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Wage Inequality and Input Trade Liberalization: Firm-Level Evidence from China[1]

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Abstract: This paper investigates how input trade liberalization affects firm-level wage inequality between skilled and unskilled labor. A fall in input tariffs generates increased firm profits, which, in turn, widens wage inequality since skilled labor enjoys a larger proportion of the incremental profits. In the paper we analyze this type of channel with an augmented Amiti-Davis(2012) model. Using Chinese firm-level production data, we first estimate and calculate firm-level wage inequality. We find that, in China, wage inequality is much greater than it is in the U.S. After controlling for possible endogeneity, we find empirical evidence consistent with our theoretical prediction that input trade liberalization widens firm-level wage inequality. Reductions in input tariffs are found to increase firm-level wage inequality by approximately 23% during the period under study.

JEL Classifications: F10, F12, F14
Keywords: Wage Inequality, Input Trade Liberalization, Firm Evidence

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1 Introduction

The impact of trade liberalization on wage inequality between skilled and unskilled labor is one of the most important research topics in empirical international trade. Initially, trade economists focused on the nexus between outsourcing and wage inequality. Previous works, such as Feenstra and Hanson (1996, 1999) and Grossman and Rossi-Hansberg (2008), investigated the impact of outsourcing on wage inequality. Feenstra and Hanson (1999, 2003) argued that, in the presence of vertical integration, outsourcing would increase wage inequality in developed countries like the U.S in the same manner as did technological developement. Grossman and Rossi-Hansberg (2008) argued that the gains from improved offshoring opportunities could be shared by all domestic parties. As such, less costly offshoring might not necessarily affect wage inequality between skilled and unskilled labor. Recently, research interests shifted to an examination of the impact of trade liberalization on wages. Amiti and Davis (2012) analyzed Indonesian firm-level data and found that output tariff reductions lowered wages at import-competing firms but raised wages at exporting firms. Meanwhile, input tariffs fostered wages at import-using firms relative to those firms that only used domestic intermediate inputs.

Different from Amiti and Davis (2012), this paper focuses on the impact of input trade liberalization on firm-level wage inequality between skilled and unskilled labor. This approach is in line with Feenstra and Hanson (1996, 1999). We analyze Chinese firm-level data and find that input tariff reductions widen the within-firm wage inequality. This is mainly because input tariff reductions generate more profits, which, in turn, increase within-firm wage inequality since skilled labor enjoys a larger proportion of the incremental profit, as suggested by the fair-wages literature (e.g. Egger and Kleickemier, 2012). In this paper, we extend Amiti and Davis (2012) to introduce wage inequality to the model, and we clearly predict a negative relationship between input tariffs and wage inequality.

This paper contributes to the literature in at least four important ways. First, it provides direct evidence of China's firm-level wage inequality in the new century. We first estimate and compute wage gaps between skilled and unskilled labor, and find that the absolute annual wage gap in the sample is RMB 11,320 (equivalently, \$1,800). In addition, the relative wage inequality is 2.21–with wages for skilled labor more than twice that for unskilled labor. This figure is much higher than the one found in the U.S. (approximately 1.7) during the same period of 2000 to 2006 (Feenstra, 2010). The figure is also higher than the one in European countries, largely due to the fact that European countries typically have much stronger labor unions (Kranz, 2006). Perhaps because of data limitations, previous work on wage inequality only focused on urban industrial-level data (e.g., Khan and Riskin, 1998) or limited survey small sample data (e.g., Xu and Li, 2008). To the best of our knowledge, this paper is the first to use rich and disaggregated full-sample firm-level data to explore the issue. Our findings, therefore, provide micro-level evidence to understand the exaggerated aggregated wage inequality in China.

Second, the paper enriches our understanding of the sources of China's growing wage–and, it follows, income inequality, as wage inequality is an important component of income inequality.[1] Ongoing trade liberalization and rising wage inequality simultaneously occur in many developing countries such as Argentina (Galiani and Sanguinetti, 2003), Chile (Beyer *et al.*, 1999) and other Latin American countries (Atolia, 2007). As the second largest economy and the largest exporter in the world, China is also one of the countries with greatest income inequality. China's Gini coefficient in 2012 was 0.49, which is much higher than the figure in the U.S. (aproximately 0.30). It is a concern that this growing income inequality might challenge both China's sustainable growth and the world's economic growth in the near future as China has become the locomotive of world economic growth since the recent global financial crisis (Lin, 2012).

Third, our paper contributes to an understanding of the endogenous nexus between trade liberalization and wage inequality from two perspectives. On the one hand, we explore the nexus by

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

taking firm heterogeneity into account. Most previous works relied on the new-classical Heckscher-Ohlin model to test whether or not trade liberalization benefits the abundant factor and, therefore, affects income distribution between skilled and unskilled labor. If the Stopler-Samuelson theorem is supported by data, trade liberalization on imported capital-intensive goods would mitigate wage inequality in the developing countries.[2] Different from the predictions of the conventional trade theory, most empirical work finds that globalization leads to larger wage inequality (Goldberg and Pavcnik, 2007). These works usually rely on industry-level wage data or proxy wage inequality using the Gini coefficient, a standard indicator of income inequality (e.g., Beyer *et al.*, 1999). The absence of firm and worker heterogeneity in these works also makes wage inequality within firms a type of "black-box." Our paper tries to fill this gap.[3] On the other hand, previous works usually concentrated on trade liberalization on final goods. For example, Han *et al.* (2012) finds that China's accession to the World Trade Organization since 2001 was strongly associated with widening wage inequality in China. 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 cause the sharp increase in U.S. social benefit claims. However, imported intermediate inputs are found to be crucial to boosting firm productivity for many countries, such as the U.S. (Hanson et al., 2005), Indonesia (Amiti and Konings, 2007), India (Topalova and Khandelwal, 2011) and China (Yu, 2011), which could also, in turn, affect wage inequality. In this paper we turn our focus to the impact of input trade liberalization on wage inequality.

Finally, our paper makes a methodological contribution to the literature by estimating and calculating the measured wage inequality. Similar to other previous works, due to the data limitations,

[2] Previous works have also a debated 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 U.S. However, Lawrence and Slaughter (1993) reviewed historical data on the prices of labor-intensive and capital-intensive goods and found that the movement of the relative prices of these two types of goods may suggest wage equality according to FPE.

[3] An outstanding exception is that of Akerman *et al.* (2013), which finds that trade liberalization not only enhances the dispersion of revenues across heterogenous firms but also widens wage inequality across workers and firms. We are also in line with Groizard *et al.* (2012), which explores the endogenous nexus between trade liberalization and job flow in California.

we are not able to analyze firm-level wage inequality. However, we have information on firm-level average wages and the proportion of skilled labor share. With these data, we are able to introduce a variety of approaches to estimate and calculate firm-level wage inequality (both in absolute and relative terms) by borrowing the idea of "fair wages," a standard and widely accepted theory in labor economics. We find that our estimates of input trade liberalization on wage inequality are insensitive by using our different measures of firm-level wage inequality.

In this paper, we first develop a model that distinguishes import tariff reductions between intermediate inputs and final goods and we derive the impact of input tariff reductions on wage inequality in a set-up with heterogeneous firms à la Amiti and Davis (2012). We argue that input tariff reductions would lower a firm's costs and thus increase its profitability. As introduced in the fair-wage literature (e.g., Egger and Kreickemeier, 2012), wages for both skilled and unskilled labor depend on a firm's profitability. Since skilled workers usually have more bargaining power than do the unskilled, the former would have a greater share of the profit margin. As a result, input tariff reductions increases a firm's profitability and widens its wage inequality. Compared with Amiti and Davis (2012), a novel element in our model is that we consider worker heterogeneity. As well, we focus on the impact of input tariff reductions on wage inequality after controlling for factors like output tariff reductions.

We test our augmented Amiti and Davis (2011) model using a rich Chinese firm-level data set for the period 2000 to 2006. Our first step is to estimate and calculate firm-level wage inequality in three different ways. We first obtain the wage gap between skilled and unskilled labor using a firm's total profit as a proxy for its profitablity. Since a firm's total profit is volatile with its size, we then adopt a firm's profit-sales ratio as an alternative proxy to estimate a firm's wage inequality. Different from the related literature on measures of wage inequality, we take an additional step to denote wage inequality as the ratio between skilled and unskilled wages. Since all such measured wage inequality is estimated as opposed to observed, it may be a concern that some observations are estimated more precisely than others. We, therefore, compute the standard deviation of a firm's relative wages across firms within an industry and multiply a firm's relative wages as a new measure of a firm's wage inequality.[4] After controlling for possible endogeneity issues from reverse causality or omitted variables, we find that input trade liberalization widens wage inequality within firms. Such findings are robust to different measures of wage inequality, as well as different empirical specifications and data spans.

The rest of the paper is organized as follows. Section 2 provides a theoretical model to show that input trade liberalization increases wage inequality. Section 3 describles the data and measures the key variables used in the estimates. Section 4 presents the empirical evidence and, finally, Section 5 provides some concluding remarks.

2 The Model

In order to investigate the effect of trade liberalization on wage inequality, instead of focusing on homogeneous labor, we extend the $(n+1)$-country model in Amiti and Davis (2011) by introducing both skilled and unskilled workers into the final goods production.

2.1 Consumption (of final goods)

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

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

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

[4] Feenstra et al. (2013) also use this approach to handle trade uncertainty regarding Chinese firms' exports.

2.2 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, $m_f(j) \in [0,1]$.[5] These inputs are produced under constant return-to-scales, 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 $\lambda_v = (\phi_v, \theta_v, t_{Mv}, t_{Xv})$. The respective elements are the firm's production technology (productivity ϕ_v), the required share of skilled labor in production θ_v, and the idiosyncratic components of marginal trade costs in imports t_{Mv} and exports t_{Xv}. That is, for a given technology ϕ_v, we assume that production requires each firm to employ a particular share of the skilled labor (presumably ϕ_v and θ_v are positively correlated).

After learning their characteristics, some firms exit without producing, and the remaining mass of firms M will choose labor (both skilled and unskilled) and intermediate inputs to produce final outputs destined for each market to maximize profits. Steady state requires that new entries matches firm exits (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:

$$q_v = \phi_v L^{\alpha} M^{1-\alpha} - f, \tag{2}$$

where ϕ_v is the firm-specific technology/productivity parameter and f is the fixed cost of production. We assume thereafter that all fixed costs are in units of domestic intermediates.[6]

[5] 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).

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

The composite labor input L is given by,

$$L = \min\{\frac{l_s}{\theta_v}, \frac{l_u}{1-\theta_v}\} \tag{3}$$

where l_s and l_u are skilled and unskilled labor inputs, and θ_v is the share of the skilled workers employed. Therefore, $\frac{\theta_v}{1-\theta_v}$ is the firm-specific skilled-unskilled labor ratio.

Unlike unskilled labor, skilled labor receives a wage, w_v, that is related to the performance of the firm for which they work. Following the fair-wage argument in Amiti and Davis (2011), we assume that $w_v = w(\pi_v)$ is a function of a firm's profit because, unlike unskilled workers, skilled workers have some bargaining power in production. Specifically, we assume that $w(0) = \underline{w}$, $0 < w'(\pi_v) < \infty$, $\underline{w} \leq w(\pi_v) \leq \overline{w}$. Therefore, the wage for the composite labor in (3) becomes,

$$\begin{aligned} W_v(\pi_v) &= \theta_v w(\pi_v) + (1-\theta_v)\underline{w} \\ &= \theta_v[w(\pi_v) - \underline{w}] + \underline{w} \\ \text{or}, W_v(\pi_v) &= \theta_v \Delta w_v + \underline{w} \end{aligned} \tag{4}$$

where $\Delta w_v = w(\pi_v) - \underline{w}$ is the wage gap between skilled and unskilled labor. Furthermore, since $W_v' = \theta_v w'$, the relationship between W_v and π_v in (4) is illustrated in Figure 1.

For simplicity, we assume that unskilled labor has little bargaining power and therefore their wage is unrelated to a firm's profit. Without loss of generality, we normalize the unskilled wage to unity. 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,

$$P_{M_v} = [1 + n\tau_{Mv}^{1-\gamma}]^{\frac{1}{1-\gamma}} \leq 1 \tag{5}$$

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

Therefore, the marginal cost corresponding to (2) is

$$\begin{aligned} c_v &= \frac{kW_v^{\alpha} P_{M_v}^{1-\alpha}}{\phi_v} \\ &= \frac{kW_v^{\alpha}[1+n\tau_{Mv}^{1-\gamma}]^{\frac{1-\alpha}{1-\gamma}}}{\phi_v}, \end{aligned} \tag{6}$$

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 $p_{vd} = c_v/\rho$. Thus, revenue in the domestic market becomes

$$\begin{aligned} r_{vd} &= RP^{\sigma-1}p_{vd}^{1-\sigma} \\ &= RP^{\sigma-1}[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma}[1+n\tau_{Mv}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}} \end{aligned} \tag{7}$$

The total revenue is

$$\begin{aligned} r_v &= (1+n\tau_{Xv}^{1-\sigma})r_{vd} \\ &= (1+n\tau_{Xv}^{1-\sigma})RP^{\sigma-1}[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma}[1+n\tau_{Mv}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}} \end{aligned} \tag{8}$$

where $\tau_{Xv} = \tau_X t_{Xv} > 1$ is firm v's idiosyncratic iceberg export cost to serve a foreign market, which consists of a common component $\tau_X > 1$ and a firm-specific component $t_{Xv} \geq 1$. Notice that (8) reflects the fact that, in addition to the domestic market, exporting gives a firm access to n additional foreign markets, each of which is $\tau_{Xv}^{1-\sigma} < 1$ times the size of the former.

Therefore, the profit for a firm with both exported final goods and imported intermediates is

$$\begin{aligned} \pi_v(W_v) &= \frac{r_v}{\sigma} - [f + n(f_X + f_M)] \\ &= (1+n\tau_{Xv}^{1-\sigma})(\frac{RP^{\sigma-1}}{\sigma})[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma}[1+n\tau_{Mv}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}} - [f + n(f_X + f_M)] \end{aligned} \tag{9}$$

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

$$\pi_v(W_v) = (1 + n\tau_{Xv}^{1-\sigma})(\frac{RP^{\sigma-1}}{\sigma})[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma} - (f + nf_X). \tag{10}$$

When a firm only imports intermediates, it profit becomes

$$\pi_v(W_v) = (\frac{RP^{\sigma-1}}{\sigma})[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma}[1 + n\tau_{Mv}^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}} - (f + nf_M) \tag{11}$$

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

$$\pi_v(W_v) = (\frac{RP^{\sigma-1}}{\sigma})[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma} - f \tag{12}$$

Firms whose profits are negative exist the market completely.

For given macro variables (i.e., R and P), Eq. (4), together with any of Eq.(9)-(12), can determine a firm's profit and wages for the composite labor (and, therefore, the wage gap or the skilled wage using Eq. (4)). 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 (2011), 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.[7] 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 $\pi_v = \pi(\lambda_v, \widehat{\phi}^*)$, where $\widehat{\phi}^*$ is the notional cut-off productivity because zero-profit firms have wages equal to unity (see Eq. (4)):

$$\pi(\widehat{\phi}^*, W_v(0)) = (\frac{RP^{\sigma-1}}{\sigma})[\frac{k}{\rho\widehat{\phi}^*}]^{1-\sigma} - f = 0. \tag{13}$$

[7]Notice that the net gains from importing intermediates are $[(1+n\tau_{Mv}^{1-\gamma})^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}} - 1](\frac{RP^{\sigma-1}}{\sigma})[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma} - nf_M$. For a zero-profit firm, $(\frac{RP^{\sigma-1}}{\sigma})[\frac{kW_v^{\alpha}}{\rho\phi_v}]^{1-\sigma} = f$. 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.

From Eq.(13), we can obtain the macro values consistent with $\widehat{\phi}^*$:

$$RP^{\sigma-1} = \sigma f(\frac{k}{\rho\widehat{\phi}^*})^{1-\sigma}. \tag{14}$$

With Eq.(14), from the previous firm's optimization problem we can obtain $\pi_v = \pi(\lambda_v, \widehat{\phi}^*)$, which is consistent with this notional cut-off and all other equilibrium variables.

Therefore, using Eq.(9) and Eq.(4), it is straightforward to obtain the following proposition.

Proposition *A reduction of t_{Mv} increases the firm wage gap Δw_v between skilled and unskilled labor.*

This result can be illustrated using Figure 1. From Eq.(9) notice that $\pi'(W_v) < 0$ (i.e. higher wages reduce profits, *ceteris paribus*) and the intersection of $W_v(\pi_v)$-curve and $\pi_v(W_v)$-curve determines the equilibrium firm profit and wage (for a given mode). A reduction of t_{Mv} shifts the $\pi_v(W_v)$-curve up and, as a result, raises both π_v and W_v. Consequently, from Eq.(4), the wage gap increases.

3 Data, Measures and Empirics

3.1 Data

To investigate the impact of trade liberalization (mainly in terms of input tariff reductions) on a firm's wages gap, in this paper we rely on the following three highly disaggregated large panel data sets: firm-level production data complied by China's National Bureau of Statistics (NBS), HS 8-digit trade data reported by China's General Administration of Customs (GAC), and China's import tariffs (*ad valorem*) data at an HS 6-digit level as maintained by the World Integrated Trade Solution (WITS) of the World Bank.

China's NBS conducts an annual survey on two types of manufacturing firms: all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed RMB 5 million ($770,000). The sample used in this paper is approximately 230,000 manufacturing firms per year from varying from 162,885 firms in 2000 to 301,961 firms in 2006. On average, the sample accounts for more than 95% of China's total annual output in the manufacturing sectors.[8] 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 now widely used in research, including, among others, Cai and Liu (2009), Yu (2011), Brandt *et al.* (2012), and Feenstra *et al.* (2013). However, some unqualified firms are wrongly included in the data set largely because of misreporting by some firms. Following Feenstra et al. (2013), we keep the observations in our analysis according to the requirements of generally accepted accounting principles (GAAP) if all of the following holds: (1) total assets exceed liquid assets; (2) total assets exceed total fixed assets; (3) the net value of fixed assets is smaller than total assets; (4) the firm's identification number exists and is unique and (5) the established time is valid. Accordingly, the total number of firms covered in the data set is reduced from 615,951 to 438,165. Approximately one-third of the firms are removed from the sample after the rigorous filter is applied.

Although the firm-level production data set also includes a firm's export value, it keeps silent on the shipment of each exportable goods, which is important if we are to understand the role of processing trade on the nexus between wage inequality and input trade liberalization. Therefore, we turned to the customs transaction-level trade data set. The GAC provides highly disaggregated monthly transaction-level trade data for the period 2000 to 2006 at the HS 8-digit level. The number of monthly observations increases from 786,524 in January 2000 to 2,306,563 in December 2006. The trade data set also provides shipment information for each transaction–processing or ordinary–which is important given that about half of all Chinese exports are processing exports. Since the data set also provides firm information, such as the firm's name (in Chinese), phone number, and zip code, we are able to match the firm-level production data set and trade data set following Yu and Tian (2012).

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

It is important to note that some Chinese firms do not have their own production activity, but rather import goods and then sell them to other domestic companies or export goods collected from other domestic firms (Ahn *et al.*, 2011). To ensure the precision of our estimates, we exclude such trading companies from the sample in all estimates. In particular, firms with names that include any Chinese characters for Trading Company or Importing and Exporting Company are excluded from the sample since trading companies are required to register with a name that contains these Chinese characters.

3.2 Measures

Our theoretical framework suggests that a fall in input trade costs widens wage inequality between skilled and unskilled labor. We test this theoretical conjecture using Chinese firm-level production data. In this paper, firm-level wage inequality is first taken as the absolute wage gap between skilled and unskilled labor. Since previous works such as Feenstra and Hanson (1996, 1999) also measure wage inequality in a relative term, we also use a relative wage ratio (i.e., skilled wages divided by unskilled wages) as an alternative index and run additional robustness checks. We consider the following empirical framework:

$$w_{it}^s - w_{it}^u = E(\beta IIT_{it} + \boldsymbol{\gamma}\mathbf{X}_{it}|\mathbf{Z}_{it}) + \epsilon_{it}, \tag{15}$$

where w_{it}^s and w_{it}^u are the wages paid to the skilled and unskilled labor for firm i at year t, respectively. IIT is industy-level input tariffs, which are our key regressors. $\mathbf{X}_{it}$ denotes all regressors of interest. $\mathbf{Z}_{it} = (IIT_{it}, \mathbf{X}_{it})$ is a combined vector that includes both input tariffs and other control variables.

Although this empirical specification seems straightforward, it faces an important empirical challenge: a firm's skilled and unskilled wages are unavailable. The only available data in Chinese firm production data are a firm's average wages. Therefore, to investigate the impact of input trade liberalization on a firm's wage inequality, our empirical specifications consist of two steps. The first step is to compute the measured firm-level wages inequality, which is taken as the regressand in the second step's estimates.

3.2.1 Measures of Firm-Level Wage Inequality

By allowing that skilled wages are different across firms within an industry, skilled wages (w^s_{ijt}) paid by a firm i of industry j in year t can be decomposed to two components: industrial average skilled wages (w^s_{jt}) and a firm-specific error term (ε^s_{ijt}): $w^s_{ijt} = w^s_{jt} + \varepsilon^s_{ijt}$. Analogously, a firm's unskilled wages are decomposed to industrial average unskilled wages and a firm-specific residual: $w^u_{ijt} = w^u_{jt} + \varepsilon^u_{ijt}$. Therefore, a firm's wages inequality can be expressed as

$$wgap1_{ijt} \equiv w^s_{ijt} - w^u_{ijt} = (w^s_{jt} - w^u_{jt}) + (\varepsilon^s_{ijt} - \varepsilon^u_{ijt}), \tag{16}$$

where the first equality is by definition. In the second equality, the first term is industry-level wages inequality (denoted as α_{jt}) whereas the second term is the firm-level difference in the skilled and unskilled wage residuals. As suggested by our theoretical model, such wage residuals are a function of a firm's profitability. If a firm is more profitable, it will allocate more dividends to skilled workers than to unskilled workers, *ceteris paribus*. Since larger firms (i.e., with more sales) usually have more profits, we measure a firm's profitability as firm profits over sales. However, our main estimation results remain robust even if we use a firm's total profit as a proxy for its profitability, as discussed later. The within-firm wages residuals thus can be estimated as $\varepsilon^s_{ijt} - \varepsilon^u_{ijt} = \beta_{jt}\pi_{ijt}$ where π_{ijt} is a firm's profitability and β_{jt} is the estimated coefficient for industry j in year t, which is presumed to be identical across firms within an industry. [9] Hence, a firm's wages inequality is given by:

$$wgap1_{ijt} = \alpha_{jt} + \beta_{jt}\pi_{ijt} \tag{17}$$

We then estimate the coefficients in Eq. (17) by industry and year by taking advantage of data on average wages and share of skilled labor. Denoting θ_{ijt} the skilled labor share which is measured by

[9] As a robustness check, we allow that the estimated coefficient of a firm's profitability varies by firms within an industry. See Section 4.6 for a detailed discussion.

the share of employees with at least some college education, a firm's average wage can be theoretically expressed as (see Appendix A for details):

$$\overline{w}_{ijt} \equiv \theta_{ijt} w^{s}_{ijt} + (1-\theta_{ijt}) w^{u}_{ijt} \tag{18}$$

$$= w^{u}_{jt} + \alpha_{jt}\theta_{ijt} + \beta_{jt}(\theta_{ijt}\pi_{ijt}) + \varepsilon^{u}_{ijt}. \tag{19}$$

With data on a firm's average wages, skilled labor share and firm profitability, we can estimate the coefficients $\widehat{\alpha}_{jt}$ and $\widehat{\beta}_{jt}$. Note that since the term w^{u}_{jt} is varied by industry j and by year t, we estimate Eq. (18) by industry and by year so that w^{u}_{jt} is treated as a constant term in each regression. The measured firm-level wage inequality can be computed by backing up the coefficients of $\widehat{\alpha}_{jt}$ and $\widehat{\beta}_{jt}$:

$$\widehat{wgap1}_{ijt} = \widehat{\alpha}_{jt} + \widehat{\beta}_{jt}\pi_{ijt}. \tag{20}$$

Column (1) of Table 1 presents the year-average measured firm-level wage inequality ($\widehat{wgap1}_{ijt}$) by Chinese two-digit industry. The mean of firm wage inequality, measured by the wages gap between skilled labor and unskilled labor in an *absolute* term, is RMB 11,320 (or equivalently, \$1400), with a relatively large standard deviation as also reported in columns (1)-(2) of Table 2A. This large standard deviation is likely due to the inclusions of outlier industries such as tobacco (code: 16. See column (1) of Table 2), which has an extremely high measured wage inequality. To ensure that our estimates are not contaminated by such outliers, we drop firms from the tobacco industry from our estimations.

[Insert Table 1 Here]

3.2.2 Measures of Input Tariffs

Now we turn to measure input tariffs. Inspired by Amiti-Konings (2007) and Topalova and Khandelwal (2011), we construct the industry-level input tariffs, IIT_{jt}, as follows:

$$IIT_{jt} = \sum\nolimits_n \left(\frac{input_{nj}^{2002}}{\sum_n input_{nj}^{2002}} \right) \cdot \tau_{nt}, \tag{21}$$

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

We use China's Input-Output Table from 2002 to construct the weight since NBS reports the Input-Output Table every five years and our data spread from 2000 to 2006. The industrial input tariffs are obtained in the following way. First, as there are 71 manufacturing sectors reported in China's Input-Output Table (2002) and only 40 manufacturing sectors reported in Chinese industrial classifications (CIC), we start by making a concordance between the Input-Output Table and the CIC sectors. Secondly, we match the CIC sectors with International Standard Industrial Classifications (ISIC, rev. 3).[10] Third, we make another concordance to link ISIC and the HS 6-digit trade data where we can find the corresponding tariffs from the WITS. Fourth, we calculate the industry-level tariffs that are aggregated to the CIC sectorial level.[11] In particular, the simple average tariffs are used to calculate industry-level tariffs as follows:

$$\tau_{nt} = \frac{1}{N} \sum\nolimits_{k \in n, k=1}^{N} \tau_{kt}, \tag{22}$$

where k denotes products (at the HS 8-digit level) in industry n. We use these simple average tariffs as a default measure in the main estimates that follow. Finally, we calculate the industry-level *input* tariffs using Eq. (21). Analogously, the industry-level *output* tariff for industry n in year t is also directly obtained from Eq. (22).

To see how the input tariff reductions affect a firm's wages inequality, it is worthwhile to examine the evolution of China's trade liberalization and wage inequality throughout the sample period. Table 2A reports the mean and standard deviation for these key variables. As shown in columns (1)-(4)

[10] Note that China's government adjusted its CIC in 2003. Therefore we also make similar adjustments in our data.
[11] We do not report the input weights by industry to save space; these data are available upon request.

of Table 2A, the average industry input tariffs were cut in half from 16.6% in 2000 to 8.6% in 2006, and their standard deviation also dropped by about two-thirds over the same period. Industrial output tariffs are relatively higher than input tariffs. Industrial output tariffs also clearly exhibit a sharp declining trend during the sample period. In sharp contrast, firm wage inequality increases over the years in question. As seen in columns (5)-(6) of Table 2A, a firm's annual wages gap doubles from RMB 6,000 in 2000 to RMB 12,500 in 2006 (or equivalently, from $750 to $1,560). Its standard deviation even exhibits a 6.5 times increase, implying that input trade liberalization and wage inequality widening occur simultaneously during the sample period. Table 2B also provides some basic statistical information for the key variables used in the estimations.

[Insert Table 2 Here]

4 Estimation Results

4.1 Baseline Results

After obtaining both measured firm-level wage inequality and industry-level input tariffs, we are ready to run the following regressions:

$$\widehat{wgap1}_{ijt} = \beta_0 + \beta_1 IIT_{jt} + \boldsymbol{\gamma}\mathbf{X} + \varpi_i + \gamma_t + \mu_{it}, \tag{23}$$

where $\mathbf{X}$ includes other control variables such as industry output tariffs and other firm characteristics (e.g., type of ownership, size and productivity). The error term in Eq. (23) can be further decomposed to three terms: (1) a firm-specific fixed effects ϖ_i to control for time-invariant factors such as a firm's unobserved managerial ability; (2) year-specific fixed effects η_t to control for firm-invariant factors such as Chinese RMB appreciation since 2005; and (3) an error term μ_{it} for other unspecified characteristics.

In practise, however, we encounter another data restriction when performing such an empirical specification. We only have information about skilled and unskilled labor (i.e., education) for 2004 because NBS only included skilled and unskilled labor information on their 2004 census questionnaire. To get around these data limitations, we compute a proxy of the skilled-labor share for all other years by multiplying the skilled-labor share in 2004 with a provincial skilled-labor share in all years using 2004 as the base year. Because such a proxy can only capture the firm-specific variation in skilled-labor share for 2004, we perform the cross-firm estimation using data in 2004 only as a later robustness check.

We start our estimations by running a simple regression of industry input tariffs on firm wages inequality. By abstracting all control variables away, the fixed-effects estimates in column (1) of Table 3 show that a fall in industry input tariffs tends to result in more wage inequality. The intuition is straightforward. With input trade liberalization, firms are able to generate more profits by saving on input costs, which, in turn, widens the wage gap since skilled workers enjoy a larger proportion of the incremental profit, as suggested by our theoretical model. One may be curious whether such a cost-saving effect could be weakened by tougher import competition effects due to the inclusion of output tariffs (Amiti and Konings, 2007). Meanwhile, other firm characteristics, such as a firm's type of ownership, size (measured by log of firm employment) or productivity (measured by the Olley-Pakes (1996) (TFP), could also affect a firm's wage gap. We therefore include all such control variables in column (2) and we still see a negative and significant estimate for industry input tariffs. In addition, output trade liberalization tends to narrow wages inequality, possibly, due to the tougher import competition and consequent decline in firm profitability (Horn et al. 1995). Interestingly, the coefficient of firm productivity (in a form of log TFP) is negative. But this is not a worry since it is insignificant. Note that SOEs and foreign indicators (FIEs) are still present in the estimates after controlling for firm-sepecific and year-specific fixed effects. This is merely because some SOEs (FIEs) could switch to non-SOEs (non-FIEs) or vice versus.[12]

[12] Table 2 in the appendix presents the transitional probability for SOEs and FIEs, respectively.

4.2 The Role of Processing Trade

As mentioned in Feenstra *et al.* (2013) and also seen in Table 2B, approximately 4.5% of firms are pure exporters that sell all of their products abroad. An interesting observation is that most pure exporters are processing firms that enjoy the special tariffs treatment (i.e., free duty) for importing (e.g., Yu, 2011; Dai et al., 2012). The appearance of processing firms suggests two helpful clues for our identification. First, with the inclusion of processing firms, our estimates of input trade liberalization on wage inequality may be under-estimated since the appearance of processing firms, which are already duty-free, would dilute the magnitude of our estimations. Ideally we need to remove from the sample those processing firms where processing imports equal total imports. However, the NBS firm-level data set does not have this type of processing variable. Nevertheless, by definition, a processing firm is also a pure exporter (although it is not necessary that a pure exporter be a processing firm). Therefore, we can re-run the fixed-effects estimates after removing the pure exporters in column (3) of Table 3. The coefficient of input tariffs is still negative and significant, with a relatively larger magnitude than its counterpart in column (2) where pure exporters are included.

Second, processing trade also serves as a clean natural experiment for our estimations. Because processing imports are already duty free, the ongoing input tariffs reduction must have no impact on wage inequality in those processing firms. We therefore run regressions for processing firms only. If our theory is supported by the data, industry input tariffs should not have a statistically significant impact on the processing firms' wage inequality.[13]

Although we do not know which firms exactly are processing firms from the NBS firm data set, the customs trade data set reveals this information. Therefore, we can merge the firm production data set and customs trade data set to identify processing firms in the firm data set. As discussed in previous work like Yu and Tian (2012) and Wang and Yu (2012), such a matching is challenging

[13] However, note that we should not expect the coefficient of input tariffs on the processing firms' wage gap to be zero since input tariffs are still measured at the industry level, but not at the firm level.

and imperfect since the two data sets are lack of common identification numbers. By using a firm's Chinese name, phone number, and zip code as common variables, we are able to merge approximately 40% of exporters and 53% of total exports in the firm production data set. Since such an exercise is imperfect, some processing firms may be mis-classified as non-processing in the augmented firm data set that includes processing information. Nevertheless, as a placebo test, our estimates with processing firms only in column (4) of Table 3 still help us to understand the impact of input trade liberalization on wage inequality. Meanwhile, previous works like Yu (2011) also point out that less productive firms could self-select to engage in processing trade. To incorporate this feature, the variable of firm productivity is taken as a one-year lag in column (5). In this sub-sample estimates with only processing firms, the coefficient of input tariffs is insignificant, which is consistent with our expectation that processing imports are already duty-free and, as a result, ongoing input trade liberalization does not have an impact on a firm's wage inequality.

[Insert Table 3 Here]

4.3 Endogeneity Issues

Thus far, we treat input trade liberalization exogenous. However, tariff formation could be endogenous in the sense that wage inequality could reversely affect tariff changes. With widening wage inequality, unskilled workers could blame free-trade policy and form labor unions to lobby the government for temporary trade protection (Bagwell and Staiger, 1990; Grossman and Helpman, 1994; Bown and Crowley, 2013). Although this happens in developed countries like the U.S. (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. As well, it is these types of political factors are time invariant, then our fixed-effect panel estimates in Table 3 have accounted and controlled for them (Goldberg and Pavcnik, 2005). However, if they are time variant, we need to use the instrument variables (IV)-approach to control for these types of endogeneity issues.

It is always challenging to find an ideal instrument for tariffs. Inspired by Amiti and Konings (2007), we use the one-year lag of industry input tariffs as current tariffs. The economic rationale is that industries with strong trade protection in the previous period are more likely to maintain relatively high tariffs in the current period. Of course, we perform related statistical tests to check for the validity of such an instrument. Table 4 performs the two-stage least squares (2SLS) estimates by treating industry input tariffs as endogenous.

Column (1) of Table 4, once again, abstracts away all control variables and includes only industry input tariffs as the regressor. The coefficient of industry input tariffs is negative and significant. Like its counterpart in column (2) of Table 3, the 2SLS estimates in column (2) of Table 4 include industry output tariffs and many other control variables. The estimated coefficient of industry input tariffs is also close to its counterpart in the OLS estimates in Table 3. A 10 percentage point fall in industry input tariffs leads to an approximately 12.1 point increase in a firm's wage inequality, *ceteris paribus*. By dropping pure exporters from the sample, the estimated coefficient of input tariffs is slightly larger than that in column (2), which, in turn, suggests that the inclusion of pure processing firms could dilute the impact of input trade liberalization on a firm's wage inequality. As a placebo test, the 2SLS estimates in column (4) include only processing firms and we still find that the effect on processing firms is statistically insignificant, as anticipated.

Still, one may be worried that, in reality, it may take some times for firms to respond to tariff changes. The one-lag input tariffs may still be correlated with the residual of 2SLS-level estimates, which may violate the exclusion requirement for an instrument. To address this concern, and inspired by Amiti and Davis (2011), we can use one-lag period of input tariffs as the instrument in a first-differenced equation.[14] The economic rationale is that the lag input tariffs are less likely to influence the time difference of input tariffs (Trefler, 2004). The first-differenced 2SLS estimates using one-lag of input tariffs as the instrument is reported in the last column of Table 4. All regressors in that

[14] Amiti and Davis (2011) adopt five-period difference estimations. Introducing a longer period (e.g., two-period) differenced equation does not change our estimation results in a quantitative way, although there is a cost as we lose much of the sample in such a short panel.

column are in the form of first difference. Once again, the coefficient of input tariffs is negative and statistically significant, with a magnitude close to its counterpart in the full-sample 2SLS-level estimates of column (3).

The bottom module of Table 4 provides the first-stage estimates for all specifications. The coefficients of the instruments are highly statistically significant. In addition, several tests were performed to verify the quality of the instruments. First, we use the Kleibergen–Paap LM χ^2 statistic to check whether the excluded instruments are correlated with the endogenous regressors. As shown in the upper module of Table 4, the null hypothesis that the model is under-identified is rejected at the one percent significance level. Second, the Kleibergen–Paap (2006) F-statistics provide strong evidence for rejecting the null hypothesis that the first stage is weakly identified at a highly significant level. All these tests suggest that our instrument is valid and that the specifications are well justified.

[Insert Table 4 Here]

4.4 Cross-Firms versus Time-Series Variations

Because we do not have a firm's skilled and unskilled labor data for any year except 2004, we have to multiply a proportion of skilled labor at the province-year level using 2004 as a base year to construct the variable of firm-year wage inequality. This may generate a concern as to whether or not our results are driven by provincial heterogeneity rather than firm heterogeneity.[15] To address this concern, we perform two placebo tests, as follows.

The first robustness check is to drop samples in all years except 2004. We perform the cross-section OLS estimates with data from 2004 only in column (1) of Table 5. We also include two-digit industry fixed effects to wash out unspecified industry characteristics. The coefficient of input tariffs is still negative and significant, indicating that input trade liberalization widens a firm's wage inequality. Still, we suspect that the OLS fixed-effects estimates may be biased due to possible endogeneity issues caused by omitted variables or reverse causality. Column (2) of Table 5 performs the 2SLS

[15] Note that including provincial dummies in the regressions does not change our estimation results. Since firms do not change their locations, all province-level fixed effects are automatically absorbed by firm-level fixed effects.

estimates using one-period lag of input tariffs as the instrument. It turns out that the coefficient of input tariffs is relatively close to its counterpart for the full-sample 2SLS estimate in column (2) of Table 4, which confirms that our full-sample estimates are not driven by the adoption of a relatively aggregated multiplier (i.e. the province-year skilled-labor share).

The second, robustness check is to narrow down the time-series window. Since we only have one-year of data on skilled (and unskilled) labor, one may worry that running regression for a seven-year period (2000 to 2006) may generate some serial correlations or cause some concern of unit roots that may be prevalent in long-period estimates. To address this, we shut down the long time-series window and only focus on a three-years period (2003 to 2005). We then perform the fixed-effects OLS estimates in column (3) and 2SLS estimates in column (4) of Table 5. After controlling for the endogeneity, the coefficient of input tariffs in the 2SLS estimates in column (4) has an identical negative sign and a fairly close magnitude as compared to its counterpart of the full-sample 2SLS estimates in column (2) of Table 4. Thus, it is safely to conclude that our results are insensitive to the adoption of the province-year skilled-labor share as a remedy to data restrictions.

[Insert Table 5 Here]

4.5 Robustness Checks using Alternative Measures

As usual, the industry input tariffs are calculated using a simple-average tariffs within each Common Industrial Classification (CIC) 2-digit industry level as shown in Eq. (22). Although taking the simple average across product within an industry seems straightforward, it bears a cost as the import heterogeneity for products within the industry is ignored. For example, suppose a firm imports 70% of lumber and 30% of steel. Tariffs on lumber are apparently more important to the firm than those on steel. However, a simple-average tariffs cannot take such a difference into account. To address this, we consider the following weighted input tariffs:

$$\tau_{nt} = \sum_{k\in n} \left(\frac{m_{kt}}{\sum_{k\in n} m_{kt}} \right) \tau_{kt}, \tag{24}$$

where m_{kt} is the import values for product k within a CIC 2-digit industry n in year t. Once we obtain these weighted input tariffs, we plug them back into Eq. (21) to obtain the weighted industry input tariffs ($wiit_{it}$).[16]

Table 6 reports the estimates using weighted industry input tariffs. The fixed-effects OLS estimates in column (1) show that the coefficient of input tariffs is still negative and significant after considering the importance of import heterogeneity within an industry. To rule out possible estimation bias due to the inclusion of processing imports, column (2) drops pure exporters from the sample and still yields results similar to those in column (1). Columns (3)-(4) perform the 2SLS estimations to control for the possible endogeneity of the weighted input tariffs. A one-period lag of industry input tariffs is still served as the IV with a consequent change. The simple average tariffs calculated in Eq. (22) is replaced with weighted average tariffs in Eq. (24). After controlling for the endogeneity, estimates in columns (3)-(4), once again, suggest that industry input trade liberalization tends to widen firm-level wage inequality.

[Insert Table 6 Here]

Thus far, a firm's wage inequality is measured in an absolute term as the wage difference between skilled and unskilled labor. It is worthwhile to check whether our estimates are robust when the wage inequality is measured as relative wages between skilled and unskilled labor a là Feenstra and Hanson (1996, 1999). Table 7 accomplishes this task. The regressand in all estimates except column (5) is the relative wage difference in which a firm's skilled and unskilled wages are calculated as mentioned previously. As seen in Table 2B, the overall annual relative wages during the sample period is 2.21, which is significantly higher than that in the U.S.(1.75). Column (3) of Table 1 reports the relative wages by industry. The OLS estimates in column (1) of Table 7 and the 2SLS estimates in column (2) of Table 7 cover the seven-year sample (2000 to 2006) and, once again, find that input tariff

[16] There is a caveat to this. As pointed out by Topalova and Khandelwal (2011), such a weighted industry input tariff may understate the actual input tariff reduction since the imported inputs with lower tariffs may receive higher import volume and thus have higher weights in Eq.(24). Therefore, the calculation using weighted tariffs and the associated estimations in Table 6 should be treated as lower-bound estimates of the effects of input tariffs on wage inequality.

reductions widen a firm's wage inequality. The magnitude of the coefficient of input tariffs seems to be too small. We suspect that this is largely because of the spread of the provincial share of skilled labor in such a long time window. Therefore, we run the 2SLS estimates in column (3) with data from 2004 only and in column (4) with data from 2003 to 2005. It turns out that the coefficient of input tariffs are still negative and significant, but much larger than the counterparts in columns (1)-(2).

Still, the regressand used in all estimations is a measure of wage inequality (in both absolute and relative terms). As the observations are estimated but not observed, it is worthwhile to control for the fact that some observations are estimated more precisely than others. Therefore, we compute the standard deviation of a firm's relative wages across firms within an industry and multiply a firm's relative wages as the regressand in Table 7 (refer to weighted relative wages $\widehat{wrwage}_{ijt}$ with a relatively large mean, 2.89, as reported in Table 2B). The last two columns of Table 1 report the standard deviation and the mean of weighted relative wages by two-level Chinese industry. The coefficient of input tariffs is negative and significant again; more importantly, its magnitude is quite close to that in column (4). Thus, our estimates remain robust and consistent with our theoretical prediction that input trade liberalization widens firm-level wage inequality.

[Insert Table 7 Here]

To obtain firm-level wages inequality, we rely on the argument of fair wages. Firms will allocate more profits to its skilled workers. Since larger firms usually have more profits, we divide firm profits by firm sales to capture profitability and use this to estimate firm-level wage inequality as in Eq. (20). It is interesting to ask whether our main findings are sensitive to the measure of profitability. We then replace a firm's profits-sales ratio with total profits and re-estimate Eq. (17) to obtain firm-level wage inequality (refer to $\widehat{wgap2}_{ijt}$). By using this alternative wage inequality as the regressand, Table 8 runs fixed-effects regressions with different specifications. Column (1) includes all samples during the period 2000 to 2006, whereas column (2) excludes pure exporters. We see that declining input tariffs lead to an increase in a firm's wages inequality. Column (3) takes a further step by replacing the level of a firm's wage inequality with the first-difference in wage inequality; it yields results similar to before. To rule out the possibility that such a result is due to the adoption of provincial skilled share as the multiplier, estimates in column (4) retain data for only 2004, and those in column (5) focus on the shorter period 2003 to 2005. Nevertheless, all specifications confirm that input trade liberalization widens a firm's wage inequality.

[Insert Table 8 Here]

Our last step is to offer a more intuitive economic interpretation for our estimation results. As shown in column (2) of Table 7, the coefficient of industry input tariffs is -0.06, implying that a 10 percentage point fall in input tariffs leads to a 0.6 point increase in relative wage inequality. Average input tariffs were cut by about eight percentage points (from 16.57 percent in 2000 to 8.60 percent in 2006). As such, this predicts a $0.06 \times 7.97 = 0.48$ point increase in a firm's relative wages and accounts for approximately 23% of a firm's relative wages, which equals about 2.1 in 2000. Such a finding is close to that in Feenstra and Hanson (1999), which posits the figure of 15 to 40% for the impact of outsourcing on wage inequality in the United States in the 1980s.

4.6 Alternative Estimates with Industry Minimum Wages

Thus far, to estimate the effects of input trade liberalization on a firm's wage inequality, we first estimate and calculate the firm-level wages inequality by taking advantage of information about a firm's profits. In that way, the industrial minimum wage is abstracted away since it is fully captured by the within-industry wages differential $w^s_{jt} - w^u_{jt} = \alpha_{jt}$. Still, it is worthwhile to explicitly examine the role of minimum wage across industry and over time (Anwar and Sun, 2012). To do this, we construct a measured industry-level wage inequality.

Consider the following specification for unskilled wages $w^u_{ijt} = w^{\min}_{jt}(1 + s_{ijt})$, where $w^{\min}_{jt}$ is the minimum wage of four-digit industry j in year t and s_{ijt} is the premium set by firm i of four-digit industry j in year t. Inserting such a wage premium equation into Eq. (18) of a firm's average wages, we have

$$\overline{w}_{ijt} = \theta_{ijt} w_{ijt}^{s} + (1 - \theta_{ijt}) w_{jt}^{\min}(1 + s_{ijt}). \tag{25}$$

By allowing firm-level wage heterogeneity for both skilled (ε_{ijt}^{s}) and unskilled labor (ε_{ijt}^{u}) within each industry, we have

$$\overline{w}_{ijt} = \theta_{ijt}(w_{jt}^{s} + \varepsilon_{ijt}^{s}) + (1 - \theta_{ijt})(w_{jt}^{\min}(1 + s_{ijt}) + \varepsilon_{ijt}^{u}). \tag{26}$$

By absorbing all terms with wage residuals $\theta_{ijt}\varepsilon_{ijt}^{s} + (1 - \theta_{ijt})\varepsilon_{ijt}^{u}$ into the error term, we can estimate the following equation for each four-digit industry j in different years t with data on skilled labor share θ_{ijt} and industry minimum wage $w_{jt}^{\min}$:

$$\widehat{\overline{w}}_{ijt} = \hat{\alpha}_{1jt}\theta_{ijt} + \hat{\alpha}_{2jt}((1 - \theta_{ijt}) w_{jt}^{\min}) \tag{27}$$

where the estimated coefficient $\hat{\alpha}_{1jt}$ denotes industrial skilled wages (w_{jt}^{s}) and $\hat{\alpha}_{2jt}$ corresponds to the industrial wage premium $(1 + s_{it})$ for industry j at year t. Once the measured wage inequality is obtained by backing up the coefficients $\hat{\alpha}_{1jt}$ and $\hat{\alpha}_{2jt}$, we then obtain the CIC 4-digit industry level wages inequality ($\widehat{wgap3}_{jt}$):

$$\widehat{wgap3}_{jt} \equiv \hat{\alpha}_{1jt} - \hat{\alpha}_{2jt} w_{jt,}^{\min}. \tag{28}$$

Table 1 in the appendix reports the mean of industrial wages inequality at an aggregated CIC two-digit industry level. By way of comparison, the measured firm-level wage inequality ($\widehat{wgap1}_{ijt}$) is at a more disaggregated level, but it has to rely on the "fair wages" argument. Namely, that firms will allocate profits disproportionately between skilled and unskilled labor. More precisely, skilled labor can access a larger proportion of a firm's profits. The measured four-digit industry-level wage inequality ($\widehat{wgap3}_{jt}$) is more flexible and needs not depending on such a theoretical hypothesis, although it is not able to capture the wages inequality across firms within an industry. Nevertheless, it is still worthwhile to serve as a robustness check for our main question: whether or not input trade liberalization widens wage inequality.

Table 9 presents the estimation results using such industry-level wage inequality as the regressand. Column (1) starts with the OLS estimates. Note that the regressand $\widehat{wgap3}_{jt}$ is measured at the CIC 4-digit level. Thus the number of observations is reduced to 1,750. We include weighted industry input tariffs ($wiit_{jt}$) and industry output tariffs in all estimates. We also include industry-level average log TFP with one lag to see whether industrial productivity affects the industrial wage gap. It turns out that the coefficient of industry input tariffs is negative but insignificant. We suspect that this is due to the lack of controlling fixed effects. We therefore run the year-specific and industry-specfic fixed effects in the rest of Table 9. Estimates in column (2) show that the coefficient of industry input tariffs turns out to be significant. In columns (3)-(4) we include industry-average log employment to control for industry size and still find that input tariff reductions widen wage inequality. As shown in column (4), such a finding is still robust if we exclude pure exporters. Thus, our main findings are robust to different measures of wages inequality and industrial input tariffs.

[Insert Table 9 Here]

5 Concluding Remarks

In this paper, we first develop a theoretical framework that input trade liberalization leads to higher firm profitability via the channel of fair wage argument, which in turn widens the wages gap between skilled and unskilled labor since the former, in general, has higher bargaining power regarding sharing a firm's residual profit. We then provide rich empirical evidence to test such a theoretical conjecture. Thanks to the very rich Chinese firm-level production data set, we are able to construct related measures on wage inequality and input tariffs. After controlling for endogeneity issues, we find that a fall in input trade costs leads to an increase in the wage gap. Input trade liberalization in the new century in China results in an increase in wage inequality in approximately one-quarter of Chinese firms.

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Table 1: Measured Firm-Level Wages Inequality

Adjusted Chinese Industrial Classfications	$\widehat{wgap1}_i$	$\widehat{wgap2}_i$	$\widehat{rwage}_i$	Std.Dev	$\widehat{wrwage}_i$
Processing of Foods (13)	4.546	4.658	2.025	1.765	3.573
Manufacturing of Foods (14)	11.58	8.980	2.907	2.861	8.316
Manufacture of Beverages (15)	7.704	7.445	2.617	2.756	7.214
Manufacture of Tobacco (16)	109.1	47.96	3.533	3.259	11.51
Manufacture of Textile (17)	4.803	5.535	1.859	1.609	2.992
Manufacture of Apparel, Footwear,Caps (18)	3.428	3.424	1.570	0.996	1.564
Manufacture of Leather, Fur, Feather (19)	3.768	2.880	1.849	1.767	3.267
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm,Straw Products (20)	2.107	4.340	1.975	1.856	3.667
Manufacture of Furniture (21)	2.933	6.308	1.606	1.299	2.086
Manufacture of Paper and Paper Products (22)	13.96	9.158	2.293	2.003	4.594
Printing, Reproduction of Recording Media (23)	4.581	4.575	1.715	1.211	2.076
Mfg. For Culture, Education, Sports (24)	9.356	14.08	2.151	2.141	4.604
Processing of Petroleum, Coking, Fuel (25)	11.71	11.51	3.002	3.090	9.274
Manufacture of Raw Chemical Materials (26)	13.03	11.88	3.029	2.825	8.558
Manufacture of Medicines (27)	12.56	11.36	2.957	3.124	9.236
Manufacture of Chemical Fibers (28)	11.41	9.449	2.315	2.160	5.000
Manufacture of Rubber (29)	5.305	5.311	1.835	1.322	2.426
Manufacture of Plastics (30)	6.788	6.836	2.050	1.611	3.303
Manufacture of Non-metallic Mineral goods (31)	4.244	4.125	1.834	1.429	2.622
Smelting Pressing of Ferrous Metals (32)	5.768	5.534	1.784	1.270	2.266
Smelting Pressing of Non-ferrous Metals (33)	6.590	6.577	2.035	1.697	3.454
Manufacture of Metal Products (34)	6.868	6.723	1.995	1.608	3.207
Manufacture of General Purpose Machinery (35)	8.005	7.609	2.236	2.035	4.552
Manufacture of Special Purpose Machinery (36)	11.92	11.05	2.770	2.613	7.239
Manufacture of Transport Equipment (37)	10.65	8.815	2.361	2.308	5.449
Electrical Machinery Equipment (39)	8.220	9.327	2.518	2.287	5.759
Computers Other Electronic Equipment (40)	15.98	16.43	3.120	2.997	9.352
Manufacture of Measuring Instruments (41)	15.25	13.93	2.966	2.911	8.634
Manufacture of Artwork (42)	21.12	10.22	2.172	1.994	4.331

Notes: Unit in columns (1), (2), and (5) is RMB 1,000 (equivalent to $125). Standard errors for each coefficient are not reported to save space though available upon request. The wage inequality index $\widehat{wgap1}_i$ (and the alternative wage inequality index $\widehat{wgap2}_i$) is computed by Eq. (20) with profit-sales ratio (firm's total profit) as a proxy of firm's profitability. Firm's relative wages ($\widehat{rwage}_i$) is the ratio of firm's skilled wages over unskilled wages which are calcuated by Eq. (20) with profit-sales ratio as a proxy of firm's profitability. Standard deviation of firm's relative wages across firms within an industry are reported in the second last column. The last column ($\widehat{wrwage}_i$) is obtained by using industrial standard deviation as in the second last column to multiply firm's relative wages by industry.

Table 2A: China's Output Tariffs and Input Tariffs

Year	Ind. Input Tariffs		Ind. Output Tariffs		Firm Wage Gap	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)
2000	16.57	4.13	20.34	8.44	6.03	6.48
2001	14.81	3.34	17.38	6.05	7.88	15.48
2002	11.54	2.69	13.67	5.86	8.35	115.9
2003	10.15	2.11	12.27	5.20	5.75	5.82
2004	9.18	1.80	11.04	4.56	11.73	24.63
2005	8.84	1.67	10.32	4.42	12.01	34.36
2006	8.60	1.60	10.11	4.15	12.51	41.90
All years	10.11	3.17	12.16	5.91	11.32	352.7

Notes: This table reports the mean and standard deviation of 3-digit industry-level output tariffs in Columns (1)-(2) and industry-level input tariffs that are constructed as described in Eq.(21) in Columns (3)-(4) in the text. Measured firm-level wages inequality ($\widehat{wgap1}_{ijt}$) in columns (1) and (2) are carefully described in the text with a unit of RMB 1,000 (or equivalently \$125 during the sample period).

Table 2B: Summary Statistics of Key Variables (2000-2006)

Variables	Mean	Std. Dev.
Measured Firm Wages Gap (RMB 1,000: $\widehat{wgap1}_{ijt}$)	11.32	352.7
Measured Firm Wages Gap (RMB 1,000: $\widehat{wgap2}_{ijt}$)	9.59	280.2
Measured Industry Wages Gap (RMB 1,000: $\widehat{wgap3}_{ijt}$)	5.23	24.09
Measured Firm Relative Wages ($\widehat{rwage}_{ijt}$)	2.21	2.09
Measured Weighted Firm Relative Wages ($\widehat{wrwage}_{ijt}$)	2.89	4.81
Industry Input Tariffs (%)	9.72	2.97
Weighted Industry Input Tariffs (%)	9.15	3.22
Industry Output Tariffs (%)	11.07	8.19
Log of Firm Labor	4.90	1.10
SOEs Indicator	.055	.228
Foreign Indicator	.222	.415
Pure Exporters	.044	.207
Pure Processing Firms	.028	.161

Notes: RMB 1 is equivalent to \$0.125 during the sample period. Information of pure processing firms are only available after matching firm production data and customs trade data together.

Table 3: OLS Estimates using Measured Firm-Level Wage Inequality

Measured Firm's Wages Gap ($\widehat{wgap1}_{ijt}$)	(1)	(2)	(3)	(4)
Industry Input Tariffs	-0.264***	-0.659***	-0.744***	.361
	(-3.29)	(-4.58)	(-4.78)	(1.33)
Industry Output Tariffs		0.068***	0.081***	-.227***
		(7.84)	(8.99)	(-2.07)
State-owned Enterprises		0.781	0.765	–
		(0.72)	(0.71)	
Foreign Firms		-0.012	0.024	-3.524
		(-0.06)	(0.11)	(-0.91)
Log of Firm Employment		0.029	0.062	-1.893
		(0.36)	(0.73)	(-1.27)
Log of Firm TFP		-0.165	-0.155	
		(-1.56)	(-1.39)	
One Lag of Firm Log TFP				-5.36
				(-1.37)
Year-specific Fixed Effects	Yes	Yes	Yes	Yes
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes
Pure Exporters Included	Yes	Yes	No	Yes
Pure Processing Exporters Only	No	No	No	Yes
Observations	526,969	352,600	332,893	4,522
R-squared	0.02	0.02	0.02	0.04

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *** (**,*) denotes the significance at 1% (5%, 10%) level. Columns (1) and (2) includes the entire sample. Column (3) drops pure exporters. Column (4) includes pure processing firms only.

Table 4: 2SLS Estimates using Measured Firm-Level Wage Inequality

Regressand:	(1)	(2)	(3)	(4)	(5)
Measured Firm's Wages Gap	$\widehat{wgap1}_{ijt}$	$\widehat{wgap1}_{ijt}$	$\widehat{wgap1}_{ijt}$	$\widehat{wgap1}_{ijt}$	$\Delta\widehat{wgap1}_{ijt}$
Industry Input Tariffs	-0.559***	-1.204***	-1.257***	0.906	-1.563***
	(-3.66)	(-4.10)	(-4.10)	(1.44)	(-5.95)
Industry Output Tariffs		0.118***	0.122***	-0.250***	0.163***
		(10.74)	(10.71)	(-2.21)	(12.28)
State-owned Enterprises		1.010	1.020	–	3.400***
		(0.87)	(0.87)		(3.38)
Foreign Firms		0.106	0.196	-3.604	-0.218
		(0.37)	(0.64)	(-0.93)	(-0.23)
Log of Firm Employment		-0.033	0.024	-1.885	-0.159
		(-0.27)	(0.19)	(-1.26)	(-0.66)
Log of Firm TFP		0.024	0.034		
		(0.16)	(0.21)		
One Lag of Firm TFP				-5.386	-0.240
				(-1.38)	(-0.97)
Kleibergen-Paap rk LM χ^2 statistic	3,033†	2,484†	2,296†	68.20†	30,139†
Kleibergen-Paap Wald rk F statistic	12,469†	7,285†	6,811†	216.5†	40,365†
Year-Specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm-Specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pure Exporters Included	Yes	Yes	No	Yes	Yes
Pure Processing Exporters Only	No	No	No	Yes	No
Observations	316,040	213,205	201,856	2,023	118,980
R-squared	0.02	0.02	0.02	0.04	0.01
		First-Stage Regressions			
IV: One-Lag Industry Input Tariffs	.500***	.417***	.418***	.453***	-.160***
	(111.6)	(85.36)	(82.53)	(14.72)	(-200.9)

Notes: Robust t-values corrected for clustering at the firm level in parentheses.*,**(***) indicates significance at the 10,5 and 1 percent level, respectively. $^\dagger(^\ddagger)$ indicates significance of p-value at the 1(5) percent level. Regressands in Columns (1)-(4) are levels of firm's wages inequality ($\widehat{wgap1}_{ijt}$) whereas that in Column (5) is the first difference of firm's wage inequality ($\Delta\widehat{wgap1}_{ijt}$). Correspondingly, regressors in Columns (1)-(4) are in levels whereas those in Column (5) are in the first difference. IV reports the coefficient of one-lag industry input tariffs using current industry input tariffs as the regressand. Columns (1), (2), and (5) include all sample. Column (3) includes all sample except pure exporters. Column (4) includes pure processing firms only.

Table 5: Cross-Section and Shorter Panel Estimates

Econometric Methods:	OLS	2SLS	OLS	2SLS
Measured Firm's Wages Gap ($\widehat{wgap1}_{ijt}$)	(1)	(2)	(3)	(4)
Industry Input Tariffs	-0.844***	-1.558***	-1.905***	-1.123*
	(-7.29)	(-6.28)	(-7.96)	(-1.79)
Industry Output Tariffs	0.317***	0.299***	-0.049***	-0.066**
	(7.91)	(16.63)	(-3.01)	(-2.16)
State-owned Enterprises	2.948**	2.994***	4.613*	4.889***
	(2.53)	(6.34)	(1.81)	(3.19)
Foreign Firms	0.194	0.211	-0.236	-0.256
	(1.33)	(0.96)	(-0.54)	(-0.16)
Log of Firm Employment	0.104	0.110	-0.074	-0.037
	(1.36)	(1.33)	(-0.30)	(-0.09)
One Lag of Firm TFP	0.620**	0.644***	-0.271	-0.291
	(2.10)	(2.63)	(-0.68)	(-0.69)
Kleibergen-Paap rk LM χ^2 statistic	–	15,160†	–	6,341†
Kleibergen-Paap Wald rk F statistic		22,858†		7,328†
Year-specific Fixed Effects	No	No	Yes	Yes
Firm-specific Fixed Effects	No	No	Yes	Yes
2-digit Industry Fixed Effects	Yes	Yes	No	No
Years Coverage	2004		2003-2005	
Observations	45,636	44,953	135,226	83,341
R-squared	0.57	0.57	0.01	0.02
First-Stage Regressions				
IV: One-Lag Industry Input Tariffs	–	0.354***	–	0.186***
		(151.2)		(85.61)

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *** (**,*) denotes the significance at 1% (5%, 10%) level. Columns (1)-(2) includes sample in 2004 only. Columns (3)-(4) includes sample during 2003-2005. In the first-stage estimates, IV reports the coefficient of one-lag industry input tariffs using current industry input tariffs as the regressand.

Table 6: More 2SLS Estimates using Alternative Tariffs Measure

Econometric Methods:	OLS		2SLS	
Measured Firm's Wages Gap ($\widehat{wgap1}_{ijt}$)	(1)	(2)	(3)	(4)
Weighted Industry Input Tariffs ($wiit_{jt}$)	-0.665***	-0.766***	-2.372***	-2.429***
	(-5.04)	(-5.39)	(-5.22)	(-5.11)
Industry Output Tariffs	0.076***	0.091***	0.158***	0.163***
	(10.51)	(12.42)	(14.90)	(14.91)
State-owned Enterprises	0.636	0.603	0.581	0.612
	(0.59)	(0.56)	(0.51)	(0.53)
Foreign Firms	-0.017	0.023	0.153	0.264
	(-0.08)	(0.11)	(0.51)	(0.84)
Log of Firm Employment	0.032	0.065	-0.042	0.011
	(0.40)	(0.76)	(-0.34)	(0.08)
Log of Firm TFP	-0.116	-0.102	0.119	0.129
	(-1.08)	(-0.90)	(0.77)	(0.81)
Kleibergen-Paap rk LM χ^2 statistic	–	–	1,742†	1,609†
Kleibergen-Paap Wald rk F statistic			9,829†	9,339†
Year-specific Fixed Effects	Yes	Yes	Yes	Yes
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes
Pure Exporter Included	Yes	No	Yes	No
Observations	352,600	332,893	213,205	201,856
R-squared	0.02	0.02	0.01	0.01
First-Stage Regressions				
IV: One-Lag Weighted Industry Input Tariffs	–	–	0.452***	0.453***
			(99.15)	(96.64)

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *** (**,*) denotes the significance at 1% (5%, 10%) level. Columns (1) and (3) include the entire sample whereas columns (2) and (4) include the entire sample except pure exporters. In the first-stage estimates, IV reports the coefficient of one-lag industry input tariffs using current industry input tariffs as the regressand.

Table 7: 2SLS Estimates using Measured Firm-Level Relative Wage Inequality

Econometric Method:	OLS	2SLS			
Regressand:	$\widehat{rwage}_{ijt}$	$\widehat{rwage}_{ijt}$	$\widehat{rwage}_{ijt}$	$\widehat{rwage}_{ijt}$	$\widehat{wrwage}_{ijt}$
	(1)	(2)	(3)	(4)	(5)
Industry Input Tariffs	-0.039***	-0.060***	-0.314***	-0.513***	-0.580***
	(-7.01)	(-4.51)	(-9.09)	(-12.32)	(-6.65)
Industry Output Tariffs	0.009***	0.005***	0.049***	0.027***	0.042***
	(10.75)	(5.09)	(18.72)	(11.98)	(9.51)
State-owned Enterprises	-0.101*	-0.108	0.030	-0.165	-0.266
	(-1.73)	(-1.44)	(0.50)	(-1.56)	(-1.17)
Foreign Firms	-0.059	-0.147**	-0.353***	-0.070	0.082
	(-1.15)	(-2.35)	(-13.35)	(-0.61)	(0.30)
Log of Firm Employment	0.184***	0.284***	0.021**	0.196***	0.385***
	(12.50)	(13.87)	(2.02)	(6.63)	(4.75)
Log of Firm TFP	-0.011	-0.006	-0.092**	0.012	-0.020
	(-0.66)	(-0.25)	(-2.20)	(0.36)	(-0.23)
Kleibergen-Paap rk LM χ^2 statistic		1,871†	11,342†	7,354†	2,908†
Kleibergen-Paap Wald rk F statistic		5,610†	16,043†	8,721†	2,628†
Year-Specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm-Specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Coveraged	2000-2006		2004	2003-2005	
Observations	319,588	189,721	38,628	81,217	81,217
R-squared	0.03	0.03	0.09	0.04	0.03
	First-Stage Regressions				
IV: One-Lag Industry Input Tariffs	–	.395***	.317***	.182***	.182***
		(74.90)	(126.6)	(93.38)	(51.27)

Notes: Robust t-values corrected for clustering at the firm level in parentheses.*,**(***) indicates significance at the 10,5 and 1 percent level, respectively. $^\dagger(^\ddagger)$ indicates significance of p-value at the 1(5) percent level. Regressands in Columns (1)-(4) are firm-level firm's relative wages, $\widehat{rwage}_{ijt}$, which is defined as computed skilled wages over unskilled wages whereas that in Column (5) is the firm's relative wages multipled by its sectoral standard devivation ($\widehat{wrwage}_{ijt}$). IV reports the coefficient of one-lag industry input tariffs using current industry input tariffs as the regressand. Columns (1)-(2) include the entire sample. Columns (4)-(5) include the sample during 2003-2005 whereas column (3) covers the sample in 2004 only.

Table 8: Estimates using Alternative Firm-Level Wage Inequality

Regressand:	(1)	(2)	(3)	(4)	(5)
Measured Firm's Wages Gap	$\widehat{wgap2}_{ijt}$	$\widehat{wgap2}_{ijt}$	$\Delta\widehat{wgap2}_{ijt}$	$\widehat{wgap2}_{ijt}$	$\widehat{wgap2}_{ijt}$
Industry Input Tariffs	-0.135***	-0.126***	-0.533***	-0.627***	-0.726***
	(-14.34)	(-12.71)	(-24.63)	(-27.69)	(-31.48)
Industry Output Tariffs	0.051***	0.050***	0.017***	0.234***	0.045***
	(33.41)	(32.08)	(11.18)	(68.63)	(18.05)
State-owned Enterprises	-0.100	-0.105	0.139	0.087	0.008
	(-0.98)	(-1.03)	(1.15)	(1.10)	(0.06)
Foreign Firms	-0.024	-0.086	-0.003	0.164***	-0.088
	(-0.26)	(-0.89)	(-0.03)	(5.24)	(-0.69)
Log of Firm Employment	0.236***	0.237***	0.166***	0.156***	0.123***
	(10.41)	(10.04)	(6.09)	(12.52)	(3.65)
Log of Firm TFP	0.195***	0.201***	0.124***	0.587***	0.144***
	(6.78)	(6.71)	(3.87)	(12.98)	(3.53)
Year-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry-specific Fixed Effects	No	No	No	Yes	No
Pure Exporters Included	Yes	No	Yes	Yes	Yes
Year Coveraged		2000-2006		2004	2003-2005
Observations	366,356	345,807	207,541	96,226	232,411
R-squared	0.18	0.18	0.14	0.33	0.25

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *** (**,*) denotes the significance at 1% (5%, 10%) level. Columns (1) and (3) includes the entire sample, whereas column (2) includes the entire sample except pure exporters. Column (4) includes data in 2004 only. Column (5) include data in 2003-2005. Regressands in all columns except column (3) are levels of firm's wages inequality ($\widehat{wgap2}_{ijt}$), whereas that in Column (3) is the first difference of firm's wage inequality ($\Delta\widehat{wgap2}_{ijt}$). Correspondingly, regressors in all columns except column (3) are in levels, whereas those in Column (3) are in the first difference.

Table 9: More Estimates using Alternative Industrial Wage Inequality

Measured Industry Wages Gap ($\widehat{wgap3}_{jt}$)	(1)	(2)	(3)	(4)
Weighted Industry Input Tariffs ($wiit_{jt}$)	-0.119	-0.548***	-0.546***	-0.625***
	(-1.59)	(-2.98)	(-2.96)	(-3.27)
Industry Output Tariffs	-0.001	0.051	0.051	0.065
	(-0.03)	(1.20)	(1.21)	(1.47)
Industry-Level Log Employment			0.094	0.211
			(0.39)	(0.83)
Industry-Level Log TFP with One-Lag	0.596			
	(0.49)			
Year-specific Fixed Effects	No	Yes	Yes	Yes
Firm-specific Fixed Effects	No	Yes	Yes	Yes
Pure Exporters Included	Yes	Yes	Yes	No
Observations	1,750	1,750	1,750	1,657
R-squared	0.01	0.03	0.03	0.04

Notes: Robust t-values corrected for clustering at the firm level in parentheses. *** (**,*) denotes the significance at 1% (5%, 10%) level. The regressand is measured industry-level wage gap as discussed in Eq. (28) in the text.

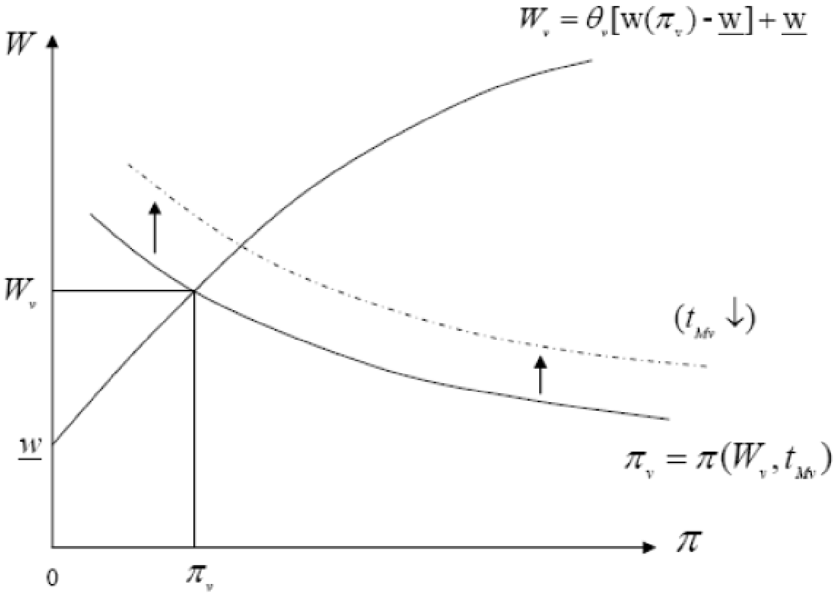

Figure 1: Determinatin of Firm Average Wages and Profit

5.1 Appendix A: The Measured Wage Inequality

In this appendix we describe how we construct firm-level and industrial wage inequality. We start from the derivation of measured firm-level wage inequality. Notice that firm i's average wage in industry j at year t can be expressed as

$$\begin{aligned}
\overline{w}_{ijt} &= \theta_{ijt} w^s_{ijt} + (1-\theta_{ijt}) w^u_{ijt} \\
&= \theta_{ijt}(w^s_{jt} + \varepsilon^s_{ijt}) + (1-\theta_{ijt}) w^u_{ijt} \\
&= \theta_{ijt}(w^u_{jt} + \alpha_{jt}) + \theta_{ijt}\varepsilon^s_{ijt} + (1-\theta_{ijt}) w^u_{jt} + (1-\theta_{ijt})\varepsilon^u_{ijt} \\
&= w^u_{jt} + \theta_{ijt}\alpha_{it} + \theta_{ijt}(\varepsilon^s_{ijt} - \varepsilon^u_{ijt}) + \varepsilon^u_{ijt} \\
&= w^u_{jt} + \alpha_{it}\theta_{ijt} + \beta_{jt}(\theta_{ijt}\pi_{ijt}) + \varepsilon^u_{ijt}.
\end{aligned} \tag{29}$$

The second equality follows the definition of $w^s_{ijt} = w^s_{jt} + \varepsilon^s_{ijt}$ and $w^u_{ijt} = w^u_{jt} + \varepsilon^u_{ijt}$. The third equality is due to within-industry wage differential $w^s_{jt} - w^u_{jt} = \alpha_{jt}$. Rearranging the fourth equality, we can easily obtain the last equality by using the equation of within-firm wage differential $\varepsilon^s_{ijt} - \varepsilon^u_{ijt} = \beta_{jt}\pi_{ijt}$. Therefore, the firm-level wage inequality is calculated using the estimated coefficients $\widehat{\alpha}_{jt}$ and $\widehat{\beta}_{jt}$

$$\widehat{wgap1}_{ijt} = \widehat{\alpha}_{jt} + \widehat{\beta}_{jt}\pi_{ijt}.$$

Alternatively, we can estimate and calculate the industry-level wage inequality ($\widehat{wgap3_{jt}}$) as follows. Consider the following specification for unskilled wage $w^u_{ijt} = w^{\min}_{jt}(1+s_{ijt})$, where $w^{\min}_{ijt}$ is the minimum wage and s_{ijt} is the premium set by firm i of four-digit industry j at year t. Inserting this equation of wage premium to Eq. (29) of firm i's average wage, we have:

$$\overline{w}_{ijt} = \theta_{ijt} w^s_{ijt} + (1-\theta_{ijt}) w^{\min}_{jt}(1+s_{ijt}). \tag{30}$$

By allowing firm-level wage heterogeneity for both skilled (ε^s_{ijt}) and unskilled labor (ε^u_{ijt}) within each industry, we have

$$\overline{w}_{ijt} = \theta_{ijt}(w^s_{jt} + \varepsilon^s_{ijt}) + (1-\theta_{ijt})(w^{\min}_{jt}(1+s_{ijt}) + \varepsilon^u_{ijt}). \tag{31}$$

Therefore, we can estimate the following equation for each four-digit industry j in different years t

$$\widehat{\overline{w}}_{ijt} = \hat{\alpha}_{1jt}\theta_{ijt} + \hat{\alpha}_{2jt}(1-\theta_{ijt}) w^{\min}_{jt}, \tag{32}$$

where the estimated coefficient $\hat{\alpha}_{1jt}$ denotes industrial skilled wage and $\hat{\alpha}_{2jt}$ is corresponding to the industrial wage premium $(1+s_{it})$ for industry j at year t. Notice that

$$w^s_{ijt} - w^u_{ijt} = (w^s_{jt} - w^u_{jt}) + (\theta_{ijt}\varepsilon^s_{ijt} - (1-\theta_{ijt})\varepsilon^u_{ijt}). \tag{33}$$

After Eq. (32) is estimated, we combine Eq. (15) and Eq. (33) to obtain:

$$(w^s_{jt} - w^u_{jt}) = E(\boldsymbol{\beta}\mathbf{X}_{it}|\mathbf{X}_{it}) + (\epsilon_{it} - \theta_{ijt}\varepsilon^s_{ijt} - (1-\theta_{ijt})\varepsilon^u_{ijt}).$$

Therefore, the measured wage inequality can be computed as following (using $\hat{\alpha}_{1jt}$ and $\hat{\alpha}_{2jt}$):

$$\begin{aligned}\widehat{wgap3}_{jt} &\equiv \hat{\alpha}_{1jt} - \hat{\alpha}_{2jt} w_{jt,}^{\min} \\ &= E(\boldsymbol{\beta}\mathbf{X}_{it}|\mathbf{X}_{it}) + (\epsilon_{it} - \theta_{ijt}\varepsilon_{it}^{s} - (1-\theta_{ijt})\varepsilon_{it}^{u}), \\ &= \phi_0 + \phi_1 IIT_{jt} + \mu_{it} + \varpi_j + \gamma_t + \mu_{it}\end{aligned} \tag{34}$$

where the error term in Eq. (23) can be decomposed into three terms as in Eq. (11): (i) a industry-specific fixed effect ϖ_i to control for time-invariant factors such as a firm's managerial ability; (ii) a year-specific fixed effect η_t to control for firm-invariant factors such as Chinese RMB appreciation; and (iii) an error term μ_{it} for other unspecified factors.

Appendix Table 1: Estimated Skilled and Unskilled Wages of Chinese Firms

Adjusted Chinese Industrial Classfications	Skilled Wages $\hat{\alpha}_{1jt}$	Unskilled Premium $\hat{\alpha}_{2jt}$	Unskilled Wages $\hat{\alpha}_{2jt}w_{jt}^{\min}$	Measured Wage Inequality $\hat{\alpha}_{1jt} - \hat{\alpha}_{2jt}w_{jt}^{\min}$
Processing of Foods (13)	16.43	7.73	3.58	12.85
Manufacturing of Foods (14)	17.74	6.37	5.48	12.26
Manufacture of Beverages (15)	16.06	7.78	4.64	11.42
Manufacture of Tobacco (16)	36.69	4.40	7.07	29.62
Manufacture of Textile (17)	19.48	8.71	4.21	15.27
Manufacture of Apparel, Footwear & Caps (18)	22.32	21.85	3.21	19.11
Manufacture of Leather, Fur, & Feather (19)	17.09	9.33	7.35	9.74
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm & Straw Products (20)	16.50	11.13	6.02	10.48
Manufacture of Furniture (21)	21.66	5.47	3.88	17.78
Manufacture of Paper & Paper Products (22)	19.46	14.25	4.38	15.07
Printing, Reproduction of Recording Media (23)	19.81	15.76	6.51	13.29
Mfg. For Culture, Education & Sport (24)	20.85	3.57	5.42	15.42
Processing of Petroleum, Coking, &Fuel (25)	21.84	4.73	3.60	18.23
Manufacture of Raw Chemical Materials (26)	20.95	6.38	5.07	15.87
Manufacture of Medicines (27)	17.63	16.58	5.91	11.72
Manufacture of Chemical Fibers (28)	17.98	4.31	7.26	10.72
Manufacture of Rubber (29)	17.67	7.89	6.85	10.81
Manufacture of Plastics (30)	19.24	10.86	7.46	11.77
Manufacture of Non-metallic Mineral goods (31)	18.69	7.02	4.14	14.54
Smelting & Pressing of Ferrous Metals (32)	18.02	22.37	8.15	9.86
Smelting & Pressing of Non-ferrous Metals (33)	20.53	4.30	5.16	15.36
Manufacture of Metal Products (34)	21.41	6.22	5.15	16.26
Manufacture of General Purpose Machinery (35)	20.45	7.28	5.75	14.69
Manufacture of Special Purpose Machinery (36)	20.94	4.04	6.03	14.90
Manufacture of Transport Equipment (37)	21.35	3.46	3.96	17.39
Electrical Machinery & Equipment (39)	22.26	5.017	5.274	16.992
Computers & Other Electronic Equipment (40)	23.16	5.246	5.151	18.018
Manufacture of Measuring Instruments & Machinery for Cultural Activity & Office Work (41)	23.50	3.538	5.059	18.446
Manufacture of Artwork (42)	20.49	5.110	5.850	14.646

Notes: Unit is RMB 1,000 (equivalent to $125 during the period 2000-2007). We do not report standard errors for each coefficient to save space though available upon request. The wage gap is computed by the difference between estimated industry-level skilled wages ($\hat{\alpha}_{1jt}$) and unskilled wages which is the product of $\hat{\alpha}_{2jt}$ and industry-year minimum wages $w_{jt}^{\min}$ by industry and by year.

Appendix Table 2A: Transitional Probability for State-owned Enterprises (SOEs)

Probability (%)	Next Period		
Current Period	SOEs	Non-SOEs	Total
SOEs	99.87	0.13	100
Non-SOEs	13.01	86.99	100
Total	98.21	1.79	100

Appendix Table 2B: Transitional Probability for Foreign Firms

Probability (%)	Next Period		
Current Period	Foreign Firms	Non-Foreign Firms	Total
Foreign Firms	98.32	1.62	100
Non-Foreign Firms	0.96	99.04	100
Total	38.22	61.78	100