Measured Skill Premia and Input Trade Liberalization: Evidence from Chinese Firms*

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Abstract

Using Chinese firm-level production data, this paper develops a Mincer (1974)-type approach to investigate the impact of input trade liberalization on firms' wage inequality between skilled and unskilled workers (or skill premium). When controlling for product-market tariffs in a firm's industry, we find robust evidence that reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces. This effect is more pronounced at ordinary (non-processing) firms. We also provide evidence that reduced input tariffs in a firm's industry are associated with higher value added and profits at firms with more skilled workforces.

JEL Classifications: F10, F12, F14

Keywords: Skill Premium, Input Trade Liberalization, Firm Evidence

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1 Introduction

Tariffs have declined dramatically worldwide as a result of many rounds of trade negotiations under the General Agreement on Tariffs and Trade (GATT)/World Trade Organization (WTO) (Bagwell and Staiger, 1999). The labor markets in each country have been impacted by the trade liberalization in final-goods and intermediate-input sectors. The question of how trade liberalization affects wage inequality between skilled and unskilled workers, especially for developing countries, has once again become one of the research focuses in the international trade literature.

Most of the early studies in the literature follow the Heckscher-Ohlin model to test whether trade liberalization benefits the abundant factors. According to the Stopler-Samuelson theorem, trade liberalization would mitigate wage inequality between skilled and unskilled labor in the developing countries. However, this theoretical assertion has received little empirical support because most studies find increased skill premium in both developed and developing countries.[1] For example, Feenstra and Hanson (1996, 1999) find that, in the presence of vertical integration and international outsourcing, freer trade could actually increase skill premium in both developed and developing countries.[2]

Recent studies in the literature use firm-level data to investigate the impact of globalization on wage inequality but they mainly focus on the impact of export-side trade liberalization (e.g. Verhoogen, 2008; Bustos, 2011; Frías et al., 2012, Helpman et al., 2017). For example, using Brazilian data, Helpman et al. (2017) find that much of the overall wage inequality occurs within sector-occupations, which is mainly driven by wage dispersion between, rather than within, firms. However, the impact of input trade liberalization on firm-level wage inequality is equally important and may also have distinct differences in how the employers might share the surplus with various input factors because of their different bargaining power. In particular, imported intermediate inputs have been found to be crucial for boosting firm productivity in both developed and developing countries such

[1] Previous works have contributed to an intense discussion on the validity of factor price equalization (FPE) in explaining wage inequality in developed countries. See Johnson and Stafford (1993), Leamer (1993, 1996), and Lawrence and Slaughter (1993), among many others.

[2] Technology is identified as the major factor driving wage inequality; international trade is nevertheless also believed to play an important role. See more details in Feenstra and Hanson (1996, 1999).

as the United States (Hanson et al. 2005), Indonesia (Amiti and Konings 2007), India (Goldberg et al., 2010; Topalova and Khandelwal, 2011), and China (Yu 2015).

The purpose of the present paper is to investigate the impact of input trade liberalization on wage inequality in China and intend to make the following two contributions to the literature. First, investigations on the impact of input trade liberalization on wage inequality in developing countries usually rely on industry-level wage data, household survey data, and the Gini coefficient as a proxy for income inequality (e.g., Beyer et al. 1999).[3] For example, using urban industrial survey data, Han et al. (2012) found that widening wage inequality in China was strongly associated with China's accession to the WTO in 2001.[4] In the present paper, we use Chinese firm-level production and customs' trade data to investigate the impact of tariff reductions for imported inputs on firm-level skill premium in China. To our knowledge, this is the first paper to investigate how import trade liberalization affects firm-level skill premium for manufacturing firms in China, the largest developing country in the world. The study could enrich our understanding of the sources of China's growing income inequality from the wage differentials at the firm levels.[5]

Second, a major challenge to investigate firm-level wage inequality between skilled and unskilled labor in China, as in most developing countries, is lack of data for direct firm-level wages for skilled and unskilled workers. To overcome this major obstacle, the current paper has developed a method of constructing firm-level skill premium from a firm's average wage and share of skilled labor. Together with a Mincer-type regression, we are able to estimate the impact of input trade liberalization on firm-level skill premium in China. This method can be applied to other research facing similar data limitations.

Using firm-level production and transaction-level trade data from China, we find that, when

[3] An outstanding exception is Akerman et al. (2013), who find that trade liberalization not only enhances the dispersion of revenues across heterogeneous firms, but also widens wage inequality across workers and firms. This paper is also in line with Groizard et al. (2014) who explore the endogenous nexus between trade liberalization and job flow in California and Rodriguez-Lopez and Yu (2017) who examine the relationship between all-around trade liberalization and firm-level employment in China. Furusawa and Konishi (2014) propose a model to interpret why international trade can increase wage inequality between top income earners and others, and thus cause job polarization.

[4] Autor et al. (2013) show that China' s exports to the American market have significantly contributed to the aggregate decline in the U.S. manufacturing employment and caused the sharp increases in U.S. social benefit claims.

[5] Khan and Riskin (1998) found that wage inequality contributed to half of the income inequality in China in 1995.

controlling for product-market tariffs (i.e., output tariffs) in a firm's industry, the reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces. This effect is more pronounced at ordinary (non-processing) firms. Compared with processing importers, ordinary importers respond more forcefully to input trade liberalization in their wage schedule. Our main finding that input trade liberalization increases firm-level skill premium in China is robust for all three regions (east, central and west) in China, as well as for different measures of wage inequality, different empirical specifications and data spans. By contrast, output trade liberalization, which is measured by product-market tariffs reduction, show opposite signs of the effect of import tariffs on the skill premium at firms with more skill-intensive production. However, the product-market tariff effects are not robustly significant across specifications.

Inspired by the literature on "fair wages" (e.g. Egger and Kreickemeier, 2012), we also provide an interpretation for our main finding that input trade liberalization leads to an increase in firm skill premium. If skilled workers have greater bargaining power with their employers than unskilled workers, incomes of the skilled workers shall be more closely linked to firms' economic profits but the incomes of unskilled workers shall be more in line with those of other firms in the same industry. Thus, a fall in input tariffs increases the firm's value-added, which in turn raises the firm's skill premium because the skilled labor commands a larger proportion of the incremental surplus than the unskilled labor. We also provide some evidence for our conjecture.

In addition to the literature discussed earlier, our paper is also closely related to the studies on how import trade liberalization affects skill compositions and factor returns. For example, using data from multinational companies, Biscourp and Kramarz (2007) examine the impact of offshoring on plant-level skill composition in France. Similarly, Becker et al. (2013) investigate the impact of offshoring on firm-level task composition and wages in Germany. Amiti and Davis (2011) is another influential study that investigates the impact of output and input tariff reductions on wages. In particular, they find that a reduction in input tariffs raises wages at import-using firms relative to those using only domestic intermediate inputs. However, these studies do not focus on firm wage inequality, or skill premium.

The rest of the paper is organized as follows. Section 2 describes the data and introduces the econometric methods to measure firm skill premium and the empirical specifications of Mincer regression. Section 3 presents the main empirical evidence, offers robustness checks and discussion on the possible mechanism. Section 4 concludes.

2 Data, Measures, and Empirics

2.1 Data

To investigate the impact of input trade liberalization on firms' skill premium, our analysis uses the following three disaggregated panel data sets: firm-level production data compiled by China's National Bureau of Statistics (NBS), production-level trade data maintained by China's General Administration of Customs, and China's import tariff (ad valorem) data at the HS 6-digit level, maintained by the World Integrated Trade Solution (WITS) database of the World Bank.

China's NBS conducts an annual survey of industrial firms (ASIF) with two types of manufacturing firms: all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed RMB 5 million (or equivalently $725,000). The sample used in this paper has approximately 230,000 manufacturing firms per year, varying from 162,885 firms in 2000 to 301,961 firms in 2006. On average, the sample accounts for more than 95 percent of China's total annual output in the manufacturing sectors.[6] The data set covers more than 100 accounting variables and contains all of the information from the main accounting sheets, which includes balance sheets, loss and profit sheets and cash flow statements.

Given its rich information, the firm-level production data set is widely used in research by, among others, Cai and Liu (2009), Brandt et al. (2012), and Feenstra et al. (2014). However, the data set has two limitations for our research purpose. The first one is common: some unqualified firms are wrongly included in the data set, largely because of mis-reporting or false recording. Thus, following Feenstra et al. (2014), we keep the observations in our analysis according to the requirements of the

[6] In 2006, the total value added of all the firms included in the survey was RMB 9,107 billion, which accounted for 99 percent of the value added of all firms in the manufacturing sectors (RMB 9,131 billion), as reported by China' s Statistics Yearbook (2007).

Generally Accepted Accounting Principles (GAAP).[7] Accordingly, the total number of firms covered in the data set was reduced from 615,951 to 438,165, and approximately one-third of the firms were removed from the sample after the rigorous filter was applied. The drop in the percentage of sales is only around 25 percent. Thus, the drop in sales is smaller, since larger firms meet the GAAP more frequently. This suggests that larger firms that follow GAAP may generate larger rents per worker, so they have a large surplus to share and the measured effect of reduced input tariffs might be an upper bound.

The second limitation of the data is specific to the present paper. The data set does not separate wages for skilled and unskilled labor. Furthermore, the numbers (i.e. the share) of skilled and unskilled workers are only available for 2004. To overcome this problem, we conduct our baseline test on cross-firm data for 2004. Then we carry out panel data tests that include other years by multiplying the skilled labor shares in 2004 by the change in the skilled labor share (relative to 2004) at the provincial level. To ensure the precision of our estimates, we exclude the pure trade intermediaries (that do not have production activities) from the sample in all the estimates. The trade intermediaries are identified according to the same procedures as in Ahn et al. (2011).

Finally, we use customs' data to match with the firm-level production data so that we are able to identify each firm's importing and processing status. As introduced in Feenstra et al. (2014), the production-level trade data maintained by China's General Administration of Customs include a large variety of information such as each trading firm's importing (or exporting) status and processing (or non-processing) status. Such information is essential for us to conduct our empirical estimations, which will be discussed shortly.

2.2 Measures

This subsection starts by introducing the index of input trade liberalization, and then focuses on constructing firm-level measured skill premium because the data sets do not directly provide firm-level wages for skilled and unskilled labor.

[7] We keep observations if all of the following hold: (1) total assets exceed liquid assets; (2) total assets exceed total fixed assets; (3) the net value of fixed assets is less than that of total assets; (4) the firm's identification number exists and is unique, and (5) the established time is valid.

2.2.1 Measures of Input Tariffs

Inspired by Amiti and Konings (2007) and Topalova and Khandelwal (2011), we construct the industry-level input tariffs, IT_j, as follows:

$$IT_j = \sum\nolimits_n \left(\frac{input_{nj}^{2002}}{\sum_n input_{nj}^{2002}} \right) \tau_n, \tag{1}$$

where IT_j denotes the industry-level input tariffs facing firms in industry j in 2004 and τ_n is the tariff on input n in 2004. The weight in parentheses is the production cost share of input n in industry j.

We use China's Input-Output Table of 2002 to construct the weight because NBS reports the Input-Output Table every five years and our data are for 2004. In the spirit of Bartik (1991), we use the input-output matrix from 2002 to compute the relevant weighted industry input tariffs since the weight in 2002 reflects the initial conditions prior to China's tariff cuts in 2004.[8] The industrial input tariffs are obtained as follows. First, since there are 71 manufacturing sectors reported in China's Input-Output Table (2002) and only 28 manufacturing sectors reported in the Chinese Industrial Classification (CIC), we start by making a concordance between the Input-Output Table and the CIC sectors. Second, we match the CIC sectors with the International Standard Industrial Classification (ISIC, rev. 3).[9] Third, we make another concordance to link the ISIC and HS 6-digit trade data, where we can find the corresponding tariffs from the WITS database. Fourth, we calculate the industry-level tariffs that are aggregated to the CIC sector level.[10] Since simple-average tariffs cannot take into account the difference of the importance of imports, we consider the following weighted industrial tariffs:

$$\tau_n = \sum\nolimits_{k \in n} \left(\frac{m_k}{\sum_{k \in n} m_k} \right) \tau_k, \tag{2}$$

where m_k is the import values for product k in CIC 2-digit industry n in 2004. Finally, we calculate the industry-level *input* tariffs using Equation (1). The industry-level *output* tariff for industry n in

[8] By the same token, we use China' s Input-Output Table of 1997 to construct the initial weight of the input tariffs for the sample period of 2000–06 in our robustness checks.

[9] Since Chinese government adjusted its CIC in 2003, we also made similar adjustments in our data.

[10] We do not report the input weight by industry to save space; these data are available upon request.

2004 is also obtained from Equation (2).

To see how the input tariff reductions affect firms' skill premium, we examine the evolution of China's trade liberalization throughout the sample period. Table 1A reports the mean and standard deviation for this key variable by spreading the sample from 2000 to 2006. As shown in Table 1A, the average industry input tariffs were cut in half, from 15.73 percent in 2000 to 7.71 percent in 2006, and their standard deviation also dropped by about a half over the same period. The industry input tariffs were around half of their initial levels in 2000, before the WTO accession. Finally, the industry input tariffs in 2004 were also lower than the corresponding industry output tariffs, as shown in Table 1B.

[Insert Table 1A Here]

2.2.2 Measures of Skill Premium

The skill premium is defined as $s_{it} \equiv (w_{it}^s - w_{it}^u)/w_{it}^u$ for the skilled wages (w_{it}^s) and unskilled wages (w_{it}^u).[11] Given the share of firm i's skilled workers (θ_{it}), the firm average wage ($\overline{w_{it}}$) can be written as $\overline{w_{it}} = \theta_{it} w_{it}^s + (1-\theta_{it}) w_{it}^u$ or, relative to the unskilled wages, $\overline{w_{it}}/w_{it}^u = 1 + \theta_{it} s_{it}$. Hence, the log term of the average wage is:

$$\ln(\overline{w_{it}}) = \ln(w_{it}^u) + \ln(1 + \theta_{it} s_{it}). \tag{3}$$

When $\theta_{it} s_{it}$ is small, we can omit the higher-order terms and have $\ln(1 + \theta_{it} s_{it}) \approx \theta_{it} s_{it}$. Therefore,

$$\ln(\overline{w_{it}}) \approx \ln(w_{it}^u) + \theta_{it} s_{it}. \tag{4}$$

The key advantage of Eq.(4) is that it gives rise to a plausible Mincer-type regression for our empirical estimation. The trade-off is that, if $\theta_{it} s_{it}$ is not small enough, our Mincer-type regressions are not precise enough to interpret the economic magnitudes of the estimated coefficients. Hence, in the rest of the paper, economic interpretation should be focused on the sign, rather than the magnitude, of

[11] Wage inequality and skilled wage premium are monotonically related although they are two different concepts. Inequality measures are typically statistics that capture dispersion or variance (see e.g. Shorrocks 1980) – that is second-order. In contrast, skill premium reflects a relative difference in first-order moments. We thank a referee for pointing this out.

our estimates.[12]

Table 1B reports the summary statistics for the key variables used in our estimations. In the firm data set, information on firms' skilled labor share is available only for 2004, although firms' average wages are available for 2000–06. Since firms' skill share is crucial in Specification (4), we use the cross-section data for 2004 to conduct the main analysis and a panel sample for 2000–06 for robustness checks only. Since the firm-level data set provides employment information on skilled and unskilled labor only for 2004, we use a proxy for the skilled labor share for all other years. To obtain the proxy ($\hat{\theta}_{it}$), we multiply the skilled labor share in 2004 ($\theta_{i,2004}$) by the provincial skilled labor share (η_{rt}) in all years, using 2004 as the base year: $\hat{\theta}_{it} \equiv \eta_{rt}\theta_{i,2004}$. Table 1B reports the mean and standard deviation of the key variables for the samples for 2004 and 2000–06.

Three variables in Table 1B relate to wage information. The first is firm average wage, which is reported from the data sets directly. The second is the measured wage premium (μ_i), which is defined as firm i's log wage relative to that of the average firm in industry j and region r (to be discussed in details in the next section). The last wage variable is the measured unskilled wage. Since the annual survey of industrial firms does not provide firm-level unskilled wages, we define the measured unskilled wage as the minimum level of firm wages in each (3-digit) industry-province pair based on the following two observations. First, as shown in Table 1B, firms' average wages are significantly positively correlated with the skill share,[13] but the mean of measured unskilled wages is much lower than that of the firms' average wage (around 15 percent). Second, according to Anwar and Sun (2012), wages of unskilled workers in China are actually different across industries and provinces, especially after 2004. As a robustness check, however, we also use an alternative measure of the unskilled wages for our estimations. Finally, the firm-level data set for 2004 reports five education levels: graduate (and above), university, college, high school, and below middle school. As in most studies, we define skilled workers as employees with a college degree or higher.

[12] Higher-order terms under a proper McLaurin expansion, however, would not be estimable given the sample size and measurement error. We appreciate a referee for pointing this out.

[13] A simple regression of firms' average wage on the skilled share, using the sample for 2004 and controlling for 3-digit industry fixed effects and province fixed effects, suggests a positive coefficient of the skilled share that is highly significant at the conventional statistical level (t-value = 77.25).

[Insert Table 1B Here]

2.3 Mincer Empirical Specification

Let us suppose that firm i's skill premium, s_i, takes a linear form

$$s_{it} = \sum_{p=0}^{P} \gamma_p x_{it}^p + \epsilon_{it}. \tag{5}$$

where x_{it}^p denotes a vector of predictors. From Equations (4) and (5), we obtain the following Mincer-type empirical specification:

$$\begin{aligned} \ln(\overline{w_{it}}) \quad = \quad & \gamma_0 + \gamma_u \ln(w_{it}^u) + \gamma_0 \hat{\theta}_{it} + \gamma_1(\hat{\theta}_{it} IT_{jt}) + \gamma_2(\hat{\theta}_{it} IT_{jt}) IM_{it} + \gamma_3(\hat{\theta}_{it} PT_{jt}) \\ & + \gamma_4(\hat{\theta}_{it} PT_{jt}) FX_{it} + \gamma_5(\hat{\theta}_{it} FX_{it}) + \gamma_6(\hat{\theta}_{it} IM_{it}) + \gamma_7 IT_{jt} + \gamma_8 PT_{jt} + \\ & \gamma_9 IM_{it} + \gamma_{10} FX_{it} + \gamma_{11} \mu_{it} + \gamma_{12} \hat{\theta}_{it} \mu_{it} + \boldsymbol{\gamma} \mathbf{X}_{ijt} + \delta_i + \delta_{jr} + \delta_t + \varepsilon_{it}, \end{aligned} \tag{6}$$

where the error term is defined as $\varepsilon_{it} \equiv \hat{\theta}_{it} \epsilon_{it}$. The main regressors in this Mincer regression include three sets of variables:(i) we include unskilled wage ($\ln(w_{it}^u)$), measured skilled labor share ($\hat{\theta}_{it}$) and its interaction with input tariffs (IT_{jt}) and output tariffs (PT_{jt});[14] (ii) we also include import dummy (IM_{it}) (export dummy, FX_{it}) and its interaction with tariffs; (iii) We also include the own terms and their interaction terms with skill share of firm-level controls $\mathbf{X}_{ijt}$ such as firm ownership (state-owned enterprise, foreign firm, or private firm), firm size (poxied by firms' log sales), and firm productivity; finally, (iv) in addition to firm-specific fixed-effects (δ_i), interacted industry-region fixed-effects (δ_{jr}), and year-specific fixed-effects (δ_t), we also include firm wage premium, defined as $\mu_{it} \equiv \ln \bar{w}_{it} - \sum_{i \in I(jr)}^{N} (\ln \bar{w}_{it})/|Jr|$, where $|Jr|$ is the cardinality of the set of firms in industry-region pair jr, and its interaction with firms' skill share in the regression.

Among the regressors, there are five important points that are worth noting. First and foremost, among the set of predictors, the most important variable of interest is the average intermediate input

[14] Note that we do not restrict the coefficient of the unskilled wage γ_u to unity given that it is not the observed firm-level low-skilled wage, although our main estimation results won't change even with such a restriction.

tariffs in industry j (IT_j) that firm i is associated with. If the coefficient γ_1 in Eq. (6) is negative and statistically significant, it suggests that input trade liberalization would increase firm skill premium. It is also reasonable to anticipate that the impact of input trade liberalization on skill premium would be stronger for ordinary (i.e., non-processing) importing firms, since processing imports have already enjoyed the special treatment of free duty (Yu, 2015) and hence would be less impacted by a further input trade liberalization. Thus, we expect that γ_2, the triple interaction term among skill share, intermediate input tariffs, and the importer indicator, should be negative. By constrast, another triple interaction term among skill share, intermediate input tariffs, and the processing indicator (not shown in the Eq. (6)) is expected to be positive.

Second, we include the industry average output tariff (PT_j) and its interaction with the firm export indicator as control variables for the reasons as follows. After its accession to the WTO, China cut not only its intermediate input tariffs, but also its final output tariffs (see Yu, 2015, for a detailed discussion). It would be expected that the impact of output trade liberalization on wage inequality may be different between exporting firms and non-exporting firms. Thus, the interactions of output tariffs with firm-level exporting indicators are introduced for that purpose (see Biscourp and Kramarz, 2007; Verhoogen, 2008). Of course, skill premium in exporting (importing) firms may be affected through channels other than trade liberalization. We thus also include firms' own exporting and importing indicators in the regressions.

Third and equally important, the regression equation (6) requires panel data. However, we have recorded data on the share of skilled labor only for year 2004, and a proxy for the share of skilled labor for other years: $\hat{\theta}_{it} \equiv \eta_{rt}\theta_{i,2004}$, $\hat{\theta}_{it}$, which is the skilled labor share in 2004 ($\theta_{i,2004}$) multiplied by the provincial skilled labor share (η_{rt}) in all other years by using 2004 as the base year. The limitation of using the above panel-data estimation is that the within-firm variation generated by the interaction terms of $\hat{\theta}_{it}$ are mainly from the η_{rt} portion. Thus, we will first use 2004 data and the following baseline cross-section regression for our estimation:

$$
\begin{aligned}
\ln(\overline{w_i}) \quad = \quad & \gamma_c + \gamma_u \ln(w_i^u) + \gamma_0\theta_i + \gamma_1(\theta_i IT_j) + \gamma_2(\theta_i IT_j)IM_i + \gamma_3(\theta_i PT_j) \\
& +\gamma_4(\theta_i PT_j)FX_i + \gamma_5(\theta_i FX_i) + \gamma_6(\theta_i IM_i) + \gamma_7 IT_j + \gamma_8 PT_j \\
& +\gamma_9 IM_i + \gamma_{10} FX_i + \gamma_{11}\mu_i + \gamma_{12}\theta_i\mu_i + \boldsymbol{\gamma}\mathbf{X}_i + \delta_{jr} + \varepsilon_i.
\end{aligned} \tag{7}
$$

Fourth, μ_{it} is firm i's log wage relative to the average firm in industry j and province r. These wage premia (or discounts) can come from different skill composition of firm i's workforce, or the different surplus that firm i generates. It is important to emphasize that this variable plays an important role here. It helps us properly control for between-firm skill premium (e.g. Egger and Kreichemeier, 2009; Amiti and Davis, 2011; Helpman et al., 2017). In the cross-section regression in Eq.(7), with proper region-industry fixed effects, the second component ($\sum_{i\in I(jr)}^{N}(\ln \bar{w}_i)/|Jr|$) of the measured between-firm wage premium (μ_{it}) should be fully absorbed into the industry fixed effects. Thus, the OLS estimator would then exhibit a coefficient of the variable μ_{it} close to unity. The interaction term $\theta_i\mu_i$ is also needed for our Mincer-regression specification.

Finally, our empirical specifications implicitly draw on theory suggested by Helpman et al. (2010). By treating multiple skill groups in the firm-level framework, the regression residuals will depend on (i) the tightness of the local labor market in a province-industry pair, (ii) the locally available skilled workers in an industry and location, (iii) firms' anticipated performance and associated wage offers, and (iv) any firm-specific shocks to the wage bargaining or screening technology (Blaum et al., 2015; Helpman et al., 2017). Thus, we add the following three sets of dummies in the regressions. First, we include province-specific fixed effects to control for province-invariant but unobservable factors (such as export subsidy rates, etc.). Second, we include 2-digit industry-specific fixed effects, which control for industry-invariant factors such as industrial capital intensity. Third, we allow for a full set of interacted industry-province dummies to absorb local labor market conditions. The remaining identifying assumption is the idiosyncratic effect $\varepsilon_i \sim N(0, \sigma^2)$, which takes into account firms' anticipated performance and firm-specific shocks that do not differentially affect individual skill groups.

Some studies have investigated whether more productive firms use more skill-biased technology (e.g., Verhoogen, 2008; Bustos, 2011). It is possible that trade liberalization induces the most productive firms to adopt skill-biased technology or upgrade product quality, and hence increases the demand for skilled labor for these firms. If such a multi-collinearity problem is a big concern, our data should exhibit a strong negative correlation between input tariffs and the skill share. However, this is not the case for our sample as the simple correlation in 2004 cross-section data between industrial input tariffs and the skill share is small (-0.11). Moreover, the simple correlation in the whole sample for 2000–06 is even smaller in absolute value (-0.06). The low correlations suggest that the change of firms' skill share is not sensitive to the change of trade liberalization, at least in our current sample.

3 Estimation Results

3.1 Baseline Mincer Regressions

Table 2 presents the baseline results for the cross-section empirical specification (7). Since the firm-level data set does not report firms' import status, Table 2 does not include the importer indicator. Columns (1) and (2) are a single regression in which column (1) reports the own coefficient of each regressor whereas column (2) reports its corresponding coefficient interacted with the skill share. From column (2), the coefficient of industry input tariffs interacted with firm skill share, the key variable of interest, is negative and statistically significant, suggesting that input trade liberalization tends to increase skill premium. Sheng and Yang (2016) provide evidence that foreign firms in China attract more skill-intensive production, which in turn would raise firms' skill premium. Thus, we include the interactions of skill share with the foreign indicator and with the SOE indicator in the regression.[15] The positive sign of the coefficient of the foreign indicator ascertains the finding in Sheng and Yang (2016). We also include firm size (proxied by firms' log sales) and firm total factor

[15] 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), and state-owned and collective joint venture enterprises (143), but exclude state-owned limited corporations (151). In contrast, foreign firms include the following firms: foreign-invested joint-stock corporations (code: 310), foreign-invested joint venture enterprises (320), fully foreign-invested firms (330), foreign-invested limited corporations (340), Hong Kong/Macao/Taiwan joint-stock corporations (210), Hong Kong/Macao/Taiwan joint venture enterprises (220), fully Hong Kong/Macao/Taiwan-invested enterprises (230), and Hong Kong/Macao/Taiwan-invested limited corporations (240).

productivity (measured by the augmented Olley-Pakes (1996) approach, as suggested by Yu, 2015). Exporting firms may have their own channels affecting the skill premium. We thus interact the skill share with the exporting indicator in column (2). Consistent with most of the previous studies, we find that the skill premium is higher for larger firms, more productive firms, and exporting firms.

It is also reasonable to anticipate that firms of different sizes may respond differently to input tariffs. Therefore, we run another regression with results jointly shown in columns (3) and (4). Specifically, we include a triple interaction term among the skill share, input tariffs, and firms' log sales. Importantly, the skill share is an important predictor in itself, beyond size (log sales), and that the skill share prediction is slightly weaker at larger firms. Because the coefficient of the novel triple interaction term among input tariffs, skill share, and log sales has a different (*i.e.*, positive) sign than that of the interaction term between input tariffs and skill share, we take a further step to evaluate their net effect at the sample mean. Overall, the net effect of input tariffs on firm average wages is still negative since $(-0.181 + 0.013 \times 9.94) \times 0.449 < 0$ given that the sample mean of log of firm sales is 9.94 whereas that of firm skilled share is 0.449 as seen from Table 1B. Thus, the counteracting effect generated by the new triple term with log sales does not overwhelm our previous main finding.

As recognized by Cai (2010), China's labor force generally migrates from the inland (i.e., western and middle) provinces to the costal (eastern) provinces. It is reasonable to expect that firms have different wage premiums in the different regions. We thus classify all 31 provinces into three regions: east, middle, and west. In the single regression as reported in columns (3) and (4), we also take a step further to control for region-specific fixed effects and industry-specific fixed effects to take into account local market tightness (as discussed earlier). In addition, we also include a full set of interacted industry-region dummies. With such rich sets of fixed effects controlled, the coefficient of input tariffs interacted with skill share – our main interest in the estimation – still remains negative and statistically significant.

[Insert Table 2 Here]

Our main empirical specification (6) also permits a regional analysis by grouping the sample for 2004 into three regions: east, central, and west. We first split the entire national sample into 31 provinces and then repeat the Mincer regression, similar to columns (3-4) of Table 2, for the east region, central region and west region. Results are reported in columns (1-2), (3-4), and (5-6) of Table 3, respectively. In each regression, we control for the interacted province and industry fixed effects. According to the China Regional Statistical Yearbook, the eastern region includes fifteen provinces, the central includes six provinces, and the western region includes the rest of the provinces.[16] Thus, the regional regression for the eastern region has the largest number of observations, followed by the west region, and then by the central region. In the three regressions shown in Table 3, the interaction terms between industry input tariffs and skill share are all negative and highly statistically significant.[17] Thus, our main finding that reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces is robust for all three regions in China.

[Insert Table 3 Here]

3.2 Mincer Regressions using Matched Sample

Tables 2 and 3 use the firm-level data set for 2004 to conduct the regressions. The advantage of using only this data set is that it contains all manufacturing firms. Yet, the data set does not contain information on firms' import status. To overcome this data challenge, we match the ASIF data set with the product-level customs data to perform similar Mincer-type regression in Table 4.[18]

Columns (1) and (2) in Table 4 are a single regression with industry-region fixed-effects in which column (1) reports the own coefficient of each regressor whereas column (2) reports the corresponding variables interacted with skill share. Different from estimates in Table 2, we include firms' importing status in estimates of Table 4 since this variable can better capture firm's exposures to globalization. The regression shown in columns (1) and (2) includes the own variable of firms' importing indicator

[16] In particular, the eastern region includes the following 15 provinces: Heilongjiang, Jilin, Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Anhui, Zhejiang, Shanghai, Fujian, Guangdong, Guangxi, and Hainan. The middle region includes the following six provinces: Inner Mongolia, Shanxi, Henan, Hubei, Hunan, and Jiangxi. Finally, the western region includes the rest of the provinces.

[17] Yet, we also see some regional disparity from Table 3. In particular, the own terms of industry input tariffs in each region have different signs and magnitudes.

[18] The detailed matching method and procedure are introduced in Yu (2015).

and its interaction with the skill share. The coefficient of industry input tariffs interacted with the skill share is negative and statistically significant, suggesting that reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces. In addition, the regression includes a triple interaction term among the importer indicator, skill share, and industry input tariffs. The negative, though insignificant, triple interaction term hints that importers might respond more forcefully to input trade liberalization in their wage schedule.

Furthermore, import processing firms may behave differently from ordinary firms, as suggested by Dai et al. (2016). By definition, import processing firms are firms that import raw material or intermediate inputs and then, after local processing or assembly, export the value-added final goods (Feenstra and Hanson, 2005). A processing indicator is defined as one (1) if a firm has any processing imports and zero (0) otherwise. As processing imports have zero import tariffs (Yu, 2015), the effect of input trade liberalization on firms' skill premium is expected to be less pronounced for an industry with many import processing firms.

We run another regression which is jointly reported in columns (3)-(5). As before, column (3) reports the own coefficients of regressors whereas column (4) shows the coefficients of their interaction with skill share. Column (5) reports the coefficient of triple interaction among input (output) tariffs, skill share, and processing indicator. Similar to our previous findings, reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces, because the coefficient between industry input tariffs and skill premium is negative and statistically significant. The novel finding is that the coefficient of the triple interaction term between industry input tariffs, skill share, and processing indicator is positive and statistically significant, suggesting that the effect of input trade liberalization on firms' skill premium is more pronounced for non-processing (*i.e.*, ordinary) firms.

To see this more precisely, we can take one step further to evaluate the net effect of input trade liberalization on firm wages. As shown in the single regression of columns (3)-(5), there are three types of firms in the regression: non-importing firms, ordinary importers, and processing importers. The net effect of input tariffs on firm average wage for non-importing firms is $0.029 - 0.088 \times 0.45 < 0$

given that the sample mean of firm's skill share is 0.45 and the own coefficient of input tariffs is 0.029 whereas that of the interaction between input tariffs and skill share is -0.088. Similarly, the net effect for ordinary importers (i.e., importer indicator equals one) is $0.029 - (0.088 + 0.017) \times 0.45 < 0$ given that the coefficient of the triple interaction term among input tariffs, skill share and import indicator is -0.017. These two results are consistent with our previous main finding that a fall in industry input tariffs is associated with a higher skill premium at firms with more skilled workforces.

By contrast, the net effect of input tariffs on firm wages for processing firms is positive since it equals $0.029 + (0.137 - 0.088 - 0.017) \times 0.45 > 0$ given that the coefficient of the triple interaction term among input tariffs, skill share and processing indicator is 0.137. The finding that the sample-mean effect for processing exporters is overturned is also intuitive. Processing imports in China enjoy a special treatment of free duty (see, *e.g.*, Yu, 2015). Thus, further import tariff reductions on processing input encourage processing exporters to switch to ordinary exporters over time, as found by Brandt and Morrow (2017), which in turn lower the employment demand for processing exporters. Accordingly, the average wages for processing firms fall, as shown in the regression of Columns (3)-(5) of Table 4.

[Insert Table 4 Here]

3.3 Estimates using Panel Data

So far, we have used data only for 2004 to estimate the Mincer regressions, because data on firms' skill shares are only available for census year of 2004. The empirical specifications are useful for understanding cross-section firms' skill premium. To gain a better understanding on the variation of within-firm skill premium in response to input trade liberalization, in this section we make an effort to use the panel data for the period of 2000–06.

Since data on the share of skilled labor are available only for year 2004, to compute a proxy for the skilled labor share for all other years from 2000 to 2006, we multiply the skilled labor share in 2004 by the provincial skilled labor share in all the other years using 2004 as the base year. In addition, industry input and output tariffs are now calculated using the Input-Output Table for 1997 to obtain the corresponding weights because the information in the Input-Output Table of 1997 reflects the initial conditions prior to China's trade liberalization in 2001 (Bartik, 1991).

As data on the share of skilled labor are unavailable for years other than 2004, we compute a proxy for the skilled labor share (θ_{it}) for all other years from 2000 to 2006 by multiplying the skilled labor share in 2004 with the provincial skilled labor share in all other years using 2004 as the base year. Equally important, industry input and output tariffs are now calculated using the Input-Output Table for 1997 to calculate the corresponding weights, as the weights in 1997 reflect the initial conditions prior to China's trade liberalization in 2001, as suggested by Bartik (1991).

With cross-section data in 2004, Table 2 has already demonstrated that the results for empirical specification with both own coefficients and coefficients interacted with skill share for each regressor are very close to those without own coefficients. Since the latter specification follows Mincer regressions more closely, in the panel-data analysis we only report those empirical results of estimation with the coefficients interacted with firms' skill share.

Column (1) of Table 5 reports the Mincer regression results by using the 1997 Input-Output Table and controlling year-specific fixed-effects, industry-specific fixed effects, and region-specific fixed effects, respectively. The estimation results are very close to their counterparts in the last two columns of Table 2. The coefficient of industry input tariffs interacted with firms' skill share is negative and statistically significant, indicating that input trade liberalization increases firm's skill premium over time. Similar to the estimation results shown in column (6) of Table 2, the coefficient of output tariffs interacted with the skill share is positive, for the same reason discussed earlier. Estimates in column (2) take a step further to run a more parsimonious regression by controlling the interacted industry and region fixed effects. All regressors have very similar coefficients to their counterparts in column (1).

Finally, it is possible that firms may take more time to respond to tariff reductions in their wage schedule. In our last enrichment, column (3) of Table 5 instead uses firms' past (i.e., one-year lag) export status and past performance (sing log sales or total factor productivity as a proxy). The estimation results for all the variables in column (3), with some variables in one-lag period are close to their counterparts in column (2) when all variables are in the current period. In all cases, the coefficients of industry input tariffs are found to be negative and statistically significant for all the regressions.

[Insert Table 5 Here]

3.4 Endogeneity Issues

In the previous estimations, input trade liberalization was considered as exogenous. However, tariff formation could be endogenous in the sense that skill premium could have a reverse effect on tariff changes. With widening skill premium, unskilled workers could blame free trade policies and form labor unions to lobby the government for temporary trade protection (Bagwell and Staiger, 1990, 1999; Bown and Crowley, 2013). Although this happens in developed countries like the United States (Goldberg and Maggi, 1999) and in some developing countries like Turkey (Gawande and Bandyopadhyay, 2000), it is less likely to happen in China because labor unions in China are symbolic organizations. In addition, if these types of political factors are time invariant, they should have been accounted and statistically controlled for by the fixed-effect panel estimates in Table 5 (Goldberg and Pavcnik, 2007). However, if they are time variant, the estimations of the related Mincer regressions in Table 5 would be biased.

Moreover, if the residual in Eq. (6), ε_{it}, is related to the firm's measured skill share ($\hat{\theta}_{it}$), the estimated coefficients will be biased. As a robustness check, below we use the instrumental variables (IV) approach to address the potential endogeneity issues. If the negative reverse causality is a main source of endogeneity issue, we should expect that the key estimated coefficient for the interaction term between input tariffs and skill share under the two-stage least square (2SLS) approach should be greater than its counterpart under the OLS approach.

It is challenging to find an ideal instrument for tariffs. Inspired by Trefler (2004) and Amiti and Davis (2011), we use the one-year lag of industry input tariffs as the instrument of the first difference in industrial input tariffs. The economic rationale is that lagged input tariffs are less likely to influence the time difference of input tariffs (Trefler, 2004). In particular, we consider the following first-difference Mincer regression:

$$
\begin{aligned}
\triangle \ln(\overline{w_{it}}) \quad = \quad & \gamma_c + \gamma_u \triangle \ln(w_{it}^u) + \gamma_0 \triangle \hat{\theta}_{it} + \gamma_1 \triangle (\hat{\theta}_{it} IT_{jt}) + \gamma_2 \triangle (\hat{\theta}_{it} IT_{jt}) IM_{it} + \gamma_3 \triangle (\hat{\theta}_{it} PT_{jt}) \\
& + \gamma_4 \triangle (\hat{\theta}_{it} PT_{jt}) FX_{it} + \gamma_5 \triangle (\hat{\theta}_{it} FX_{it}) + \gamma_6 \triangle (\hat{\theta}_{it} IM_{it}) + \gamma_7 \triangle IT_{jt} + \gamma_8 \triangle PT_{jt} + \\
& \gamma_9 \triangle IM_{it} + \gamma_{10} \triangle FX_{it} + \boldsymbol{\gamma} \triangle \mathbf{X}_{it} + \delta_i + \delta_{jr} + \delta_t + \varepsilon_{it}, \qquad (8)
\end{aligned}
$$

Accordingly, the regressand and all regressors in Table 6 are in the first difference. Columns (1) and (2) are a single OLS regression in which IV reports the coefficients of the own one-lag industry input tariffs and its interaction with firm skill share using the first difference in industry input tariffs and its interaction with firm skill share as the regressands. Once again, the interaction term between skill share and industry input tariffs is negative and statistically significant, which is consistent with our previous findings. Finally, to show that our 2SLS estimation results are robust to the inclusion of the own terms of the regressors, we run another single estimation by abstracting away the own coefficients of related regressors, which is jointly reported in columns (3) and (4). Similarly, the regression in columns (3) and (4) use the one-lag industry input tariffs interacted with firm skill share as the instrument whereas the first difference in industry input tariffs interacted with firm skill share is served as the regressand. Again, the coefficient of industry input tariffs, the variable of our key interests, is negative and statistically significant. Thus, the 2SLS estimation results are consistent with our previous OLS estimates.

We now perform related statistical tests to check the validity of the instrument. The bottom module in Table 6 provides the first-stage estimates for all specifications. The coefficients of the instruments are negative and highly statistically significant, suggesting that it is more challenging to remove tariff barriers in industries with high initial tariffs. In addition, several tests were performed to verify the quality of the instruments. First, we use the Anderson canon correlated LM χ^2 statistic to check whether the excluded instruments are correlated with the endogenous regressors. As shown in the upper module in Table 6, the null hypothesis that the model is under-identified is rejected at the 1 percent significance level. Second, the Cragg-Donald Wald F-statistic provides strong evidence for rejecting the null hypothesis that the first stage is weakly identified at a high significance level. The tests suggest that the instrument is valid and the specifications are well justified.

[Insert Table 6 Here]

3.5 On the Possible Mechanism[19]

The objective of this section is to discuss a possible mechanism to enrich our understanding of the main empirical finding that input trade liberalization leads to an increase in firms' skill premium and provide some evidence for our theoretical conjecture. Inspired by the literature on "fair wages" (e.g. Egger and Kreickemeier, 2012), a possible mechanism to interpret our empirical findings is that skilled workers have greater bargaining power with their employers than unskilled workers.[20] As a result, the incomes of skilled workers are more closely linked to firms' profits but the incomes of unskilled workers are more in line with those of other firms in the same industry. Thus, a fall in input tariffs increases the firm's economic profit, which in turn raises firms' skill premium because the skilled labor commands a larger proportion of the incremental surplus than the unskilled labor.[21]

To check whether such a conjecture is supported by the data, we replace the firm's average wage, the regressand in our Mincer-type regressions, with the firm's value-added per worker. Value-added per worker is one possible measure of labor productivity or, more generally, a proxy to the firm's surplus per worker. If input tariff reductions raise the firm's skill premium, we should observe that input trade liberalization also increases the firm's value-added per worker because value-added per worker can be treated as another side of the same coin of firms' skill premium. It is the core of our paper's main hypothesis that intermediate input tariffs move value-added per worker in essentially the same way as they move the average wage (per worker), which is directly testable.

[19] We thank a referee for providing great comments and suggestions on this sub-section.

[20] We are aware that our findings are also consistent with both the bargaining model of Helpman et al. (2010) and the efficiency wage model of Amiti and Davis (2011). On the broad interpretation of our findings, higher value added means firms generate more surplus to share. The surplus may be skill group specific (see appendix to Helpman et al., 2010) or general. In the former case, workers of different skill might have the same bargaining power but generate more additional surplus. In the latter case, more skilled workers might command stronger bargaining power. Note, all these models do not allow for bargaining power to change with trade liberalization because they have no unions but use individual wage determination instead. This may be quite adequate for China, where labor unions are merely symbolic.

[21] We provide a therotical framework for such a mechanism in our working paper (see Chen et al., 2016).

Specifically, we replace log of firm average wage with log of firm value-added per worker in the empirical specification in Eq. (7). To ensure that our estimation results are not contaminated by using the time-series proxy of the firm's skill share, we focus on cross-section data in 2004 and report the estimation results in Table 7. The estimates in column (1) of Table 7 are obtained by using the ASIF-customs matched data (as used in Table 4). After controlling a rich set of interacted region and industry fixed effects, the regression results show that the key coefficient of industry input tariffs interacted with skill share is negative and statistically significant, suggesting that input trade liberalization increases the firm's value-added per worker.

The advantage of using ASIF-customs matched data is to allow us to govern firms' importing status, but it is at the expense of reducing the number of observations since the matching between the two datasets (i.e., ASIF dataset and customs dataset) is imperfect (see more discussions in Yu, 2015). To see whether our findings are robust to different regression samples, column (3) runs the same regression as column (1) but instead uses the ASIF data set only. The key variable of interest, the interaction term between input tariffs and skill share, still exhibits a negative sign and statistically significant, indicating that our findings are robust by using different data sample.

Finally, we also replace the regressand of log average value-added with that of log per-worker profit and run the regressions using ASIF-customs matched data in column (2) and sole ASIF data in column (4), respectively.[22] Our key finding is robust in all specifications: When controlling for product-market tariffs in a firm's industry, reduced input tariffs in a firm's industry are associated with higher surplus per worker or overall profits at firms with skill intensive production (skilled workforces).

[Insert Table 7 Here]

Although our interpretation is consistent with the evidence, it does not rule out other possible channels or mechanisms. There are other possible interpretations. For instance, an additionally employed skilled worker may generate a larger surplus, all else equal, and yet might receive a smaller

[22] The number of observations in columns (2) and (4) is smaller than their counterpart in columns (1) and (3), because some firms with negative profits are dropped out.

share than unskilled workers (after bargaining). The large incremental surplus can be more than proportionally larger than the bargaining share difference to unskilled workers. Thus, skilled workers may seem to capture a larger proportion of the incremental surplus, but really they simply generate more surplus. However, we cannot validate this argument because it requires that the data contain variables that would directly measure the bargaining weight by skill groups, or related quantities.

4 Concluding Remarks

China has experienced dramatic tariff reductions since its accession to the WTO in 2001. At the same time, wage inequality between skilled and unskilled labor of Chinese manufacturing firms has also increased significantly. To our knowledge, so far there is no study using micro-level evidence to explore the link between the two because there are no firm-level data on wages for skilled and unskilled labor. In this paper, we have developed a Mincer-type econometric approach to estimate firms' skill premium based on imperfect Chinese firm-level data on wage information. As in other ambitious attempts to investigate important issues with imperfect data, some compromises were made to conduct our estimations. Nevertheless, the finding that a fall in input tariffs is associated with an increase in the skill premium at firms with more skilled workforces is robust under different econometric specifications.

Such a finding is consistent with the idea that firms share the additional surplus generated by input trade liberalization mostly with skilled workers. Potential reasons for the observed increase in relative skill earnings at more skill intensive firms include technological and institutional factors: skills might be complementary with newly accessible foreign inputs on the technological side, or skilled workers might command stronger bargaining power over additional surplus generated under input trade liberalization.

Our findings also have rich policy implications. Trade liberalization can increase skill demand in China by prompting firms to use intermediate inputs that raise firms' surplus. This happens either because less expensive or newly accessible inputs are complementary to skill or because skilled workers have a stronger bargaining power in their negotiation over the newly generated surplus. In any case, input trade liberalization is an appropriate policy instrument to foster firms' surplus.

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Table 1A: China's Industrial Input Tariffs

Year	2000	2001	2002	2003	2004	2005	2006	Average
Ind. Input Tariffs	15.73	14.35	10.52	9.21	8.21	7.84	7.71	9.14
Std. Dev.	3.90	3.10	2.78	2.31	2.08	1.85	1.72	3.22

Notes: This table reports the mean and standard deviation of 3-digit industry-level input tariffs.

Table 1B: Summary Statistics of Key Variables (2000-06)

Year Coverage	2004 Only		2000-06	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Firm Average Wage	12.807	9.385	13.231	9.843
Firm Skilled Share	0.449	0.285	0.437	0.272
Industry Input Tariffs (%)	8.219	2.084	9.147	3.220
Industry Output Tariffs (%)	10.111	6.591	11.073	8.195
Measured Unskilled Wage	1.350	1.441	1.382	1.497
Log of Firm Sales	9.939	1.178	10.161	1.205
Log of Firm Labor	4.708	1.088	4.903	1.103
Exporter Indicator	0.287	0.452	0.292	0.455
Processing Indicator	0.32	0.46	–	–
Importer Indicator	0.36	0.47	–	–
Log TFP (Olley-Pakes)	1.153	0.354	1.155	0.347
SOEs Indicator	0.038	0.191	0.056	0.229
Foreign Indicator	0.213	0.409	0.222	0.416
Wage Premium	0.453	8.796	0.001	9.235
Year	2004	–	2003	1.739

Notes: The import indicator is only available in the customs firm matched data set. The first two columns cover ASIF data for 2004 only, whereas the last two columns cover ASIF data for 2000–06.

Table 2: Baseline Mincer Regression Using Data for 2004

Firm Average Wages	(1)	(2)	(3)	(4)
		× skill share		×skill share
Measured Unskilled Wages	0.306***		0.309***	
	(13.94)		(12.62)	
Skill Share	-0.963**		0.252	
	(-2.55)		(0.39)	
Industry Input Tariffs	-0.167***	-0.042**	-0.064***	-0.181**
	(-20.13)	(-2.00)	(-6.78)	(-2.37)
Industry Input Tariffs	–	–	–	0.013*
× Log Sales				(1.76)
Industry Output Tariffs	0.005*	-0.012**	0.016***	-0.013***
	(1.88)	(-1.96)	(7.40)	(-2.67)
Industry Output Tariffs	–	–	–	0.003
× Exporter Indicator				(0.62)
SOEs	-0.162	0.206	-0.028	-0.194
	(-0.91)	(0.76)	(-0.21)	(-0.94)
Foreign Indicator	0.708***	1.175***	0.560***	0.490***
	(18.57)	(14.00)	(18.53)	(7.36)
Log Sales	-0.088***	0.133***	-0.128***	-0.017
	(-5.55)	(4.28)	(-10.24)	(-0.28)
TFP(Olley-Pakes)	0.658***	0.453***	0.369***	0.309***
	(10.03)	(3.47)	(8.11)	(3.48)
Exporter Indicator	0.080**	0.410***	0.169***	0.004
	(2.52)	(5.42)	(6.47)	(0.05)
Wage Premium	0.906***	0.111***	0.955***	0.059***
	(271.6)	(22.81)	(419.9)	(16.80)
Region FE	No		Yes	
Industry FE	No		Yes	
Region×Industry FE	No		Yes	
Observations	119,334		119,334	
R-squared	0.90		0.94	

Notes: Robust t-values corrected for clustering at the firm level are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. Columns (1) and (2) are a single OLS regression in which column (2) reports the interaction with skill share for related variables. Similarly, columns (3) and (4) are a single regression with industry-region fixed effects.

Table 3: Regional Mincer Regression Using Data for 2004

Firm's Regions	East		Central		West	
Firm Average Wages	(1)	(2)	(3)	(4)	(5)	(6)
		× skill share		×skill share		×skill share
Measured Unskilled Wages	0.384***		0.388***		0.304***	
	(21.52)		(17.60)		(24.48)	
Skill Share	4.907***		4.694***		9.302***	
	(3.98)		(3.88)		(6.89)	
Industry Input Tariffs	-0.043***	-0.641***	0.057***	-0.443***	0.064***	-1.079***
	(-7.15)	(-3.85)	(2.61)	(-3.20)	(5.61)	(-6.52)
Industry Output Tariffs	0.003*	0.003	-0.045***	0.025**	-0.008***	-0.005
	(1.76)	(0.48)	(-6.82)	(2.30)	(-3.67)	(-0.86)
Industry Output Tariffs		-0.023***		-0.012		-0.015*
× Exporter Indicator		(-4.42)		(-0.80)		(-1.94)
SOEs	0.250*	-0.052	-0.145	0.572**	0.294**	0.097
	(1.93)	(-0.26)	(-0.90)	(2.27)	(2.05)	(0.42)
Foreign Indicator	-0.163***	0.314***	0.105	0.081	-0.076**	0.115
	(-7.81)	(6.81)	(0.75)	(0.37)	(-2.07)	(1.41)
Log Sales	0.040***	-0.403***	0.123***	-0.452***	0.094***	-0.827***
	(4.30)	(-3.38)	(4.08)	(-3.91)	(5.56)	(-6.22)
TFP(Olley-Pakes)	0.184***	-0.026	0.405***	-0.223	0.487***	-0.181
	(5.57)	(-0.47)	(3.53)	(-1.39)	(7.64)	(-1.39)
Exporter Indicator	-0.185***	0.223***	0.300***	-0.219	-0.146***	0.169*
	(-10.16)	(3.75)	(3.52)	(-1.02)	(-5.28)	(1.84)
Wage Premium	0.977***	0.021***	0.959***	0.032***	0.981***	0.017***
	(617.54)	(8.96)	(121.08)	(2.81)	(366.17)	(3.60)
Log Sales		0.063***		0.051***		0.106***
×Industry Input Tariffs		(3.82)		(3.93)		(6.57)
Province FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Province×Industry FE	Yes		Yes		Yes	
Observations	77,742		7,851		33,741	
R-squared	0.98		0.97		0.97	

Notes: Robust t-values corrected for clustering at the firm level are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. Columns (1) and (2) are a single OLS regression for firms located in eastern China in which column (2) reports the interaction with skill share for related variables. Similarly, Columns (3) and (4) are a single regression for firms located in central China. Columns (5) and (6) are a single regression for firms located in western China.

Table 4: Mincer Regression Using Matched Data for 2004

Firm Average Wages	(1)	(2)	(3)	(4)	(5)
		× skill share		×skill share	×skill share ×processing indicator
Measured Unskilled Wages	0.210***		0.209***		
	(8.89)		(8.93)		
Skill Share	0.988		1.175*		
	(1.49)		(1.76)		
Industry Input Tariffs	0.022	-0.069*	0.029	-0.088**	0.137***
	(0.83)	(-1.91)	(1.06)	(-2.34)	(3.77)
Industry Input Tariffs × Importer Indicator		-0.013		-0.017	
		(-0.40)		(-0.53)	
Industry Output Tariffs	0.029***	-0.012	0.027***	-0.008	0.017
	(5.30)	(-0.68)	(5.05)	(-0.44)	(1.22)
Industry Output Tariffs × Exporter Indicator		-0.015		-0.018	
		(-0.91)		(-1.12)	
SOEs	-0.700	1.277	-0.714	1.304	
	(-0.84)	(1.04)	(-0.85)	(1.06)	
Foreign Indicator	0.613***	0.122	0.606***	0.162	
	(10.43)	(0.85)	(10.15)	(1.12)	
Log Sales	0.079***	-0.172***	0.082***	-0.180***	
	(3.13)	(-3.35)	(3.24)	(-3.49)	
TFP(Olley-Pakes)	0.041	0.673***	0.044	0.667***	
	(0.41)	(2.85)	(0.43)	(2.83)	
Exporter Indicator	-0.077	0.500*	-0.083	0.570**	
	(-0.62)	(1.74)	(-0.66)	(1.96)	
Importer Indicator	0.138**	0.570*	0.144**	0.596*	
	(2.21)	(1.80)	(2.29)	(1.89)	
Processing Indicator			0.044	-1.698***	
			(0.73)	(-4.65)	
Wage Premium	0.972***	0.049***	0.972***	0.048***	
	(221.45)	(6.76)	(221.61)	(6.62)	
Region×Industry FE	Yes			Yes	
R-squared	0.88			0.93	

Notes: Robust t-values corrected for clustering at the firm level are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. Columns (1) and (2) are a single regression with industry-region fixed effect in which column (2) reports the interaction with skill share for related variables. Similarly, Columns (3)-(5) are a single fixed-effects regression with region-industry fixed effects and additional controls. Numbers of observations in each regression are 18,820.

Table 5: Mincer Regression Using the 1997 IO table (2000-06)

Variable:	Current period		One-lag
Regressand: Firm Average Wages	(1)	(2)	(3)
Measured Unskilled Wages	0.203***	0.285***	0.255***
	(22.86)	(31.97)	(23.78)
Skill Share	0.960*	0.935*	-0.670
	(1.88)	(1.88)	(-1.08)
Skill Share×Industry Input Tariffs	-0.454***	-0.244***	-0.153**
	(-8.10)	(-4.43)	(-2.13)
Skill Share×Industry Output Tariffs	0.015***	0.012***	0.023***
	(3.82)	(2.94)	(4.54)
Skill Share×Industry Output Tariffs	-0.000	0.037***	0.026***
× (One-lag) Exporter Indicator	(-0.03)	(5.40)	(3.11)
Skill Share×SOEs	0.394***	0.433***	0.712***
	(3.79)	(4.48)	(5.85)
Skill Share×Foreign Indicator	2.329***	1.406***	1.293***
	(42.10)	(27.00)	(20.47)
Skill Share× Log Sales	-0.188***	-0.223***	-0.184***
	(-3.79)	(-4.69)	(-3.11)
Skill Share × (One-lag) Olley-Pakes TFP	1.876***	1.198***	0.921***
	(27.01)	(18.53)	(11.31)
Skill Share × (One-lag) Exporter Indicator	0.643***	-0.103	0.100
	(6.39)	(-1.09)	(0.89)
Skill Share × Wage Premium	1.288***	1.299***	1.372***
	(574.20)	(623.74)	(552.14)
Skill Share×Industry Input Tariffs	0.034***	0.026***	0.020***
× (One-lag) Log Sales	(6.26)	(4.90)	(2.94)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Region× Industry Fixed Effects	No	Yes	Yes
Observations	507,084	507,084	345,543
R-squared	0.75	0.78	0.77

Notes: Robust t-values corrected for clustering at the firm level are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. Estimates in column (3) report the results with one-lag variables shown in parentheses.

Table 6: 2SLS Estimates Using Panel Data (2000-06)

First Difference in Firm Average Wages	(1)	(2)	(3)	(4)
First Difference in:		× skill share		×skill share
Industry Input Tariffs	0.210***	-0.546***		-0.145***
	(6.71)	(-9.28)		(-2.93)
Measured Unskilled Wages	0.114***		0.115***	
	(4.28)		(4.34)	
Skill Share	-5.251***		-29.285***	
	(-2.66)		(-16.15)	
Industry Output Tariffs	-0.012***	0.025***		0.004
	(-3.02)	(2.92)		(0.75)
Industry Output Tariffs		-0.001		-0.001
× Exporter Indicator		(-0.13)		(-0.15)
SOEs	-0.761*	1.430*		0.272
	(-1.74)	(1.96)		(0.91)
Foreign Indicator	0.744**	-1.322**		-0.148
	(2.42)	(-2.32)		(-0.49)
Log Sales	1.818***	-0.125		2.856***
	(29.15)	(-1.04)		(44.71)
TFP(Olley-Pakes)	0.579***	0.072		0.959***
	(6.56)	(0.45)		(11.40)
Exporter Indicator	-0.136	0.182		-0.065
	(-1.50)	(0.91)		(-0.48)
Anderson canon. corr. LM statistic	43.21†		86.40†	
Cragg-Donald Wald F statistic	1.4e+05†		2.3e+05†	
Year Fixed Effects	Yes		Yes	
Region×Industry FE	Yes		Yes	
Observations	326,211		326,211	
First-Stage Regressions				
IV: One-Lag Industry Input Tariffs	-0.577***	-0.112***	–	-.0128***
	(-864.1)	(-472.7)		(-483.8)

Notes: Robust t-values corrected for clustering at the firm level are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. † indicates significance of the p-value at the 1 percent level. The regressand and all regressors are in the first difference. Columns (1) and (2) are a single OLS regression in which IV reports the coefficients of the own one-lag industry input tariffs and its interaction with firm skill share using the first difference in industry input tariffs and its interaction with firm skill share as the regressands. Similarly, columns (3) and (4) are another single regression in which IV reports the coefficients of the one-lag industry input tariffs interacted with firm skill share using the first difference in industry input tariffs interacted with firm skill share as the regressand.

Table 7: Robustness Checks with Value-added and Profit

Data Coverage	2004 Matched Data		2004 Data	
Regressand	Value-added per worker	Profit per worker	Value-added per worker	Profit per worker
	(1)	(2)	(3)	(4)
Measured Unskilled Wages	0.012*	0.070***	-0.010***	0.028***
	(1.72)	(4.86)	(-3.69)	(7.93)
Skill Share	-2.561***	-0.422	-5.329***	-4.614***
	(-5.34)	(-1.58)	(-60.12)	(-54.71)
Skill Share × Industry Input Tariffs	-0.022**	-0.061***	-0.007*	-0.031***
	(-2.01)	(-4.48)	(-1.94)	(-5.97)
Skill Share × Industry Input Tariffs	0.010***	0.030***		
× Importer Indicator	(2.81)	(5.99)		
Skill Share × Industry Output Tariffs	0.014***	0.009	0.002	0.000
	(3.95)	(1.50)	(1.47)	(0.10)
Skill Share × Industry Output Tariffs	-0.015***	-0.017***	-0.001	-0.007***
× Exporter Indicator	(-4.85)	(-3.13)	(-0.79)	(-2.89)
Skill Share × SOEs	-0.384***	-0.794***	-0.578***	-0.952***
	(-5.21)	(-5.90)	(-21.11)	(-22.87)
Skill Share × Foreign Indicator	0.122***	0.297***	0.179***	0.517***
	(3.94)	(7.00)	(13.09)	(25.09)
Skill Share × TFP(Olley-Pakes)	2.688***	1.139***	2.139***	0.777***
	(7.23)	(5.89)	(18.77)	(14.50)
Skill Share × Wage Premium	0.025***	0.035***	0.016***	0.024***
	(12.23)	(16.05)	(24.63)	(27.30)
Region Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Region×Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,709	14,810	111,070	97,772
R-squared	0.40	0.27	0.36	0.22

Notes: Robust t-values corrected for clustering at the firm level are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively.

5 Appendix: Estimates using Alternative Measured Unskilled Wages (Online Only, Not for publication)

In this subsection we will check whether our main results are robust to an alternative measure of unskilled wages. Specifically, we will check whether the new measure matches the aggregate data reported by the outside data source. If so, we can use the new measure to run empirical specification (6).

From our firm-level data set, we first redefine unskilled wages as the 25th percentile of firms' wage bills by province – reported in column (2) in Table A1. Once we have this unskilled wage variable, we follow the same procedure as in Section 2.2.2 (i.e. $s_i \equiv (w_i^s - w_i^u)/w_i^u$) and obtain skilled wages and skill premium – reported in columns (1) and (3), respectively.

To compare with other publicly available aggregate data sets, we use rural wages from China's Statistical Yearbook (2004) as a proxy for unskilled wages – reported in column (5) in Table A1. We use the simple average of wages in the computer service, finance, scientific research, and education sectors by province from China's Statistical Yearbook (2004) as a proxy for skilled wages – reported in column (4), and then calculate the corresponding skill premium – reported in column (6) in Table A1.

Comparing column (3) with column (6), we find that the measures of skill premium from our firm-level data and the public aggregate data are very close. In particular, the provincial average skill premium is 1.63 from our firm-level data, which is close to 1.58 from the public aggregate data (see the last row of Table A1).

[Insert Appendix Table A1 Here]

Since the new measure broadly matches the aggregate data reported by the outside data source, we can run empirical specification (6) with the new measured unskilled wages, using the firm-customs matched data for 2004. Since our new measured unskilled wages do not vary by industry, we only control for 2-digit industry fixed effects in all the regressions. As reported in Table A2, the coefficients for all the variables are very close to their counterparts in Table 2. In particular, the coefficients of own industry input tariffs and its interaction with the importer indicator are negative and statistically significant, suggesting that input trade liberalization increases skill premium, and the effect is more pronounced for importing firms. After controlling for province and industry fixed effects in the last column in Table A2, the coefficient of the own industry output tariffs is also positive and statistically significant, whereas that of its interaction with the exporter indicator is negative and statistically significant. These findings are, once again, consistent with the previous findings. Thus, our main results remain robust to the alternative measure of unskilled wages.

[Insert Appendix Table A2 Here]

Appendix Table A1: Wages Data Comparisons in 2004

Data Source	ASIF Data in 2004			External Data in 2004		
Average Wages by Skill Group	Skilled	Unskilled	Premium	Skilled	Unskilled	Premium
Province	(1)	(2)	(3)	(4)	(5)	(6)
Anhui	17.728	6.323	1.80	16.612	6.758	1.46
Beijing	34.667	10.370	2.34	53.019	14.677	2.61
Chongqing	18.105	7.362	1.46	21.981	9.871	1.23
Fujian	25.190	8.166	2.08	26.482	9.027	1.93
Gansu	14.205	6.000	1.37	15.094	9.310	0.62
Guangdong	25.044	8.509	1.94	36.138	9.952	2.63
Guangxi	16.420	6.132	1.68	19.716	7.661	1.57
Guizhou	18.875	6.538	1.89	16.300	9.665	0.69
Hainan	17.251	6.651	1.59	23.251	6.206	2.75
Hebei	16.121	6.000	1.69	18.233	5.367	2.40
Heilongjiang	14.378	6.120	1.35	21.129	5.872	2.60
Henan	12.364	5.590	1.21	16.228	6.886	1.36
Hubei	14.734	6.295	1.34	16.770	5.600	1.99
Hunan	16.077	7.016	1.29	19.597	6.961	1.82
InnerMongolia	18.282	7.500	1.44	17.316	7.677	1.26
Jiangsu	18.868	8.889	1.12	28.246	8.059	2.50
Jiangxi	13.900	6.032	1.30	16.008	6.291	1.54
Jilin	15.190	6.000	1.53	17.901	5.790	2.09
Liaoning	20.344	6.571	2.10	24.101	5.645	3.27
Ningxia	15.520	6.914	1.24	20.963	8.500	1.47
Qinghai	20.499	7.056	1.91	23.771	12.324	0.93
Shaanxi	14.910	6.298	1.37	20.037	8.783	1.28
Shandong	15.251	6.250	1.44	21.874	9.840	1.22
Shanghai	35.366	11.145	2.17	42.622	22.057	0.93
Shanxi	16.368	6.368	1.57	17.255	8.691	0.99
Sichuan	15.533	6.717	1.31	21.943	9.401	1.33
Tianjin	34.902	8.857	2.94	31.357	15.514	1.02
Tibet	30.107	10.053	1.99	36.299	22.438	0.62
Xinjiang	18.761	8.889	1.11	20.657	9.300	1.22
Yunnan	21.168	7.788	1.72	18.364	10.183	0.80
Zhejiang	23.552	9.575	1.46	38.695	21.149	0.83
Provincial Average	19.667	7.354	1.63	23.805	9.853	1.58

Notes: The low-skilled wages in cloumn (1) are defined as the 25% percentile of firm wages by province whereas the high-skilled wages are calculated according to Eq. (1). The interpretations on external data see the Appendix.

Appendix Table A2: Estimates using Matched Data and Alternative Measured Unskilled Wages (2004)

Firm Average Wages	(1)	(2)	(3)
Alternative Measured Unskilled Wages	0.008	0.006	0.007
	(0.53)	(0.38)	(0.57)
Skill Share×Industry Input Tariffs	-0.117***	-0.105***	-0.120***
	(-3.52)	(-3.15)	(-3.50)
Skill Share × Industry Input Tariffs	-0.118**	-0.114**	-0.100**
× Importer Indicator	(-2.41)	(-2.33)	(-2.05)
Skill Share× Industry Output Tariffs	0.032	0.027	0.031**
	(1.35)	(1.15)	(2.20)
Skill Share× Industry Output Tariffs	-0.047**	-0.042*	-0.047***
× Exporter Indicator	(-1.98)	(-1.74)	(-3.20)
Skill Share× SOEs	1.506***	1.498***	1.522***
	(3.56)	(3.55)	(3.81)
Skill Share× Foreign Indicator	1.031***	1.134***	1.003***
	(8.04)	(8.70)	(8.43)
Skill Share× Log Employment	-0.064	-0.075	-0.061**
	(-1.26)	(-1.46)	(-2.39)
Skill Share × TFP(Olley-Pakes)	0.969***	0.947***	0.973***
	(4.34)	(4.27)	(3.79)
Skill Share × Exporter Indicator	1.005***	1.052***	1.015***
	(3.37)	(3.53)	(5.03)
Skill Share	1.281***	1.279***	1.282***
× Wage Premium	(97.77)	(97.30)	(156.18)
Skill Share × Importer Indicator	-0.019	-0.104	-0.186
	(-0.04)	(-0.22)	(-0.42)
Skill Share×Processing Indicator		-0.932***	
		(-5.39)	
Industry Fixed Effects	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	No	No	Yes
Observations	18,820	18,820	18,820
R-squared	0.80	0.80	0.80

Notes: Robust t-values corrected for clustering at the firm level in parentheses.*,**(***) indicates significance at the 10,5 and 1 percent level, respectively. The alternative measured unskilled wages are constructed by the 25 percentile of firm's wage bills by province. Columns (1) and (2) control for region fixed effects. Finally, column (3) controls for province fixed effects. Two-digit industry level fixed effects are included in all specifications.