Input Trade Liberalization and Wage Inequality: Firm-Level Evidence from China*

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Abstract

Whether China's accession to the WTO has exacerbated or mitigated the wages gap? Yet there is neither theoretical consensus nor consistent empirical evidences. In this paper, we first extend Bernard *et al.*'s (2007) model and show that input trade liberalization in an unskilled labor abundant country such as China could reduce wages gap between the skilled labor and unskilled labor. We then provide rich empirical exercises to confirm such a theoretical conjecture. After controlling for various firm characteristics such as firm size, productivity and trading partners' trade liberalization, our rich empirical investigations confirm that a fall in input trade costs will lead to a significant decrease in wages gap: a 1% decrease in input tariffs could result in a 0.27% fall in wages gap. Given the fact that China's actual tariff reduction from 2000 to 2006 is about 17%, freer imports during that period may have helped China mitigate its wage inequality by 4.6%. The empirical finding is robust to various alternative specifications.

JEL Classifications: F10, F12, F14

Keywords: Wage Gap, Imported Intermediate Inputs, Trade Liberalization

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1 Introduction

Since mid-1980s, China has gradually loosened its restriction on labor mobility. Quickly an increasing number of farmers has been working in manufacturing sector in urban areas, attracted by much higher labor compensation. They are usually called "migrant rural workers". The number of rural workers[1] was about 225 million in 2009. About 63% of the workers chose to work in town rather than in their rural neighborhood (Cai, 2010). Such abundant labor supply effectively keeps China's unskilled labor wages at a fairly low level and makes China's labor intensive products very competitive in the world market. Enjoying the huge benefit from cheap unskilled labor as well as the global trade liberalization, China has experienced steadily fast growth in international trade and emerged to be one of the largest trading countries in the world. At the same time, wages paid to skilled workers, especially in export sectors and multinationals, also increased very fast. Internationally competitive wages have attracted high skilled labor, who previously work in the developed countries, to return to China, making China change from a country with a net 'Brain Drain' before 1990s to 'Brain Circulation' after 2000 (Chen, 2010). It has been suggested that trade liberalization is the key reason for the enlarging wages gap between the skilled and unskilled workers in China. For example, based on 1500 Chinese firms from 1998 to 2000, Li and Xu (2008) find that international trade led to a net increase in the relative demand for skilled labor (which in turn implies a higher wages gap).

However, wages of the rural workers (i.e. the unskilled labor) in China have increased substantially since China joined the WTO in 2001. For example, both Nike and Adidas have closed their factories in the end of 2012 due to the fast increasing (unskilled) labor cost in China. According to the China Rural Household Annual Survey, the nominal wages for rural workers increased by almost 50% during 2003 to 2008, or almost 30% in real terms (Cai, 2010a). Though there might be other factors driving up the unskilled labor wages, we believe that the surging demand on unskilled labor,

[1] Rural workers are defined as the former farmers who work more than 6 months in nonagricultural sector.

due to vast trade liberalization, is no doubtably one of the most important reasons. Zhejiang and Guangdong, the two provinces that rely on international trade most intensively, have been reporting their increasing (unskilled) labor shortage since 2003.

There have been mixed views about how trade liberalization affects wages gap. Since 1980s, trade economists have been debating on whether trade liberalization leads to wages gap and whether the factor price equalization (FPE) theorem of the Heckscher-Ohlin (H-O) model can help to explain the enlarging wages gap in the U.S. and many other OECD countries. For example, Johnson and Stafford (1993), Leamer (1993, 1996) argue that FPE can explain the wages gap between skilled and unskilled workers in the U.S. However, Slaughter and Lawrence (1993) checked historical data about the prices of labor-intensive goods and capital intensive goods and found that the movement of the relative prices of these two types of goods may suggest wages equality according to FPE. Furthermore, they showed that it was the technological progress that could explain the enlarged wages gap. Incorporating firm heterogeneity in the framework of H-O, Bernard, Redding, and Schott (hereafter BRS, 2007) show that firms' reactions to trade liberalization at the industry level magnify countries' comparative advantage: reduction in trade costs results in firms in comparative advantage industries more likely to expand, export, and having higher job turnover. Moreover, the H-O prediction on wage inequality is still valid: less costly trade leads to smaller wage inequality between the skill and unskilled labors.

While most of the literature still focuses on trade liberlatization impact of final goods on wages inqeaulity, the role of such liberalization in intermediates and its impact on wages inequality is largely ignored. Yet it is believed that the recent surge in fragmentation and offshoring of production processes (e.g. as documented by Hummels, Ishii, and Yi, 2001; Amiti and Wei, 2005) could be a new channel for trade liberalization to affect wages gap. For example, Feenstra and Hanson (2001) argue that trade in intermediate inputs significantly affects the manufacturing sector but the mechanism also works via the technological development – more intermediate inputs improve technology – and the benefit of such technological progress mainly goes to non-production workers (skilled workers).

However, Edwards and Lawrence (2010) argue that trade should not be responsible for wages gap for two reasons. First, domestic goods and imported goods are in fact non-substitutes. Second, they find the US imports from developing countries are actually more capital intensive (i.e. the share of imports that are deemed as capital intensive goods is higher than that from developed countries), which, as suggested by trade theory, should contribute to wages equality.

China is the world largest developing country which is experiencing great reform/relaxation on both labor market and goods market. Thus whether China's accession to the WTO has exacerbated or mitigated the wages gap remains as a fairly important question to be investigated. A very important yet long overlooked characteristic in China's trade is that China's deep engagement in trading intermediates. Feenstra and Wei (2010), based on highly disaggregated data (HS-8 and HS-10), show that China's trade is more focusing on intermediates (and typically adding labor-intensive service in trade) than other countries in the world. Therefore in this paper we extend BRS (2007) by taking into account the production of intermediate input. We argue that trade liberalization in imported intermediate inputs has the same effect as it has on final goods as in BRS (2007). That is, less trade costs on imported inputs will lead to a smaller wage inequality between the skilled and unskilled labor. More importantly, we investigate enriched China's firm-level and custom data from 2000 to 2006. The results support the theoretical prediction and are robust under various specifications.

Our paper contributes to the existing literature of trade liberalization and wages gap in threefold. First, to our best knowledge, based on highly disaggregated firm-level data, this is the first paper to study how trade liberalization affects wages gap for China, the largest developing country and the second-largest economy in the world. Second, to closely measure the magnitude of the impact of trade liberalization on wages gap, we construct detailed tariffs measures. Based on a highly disaggregated firm-level data and transaction-level customs trade data sets, we construct three-digit Chinese industry classifications (CIC) input tariffs and output tariffs. We further consider firm-specific output tariffs and firm-specific external output tariffs to control for trade liberalization occurred in China's trading partners. Third, we extend the BRS(2007) model by incorporating production of intermediate input and show that tariff reduction on inputs has the same effect as it has on final goods. Interestingly and importantly, we obtain a novel empirical finding–the input tariff reduction leads to a fall in wages gap: given the benchmark estimate, a 1% reduction on input tariff could mitigate wage inequality in China's manufacturing sector by 0.27%. This has a rich policy implication: when taking global production network into account, input trade liberalization is helpful to reduce the income inequality between skilled labor and unskilled labor.

The rest of the paper is organized as follows. In Section 2 we provide a theoretical model to show that trade liberalization in imported input will reduce wages gap. In Section 3 we test the theoretical result using highly disaggregated Chinese firm-level data from 2000 to 2006. Various robustness checks are also conducted. Section 4 concludes.

2 The Model

2.1 Demand

Assume a representative agent's utility is given by

$$U = C_1^{\alpha} C_2^{1-\alpha} \tag{1}$$

where C_i $(i = 1, 2)$ is a composite good as defined below

$$C_i = \left[\int_{\omega \in \Omega_i} q_i(\omega)^{\rho} d\omega \right]^{1/\rho} \tag{2}$$

where ω is a variety of the goods in consumption basket Ω_i. $q_i(\omega)$ is the consumption on variety ω. $0 < \rho = \frac{\sigma-1}{\sigma} < 1$ is the inverse markup and $\sigma > 1$ denotes the elasticity of substitution between varieties. Therefore the exact price index is,

$$P_i = \left[\int_{\omega \in \Omega_i} p_i(\omega)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \tag{3}$$

Due to the dual structure of aggregate utility and quantity, i.e. $C_i \equiv Q_i$, we can further express the demand quantity and revenue/expenditure, $r_i(\omega)$ on variety ω,

$$q_i(\omega) = Q_i \left[\frac{p_i(\omega)}{P_i}\right]^{-\sigma} \tag{4}$$

$$r_i(\omega) = R_i \left[\frac{p_i(\omega)}{P_i}\right]^{1-\sigma} \tag{5}$$

where $R_i = P_i Q_i = \int_{\omega \in \Omega_i} r_i(\omega) d\omega$ denotes the aggregate expenditure on composite good C_i.

2.2 Production

There are two production sectors, one for non-tradable final goods C_1 and C_2 (for instance, goods sold in supermarkets with sales services), the other for corresponding tradable intermediate inputs. There are two factors of production: skilled labor (H) and unskilled labor (L). Factors are free mobile within a country such that the wages w_s and w_u (paid to the skilled and unskilled, respectively) are identical across firms which are determined in the (aggregate) factor markets.

Assume the input market is perfectly competitive. There is no entry cost. Firms engaging in input production are assigned with the an identical productivity, $\varphi_m = 1$, and the inputs they produce are identical within each sector within the same country. The production for input is Cobb-Douglas:

$$M_i = A H_{mi}^{\beta_i} L_{mi}^{1-\beta_i} \qquad i = 1, 2.$$

where $A = \beta_i^{\beta_i}(1-\beta_i)^{1-\beta_i}$. Then the price index for domestic input is simply $P_{mi}^d = w_s^{\beta_i} w_u^{1-\beta_i}$.

The production for final goods follows typical Melitz (2003) models: prior to entry potential firms for industry i sink a cost of $f_{ei} w_s^{\beta_i} w_u^{1-\beta_i}$ and randomly draw a productivity φ for this final production from the support [1,Ψ]. When operating, firms need to pay a beachhead cost $f_i w_s^{\beta_i} w_u^{1-\beta_i}$ in each period and face an exogenous death rate δ. When producing, firms need to input H and L and intermediate inputs whose price index is P_m. Importing firms also need to pay a fixed importing cost $f_{im} w_s^{\beta_i} w_u^{1-\beta_i}$ each period.[2] The imported inputs, however, cost $\tau_m P_{mi}^f$, where $\tau_m > 1$ is the iceberg cost. The intermediate input cost follows a CES form as in Amiti and Davis (2011):[3]

$$P_{mi} = \begin{cases} P_{mi}^d & \text{without imported inputs} \\ \left[\left(P_{mi}^d\right)^{1-\gamma} + \left(\tau_m P_{mi}^f\right)^{1-\gamma}\right]^{\frac{1}{1-\gamma}} = P_{mi}(\tau)\ (< P_{mi}^d) & \text{with imported inputs} \end{cases}$$

where $\gamma > 1$ is the elasticity of substitution between imported input varieties. It is intermediate that $P'_{mij}(\tau) > 0$. That is, less costly trade (i.e. τ decreases) reduces firms' cost on intermediate inputs. Similar to BRS (2007), we have the following the cost function,

$$\Gamma_{ij} = \left[f_i + \frac{q_{ij}}{\varphi_{ij}}\right] w_s^{\beta_i} w_u^{1-\beta_i} P_m \tag{6}$$

It is worth noting that given the structure of entry cost, the production costs for intermediate input (including fixed importing cost, if any) and final goods (including beachhead cost), the factor intensities of each firm (λ) in both sectors are indeed fixed : $\lambda_i = \frac{L_{ei}}{H_{ei}} = \frac{L_{mi}}{H_{mi}} = \frac{L_{gi}}{H_{gi}} = \frac{\beta_i}{1-\beta_i}$, where the subscripts "$e$", "$m$", and "$p$" refer to entry, intermediate goods, and final goods, respectively. Such a fixed sector-specific factor intensity enables us to investigate the impact of trade liberalization to factor wages in a H-O framework even though we incorporate firm heterogenity (in productivity) here.

Given the iso-elastic demand curve, the pricing rule (for final output) to a monopolistic firm j in industry i is:[4]

$$p_{ij} = \frac{MC_{ij}}{\rho} = \begin{cases} \frac{w_s^{\beta_i} w_u^{1-\beta_i}}{\rho\varphi_{ij}} & \text{without imported inputs} \\ \frac{w_s^{\beta_i} w_u^{1-\beta_i}}{\rho\varphi_{ij}} P_{mi}(\tau) & \text{with imported inputs} \end{cases} \tag{7}$$

The (domestic) sales revenue r_{ij} is

[2] To ensure not all domestic firms also import, we assume $f_{im} > f_i$.
[3] That is, domestic and imported inputs are different varieties. For simplicity we do not further assume varieties produced within a country.
[4] As in Melitz (2003), we assume single-product firm, thus we use firm ID (i.e. "ij" to replace consumption variety "ω".

$$r_{ij} = \begin{cases} R_i \left[\frac{w_s^{\beta_i} w_u^{1-\beta_i}}{\varphi_{ij} \rho P_i} \right]^{1-\sigma} & \text{without imported inputs} \\ R_i \left[\frac{w_s^{\beta_i} w_u^{1-\beta_i}}{\varphi_{ij} \rho P_i} P_{mi}(\tau) \right]^{1-\sigma} & \text{with imported inputs} \end{cases} \tag{8}$$

Thus the profit is given by:

$$\pi_{ij} = \begin{cases} \frac{R_i}{\sigma} \left[\frac{w_s^{\beta_i} w_u^{1-\beta_i}}{\varphi_{ij} \rho P_i} \right]^{1-\sigma} - f_i w_s^{\beta_i} w_u^{1-\beta_i} & \text{without imported inputs} \\ \frac{R_i}{\sigma} \left[\frac{w_s^{\beta_i} w_u^{1-\beta_i}}{\varphi_{ij} \rho P_i} P_{mi}(\tau) \right]^{1-\sigma} - (f_i + f_{im}) w_s^{\beta_i} w_u^{1-\beta_i} & \text{with imported inputs} \end{cases} \tag{9}$$

2.3 Steady-State General Equilibrium

In steady-state general equilibrium, the following five conditions must be held:

A: zero profit conditions plus free entry jointly determine cut-off productivity for importers and domestic producers given w_s and w_u;

B: final goods market equilibrium: entry equals exit;

C: input market equilibrium: domestic plus imported input equals input demand;

D: factor market equilibrium: $H_1 + H_2 = \overline{H}$, $H_i = H_{gi} + H_{ei} + H_{mi}$, $L_1 + L_2 = \overline{L}$, $L_i = L_{gi} + L_{ei} + L_{mi}$;

E: balance of payment: exports equal imports.

With these conditions, we can derive the equilibrium values for prices, wages, cut-off productivities, and resource allocation.

Inspecting of the price, profit and revenue equations with the counterparts (equation (18)-(22)) in BRS (2007), we can find the effects of freer imports are similar to those of freer exports in BRS (2007). The only difference in this paper is that our model replaces the export cost term τ_x in BRS (2007) with the price index of intermediate inputs $P_m(\tau_m)$. Since $P_m(\tau)$ is a monotonic increasing function in import tariff τ_m, the reduction on imports tariff has the same effect as the reduction on export tariff τ_x. Similar to the proposition 7(a) in BRS (2007), we can have the following proposition:[5]

[5] Since the price, revenue, and profit structure resemble those in BRS (2007) with only $P_m(\tau)$ replacing τ, the proof for the proposition is identical to that in BRS (2007) and thus is not provided.

[**Proposition**] The impacts of freer imports resemble those of freer exports in BRS (2007). Particularly, freer imports benefit the abundant factor. That is, freer imports lead to smaller wage inequality in unskilled labor abundant country.

Intuitively, countries tend to import more intermdieates (with cheaper prices) that they do not have comparative advantage to produce when input trade liberalization takes place. Hence lower import barrier in intermediate inputs results in more input trade and indirectly more inflows of the scarce factors of home country from foreign country. As a result, in a country with abundant unskilled labor such as China we should have mitigated wages inequality when freer trade in intermediate input takes place.

3 Data and Measures

3.1 The Data

To investigate the impact of trade liberalization (mainly in terms of input tariffs reduction) on firm's wages gap, in this paper we rely on the following three highly disaggregated large panel data sets: firm-level production data provided by China's National Bureau of Statistics (NBS), HS 8-digit trade data reported by China's General Administration of Customs (GAC), and China's import tariffs data maintained by the World Integrated Trade Solution (WITS) of World bank.

China's NBS conducts an annual survey on "above-scale" manufacturing firms–the medium and large size manufacturing enterprises whose registered capital are above 5 million RMB (or equivalently US$ 800,000). The sample used in this paper covers around 230,000 manufacturing firms per year from 2000 to 2006 which on average accounts for around 95% of China's total annual output in manufacturing sector.[6] The data set contains entire information of main accounting sheets which includes more than 100 variables. For example, the data provides firm information on annual sales, value-added, capital stock, employment, etc. for both state owned enterprises (SOEs) and non-SOEs.

[6] In 2006, the value-added of above-sale firms in the survey is RMB 9,107 billion, which accounts for 99% of the value-added of all firms in manufaturing sectors, RMB 9,131 billion, as reported by China's Statistic Yearbook (2007).

The number of firms included in annual survey increased from about 160 thousand in 2000 to 301 thousand in 2006. However, we have to be cautious about data quality since many unqualified firms are included largely because of mis-reporting by some firms. Following Feenstra-Li-Yu (2011), we delete observations according to the basic rules of generally accepted accounting principles if any of the following holds: (1) liquid assets exceed than total assets; (2) total fixed assets exceed 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). Accordingly, the total number of firms covered in the data set is reduced from 615,951 to 438,165, around 1/3 of firms are dropped from the sample after such a filter process.

The GAC provides highly disaggregated monthly transaction-level trade data during 2000-2006 at the HS 8-digit level. The number of monthly observations increases from around 78 thousand in January 2000 to more than 230 thousand in December 2006. An important feature of the data is that it provides the type of trade, processing or ordinary, which is very important and quite a special issue in China since more than 30% of Chinese trade is related to processing trade. Furthermore, the data also provides firm information (*i.e.,* name, address, phone number, etc.) and thus a match with the survey data is possible. We use the methods proposed by Yu and Tian (2012) to match these two data and end up with around 40% of number of exporting firms and around 53% of total exports in the firm-level production data.[7] Hence, our matching results are highly comparable to other studies that use the two data sets such as Ma *et al.* (2011) and Ge *et al.* (2011). For reader's information, we also provide a detailed matching procedure in Appendix A.

China's import tariff (Ad Valorem) data from WITS are available at the HS 6-digit level for the period 2000–2006, which we match with the trade data at the HS 8-digit level. That is, all the HS-8

[7] Although both firm-level production data and transaction-level trade data contain a variable of firm's identification number, it is challenging to match them together since their coding systems are completely different and share no any common characteristics. To address this challenge, Yu and Tian (2012) suggest two ways to match trade data and industrial survey data. First, they match two data sets by firm's name and year. Furthermore, they use another matching technique to serve as a supplement. Specifically, they rely on two other common variables to identify firms, namely, zip code and the last seven digits of a firm's phone number.

imports under the same HS-6 category share the same tariff.

3.2 Measuring Firm and Industry Specific Tariffs

It is tricky to measure input and output tariff. A firm could produce multiple products and thus faces multiple tariffs. Furthermore, due to competition, firms may be affected by the so called external tariff which are the general tariff level other than its specific tariffs. In this paper, our focus is the change of input tariffs, which is measured by industry-level input tariffs (IIT_{ft}) following Amiti-Konings (2007) and Topalova and Khandelwal (2011).[8] In particular, the industry-level input tariffs, IIT_{ft}, is measured by

$$IIT_{ft} = \sum_n \left(\frac{input_{nf}^{2002}}{\sum_n input_{nf}^{2002}} \right) \cdot \tau_{nt}, \tag{10}$$

where IIT_{ft} denotes the industry level input tariffs facing firms in industry f in year t. τ_{nt} is the tariff of input n in year t. The weight in parenthesis is measured as the cost share of input n in the production of industry f.

We use China's Input-Output Table in 2002 to construct the weight since NBS reports the Input-Output Table in every five years and our data spread over 2000-2006. Particularly, we proceed with the following steps: Firstly, since there are 71 manufacturing sectors reported in China's Input-Output Table (2002) and only 40 manufacturing sectors reported in Chinese industrial classifications (henceforth CIC), we start to make a concordance between the Input-Output Table and the CIC sectors.[9] Secondly, we match the CIC sectors with international standard industrial classifications (ISIC, rev. 3).[10] Thirdly, we make another concordance to link ISIC and harmonized system (HS) 6-digit in which we can find the corresponding tariffs from the WTO. Fourth, we calculate the

[8] Though we could construct firm-level input tariffs, as argued in Amiti and Davis (2011), it would cause problems relating to sample selection bias and introduce an endogeneity problem since importers may access cheaper input and thus have lower weighted tariff facing them. Such advantage may result in higher profitability of importing firms and thus their wages to skilled employees. Hence we constructed input tariff at the industry level.

[9] China's Input-Output Table is complied in every five years with the most recent updates in 2007. Since our data sample spreads between 2000 and 2006, we therefore adopt the Input-Output Table in 2002.

[10] Note that China's government adjusted its CIC in 2003. We hence also concord such adjustment in our data.

industry-level tariffs which are aggregated to the CIC sectorial level.[11] In particular, the simple average tariffs are used to calculate industry-level tariffs as follows:

$$\tau_{nt} = \frac{1}{N} \sum\nolimits_{k \in n, k=1}^{N} \tau_{kt}, \tag{11}$$

where k denotes products in industry n. We use such simple-average tariffs as a default measure in the following main estimates. Finally, we calculate the industry-level input tariffs using the formula (10).

To control for the effect of output tariffs, following Yu (2011), we also construct two relevant firm-specific output tariff indexes: weighted output tariff index (FOT_{it}) and firm-specific external tariffs (FET_{it}). The first tariff index, FOT_{it}, is given by

$$FOT_{it} = \sum\nolimits_{k} \left(\frac{v_{it}^{k}}{\sum_{k} v_{it}^{k}} \right) \tau_{t}^{k}, \tag{12}$$

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, $\sum_k v_{it}^k$. 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:

$$v_{it}^{k} = \frac{X_{it}^{k}}{\sum_{k} X_{it}^{k}} (Y_{it} - \sum\nolimits_{k} X_{it}^{k}), \tag{13}$$

where Y_{it} is the firm's total sales, and X_{it}^k is product k's exports for firm i at year t. The difference in parentheses measures firm i's total domestic sales. The first term at the right hand side of Eq.(13) measures the proportion of product k's exports over firm i's total exports.[12]

The second tariff index, FET_{it}, is

[11] We do not report the input weights by industry to save space, though available upon request.

[12] However, a caveat exists: due to data restriction, the weights of products that are only sold domestically cannot be calculated using this approach.

$$FET_{it} = \sum_k \left[(\frac{X_{it}^k}{\sum_k X_{it}^k}) \sum_c (\frac{X_{ikt}^c}{\sum_c X_{ikt}^c}) \tau_{kt}^c \right], \qquad (14)$$

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, $X_{ikt}^c / \sum_c X_{ikt}^c$, 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, $X_{it}^k / \sum_k X_{it}^k$ measures the proportion of product k's exports over firm i's total exports.

3.3 Empirical Specifications

Our theoretical framework suggests that a fall in input trade costs reduces wages gap between skilled labor and unskilled labor. We now turn to test this theoretical conjecture using Chinese firm-level production data. In particular, we consider a following empirical framework:

$$s_{it} = \alpha_0 + \alpha_1 IIT_{it} + \alpha_2 FOT_{it} + \alpha_3 FET_{it} + \alpha_4 PE_{it} + \beta \mathbf{X}_{it} + \varpi_i + \sum_t D_t + \mu_{it,} \qquad (15)$$

where s_{it} is the firm specific skill premium (*i.e.*, wages gap) which is defined as the wages difference between the skilled and unskilled in year t. IIT_{it} is industry input tariffs for firm i at year t, as discussed in (10). FOT_{it} and FET_{it} are firm-specific output tariffs and external tariffs, as discussed in (12) and (14), respectively. PE_{it} is a processing indicator which equals one if firm i has any processing imports in year t. $\mathbf{X}_{it}$ denotes other firm characteristics such as type of ownership (*i.e.*, SOEs, Foreign Invested Enterprises or FIEs). Finally, the last three variables are: (1) firm-specific fixed effects ϖ_i to control for time-invariant factors such as a firm's location; (2) year-specific fixed effects $\sum_s D_t$ to control for firm-invariant factors such as Chinese *RMB* appreciation; and (3) an error term μ_{it} for other unspecified factors.

However, data on firm-specific skill premium s are unavailable. The only available data are firm's average wages. Denoting w_s and w_u the wages paid to the skilled labor and unskilled labor respectively; θ_s the skilled labor share which is measured by the share of employees with at least senior high school's diploma, firm's average wages can be theoretically expressed as $\overline{w} = \theta_s w_s + (1 - \theta_s) w_u$. Thus we can infer the skill premium s by

$$s_{it} = \frac{\overline{w}_{it}}{\theta_{sit}} - \frac{w_{uit}}{\theta_{sit}}. \tag{16}$$

The unskilled labor in China is presumed to get homogeneous compensation ($w_{uit} = w_{ut}$) since unskilled labor, relative to the skilled, is easy to substitute and thus facing a quite competitive market. Thus, Eq.(16) can be re-written as,

$$\frac{\overline{w}_{it}}{\theta_{sit}} = \alpha_0 + \alpha_1 IIT_{it} + \alpha_2 FOT_{it} + \alpha_3 FET_{it} + \alpha_4 PE_{it} + \beta \mathbf{X}_{it} \tag{17}$$

$$+\varpi_i + \sum\nolimits_t D_t + \sum\nolimits_t D_t/\theta_{sit} + \mu_{it}, \tag{18}$$

where the term $\frac{w_{ut}}{\theta_{sit}}$ is moved to the right hand side of the equation and controlled by an interaction term, $\sum_t D_t/\theta_{sit}$, between year dummies and the inverse the skilled-labor share. And we refer to the LHS variable, $\frac{\overline{w}_{it}}{\theta_{sit}}$, as the "measured wages gap". However, since we only have skill (*i.e.,* education) information in the 2004 national census data, we are not able to obtain the exact data on firm specific skilled-labor share in other years. To detour such a data challenge, we construct a proxy for skilled-labor share for 2000-2006 (except 2004) by multiplying skilled-labor share data in 2004 by a normalized province-level average skilled labor share in the corresponding years with 2004 being the base year. A caveat is that such a proxy cannot capture the firm specific variation in skill-labor share for other years than 2004. We also perform the cross-firm estimation only using skilled labor share data in 2004 as a robustness check for our key estimates.

Table 1 reports descriptive statistics for key variables in both full-sample firm-level production data set and matched-sample data set. The full-sample data cover all above-scale Chinese manufacturing firms but missing important information such as destinations of sales (*i.e.,* domestic or international), product categories of import and exports (if any), etc. The matched data, on the other hand, provides detailed information on firms' imports and exports (*i.e.,* variety and value) with corresponding tariffs but suffer from a much smaller sample size. Specifically, in the full sample, the average input tariffs is about 9.72% and the measured wages gap is around 32.5 thousand RMB. The corresponding numbers (9.99% and 38.6 thousand, respectively) in the matched data are quite similar. Yet these two data sets differ in many dimensions. Namely, firms in matched data are: (1) on average larger, with 438 employees per firm versus 274 in the full sample; (2) containing more FIEs (61.5%) and less SOEs (1.8%) than (22.2% and 5.5%, respectively) the full sample; (3) more productive than those in full sample. The log of firm TFP in the matched sample is 1.27 whereas its counterpart in the full sample is only 1.15. Furthermore, Table 1 also reports that in the matched data about 65.6% of firms engage in processing trade and on average 57.8% of the trade is processing trade. In addition, two types of firm specific output tariffs, *i.e.,* the FOT and FET, are on average slightly lower than the input tariffs.

[Insert Table 1 Here]

4 Estimation Results

4.1 Baseline Results from Full-sample Data

We first report the benchmark results in Table 2 based on the full sample firm-level production data set. Column (1) shows that the reduction of industry input tariffs significantly mitigate wages gap. It remains significant after we control for firm specific characteristics such as firm's ownership type in Columns (2) and (3), firm size (measured by log of employment) in Column (3), and its productivity in Column (4). In particular, Column (4) suggests that a 1% decrease in input tariffs leads to around a 0.27% fall in wages gap, after controlling for other variables. According to Chen and Ma (2012), China's actual tariff reduction from 2000 to 2006 is about 17%, which means freer imports during that period may have helped China mitigate its wage inequality by 4.6%. Alternatively, suppose that China's input tariffs reduce from current 10% to zero, then its manufacturing wages gap could further decrease by as much as 2.7%. In addition, the wages gap is much larger in both SOEs and FIEs than in private ones. Firm size also matters for wages gap: larger firms tend to have smaller inequality. This finding might result from a resource reallocation effect due to globalization: further trade liberalization forces Chinese firms to specialize more on the (unskilled) labor intensive production (procedure) which China has vast advantage in and hence lead to a faster demand growth on the unskilled labor, which in turn generates a larger firm size and a faster growth in unskilled labor wages. Finally, firm productivity improvement widens wages gap, as confirmed by many empirical studies such as Amiti and Davis (2011).

[Insert Table 2 Here]

To eliminate the time-invariant firm-specific effects, we take one-period (year) difference and two-period (year) difference. Furthermore, the firm-level skill share is only available in 2004, it is a concern that the unchanged skill share variation across firms might affect our estimates. So we also investigate a shorter period from 2003 to 2005 where the within firm skill share between 2004 and 2003 & 2005 respectively should not vary in a significant way. The results are reported by the one–period difference and two–period difference estimates in Tables 3 and 4, respectively. Column (1) of Table 3 shows that the annual reduction rate in input tariffs can significantly slow down the speed of the wages gap even after we control for the ownership and firm size. Column (2) shows that the result still holds when we in addition control for firm productivity. Column (3) and (4) repeat the exercises but just based on the annual difference data during 2003-2005. The results once again confirm that reduction rate in input tariffs would lead to a slower speed of wages gap.

[Insert Table 3 Here]

However, the one-year difference data may not have enough variation, so we conduct the same regression but base on two-year difference data as suggested in Amiti and Davis (2011).[13] As shown

[13] Amiti and Davis (2011) use one year difference and three year difference data to address for the time variation problem in data. Given our time span is only 7 years and we only have firm level skill share data in 2004, we use one- and two-year difference data.

in Table 4, when we use two-year difference data, the effect of input tariffs reduction is still very significant but with a relatively larger magnitude. The larger findings are not surprising given that the two-year difference data contains more variation overtime and thus the input tariffs effect is more pronounced. As for the control variables, we find quite similar results: the significance of firm ownership varies in different specifications, and particularly we find that FIEs in 2003 to 2005 have a slower speed of wages gap the private firms. Finally, as found in Table 2, firm size and firm productivity have opposite effects on the change rate of wages gap with larger firms having smaller changes in inequality whereas more productive firms having faster changes.

[Insert Table 4 Here]

4.2 The Role of Processing Trade in Matched Sample

We now turn our gear to focus on the firms involving in international trade by using the matched data. Detailed information on product level imports and exports enable us to further control for the effect of output tariff changes. Estimates in Column (1) of Table 5 suggests that the input tariffs reduction in trading firms has almost the same impact on wages gap regardless of controlling for other firm specific factors, though with a less significance, compared to the corresponding estimates in Table 2. Turning to the impact of output tariffs reduction on wages gap, Column (1) shows that output tariffs reduction also leads to a fall in wages gaps. One possible reason is due to a resource reallocation effect: tariff reduction on the products that Chinese firms also produce leads to a more fierce output market competition, and thus force Chinese firms to be more specialized on the production (procedure) which they have comparative advantage in. That is, output tariff reduction facing China's firms may lead them to be more specialized in (unskilled) labor intensive production (procedures) which results in an increasing demand on unskilled labor and hence a relatively higher increase in wages paid to unskilled labor.

One might suspect that such a result is sensitive to the measure of firm-specific output tariffs. As shown in Equ. (8), to construct firm-specific tariffs, we have to presume that the domestic sales and foreign sales for a product is of the same proportion due to data restriction. Admittedly, this is a pretty strong assumption. To detour such an empirical challenge, we therefore adopt industry-specific output tariffs as done in Amiti and Konings (2007). We measure industry output tariffs at the two-digit Chinese industrial classifications (CIC) level and use it to replace the firm-specific output tariffs in Column (2) of Table 5. Once again, the coefficient of our key variable, firm-specific input tariffs, is insensitive in term of both economic magnitude and statistical significance. Columns (1) and (2) also control for the impact of firm-specific external tariffs, firm size, and firm productivity. It turns that the weighted external tariffs have no significant effects on wages gap. However, larger firms tend to have smaller wages gap whereas more productive firms tend to have larger wages gap.

[Insert Table 5 Here]

We now go further to explore how the impact of input tariffs on wages gap varies by firm type of shipment. As documented in Yu (2011), there are three types of Chinese importers reported in China's customs: firms engaging in 100% ordinary trade (*i.e.*, pure ordinary importers), those engaging in 100% processing imports (*i.e.*, pure processing firms), and those involving in both ordinary and processing trade (*i.e.,* the hybrid firms). Note that such a classification is different from other researches based on type of processing. For example, Feenstra and Hanson (2005) introduce two types of processing trade in China–processing with *assembly* and processing with *inputs.* The former one refers to those processing tasks that firms passively receive intermediate inputs from their foreign clients. After assembling in China, such final goods have to return to same designated foreign clients. In contrast, the latter one refers to those processing tasks that firms import intermediate inputs and then adopt their own technology to produce final goods in China, which could to sale to anywhere in the world. It is important to stress that both pure processing and hybrid firms could engage in both processing assembly and processing inputs.

More interestingly, although processing firms in China enjoy a special tariff treatment (i.e., zero import tariffs) on their imported inputs, firms that engaged in processing with inputs indeed have to pay duties on imported materials from abroad, but then they can get the full amount of the duty as a rebate. In this regard, firms engaged in processing with inputs have stronger demands on cash flow and face more stringent credit constraints (Feenstra *et al.*, 2011). The important message here is that the further reduction in input tariffs still have some impact on pure processing firms if they engage in processing with inputs.

With this background in mind, we then apply the same regression to these three groups of firms, respectively. Columns (3) and (4) reveal that the wages gap in firms with pure ordinary or processing trade are indeed not sensitive to input tariffs reduction. The overall sensitivity found in the whole sample actually results from the hybrid firms as indicated in Column (5). This finding is surprising because intuitively pure ordinary should be affected by the reduction in input tariffs the most. The results may be due to two following reasons. Firstly, firms with pure ordinary trade rely more on domestic market, in terms of both imports and exports, than the other two types of firms. Secondly, in hybrid firms the products for processing trade and ordinary trade may be very similar, therefore their imported inputs could be highly complementary to (unskilled) labor, which is the typical characteristic of the production for processing goods. Column (5) also indicates that wages gap in hybrid firms is also sensitive to the reduction on output tariffs which results in the overall sensitivity in the whole sample as reported in Column(2). Thus, we can infer that the reallocation effect main takes place in the (large) hybrid trading firms. In any sense, the effects of input tariff reduction for the whole sample is indeed mainly driven by hybrid firms, by comparing the related magnitudes in each column.

Finally, firm-specific external tariffs, as indicated in Columns (3) and (4), only have negligible effects to pure ordinary and pure processing firms. Columns (3) and (4) also show that wages gap is smaller in SOEs engaging in pure ordinary trade whereas larger in firms engaging in pure processing trade. Once again, the matched data, whether in whole sample or sub-samples, Columns (2)-(5) confirm that firms size has negative effects on inequality whereas productivity positively affects it.

[Insert Table 6 Here]

To explore the role of processing trade on wages gap, we introduce a processing dummy (i.e., a firm is a processing firm if it has any processing imports). However, such a short-cut may lose some other important information. For example, it is incapable to distinguish the difference of the extent to processing imports. Therefore, Columns (2)-(4) of Table 6 use the extent to processing, defined as firm's total processing imports over firm's total imports, to replace the processing dummy. Equally importantly, although the unskilled labor wages is assumed to be homogeneous across firms and is controlled by a interaction term, it nevertheless may vary cross regions substantially given China's regional economic development is fairly unbalanced. Hence we introduce the provincial rural average wages income as a proxy for the unskilled labor wages in different regions given the fact that the majority of unskilled labor in firms are rural migration workers.[14]

Column (1) of Table 6 reports the estimates when processing firms are still measured as a processing dummy but use rural wages to substitute unskilled labor wages. The input tariffs reduction is still estimated to mitigate wages gap in a significant way. In contrast, in Columns (2)-(4) the processing dummies is substituted by firm's extent to processing imports. Column (2) shows that the impact of input tariffs reduction become less significant (from 5% confidence level to 10%) but the sign remains the same. Column (3) shows the estimates when we still use skill-year dummy interaction term to control for unskilled labor wages. The results are almost identical to those in Column (2), which implies that using provincial rural average wages income as a proxy to the unskilled labor wages, *i.e.,* further controlling for regional effects, is almost the same as using the interaction term.

Finally, Column (4) reports the estimation results based on 2004 data only. The results indicate that firms facing lower input tariffs tend to have smaller wages gap. However, it is interesting to find that the cross-firm estimates in Column (4) differ from the panel estimates in Columns (2) and (3) in terms of processing indicator and firm size: in 2004 processing firms have larger wages gap

[14] The provincial rural wage incomes from 2000 to 2006 are reported in China Statistical Yearbook (2001-2007).

but they have smaller one overtime during 2000 to 2006; smaller firms in 2004 tend to have smaller wages gap whereas the larger firms have such effect overtime. Such a difference may imply that the within-firm time effects differ from the cross-firm effect and the former dominates. That is, processing firms mitigate their wages gap whereas expanding firms have a smaller skill premium as might be suggested by the resource reallocation effect due to freer trade. Firm productivity, nevertheless, is still positively related to wages gap.

4.3 Alternative Measures of Industry Input Tariffs

Thus far, the industry input tariffs are measured using a simple-average weight. This might raise a concern that firm's heterogeneity of using imported inputs within an industry may result in a different picture of tariff reduction than otherwise measured by simple average. To address such a possible concern, a following alternative measure of industry input tariffs is also adopted:

$$\tau_{nt} = \sum\nolimits_{k \in n} \left(\frac{m_{kt}}{\sum_{k \in n} m_{kt}} \right) \tau_{kt}, \tag{19}$$

where m_{kt} is the import values for product k in year t.[15] That is, product imports and firm's total import are used to construct such an alternative industry input tariffs.

Table 7 reports the estimates using such an alternative measure of industry input tariffs. Columns (1) and (2) use processing dummy as the indicator whereas Columns (3) and (4) use the extent to processing. Furthermore, the odd columns use the skill labor share-time interaction term whereas the even columns use the provincial rural wages income (adjusted by skill labor share) to measure the effect of unskilled labor wages. Once again, the estimates of industry input tariffs in these four specifications are all significantly positive which repeatedly confirm that a reduction in input tariffs help mitigate wages gap. Firm size and productivity still have very significant effects on wages gap as suggested in previous estimations. The results in Columns (1) and (3) are similar to those in Columns (2) and (4) respectively, which suggests the two different ways of controlling unskilled labor

[15] Of course, the trade-off is that in weighted IIT the imported inputs with lower tariff may receive higher import volume and thus higher weights. Hence the weighted IIT may overstate the reduction on input tariffs.

wages effect have negligible difference in estimation.

[Insert Table 7 Here]

However, a potential shortcoming of both simple and weighted industry-level input tariffs is that one cannot distinguish *imported* intermediate inputs from *domestic* intermediate inputs. For example, with an identical amount of intermediate inputs, some firms may use more imported intermediate inputs whereas the other firms may use more domestic intermediate inputs. To overcome such a potential pitfall, we then constructed an import-adjusted industry-level input tariffs as follows:

$$IIT_{ft}^{Alt} = \sum_n \left(\frac{input_{nf}^{2002}}{\sum_n input_{nf}^{2002}} \frac{m_{nt}}{y_{nt}} \right) \cdot \tau_{nt}, \tag{20}$$

where the second term in the parenthesis measures the share of imported intermediate inputs (m_{nt}) to total inputs (y_{nt}) in industry f in year t. Correspondingly, the tariff τ_{nt} can be measured by using (11) or (19). As a result, we have two other alternative measure of industry input tariffs: import-adjusted *simple* industry-level input tariffs when (11) and (20) are adopted and import-adjusted *weighted* industry-level input tariffs when (19) and (20) are adopted.

[Insert Table 8 Here]

Table 8 reports the results using such two import-adjusted industry input tariffs. In particular, we use the simple import-adjusted industry input tariffs in Columns (1) and (3) and weighted import-adjusted industry input tariffs in Columns (2) and (4). Columns (1) and (2) are based on the full sample and they show no difference in estimates no matter which import-adjusted industry input tariffs is used. Furthermore, the results are almost identical to their counterparts shown in Column (4) of Table 2. Columns (3) and (4) also show that there is no difference between the *simple* import-adjusted industry input tariffs and the weighted one if we use the matched data. In addition, the results are also very similar to the comparable results in Column (3) of Table 6. Therefore, we can conclude that distinguishing the imported inputs with the domestic ones in constructing industry input tariffs have negligible difference with the previous results based on unadjusted industry input tariffs.

4.4 Further Robustness Checks

Finally, since we only have firm-level observations on skilled-labor share in 2004 we have to assume that there is no within-firm variation in skilled-labor share overtime. To make sure that our results are not qualitatively affected by this assumption, we apply the same regression for the industrial survey data and matched data in only 2004. That is, we only do a cross firm regression and thus we want to check whether firms facing lower input tariffs have smaller wages gap. Table 9 reports the results based on cross-firm estimates. Columns (1) and (2) report the estimates of industry input tariffs based on full sample data with Column (1) only controlling for ownership but Column (2) also controlling for firm size and productivity. The results in both show that firms facing lower input tariffs tend to have smaller wages gap. Columns (3) and (4) repeat the same exercises as in Columns (1) and (2) respectively but based on matched data. They report the almost the same results for industry input tariffs effects as in the first two columns. Exploring the enriched data on trade, we further control for the firm-specific output tariffs and external tariffs as well as the processing trade (measured by processing dummy) and report the results in Column (5). It shows that the result for industry input tariffs is very robust in terms of the significance and even magnitude when we add more control variables. Overall the cross-firm results also show that in 2004 the wages gap is on average smaller in SOEs but larger in firms with larger scale, higher productivity, or owned by foreign investors. In sum, our results, under various specifications, confirm that the reduction on input tariffs leads to a smaller wages gap.

[Insert Table 9 Here]

5 Concluding Remarks

The relationship between trade liberalization and wages gap has been widely studied. Yet there is still neither theoretical consensus nor consistent empirical evidences across countries or overtime. However, as one of the most populated and largest trading countries, China is particularly concerned with this issue.

In this paper, we first extend BRS'(2007) theoretical framework by incorporating production and trade in intermediates and show that input trade liberalization in a developing country such as China could reduce wages gap between the skilled labor and unskilled labor. That is, lower import barrier in intermediate inputs in China results in more input trade and thus indirectly more inflows of the scarce factors, i.e. skilled labor, from foreign countries, which leads to less wage inequality between the skilled and unskilled labor.

We then provide rich empirical exercises to confirm such a theoretical conjecture. Thanks to the very rich Chinese firm-level production data and transaction-level trade data, we are able to construct relevant measures of input trade costs. After controlling for various firm characteristics such as size, productivity and trading partners' trade liberalization, our empirical investigation suggests that a fall in input trade costs leads to a decrease in wages gap in a significant way: a 1% decrease in input tariffs leads to around a 0.27% fall in wages gap, after controlling for other relevant variables. In other words, China's actual tariff reduction from 2000 to 2006 is about 17%, which means freer imports during that period may have helped China mitigate its wage inequality by 4.6%. The empirical findings are robust under various specifications.

Several extensions merit special consideration. One of which is to access more rich data on detailed skilled wages and unskilled wages. Another possible extension is to explore the detailed channels and mechanisms for the impact of trade liberalization on both exports and imports on wage gap. These are all possible research topics in the future.

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Table 1: Summary Statistics (2000-2006)

Variables	Mean	Std. Dev.	Min.	Max
		Full Sample		
Industry Input Tariffs	0.10	2.97	0.04	0.48
Log of Measured Firm's wages Gap	10.39	.969	1.44	18.09
Log of Firm Labor	4.92	1.10	2.30	11.9
Log Firm TFP (Olley-Pakes)	1.15	.346	-2.47	12.85
SOEs Indicator	.055	.228	0	1
Foreign Indicator	.222	.415	0	1
		Matched Sample		
Log of Measured Firm's wages Gap	10.56	.918	2.87	18.09
Industry Input Tariffs	0.10	3.03	0.04	0.48
Log of Firm TFP (Olley-Pakes)	1.27	.331	-1.55	10.30
Processing Indicator	.656	.475	0	1
Extents to Processing Activity	.578	.463	0	1
Firm-Level Output Tariffs	0.09	7.95	0	0.80
Firm-Level External Tariffs	0.08	17.23	0	29.99
SOEs Indicator	.018	.136	0	1
Foreign Indicator	.615	.486	0	1

Table 2: Benchmark Estimates of Input Duty on wages Gap (Full-Sample Data)

Log of Measured Firm's wages Gap	(1)	(2)	(3)	(4)
Industry Input Tariffs	0.385***	0.385***	0.278***	0.268**
	(6.38)	(6.38)	(4.67)	(4.50)
State-owned Enterprises		0.004	0.032***	0.034***
		(0.50)	(4.08)	(4.27)
Firm-Invested Enterprises		0.023***	0.034***	0.033***
		(3.04)	(4.44)	(4.45)
Log of Firm Employment			-0.181***	-0.179***
			(-101.3)	(-100.3)
Log of Firm TFP				0.112***
				(47.92)
Observations	593,422	593,422	593,422	592,169
Year-specific Fixed Effects	Yes	Yes	Yes	Yes
1/Skilled-Labor Share $\times$ Year Dummy	Yes	Yes	Yes	Yes
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.203	0.203	0.222	0.227

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level.

Table 3: One-year Difference Estimates of Input Duty on wages Gap (Full-Sample Data)

First-Difference in	Period 2000-2006		Period 2003-2005	
Log of Measured Firm's wages Gap	(1)	(2)	(3)	(4)
First-Difference in Industry Input Tariffs	0.215***	1.96***	1.10***	1.01***
	(31.77)	(29.01)	(9.22)	(8.41)
State-owned Enterprises	0.002	0.007**	0.006	0.010*
	(0.62)	(2.08)	(1.11)	(1.74)
Foreign-Invested Enterprises	0.006***	0.002	-0.002	-0.006***
	(3.95)	(1.30)	(-0.98)	(-2.72)
Log of Firm Employment	-0.024***	-0.023***	-0.017***	-0.016***
	(-35.27)	(-35.39)	(-17.06)	(-17.13)
Log of Firm TFP		0.084***		0.081***
		(26.83)		(18.83)
Observations	387,582	387,582	221,791	221,791

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level.

Table 4: Two-year Difference Estimates of Input Duty on wages Gap (Full-Sample Data)

Second-Difference in Log of Measured Firm's wages Gap	Period 2000-2006 (1)	(2)	Period 2003-2005 (3)	(4)
Second-Difference in Industry Input Tariffs	3.34***	3.16***	2.29***	2.21***
	(55.20)	(52.20)	(27.37)	(26.49)
State-owned Enterprises	0.005	0.012**	0.020**	0.027***
	(0.77)	(2.02)	(2.34)	(3.14)
Foreign-Invested Enterprises	0.004*	-0.001	-0.016***	-0.021***
	(1.65)	(-0.41)	(-4.12)	(-5.48)
Log of Firm Employment	-0.026***	-0.026***	-0.018***	-0.019***
	(-22.73)	(-23.29)	(-11.07)	(-11.74)
Log of Firm TFP		0.128***		0.114***
		(24.04)		(14.48)
Observations	259,745	259,456	128,874	128,715

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level.

Table 5: Estimates of Input Duty on wages Gap (Matched-Sample Data)

Log of Measured Firm's wages Gap	All Matched-Sample		Pure Ordinary	Pure Processing	Hybrid Firms
	(1)	(2)	(3)	(4)	(5)
Industry Input Tariffs	0.382**	0.385*	0.063	-0.223	0.876**
	(2.06)	(1.94)	(0.25)	(-0.33)	(2.52)
Firm-specific Output Tariffs	0.095***		0.052		0.160**
	(2.59)		(1.01)		(2.56)
Industry Output Tariffs		0.049			
		(0.76)			
Firm-specific External Tariffs	0.005	0.003	0.029**	-0.154*	-0.020
	(0.56)	(0.35)	(2.04)	(-1.81)	(-0.85)
State-owned Enterprises	-0.045	-.040	-0.062*	1.371**	-0.010
	(-1.47)	(-1.33)	(-1.82)	(2.54)	(-0.11)
Foreign-Invested Enterprises	0.027	.021	0.016	0.032	0.020
	(1.46)	(1.10)	(0.68)	(0.39)	(0.51)
Processing Dummy	0.002	0.002	–	–	–
	(0.41)	(0.40)			
Log of Firm Employment	-0.215***	-0.219**	-0.205***	-0.196***	-0.232***
	(-43.46)	(-41.97)	(-32.63)	(-9.69)	(-22.70)
Log of Firm TFP	0.098***	0.112**	0.115***	0.050**	0.060***
	(15.62)	(17.01)	(13.83)	(2.29)	(5.16)
Observations	94,651		65,316	10,709	29,335
Year-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
1/Skilled-Labor Share × Year Dummy	Yes	Yes	Yes	Yes	Yes
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.184	0.214	0.209	0.200	0.218

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level.

Table 6: Estimates of Input Duty on wages Gap (Matched-Sample Data)

Log of Measured Firm's wages Gap	Processing	Extent to Processing		
	Dummy	2000-2006		2004 Only
	(1)	(2)	(3)	(4)
Industry Input Tariffs	0.472**	0.706*	0.695*	0.209***
	(2.14)	(1.69)	(1.65)	(3.15)
Firm-specific Output Tariffs	0.071*	0.175**	0.178**	0.246
	(1.75)	(2.24)	(2.28)	(1.56)
Firm-specific External Tariffs	-0.006	-0.009	-0.010	0.155
	(-0.65)	(-0.81)	(-0.83)	(1.09)
Processing Indicators	-0.002	-0.036***	-0.036***	0.137***
	(-0.40)	(-2.72)	(-2.72)	(5.75)
State-owned Enterprises	-0.036	-0.016	-0.008	-0.207**
	(-0.91)	(-0.19)	(-0.10)	(-2.30)
Foreign Invested Firms	0.013	0.058	0.057	0.085***
	(0.59)	(1.18)	(1.15)	(2.80)
Log of Firm Employment	-0.186***	-0.185***	-0.187***	0.063***
	(-31.86)	(-15.46)	(-15.60)	(7.08)
Log of Firm TFP	0.111***	0.048***	0.047***	0.075**
	(14.32)	(3.48)	(3.43)	(2.37)
Provincial Rural Income/Skilled-Labor Share	-0.000***	-0.000***	–	–
	(-9.66)	(-2.95)		
Observations	67,805	23,200	23,200	5,765
R-squared	0.21	0.21	0.20	0.02
Year 2004 Covered Only	No	No	No	Yes
Year-Specific Fixed Effects	Yes	Yes	Yes	No
1/Skilled-Labor Share × Year Dummies	No	No	Yes	No
Firm-Specific Fixed Effects	Yes	Yes	Yes	No

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level.

Table 7: Estimates with Weighted Input Duty (Matched-Sample Data)

Log of Measured Firm's wages Gap	Processing Dummy		Extent to Processing	
	(1)	(2)	(3)	(4)
Industry Input Tariffs (Weighted)	0.006***	0.006***	0.013***	0.013***
	(3.31)	(3.37)	(3.49)	(3.54)
Firm-specific Output Tariffs	0.001*	0.001	0.002**	0.002**
	(1.79)	(1.57)	(2.10)	(2.05)
Firm-specific External Tariffs	-0.000	-0.000	-0.000	-0.000
	(-0.62)	(-0.66)	(-0.85)	(-0.83)
Processing Indicators	-0.004	-0.002	-0.036***	-0.035***
	(-0.61)	(-0.43)	(-2.69)	(-2.69)
State-owned Enterprises	-0.033	-0.034	-0.007	-0.015
	(-0.86)	(-0.89)	(-0.09)	(-0.18)
Foreign Invested Firms	0.013	0.013	0.056	0.057
	(0.58)	(0.59)	(1.14)	(1.17)
Log of Firm Employment	-0.189***	-0.186***	-0.188***	-0.186***
	(-32.35)	(-31.89)	(-15.64)	(-15.51)
Log of Firm TFP	0.112***	0.111***	0.047***	0.047***
	(14.46)	(14.34)	(3.40)	(3.45)
Provincial Rural Income/Skilled-Labor Share		-0.000***		-0.000***
		(-9.63)		(-2.97)
Observations	67,805	67,805	23,200	23,200
Year Specific Fixed Effects	Yes	Yes	Yes	Yes
1/Skilled-Labor Share × Year Dummies	Yes	No	Yes	No
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.205	0.206	0.206	0.206

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level. The industry input tariffs (weighted) are calculated by using equ. (10) and (19).

Table 8: Estimates with Import-adjusted Industry Input Duty

Log of Measured Firm's wages Gap	(1)	(2)	(3)	(4)
Import-Adjusted Industry Input Duty	0.162**		0.655*	
	(2.23)		(1.95)	
Import-Adjusted Industry Input Duty (w/ weight)		0.159**		0.686**
		(2.19)		(2.02)
State-Owned-Enterprises	0.033***	0.033***	-0.001	-0.001
	(4.23)	(4.23)	(-0.01)	(-0.01)
Foreign-Invested-Enterprises	0.034***	0.034***	0.081*	0.081*
	(4.46)	(4.46)	(1.86)	(1.86)
Log of Firm Employment	-0.179***	-0.179***	-0.186***	-0.186***
	(-100.43)	(-100.43)	(-15.85)	(-15.86)
Log of TFP	0.112***	0.112***	0.053***	0.053***
	(47.92)	(47.92)	(3.88)	(3.88)
Extent to Processing			-0.029**	-0.029**
			(-2.21)	(-2.21)
Firm-specific Output Tariffs			0.179**	0.178**
			(2.36)	(2.34)
Firm-specific External Tariffs			-0.008	-0.008
			(-0.71)	(-0.71)
Observations	592,169	592,169	23,200	23,200
Year-specific Fixed Effects	Yes	Yes	Yes	Yes
1/Skilled-Labor Share $\times$ $YearDummies$	Yes	Yes	Yes	Yes
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.227	0.227	0.211	0.211

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level. The imported-adjusted simple industry input tariffs are calculated by using equ. (20) and (11) whereas the imported-adjusted weighted industry input tariffs are calculated by using equ. (20) and (19).

Table 9: Estimates of Input Duty on wages Gap in 2004

Log of Measured Firm's wages Gap	Full-Sample Data		Matched Data		
	(1)	(2)	(3)	(4)	(5)
Industry Input Duty	10.77***	10.96***	9.91***	9.71***	9.80***
	(15.91)	(16.20)	(3.69)	(3.57)	(3.60)
State-Owned-Enterprises	-0.266***	-0.266***	-0.161***	-0.186***	-0.188***
	(-19.66)	(-19.49)	(-3.61)	(-4.04)	(-4.09)
Foreign-Invested-Enterprises	0.089***	0.084***	0.129***	0.130***	0.129***
	(15.84)	(14.95)	(11.06)	(10.48)	(9.83)
Log of Firm Employment		0.003		0.038***	0.038***
		(1.38)		(7.25)	(7.27)
Log of TFP		0.069***		0.115***	0.116***
		(9.21)		(6.15)	(6.17)
Firm-specific Output Tariffs					-0.135
					(-1.46)
Firm-specific External Tariffs					-0.191***
					(-2.81)
Processing Indicator					-0.013
					(-0.98)
CIC 3-digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	152,672	152,374	25,645	23,295	23,295
R-squared	0.07	0.07	0.07	0.07	0.07

Notes: Numbers in parenthesis are t-value. *** (**,*) denotes the significance at 1%(5%, 10%) level.

6 Appendix A: Matching Procedures

My discussion on matching the two dataset (i.e., firm-level production data and firm-customs data) here draws heavily from Yu(2011) and Yu and Tian (2012). As mentioned in the text, I go through two steps to merge transaction-level trade data with firm-level production data. In the first step, I match the two data sets by firm name and year. The year variable is a necessarily auxiliary identifier since some firms could have different names across years and newcomers could possibly take their original names. Using the raw (*i.e.*, unfiltered) production data set, I come up with 83,679 merged firms; this number is further reduced to 69,623 with the more accurate filtered production data set.

In the second step, I use another matching technique as a supplement. In particular, I adopt two other common variables to identify firms: zip code and the last seven digits of a firm's phone number. The rationale is that firms should have different and unique phone numbers within a postal district. Although this method seems straightforward, subtle technical and practical difficulties still exist. For instance, the production-level trade data set includes both area codes and a hyphen in phone numbers, whereas the firm-level production data set does not. Therefore, I use the last seven digits of the phone number to serve as the proxy for firm identification for two reasons. First, in 2000–2006, some large Chinese cities (e.g., Shantou in Guangdong province) added one more digit at the start of their seven-digit phone numbers. Therefore, sticking to the last seven digits of the number will not confuse firm identification. Second, in the original data set, phone numbers are defined as a string of characters with the phone zip code; however, it is inappropriate to de-string such characters to numerals because a hyphen is used to connect the zip code and phone number. Using the last seven-digit sub-string neatly solves this problem.

A firm might not include its name information in either the trade or the production data set. Similarly, a firm could lose its phone and/or zip code information. To be sure that our merged data set can cover as many common firms as possible, I then include observations in the matched data set if a firm occurs in *either* the name-adopted matched data set *or* the phone-and-post-adopted matched data set.

As shown in Appendix Table A1, Column (1) reports number of number of observations of HS eight-digit monthly transaction-level trade data from China's General Administration of Customs by year. As shown in the bottom of Column (1), there are more than 118 million trade transactions conducted by 286,819 firms during the seven years. Meanwhile, if no further data cleaning and stringent filter criteria are adopted as introduced in the text, Column (3) shows that there are 615,591 large manufacturing firms in China. However, after the stringent filter according to the requirement of GAAP, around 70% of them survive–number of the filtered firms is 438,165 as seen in the bottom of Column (4). Accordingly, Column (5) reports number of matched firms using exactly identical company's names in both trade data set and raw production data set. By contrast, Column (6) reports number of matched firms using exactly identical company's names in both trade data set and filtered production data set, which results in 69,623 matched firms.

Column (7) reports number of matched firms using exactly identical company's names and exactly identical zip code and phone numbers in both trade data set and raw production data set. Clearly, the number of merged firms increases to 91,299. By way of comparison, my matching performance is highly comparable with that of other similar studies. For example, Ge *et al.* (2011) used the same data sets and similar matching techniques, but ended up with only 86,336 merged firms. Finally, if I match the more stringent filtered production data set with the firm-level data set using exactly identical company's names and zip-phone code numbers, I end up with 76,823 firms in total, as shown in the last Column of Appendix Table A1. I then take such firms to my regressions since they are the most reliable firms that can pass various stringent filtering process in the accounting production data.

After merging both product-level trade data and firm-level production data, The 76,823 common trading firms account for approximately 27% of 286,819 firms in the product-level trade data set and approximately 17% of 438,146 valid firms in firm-level production data set (11% of the valid firms are exporters whereas 6% of them are importers). Given that only 27% of firms are exporters in the firm-level production data set (see, for example, Feenstra et al., 2011), the merged data set hence accounted for around 40% of the *filtered* full-sample firm-level production data set in terms of number of exporters, and around 53% of exports in terms of export value.

Appendix Table A1: Matched Statistics–Number of Firms

Year	Trade Data		Production Data		Matched Data			
# of	Transactions	Firms	Raw Firms	Filtered Firms	w/ Raw Firms	w/ Filtered Firms	w/ Raw Firms	w/ Filtered Firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2000	10,586,696	80,232	162,883	83,628	18,580	12,842	21,425	15,748
2001	12,667,685	87,404	169,031	100,100	21,583	15,645	24,959	19,091
2002	14,032,675	95,579	181,557	110,530	24,696	18,140	28,759	22,291
2003	18,069,404	113,147	196,222	129,508	28,898	21,837	33,901	26,930
2004	21,402,355	134,895	277,004	199,927	44,338	35,007	49,891	40,711
2005	24,889,639	136,604	271,835	198,302	44,387	34,958	49,891	40,387
2006	16,685,377	197,806	301,960	224,854	53,748	42,833	49,680	47,591
All Year	118,333,831	286,819	615,951	438,165	83,679	69,623	91,299	76,823

Notes: Column (1) reports number of observations of HS eight-digit monthly transaction-level trade data from China's General Administration of Customs by year. Column (2) reports number of firms covered in the transaction-level trade data by year. Column (3) reports number of firms covered in the firm-level production data set compiled by China's National Bureau of Statistics without any filter and cleaning. By contrast, Column (4) presents number of firms covered in the firm-level production data set with careful filter according to the requirement of GAAP. Accordingly, Column (5) reports number of matched firms using exactly identical company's names in both trade data set and raw production data set. By contrast, Column (6) reports number of matched firms using exactly identical company's names in both trade data set and filtered production data set. Finally, Column (7) reports number of matched firms using exactly identical company's names and exactly identical zip code and phone numbers in both trade data set and raw production data set. By contrast, Column (8) reports number of matched firms using exactly identical company's names and exactly identical zip code and phone numbers in both trade data set and filtered production data set.