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JEL Classifications: F10, F12, F14

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1 Introduction

Tariffs have declined dramatically worldwide as a result of many rounds of General Agreement on Tariffs and Trade/World Trade Organization (WTO) trade negotiations (Bagwell and Staiger 1999). Trade liberalization has generated profound effects on not only final goods, but also intermediate inputs and factors, mainly via global supply chains. The question of how trade liberalization affects wages and income distributions, especially for developing countries, has again become one of the research focuses in the international trade literature.

Most of the earlier studies relied on the Heckscher-Ohlin model for guidance in testing whether trade liberalization benefits the abundant factor. According to the Stopler-Samuelson theorem, trade liberalization on imported capital-intensive goods would mitigate wage inequality between skilled and unskilled labor in developing countries. But that theoretical assertion has received little support from empirical evidence.[1] Feenstra and Hanson (1996, 1999) find that, in the presence of vertical integration and international outsourcing, freer trade could increase wage inequality in developed and developing countries.[2] A few recent papers discuss firm-level wage inequality in the context of globalization (e.g., Egger and Kreickemeier 2009; Amiti and Davis 2011; Helpman et al. 2016). Most of these studies investigate between-firm wage inequality. The present paper instead takes a step forward to examine within-firm wage inequality between skilled and unskilled labor, or equivalently, the skill premium.

Some pioneering works on the impact of trade liberalization on within-firm wage inequality focus mainly on the aspect of export market access (see, for example, Verhoogen 2008; Bustos 2011; Frías et al. 2012). However, it is also important to understand the impact of input trade liberalization on wage inequality. For example, imported intermediate inputs have been found to be crucial for boosting firm productivity in many countries, such as the United States (Hanson et al. 2005),

[1] Previous works have contributed to an intense discussion on the validity of factor price equalization (FPE) in explaining wage inequality in developed countries. For example, Johnson and Stafford (1993) and Leamer (1993, 1996) argue that FPE can explain the wage gap between skilled and unskilled workers in the United States. However, Lawrence and Slaughter (1993) review historical data on the prices of labor-intensive and capital-intensive goods and find that the movement of the relative prices of these two types of goods may suggest wage equality according to FPE.

[2] Technology is identified as the major factor driving wage inequality; international trade is nevertheless also believed to play an important role.

Indonesia (Amiti and Konings 2007), India (Goldberg et al. 2010; Topalova and Khandelwal 2011), and China (Yu 2015). Some studies have investigated how input trade liberalization may affect factor returns. For example, Biscourp and Kramarz (2007) document the impact of offshoring on plant-level skill composition in France (but not wage inequality). Becker et al. (2013) investigate the impact of offshoring on firm-level task composition and wages in Germany (but only within multinational firms). The absence of firm and worker heterogeneity makes wage inequality within firms a "black-box." The current paper attempts to fill this gap by investigating the impact of tariff reductions for imported inputs on within-firm wage inequality.[3]

We use firm-level production data and transaction-level trade data from China, and find that input trade liberalization tends to widen within-firm wage inequality. The effect is more pronounced for importing firms. In addition, we find wage polarization in China: the middle range of workers in the skill distribution has gained relatively less in real terms from input trade liberalization compared with less and more skilled workers.

This paper is closely related to the following literature. Helpman et al. (2016) is a recent study on the issue of trade and wage inequality in a model of heterogeneous firms. Using Brazilian data, they find that wage inequality does not mainly stem from cross-sector occupation differences but from between occupations. Amiti and Davis (2012) is another recent study that investigates the impact on wages (but not wage inequality) of output and input tariff reductions. In particular, they find that a reduction in input tariffs raises wages at import-using firms relative to those at firms that use only domestic intermediate inputs. Investigations on the impact of input trade liberalization on wage inequality in developing countries, however, usually rely on industry-level wage data, household survey data, and proxy wage inequality using the Gini coefficient, a standard indicator of income inequality (e.g., Beyer et al. 1999). For example, using urban industrial survey data, Han et al. (2012) find that widening wage inequality in China is strongly associated with China's accession to

[3]An outstanding exception is that of 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. Furusawa and Konishi (2014) propose a model to interpret why international trade can widen the wage gap between top income earners and others, and thus cause job polarization.

the WTO in 2001.[4]

To our knowledge, this is the first paper to investigate how input trade liberalization affects within-firm inequality in China, the world's largest trading nation, as well as the largest developing country. The paper makes the following two contributions to the literature. First, it provides a methodology for constructing firm-level measured wage inequality from firm rent and labor shares, which can be applied to other research projects facing similar data constraints. Second, the paper provides direct evidence that input tariff reductions increase within-firm wage inequality between skilled and unskilled workers. Moreover, the impact of input trade liberalization on within-firm wage inequality is found to be more pronounced for importing firms. Interestingly, the phenomenon of wage polarization also exists in China, as it does in developed countries. Therefore, this study enriches the understanding of the sources of China's growing income inequality, of which wage inequality is an important component.[5]

It is important to stress that the firm-level data set provides employment information on skilled and unskilled labor only for 2004 (i.e., the third year of China's industrial census). Thus, we rely on cross-section regressions in the paper. For the robustness checks, we also conduct panel regressions, by computing a proxy of the share of skilled labor for all other years and provinces.

To check whether our main findings are sensitive to the Mincer-type approach, we also develop a two-step empirical specification to examine the role of input trade liberalization on wage inequality. In particular, we first obtain the skill premium between skilled and unskilled labor using a firm's value-added as a proxy for its profitability. After the index of within-firm wage inequality is measured, our second-step estimation is to examine the role of input trade liberalization on measured wage inequality. After controlling for possible endogeneity issues from reverse causality and omitted variables, we find that input trade liberalization widens within-firm wage inequality. Our main empirical findings are robust in the streamlined, one-step main approach and the two-step alternative approach.

[4] Autor et al. (2013) stresses that China' s exports to the American market significantly contribute to the aggregate decline in the U.S. manufacturing employment and causes the sharp increase in U.S. social benefit claims.

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

The rest of the paper is organized as follows. Section 2 describes the data and introduces the econometric methods to measure within-firm wage inequality and its related empirical specifications. Section 3 presents the main empirical evidence. Section 4 presents an alternative empirical approach as a robustness check. Section 5 concludes, and the appendix provides a theoretical interpretation.

2 Data, Measures, and Empirics

2.1 Data

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

China's NBS conducts an annual survey of two types of manufacturing firms: all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed RMB 5 million (about USD830,000). The sample used in this paper is 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 Generally Accepted Accounting Principles (GAAP).[7] Accordingly, the total number of firms covered

[6] In 2006, the value added of above-sale firms 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).

[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.

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.

The second limitation is specific to the present paper. The data set does not include 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 empirical tests on cross-firm data for 2004. We carry out robustness 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.

Some of the firms in the data are pure trade intermediaries that do not have production activities. To ensure the precision of our estimates, we exclude these firms from the sample in all the estimates. In particular, trade intermediaries are selected according to the same procedures as in Ahn et al. (2011).

2.2 Measures

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

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, IIT_j, as follows:

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

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

We use China's Input-Output Table for 2002 to construct the weight, since NBS reports the Input-Output Table every five years and our data are for 2004. As suggested by Bartik (1991), we use the input-output matrix from 2002 to compute the relevant weighted industry input tariffs, as 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 in the importance of imports, we consider the following weighted input 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 value for product k in CIC 2-digit industry n in 2004. We use simple average tariffs as the default measure in the main estimates that follow. Finally, we calculate the industry-level *input* tariffs using Equation (1). Similarly, the output tariff of industry n is defined as the average tariffs on the imports of the same industry n in 2004 according to Equation (2).

To see how the input tariff reductions affect firms' wage inequality, 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 two-thirds over the same period. The industry input tariffs were around half 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.

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

[9] China's government adjusted its CIC in 2003. Therefore we also make similar adjustments in our data.

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

[Insert Table 1A Here]

2.2.2 Measures of Within-firm Wage Inequality

We start by defining wage inequality (or equivalently, the skill premium), s, as follows:

$$s_i \equiv (w_i^s - w_i^u)/w_i^u \tag{3}$$

where w_i^s and w_i^u are skilled and unskilled wages for firm i, respectively. By definition, the average wage $\overline{w_i}$ can be written as:

$$\overline{w_i} = \theta_i w_i^s + (1-\theta_i) w_i^u$$

where θ_i is firm i's skilled labor share. Thus, we have:

$$\overline{w_i}/w_i^u = \theta_i w_i^s / w_i^u + (1-\theta_i)$$

or equivalently, taking logarithms on both sides to obtain:

$$\ln(\overline{w_i}) - \ln(w_i^u) = \ln\left[\theta_i w_i^s / w_i^u + (1-\theta_i)\right]$$

We now define $f(\theta_i) \equiv \ln(\overline{w_i}) - \ln(w_i^u)$ and apply the Maclaurin series to obtain

$$f(\theta_i) = f(0) + f'(0)\theta_i + o(\theta_i) = 0 + \theta_i s_i + o(\theta_i),$$

where $o(\theta_i)$ represents the remaining high-polynominal terms. Or equivalently:

$$\ln(\overline{w_i}) = \ln(w_i^u) + \theta_i s_i + o(\theta_i). \tag{4}$$

So far there is neither economic reasoning nor identifying assumptions; the terms are all simply noncontroversial definitions. The core of the analysis lies in the following specification of wage inequality.

Table 1B reports the summary statistics for the key variables used in the 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. As firms' skilled 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 only provides employment information on skilled and unskilled labor for 2004, we use a proxy for the skilled labor share for all other years. The proxy is calculated by multiplying the skilled labor share in 2004 by the provincial skilled labor share in all years, using 2004 as the base year. 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 for both data sets directly. The second is the measured between-firm wage premium (ϑ_i), which is defined as firm i's log wage premium relative to the average firm in industry j , which will be discussed carefully shortly. The last wage variable is the measured unskilled wage.

It is important to stress that neither skilled wages nor unskilled wages are available in the firm-level production data set. To tackle this data challenge, we define the measured unskilled wage as the minimum level of firm wages in each (3-digit) industry-province pair, for the following two reasons. First, recent studies, such as Anwar and Sun (2012), note that the wages of unskilled workers are different across industries and provinces in China, especially after 2004. Second, within each industry-province pair, firms' average wages are significantly positively correlated with the skill share.[11] As illustrated in Table 1B, the mean of measured unskilled wages in 2004 is much lower than (i.e., around 15 percent of) that of the firms' average wage. Nevertheless, we also provide an alternative measure of the unskilled wage as a robustness check later. Finally, the firm-level data set for 2004 reports five education levels: graduate (and above), university, college, high school, and below middle school. As usual, we define skilled workers as employees with a college degree or higher.

[Insert Table 1B Here]

[11] 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, which is highly significant at the conventional statistical level (t-value = 77.25).

2.3 Mincer Empirical Specification

Without loss of generality, let us suppose that firm i's wage inequality, s_i, takes a linear form

$$s_i = \sum\nolimits_{p=1}^{P} \gamma_p x_{ip} + \epsilon_i. \tag{5}$$

where x_{ip} denotes a vector of predictors, which we will specify shortly. Combining Equations (4) and (5), we obtain the following main Mincer-type (1974) empirical specification:

$$\begin{aligned}
\ln(\overline{w_i}) \quad = \quad & \gamma_0 + \gamma_u \ln(w_{ir}^u) + \gamma_1(\theta_i \times IT_j) + \gamma_2(\theta_i \times IT_j) \times IM_i + \gamma_3(\theta_i \times PT_j) \\
& + \gamma_4(\theta_i \times PT_j) \times FX_i + \gamma_5(\theta_i \times FX_i) + \gamma_6(\theta_i \times IM_i) \\
& + \gamma_7(\theta_i \times \vartheta_i) + \boldsymbol{\gamma}(\theta_i \cdot \mathbf{X}_i) + \varepsilon_i
\end{aligned} \tag{6}$$

where the error term is defined as $\varepsilon_i \equiv \theta_i \epsilon_i + o(\theta_i)$. In this Mincer regression, all the regressors (except the intercept constant term and the unskilled wage variable) include a component of firm i's skilled labor share θ_i. We do not restrict the coefficient of the variable $\ln(w_{ir}^u)$ to unity, and hence it is less likely that our key variables of interest would be biased by using measured unskilled wages.

First and foremost, among the set of predictors, the most important variable of interest is the average intermediate input tariff of firm i in industry j (IT_j). If the coefficient γ_1 is negative and statistically significant, it suggests that input trade liberalization would widen firm wage inequality. It is also reasonable to anticipate that the impact of input trade liberalization on wage inequality would be stronger for importing firms. Thus, we expect that the interaction term γ_2 between intermediate input tariffs and the importer indicator is also statistically and significantly negative.

Second, we include the industry average output tariff (PT_j) and its interaction with the firm export indicator as control variables for two reasons. 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). Moreover, it would be expected that the impact of output trade liberalization on wage inequality may be different between exporting firms and non-exporting firms. In this sense, as inspired by Biscourp and Kramarz (2007) and Verhoogen (2008) the interactions of input (output) industrial tariffs with firm-level importer (exporter) indicators are used to analyze heterogeneous employer responses directly, . Of course, wage inequality in exporting (importing) firms may be affected through channels other than trade liberalization. We thus also include firms' own exporting (importing) indicators in the regressions.

Third and equally important, ϑ_i is firm i's log wage premium relative to the average firm in industry j (and province r), as $\vartheta_i \equiv \ln W_i - \sum_{i \in I(jr)}^{N} (\ln W_i)/N$, where $i \in I(jr)$ denotes the firms in industry j (and province r). These wage premiums (or discounts) can result from the different skill composition of firm i's workforce, or the different surplus that firm i generates. It is important to stress that this variable plays an important role here. It helps us properly control for between-firm wage inequality, as inspired by earlier works, such as Egger and Kreichemeier (2009), Amiti and Davis (2011), and Helpman et al. (2016). Thus, our empirical specification essentially focuses on within-firm wage inequality.

Finally, empirical specification (6) implicitly draws on theory suggested by Helpman et al. (2010a). By treating multiple skill groups in the firm-level framework, the regression residual ε_i 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) the firms' anticipated performance and associated wage offers, and (iv) any firm-specific shocks to the wage bargaining or screening technology (Helpman et al., 2016).

As suggested by Helpman et al. (2010b) and Blaum et al. (2015), the variable of firm i's log wage premium relative to the average firm (ϑ_i) absorbs any firm-specific wage components. Furthermore, to control for the other three factors, we add three sets of dummies in the regressions. First, we include province-specific fixed effects, which control for industry-invariant but unobservable factors. Second, we include 3-digit industry-specific fixed effects, which control for province-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 $\mu_i \sim N(0, \sigma^2)$, which takes into account firms' anticipated performance and firm-specific shocks that similarly affect individual skill groups.

Related literature has investigated whether more productive firms use more skill-biased technology (e.g., see Verhoogen 2008; Bustos 2011). It is possible that trade liberalization induces the most productive firms to adopt skill-biased technology or update product quality, and hence increases the demand for skilled labor for these firms. If so, our Mincer estimated results may be biased. However, the sample for 2004 shows that the simple correlation between industrial input tariffs and the skilled share is negative and relatively small (-0.11). Moreover, the simple correlation in the whole sample for 2000–06 is even smaller in absolute value (-0.06), suggesting that multicollinearity of the key variables in our regressions is not severe.

3 Estimation Results

3.1 Baseline Mincer Results

Table 2 presents the baseline results for empirical specification (6). As the firm-level data set does not report firms' import status, Table 2 abstracts away from import status for now. All the regressors, except the constant term and the measured unskilled wage, contain the skilled share variable. In column (1) in Table 2, the coefficient of industry input tariffs, the key variable of interest, is negative and statistically significant, suggesting that input trade liberalization tends to widen wage inequality. By contrast, the coefficient of industry output tariffs is positive and statistically significant, indicating that output trade liberalization tends to narrow wage inequality. Sheng and Yang (2015) find that foreign firms in China could attract more skill-intensive production, which in turn would raise firms' skill premium. Thus, we include the interactions of skilled share with the foreign indicator and with the SOE indicator in the regression.[12] The positive sign of the coefficient of the foreign indicator ascertains the finding in Sheng and Yang (2015). We also include firm size (proxied by firms' log

[12] 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).

sales) and firm total factor productivity (measured by the augmented Olley-Pakes 1996 approach, as suggested by Yu, 2015). We find that larger firms and more productive firms have a higher skill premium.

Exporting firms may have their own channels affecting the skill premium. We thus interact the skilled share with the exporting indicator in column (2) in Table 2. Moreover, processing firms may behave differently from ordinary firms, as suggested by Dai et al. (forthcoming). The firm-level data set does not include firms' processing information. But pure exporting firms that export 100 percent of their products are more likely to be processing firms. We thus interact the skilled share with the pure exporter indicator in column (2). The estimates show that exporting firms have a greater skill premium than non-exporters. Interestingly, pure exporting firms have a lower skill premium than ordinary firms.

It is also reasonable to anticipate that exporters respond heterogeneously to output tariffs in their wage schedule. Therefore, column (3) in Table 2 includes a triple interaction term among the skilled share, output tariffs, and the exporter indicator. It turns out that exporting firms slightly narrow their skilled premium more mildly in response to output trade liberalization, as seen by checking the two interacted terms with output tariffs. Column (4) takes a step further to account for region-specific fixed effects and industry-specific fixed effects, to control for local market tightness. Column (5) includes a full set of interacted industry-region dummies. Finally, the effect of input trade liberalization on the skill premium may have heterogeneous impacts between large firms and small firms. Thus, estimates in the last column include a triple interaction term among the skilled share, output tariffs, and firms' log sales. Our main interest in the estimation, which remains negative and statistically significant in all specifications.

[Insert Table 2 Here]

3.2 Mincer Regressions using Matched Sample

Table 2 uses the firm-level data set for 2004 to conduct the regressions. The advantage of using this data set is that it contains all manufacturing firms. Yet, the data set does not contain information on firms' import status. Thus, the data set cannot be used to examine the possible heterogeneous effects of input trade liberalization on the skill premium. To overcome this data challenge, we match firm-level production data to the product-level customs data to perform the empirical analysis in Table 3.[13]

Column (1) in Table 3 includes an interaction term between firms' importing indicator and skilled share. In addition, it includes a triple interaction term among the importer indicator, skilled share, and industry input tariffs. The negative and statistically significant triple interaction term suggests that importers respond more forcefully to input trade liberalization in their wage schedule. By contrast, output trade liberalization tends to narrow the skill premium, whereas the response from exporting firms seems less sensitive.

In addition, we measure firm size using log employment in all the regressions in Table 3, rather than firm sales used in Table 2. The estimates in Table 3 show that all the results remain qualitatively the same, regardless of the different proxy for firm size. Column (2) also controls for firms' processing status, as we are able to extract such information from the firm-customs matched data set.

As recognized by Cai (2010), China's labor force generally migrates from the inland western and middle provinces to the costal eastern provinces. It is reasonable to expect that firms have different wage premiums in different regions. We thus classify all 30 provinces into three regions: east, middle, and west.[14] The regressions reported in columns (1) and (2) in Table 3 control for regional fixed effects. Column (3) takes a more parsimonious approach in controlling for the interacted region-industry fixed effects. Finally, column (4) controls for province fixed effects instead. The two key variables containing industry input tariffs are still negative and statistically significant. Thus, our main findings remain robust in all specifications.

We now turn to offer a more intuitive economic interpretation of our estimation results. As shown in column (3) in Table 3, the key coefficient of own industry input tariffs is -0.139, implying that

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

[14] In particular, according to the China Regional Statistical Yearbook (various years), 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.

a 10 percentage point fall in industry input tariffs (compared with other industries) causes a 1.39 percentage points increase in the skill premium. The effect is more pronounced for importers within the industry: a 2.39 percentage points increase.

[Insert Table 3 Here]

3.3 Estimates using Panel Data

Thus far, our main regressions have used data only for 2004 to estimate the Mincer regressions, because data on firms' skill shares are only available for census year 2004. The empirical specifications are good enough for us to understand within-firm wage inequality. As an extension, we explore the time-series variation in wage inequality. Table 4 picks up this task by using the panel data for 2000–06.

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 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).

For comparison, column (1) in Table 4 uses only the sample for 2004, but uses the 1997 Input-Output Table to reconstruct the weighted industry input tariffs. The estimation in column (1) is very close to its counterpart in column (1) in Table 2, which uses the 2002 Input-Output Table. By using the 1997 Input-Output Table, column (2) in Table 4 includes the entire sample for 2000–06. It turns out that the two columns yield very similar results for all the variables, in signs and magnitudes. The coefficients of industry input tariffs are negative and statistically significant in both columns. Column (3) includes the two interaction terms with the export indicator. Once again, output trade liberalization is found to narrow the skill premium, whereas the response in exporters is less. The findings are robust, even after controlling for province fixed effects and year fixed effects in column (4). Finally, it is possible that firms may take more time to respond to the wage schedule. In our last enrichment, we thus use firms' past (i.e., one-year lag) export status and past performance (proxied by log employment and total factor productivity) in column (5) in Table 4. It turns out that the estimation results for all the variables in column (5) are pretty close to their counterparts in column (4). In all cases, industry input tariffs are found to be negative and statistically significant for all the regressions.

[Insert Table 4 Here]

3.4 Estimates on Wage Polarization

As suggested by Autor et al. (2006) and Goos et al. (2009), wage inequality in developed countries exhibits a pattern of wage polarization. In particular, the middle range of workers in the skill distribution has gained relatively less, or even lost, in real terms, compared with less and more skilled workers. It is interesting to ask whether such a pattern of wage polarization also exists in China.

Since the firm-level data set for 2004 reports five education levels, skilled workers are defined as employees with a college degree or higher. To examine a possible pattern of wage polarization, we re-classify all workers into three types: high-skilled workers are defined as workers with university and above; low-skilled workers are those with education below middle school; and the rest are classified as the middle group. In this way, we now consider the following specification:

$$\begin{aligned}
\ln(\overline{w_i}) &= \gamma_0 + \gamma_l \ln(w_i^l) + \gamma_1(\theta_i^h \times IT_j) + \gamma_2(\theta_i^l \times IT_j) + \gamma_3(\theta_i^h \times PT_j) + \gamma_4(\theta_i^l \times PT_j) \\
&\quad + \gamma_5(\theta_i^h \times PT_j) \times FX_i + \gamma_6(\theta_i^l \times PT_j) \times FX_i + \gamma_7(\theta_i^h \times FX_i) + \gamma_8(\theta_i^l \times FX_i) \\
&\quad + \gamma_9(\theta_i^h \times \vartheta_i) + \gamma_{10}(\theta_i^l \times \vartheta_i) + \boldsymbol{\gamma}(\theta_i \cdot \mathbf{X}_i) + \eta_i \qquad (7)
\end{aligned}$$

where w_i^l is the measured unskilled wage and the error term is $\eta_i \equiv \theta_i^h \varepsilon_i^h + \theta_i^l \varepsilon_i^l$. The default group is middle-skill workers. Specification (7) offers the opportunity to test whether polarization is a relevant feature of the Chinese labor market.

Table 5 reports two Mincer regressions related to wage polarization. Columns (1) and (2) are single regressions. The numbers in column (1) represent coefficients for high-skilled workers, whereas those in column (2) are for low-skilled workers. After controlling for province and industry fixed effects, the coefficients of industry input tariffs for the high- and low-skilled groups are negative and statistically significant, suggesting that wage polarization does exist in China.

In addition to reporting the education level of workers, the firm-level production data set for 2004 also reports workers' technical/professional level. There are four types of professional workers: high (1.03 percent), middle (3.76 percent), low (6.46 percent), and no professional certificates (88.74 percent). Accordingly, we re-classify all workers into three skill groups by lumping the workers with low professional certificates and those without certificates as low-skilled workers. Columns (3) and (4) in Table 5 are regressions that use the information on workers' professional certificates to classify the skill groups. After controlling for province and industry fixed effects, the coefficients of industry input tariffs for both skill groups are, once again, negative and statistically significant, which ascertains that wage polarization exists not only in developed world, but also in the largest developing country–China.

We now turn to offer a possible interpretation of wage polarization in China. After input trade liberalization, more intermediate inputs are available for Chinese domestic firms. If the imported intermediate goods are mostly capital goods, such as computer-based numerical control (CNC) machines, which are directly substitutable for low-skilled workers, the number of unskilled workers demanded falls and hence the wage premium between middle-skilled workers and low-skilled workers widens. By contrast, suppose Chinese firms import more high-quality and sophisticated products from Korea and Japan, such as intermediate inputs, which will push up the demand for high-skilled workers. Accordingly, the wage premium between high-skilled workers and middle-skilled workers also widens. Thus, we observe the phenomenon of wage polarization in China.

[Insert Table 5 Here]

3.5 Estimates by Province

Our main empirical specification (6) also permits a regional analysis by restricting the sample for 2004 by province, r:

$$\begin{aligned}\ln(\overline{w_{ir}}) &= \gamma_0 + \gamma_u \ln(w_{ir}^u) + \gamma_1(\theta_{ir} \times IT_j) + \gamma_2(\theta_{ir} \times IT_j) \times IM_{ir} + \gamma_3(\theta_{ir} \times PT_j) \\ &\quad + \gamma_4(\theta_{ir} \times PT_j) \times FX_i + \gamma_5(\theta_{ir} \times FX_i) + \gamma_6(\theta_{ir} \times IM_i) \\ &\quad + \gamma_7(\theta_i \times \vartheta_i) + \boldsymbol{\gamma}(\theta_i \cdot \mathbf{X}_i) + \varepsilon_{ir} \qquad (8)\end{aligned}$$

Table 6 picks up this task by using the firm-customs matched data for 2004, as the matched data contain firms' import status and thus allow us to perform the exact regression in line with specification (6). We first split the entire national sample into 30 provinces and repeat the Mincer regression as in column (1) in Table 3. To save space, we only report the two key variables with industry input tariffs. In particular, columns (1) and (2) in Table 6 report the coefficient of industry input tariffs (interacted with skilled share) and its related t-value. Similarly, columns (3) and (4) report the coefficient of industry input tariffs and its interaction with firms' import indicator and skilled share.

As reported in Table 6, the own coefficient of industry input tariffs is negative and statistically significant, indicating that input trade liberalization tends to widen the skill premium. There are a few provinces that have the opposite (i.e., positive) sign compared with the national one. However, they are all statistically insignificant. By contrast, the coefficients of the triple interaction term shown in column (3) have much more variations, suggesting that not all importers in every province respond forcefully to input trade liberalization, although they do in the nationwide regressions.[15] Nevertheless, our main results that input trade liberalization leads to a higher skill premium are still well preserved.

[Insert Table 6 Here]

[15] One possible reason for such erratic province-level estimation results is the possible endogeneity of changes in skilled shares over time. Due to data limitations, we are not able to handle this directly, but reserve it for future study. We thank a referee for pointing this out.

3.6 Estimates using Alternative Measured Unskilled Wages

Although the firm level data set contains information on total wage bills and head counts of skill groups, it does not report skilled or unskilled wages directly. In the Mincer regressions, we have already constructed the measured unskilled wages as the minimum level of firm wages in each (3-digit) industry-province pair. This measure enjoys several advantages. Yet in this subsection we use an alternative measure of unskilled wages to see whether the main results are robust. The main purpose of this subsection is to 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).

Using the firm level data set, we first redefine low-skilled wages as the 25th percentile of firms' wage bills by province, as reported in column (2) in Table 7. By the wage identity $\overline{w_i} = \theta_i w_i^s + (1-\theta_i) w_i^u$ and the definition of wage inequality (or skill premium) $s_i \equiv (w_i^s - w_i^u)/w_i^u$, once the unskilled wage is pinned down, we are able to obtain skilled wages $w_i^s = [\overline{w_i} - (1-\theta_i)w_i^u]/\theta_i$ as reported in column (1) in Table 7. Accordingly, wage inequality (s_i) can be calculated, which is reported in column (3).

To check with other publicly available and aggregated data sets, we first extract rural wages and wages in the computer service, finance, scientific research, and education sectors by province from China's Statistical Yearbook (2004). Rural wages are treated as a proxy for unskilled wages, as reported in column (5) in Table 7. The simple average of wages in the computer service, finance, scientific research and education sectors are reported in column (5). Accordingly, we can calculate the associated wage inequality (s_i), as reported in the last column in Table 7. By checking the numbers in columns (3) and (6), we find that the measures of wage inequality from the firm level data and the outside data source are very close. In particular, as shown in the last row, the provincial average wage inequality is 1.63 reported from the firm data, which is pretty close to 1.58 reported from the outside data source.

[Insert Table 7 Here]

Since the two aggregated numbers broadly match up, we can compute the firm-level log wage premium (or discount) relative to the average firm in province r and industry j: $\vartheta_i = \ln W_i -$

$\sum_{i \in I(jr)}^{N} (\ln W_i)/N$. We now use these new measured unskilled wages to perform the Mincer specification (6). Table 8 uses the new measured unskilled wages as a proxy of $\ln(w_i^u)$, which is defined as the 25th percentile of firms' wage bills by province. We repeat all the Mincer specifications in Table 3, using the firm-customs matched data for 2004. As our new measured unskilled wages in Table 8 do not vary by industry, we control for 2-digit industry fixed effects in all the regressions in Table 8. It turns out that the coefficients for all the variables are pretty close to their counterparts in Table 3, in signs and magnitudes. 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 widens wage inequality. Furthermore, the effect is more pronounced for importing firms. After controlling for province and industry fixed effects in the last column in Table 8, 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, even using the alternative measure of unskilled wages.

[Insert Table 8 Here]

4 Further Discussion

4.1 Alternative Estimates on Skill Premium

Thus far, our estimates have been based on the Mincer specification in equation (6). Different from the streamlined, one-step approach, this subsection presents an alternative two-step procedure. In the first step, the within-firm skilled wage premium is proxied by firms' value added. The second step regresses the predicted within-firm skilled wage premium on intermediate input tariffs at the industry level. The objective of this alternative approach is to show that our main finding is still robust: input trade liberalization widens the skill premium.

Suppose that skilled wages (w_{it}^s) paid by firm i in industry j in year t can be decomposed into two components: industrial average skilled wages (w_{jt}^s) and a firm-specific term (ε_{it}^s): $w_{it}^s = w_{jt}^s + \varepsilon_{it}^s$. Likewise, the firm's unskilled wages (w_{it}^u) are decomposed into industrial average unskilled wages

(w^u_{jt}) and a firm-specific term (ε^u_{it}): $w^u_{it} = w^u_{jt} + \varepsilon^u_{it}$. By presuming that the "fair wage" theory and related evidence a là Cahuc et al. (2006) also works for China, wage residuals can be treated as a function of the firm's value added. A more profitable firm would have more dividends for skilled workers.[16] That is, wages can be determined by the market value of specific types of labor and their firm-specific incentive pay. Therefore, a firm's wage inequality in absolute terms ($abs\_premium_{it}$) can be expressed as

$$abs\_premium_{it} \equiv w^s_{it} - w^u_{it} = (w^s_{jt} - w^u_{jt}) + (\varepsilon^s_{it} - \varepsilon^u_{it}) \tag{9}$$

Here the incentive pay to labor is presumed to be positively correlated to the firm's value added (VA_i). That is, $\varepsilon^s_{it} = \beta^s_{jt} VA_{it} + \zeta^s_{it}$ and $\varepsilon^u_{it} = \beta^u_{jt} VA_{it} + \zeta^u_{it}$, where β^s_{jt} and β^u_{jt} denote the bargaining power of skilled and unskilled labor, respectively, in industry j and year t; ζ^s_{it} and ζ^u_{it} are residual firm-specific terms that are not related to value added and follow zero-mean distributions. The sample shows that unskilled labor in Chinese manufacturing firms has almost no bargaining power (i.e. $\beta_u \to 0$).[17] Intuitively, it is easier to find substitutes for unskilled labor, and thus the supply is very elastic. Hence, a firm's absolute $s$kill premium can be given by:

$$abs\_premium_{it} = \alpha_{jt} + \beta_{jt} VA_{ijt} + (\zeta^s_{it} - \zeta^u_{it}) \tag{10}$$

where $\alpha_{jt}(= w^s_{jt} - w^u_{jt})$ is the industry-level wage inequality and $\beta_{jt} VA_{it} = \varepsilon^s_{it} - \varepsilon^u_{it}$ (β_{jt} is equal to the bargaining power of the skilled labor β^s_{jt} as $\beta_u \to 0$). Moreover, a firm's average wage can be expressed as

$$\overline{w}_{it} \equiv [\theta_{it} w^s_{it} + (1-\theta_{it}) w^u_{it}] = w^u_{jt} + \alpha_j \theta_{it} + \beta_j (\theta_{it} VA_{it}) + \zeta_{it}, \tag{11}$$

[16] Various rationales support this theoretical conjecture, as discussed in section 4.2.

[17] Here unskilled labor is presumed to have very little bargaining power because of its almost-perfect substitutability in the unskilled labor market. To verify this assumption, we first conduct a regression to estimate β_s and β_u as follows: $\overline{w}_{it} \equiv [\theta_{it} w^s_{it} + (1-\theta_{it}) w^u_{it}] = [\theta_{it} w^s_{jt} + (1-\theta_{it}) w^u_{jt}] + \beta^s_j \theta_{it} VA_{it} + \beta^u_j (1-\theta_{it}) VA_{it} + \xi_{it}$

where $\xi_{it} = \theta_{it}\zeta^s_{it} + (1-\theta)\zeta^u_{it}$ is presumed to be i.i.d. Note that in the regression, the first term on the right-hand side of the regression (i.e., the term in brackets) is controlled by an industry dummy. According to the firm-level data for 2000–06, the median β_s is greater than 0.03 whereas that of β_u is less than 10^{-5}. This suggests that the bargaining power of unskilled labor in China is negligible, and thus ε^u_{it} is indeed an i.i.d in the following regressions.

where the first equality is by definition and $\zeta_{it}(= \theta_{it}\zeta_{it}^{s} + (1-\theta_{it})\zeta_{it}^{u})$ is the error term that is not correlated to firm-specific value added and follows a zero-mean distribution.

Thus, the measured wage gap can be identified once parameters α_j and β_j are correctly estimated for each industry. To this end, we first estimate the coefficients in equation (11) by industry-year pair, using data on average wages ($\overline{w}_{it}$), shares of skilled labor(θ_{it}), and firm specific value-added (VA_{it}). Since unskilled labor wage term w_{jt}^{u} varies by industry-year pair, we treat it as a constant term *in each regression* Equation (11). The measured within-firm wage inequality can be computed by using the estimated coefficients $\widehat{\alpha}_{jt}$ and $\widehat{\beta}_{jt}$:

$$\widehat{abs\_premium}_{it} = \widehat{\alpha}_{jt} + \widehat{\beta}_{jt} VA_{it}. \tag{12}$$

The second step is a standard ordinary least squares regression of industry input tariffs on the measured wage inequality ($\widehat{abs\_premium}_{it}$). Table 9 reports the empirical results for the sample for 2000–06. Column (1) starts by running a simple regression. By abstracting away all the control variables, the industry fixed-effects estimates yield a negative coefficient of industry input tariffs. Column (2) takes a step further to control for year-specific and firm-specific fixed effects and, again, finds that a fall in industry input tariffs tends to increase wage inequality. There might be a question about whether the cost-saving effect could be weakened by tougher import competition effects because of the inclusion of output tariffs (Amiti and Konings 2007). Furthermore, other firm characteristics, such as type of ownership, size (measured by log of firm employment), or firm productivity, could also affect a firm's wage inequality. Therefore, we include all such control variables in column (3), and we still see a negative and statistically significant estimate for industry input tariffs. In addition, output trade liberalization tends to narrow wage inequality.[18] These findings are consistent with their counterparts in the streamlined one-step Mincer regressions.

[18]SOEs and FIEs are still present in the estimates after controlling for firm-specific and year-specific fixed effects. This is merely because some SOEs (FIEs) could switch to non-SOEs (non-FIEs) or vice versa. To save space, we do not report the transitional probability for SOEs and FIEs, but they are available upon request.

4.2 Endogeneity Issues

In the previous estimations, we treated input trade liberalization as exogenous. However, tariff formation could be endogenous in the sense that wage inequality could have a reverse effect on tariff changes. With widening wage inequality, unskilled workers could blame the free trade policy 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 given that labor unions in China are symbolic organizations. In addition, if these types of political factors are time invariant, the fixed-effect panel estimates in column (3) of Table 9 have accounted and controlled for them (Goldberg and Pavcnik 2005). However, if they are time variant, the two-step estimates procedure could be biased.

Moreover, if the residual, ε_{it}^{u}, in Equation (11) is also correlated to firm's value-added, the estimated $\widehat{\beta}_{jt}$ is also biased. The sign of the bias depends on the selection of low-skilled workers into high value-added firms, which is theoretically ambiguous.[19] In any case, the instrumental variables (IV) approach is needed to control for these types of endogeneity issues, which is our last robustness check.

It is challenging to find an ideal instrument for tariffs. Inspired by Amiti and Davis (2012), 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). The last column in Table 9 reports the two-stage least squares estimates, treating industry input tariffs as endogenous. It turns out that input tariffs and output tariffs are statistically significant with the anticipated signs.

We now perform related statistical tests to check the validity of the instrument. The bottom module in Table 9 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

[19] We thank a referee for correctly suggesting this point.

remove tariff barriers in industries with high initial tariffs. In addition, several tests were performed to verify the quality of the instruments. First, we used 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 9, 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 highly significance level. The tests suggest that the instrument is valid and the specifications are well justified.

[Insert Table 9 Here]

4.3 Discussions on Possible Mechanisms

The objective of this subsection is to provide a possible mechanism to enrich our understanding of the main empirical finding that input trade liberalization leads to an increase in wage inequality.

Conceptually, models that focus on firm-level exporting exhibit some commonality with those focusing on firm-level importing (such as the fixed costs of accessing foreign import markets and ensuing selection). However, the impact on firm-level wage inequality of input trade liberalization could also reflect distinct differences in how employers might share the surplus with various input factors. For example, it might depend on the production relationship between imported inputs and skilled/unskilled workers. Although there has not yet been such a formal theoretical model in the literature, it is obvious that the results could go either way.

Inspired by the literature on "fair wages," such as Egger and Kreickemeier (2012), a possible interpretation of our finding is that skilled workers have greater bargaining power with their employers than unskilled workers and, as a result, the incomes of skilled workers are more closely linked to firms' economic rent (measured by value added). However, 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 firm value added, which, in turn, widens wage inequality, since skilled labor enjoys a larger proportion of the incremental profits, or more precisely, value added. The Appendix provides a simple model to explain the empirical results.

It is important to stress that this interpretation (and more formally, the theoretical framework in the Appendix) does not rule out other possible channels or mechanisms. There are other possible interpretations. For example, an additional employed skilled employee may generate a larger surplus. However, after bargaining, unskilled employees might receive a smaller share than skilled employees. The large incremental surplus can be more than proportionally larger than the bargaining share difference to unskilled workers. Accordingly, skilled workers are revealed to be associated with a larger proportion of value added or firm profitability, although we are not able to check such possible alternative channels due to data limitations.[20]

5 Concluding Remarks

China has experienced a dramatic tariff reduction since its accession to the WTO in 2001. However, the country's wage inequality and, more broadly, income inequality have also increased. To our knowledge, so far there is no micro-level evidence to explore the link between the two. Since there are no firm-level data on wages for skilled and unskilled labor, we developed a Mincer-type econometric approach to estimate within-firm wage inequality based on imperfect Chinese firm-level data on wage information. As in other ambitious attempts to investigate important issues with imperfect data, we had to make some compromises to conduct our estimates. Nevertheless, the finding that a fall in input tariffs leads to an increase in measured wage inequality is robust under different econometric specifications.

[20] We appreciate a referee for pointing this out.

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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
Pure Exporter Indicator	0.066	0.247	0.045	0.207
Importer Indicator	0.36	0.47	0.38	0.48
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
Between-firm 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 firm-level data for 2004 only, whereas the last two columns cover firm-level data for 2000–06.

Table 2: Baseline Mincer Regression Using Data for 2004

Firm Average Wages	(1)	(2)	(3)	(4)	(5)	(6)
Measured Unskilled Wages	0.293***	0.296***	0.296***	0.319***	0.353***	0.375***
	(12.42)	(12.56)	(12.55)	(12.87)	(12.76)	(17.16)
Skill Share×Industry Input Tariffs	-0.193***	-0.179***	-0.178***	-0.098***	-0.035*	-0.065**
	(-15.07)	(-13.86)	(-13.78)	(-6.79)	(-1.78)	(-2.14)
Skill Share×Industry Output Tariffs	0.011**	0.006	0.019***	0.011**	0.016**	0.005
	(2.55)	(1.48)	(3.64)	(2.38)	(2.45)	(1.01)
Skill Share×Industry Output Tariffs			-0.038***	0.003	0.007	-0.003
× Exporter Indicator			(-4.47)	(0.34)	(0.94)	(-0.45)
Skill Share×SOEs	0.153	0.161	0.169	-0.041	-0.023	0.367***
	(1.16)	(1.23)	(1.29)	(-0.37)	(-0.21)	(3.02)
Skill Share×Foreign Indicator	2.150***	1.880***	1.867***	1.132***	1.008***	1.146***
	(33.93)	(27.26)	(27.03)	(17.25)	(15.37)	(17.14)
Skill Share×Log Sales	0.169***	0.143***	0.131***	0.096***	0.055***	0.050***
	(11.41)	(9.40)	(8.53)	(6.31)	(3.22)	(2.91)
Skill Share×TFP(Olley-Pakes)	1.194***	1.246***	1.245***	0.804***	0.714***	0.969***
	(12.83)	(13.19)	(13.18)	(10.17)	(9.40)	(11.36)
Skill Share×Exporter Indicator		0.753***	1.128***	0.378***	0.364***	0.494***
		(11.65)	(10.57)	(3.78)	(3.59)	(4.90)
Skill Share×Pure Exporter Indicator		-0.319***	-0.293***	0.205*	0.055	-0.144
		(-2.81)	(-2.58)	(1.89)	(0.51)	(-1.31)
Skill Share	1.286***	1.285***	1.285***	1.293***	1.295***	1.291***
× Between-firm Wage Premium	(201.53)	(201.04)	(201.01)	(198.72)	(197.73)	(196.87)
Skill Share × Log Sales						0.007*
×Industry Input Tariffs						(1.85)
Region Fixed Effects	No	No	No	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Region × Industry Fixed Effects	No	No	No	No	Yes	No
Observations	119,334	119,334	119,334	119,334	119,334	119,334
R-squared	0.74	0.74	0.74	0.77	0.77	0.76

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. Column (4) controls for region fixed effects and industry fixed effects. Column (5) controls for a full set of interacted industry-region dummies. Column (6) adds an interaction among skill share, industry input tariffs, and log sales.

Table 3: Mincer Regression Using Matched Data for 2004

Firm Average Wages	(1)	(2)	(3)	(4)
Measured Unskilled Wages	0.385***	0.378***	0.369***	0.340***
	(12.93)	(12.78)	(17.10)	(11.59)
Skill Share×Industry Input Tariffs	-0.233***	-0.222***	-0.139***	-0.191***
	(-7.01)	(-6.71)	(-3.73)	(-6.74)
Skill Share × Industry Input Tariffs	-0.148***	-0.147***	-0.100**	-0.093**
× Importer Indicator	(-2.95)	(-2.95)	(-2.08)	(-2.18)
Skill Share× Industry Output Tariffs	0.077***	0.072***	0.035*	0.067***
	(3.28)	(3.07)	(1.75)	(3.35)
Skill Share× Industry Output Tariffs	-0.095***	-0.090***	-0.047**	-0.103***
× Exporter Indicator	(-3.96)	(-3.76)	(-2.55)	(-5.03)
Skill Share× SOEs	1.484***	1.476***	1.305***	1.734***
	(3.44)	(3.42)	(3.24)	(4.96)
Skill Share× Foreign Indicator	1.162***	1.261***	1.137***	0.362***
	(8.96)	(9.57)	(11.78)	(3.17)
Skill Share× Log Employment	0.008	-0.001	-0.055	0.279***
	(0.16)	(-0.01)	(-0.94)	(6.17)
Skill Share × TFP(Olley-Pakes)	1.202***	1.183***	0.983***	0.914***
	(5.28)	(5.23)	(3.39)	(4.70)
Skill Share × Exporter Indicator	1.577***	1.624***	0.988***	1.324***
	(5.26)	(5.43)	(3.57)	(5.34)
Skill Share	1.276***	1.273***	1.278***	1.262***
× Between-firm Wage Premium	(97.82)	(97.28)	(92.28)	(96.91)
Skill Share × Importer Indicator	0.311	0.255	-0.310	-0.154
	(0.65)	(0.53)	(-0.69)	(-0.37)
Skill Share×Processing Indicator		-0.858***		
		(-4.94)		
Region Fixed Effects	Yes	Yes	Yes	No
Province Fixed Effects	No	No	No	Yes
Region × Industry Fixed Effects	No	No	Yes	No
Observations	18,820	18,820	18,820	18,820
R-squared	0.79	0.79	0.80	0.83

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) control for region fixed effects. Column (3) controls for a full set of interacted industry-region dummies with bootstrapped replicated t-values. Finally, column (4) controls for province fixed effects.

Table 4: Mincer Regression Using the 1997 IO table (2000-06)

Firm Average Wages	(1)	(2)	(3)	(4)	(5)
Measured Unskilled Wages	0.247***	0.246***	0.248***	0.343***	0.340***
	(11.24)	(15.69)	(15.79)	(24.75)	(20.57)
Skill Share×Industry Input Tariffs	-0.060***	-0.070***	-0.076***	-0.009**	-0.048***
	(-7.58)	(-13.05)	(-14.12)	(-2.02)	(-8.03)
Skill Share×Industry Output Tariffs	0.021***	0.012***	0.019***	0.018***	0.017***
	(5.85)	(4.84)	(7.01)	(8.27)	(6.56)
Skill Share×Industry Output Tariffs			-0.020***	-0.019***	
× Exporter Indicator			(-3.62)	(-4.02)	
Skill Share×Industry Output Tariffs					-0.016***
× One Lag Exporter Indicator					(-2.92)
Skill Share×SOEs	0.252*	0.395***	0.459***	1.311***	1.370***
	(1.89)	(3.70)	(4.31)	(15.52)	(13.26)
Skill Share×Foreign Indicator	2.334***	2.406***	2.070***	-0.175***	-0.386***
	(38.30)	(44.64)	(36.60)	(-3.75)	(-6.96)
Skill Share×Log Employment	-0.126***	-0.286***	-0.345***	0.179***	
	(-7.08)	(-19.77)	(-23.61)	(15.32)	
Skill Share × One-Lag Log Employment					0.166***
					(11.86)
Skill Share × TFP(Olley-Pakes)	1.821***	1.904***	1.963***	0.882***	
	(21.48)	(36.11)	(36.44)	(22.63)	
Skill Share × One-Lag TFP(Olley-Pakes)					0.560***
					(12.12)
Skill Share × Exporter Indicator			1.179***	0.077	
			(14.84)	(1.17)	
Skill Share × One Lag Exporter Indicator					0.074
					(0.97)
Skill Share × Between-firm Wage Premium	1.287***	1.392***	1.390***	1.376***	1.432***
	(216.83)	(306.03)	(305.74)	(310.75)	(263.00)
Provincial Fixed Effects	No	No	No	Yes	Yes
Year Fixed Effects	No	No	No	Yes	Yes
Year Covered	2004	2000-06	2000-06	2000-06	2000-06
Observations	131,475	507,084	507,084	506,993	345,513
R-squared	0.75	0.74	0.74	0.80	0.79

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.

Table 5: Mincer Regression Using Three Skill Categories (2004)

Skill Level Category:	High	Low	High	Low
Regressand: Firm Avergae Wages	(1)	(2)	(3)	(4)
Measured Unskilled Wages	0.175***		0.177***	
	(15.87)		(41.44)	
Skill Share×Industry Input Tariffs	-0.313***	-0.087***	-0.235***	-0.075***
	(-5.20)	(-7.62)	(-10.11)	(-19.53)
Skill Share×Industry Output Tariffs	0.062***	-0.010	-0.052***	-0.004***
	(2.28)	(-0.53)	(-4.89)	(-3.53)
Skill Share×Industry Output Tariffs	0.134***	-0.003	0.007	0.004**
× Exporter Indicator	(2.79)	(-0.71)	(0.34)	(2.06)
Skill Share×SOEs	1.767***	0.431***	1.473***	0.098***
	(2.52)	(2.70)	(5.77)	(2.57)
Skill Share×Foreign Indicator	2.057***	-0.083*	1.116***	0.049***
	(6.33)	(-1.64)	(7.65)	(3.57)
Skill Share×Log Employment	0.939***	-0.015	0.409***	-0.061***
	(9.66)	(-0.94)	(10.25)	(-12.72)
Skill Share × TFP(Olley-Pakes)	-1.989***	0.370***	0.003	0.162***
	(-9.92)	(6.77)	(0.03)	(11.08)
Skill Share × Exporter Indicator	3.360***	0.158	-0.104	0.023
	(6.36)	(0.95)	(-0.44)	(1.05)
Skill Share	2.067***	1.420***	1.441***	1.024***
× Between-firm Wage Premium	(269.8)	(526.1)	(384.7)	(1627)
Province Fixed Effects	Yes		Yes	
Industry Fixed Effects	Yes		Yes	
Observations	119,334		118,793	
R-squared	0.82		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. There are three levels of skilled workers in the regressions, in which the middle skill level workers are used as a default reference group. Columns (1) and (2) are a single regression with both industry and province fixed effects. Columns (3) and (4) are a single regression with both industry and province fixed effects, using workers' technical certificates to classify three types of skilled workers.

Table 6: Provincial Mincer Regression Using Matched Data for 2004

Key Variable	Skill Share × Industry Input Tariffs		Skill Share × Industry Input Tariffs × Importer Indicator	
Province	Coefficient	t-value	Coefficient	t-value
Anhui	-0.588	(-1.56)	0.577	(1.39)
Beijing	-0.514**	(-2.08)	-0.311	(-0.86)
Chongqing	-0.142	(-0.63)	-0.213	(-1.61)
Fujian	-0.266**	(-2.27)	-0.005	(-0.02)
Gangsu	-1.136*	(-2.12)	-5.074***	(-2.82)
Giuzhou	-0.250***	(-3.09)	-0.179	(-1.58)
Guangdong	-0.092	(-0.39)	-0.826*	(-1.64)
Guangxi	-0.946**	(-43.21)	10.984***	(14.08)
Hainan	1.162	(0.85)	-2.114	(-1.25)
Hebei	-0.076	(-0.68)	0.039	(0.25)
Heilongjiang	-0.675	(-1.20)	2.848***	(4.72)
Henan	0.077	(0.41)	1.384*	(1.68)
Hubei	0.090	(0.59)	0.383	(1.26)
Hunan	0.003	(0.02)	0.423***	(2.47)
Inner Mogolia	-1.226***	(-3.25)	1.684	(1.47)
Jiangxi	-0.265	(-1.37)	0.394	(1.30)
Jiansu	-0.267***	(-3.60)	0.101	(1.07)
Jilin	0.178	(0.40)	1.022	(1.17)
Liaoning	0.135	(0.99)	-0.054	(-0.27)
Qinghai	0.244	-0.01	0.965	-0.01
Shangdong	0.131	(0.39)	1.090*	(1.82)
Shanghai	-0.012	(-0.17)	-0.252***	(-2.89)
Shangxi	-0.539***	(-3.70)	-0.079	(-0.43)
Shaanxi	0.051	(0.20)	-0.270	(-0.98)
Sichuan	-0.128	(-0.70)	0.203	(0.75)
Tianjin	-0.024	(-0.17)	-0.489***	(-2.47)
Xinjiang	2.756**	(2.14)	-2.449*	(-1.75)
Yunnan	-0.501	(-1.49)	-0.691**	(-2.10)
Zhejiang	-0.297***	(-4.15)	0.654***	(2.86)

Notes: This table repeats the provincial Mincer regression specified in column (1) in Table 3 by using firm-customs matching data for 2004. 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) report the coefficient and t-value of the variable of skill share interacted with industry input tariffs, respectively. Columns (3) and (4) report the coefficient and t-value of the variable of skill share interacted with industry input tariffs and the importer indicator.

Table 7: Wage Data Comparisons for 2004

Data Source	Firm-level Data in 2004			External Data in 2004		
Average Wages by Skill Group	Skilled	Unskilled	Inequality	Skilled	Unskilled	Inequality
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 column (2) are defined as the 25% percentile of firm wages by province. For the calculations and interpretation of the variables in other columns, see the related text.

Table 8: Mincer Regression Using Matched Data and Alternative Measured Unskilled Wages (2004)

Firm Average Wages	(1)	(2)	(3)	(4)
Alternative Measured Unskilled Wages	0.008	0.006	0.015	0.007
	(0.53)	(0.38)	(1.12)	(0.57)
Skill Share×Industry Input Tariffs	-0.117***	-0.105***	-0.086***	-0.120***
	(-3.52)	(-3.15)	(-3.05)	(-3.50)
Skill Share × Industry Input Tariffs	-0.118**	-0.114**	-0.065	-0.100**
× Importer Indicator	(-2.41)	(-2.33)	(-1.56)	(-2.05)
Skill Share× Industry Output Tariffs	0.032	0.027	0.022	0.031**
	(1.35)	(1.15)	(1.09)	(2.20)
Skill Share× Industry Output Tariffs	-0.047**	-0.042*	-0.052***	-0.047***
× Exporter Indicator	(-1.98)	(-1.74)	(-2.58)	(-3.20)
Skill Share× SOEs	1.506***	1.498***	1.683***	1.522***
	(3.56)	(3.55)	(4.96)	(3.81)
Skill Share× Foreign Indicator	1.031***	1.134***	0.359***	1.003***
	(8.04)	(8.70)	(3.17)	(8.43)
Skill Share× Log Employment	-0.064	-0.075	0.219***	-0.061**
	(-1.26)	(-1.46)	(4.94)	(-2.39)
Skill Share × TFP(Olley-Pakes)	0.969***	0.947***	0.694***	0.973***
	(4.34)	(4.27)	(3.66)	(3.79)
Skill Share × Exporter Indicator	1.005***	1.052***	0.717***	1.015***
	(3.37)	(3.53)	(2.90)	(5.03)
Skill Share	1.281***	1.279***	1.265***	1.282***
× Between-firm Wage Premium	(97.77)	(97.30)	(96.94)	(156.18)
Skill Share × Importer Indicator	-0.019	-0.104	-0.565	-0.186
	(-0.04)	(-0.22)	(-1.39)	(-0.42)
Skill Share×Processing Indicator		-0.932***		
		(-5.39)		
Industry Fixed Effects	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	No
Province Fixed Effects	No	No	No	Yes
Region × Industry Fixed Effects	No	No	Yes	No
Observations	18,820	18,820	18,820	18,820
R-squared	0.80	0.80	0.83	0.80

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. The alternative measured unskilled wages are constructed by the 25th percentile of firms' wage bills by province. Columns (1) and (2) control for region fixed effects. Column (3) controls for a full set of interacted industry-region dummies with bootstrapped replicated t-values. Finally, column (4) controls for province fixed effects. Two-digit industry-level fixed effects are included in all specifications.

Table 9: Two-step Estimates of Wage Inequality Using Firm Value-Added Data

Econometric Method:	OLS			2SLS
Regressand:	(1)	(2)	(3)	(4)
Measured Firm's Wage Inequality	$\widehat{abs\_premium}_{it}$	$\widehat{abs\_premium}_{it}$	$\widehat{abs\_premium}_{it}$	$\Delta\widehat{abs\_premium}_{it}$
Industry Input Tariffs	-0.534***	-0.071***	-0.138***	-0.083**
	(-53.87)	(-7.65)	(-12.92)	(-4.69)
Industry Output Tariffs			0.018***	0.012***
			(11.26)	(9.90)
State-owned Enterprises			-0.070	0.242**
			(-0.55)	(2.52)
Foreign Firms			-0.026	0.097
			(-0.31)	(1.14)
Log of Firm Employment			0.058**	0.040**
			(2.47)	(1.98)
Firm Relative TFP			4.754***	5.494***
			(41.16)	(91.43)
Cragg-Donald Wald F-statistic				1.1e+05†
Anderson canon. corr. LM χ^2				76,422†
Industry-Specific Fixed Effects	Yes	No	No	Yes
Year-Specific Fixed Effects	No	Yes	Yes	Yes
Firm-Specific Fixed Effects	No	Yes	Yes	No
Year Covered	2004	2000-06	2000-06	2000-06
Observations	152,658	593,207	398,894	242,895
R-squared	0.37	0.06	0.11	0.08
		First-Stage Regressions		
IV: One-Lag Industry Input Tariffs	–	–	–	-0.297***
				(-333.9)

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. Regressands in columns (1)-(3) are levels of the firm wage gap ($\widehat{wgap}_{ijt}$). The regressand and all regressors in column (4) are in the first difference. IV reports the coefficient of one-lag industry input tariffs using the first difference in firms' wage inequality as the regressand in column (3). All columns except column (1) include the whole sample. Column (1) includes the sample for 2004 only.

Appendix: A Theoretical Intepretation

This appendix develops a simple theoretical framework to explain our key empirical finding that input trade liberalization increases wage inequality. To investigate the effect of trade liberalization on wage inequality, instead of focusing on homogeneous labor, we extend the n-countries model in Amiti and Davis (2012) by introducing skilled and unskilled workers into final goods production.

- **Consumption (of Final Goods)**

A representative consumer allocates her expenditure E across a continuum of available final goods varieties i to

$$\underset{p(i)}{\text{Min}}\ E = \int p(i)q\,(i)\,di \quad \text{s.t.} \quad \left[\int q\,(i)^{\frac{\sigma-1}{\sigma}}\,di\right]^{\frac{\sigma}{\sigma-1}} = U \tag{13}$$

where p denotes the price, q the quantity for variety i, and $\sigma > 1$ is the elasticity of substitution between final goods varieties. The demand curve for final product i is $q(i) = Q[p(i)/P]^{-\sigma}$ and the corresponding revenue is $r(i) = R[p(i)/P]^{1-\sigma}$, where $Q \equiv U$ and P is an aggregate price index given by $P = [\int p(i)^{1-\sigma}di]^{\frac{1}{1-\sigma}}$ with $PQ = R$.

- **Production of Final Goods (and Intermediate Inputs)**

Each country has a sector of intermediate inputs that are available in a fixed measure of varieties on a unit interval, $[0, 1]$.[21] These inputs are produced under constant returns to scale, with one unit of unskilled labor producing one unit of the intermediate input. Therefore, under free entry, the local price of the domestic intermediate inputs is also equal to the unskilled wage $\underline{w}$.

To produce final goods, each potential entrant/firm has to incur a sunk cost f_e to obtain a random draw $\lambda_i = (\phi_i, \theta_i, t_{Mi}, t_{Xi})$. The respective elements are the firm's production technology (productivity ϕ_i), the required share of skilled labor in production θ_i, and the idiosyncratic components of marginal trade costs in importing and exporting (t_{Mi} and t_{Xi}). That is, for a given technology ϕ_i, we assume that production requires each firm to employ a particular share of skilled labor (presumably, ϕ_i and θ_i are positively correlated).

After learning their characteristics, some firms exit without producing, and the remaining mass of firms M will choose labor (skilled and unskilled) and intermediate inputs to produce the final outputs destined for each market to maximize profits. The steady state requires that new entry rate matches firm exit rate (at a constant hazard death rate).

Firm technology is represented by the following Cobb-Douglas production function with a composite intermediate input M and a composite labor input L:

$$q_i = \phi_i L^{\alpha} M^{1-\alpha} - f. \tag{14}$$

where f is the fixed cost of production. We assume hereafter that all fixed costs are in units of domestic intermediates.[22]

The composite labor input L is given by,

$$L = \min\{\frac{l_i^s}{\theta_i}, \frac{l_i^u}{1-\theta_i}\} \tag{15}$$

[21] The assumption of a fixed measure for domestic intermediate inputs avoids the complication of multiple equilibria. See further discussion of this issue in Venables (1996) and Amiti and Davis (2011).

[22] This assumption is similar to that in Helpman, Itskhoki, and Redding (2010b), in which firm fixed costs are paid in a competitive outside good.

where l_i^s and l_i^u are skilled and unskilled labor inputs. $\frac{\theta_i}{1-\theta_i}$ is the skilled-unskilled labor ratio. The Leontief specification allows us to explain our main result in the most transparent way. An alternative specification allowing for substitution between skilled and unskilled labor produces the same insight, but complicates the model significantly.

Unlike unskilled labor, skilled labor receives a wage, w_i^s, that is related to the performance of the firm for which they work. Following the fair-wage argument in Amiti and Davis (2011), the skilled-labor wage, $w_i^s = w(\pi_i)$, is a function of the firm's profit/economic rent (in the main text we use value-added to measure the economic rent). As inspired by Acemoglu and Pischke (1999) and later evident from Cahuc *et al.* (2006), we assume that skilled workers have more bargaining power in production than unskilled workers, which is normalized to zero as a benchmark. Specifically, we assume that $w_i^u = \underline{w}$, $w_i^s = w(\pi_i) > \underline{w}$, and $w'(\pi_i) > 0$. Therefore, the wage for the composite labor in equation (15) becomes,

$$\begin{aligned} \overline{w}_i(\pi_i) &= \theta_i w(\pi_i) + (1-\theta_i)\underline{w} \\ &= \theta_i[w(\pi_i) - \underline{w}] + \underline{w} \\ \text{or}, \overline{w}_i(\pi_i) &= \theta_i \Delta w_i + \underline{w} \end{aligned} \tag{16}$$

where $\Delta w_i = w(\pi_i) - \underline{w}$ is the wage gap between skilled and unskilled labor. Furthermore, since $\overline{w}_i' = \theta_i w'$, the relationship between $\overline{w}_i$ and π_i in equation (16) is illustrated in Figure A1.

[Insert Figure A1 Here]

Without loss of generality, we normalize the unskilled wage to unity.[23] Thus, the local price of the domestic intermediate inputs of each country is also equal to unity, and the price index of the composite intermediate inputs becomes

$$P_{M_i} = [1 + n\tau_{Mi}^{1-\gamma}]^{\frac{1}{1-\gamma}} \leq 1 \tag{17}$$

where $\tau_{Mi} = \tau_M t_{Mi} > 1$ is the effective price (to firm i) of the intermediate inputs from a foreign country that consists of a common iceberg component $\tau_M > 1$ and a firm-specific component $t_{Mi} \geq 1$. Parameter $\gamma > 1$ is the elasticity of substitution between any two varieties of intermediates.

Therefore, the marginal cost corresponding to equation (14) is

$$\begin{aligned} c_i &= \frac{k\overline{w}_i^{\alpha} P_{M_i}^{1-\alpha}}{\phi_i} \\ &= \frac{k\overline{w}_i^{\alpha}[1 + n\tau_{Mi}^{1-\gamma}]^{\frac{1-\alpha}{1-\gamma}}}{\phi_i}, \end{aligned} \tag{18}$$

where $k \equiv \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$. Because of the mark-up pricing rule, the domestic price of a final goods variety is $p_{id} = c_i/\rho$. Thus, revenue for firm i in the domestic market becomes

$$\begin{aligned} r_{id} &= RP^{\sigma-1} p_{id}^{1-\sigma} \\ &= RP^{\sigma-1}[\frac{kW_i^{\alpha}}{\rho\phi_i}]^{1-\sigma}[1 + n\tau_{Mi}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}} \end{aligned} \tag{19}$$

[23] For simplicity, we do not model the unskilled labor wage as a function of firm profit, although our theoretical prediction still holds if we do so.

The total revenue is

$$\begin{aligned} r_i &= (1+n\tau_{Xi}^{1-\sigma})r_{id} \\ &= (1+n\tau_{Xi}^{1-\sigma})RP^{\sigma-1}[\frac{k\overline{w}_i^{\alpha}}{\rho\phi_i}]^{1-\sigma}[1+n\tau_{Mi}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}} \end{aligned} \tag{20}$$

where $\tau_{Xi}=\tau_X t_{Xi}>1$ is firm i's idiosyncratic iceberg export cost to serve a foreign market, which consists of a common component $\tau_X>1$ and a firm-specific component $t_{Xi}\geq 1$. Notice that equation (20) reflects the fact that, in addition to the domestic market, exporting gives a firm access to n additional foreign markets, each of which is $\tau_{Xi}^{1-\sigma}<1$ times the size of the former.

Therefore, the profit for a firm that exports final goods and imports intermediates is

$$\begin{aligned} \pi_i(\overline{w}_i) &= \frac{r_i}{\sigma}-[f+n(f_X+f_M)] \\ &= (1+n\tau_{Xi}^{1-\sigma})(\frac{RP^{\sigma-1}}{\sigma})[\frac{k\overline{w}_i^{\alpha}}{\rho\phi_i}]^{1-\sigma}[1+n\tau_{Mi}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}}-[f+n(f_X+f_M)] \end{aligned} \tag{21}$$

where f is the fixed cost of production, f_X (*resp.* f_M) is the fixed cost of exporting to (*resp.* fixed cost of importing from) a foreign country. When a firm only exports final goods, its profit becomes

$$\pi_i(\overline{w}_i)=(1+n\tau_{Xi}^{1-\sigma})(\frac{RP^{\sigma-1}}{\sigma})[\frac{k\overline{w}_i^{\alpha}}{\rho\phi_i}]^{1-\sigma}-(f+nf_X). \tag{22}$$

When a firm only imports intermediates, its profit becomes

$$\pi_i(\overline{w}_i)=(\frac{RP^{\sigma-1}}{\sigma})[\frac{k\overline{w}_i^{\alpha}}{\rho\phi_i}]^{1-\sigma}[1+n\tau_{Mi}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}}-(f+nf_M) \tag{23}$$

When a firm only serves the domestic market, its profit is

$$\pi_i(\overline{w}_i)=(\frac{RP^{\sigma-1}}{\sigma})[\frac{k\overline{w}_i^{\alpha}}{\rho\phi_i}]^{1-\sigma}-f \tag{24}$$

Firms whose profits are negative exit the market completely.

For given macro variables (i.e., R and P), Equation (16), together with the corresponding one in Equations (21) to (24), can determine a firm's profit and wages for the composite labor (and, therefore, the wage gap or the skilled wage using Equation (16)). Among these four modes, each firm chooses the one that maximizes its profit. Thus, firm wages, profits and all other variables are determined conditional on the macro variables.

Following Amiti and Davis (2012), since most firms neither export nor import, we assume that (i) $f_X\geq f$ and (ii) $f_M>(\frac{f}{n})[(1+n\tau_M^{1-\gamma})^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}}-1]$. The first assumption ensures that zero-profit firms do not export and the second that a firm earning zero profit when it fails to import intermediates will not find it advantageous to import intermediates.[24] Together, these assumptions imply that there is an equilibrium cut-off such that a firm survives if and only if $\phi\geq\phi^*$. Therefore, the profits of a firm conditional on the cut-off can be written as $\pi_i=\pi(\lambda_i,\widehat{\phi}^*)$, where $\widehat{\phi}^*$ is the

[24] The net gains from importing intermediates are $[(1+n\tau_{Mv}^{1-\gamma})^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}}-1](\frac{RP^{\sigma-1}}{\sigma})[\frac{k\overline{w}_v^{\alpha}}{\rho\phi_v}]^{1-\sigma}-nf_M$. For a zero-profit firm, $(\frac{RP^{\sigma-1}}{\sigma})[\frac{k\overline{w}_v^{\alpha}}{\rho\phi_v}]^{1-\sigma}=f$. Therefore (setting $t_{Mv}=1$), the condition $[(1+n\tau_M^{1-\gamma})^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}}-1]f-nf_M<0$ means that the maximum gain from importing intermediates is negative.

notional cut-off productivity because zero-profit firms have wages equal to unity (see Equation (16)):

$$\pi(\widehat{\phi}^*, \overline{w}_i(0)) = (\frac{RP^{\sigma-1}}{\sigma})[\frac{k}{\rho\widehat{\phi}^*}]^{1-\sigma} - f = 0. \tag{25}$$

From Equation (25), we can obtain the macro values consistent with $\widehat{\phi}^*$:

$$RP^{\sigma-1} = \sigma f(\frac{k}{\rho\widehat{\phi}^*})^{1-\sigma}. \tag{26}$$

With Equation (26), from the previous firm's optimization problem we can obtain $\pi_i = \pi(\lambda_i, \widehat{\phi}^*)$, which is consistent with this notional cut-off and all other equilibrium variables.

Therefore, using Equation (21) and Equation (16), it is straightforward to obtain the following proposition.

Proposition: *A reduction of t_{Mi} increases the firm-level wage inequality Δw_i between skilled and unskilled labor.*

This result is illustrated in Figure A1. From Equation (21) notice that $\pi'(\overline{w}_i) < 0$ (i.e., higher wages reduce profits, *ceteris paribus*) and the intersection of the $\overline{w}_i(\pi_i)$ curve and the $\pi_i(\overline{w}_i)$ curve determines the equilibrium firm profit and wage (for a given mode). A reduction of t_{Mi} shifts the $\pi_i(\overline{w}_i)$ curve up and, as a result, raises both π_i and $\overline{w}_i$. Consequently, from Equation (16), the wage gap increases.

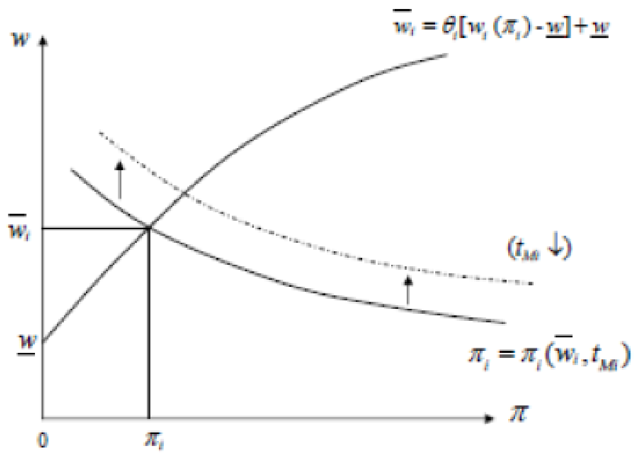

Figure A1: Determination of Firm Average Wages and Profit