese) 7(3), pp.809-826.

[28] 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.

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

[30] 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.

[31] 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.

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

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

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

[35] Li, Zhiyuan and Miaojie Yu (2009), "Export, Firm's Productivity, and Credit Constraints: An Firm-Level Empirical Investigation of China", CCER Working Paper No. 2009E05, Peking University, China.

[36] Lin, Yifu, Justin (2009), Economic Development and Transition: Thoughts, Strategy, and Viability, Cambridge University.

[37] Lu, Jiangyong, Yi Lu, and Zhigang Tao (2009), "Exporting Behavior of Foreign Afflicates: Theory and Evidence", *Journal of International Economics*, forthcoming

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

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

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

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

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

[43] 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.

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

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

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

[47] 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.

[48] 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.

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

[50] Wooldridge, Jeffrey M.(2002), *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

[51] Wu, Jinglian (2005), "Understanding and Interpreting Chinese Economic Reform," Thomson, Mason, Ohio.

[52] Yao, Yang and Miaojie Yu (2009), "Labor, Demography, and the Export-Oriented Growth Model in China," *Journal of Comparative Economic Studies* 5, pp. 61-78.

[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.

[55] Zheng, Jinghai, Hu, Angang, and Arne Bigsten (2009), "Can China's Growth be Sustained? A Productivity Perspective", *World Development,* 37(4), pp. 874-888.

Table 1: Basic Summary of Dataset

#. 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
Total # of Trading Firms (2000-06)							(# = 654,352)
Valid Firms[c]	21,869	17,485	12,625	15,241	40,143	55,168	55,493
Total # of Trading Firms (2000-06)[d]							(# = 218,024)
			Firm-Level Production Data				
Firms	162,885	171,256	181,557	196,222	276,474	271,835	301,961
Total # of Trading Firms (2000-06)							(# = 1,033,276)
Valid Firms[e]	43,239	35,374	37,037	53,843	86,477	72,626	104,677
Total # of Valid Firms[f]							(# = 433,273)
Total # of Merged Firms							(# =31,393)

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 after merging. (d) The total number of trading firms is the sum of valid trading firms in (b) over the period 2000–2006. (e) Valid firms refers to the number of firms for merging reported in the firm's accounting dataset. (f) The total number of valid firms refers to the sum of valid trading firms in (e) over the period 2000–2006. (g) Total number of merging firms indicates numbers of common firms in both customs and accounting datasets.

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
	Firm's Duty	.94	.11	.08	.16	.12	.09	.28
(06-15)	Product Duty	16.66	15.16	11.42	10.99	9.93	9.43	9.52
	Firm's Duty	1.56	.58	.51	.36	.41	.40	.54
(16-24)	Product Duty	20.23	16.49	14.26	13.42	12.65	11.76	10.32
	Firm's Duty	3.33	2.53	1.42	1.24	1.22	1.32	1.63
(25-27)	Product Duty	12.25	11.58	7.96	7.65	7.12	6.93	7.00
	Firm's Duty	6.19	5.32	4.08	3.73	3.26	3.40	3.47
(28-38)	Product Duty	15.16	13.81	9.64	8.84	8.08	7.69	7.64
	Firm's Duty	7.87	7.26	5.23	4.96	4.49	4.23	4.51
(39-40)	Product Duty	17.53	16.10	11.69	10.36	9.39	8.89	8.96
	Firm's Duty	8.33	7.35	5.38	4.71	4.12	3.82	5.80
(41-43)	Product Duty	22.42	19.38	15.93	14.61	12.82	12.11	11.75
	Firm's Duty	14.25	11.63	8.79	7.87	6.75	6.47	6.54
(44-49)	Product Duty	18.34	16.31	12.04	10.46	9.13	8.22	8.49
	Firm's Duty	10.64	9.74	7.11	5.59	4.84	4.07	4.58
(50-63)	Product Duty	26.79	21.81	17.92	15.69	13.66	12.50	12.47
	Firm's Duty	20.10	15.35	12.96	11.28	9.92	9.23	9.40
(64-67)	Product Duty	22.88	21.51	18.05	17.10	15.99	15.76	15.26
	Firm's Duty	19.17	18.35	17.06	16.36	15.80	15.20	15.48
(68-71)	Product Duty	18.98	17.97	14.01	12.87	11.37	10.98	10.69
	Firm's Duty	13.08	11.65	8.60	8.00	6.77	6.77	6.71
(72-83)	Product Duty	14.56	13.48	10.12	9.38	8.79	8.65	8.80
	Firm's Duty	9.27	8.84	6.39	5.71	5.41	5.08	5.34
(84-85)	Product Duty	13.59	12.71	7.63	6.61	6.10	5.85	5.84
	Firm's Duty	7.36	7.02	4.64	4.18	3.76	3.51	3.62
(86-89)	Product Duty	19.71	17.43	15.80	13.66	12.63	12.61	11.78
	Firm's Duty	10.18	11.60	7.15	8.01	8.25	6.58	4.88
(90-97)	Product Duty	19.12	16.34	12.74	11.39	9.95	9.07	8.97
	Firm's Duty	11.63	9.81	7.78	6.41	5.77	4.71	5.00
Average	Product Duty	18.53	16.24	12.09	10.66	9.48	8.97	8.87
	Firm's Duty	10.76	9.34	7.15	6.33	5.63	5.24	5.62

Sources: Author's own calculation.

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

HS 2-digit	Labor		Materials		Capital	
	OP	GMM	OP	GMM	OP	GMM
Animal & Animal Products	.058**	.053	.887**	.970**	.047**	-.022
(01-05)	(3.48)	(.87)	(55.08)	(17.71)	(2.52)	(-.43)
Vegetable Products (06-15)	.007	.031**	.891**	.571**	.048**	.019
	(.49)	(8.55)	(69.85)	(9.82)	(5.93)	(.46)
Foodstuffs (16-24)	.034**	-.020	.870**	.595**	.055**	.027
	(2.59)	(-.25)	(67.81)	(10.73)	(2.28)	(.46)
Mineral Products (25-27)	.042**	.241**	.871**	.671**	.174**	.089
	(2.07)	(3.78)	(50.63)	(15.51)	(3.76)	(1.57)
Chemicals & Allied	.010	.127**	.833**	.488	.114**	.071
Industries (28-38)	(1.44)	(1.95)	(117.22)	(10.99)	(10.02)	(1.48)
Plastics / Rubbers (39-40)	.057**	.321**	.798**	.298**	.089**	-.003
	(7.41)	(6.98)	(104.04)	(4.54)	(6.92)	(-.08)
Raw Hides, Skins, Leather	.104**	.125*	.804**	.738**	.045**	.043
& Furs (41-43)	(7.75)	(1.85)	(63.86)	(11.55)	(1.96)	(.66)
Wood & Wood Products	.031**	.041	.859**	.266**	.007	.118**
(44-49)	(3.38)	(.46)	(96.24)	(6.83)	(.47)	(2.99)
Textiles (50-63)	.091**	.157**	.806**	.653**	.058**	.043*
	(21.00)	(4.81)	(193.88)	(22.96)	(8.80)	(1.95)
Footwear / Headgear (64-67)	.071**	.138	.857**	.703**	.037**	-.108**
	(5.71)	(1.62)	(70.97)	(10.77)	(3.94)	(-2.38)
Stone / Glass (68-71)	.115**	.233**	.763**	.448**	.106**	.063
	(9.36)	(3.56)	(60.03)	(11.58)	(10.51)	(1.16)
Metals (72-83)	.050**	.191**	.815**	.400**	.099**	.084**
	(6.98)	(4.22)	(126.90)	(11.67)	(28.52)	(2.72)
Machinery/Electrical (84-85)	.067**	.056	.822**	.548**	.090**	.175**
	(13.48)	(1.15)	(196.42)	(13.43)	(10.77)	(4.97)
Transportation (86-89)	.039**	.147*	.882**	.426**	.080**	.068
	(2.62)	(1.70)	(68.08)	(8.81)	(2.89)	(1.08)
Miscellaneous (90-98)	.081**	.195**	.786**	.276**	.119**	.007
	(8.97)	(3.58)	(95.27)	(8.15)	(8.38)	(.22)
All industries	.052**	.240**	.820**	.486**	.117**	.001
(w/ industrial deflator only)	(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	Obs.	Mean	Std. Dev.	Min	Max
		HS 8-Digit Product-Level Observations			
Product's ID (HS 8-Digit)	17,170,619	6.67e+07	2.14e+07	1031000	9.80e+07
HS 6-Digit AV Tariff	9,851,216	.112	.773	0	90
HS 6-Digit AV Tariff in 1996 (%)	9,196,753	25.538	14.835	0	120
Product's Trading Value (RMB)	16,262,159	70499.77	856771.9	0	4.40e+08
Product Duty's Weight[a]	16,262,159	.006	.028	0	1
Firm's Weighted Duty[b]	9,304,869	.072	.396	0	65
Log Real Materials (M)	17,148,596	18.401	1.836	6.907	24.565
Log Employment (L)	17,170,641	6.254	1.339	2.302	11.907
Lag Real Capital (K)	17,153,244	17.631	1.932	6.907	24.281
Price Deflator	9,817,924	.972	.097	.845	2.115
Log Real Sales (Industrial Deflated)	17,170,641	11.818	1.797	7.979	17.814
Trading Type	1,0404,300	12.228	4.510	10	39
		Firm-Level Observations for Estimation			
Year	101,518	2003.491	1.889	2000	2006
Trading Firm's ID	101,518	3.52e+09	8.31e+08	1.10e+09	6.52e+09
Firm's TFP (Olley-Pakes)	101,292	1.188	.349	-1.869	11.501
Firm's TFP (System-GMM)	101,292	7.860	.583	5.215	14.946
Dummy of Processing Firm (PE_{ij})	101,518	.626	.483	0	1
Firm's Product-Weighted Tariff (τ_{ijt})	101,518	.0667	.0706	0	.802
$\tau_{ijt} \times PE_{ij}$	101,518	.042	.063	0	.802
Dummy of Exporting Firm (EF_{ij})	101,518	.480	.499	0	1
IV (τ_{ijt}^{1996})	89,494	.255	.143	0	1.198
Firm's Markup in Pervious Year	68,179	1.046	.473	-85.021	47.315
Industrial Markup in Pervious Year	68,180	1.053	.012	.836	1.148
Herfindahl Index in Pervious Year	68,180	.001	.003	3.09e-07	.602
$\ln(K/L)_{it}$	101,401	4.195	1.370	-5.777	14.940
SOEs Dummy	101,518	.017	.129	0	1
FIEs Dummy (exclusive H/M/T)	101,518	.332	.471	0	1
FIEs Dummy (FIE_{it})	101,518	.667	.471	0	1
$FIE_{it} \times PE_{ij}$	101,518	.516	.499	0	1
$SOE_{it} \times PE_{ij}$	101,518	.007	.087	0	1
$FIE_{it} \times \ln(K/L)_{it}$	101,518	2.859	2.337	-5.274	14.940
Trading Type	64,003	14.728	8.744	10	39

Notes: (a) Product's duty weight is defined as the ratio of product's value over firm's over in each year. (b) Firm's weighted duty at product level is the product of the weight of each product and its duty at HS 6-digit level.

Table 6: Benchmark Estimates

Regressand: TFP_{it}^{OP}	OLS				Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
τ_{it}	-.322**	-.414**	-.423**	-.424**	-.418**	-.426**	-.426**
	(-22.34)	(-21.79)	(-22.26)	(-22.25)	(-12.83)	(-13.00)	(-13.01)
PE_{it}	.015**	.021**	.033**	.033**	.028**	.038**	.037**
	(7.00)	(8.04)	(7.64)	(7.57)	(6.24)	(4.65)	(4.58)
$(\ln K/L)_{it}$		-.027**	-.025**	-.024**	-.030**	-.028**	-.026**
		(-23.34)	(-21.73)	(-12.20)	(-19.27)	(-17.75)	(-8.79)
$Foreign_{it}$		.059**			.069**		
		(20.31)			(15.25)		
FIE_{it}			.043**	.049**		.052**	.063**
			(10.66)	(4.75)		(7.68)	(4.20)
SOE_{it}		-.060**	-.079**	-.080**	-.060**	-.085**	-.086**
		(-5.53)	(-5.64)	(-5.68)	(-3.73)	(-3.74)	(-3.80)
$markup_{it-1}$		.024*	.024*	.025*	.017**	.018**	.018**
		(1.80)	(1.83)	(1.83)	(5.25)	(5.54)	(5.53)
ind_markup_{it-1}		-.029	-.036	-.037	.825**	.828**	.822**
		(-.29)	(-.36)	(-.37)	(3.71)	(3.72)	(3.68)
$H\,\mathrm{erf}_{it-1}$		.326	.344	.345	1.089	1.105	1.107
		(.99)	(1.07)	(1.07)	(1.43)	(1.44)	(1.44)
$FIE_{it} \times PE_{it}$			-.023**	-.022**		-.021**	-.020**
			(-3.96)	(-3.88)		(-2.10)	(-2.01)
$SOE_{it} \times PE_{it}$			.035	.035*		.062*	.062*
			(1.63)	(1.64)		(1.73)	(1.74)
$FIE_{it} \times (\ln K/L)_{it}$				-.001			-.003
				(-.60)			(-.84)
Firm Fixed Effects	No	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes	Yes
Observations	101,292	68,041	68,041	68,041	68,041	68,041	68,041
Prob.>F					.000	.000	.000
Root MSE	.348	.329	.330	.330			
R-squared	.005	.023	.019	.019	.041	.035	.034

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

Table 7: Estimates by Industry

Industries Covered:	All Industries w/o Tobacco & Arms		High-Tech Only		Textile Only		Machinery Only	
Method:	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Regressand: TFP_{it}^{OP}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
τ_{it}	-.423**	-.426**	-.609**	-.604**	-.106**	-.148**	-.650**	-.630**
	(-22.24)	(-13.01)	(-8.15)	(-6.46)	(2.20)	(-2.30)	(-11.67)	(-7.99)
PE_{it}	.033**	.037**	.010	.017	.023**	.031**	.026**	.022
	(7.58)	(4.58)	(.91)	(.90)	(2.87)	(2.15)	(2.64)	(1.29)
$(\ln K/L)_{it}$	-.024**	-.026**	-.023**	-.030**	-.042**	-.044**	-.019**	-.024**
	(-12.22)	(-8.79)	(-3.33)	(-3.87)	(-11.25)	(-7.96)	(-3.51)	(-3.58)
FIE_{it}	.048**	.063**	.043	.024	.112**	.079**	.098**	.076**
	(4.72)	(4.20)	(1.23)	(.57)	(5.76)	(2.75)	(3.25)	(2.12)
SOE_{it}	-.080**	-.086**	-.126**	-.115**	-.133**	-.165**	-.101**	-.104**
	(-5.68)	(-3.81)	(-4.20)	(-2.20)	(-3.85)	(-3.00)	(-3.99)	(-2.34)
$markup_{it-1}$	.024*	.018**	.010	.008	.265**	.230**	.014	.010
	(1.83)	(5.53)	(1.13)	(2.30)	(3.67)	(6.80)	(1.13)	(2.57)
ind_markup_{it-1}	-.036	.821**	-.679*	.437	-.641*	.658	-1.125**	-.569
	(-.36)	(3.68)	(-1.95)	(.81)	(1.92)	(1.20)	(-3.91)	(-1.15)
$H\,\mathrm{erf}_{it-1}$	.353	1.118	3.627*	.874	-1.233	-4.346	-.279**	-.280
	(1.09)	(1.46)	(1.71)	(.18)	(-.99)	(-1.06)	(-2.25)	(-.49)
$FIE_{it} \times PE_{it}$	-.022**	-.020**	-.002	-.000	-.035**	-.038**	-.021	-.020
	(-3.87)	(-2.00)	(-.17)	(-.18)	(-3.08)	(-2.02)	(-1.49)	(-.92)
$SOE_{it} \times PE_{it}$	.035*	.063*	.123**	.135*	.078	.133*	.091**	.131**
	(1.64)	(1.74)	(2.92)	(1.90)	(1.58)	(1.71)	(2.28)	(2.09)
$FIE_{it} \times (\ln K/L)_{it}$	-.001	-.003	.001	.007	-.017**	-.008	-.006	-.001
	(-.59)	(-.84)	(.21)	(.84)	(-3.42)	(-1.22)	(-1.05)	(-.11)
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	68,036	68,036	7,940	7,940	12,186	12,186	13,548	13,548
Root MSE	.330		.317		.290		.346	
Prob.>F	.000	.000	.000	.000	.000	.000	.000	.000
R-squared	.019	.035	.024	.029	.065	.016	.027	.031

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

Table 8: Regressions in Difference

Regressand: ΔTFP_{it}^{OP}	1^{st} Diff		2^{nd} Diff		3^{rd} Diff	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\tau_{it}$	-.112**	-.114**	-.210**	-.108**	-.160**	-.014
	(-2.67)	(-2.42)	(-5.41)	(-2.11)	(-3.78)	(-.24)
ΔPE_{it}	.003	.009**	.011**	.010*	.015**	.016**
	(.80)	(2.14)	(2.53)	(1.74)	(2.38)	(1.97)
$\Delta(\ln K/L)_{it}$		-.049		-.043**		-.033**
		(-10.29)		(-7.94)		(-4.92)
ΔFIE_{it}	-.020	-.033	-.028	-.036	-.001	-.018
	(-1.25)	(-1.27)	(-1.57)	(-1.35)	(-.05)	(-.52)
ΔSOE_{it}	-.029	-.021	-.042	-.044	-.130**	-.159**
	(-1.37)	(-.80)	(-1.51)	(-1.47)	(-3.53)	(-2.95)
$\Delta markup_{it-1}$		-.011**		.013		-.001
		(-2.39)		(1.46)		(-.07)
Δind_markup_{it-1}		-.387**		-.625**		-.559**
		(-3.72)		(-4.47)		(-3.44)
$\Delta H\,\mathrm{erf}_{it-1}$		-.229		.041		-.116
		(-1.02)		(.17)		(-.42)
$\Delta FIE_{it} \times \Delta PE_{it}$		.022		.033		.041
		(.58)		(.90)		(.72)
$\Delta SOE_{it} \times \Delta PE_{it}$		-.163*		-.095		-.139
		(-1.67)		(-1.12)		(-1.24)
$\Delta FIE_{it} \times \Delta(\ln K/L)_{it}$		-.008		.014		.099
		(-.33)		(.40)		(.99)
Observations	67,909	43,989	43,996	26,129	26,113	14,982
Root MSE	.363	.346	.389	.371	.389	.378
R-squared	.001	.006	.001	.001	.002	.007

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

Table 9: Alternative Estimates on Productivity

Regressand: TFP_{it}^{GMM}	All Industry		Assembly		No Switchers	Interaction
Method:	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
τ_{it}	-.719**	-.660**	-.663**	-.612**	-.827**	-.207**
	(-24.06)	(-12.73)	(-22.11)	(-11.70)	(-23.16)	(-2.70)
PE_{it}	.153**	.161**	.072**	.061**	.207**	.217**
	(21.88)	(12.60)	(5.04)	(2.58)	(20.74)	(14.93)
$(\ln K/L)_{it}$	.242**	.236**	.249**	.241**	.229**	.235**
	(75.94)	(50.41)	(76.38)	(51.38)	(57.57)	(50.51)
FIE_{it}	.112**	.116**	.158**	.160**	.045**	.129**
	(7.23)	(4.87)	(10.23)	(6.82)	(2.42)	(5.43)
SOE_{it}	-.022	-.074	.042**	.028	-.058**	-.071**
	(-.93)	(-2.01)	(2.26)	(1.04)	(-2.11)	(-1.98)
$markup_{it-1}$	.039**	.026**	.038**	.027**	.095**	.026**
	(2.07)	(5.12)	(2.09)	(5.24)	(1.97)	(5.08)
ind_markup_{it-1}	-.182	.874**	-.164	.747**	-.275	.965**
	(-1.21)	(2.47)	(-1.09)	(2.10)	(-1.53)	(2.73)
$H\,\mathrm{erf}_{it-1}$	1.506**	3.299**	1.242**	2.562**	1.282**	3.322**
	(3.77)	(2.71)	(2.97)	(2.10)	(2.97)	(2.74)
$FIE_{it} \times PE_{it}$	-.059**	-.062**	-.115**	-.107**	-.114**	-.065**
	(-6.76)	(-3.84)	(-7.28)	(-4.03)	(-9.16)	(-4.04)
$SOE_{it} \times PE_{it}$	.087**	.208**	-.087	-.020	.114**	.198**
	(2.48)	(3.64)	(-1.33)	(-.19)	(2.56)	(3.46)
$FIE_{it} \times (\ln K/L)_{it}$	-.041**	-.039**	-.045**	-.041**	-.017**	-.042**
	(-11.24)	(-7.18)	(-12.08)	(-7.65)	(-3.84)	(-7.75)
$\tau_{it} \times PE_{it}$						-.861**
						(-8.05)
Firm Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	68,041	68,041	68,041	68,041	49,900	13,548
Root MSE	.497		.499		.346	
Prob.>F	.000	.000	.000	.000	.000	.000
R-squared	.275	.284	.268	.275	.297	.285

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

Table 10: IV Estimates

Regressand: TFP_{it}^{OP}	IV			IV Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
τ_{it}	-1.216**	-1.240**	-1.240**	-1.267**	-1.294**	-1.294**
	(-28.36)	(-28.73)	(-28.71)	(-19.25)	(-19.61)	(-19.61)
PE_{it}	.009**	.028**	.028**	.008	.028**	.028**
	(2.71)	(6.02)	(6.02)	(1.46)	(3.40)	(3.34)
$(\ln K/L)_{it}$	-.034**	-.031**	-.032**	-.037**	-.034**	-.033**
	(-25.19)	(-23.84)	(-14.56)	(-21.49)	(-20.01)	(-10.43)
$Foreign_{it}$	.044**	–	–	.041**	–	–
	(7.67)			(4.48)		
FIE_{it}	–	.037**	.036**	–	.044**	.054**
		(8.37)	(3.29)		(6.03)	(3.37)
SOE_{it}	-.065**	-.060**	.059**	-.086**	-.075**	-.077**
	(-4.42)	(-4.07)	(-4.05)	(-3.25)	(-2.91)	(-2.96)
$markup_{it-1}$	.026	.028	.028	.017**	.018**	.018**
	(1.61)	(1.63)	(1.63)	(5.37)	(5.63)	(5.62)
ind_markup_{it-1}	.224**	.214*	.214*	.804**	.794**	.787**
	(2.05)	(1.95)	(1.95)	(3.41)	(3.35)	(3.32)
$H\,\mathrm{erf}_{it-1}$	-.091	-.065	-.066	.290	.344	.348
	(-.43)	(-.31)	(-.32)	(.37)	(.44)	(.44)
$Foreign_{it} \times PE_{it}$	.013*	–	–	.031**	–	
	(1.93)			(2.84)		
$FIE_{it} \times PE_{it}$	–	-.024**	-.024**	–	-.020**	-.019**
		(-3.92)	(-3.92)		(-1.93)	(-1.86)
$SOE_{it} \times PE_{it}$	.021	.001	.001	.056	.035	.035
	(.97)	(.08)	(.08)	(1.52)	(.92)	(.93)
$FIE_{it} \times (\ln K/L)_{it}$			.000			-.002
			(.09)			(-.64)
τ_{it}^{1996} (IV in the First-stage)	.266**	.251**	.252**			
	(142.64)	(121.11)	(121.02)			
Kleibergen-Paap rk LM statistic	$12395.9^{\dagger}$	$8664.87^{\dagger}$	$8657.49^{\dagger}$			
Kleibergen-Paap Wald rk F statistic	$20346.26^{\dagger}$	$14671.27^{\dagger}$	$14649.54^{\dagger}$			
Anderson-Rubin χ^2 Statistic	$1080.75^{\dagger}$	$863.43^{\dagger}$	$862.41^{\dagger}$			
Stock-Wright LM S Statistic	$1053.07^{\dagger}$	$836.95^{\dagger}$	$836.06^{\dagger}$			
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	60,749	60,749	60,749	60,749	60,749	60,749
(Centered) R-squared	.001	.001	.001	.020	.005	.006

Notes: Robust t-values in parentheses. *(**) is 10(5) % significance. † is p-value less than 0.01.

Table 11: IV Estimates by Processing Types

Regressand: TFP_{it}^{OP}	Assembly		Imported Materials		Assembly&PEIM	
	(1)	(2)	(3)	(4)	(5)	(6)
τ_{it}	-1.264**	-1.332**	-.371**	-.406**	-1.255**	-1.331**
	(-29.00)	(-20.02)	(-8.02)	(-7.29)	(-28.41)	(-20.00)
Assembly (ASM_{it})	.034**	.039**	–	–	–	–
	(3.47)	(2.63)				
Imported Materials ($PEIM_{it}$)	–	–	.030**	.033**	–	–
			(3.02)	(2.40)		
$ASIM_{it}$	–	–	–	–	.024**	.037**
					(2.78)	(2.64)
$(\ln K/L)_{it}$	-.030**	-.032	-.027**	-.032**	-.030**	-.032**
	(-13.99)	(-10.11)	(-6.41)	(-6.36)	(-13.98)	(-10.11)
FIE_{it}	.029**	.047**	.120**	.121**	.031**	.046**
	(2.63)	(3.03)	(5.94)	(5.01)	(2.80)	(3.01)
SOE_{it}	-.051**	-.061**	-.086**	-.085**	-.047**	-.062**
	(-4.43)	(-3.29)	(-3.97)	(-3.99)	(-3.89)	(-3.17)
$markup_{it-1}$	.028	.018**	.017	.017**	.028	.018**
	(1.63)	(5.62)	(1.43)	(3.88)	(1.63)	(5.58)
ind_markup_{it-1}	.216**	.767**	-.349**	.400	.145	.779**
	(1.97)	(3.23)	(-2.18)	(1.45)	(1.29)	(3.28)
$H\,\mathrm{erf}_{it-1}$	-.080	.324	.114	.302	-.080	.323
	(-.39)	(.41)	(.69)	(.61)	(-.39)	(.41)
$FIE_{it} \times ASM_{it}$	-.009	-.005	–	–	–	–
	(-.89)	(-.34)				
$FIE_{it} \times PEIM_{it}$	–	–	-.050**	-.055**	–	–
			(-4.16)	(-3.55)		
$FIE_{it} \times ASIM_{it}$	–	–	–	–	-.011	-.005
					(-1.15)	(-.38)
$SOE_{it} \times ASM_{it}$	-.046	.051	–	–	–	–
	(-.95)	(.78)				
$SOE_{it} \times PEIM_{it}$	–	–	.026	.030	–	–
			(.67)	(.76)		
$SOE_{it} \times ASIM_{it}$	–	–	–	–	-.055	.038
					(-1.56)	(.73)
$FIE_{it} \times (\ln K/L)_{it}$	-.000	-.002	-.010**	-.009*	-.001	-.002
	(-.08)	(-.63)	(-2.20)	(-1.69)	(-.19)	(-.65)
Firm Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	60,749	60,749	17,302	17,302	60,749	60,749
R-squared	.001	.015	.003	.003	.001	.015

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

Table 12: Estimates with Interaction Effect between Tariffs and Processing Trade

Regressand: TFP_{it}^{OP}	All Sample			ASM	PEIM	ASM+PEIM
	OLS	FE	IV+FE	FE	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)
τ_{it}	-.287**	-.320**	-1.448**	-.429**	-.145**	-.453**
	(-11.10)	(-6.63)	(-9.40)	(-12.27)	(-1.96)	(-12.21)
$\tau_{it} \times PE_{it}$	-.233**	-.200**	1.124**	-.011	-.068	.109
	(-6.37)	(-2.97)	(6.90)	(-.11)	(-.72)	(1.20)
PE_{it}	.048**	.050**	-.062**	.035**	.044**	.023
	(9.43)	(5.44)	(-4.22)	(2.06)	(2.19)	(1.48)
$(\ln K/L)_{it}$	-.024**	-.025**	-.027**	-.024**	-.022**	-.024**
	(-12.16)	(-8.78)	(-9.12)	(-8.34)	(-3.12)	(-8.36)
FIE_{it}	.052**	.066**	.037**	.062**	.124**	.060**
	(5.07)	(4.40)	(2.47)	(4.26)	(3.56)	(4.11)
SOE_{it}	-.078**	-.085**	-.070**	-.061**	-.076**	-.064**
	(5.57)	(-3.77)	(-2.86)	(-3.56)	(-2.70)	(-3.55)
$markup_{it-1}$	.024*	.017**	.017**	.018	.004	.017**
	(1.83)	(5.51)	(5.72)	(5.57)	(1.55)	(5.54)
ind_markup_{it-1}	-.012	.842**	.698**	.815	.544	.820**
	(-.12)	(3.77)	(3.07)	(3.65)	(1.60)	(3.67)
$H\,\mathrm{erf}_{it-1}$	.347	1.113	.156	1.000	9.831	1.009
	(1.07)	(1.45)	(.21)	(1.30)	(1.40)	(1.32)
$FIE_{it} \times PE_{it}$	-.023**	-.021**	-.017*	-.012	-.050**	-.006
	(-4.07)	(-2.08)	(-1.71)	(-.72)	(-2.51)	(-.43)
$SOE_{it} \times PE_{it}$	.032	.060*	.055	.069	.011	.063
	(1.48)	(1.67)	(1.54)	(1.04)	(.23)	(1.18)
$FIE_{it} \times (\ln K/L)_{it}$	-.002	-.003	.002	-.002	-.008	-.002
	(-0.89)	(-1.04)	(.76)	(-.86)	(-1.09)	(-.80)
Firm Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Observations	68,041	68,041	60,749	68,041	6812	60,749
Prob>F (Prob> χ^2)	.000	.000	.000	.000	.000	.000
(Centered) R-squared	.002	.03		.033	.026	.033
Years Coverage		2000-06		2000-01	2000-06	

Notes: Robust clustered t-values in parentheses. *(**) is 10(5) % significance . † means the p-value is less than 0.01.

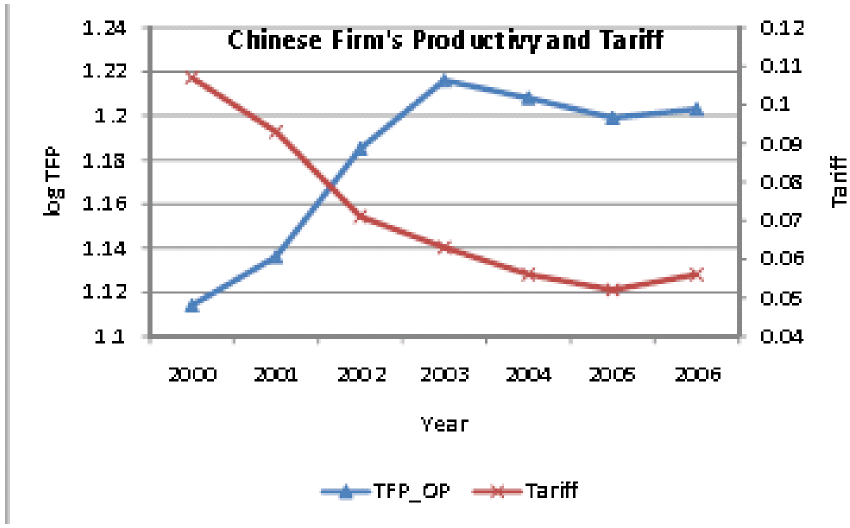
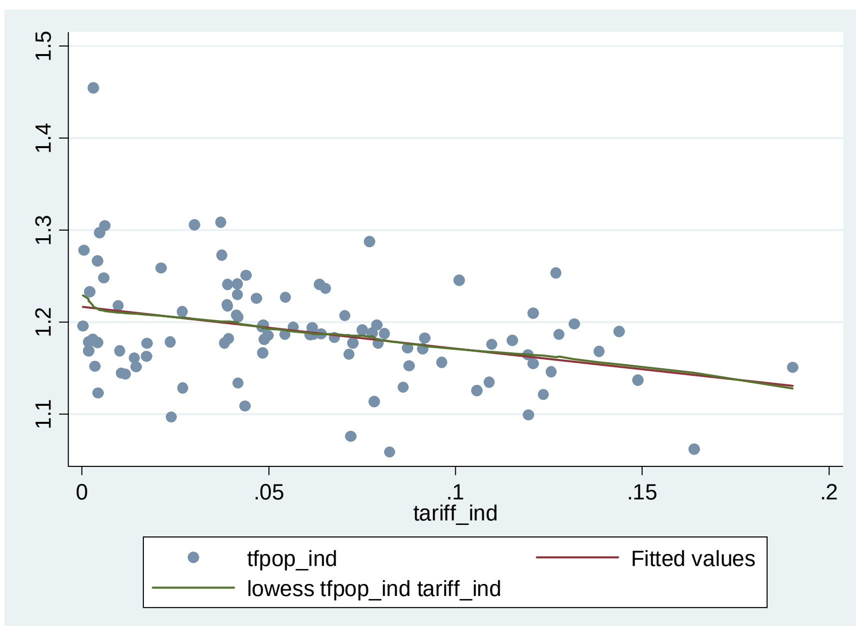


Figure 1: Chinese Firm's Productivity and Tariffs (2000-2006)

Sources: Author's own calculation from the sample



Notes: Here I drop two outlier of industries: Tobacco (HS code:24) with a maximum of TFP and Arms (HS code: 93) with a minimum of TFP

Figure 2: TFP and Ad Valorem Duties by HS 2-digit Industry

6 Appendix

6.1 Appendix A: Measuring TFP

Econometricians have tried hard to address these empirical challenges, 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)::

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

where EF_{it} is a dummy to measure whether firm i exports in year t. Therefore, the inverse function of (6) is $\upsilon_{it} = \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it})$.[27] The unobserved productivity also depends on log capital and the firm's export decisions. Accordingly, the estimation specification (2) can now be written as:

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

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, and the firm's export dummy to approximate $g(\cdot)$.[28] In addition, since my firm dataset is from 1998 to 2005, 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:

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

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:

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

[27] 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.

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

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 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 industry j is obtained once the estimated coefficient $\hat{\beta}_k$ is obtained:

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