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

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Abstract

This paper explores how reductions in tariffs on imported inputs and final goods affect firm productivity by exploiting the special tariff treatment that processing firms apply on imported inputs as opposed to those of non-processing firms. Highly disaggregated Chinese transaction-level trade data and firm-level production data from 2000 to 2006 are used to construct firm-level input and output tariffs. Careful examination of the extent of firm engagement in processing trade and in controlling for various sources of endogeneity reveal that less productive firms choose to engage in processing trade. More importantly, unlike previous findings, reductions in output tariffs have a greater effect on productivity improvement compared with reductions in input tariffs due, in large part, to the fact that processing trade in China enjoys zero tariffs on imported inputs.

JEL: F1, L1, O1, O2

Keywords: Processing Trade, Productivity, Trade Liberalization, Firm Heterogeneity, Chinese Products

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1 Introduction

The effect of trade liberalization on firm productivity is one of the most important research topics in empirical trade. In earlier periods, trade economists primarily focused on the effect of cutting tariffs on final goods. At present, research interest has shifted to the exploration of the effect of tariff reductions on imported intermediate inputs, which is usually less than the effect on final goods (Amiti and Konings, 2007; Goldberg *et al.*, 2010; Topalova and Khandelwal, 2011). Amiti and Konings (2007) used Indonesian firm-level data and found that firm gains from the reduction of input tariffs is at least twice as much as those from cutting output tariffs. Furthermore, Topalova and Khandelwal (2011) found that such a gain difference could be exaggerated to approximately ten times in magnitude in several industries, based on India's firm-level data. They forcefully argue that the primary reason for this result is that in boosting firm productivity, access to better intermediate inputs through the reduction of input tariffs is more important than the pro-competitive effect of the reduction of output tariffs.

Unlike such evidence, the present paper shows that output tariff reduction has a greater effect on productivity improvement compared with input tariff reduction based on Chinese firm-level and disaggregated transaction-level data. This result in China is primarily attributable to the special tariff treatment afforded to imported inputs by processing firms as opposed to non-processing firms. Specifically, the impact of output tariffs on firm productivity is through a pro-competitive channel by both pressuring firms to be more productive and weeding less productive firms out of the market, whereas the impact of input tariff on firm productivity is via access to a larger variety of inputs. More importantly, processing imports, which account for half of total imports in China, enjoy zero tariffs. Hence, further tariff reductions on imported intermediate inputs have no impact on firms that entirely engage in processing trade, though they still have some impact on firms that engage in both processing trade and non-processing trade. As a result, the firm gains from further tariff reductions on imported intermediate inputs are hence, smaller.

Such a finding is interesting not only because China is the second largest economy and the largest emerging economy in the world, but also because processing trade is a popular trade pattern in many developing countries. Although there have been some works on trade reform in both developed countries and developing countries,[1] the interaction between trade reform and processing trade is rarely explored.

[1] The studies testing data on developed countries, among others, include Bernard *et al.* (2003) and Bernard and

Hence, understanding the productivity gains from trade reform under any special tariff treatment afforded to processing trade is essential.

Processing trade is the process by which a domestic firm initially obtains raw materials or intermediate inputs from abroad, and after local processing, exports the value-added final goods. Governments typically encourage processing trade by offering tariff reductions or even exemptions on the processing of intermediate goods. Through the use of a processing indicator to measure whether a firm engages in processing trade, I find that Chinese processing firms have low productivity. More importantly, Chinese firms with low productivity choose to engage in processing trade, possibly to access cheaper imported intermediate inputs.

The effect of tariff reductions on firm productivity is explored by merging both Chinese firm-level production data and disaggregated transaction-level trade data during 2000–2006. Through the use of this novel and unique merged data set, firm-specific output tariffs and, more interestingly; firm-specific input tariffs in the main estimates can be constructed. I even construct the firm-specific external tariffs which measure the reduction in the tariffs that Chinese exporters faced in their export destinations as a robustness check.

Although previous works have successfully measured output tariffs at the firm level, measuring input tariffs at the firm level is challenging primarily because of data restrictions. Studies are usually conducted at the industrial level to circumvent this empirical challenge using input and output tables, as adopted by Amiti and Konings (2007), or by measuring efficient tariff protection, as utilized by Topalova and Khandelwal (2011). The current paper is one of the first to measure input tariff directly at the firm level.

Previous studies on processing trade in China contribute to distinguishing a firm's processing type, which can be either processing with assembly or processing with imported inputs (see, for example, Feenstra and Hanson, 2005; Fernandes and Tang, 2010). The current paper also considers this distinction. However, the present work focuses on another very interesting phenomenon, that is, the fact that some Chinese firms are involved in both processing and ordinary trade, whereas others are only

Jensen (2004) for the United States and Trefler (2004) for Canada. However, more evidence has been found in developing countries, such as Bustos (2009) for Argentina, Schor (2004) for Brazil, Tybout *et al.* (1991) and Pavcnik (2002) for Chile, Fernandes for Columbia (2007), Harrison (1994) for Cote d'Ivoire, Krishna and Mitra (1998) and Topalova and Khandelwal (2010) for India, Amiti and Konings (2007) for Indonesia, Iscan (1998) for Mexico and Levinsohn (1993) for Turkey. Other research, such as those of Van Biesebroeck (2005), De Loecker (2007), Park *et al.* (2010), Lu *et al.* (2010), and Lu (2011) also explore the nexus between export growth and productivity improvement.

involved in one type. Hence, this information must be considered in constructing firm-specific input tariffs.

In particular, based on whether a Chinese firm is involved in imports and whether it engages in the processing of imports, all Chinese firms are classified into four categories, namely, non-importing firms, ordinary importers, pure processing importers, and hybrid importers. Ordinary importers are firms that only engage in non-processing imports, whereas pure processing importers are firms that only process imports. In contrast, hybrid importers are firms that engage in both ordinary and processing trade. This information enables the clear construction of firm-specific input tariffs.

I then follow the standard procedure to investigate the firm productivity gains from reducing input and output tariffs in two steps (e.g., Pavcnik, 2002; Amiti and Konings, 2007; Fernandes, 2007; Topalova and Khandelwal, 2011). First, the total factor productivity (TFP) of a firm is measured using the methodology of Olley and Pakes (1996), with a number of necessary modifications and extensions to fit Chinese reality. One of the important assumptions of the Olley–Pakes approach is that capital is more actively responsive to unobserved productivity. However, the fact that China is a labor-abundant country, thereby having relatively low labor costs, may be a cause for concern. When facing a productivity shock, Chinese firms normally adjust their labor input to re-optimize production behavior (Blomström and Kokko, 1996). Moreover, ignoring the role of the lagged productivity of a firm may result in some serial correlation (Fernandes, 2007). Therefore, the Blundell and Bond (1998) system GMM approach is adopted as an alternative way to measure TFP.

Next, I then explore the relationship between firm productivity and firm-specific output tariffs and firm-specific input tariffs. To enrich our understanding on processing trade, I measure the processing variable in three ways. First, I use a processing indicator to identify whether or not a firm engages in processing trade. However, firm's decision to processing itself is endogenous. To control for that, I next take a step forward to adopt the binary treatment approach to estimate the firm's predicted processing probability to serve as a substitute to the processing dummy. The estimates from both approaches suggest that processing firms have lower productivities compared with non-processing firms. Finally, a continuous measure of the extent to which individual firms engage in processing trade is constructed using transaction-level trade data, which provide information on products that firms import and export under the processing and ordinary (*i.e.*, non-processing) trade regimes. Given that other factors are constant, a high degree of engagement in processing trade reduces firm productivity.

Moreover, understanding the mechanisms through which firm productivity improves in response to trade reform is also important. Inspired by previous studies, such as that of Amiti and Konings (2007), Bustos (2009), and Goldberg *et al.* (2010), the impact of input tariffs on productivity is straightforward as lower tariffs induce a larger variety of inputs. By contrast, the impact of output tariffs on productivity could work directly by pressuring firms to be more productive, and/or indirectly by weeding less productive firms out of the market. The paper finds strong evidence for such two mechanisms for Chinese firms. In addition, several possible firm channels, namely, industrial markups, scope, and R&D, are also discussed. Unlike Amiti and Konings (2007), the data used in the present work include information on exporter scope. Thus, the product scope can be directly measured, as done by Goldberg *et al.* (2010). In addition, similar to Bustos (2011), information on R&D expenses are also considered, and firms facing tougher import competition attributable to reduced output tariffs are found to spend more on R&D to boost productivity.

Finally, I also carefully control for the endogeneity of firm-specific input and output tariffs. Two different endogeneity sources exist for these tariff variables. The first endogeneity issue is the possible reverse causality of firm productivity. Tariffs may be granted in response to domestic special interest groups, the pressure of which could be significant in countries such as India (Topalova and Khandelwal, 2011) or low in countries such as Indonesia (Amiti and Konings, 2007). Given that China acceded to the WTO in 2001, domestic pressure may not play a key role in the years 2000–2006, which are examined in the present paper. However, for the sake of completeness, the instrumental variable (IV) approach is also adopted to control for such a possible reverse causality.

The other endogeneity issue results from the measures of the tariff variables themselves, which is attributable to the negative effect of the tariff line on the import value of a product, which serves as a weight in firm-specific input (output) tariffs. To control for such an endogeneity, I then experiment two measures on the import value of a firm: the first one takes firm's import value during the first year in the sample to construct a fixed weight for firm-specific input (output) tariffs; whereas the other adopts firm's import value in the previous year in the sample to have a floating weight for firm-specific input (output) tariffs. After controlling for a variety of endogeneity, I still find robust evidence that output tariff reduction affects productivity improvement more than cutting input tariffs.

The remainder of the paper is organized as follows. Section 2 introduces the special tariff treatment on Chinese processing trade. Section 3 discusses the measures of key variables and the econometric method. Section 4 describes the unique data used in the present paper. Section 5 presents the primary estimation results and sensitivity analysis. Finally, Section 6 concludes.

2 Special Tariff Treatment on Processing Trade

Processing trade in China began in the early 1980s. As an important means of trade liberalization, the government encourages Chinese firms to import all or part of raw materials and intermediate inputs, and re-export final value-added goods after local processing or assembly. Today, the General Administration of Customs reports 16 specific types of processing trade in China.[2]

Among these types, two are the most important, namely, processing trade with assembly and processing trade with inputs.[3] These two types of processing trade have two key differences. For processing with assembly, a domestic Chinese firm obtains raw materials and parts from its foreign trading partners *without* any payment. However, after local processing, the firm has to sell its products to the same firm by charging an assembly fee. By contrast, for processing exports with inputs, a domestic Chinese firm pays for raw materials from a foreign seller. After local processing, the Chinese firm can then sell its final goods to other foreign countries.

More importantly, processing trade in China enjoys special treatment for import tariffs. Essentially all types of processing trade are imported duty free. Still, a few fine differences exist between the two most important types. In particular, processing assembly is 100% duty-free. A firm accessing assembly for foreign companies immediately enjoys duty-free importation. By contrast, a firm involved in processing with inputs still pays duties on imported materials from abroad. However, when the value-added products are exported, the authorities return the full amount of the duty to the Chinese firm as a rebate. Thus, firms engaged in processing with inputs have stronger demands on cash flow and have to bear extra interest expenses compared with those involved in processing with assembly. Hence, processing firms with inputs are more credit constrained than processing firms with assembly. These differences will be considered in the construction of firm-specific input tariffs in the next section.

[Insert Figure 1 Here]

Figure 1 shows that compared with ordinary exports, processing exports in China only accounted for a small proportion of total exports in the early 1980s. However, China's processing exports dramatically

[2] Such types of processing trade include, among others, foreign aid (code: 12), assembly (14), processing with inputs (15), compensation trade (13), goods on consignment (16), goods 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).

[3] Processing with assembly also refers to "processing with supplied materials" as stated in the official reports of Customs or "pure assembly" as adopted in Feenstra and Hanson (2005). Correspondingly, processing with inputs is also called "processing with imported materials" or "input and assembly".

increased in the early 1990s and began to dominate over ordinary exports in 1992, when China officially announced the adoption of a market economy. Going forward, processing exports accounted for over 50% of China's total exports. Interestingly, processing exports with assembly were more popular in the 1980s because most Chinese firms lacked the capital for importation. On the other hand, processing exports with inputs have been more prevalent since the 1990s.

[Insert Figure 2 Here]

The primary objective of the current paper is to determine how a firm's TFP reacts to output and input tariff reductions with the presence of special tariff treatments on processing trade. Therefore, understanding whether a firm engages in processing activity is important. All Chinese firms are therefore classified into four types, namely, non-importing firms and three types of importing firms: ordinary importers, hybrid processing importers, and pure processing importers. As shown in Figure 2, non-importing firms do not engage in importation. All raw materials and intermediate inputs are locally acquired. However, non-importing firms can sell their final goods domestically and internationally [as shown in arrow (1)].

Among the three types of importers, ordinary importers refer to firms that import at least part of their intermediate inputs, but sell all final goods domestically [see arrow (2)]. In sharp contrast, pure processing importers refer to firms only engaged in processing activities, shown as dotted lines in the figure. Pure processing importers purchase 100% of raw materials and intermediate inputs abroad and re-export their final value-added goods [i.e., arrow (5)]. Such firms clearly enjoy the privilege of duty-free import. Finally, and perhaps the most interesting type of firm, "hybrid" processing importers engage in both ordinary imports [i.e., arrow (3)] and processing imports [i.e., arrow (4)]. Such firms enjoy free duties for their processing imports, but still pay import duties for ordinary imports. Here it is important to stress that processing trade of both hybrid and pure processing importers could include *any processing types*, such as assembly and processing with inputs.

3 Measures and Empirics

In this section, I first introduce the measures of the three key variables: firm's TFP, firm-specific output tariffs, firm-specific input tariffs, followed by an empirical investigation of the effect of tariff reductions on productivity.

3.1 TFP Measures

I first use the augmented Olley-Pakes (1996) approach to construct measures of Chinese firm-level TFP following Amiti and Konings (2007) and Feenstra *et al.* (2011). Assuming a Cobb-Douglas production function, the usual estimation equation for firm's TFP is as follows:

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_k \ln K_{it} + \beta_l \ln L_{it} + \epsilon_{it}, \tag{1}$$

where Y_{it}, M_{it}, K_{it}, L_{it} refer to firm i's output, materials, capital, and labor at year t, respectively. Traditionally, TFP is measured by the estimated Solow residual between the true data on output and its fitted value using the OLS approach. However, the OLS 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 firm's maximized choice becomes biased without this consideration. In addition, the firm's dynamic behavior also introduces selection bias. With international competition, firms with low productivity would collapse and exit the market, whereas those with high productivity remain (Melitz, 2003). In a panel data set, the observed firms are those that have already survived. By contrast, firms with low productivity that have collapsed and exited the market are excluded from the data set, indicating that the samples covered in the regression are not randomly selected, which, in turn, results in estimation bias.

Olley and Pakes (1996) provided an econometric methodology to deal with both the simultaneity bias and selection bias in measured TFP. Subsequently, numerous studies, such as those by De Loecker (2011), Amiti and Konings (2007), and Keller and Yeaple (2009), among others, have modified and tailored their approaches to calculating TFP. In the present paper, I adopt the Olley–Pakes approach to estimate and calculate a firm's TFP with some extensions.

Firstly and most importantly, I use deflated prices at firm productivity level to measure TFP. Previous studies such as Felipe *et al.* (2004) stressed the estimation bias of using monetary terms to measure output when estimating the production function. In that way, one actually estimates an accounting identity. Hence, I first adopt different price deflators for inputs and outputs. Data on input deflators and output deflators are directly from Brandt *et al.* (2011) in which the output deflators are constructed using "reference price" information from *China's Statistical Yearbooks* whereas input deflators are constructed based on output deflators and China's national input-output table (2002).[4]

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

Thirdly, I also consider firm's processing behavior in the TFP realization by constructing two dummy variables, namely, an export dummy (one denotes export and no export otherwise) and an import dummy (one denotes import and no export otherwise). The idea is that both exporting and importing behavior of a processing firm may affect its production maximization problem.

Finally, constructing the real investment variable is essential when using the Olley–Pakes (1996) approach.[5] As usual, I adopt the perpetual inventory method to investigate the law of motion for real capital and real investment. Rather than assigning an arbitrary number for the depreciation ratio, I use the exact firm's real depreciation provided by the Chinese firm-level data set.[6][7]

As discussed above, the augmented Olley–Pakes approach assumes that capital responds to the unobserved productivity shock with a Markov process, whereas other input factors respond without any dynamic effects. However, labor may also be correlated with unobserved productivity shock (Ackerberg *et al.*, 2006). This consideration may fit more closely with China's case given that the country is labor abundant. When facing an unobserved productivity shock, firms might re-optimize their production behavior by adjusting their labor rather than their capital. I then use the Blundell–Bond (1998) system GMM approach to capture the dynamic effects of other input factors. By assuming that the unobserved productivity shock depends on a firm's previous period realizations, the system GMM approach models TFP as affected by all types of a firm's inputs in both current and past realizations.[8] In particular,

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

[5] In the literature, the Levinsohn and Petrin (2003) approach is also popular in constructing TFP in which materials (*i.e.*, intermediate inputs) are used as a proxy variable. This approach is appropriate for firms in countries not using a large amount of imported intermediate inputs. However, such an approach may not directly apply to China, given that Chinese firms substantially rely on imported intermediate inputs, which have prices that are significantly different from those of domestic intermediate inputs (Helpern *et al.*, 2011).

[6] Note that even with the presence of a processing behavior, the data still exhibit a monotonic relationship between TFP and investment.

[7] The detailed estimation procedure is available upon request.

[8] 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 is correlated with past error shocks and autoregressive error term. By contrast, assuming that the first difference of instrumented variables is uncorrelated with the fixed effects, the system GMM approach can introduce more instruments and thereby dramatically improve efficiency.

this model has a dynamic representation as follows:

$$\ln y_{it} = \gamma_1 \ln L_{it} + \gamma_2 \ln L_{i,t-1} + \gamma_3 \ln K_{it} + \gamma_4 \ln K_{i,t-1} + \gamma_5 \ln M_{it} \quad (2)$$

$$+\gamma_6 \ln M_{i,t-1} + \gamma_7 \ln y_{i,t-1} + \varsigma_i + \zeta_t + \omega_{it}, \quad (3)$$

where ς_i is firm i's fixed effect and ζ_t is the year-specific fixed effect. The idiosyncratic term ω_{it} is serially uncorrected if no measurement error exists.[9] Consistent estimates of the coefficients in Eq. (2) can be obtained by using a system GMM approach. The idea is that labor and material inputs are not taken as exogenously given and are instead allowed to change over time as capital grows. Although the system GMM approach still faces a technical challenge to control for selection bias when a firm exits, using the approach as a robustness check in TFP estimation is still worthwhile.

3.2 Firm-Specific Output Tariffs

A firm could produce multiple products, and thus, a common product tariff line would have different effects on firm productivity. Hence, it is important to properly measure the tariff level faced by firms. Ideally, the domestic value of each product produced by a firm is used to consider the importance of a product. Instead, no such data are available. However, data on a firm's total domestic sales are available. Thus, according to Melitz (2003), a more productive firm is not only capable of selling its products domestically, but also internationally. Thus, a product would be sold domestically if it is sold abroad. I then consider a weighted output tariff index (FOT_{it}) for firm i at year t as follows:

$$FOT_{it} = \sum_k \left(\frac{v_{it}^k}{\sum_k v_{it}^k}\right)\tau_t^k, \quad (4)$$

where τ_t^k is the *ad valorem* tariff of product k in year t, whereas the ratio in the parenthesis is the value weight of product k, measured by the firm's domestic sales on product k, v_{it}^k, over the firm's total domestic sales. Assuming that a product is sold domestically and internationally at the same proportion, the following equation can be used to measure firm i's domestic sales of product k:

$$v_{it}^k = \frac{X_{it}^k}{\sum_k X_{it}^k}(Y_{it} - \sum_k X_{it}^k), \quad (5)$$

where Y_{it} is the firm's total sales, and X_{it}^k is product k's exports for firm i at year t. Therefore, the difference enclosed by the parentheses measures firm i's total domestic sales. The first term in Eq.(5)

[9] As discussed by Blundell and Bond (1998), even if a transient measurement error exists in some of the series (*i.e.*, ω_{it}~$MA(1)$), the system GMM approach can still provide consistent estimates of the coefficients in Eq. (2).

measures the proportion of product k's exports over firm i's total exports.[10]

3.3 Firm-Specific Input Tariffs

As previously mentioned, China has two types of imports, namely, processing imports and ordinary imports. In principle, processing imports are duty free. However, different types of processing imports have different policies. In particular, the processing with assembly types are fully duty free. By contrast, other processing imports , such as processing with inputs, pay the input duty upon importation, but a full-fund duty rebate can be obtained after exporting the processed final goods. As a result, such firms still bear the interests of the duty. Therefore, I construct a firm-specific input tariff index (FIT_{it}) as follows:

$$FIT_{it} = \sum_{k \in \mathring{\Theta}} \frac{m_{it}^k}{\sum_{k \in \Theta} m_{it}^k} \tau_t^k + 0.05 \sum_{k \in \tilde{\Theta}} \frac{m_{it}^k}{\sum_{k \in \Theta} m_{it}^k} \tau_t^k, \tag{6}$$

where m_{it}^k is firm i's import value on product k in year t and, as before, τ_t^k is the *ad valorem* tariff of product k in year t. $\mathring{\Theta}$ is the set of firm's ordinary imports, $\tilde{\Theta}$ is the set of all processing imports other than processing with assembly, and Θ is the set of firm's total imports. That is, $\mathring{\Theta} \cup \tilde{\Theta} \cup \hat{\Theta} = \Theta$ where $\hat{\Theta}$ is the set of processing with assembly and by definition, is 100% duty free. Thus, this set is not included in Eq. (6). Note that the first term in Eq. (6) measures the input tariffs from ordinary imports, whereas the second term measures those from processing with inputs. The real interest rate is set to 0.05 for China, as suggested in Hsieh-Klenow (2009).

3.4 Estimation Framework

To investigate the effect of both input and output tariff reductions on firm productivity, I then consider an empirical framework as follows:

$$TFP_{it}^{OP} = \alpha_0 + \alpha_1 FOT_{it} + \alpha_2 FOT_{it} \times PE_{it} + \alpha_3 FIT_{it} + \alpha_4 PE_{it} + \theta \mathbf{X}_{it} + \varpi_i + \eta_t + \mu_{it,} \tag{7}$$

where TFP_{it}^{OP} is the logarithm of firm i's Olley-Pakes type TFP in year t whereas FOT_{it} and FIT_{it} denote firm-specific weighted tariff on its final goods and intermediate goods in year t respectively. PE_{it} is a processing indicator which equals one if firm i engages in processing activity in year t, and zero

[10] However, a caveat exists: due to data restriction, the weights of products that are only sold domestically cannot be calculated using this approach. This is not a problem in the present paper since only trading firms are covered in all estimations.

otherwise. An interaction term between firm's output tariff and processing indicator is also included to capture a possible heterogeneous effect of output tariff reductions on firm productivity between processing and ordinary firms. However, an interaction term between firm-specific input tariffs and processing indicator is not included because the firm's input tariff, by construction, has already fully captured the firm's processing information, as shown in Eq. (6).

As the regressand in Eq. (7), the measured TFP is expected to capture firm's true technical efficiency only. However, here the measure TFP is also likely to pick up the differences in price, price-cost markups, and even input usage across firms (De Loecker, 2011, De Loecker and Warzynski, 2011). Admittedly, an ideal way to remove the price difference across firms is to adopt firm-specific price deflators (Foster *et al.* 2007). However, as in many other studies, such prices data are unavailable. As a compromise, I use the industrial price to deflate the firm's output. Turning to the issue of price-cost markups, as stressed by Bernard *et al.* (2003) and Topalova and Khandelwal (2011), once the price-cost markup are positively associated with true efficiency, even the revenue-based productivity can work well to capture the true efficiency as that done in physical efficiency. To control for the differences of the input usage across firms, I also adopt the system-GMM TFP and even labor productivity to replace the Olley-Pakes TFP as robustness checks.

In addition, α_4 in Eq. (7) measures other possible gains from processing trade not coursed trade liberalization. $\mathbf{X}_{it}$ denotes other firm characteristics such as type of ownership (*i.e.*, state-owned-enterprises or multinational firms). State-owned-enterprises (SOEs) are traditionally believed to have a relatively low economic efficiency, and hence, low productivity (Lin *et al.*, 2004). By contrast, multinational firms have higher productivity due in part to their superior international technology spillover (Keller and Yeaple, 2009) or less financial constraints (Manova *et al.*, 2009; Amiti and Weinstein, 2011; Feenstra *et al.*, 2011). Therefore, I construct two indicators to measure the roles of SOEs and multinational firms. Finally, the error term is divided into three components: (1) firm-specific fixed effects ϖ_i to control for time-invariant factors such as a firm's location; (2) year-specific fixed effects η_t to control for firm-invariant factors such as Chinese *RMB* appreciation; and (3) an idiosyncratic effect μ_{it} with normal distribution $\mu_{it} \sim N(0, \sigma_i^2)$ to control for other unspecified factors.

4 Data

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

Tariff data can be accessed directly from the WTO.[11] China's tariff data are available at the HS six-digit disaggregated level for the period 2000–2007.[12] Given that the product-level trade data are at the HS eight-digit level, the tariff data set is merged into the product-level trade data. Since my interest is to measure the average effect of trade liberalization on firm productivity, I use average *Ad Valorem* duty to measure trade liberalization.

4.1 Firm-Level Production Data

The sample is derived from a rich firm-level panel data set that covers $162,885$ firms in 2000 to $301,961$ firms in 2006. The data are collected and maintained by China's National Bureau of Statistics in an annual survey of manufacturing enterprises. Complete information on the three major accounting statements (*i.e.*, balance sheet, profit and loss account, and cash flow statement) are available. In brief, the data set covers two types of manufacturing firms – all SOEs and non-SOEs, the annual sales of which exceed *RMB* 5 million *RMB* (or the equivalent $770,000).[13] The data set includes over 100 financial variables listed in the main accounting statements of all these firms.

Although this data set contains rich information, some samples contain noise and are therefore misleading, largely because of mis-reporting by some firms.[14] Following Cai and Liu (2009), I clean the sample and omit outliers by using the following criteria. First, observations with missing key financial variables (such as total assets, net value of fixed assets, sales, and gross value of firm productivity output) are excluded. Second, the number of employees hired for a firm has to be no less than 10 people.[15]

Following Feenstra *et al.* (2011), I delete observations according to the basic rules of Generally

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

[12] China did not report its tariffs data in 2000. However, data from 1996 and 1997 are available. As reported in *Customs Import & Export Tariff of the P.R. C.* (various years), China did not experience dramatic tariff reductions in 1997-2000, hence the 1997 tariffs are used as serve proxy for those of 2000.

[13] 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.

[14] 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*.

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

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) an invalid established time exists (*e.g.*, the opening month is later than December or earlier than January).

4.2 Product-Level Trade Data

The extremely disaggregated product-level trade transaction data are obtained from China's General Administration of Customs.[16] It records a variety of useful information for each trading firm's product list including trading price, quantity, and value at the HS eight-digit level. More importantly, this rich data set not only includes both import and export data, but also breaks data down to many specific types of processing trade.

[Insert Table 1 Here]

Table 1 reports a simple statistical summary for Chinese product-level trade data by shipment and year. Overall, when focusing on highly disaggregated HS eight-digit level, approximately 35% of the 18,599,507 observations are ordinary trade, and 65% observations refer to processing trade. Such a proportion is similarly obtained when measured by trade volume. Approximately 35% of trade volume comprises ordinary trade. Processing with inputs accounts for over 55% whereas processing with assembly only is less than 7% during 2000-2006. The remaining 3% represent other types of processing trade, aside from assembly and processing with inputs.

4.3 Merged Data Set

Firm-level production data are crucial in measuring TFP, whereas product-level trade transaction data are non-substitutable in identifying a processing firm. However, practical difficulties immediately arise when combining the two data sets. Although these data sets share a common variable (*i.e.*, the firm's identification number), the coding system in each data set is completely different.[17] Without a common variable, the two separate data sets cannot work together.

[16] Manova and Zhang (2011) use such customs data during 2003-2005 to document several stylized facts on China's exports.

[17] In particular, the firm's codes in the product-level trade data are at 10-digit level, whereas those in the firm-level production data are at a nine-digit level, with no common elements inside.

Thus, to fix this problem, I rely on two other common variables to identify firms, namely, zip code and the last seven digits of a firm's phone number.[18] The rationale is that firms should have different and unique phone numbers within a postal district.[19] Table 2A clearly demonstrates that each firm trades multiple products with their trading partners. Notably, over 60 million *monthly* transactions during 2000-2006 were traded by only $654,352$ firms. Using both zip code and phone number to identify firms, observations are then omitted from the data if any of the following are true: (1) missing zip code or phone number; (2) invalid zip code (*i.e.*, number less than 100,000); or (3) invalid seven-digit phone number (*i.e.*, number less than 1,000,000). The rigorous filter leaves 218,024 valid firms for 2000-2006, which account for 34% of the total trading firms in the sample. Turning to the firm-level production data set, the deletion of observations with invalid zip codes or phone numbers leaves 973,207 firms. Following the same filtering process as before, 433,273 firms are then obtained over the same period, which account for 44.5% of the total production firms in the sample.

[Insert Table 2A Here]

After merging both product-level trade data and firm-level production data, I obtain 31,393 common trading firms, which only account for approximately 15% of the valid firms in the product-level trade data set and approximately 8% of the valid firms in firm-level production data set. The merged data set only contains a portion of the two large data sets; comparing several key variables in the merged data set and the two full-sample data sets is worthwhile.

Given that the firm-level production data set is crucial to the construction of the regressand to the firm's TFP, Table 2B first compares the differences between the merged data set and the full-sample firm-level data set. The merged sample clearly has higher means of sales, exports, number of employees, log of capital-labor ratio, and even log of labor productivity compared with others in the

[18] A straightforward, alternative way is to use firm's Chinese name as the identifier. As a result, however, over 85% of observations would be lost because the Chinese characters for a particular firm are not exactly identical in the two data sets.

[19] Although this method seems straightforward, subtle technical and practical difficulties still remain. For example, the phone numbers in the product-level trade data include both area phone codes and a hyphen, whereas those in the firm-level production data do not. Therefore, I use the last seven digits of the phone number to serve a proxy for firm identification for two reasons: (1) during 2000–2006, some large Chinese cities changed their phone number digits from seven to eight, which usually added one more digit at the start of the number. Therefore, sticking to the last seven digits of the number would not confuse the firm's identification; and (2) in the original data set, phone number is defined as a string of characters with the phone zip code. However, it is inappropriate to de-string such characters to numerals since a hyphen bar is used to connect the zip code and phone number. Using the last seven-digit substring solves this problem neatly.

full-sample firm-level data set. All of these findings suggest that the merged sample is skewed toward large firms. However, the imperfect match may not be a big deal for two reasons. First, by definition, even the full-sample firm-level data set only includes information on larger firms, the sales of which are higher than RMB5 million. The merged data is consistent with this characteristic. Second, the relationship between exports and productivity still exhibits a strong positive correlation, suggesting that many typical firm-heterogeneity results in Melitz (2003) are still valid in the merged data set.

[Insert Table 2B Here]

Turning to the comparison between the merged data set and full-sample transaction trade data set, Table 2C reports the merged importers by type. Ordinary importers account for 35.5% of the total merged sample, whereas processing importers account for the remaining 64.5%. These numbers are almost identical to their counterparts from the full-sample transaction-level trade data, as shown in Table 1. Hybrid processing importers comprise 28% and pure processing importers account for 36% of all firms. Measuring firms by processing type indicate that 9.3% of firms are involved in assembly and 51.4% are involved in processing with inputs.[20] Such statistics are again quite close to their counterparts in Table 1. Thus, the merged data set appears to be a suitable representative of the entire trade data set.

[Insert Table 2C Here]

4.4 Statistical Summary

Table 3 summarizes the estimates of the Olley–Pakes input elasticity of Chinese firms by clustering the HS two-digit industries into the 15 categories. The first three columns report the estimated coefficients for labor, materials, and capital by using the augmented Olley–Pakes methodology. The last row of the table shows that the implied scale elasticities are .989 by summarizing all the estimated elasticities,[21] which is close to the constant returns-to-scale elasticities.[22]

[20] Among the 9.3% of firms involved in processing with assembly, 4.2% of firms are hybrid processing importers whereas the 5.1% are pure processing importers. Similarly, among the 51.4% of firms involved in processing with inputs, 28.5% of firms are hybrid processing importers, whereas the 30.9% are pure processing importers.

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

[22] Note that the industrial deflator is used as a proxy of a firm's price. Indeed, Chinese firms might exhibit the increasing returns-to-scale property in the new century when using the firm's actual prices to calculate "physical" productivity. This subject is a possible future research topic, provided that such data are available.

Through international comparisons of the TFP estimates, the results suggest that the intermediate inputs (*i.e.*, materials) for Chinese firms are more important than those for American firms, as estimated by Keller and Yeaple (2009), or for Indonesian firms, as estimated by Amiti and Konings (2007). However, the elasticity of capital input is less important than US or Indonesian counterparts. This result further ascertains that processing trade plays a significant role in China's economic growth.

The last three columns of Table 3 report the logarithm of TFP by importer type, that is, pure ordinary, hybrid processing, and pure processing firms.[23] Within each industry, pure ordinary firms generally have higher productivity than pure processing firms. Located in between is the average productivity of hybrid processing firms, which engages in both ordinary and processing trade,[24]indicating, to some extent, the possible "self-selection" phenomenon in China's processing trade, wherein firms with lower productivity would choose to engage in processing trade.

[Insert Table 3 Here]

The importance of processing trade can be further noted from the statistical summary in Table 4, with 65.6% of merged firms involved in processing trade. The special tariff treatment on processing imports undoubtedly lowers firm-specific input tariffs, producing a sample mean of 1.4%, which is significantly lower than the mean of firm-specific output tariff (5.7%).

In addition to a firm's processing type, my merged data set also contains information on a firm's ownership type. I then construct a foreign indicator if the firm obtains any investments from other countries (regimes). A large proportion of inflow foreign investments come from Hong Kong/Macao/Taiwan, so these investments are considered in the construction of such an indicator.[25] As a result, 77% trading firms are classified as multinational affiliates. At first glance, these ratios are significantly higher than their counterparts reported in other studies, such as Feenstra *et al.* (2011). However, this finding simply results from the fact that the present paper covers only large trading firms. Large, non-trading

[23]Note that in Table 4, the measured TFP is significantly smaller than the counterparts reported in Feenstra *et al.* (2011) because the present paper measures the gross production function, whereas Feenstra *et al.* (2011) estimate a value-added production. As found Brandt *et al.* (2011) discovered, a Chinese firm's TFP measured by a gross production function is usually smaller than that measured by a value-added production function.

[24]A few exceptions are noted here. The hybrid processing firms in industries such as mineral, stone/glass, machinery and electrical sectors have higher productivity than both pure ordinary and pure processing firms.

[25]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), Hong Kong/Macao/Taiwan (henceforth, H/M/T) joint-stock corporations (210), H/M/T joint venture enterprises (220), fully H/M/T-invested enterprises (230), and H/M/T-invested limited corporations (240).

firms have been excluded accordingly. Similarly, I construct a SOEs indicator which is one if a firm has any investment from the government, and zero otherwise.[26] Finally, SOEs with annual sales lower than RMB5 million are also included to avoid missing the role of small and medium-sized firms. However, the SOEs still comprise less than 2% of large trading firms in the merged sample.

[Insert Table 4 Here]

5 Empirical Results

5.1 Benchmark Results

Figures 3A and 3B show that the average of firm-level weighted input and output tariffs across all firms declined each year from 2000 to 2006.[27] Simultaneously, a firm's TFP increased during this period. This observation implies a negative correlation between tariff reductions and firm productivity. Hence, this section explores such a nexus.

[Insert Figures 3A & 3B Here]

As described above, the attrition rate of the merged data set is high, though it is a suitable representative of the full-sample firm data. Therefore, it is reasonable to ask whether such a high attrition rate affects estimation results. Hence my estimations begin from a comparison between the full-sample data set and merged data set. Column (1) of Table 5 reports the estimates using full-sample firm-level data. Without merging with the transaction-level trade data, the firm-level data have no information on products, so it is impossible to measure output tariffs at the firm level. Also, I am not able to measure firm-level input tariffs as done in (6) since firm-level data contain no information on processing trade. Hence, the estimate in Column (1) with a full-sample of 750,243 observations concentrates on the impact on firm productivity of output tariffs, which is measured at the HS 2-digit industry-level. Clearly, industrial output tariffs are negatively associated with firm productivity.

The rest of Table 5 runs regressions by using the merged data set. For a close comparison, Column (2) of Table 5 also includes industrial tariff only but adds a processing indicator to capture whether

[26] 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).

[27] The increasing reverse trends in 2006 of both input tariffs and output tariffs are possibly due to *Reminbi* (*RMB*) appreciation in late 2005. With a stronger RMB, Chinese firms face softer import competition and have less incentives to improve their quality. In this way, the firm may end up with a higher weight.

a firm engages in processing trade. Like that in Column (1), the estimated coefficient of industrial output tariffs in Column (2) has a negative sign, which is also highly significant at the conventional level. Such a finding is robust when adding the industrial input tariffs in Column (3). Both input and output tariffs have significantly negative effects on the firm's TFP, which is consistent with the findings from Figures 3A and 3B. More importantly, the magnitude of the estimated coefficient of industry-level output tariffs is substantially larger than that of industry-level input tariffs, indicating that the effect of tariff reductions in China is significantly different from that in Indonesia or India, where input tariff reductions have a larger magnitude than output tariffs (Amiti and Konings, 2007; Topalova and Khandelwal, 2010). By measuring input and output tariffs at the firm-level, the last column of Table 5 still yields a similar result as that in Column (4).

[Insert Table 5 Here]

It is worthwhile to check whether the effects of firm-level input and output tariffs on firm productivity only pick up the role of firm size given that large firms usually have high productivities (Eaton *et al.* 2011). Column (1) of Table 6 thus includes a variable of firm's log of labor, as a measure of firm size, and controls for firm-specific and year-specific fixed effects. To understand the overall effect of input and output tariffs on firm productivity, Column (1) also abstracts from the interaction term between output tariffs and the processing indicator. It turns out that the impact of output tariffs on firm productivity is still larger than that of input tariffs. In addition, large firms exhibit high productivities, as evident from the positive and significant signs from the log of firm's labor.

Of all the specifications in Table 5, firm's ownership matters for firm productivity as well. The statistically significant and positive coefficients of the foreign indicator suggest that multinational affiliates have higher productivity than domestic firms. Similarly, after controlling for firm-specific and year-specific fixed effects, the negative and significant signs of SOEs indicator suggest that SOEs have lower productivity than Non-SOEs, which are consistent with Jefferson *et al.* (2000) and Lin *et al.* (2004), who found that Chinese SOEs have a relatively low TFP compared with Non-SOEs in China. More importantly, the processing indicators in all estimates are negative and statistically significant, ascertaining the observations in Table 3 that firms engaged in processing trade have low productivity.

[Insert Table 6 Here]

5.2 Selection to Processing

Column (1) of Table 6 shows that processing firms are associated with low productivity. However, the processing indicator variable is, in itself, endogenous. Less productive firms possibly choose to engage in processing activities. To control for this, I introduce a selection equation that estimates the probability of a firm to involve in processing based on its productivity and other variables, I then experiment using such a predicted processing probability as an alternative to the processing indicator.

In particular, I estimate the following selection equation by the Probit model:

$$\begin{aligned} \Pr(\Pr oces\sin g_{it} &= 1) = \Pr(V_{it} \geq 0) \\ &= \Phi(\alpha_0 + \alpha_1 \ln TFP_{it-1} + \alpha_2 SOE_{it} + \alpha_3 FIE_{it} + \alpha_2 \ln L_{it} + \lambda_j + \varsigma_t) \end{aligned} \tag{8}$$

where V_{it} denotes the latent variable faced by firm i. $\Phi(.)$ is the cumulative density function of the normal distribution. In addition to the logarithm of firm's previous TFP, a firm's decision to engage in processing trade is also affected by other factors, such as its ownership and size (measured by the logarithm of number of employees). Finally, I also include the HS 2-digit level industrial dummies λ_j and year dummies ς_t to control for other unspecified factors. More importantly, I begin with a sample of firms that have no exports in the previous year and but export in the current year to check which ones engage in processing exports. By this, I can rule out the possible learning effects: firms that engaged in processing trade last year are more likely to maintain operations on processing trade this year.

[Insert Table 7 Here]

Table 7 reports the estimation results for the selection equation (8) using the Probit model. With a sample of 1,943 firms that have no exports in the previous year and but export in the current year, I see that firms with lower TFP in the previous period are more likely to engage in processing trade. Similarly, large and foreign firms are more likely to engage in processing trade. However, SOEs are less likely to become processing firms, though the coefficient of SOEs is insignificant.

For comparison, Column (2) of Table 6 reports the estimation results by replacing the processing indicator with predicted processing probability for Eq. (8) over the entire sample. The predicted processing probability produces a mean close to that of the processing indicator, as shown in the summary statistics of Table 4. The inverse Mills ratios obtained from the first-step binary treatment estimates from (8) are included in the current second-step estimates.[28] Once again, in Column (2), the coefficient of firm-specific output tariffs is larger than that of firm-specific input tariffs, However, the positive sign, though insignificant, of the processing indicator seems erratic. One possible reason is the relatively crude measure of processing variable, which may over-estimate the role of processing firms. For example, if a firm only has a very small proportion of processing imports over total imports, it is still classified as a processing firm, yet its primary operation remains in ordinary trade.

5.3 Extent to Processing

To overcome such an identification challenge, I then take a step forward to consider a continuous measure of the extent to which a firm is engaged in processing trade to replace the processing indicator (and predicted processing probability). In particular, the extent of processing engagement is measured through a firm's total processing imports over total imports in each year. I then estimate the effect of firm-specific output tariff and input tariff on firm productivity in Column (3) of Table 6, by using the variable of extent to processing to replace the processing indicator.

As shown in Column (3) of Table 6, both firm-specific output tariffs and input tariffs are negatively associated with firm productivity. More importantly, the coefficient of the processing variable turns to be negative and highly statistically significant. Column (4) includes the interaction term between output tariffs and the extent of processing engagement and finds that it is insignificant, but the coefficients of other variables have a similar result to their counterparts in Column (2). More importantly, the coefficient of the firm-specific output tariffs is quite close to its counterpart in Column (1) of Table 5 in which the full-sample firm-level production dataset is adopted.

5.4 Discussion of Channels

We have seen rich evidences that both output and input tariff reductions boost firm productivity. However, we still have very little understanding about their channels. The impact of input tariffs on productively is relatively direct, as lower tariffs induce access to a larger variety of imported intermediate inputs (Helpern *et al.*, 2011). By contrast, reductions in output tariffs are found to have a pro-competitive effect (see, for example, Amiti and Konings, 2007). However, it is less clear that such a pro-competitive effect is realized by firms through improving the efficiency of firms that are present

[28] Also note that such a binary treatment approach differs from Heckman's (1979) two-step method. The regressand in the present second-step estimates (*i.e.*, firm's TFP) is observable regardless of its processing status, whereas that of Heckman's model is presumed to be censored, although the first-step of the two approaches is the same.

in the market, or through weeding less productive firms out of the market.

To test such two possible channels, I first drop firms if they are not present throughout all years during 2000-2006, yielding a balanced panel which is used for estimations in Column (5) of Table 6. Once again, the coefficient of output tariffs is negative and significant, indicating that gains of productivity from cutting output tariffs for firms are realized by pressuring firms to be more productive. As shown in Table 8A, outputs of firms that are always present increase over time, suggesting that such firms also enjoy the "scale effects" in production by moving along their average cost curves (Krugman, 1979).

[Insert Table 8A Here]

To check whether low productive firms collapse and exit from the market, the first column of Table 8B reports a simple t-test comparison between continuing firms and firms that exit in the next year. Overall, firms that exit in the next year are found to have low productivities in the present year than those continuing firms. As reported in the rest of Table 8B, the t-tests of TFP of such two groups by year convey the same message: the impact of output tariffs on firm productivity also works indirectly by weeding out low productive firms.

[Insert Table 8B Here]

By way of comparison, Amiti and Konings (2007) have discussed productivity gains from tariff reductions in Indonesia from the channels of markups and product switchers. Verifying whether or not such channels are also important for China is worthwhile.

I then check whether the measured productivity growth only picks up changes in industrial markups. Unlike Amiti and Konings (2007) who used a binary industrial concentration indicator, I include a continuous variable of a Herfindahl concentration index, defined as the sum of the squared market share in each HS 2-digit sector, in Column (1) of Table 9. The coefficient of the Herfindahl concentration index is negative and significant, indicating that firms in highly concentrated industries have low productivity, similar to the findings of Amiti and Konings (2007). However, different results are obtained when the Herfindahl index is interacted with firm-specific output and input tariffs in Column (2). In particular, the interaction of the Herfindahl index with firm-specific output tariffs is insignificant, suggesting that gains from output tariff reduction are present for all industries regardless of their competitive levels. In contrast, the interaction term of the Herfindahl index with firm-specific input tariffs is negative and significant, with a sizable magnitude of 8.56. Multiplying this value with the concentration index mean (0.01), the overall effect of firm-specific input tariffs on productivity growth is still negative,[29] suggesting that gains from input tariff reductions are higher in strong competitive sectors, but lower in less competitive industries.

Amiti and Konings (2007) forcefully argued that tariff reductions could result in firms switching their scopes from low- to high-productivity products. However, they do not have information on firm scope because of Indonesian data restrictions. Thus, they had to use a switching dummy as a compromise. However, the present merged data set includes information on exporter's scope. Many Chinese firms export multiple products, with the maximum even reaching 745 (see Table 4). A logarithm of firm's scope is included in Column (3), which yields a positive and significant coefficient, suggesting that firms exporting more products have higher productivity. In Column (4), the log of firm's scope is then interacted with firm-specific input and output tariffs. The interaction of output tariffs and log scope is found to be significant, whereas that of input tariffs and log scope is insignificant, indicating that at least a few gains from output tariff reductions are attributable to product switching, as also found by Amiti and Konings (2007). However, this channel is not important for input tariff reductions.

Last but not least, firms' productivity gains from trade reform may also result from the channel of investing in new technologies (Bustos, 2011). Firms with higher R&D expenses are expected to have higher productivity. This conjecture is verified in Column (5) by simply including a variable of the firm's log R&D. In the last column, the logarithm of R&D is also interacted with the firm-specific input and output tariffs. Interestingly, the interaction coefficient of the input tariffs and R&D is insignificant, showing that the gains from input tariff reductions do not result from investing in new technologies. In contrast, the interaction coefficient between output tariffs and R&D expenses is significant, whereas that of firm-specific output tariffs is insignificant, suggesting that R&D expenses are indeed highly important for firms to realize gains from output tariff reductions. The economic rationale is also straightforward. With tariff reduction on final goods, firms face tougher import competition. Thus, firms would strive to boost productivity by investing in new technologies.

[Insert Table 9 Here]

[29] Note that $-.525+.001\times 8.56 = -.44$.

5.5 Reverse Causality of TFP on Tariffs

Interestingly enough, the coefficient of firm-specific output tariffs have a smaller magnitude than that of input tariffs, as seen from Columns (3)-(5) in Table 6. I suspect that this is due to the endogeneity of import tariffs. Although tariff reductions are regulated by the GATT/WTO agreements, they are still, to some extent, endogenous because firms in low productivity sectors would lobby with the government for protection (Grossman and Helpman, 1994) to maintain related internationally negotiated tariffs at a relatively high level. Such a reverse causality should be controlled to obtain accurate estimates of tariff reduction effects on TFP by adopting the IV approach.

Determining a good instrument for tariffs on final and intermediate goods is usually challenging. Inspired by Amiti and Konings (2007), here I construct firm-specific output tariffs and input tariffs in 1996 as instruments, by replacing the tariff τ_k^t for product k in year t in both Eq. (4) and Eq. (6) with the tariff τ_k^{1996} for product k in 1996.[30] As a result, the firm-specific output tariff in 1996 measures the importance of such tariffs on the products that firms currently *produce*. Similarly, the firm-specific input tariffs in 1996 capture the importance of such tariffs on products that firms currently *import*. Their economic rationales are as follows. The government generally has difficulties in removing the high protection *status quo ante* from an industry with high tariffs, possibly because of the domestic pressure from special interest groups. Hence, compared with other sectors, industries with high tariffs five years before China's accession to the WTO can still be expected to have relatively high tariffs at present.

Columns (1) and (2) of Table 10 present the 2SLS estimates using Olley–Pakes TFP as the regressand. After controlling for the endogeneity of input and output tariffs, the coefficients of firm-specific input and output tariffs are significantly negative. Also, the reduction in firm's output tariffs has a greater effect on productivity improvement compared with cutting in input tariffs. Specifically, a 10% reduction in output (input) tariffs can lead to a 4.2% (3%) productivity increase.

A few Chinese firms notably do not have their own production activity, but only export goods collected from other domestic firms or import goods from abroad and then sell to other domestic companies (Ahn *et al.*, 2011). To ensure the preciseness of the estimates, I exclude such pure trading companies from my sample. First, such trading firms are identified from both production-level and transaction-level data sets using their names. In particular, firms with names including any Chinese

[30] Accordingly, I adopt the interaction between firm-specific tariff in 1996 and the extent of processing trade engagement as an additional instrument in Table 11.

characters of "Trading Company" or "Importing and Exporting company" are excluded from the sample.[31] However, only a few pure trading firms are included in the merged data set. After this filter, the 2SLS estimation results without pure trading firms are reported in Column (2) of Table 10. The results are significantly close to Column (1), which includes trading firms. In particular, the coefficient of output tariffs is larger than that of input tariffs.

Moreover, to check whether the 2SLS estimation results are sensitive to different measures of TFP, Column (3) of Table 10 replaces Olley-Pakes TFP with system GMM TFP. As a result, labor and intermediate inputs, as well as capital, are allowed to have a dynamic effect on the unobserved productivity shock. The estimates in Column (3) yield results similar to those in Column (1).

However, it may be inappropriate to measure efficiency for pure assembly firms by using the indicator of TFP. As stressed by Feenstra and Hanson (2005), firms involved in processing assembly do not have the choice to make materials themselves. These firms only passively receive free materials from foreign clients. If this condition is true, either Olley-Pakes approach or system GMM method can work very well because it assumes that a firm makes its input choices with the objective of maximizing profits. As a result, intermediate inputs like materials are a variable input that the firm can adjust to its entire productivity shock.

Also, as previously mentioned, measured TFP may also pick up the difference in prices and price-cost markups across firms. To overcome such challenges, my final robust checks in Table 10 perform the 2SLS estimates using the logarithm of firm's labor productivity as the regressand. The last column of Table 10 shows that the effect of firm-specific output tariffs on a firm's efficiency is significantly larger than that of firm-specific input tariffs, as anticipated.

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

[31] In China, pure trading companies are required to register with a name containing Chinese characters for "trading company" or "importing and exporting company".

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

Finally, the first-stage estimates reported in the lower module of Table 10 offer more supportive evidence to justify such instruments. In particular, all the t-values of the instruments are significant. The excluded F–statistics in the first stage are also significant. Thus, these statistical tests provide sufficient evidence that the instrument performs well and, therefore, the specification is well justified.

[Insert Table 10 Here]

5.6 Endogeneity Issues

Furthermore, the weight construction in firm-specific input tariffs in Eq. (6) is still endogenous because goods with high tariffs would be imported less, thus generating a lower import weight in Eq. (6). Taking an extreme example, if China imposes a prohibitive tariff on product k, then its import share on such a good would be zero, because m_{it}^k in Eq. (6) is zero. Hence, the input tariffs that a firm faces may be underestimated. Thus, to avoid such a problem, I choose firm's import value in the initial year (*i.e.*, 2000) to construct a fixed weight in the firm-specific input tariffs (FIT_{it}^{2000}) as follows:

$$FIT_{it}^{2000} = \sum_{k \in \mathring{\Theta}} \frac{m_{i,2000}^k}{\sum_{k \in \Theta} m_{i,2000}^k} \tau_t^k + 0.05 \sum_{k \in \tilde{\Theta}} \frac{m_{i,2000}^k}{\sum_{k \in \Theta} m_{i,2000}^k} \tau_t^k, \tag{9}$$

where $m_{i,2000}^k$ is firm i's imports of product k in 2000. As a result, the import weight is unaffected by tariff reductions. Along with the firm-specific input tariffs, I also construct firm-specific output tariffs by replacing the export weight X_{it}^k in Eq. (4) with a fixed export weight $X_{i,2000}^k$. I then use these two alternative measures of tariff reductions to run regressions in Table 11 as a robustness check.

[Insert Table 11 Here]

Table 11 reports the estimates using firm-level tariffs with fixed weights. For comparison, Columns (1)-(2) still use the processing indicator to denote the processing variable. It turns out that firm-specific output tariffs still have a greater effect compared with firm-specific input tariffs, even if the interaction term between firm-specific output tariffs and the processing indicator is included in Column

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

(2). Moreover, Columns (3) and (4) use the predicted processing probability from Eq. (8) to replace the processing indicator and yields similar results to Columns (1) and (2). Different from Column (2) of Table 6, here firm-specific input and output tariffs are measured with the fixed weight, It turns out that the predict processing probability turns to have a negative and significant coefficient. The last two columns of Table 11 present more evidence that firm-specific output tariffs have a greater impact on firm productivity than firm-specific input tariffs by using the extent to processing to capture firm's processing behavior.

Measuring input and output tariffs with a fixed weight is helpful to control for the endogeneity of tariffs, but it still faces a potential pitfall since the base year chosen to construct the fixed weight is arbitrary. To detour such an empirical challenge, I choose firm's import value in the previous year to construct a weight in the firm-specific input tariffs in the current year as follows:

$$FIT_{it}^{lag} = \sum_{k \in \mathring{\Theta}} \frac{m_{i,t-1}^k}{\sum_{k \in \Theta} m_{i,t-1}^k} \tau_t^k + 0.05 \sum_{k \in \tilde{\Theta}} \frac{m_{i,t-1}^k}{\sum_{k \in \Theta} m_{i,t-1}^k} \tau_t^k. \tag{10}$$

Correspondingly, the firm-specific output tariffs with one-period lag is also constructed by replacing the export weight X_{it}^k in Eq. (4) with a fixed export weight $X_{i,t-1}^k$. Using these two alternative measures of tariff reductions, Column (1) of Table 12 still finds that output tariffs have a larger coefficient than input tariffs.

5.7 Robustness Checks with External Tariffs

Thus far, the effect of China's import tariff reductions on Chinese firm's efficiency is always carefully investigated. However, although China substantially reduced its import tariffs in the new century, Chinese exporters also enjoyed large reductions in their export destinations. Access to large foreign markets could possibly create incentives for productivity upgrading, especially if such investments require substantial fixed costs. Thus, controlling for tariff reduction in China's export destinations is also worthwhile in obtaining the precise estimate of the effect of import tariff reductions on a firm's TFP.

To measure the tariff reductions in a firm's export destinations, I construct an index of firm-specific external tariffs (FET_{it}) as follows:

$$FET_{it} = \sum_k \left[\left(\frac{X_{it}^k}{\sum_k X_{it}^k}\right) \sum_c \left(\frac{X_{ikt}^c}{\sum_c X_{ikt}^c}\right) \tau_{kt}^c \right], \tag{11}$$

where τ_{kt}^{c} is product k's *ad valorem* tariff imposed by export destination country c at year t. A firm may export multiple types of products to multiple countries. The ratio in the second parentheses in Eq. (11), $X_{ikt}^{c}/\sum_{c} X_{ikt}^{c}$, measures the export ratio of product k produced by firm i but consumed in country c, yielding a weighted external tariff across Chinese firms' export destinations. Similarly, the first parenthesis in Eq. (11), $X_{it}^{k}/\sum_{k} X_{it}^{k}$, measures the proportion of product k's exports over firm i's total exports. As shown in Table 4, the mean of the firm-specific external tariff is only 0.9%, which is significantly lower than its counterpart of firm-specific import tariffs on final goods (5.7%). However, this makes good economic senses. The most important export destinations for Chinese firms are developed countries, such as the US and the EU, which usually set substaintially lower import tariffs than developing countries, such as China.

The second column of Table 12 presents the estimation results including a variable of firm's external tariffs in the regressions. The coefficient of firm-specific external tariffs has an anticipated negative sign, but is statistically insignificant. One possible reason for this is that Chinese firms have already entered foreign markets before 2000. Thus, the continuing tariff reduction at Chinese firms' export destinations no longer has a statistically significant effect on reducing export fixed costs. Nevertheless, previous findings are still quite robust. The effect of firm-specific output tariffs is similar to that of firm-specific input tariffs. Moreover, firms highly engaged in processing trade have lower productivity, *ceteris paribus*.

[Insert Table 12 Here]

5.8 Estimates by Processing Types

The remainder of Table 12 investigates the effect of firm-specific tariff reductions on productivity using the firm's processing type. I only include pure processing firms in Column (3). Accordingly, the variable of the extent of processing engagement and its interaction term with firm-specific output tariffs are automatically dropped. After controlling for firm-specific and year-specific fixed effects, the coefficient of firm-specific output tariffs is found to be lower than that of firm-specific input tariffs in absolute value, indicating that, without processing trade, firm-specific input tariffs have a greater impact on firm productivity than output tariffs. Such a finding is consistent with the findings of previous studies.

Similarly, Column (4) only includes hybrid firms that engage in both processing and ordinary trade. The coefficient of firm-specific output tariffs turns to be larger than that of input tariffs, suggesting that the reduction of input tariffs for processing trade has a much smaller impact on firm productivity than that of output tariffs. The variable of the extent of processing engagement has a negative and significant sign, indicating that higher engagement in processing trade results in lower firm productivity.

Finally, Column (5) runs the fixed-effect regression on pure processing firms. The coefficient of output tariffs is still negative and significant whereas the coefficient of input tariffs is insignificant, but still negative. As introduced above, pure processing firms include two types of processing: assembly and processing with inputs. I then run the regression with pure assembly firms only in the last column of Table 12. Thus, the variable of firm-specific input tariffs and the extent to processing are dropped automatically. The estimated coefficient of output tariffs is again statistically significant and relatively sizable.

6 Concluding Remarks

The paper explores how reductions in tariffs on imported inputs and final goods affect firms' productivity by exploiting the special tariff treatment afforded to the imported inputs by processing firms as opposed to non-processing firms in China. As a popular trade pattern in a large number of developing countries, including China, processing trade plays an important role in realization of productivity gains for firms. Since processing trade in China enjoys zero tariffs on imported inputs, I find that a reduction in output tariffs has a greater effect on productivity improvement compared with cutting in input tariffs. This finding significantly differs from that of a number of previous studies, such as those of Amiti and Konings (2007) and Topalova and Khandelwal (2011) who found the opposite effect, that is, input tariff reductions have a more substantial effect on boosting firm productivity.

The present paper is one of the first to explore the role of processing trade on Chinese firm productivity gains. The rich data set enables the determination of whether a firm engages in processing trade and the examination of the effect of the firms' extent of processing trade engagement on productivity gain. With such information, firm-specific input tariffs were also constructed, as one of the first attempts in the literature, which, in turn, enriches the understanding of the economic effect of the special tariff reform in processing trade.

Such findings are important and also have policy implications. Although countries with special treatment on processing trade enjoy fewer gains from reducing tariffs in imported inputs, tariff reductions on final goods in such countries can still generate economically significant productivity gains. In this sense, further steps in trade liberalization are necessary for producers, as well as consumers.

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Table 1: Chinese Transaction-Level Trade Data by Shipment and by Year

Percentage of Total Obs. (HS 8-Digit)

Type	Year							Total	
	2000	2001	2002	2003	2004	2005	2006	Percent	# of Obs.
10	1.80	2.87	3.51	5.42	7.25	7.94	6.77	35.45	6,593,795
14	.75	1.03	1.06	1.21	1.60	1.63	1.20	8.46	1,573,712
15	4.53	5.23	6.16	8.19	10.16	10.44	8.91	53.60	9,970,060
99	.78	.82	.11	.17	.24	.20	.16	2.48	461,940
Total	7.85	9.86	10.83	14.98	19.25	20.20	17.03	100	18,599,507

Percentage of Total Value

Type	Year							Total	
	2000	2001	2002	2003	2004	2005	2006	Percent	Amount
10	1.84	2.77	3.23	5.28	7.59	8.92	5.18	34.80	3.98e+11
14	.51	.66	.64	.82	1.44	1.96	.80	6.84	7.82e+10
15	3.84	4.38	5.86	8.54	11.83	13.58	7.37	55.40	6.84e+11
99	.98	1.02	.08	.17	.30	.27	.15	2.97	3.39e+10
Total	7.18	8.83	9.81	14.81	21.15	24.72	13.50	100	1.14e+12

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

Table 2A: Basic Summary of Trade Data and Production Data

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

Notes: (a) The HS eight-digit monthly transaction-level trade data are from China's General Administration of Customs. The firm-level annual accounting data are from China's National Bureau of Statistics. (b) Valid trading firms trading firms with a valid zip code and telephone information. (d) Valid firms refers to firms with a valid zip code and telephone information reported in the firm-level accounting data set.

Table 2B: Comparison of the Merged Dataset and the Full-sample Production Dataset

Variables	Merged Data			Full-sample Production Data		
	Mean	Min.	Max.	Mean	Min.	Max.
Sales	208,678	5000	5.03e+07	85,065	5000	1.57e+07
Exports	86,898	0	4.82e+07	16,544	0	1.52e+08
Number of Employees	545	10	148,328	274	10	165,878
Log of Capital-Labor Ratio	3.81	-5.66	10.59	3.53	-6.22	11.14
Log of Labor Productivity	3.92	-5.88	11.98	3.84	-8.96	10.79

Table 2C: Merged Importers by Type

Types of Firms	2000	2001	2002	2003	2004	2005	2006	Total	Percent
Ordinary Importers	1,659	2,324	2,910	3,931	5,090	4,894	5,070	25,878	35.5%
Processing Importers	5,393	5,947	6,254	6,562	8,160	7,602	6,999	46,917	64.5%
Hybrid Processing Importers	2,175	2,440	2,695	3,059	3,742	3,613	2,971	20,695	28.5%
Ordinary Imports	671	717	181	298	386	296	245	2,794	3.9%
Processing with Assembly	283	322	416	482	570	556	426	3,055	4.2%
Processing with Inputs	1,221	1,401	2,098	2,279	2,786	2,761	2,300	14,846	20.4%
Pure Processing Importers	3,218	3,507	3,559	3,503	4,418	3,989	4,028	26,222	36.0%
Processing with Assembly	353	493	461	490	611	632	679	3,719	5.1%
Processing with Inputs	2,865	3,014	3,098	3,013	3,807	3,357	3,349	22,503	30.9%

Table 3: Estimates of Olley-Pakes Input Elasticity of Chinese Firms

HS 2-digit	Est. Coefficients			Log of TFP (Olley-Pakes)		
Categories	Labor	Materials	Capital	Pure Ordinary	Hybrid	Pure Processing
Animal Products (01-05)	.056**	.888**	.048**	1.35	1.28	1.24
	(3.32)	(55.36)	(1.80)			
Vegetable Products (06-15)	.007	.891**	.052**	1.39	1.37	1.26
	(.49)	(68.05)	(5.49)			
Foodstuffs (16-24)	.036**	.874**	.044	1.36	1.30	1.26
	(2.23)	(68.48)	(1.07)			
Mineral Products (25-27)	.035*	.872**	.099**	1.40	1.49	1.42
	(1.70)	(51.00)	(2.69)			
Chemicals & Allied Industries (28-38)	.014**	.831**	.103**	1.41	1.42	1.32
	(1.98)	(121.70)	(7.79)			
Plastics / Rubbers (39-40)	.064**	.796**	.103**	1.43	1.41	1.33
	(8.49)	(107.17)	(5.59)			
Raw Hides, Skins, Leather & Furs (41-43)	.102**	.810**	.090**	1.29	1.28	1.27
	(7.76)	(65.53)	(3.36)			
Wood Products (44-49)	.039**	.855**	.012	1.45	.142	1.36
	(4.29)	(97.11)	(.47)			
Textiles (50-63)	.085**	.810**	.066**	1.34	1.32	1.25
	(19.50)	(192.59)	(10.38)			
Footwear / Headgear (64-67)	.072**	.864**	.033**	1.30	1.31	1.26
	(5.93)	(73.17)	(5.43)			
Stone / Glass (68-71)	.104**	.785**	.103**	1.43	1.45	1.39
	(9.14)	(67.02)	(8.19)			
Metals (72-83)	.045**	.832**	.109**	1.42	1.37	1.30
	(6.30)	(131.73)	(16.23)			
Machinery/Electrical (84-85)	.065**	.825**	.150**	1.43	1.44	1.34
	(13.36)	(206.22)	(10.83)			
Transportation (86-89)	.042**	.883**	.043**	1.35	1.34	1.28
	(2.80)	(69.58)	(3.47)			
Miscellaneous (90-98)	.083**	.796**	.098**	1.42	1.39	1.32
	(10.32)	(110.01)	(10.70)			
All industries	.052**	.820**	.117**	1.41	1.39	1.30
	(30.75)	(493.33)	(27.08)			

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

Table 4: Summary Statistics (2000-2006)

Variables	Mean	Std. Dev.	Min.	Max
Year	2003	1.88	2000	2006
Firm's Log TFP (Olley-Pakes)	1.37	.354	-1.50	11.8
Firm's Log TFP (System-GMM)	2.48	.414	-.158	10.7
Processing Indicator	.656	.475	0	1
Predicted Processing Probability	.633	.182	.003	.977
Extents to Processing Activity	.578	.463	0	1
Firm-level Output Tariffs	.057	.073	0	.65
Firm-level Input Tariffs	.014	.031	0	.86
Firm-Level External Tariffs	.009	11.3	0	9.60
Firm's Scope	8.13	14.09	1	745
Log of Firm's R&D Expenses	5.71	2.24	0	14.9
Industrial Herfindahl Index	.014	.025	.002	.825
Log of Firm's Labor	5.52	1.19	2.30	11.9
SOEs Indicator	.014	.117	0	1
Foreign Indicator	.772	.419	0	1

Table 5: Benchmark Estimates

Regressand: $\ln TFP_{it}^{OP}$	Full-sample	Merged Dataset		
	(1)	(2)	(3)	(4)
Industry Output Tariffs	-.227**	-.858**	-.706**	–
	(-41.1)	(-30.7)	(-9.65)	
Industry Input Tariffs	–	–	-.359**	–
			(-10.5)	
Firm Output Tariffs				-.425**
				(-19.5)
Firm Input Tariffs				-.246**
				(-4.95)
Processing Indicator		-.052**	-.051**	-.074**
		(-14.3)	(-13.8)	(-19.09)
Foreign Indicator	.011**	.052**	.068**	.046**
	(11.2)	(13.7)	(13.7)	(12.22)
SOEs Indicator	-.133**	-.015	-.014	-.019
	(-54.2)	(-.89)	(-.84)	(-1.16)
Observations	750,243	43,342	43,342	43,342
Prob.>F	.000	.000	.000	.000
R-squared	.01	.03	.03	.05

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

Table 6: Estimates Using Different Measures of Processing Variable

Measures of Processing:	Processing Indicator	Processing Probability	Extent to Processing		
Regressand: $\ln TFP_{it}^{OP}$	(1)	(2)	(3)	(4)	(5)
Firm Output Tariffs	-.450**	-.161**	-.287**	-.299**	-.210*
	(-12.15)	(-3.25)	(-8.58)	(-4.85)	(-1.93)
Firm Input Tariffs	-.367**	-.147*	-.388**	-.384**	-.335*
	(-5.13)	(-1.66)	(-5.04)	(-4.34)	(-1.67)
Firm Output Tariffs				.018	-.192
$\times$ Processing Variable				(0.23)	(-1.33)
Processing Variable	-.095**	.170	-.095**	-.096**	-.093**
	(-16.00)	(0.32)	(-16.20)	(-10.79)	(-6.10)
Foreign Indicator	.069**	.168**	.075**	.075**	.082**
	(14.23)	(18.81)	(15.17)	(16.86)	(6.19)
SOEs Indicator	-.057*	-.125**	-.011	-.011	-.035
	(-1.87)	(-3.88)	(-0.39)	(-0.38)	(-.77)
Log of Labor	.029**	.051**	.030**	.030**	.052**
	(14.46)	(20.32)	(14.96)	(17.25)	(14.92)
Inverse Mills Ratio		.449			
		(1.33)			
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	43,342	25,713	43,342	43,342	10,104
R-squared	.06	.10	.07	.07	.07

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

Table 7: The Probit Estimates of Selection Effects of Processing Firms

Variables	Coefficient	Variables	Coefficient
Log of TFP at Previous Period	-.330**	Foreign Indicator	.377**
	(-3.58)		(4.73)
SOEs Indicator	-.401	Log of Firm's Labor	.082**
	(-1.04)		(2.85)

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *(**) indicates significance at the 10(5) percent level. The selection model is equation (8) in the text. The regressand is firm's processing indicator. The 1,943 observations in the regressions refer to firms that do not export in the previous year but export in the present year. The 2-digit industry-specific fixed effects and year-specific fixed effects are also included in the estimation.

Table 8A: Outputs of Firms that always Present

Always-Present Firms (N=2748)	2000	2001	2002	2003	2004	2005	2006
Firm's Deflated Output	10.96	11.04	11.15	11.27	11.35	11.47	11.54

Notes: There are 2748 firms that always present during the period 2000-2006. Their deflated outputs keep increasing over times.

Table 8B: TFP Comparisons between Continuing Firms and Exiters Next Year

	Entire Sample	2001	2002	2003	2004	2005
Continuing Firms	1.369	1.259	1.276	1.335	1.404	1.432
Exiters Next Year	1.331	1.228	1.255	1.296	1.374	1.399
Difference	.038**	.031**	.020**	.039**	.029**	.033**
	(10.36)	(2.91)	(1.89)	(5.52)	(4.08)	(4.90)
Number of Exiters Next Year	17,186	1,919	1,824	4,270	5,360	3,813

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

Table 9: Channels

Regressand: $\ln TFP_{it}^{OP}$	Industrial Markup		Multi-Product Firms		R&D Expenses	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Output Tariffs	-.299**	-.345**	-.281**	-.193**	-.251*	.272
	(-4.67)	(-4.36)	(-3.71)	(-2.12)	(-1.93)	(.93)
Firm Output Tariffs	.020	.101	-.019	.014	-.066	-.177
× Extent to Processing	(.25)	(1.02)	(-.20)	(.14)	(-.35)	(-.89)
Firm Output Tariffs	–	3.17				
× Herfindahl Index		(.96)				
Firm Output Tariffs				-.076**		
× Log of Firm's Scope				(-2.08)		
Firm Output Tariffs						-.083**
× Log of Firm's R&D						(-1.97)
Firm Input Tariffs	-.382**	-.525**	-.322**	-.218	-.406**	-.316
	(-4.35)	(-4.79)	(-3.17)	(-1.20)	(-2.45)	(-.68)
Firm Input Tariffs	–	8.56**				
× Herfindahl Index		(2.10)				
Firm Input Tariffs				-.052		
× Log of Firm's Scope				(-.61)		
Firm Input Tariffs						-.016
× Log of Firm's R&D						(-0.21)
Extent to Processing	-.095**	-.096**	-.087**	-.087**	-.051**	-.046**
	(13.15)	(-13.31)	(-10.16)	(-10.18)	(-3.04)	(-2.75)
SOEs Indicator	-.010	-.011	-.031	-.030	-.050	-.050
	(-.53)	(-.55)	(-1.18)	(-1.16)	(1.61)	(-1.61)
Foreign Indicator	.075**	.075**	.077**	.079**	.093**	.092**
	(13.81)	(13.79)	(11.67)	(11.94)	(7.83)	(7.78)
Log of Labor	.030**	.030**	.034**	.033**	.016**	.016**
	(15.38)	(15.36)	(14.04)	(13.84)	(3.24)	(3.24)
Herfindahl Index	-.214*	-.307**				
	(-1.72)	(-2.07)				
Log of Firm's Scope			.007**	.001**		
			(2.73)	(6.95)		
Log of R&D					.030**	.034**
					(10.47)	(9.42)
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,326	43,326	26,059	26,059	4,895	4,895
R-squared	.071	.072	.075	.078	.136	.137

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *(**) indicates significance at the 10(5) percent level. In all estimates I exclude pure trading companies.

Table 10: IV Estimates

Regressand:	$\ln TFP_{it}^{OP}$		$\ln TFP_{it}^{GMM}$	$\ln LP_{it}$
	(1)	(2)	(3)	(4)
Firm Output Tariffs	-.421**	-.421**	-.763**	-3.27**
	(-3.41)	(-3.41)	(-5.23)	(-7.62)
Firm Input Tariffs	-.307*	-.302*	-.500**	-2.56**
	(-1.71)	(-1.68)	(-2.35)	(-4.11)
Firm Output Tariffs × Extent to Processing	.134	.135	.255	2.07**
	(.91)	(.92)	(1.47)	(4.07)
Extents to Processing	-.099**	-.099**	-.224**	-.999**
	(-9.67)	(-9.66)	(-18.50)	(-28.03)
Foreign Indicator	.075**	.076**	.066**	.104**
	(13.63)	(13.69)	(10.16)	(5.39)
SOEs Indicator	-.012	-.012	-.074**	-.059
	(-.59)	(-.61)	(-3.08)	(-.84)
Log of Labor	.031**	.031**	.050**	-.181**
	(15.41)	(15.45)	(21.26)	(-25.47)
Kleibergen-Paap rk LM χ^2 statistic	1,100†	1,100†	1,101†	1,101†
Kleibergen-Paap rk Wald F statistic	1,440†	1,440†	1,441†	1,301†
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes
Year-specific Fixed Effects	Yes	Yes	Yes	Yes
Observations	43,342	43,326	43,342	41,435
R-squared	.071	.071	.109	.150
First-Stage Regressions				
IV1: Firm-specific Output Tariffs in 1996	.002*	.002**	.002**	.002**
	(46.26)	(46.24)	(46.26)	(44.56)
IV2: Firm-specific Input Tariffs in 1996	.002**	.002**	.002**	.002**
	(70.10)	(70.08)	(70.10)	(68.57)
IV3: Firm-specific Output Tariffs in 1996	.003**	.002**	.003**	.003**
× Extent to Processing	(62.02)	(62.01)	(62.02)	(61.11)

Notes: Robust t-values in parentheses. *(**) is 10(5) % significance. † indicates significance of p-value at the 1 percent level. In the first-stage regressions, IV1 reports the coefficient of the firm-specific output tariffs in 1996 using the current firm-specific output tariffs as the regressand. Similarly, IV2 reports the coefficient of the firm-specific input tariffs in 1996 using the current firm-specific input tariffs as the regressand. Finally, IV3 reports the coefficient of the product of the firm-specific output tariffs in 1996 and the extent to processing using the product of the current firm-specific output tariffs and the extent to processing as the regressand.

Table 11: Estimates using Firm-Level Tariffs with Fixed Weights

Regressand: $\ln TFP_{it}^{OP}$	Processing Indicator		Processing Probability		Extent to Processing	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Output Tariffs (with Fixed Weight)	-.012**	-.009**	-.008*	-.027*	-.013**	-.007**
	(-2.81)	(-2.37)	(-1.73)	(-1.61)	(-2.89)	(-2.04)
Firm Input Tariffs (with Fixed Weight)	-.004**	-.004**	-.002**	-.002**	-.005**	-.005**
	(-4.67)	(-4.67)	(-3.48)	(-3.48)	(-4.48)	(-4.49)
Firm Output Tariffs (with Fixed Weight)		-.010		.028		-.023*
× Processing Variable		(-.90)		(1.30)		(-1.66)
Processing Variable	-.080**	-.080**	-.808**	-.812**	-.098**	-.097**
	(-22.35)	(-21.93)	(-5.72)	(-5.74)	(-26.62)	(-25.93)
Foreign Indicator	.065**	.065**	.149**	.149**	.067**	.067**
	(17.08)	(17.07)	(25.39)	(25.39)	(17.76)	(17.73)
SOEs Indicator	-.056**	-.056**	-.125**	-.125**	-.058**	-.058**
	(-3.27)	(-3.27)	(-6.47)	(-6.47)	(-3.42)	(-3.42)
Log of Labor	.029**	.029**	.051**	.051**	.030**	.030**
	(19.91)	(19.92)	(25.87)	(25.88)	(20.09)	(20.11)
Inverse Mills Ratio			-.177**	-1.79**		
			(-1.98)	(-2.00)		
Observations	43,342	43,342	25,713	25,713	43,342	43,342
Prob.>F	.000	.000	.000	.000	.000	.000
R-squared	.021	.021	.065	.065	.026	.026

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

Table 12: Further Estimates with Extent to Processing, by Processing Types

Regressand: $\ln TFP_{it}^{OP}$	All Importers		Pure Ordinary	Hybrid Processing	Pure Processing	Pure Assembly
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Output Tariffs (with lag)	-.713**	-.008**	-.562**	-.742**	-.556**	-.597**
	(-3.30)	(-3.08)	(-2.48)	(-4.42)	(-3.64)	(-3.16)
Firm Input Tariffs (with lag)	-.465*	-.007**	-.586**	-.625**	-.877	–
	(-1.75)	(-2.47)	(-3.22)	(-2.38)	(-0.35)	
Firm Output Tariffs (with lag)	.056	.001	–	.225	–	–
× Extent to Processing	(0.21)	(0.48)		(1.07)		
Extent to Processing	-.087**	-.078**	–	-.096**	–	–
	(-14.35)	(-11.65)		(-14.93)		
Foreign Indicator	.077**	.076**	.083**	.069**	.048**	.049**
	(16.23)	(11.68)	(11.12)	(10.90)	(6.41)	(5.75)
SOEs Indicator	-.006	-.027	-.021	-.015	-.008	-.026
	(-0.19)	(-1.19)	(-0.69)	(-0.49)	(-0.10)	(-0.33)
Log of Labor	.030**	.035**	.028**	-0.49**	.018**	.015**
	(15.61)	(15.68)	(8.52)	(10.33)	(6.16)	(3.57)
Firm External Tariffs		-.011				
		(-0.43)				
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,342	26,073	15,022	30,550	15,528	9,122
Prob.>F	.000	.000	.000	.000	.000	.000
R-squared	.067	.070	.046	.068	.052	.043

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

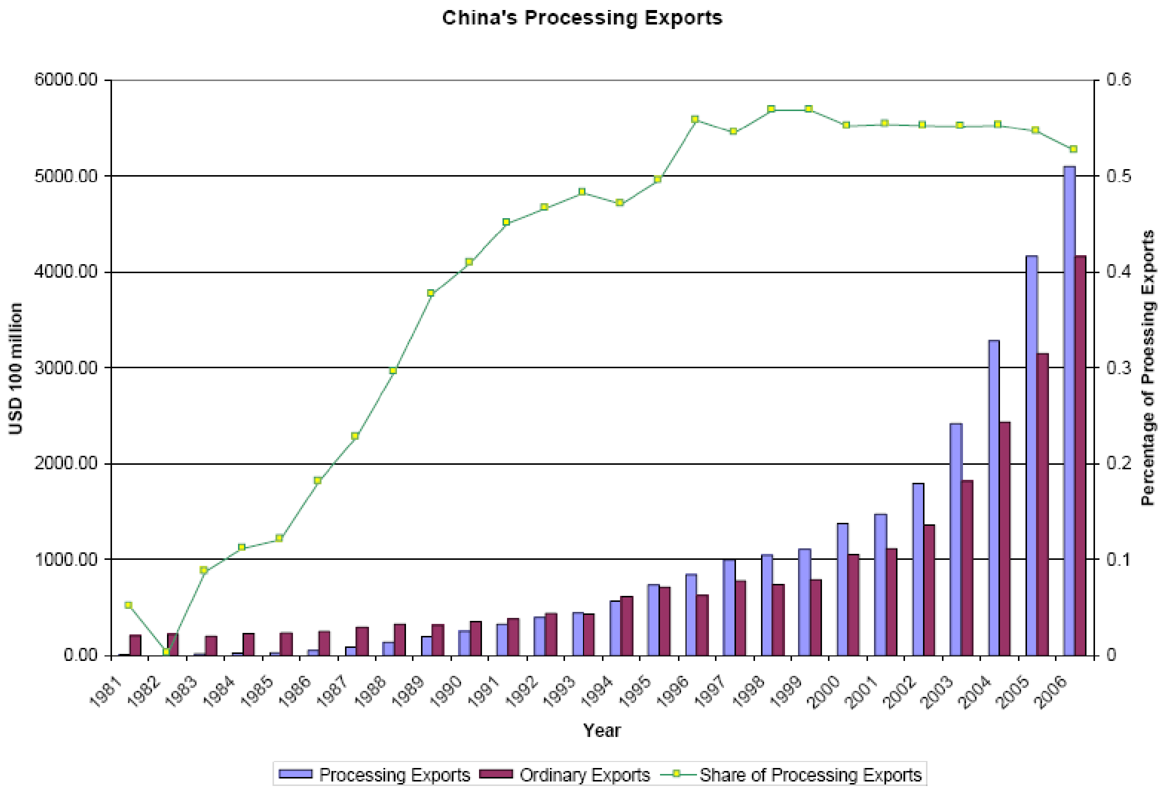

Figure 1: China's Processing Exports vs. Ordinary Exports

Sources: China's Statistical Yearbooks, various years.

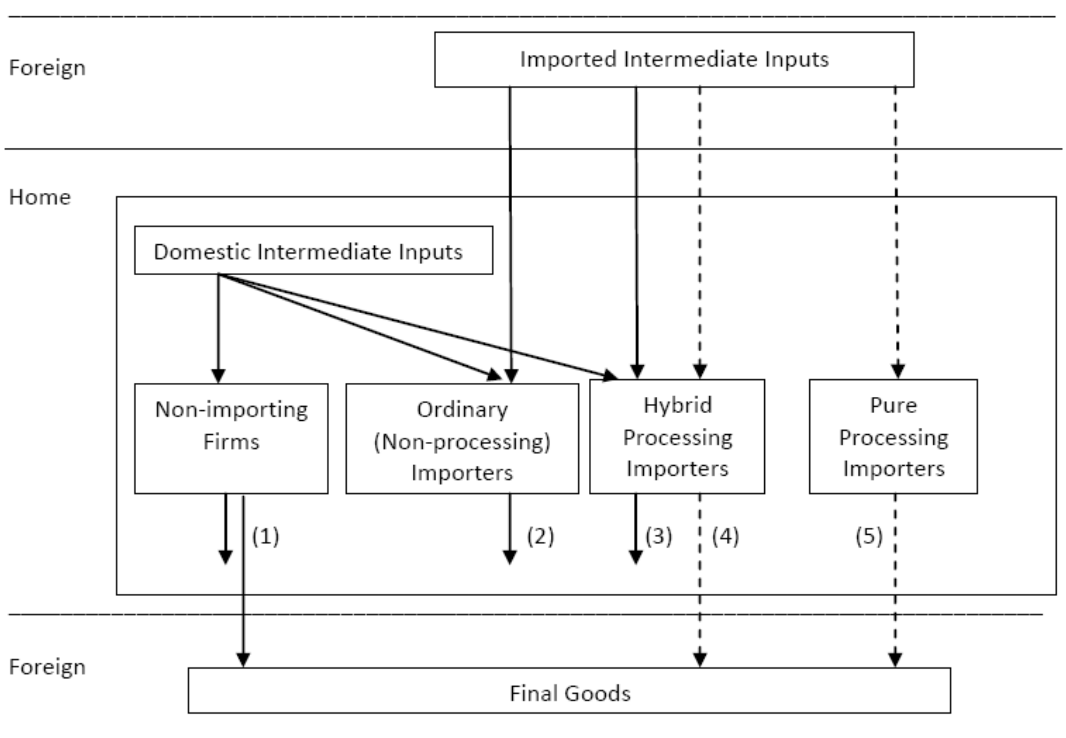

Figure 2: Four Types of Chinese Firms

Notes: Dotted lines denote firms' processing imports/exports whereas real lines represent firms' non-processing imports/exports.

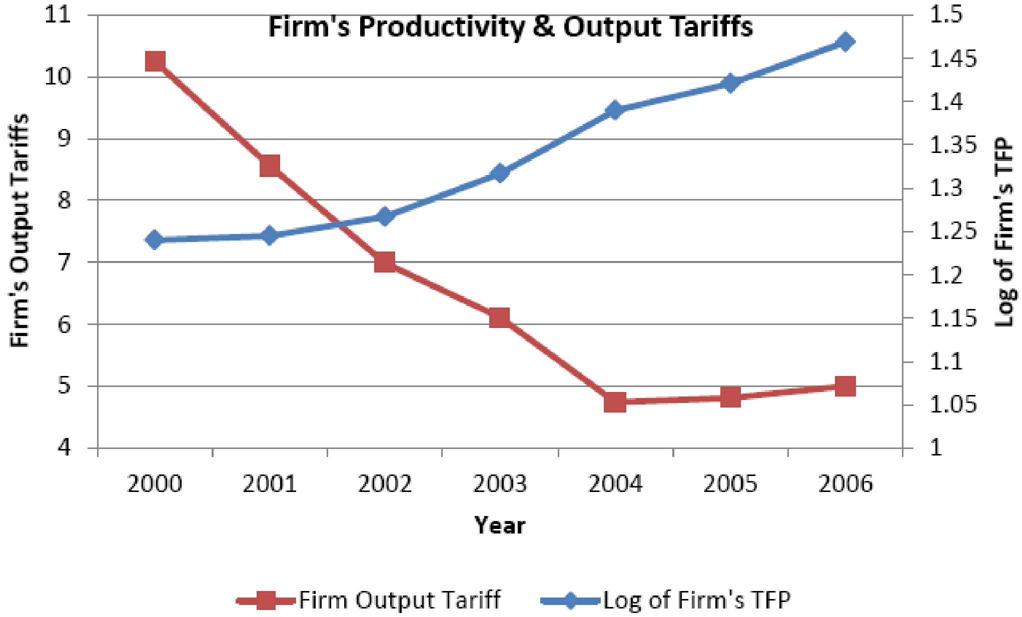

Figure 3A: Firm's Logarithm of TFP and Firm-level Output Tariffs (2000-2006)

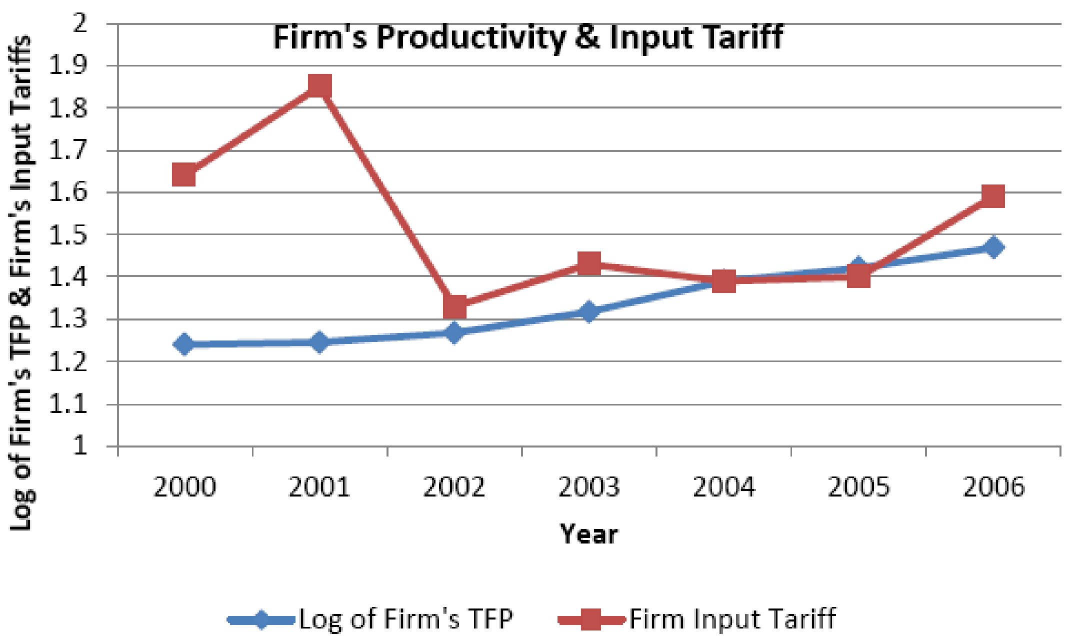

Figure 3B: Firm's Logarithm of TFP and Firm-level Input Tariffs (2000-2006)

Notes: Productivity is measured as an average of log TFP (Olley-Pakes). Firm-level weighted output tariffs and input tariffs are taken across all firms in each year in the sample.