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Globalisation and Inter-Industry Wage Differentials in China

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Abstract

This paper explores the relationship between globalisation and inter-industry wage differentials in China by using a two-stage estimation approach. Taking advantage of a rich household survey dataset, this paper estimates the wage premium for each industry in the first stage conditional on individual worker and firm characteristics. Alternative measures of globalisation are considered in the second stage; trade openness and capital openness. The regressions do not reveal a significant relationship between overall trade (import and/or export) openness and wage premia. However, disaggregation of trade into trade in final and intermediate goods is shown to matter. Increases in import (export) shares of final goods reduce (increase) the wage premium significantly, whereas imports or exports of intermediate goods do not explain differences in industry wage premia. This finding is supported by stronger effects for final goods trade in coastal than non-coastal regions. Our results also show a positive relationship between capital openness and industrial wage premium, though this finding is less robust when endogeneity issues are allowed for.

JEL classification: F14, F16, F66, J10, J31

Keywords: Globalisation, Industrial Wage Premium, China

Outline

1 Introduction

Rapid economic growth in China, its fast pace of integration into the world economy, and the accompanied increase in wage inequality have been the focus of much discussion. Research has attempted to explain rising wage inequality from different perspectives, such as for example, regionally to analyse the urban-rural wage gap, or by investigating returns to education and gender wage inequality (e.g. Ge and Yang, 2014; Appleton et al., 2014). However, relatively little research has been directed to the issue of inter-industry wage inequality that has been increasing in many countries over the past decades (Carruth et al., 2004; Abowd et al., 2012). This paper seeks to improve our understanding of the effects of globalisation on inter-industry wage differences in the context of China after joining the WTO.

Early studies use average industry wages to measure wage differentials across industries. This approach treats industry wages as being independent of workers' characteristics (Goh and Javorcik, 2007). However, workers' wages are determined by various factors, among which individual characteristics are likely to be the most important. A number of empirical studies on the determinants of inter-industry wage differentials have found that worker and firm heterogeneity accounts for a substantial part of wage variation, e.g. about 90% in France as in Abowd et al. (1999). More recent studies rely therefore on measuring wage variation across industries after controlling for worker and firm effects to evaluate the wage difference between someone working in an industry and those in other industries with the same individual characteristics.

To examine inter-industry wage differences based on differences in individual characteristics, we apply a two-stage estimation strategy in this paper. Specifically, in the first stage, using household survey data, individual wages are regressed on a vector of worker specific and job related characteristics and a set of industry dummies to yield a yearly industry wage premium. The industrial wage premium measures the part of wage variation that cannot be explained by worker-specific and firm-related differences but can be explained by industry affiliation. In the second stage, the estimated industry wage premium is pooled across years and is regressed on various globalisation-related variables at the industry level. Such a two-stage strategy was pioneered by Gaston and Trefler (1994), who investigate the effects of international trade policy on wages for a cross section of the U.S. manufacturing industries in 1983 and who find that workers in industries with higher trade exposure earn higher wages than workers with similar observable characteristics who work in low-exposure industries. They argue that the inter-industry wage structure is fairly stable over time in the U.S. and that their finding should not be affected by time-variant factors. Goldberg and Pavcnik (2005) point out that the year-to-year correlation of wage premia is much lower in developing countries than that in the U.S., which implies that the wage structure is subject to change across industries over time. They employ a two-stage strategy to identify the effect of trade liberalisation in Colombia on industry wage premia over the period 1985 to 1994. The same approach has been used by Kumar and Mishra (2008) who explore the impact of the 1991 trade liberalisation in India on the industry wage structure, and by Noria (2015) who examines the role of trade openness and foreign direct investment (FDI) in explaining inter-industry wage differentials for Mexico.

The two-stage strategy is important when studying industry-level wage variations. However, the data requirement is demanding, as extensive information on individuals is needed to estimate industrial wage premia in the first stage, among which the most critical variable is the industry classification. Previous studies on China's industry-level wage inequality and globalisation do not adequately control for individual effects because most household survey data in China report highly aggregated industry information on employment. By contrast, we exploit a rich dataset, which provides a 3-digit industry classification of an individual's workplace and which enables us not only to estimate industry wage premia by controlling for worker and firm characteristics, but which also allows us to link trade and FDI information with the predicted wage premia at an appropriate industry level. Different to other studies, this paper considers alternative dimensions of openness on wage differentials: trade and capital openness. Finally, we distinguish between the effects of trade in intermediate goods and trade in final goods.

We find in the first stage that, although industry affiliation explains only a small proportion of the overall wage variation in China (up to 4.4%) - similar to the case of Colombia (Goldberg and Pavcnik, 2005) and slightly less than for India (Kumar and Mishra, 2008), there is substantial variation in wage premia across industries which rises over the years. The substantial inter-industry wage variations are found in the second stage to be systematically related to aspects of trade and capital openness. We find a positive, but insignificant, effect of total trade on the industry differences in wage premia. This is perhaps not surprising given that trade could affect wages through various channels. Indeed, disaggregating trade into intermediate and final goods trade shows that the insignificant result is due to the opposite effects of the two types of trade. We find only a significant, negative effect of final imports on wage premia, and only a significant, positive relationship between final goods exports and wage premia. In the case of capital openness, we find that increased capital openness raises wage premia, though this finding is not robust when allowance is made for possible endogeneity. We also find significantly larger effects of trade and capital openness on wage premia in coastal regions than non-coastal regions.

The rest of the paper is organised as follows. The next section presents a brief discussion of the theoretical background and predictions for the empirical analysis. In Section 3, we set out the two-stage empirical methodology used to identify the wage effects of globalisation. Section 4 describes the data and discusses the measures of wages and globalisation used. Section 5 reports the results of the first-stage estimations of the impacts of worker and firm characteristics on wages and of the estimated, industrial wage premia. Section 6 provides the results for the second-stage modelling of the effects of trade and capital openness on differences in industrial wage premia in China. Finally, Section 7 concludes.

2 Theoretical Predictions

In theory, inter-industry wage differentials can be explained from both a competitive and a non-competitive labour market perspective (Noria, 2015). The former mainly attributes the inter-industry wage differentials to unobserved worker characteristics by means of sorting and human capital theories. The latter, however, seeks to explain wage differentials by linking workers' wages to firm performance through efficiency wage, rent-sharing and segmentation theory.

Goldberg and Pavcnik (2007) provide a comprehensive summary of the theoretical channels through which trade liberalisation affects inter-industry wage inequality. The first channel comes from short- and medium-run trade models with frictions on labour movement across industries and predicts that industries exposed to higher than average tariff cuts experience wage falls. The second channel is derived through models of imperfect competition and union bargaining, where industries that were previously protected would observe declining wage premia with trade liberalisation as a result of decreased profits. The third channel acts through industry-level productivity changes. In particular, if productivity gains from trade translate into higher wages, industries with larger exposure to trade liberalisation are expected to pay higher than average wages.

With the emerging literature on new trade theories highlighting firm heterogeneity, trade-induced productivity changes can explain wage dispersions across industries. In the seminal work by Melitz (2003), an improvement of aggregate industry productivity is achieved through market selection effects, or alternatively, the reallocation of market shares towards more efficient firms. In particular, exposure to trade subjects local firms to more competitors, which results in the exit of the least efficient firms or an increase in innovation incentives. Further, with the presence of fixed and variable costs of exporting, only the most productive firms are able to export, which in turn raises labour costs through increasing labour demand. Although the Melitz model mainly concentrates on intra-industry reallocation, it sheds light on expected inter-industry productivity differentials arising out of differences in exposure to trade.

Trade-induced technology improvements and innovations are another potential channel that yield productivity improvements. Acemoglu (2002) builds a framework where trade contributes to technology improvement. Once invented, the new technology can be adopted elsewhere, which implies that productivity resulting from average technology improvements increases. In a different model, however, Zeira (2007) assumes that innovations cannot be adopted everywhere because adoption depends on input prices, which causes productivity differences across countries. Provided that productivity enhancements lead to higher profits, trade exposure is expected to be positively correlated with industry wages.

Given the numerous channels through which trade potentially affects inter-industry wage inequality, the overall effects of trade are ambiguous. One important dimension is to distinguish between trade in intermediate goods and trade in final goods. Goldberg et al. (2010) argue that exposure to more varieties of imported intermediates allows firms to choose cheaper or better quality inputs, which promotes productivity improvements. Amiti and Cameron (2012) set up a fair wage effort mechanism where wages and profits are positively related with the fair-wage constraint. They argue that firms that import intermediate inputs have lower marginal costs than those that do not, which leads to higher profits and consequently wages ("import globalisation"). As to the export side, exporting firms are able to access foreign markets which allows them to achieve higher profits and therefore to pay higher wages than the domestically orientated ones ("export globalisation"). The direct implication of these theories is that the wage level is positively correlated with the import of intermediates or the export of final goods. In addition, inter-industry wage differentials can be explained by heterogeneous performance of firms to import intermediates and to export final goods.

Compared to trade openness, the effect of capital openness on wage inequality is relatively straightforward. FDI is the main form of China's capital flows. The new technology introduced by FDI does not only include better equipment and more advanced productive methods in Chinese firms, but also introduces new management practices and more efficient organisation skills, which all support productivity improvements and therefore lead to higher wages. FDI is found to contribute to skill-biased technological change, as most of the inflowing technology in developing countries is from industrialised and hence skill-abundant regions (Berman et al., 1998). Consequently, the introduction of new capital equipment raises the demand for skilled workers relative to the unskilled peers (Taylor, 2006). This capital-skill complementarity (Krusell et al., 2000; Burstein et al., 2011) leads to an increase in wage inequality between skilled and unskilled workers. How this affects wage variation across industries will depend upon industrial differences in the skill mix.

It is evident from this brief review of the theoretical literature that there are a variety of channels by which globalisation may influence industry wage differentials, and that these channels may act in offsetting ways leaving the net effects of globalisation ambiguous. Given this potential diversity of channels of influence and ambiguity of effect, the issue ultimately needs to be investigated empirically. Here we focus on the changes in industry wage differentials in China during a period of rapid globalisation.

3 Methodology

Following Goldberg and Pavcnik (2005), we will use a two-stage estimation approach. In the first stage, we use household survey data to estimate inter-industry wage dispersions. To this end, the log of individual wages (lnw_{jit}) is regressed on a vector of worker specific characteristics ($\mathbf{H}_{jit}$), a vector of job and workplace related features ($\mathbf{X}_{jit}$), and a set of industry dummies (I_{jit}) reflecting worker's industry affiliation:

$$lnw_{jit} = \alpha_t + \mathbf{H}^{'}_{jit}\beta_t + \mathbf{X}^{'}_{jit}\gamma_t + \sum_{i=1}^{I} \omega_{it} I_{jit} + \epsilon_{jit} \tag{1}$$

where $j = 1, 2, \ldots, J$ denotes individual, $i = 1, 2, \ldots, I, I+1$ denotes industry and t is time. The coefficient of our interest, ω_{it}, measures the wage differential between industry i and the reference industry $I + 1$. To interpret the wage premium as the variation in wages for an average worker in a given industry relative to an average worker in all other industries with the same characteristics, we normalise the wage premia for all industries with respect to an employment-weighted average following Zanchi (1998):

$$\begin{cases} wp_{i,t} = \omega_{it} - \overline{WA}_t \\ wp_{I+1,t} = -\overline{WA}_t \end{cases} \tag{2}$$

where $wp_{i,t}$ and $wp_{I+1,t}$ are the normalised wage premia for the first I industries and the omitted industry respectively. Here we assume that the omitted industry has zero effect on wages. $\overline{WA}_t$ is the employment-weighted average wage premium which is defined as:

$$\overline{WA}_t = \sum_{i=1}^{I} s_i \omega_{it} \tag{3}$$

where $s_i = n_i / \sum_{i=1}^{I+1} n_i$ is the employment share of industry i.

To yield appropriate standard errors for the normalised wage differentials, we calculate the variance-covariance matrix as:

$$\mathbf{var}(\widehat{\mathbf{wp}}) = (\mathbf{Z} - \mathbf{es}')\mathbf{var}(\hat{\omega})(\mathbf{Z} - \mathbf{es}')' \tag{4}$$

where $\mathbf{var}(\hat{\omega})$ is the variance-covariance matrix of the original estimated industry wage premia. $\mathbf{Z}$ is an $(I+1) \times I$ matrix constructed by stacking an $I \times I$ identity matrix and a $1 \times I$ row of zeros. $\mathbf{e}$ is an $(I+1) \times 1$ vector of ones, and $\mathbf{s}$ is an $I \times 1$ vector of employment shares of the first I industries. Finally, the square roots of the diagonal elements of $\mathbf{var}(\widehat{\mathbf{wp}})$ are the correct estimates of standard errors of the normalised wage premia.

As the wage differentials calculated above are given in log point form, we further transform the wage premium to express them in percentage changes as follows:

$$\widehat{wp}_{it}^{*} = exp\left[\widehat{wp_{it}} - \frac{1}{2}var(\widehat{wp_{it}})\right] - 1 \tag{5}$$

where $var(\widehat{wp_{it}})$ is the variance of the normalised wage premium of industry i as defined by equation (4).

The first-stage regressions are estimated separately by year, and in the second stage we pool the industry wage premia over time and regress them on globalisation-related industry characteristics $\mathbf{G}_{it}$.

$$\widehat{wp}_{it}^{*} = \mathbf{G}_{it}^{'}\beta_G + \theta_i + \theta_t + \nu_{it} \tag{6}$$

where θ_i refers to industry fixed effects capturing time-invariant, industry-specific characteristics, θ_t denotes year fixed effects, which control for common shocks (macro and financial) to all industries, and ν_{it} denotes the random error term. We incorporate two aspects of globalisation in the model. The first is trade openness, using total trade, import and export shares in gross output as measures, distinguishing also between trade in intermediate and final goods. The second is capital openness that is defined as the shares of FDI and foreign urban investment in fixed assets (FUIFA) in gross output separately. A large body of literature studying the effects of trade liberalisation on wage inequality (e.g. Goldberg and Pavcnik, 2005; Amiti and Cameron, 2012) has used tariffs as an alternative measure of globalisation. However, we do not consider tariffs as an appropriate measure of globalisation in the present context. One reason is that tariff reduction mostly happened before 2001 when China joined the WTO, while our sample starts from 2003. Although some tariffs were to be cut after 2001 according to the arrangements for WTO membership (Cheng, 2012), most of these cuts were in fact implemented before 2005. Further, it must be recognised that tariff cuts do not lead to trade expansion in the presence of existing, binding non-tariff barriers (NTBs) or when tariff cuts are offset by new NTBs. As a result we do not rely on an “input” measure of trade policy, but prefer to adopt “output” measures of actual trade and capital openness to measure globalisation for the present purpose since they capture the actual exposure to international influences.

4 Data and Measurements

4.1 China General Social Survey(CGSS)

The household survey data used in the first stage of our estimation strategy is the China General Social Survey (CGSS), conducted by Renmin University of China and Hong Kong University of Science and Technology. CGSS is the first continuous national social survey project in mainland China that covers both rural and urban areas (only urban areas in 2003).[1] For this study, we use five waves of data: 2003, 2005, 2006, 2008 and 2010. The data provides detailed information on earnings, demographic characteristics (gender, age, *hukou* type, marital status, education, etc.), but also contains job and workplace information. In contrast to other household survey data for China, CGSS reports a 3-digit industry classification. This enables us to combine the micro survey data with industry level data by aggregating the 3-digit industry codes into 32 2-digit industries.

[1]To make our analysis consistent over the years, we only consider urban areas for all years. Rural areas are still predominantly focused on agricultural production.

For the dependent variable, we use hourly income as the surveys of 2003 and 2005 do not report workers' wages. However, the correlation between wages and income for other years is fairly high, ranging from 0.84 to 0.98.[2] Further, Paul et al. (2012) who study the household income structure in urban China using China Household Income Project data (CHIPs) for 1987, 1995 and 2002, find that wages are the dominant source of household income. We are therefore confident that income is a reasonably good proxy for wages.

Hourly income is calculated from monthly income and weekly working hours and is expressed in 2003 values using the national consumer price index (CPI). We re-categorise the education level into eight groups.[3] Occupations are classified based on Appleton et al. (2014) into white collar (private business owners, professional or technical workers, managers, department heads and clerks) and blue collar (skilled and unskilled). Appendix Table A.1 shows the mean values of the key variables.

We also include establishment size to describe employer characteristics. The vast majority of establishments in our sample are small (with 1-49 employees). Middle-sized firms (with 100-499 employees) account for around one quarter and large workplaces with over 1000 employees account for 11.39% in 2010 and 20.17% in 2005. In addition, we include workers' overall attitudes towards their job to capture the relationship between workers and their employers. Moreover, we use workers' identification of their social and economic status to account for social relations, as people with better social relations are more likely to gain better-paid jobs.

Table A.2 reports the observed unconditional mean wage differentials across industries, defined by the difference between the reported industry average and the employment-weighted average of all industries. The data shows substantial wage dispersion across industries and years. The industry with the highest premium is real estate in both 2003 and 2005; water transport and post and telecommunications are among the highest

[2]Non-employment income accounted for only a small part of total income in general. We find in 2008 (2006) that around 90% (70%) of all workers reported that wages made up over 90% of their income and 87% (64%) reported that wages constituted all of their income.

[3]The raw data report 12 to 23 education groups across years. For the present analysis the re-categorised groups are: below elementary, elementary school, junior middle school, senior middle school, technical secondary school, junior college, college/university, and graduates and above.

paying industries in 2006 and 2008 respectively. Sectors including agriculture, hunting, forestry and fishing, wholesale trade and commission trade, paper products as well as rubber and plastics are at the bottom of the wage distribution in all years.[4]

4.2 Globalisation

Data on trade (imports, exports and total trade) and gross output at the industry level is taken from the World Input-Output database (WIOD), which provides time-series of national data on the basis of officially published input-output tables combined with national accounts and international trade statistics. A unique feature of this dataset is that trade can be easily disaggregated into trade in intermediate and final goods, which makes it possible to explore the effects of different types of trade. Another advantage of this database is that the industry classification can be easily matched with the one used in the first-stage estimation. We use the shares of FDI and foreign urban investment in fixed assets (FUIFA) in gross output to measure the degree of capital openness.[5] Industry-level FDI data is taken from various issues of *China Statistical Yearbook* and *Report on Foreign Investment in China*. FUIFA is from the *Statistical Yearbook of the Chinese Investment in Fixed Assets.*

Table 1 reports average levels of trade exposure and capital openness across industries and years. All trade openness measures, except final import shares, increased from 2003 to 2005 but decreased afterwards, from 21.3% in 2005 to 17.9% in 2010 on total trade shares for instance. These changes may in part reflect a shift in policy stance, in particular an effort to put more reliance on domestic sources of growth, as is reflected in the appreciation of the Renminbi against the U.S. dollar after 2005. It should be noted that the global financial crisis in 2007 and the subsequent global recession reduced external demand for China's exports and also reduced domestic demand, as reflected by the decreasing trends of both import and export shares after 2006.

[4]The degree of tradability varies across these sectors.

[5]According to China Statistical Yearbook, foreign investment in fixed assets refers to "foreign funds received during the reference period for the construction and purchase of investment in fixed assets (covering equipment, materials and technology), including foreign borrowings (loans from foreign governments and international financial institutions, export credit, commercial loans from foreign banks, issue of bonds and stocks overseas), foreign direct investment and other foreign investment". However, foreign investment in fixed assets in rural areas is unavailable at the industry level, thus we only consider the urban area in our analysis.

Table 1: Mean of Globalisation-Related Variables (%)

Variable	2003	2005	2006	2008	2010
a. Trade Openness					
Trade Share	18.82	21.31	20.80	19.10	17.94
Import Share	7.77	8.90	8.43	7.60	7.54
Export Share	11.42	13.33	13.13	11.99	10.79
Intermediate Import Share	5.73	7.06	6.76	6.11	6.09
Final Import Share	2.04	1.84	1.66	1.49	1.46
Intermediate Export Share	5.46	6.68	6.93	6.24	5.82
Final Export Share	5.96	6.65	6.19	5.74	4.97
b. Capital Openness					
FDI Share	1.80	1.78	1.27	1.10	0.94
FUIFA Share	2.21	2.94	2.69	2.70	1.64
Observations	32	32	32	32	32

Source: Authors calculation based on data on trade (from WIOD database), FDI (from *China Statistical Yearbook* and *Report on Foreign Investment in China*), and FUIFA (from *Statistical Yearbook of the Chinese Investment in Fixed Assets*).
Notes: Shares in this table refer to shares in gross output. FUIFA is Foreign Urban Investment in Fixed Assets.

Regarding capital openness, the share of FDI in gross output decreased dramatically from 1.8% in 2003 to 0.9% in 2010. Similar to trade openness, the decreasing trend may also be attributed to the global financial crisis, which imposed large financial constraints on multinational corporations in their home countries and the declining external demand for China's exports. Meanwhile, China's market-oriented economic reforms that promoted higher output growth than FDI growth is another reason. In particular, with the implementation of the new Enterprise Income Tax Law from 2008, tax and other incentives for foreign enterprises to invest in China were reduced.[6] Unlike FDI, the FUIFA share shows the same pattern as trade, that is it increased first from 2003 to 2005 and then decreased afterwards.

[6]Until the end of 2007, the enterprise income tax on foreign enterprises was 15% or 24% compared with the standard rate of 33%. In accordance with the new Enterprise Income Tax Law, a uniform rate of 25% has been applied to all firms since 1 January, 2008.

5 First-stage Estimation and the Industry Wage Premium

To examine the impact of industry affiliation on explaining wage differences among individuals, we estimate three specifications for each year. In the first specification as presented by equation (7), the log of hourly wages (w_{jit}) is regressed on a set of industry dummies only. The R^2 in this case measures the extent of the wage variation that can be explained by industries. In the second specification, as shown by equation (8), a vector of individual worker characteristics, $\mathbf{H}_{jit}$ (gender, age, age squared, ethnicity, *hukou* type, marital status, party membership, education, social and economic status, etc.), as well as job and firm features, $\mathbf{X}_{jit}$ (occupation, job type, size of establishment and attitudes towards job) is added. To evaluate the additional influence of industry affiliation on wages over and above the impact of individual characteristics and job features, our final specification, as illustrated by equation (9), merely accounts for individual and job characteristics.[7]

$$\ln w_{jit} = \alpha_t + \sum_{i=1}^{I} \omega_{it} I_{jit} + \epsilon_{jit} \tag{7}$$

$$\ln w_{jit} = \alpha_t + \mathbf{H}_{jit}\beta_t + \mathbf{X}_{jit}\gamma_t + \sum_{i=1}^{I} \omega_{it} I_{jit} + \epsilon_{jit} \tag{8}$$

$$\ln w_{jit} = \alpha_t + \mathbf{H}_{jit}\beta_t + \mathbf{X}_{jit}\gamma_t + \epsilon_{jit} \tag{9}$$

All first-stage regression results are consistent across years and are in line with other studies (e.g. Appleton et al., 2014). Results for 2010 are reported in Table 2, and are available on request from the authors for the other years. Men, *han* Chinese, white collar workers, *ceteris paribus*, tend to earn more. However, we do not find significant wage differentials between *hukou* types, party membership and marital status. A clear concave relationship between wages and age is observed such that wages tend to increase with age but at a declining rate. The returns to schooling, as expected, are significantly positive and strictly higher for those with higher education level. People working in foreign invested enterprises (FIEs) and joint ventures (JVs) earn significantly higher incomes in all years.

[7] We use the textile and textile products industry as the reference group in all regressions.

Table 2: First-stage Estimation Results for 2010

	Log of Monthly Income			Log of Hourly Income		
	(1)	(2)	(3)	(4)	(5)	(6)
Female		-0.326***	-0.366***		-0.277***	-0.331***
		(9.70)	(11.07)		(7.06)	(8.63)
Age		0.048***	0.050***		0.030**	0.033**
		(4.10)	(4.19)		(2.30)	(2.43)
Age^2		-0.001***	-0.001***		-0.000**	-0.000**
		(4.40)	(4.52)		(2.43)	(2.54)
Han		0.161**	0.189***		0.128*	0.165*
		(2.36)	(2.66)		(1.69)	(2.12)
Urban *Hukou*		-0.001	0.027		0.061	0.097*
		(0.02)	(0.57)		(1.15)	(1.79)
Married		0.003	-0.017		-0.013	-0.036
		(0.05)	(0.28)		(0.20)	(0.52)
Party Membership		-0.044	-0.036		-0.012	-0.002
		(0.92)	(0.73)		(0.21)	(0.04)
Education						
Elementary School		0.263***	0.249**		0.211*	0.192*
		(2.71)	(2.55)		(1.90)	(1.71)
Junior Middle School		0.277***	0.258***		0.271***	0.246**
		(3.35)	(3.12)		(2.83)	(2.56)
Senior Middle School		0.399***	0.381***		0.462***	0.439***
		(4.58)	(4.38)		(4.54)	(4.27)
Technical Secondary School		0.463***	0.465***		0.479***	0.492***
		(4.78)	(4.82)		(4.26)	(4.36)
Junior College		0.619***	0.627***		0.666***	0.686***
		(6.51)	(6.63)		(5.95)	(6.13)
College/University		0.888***	0.899***		0.907***	0.934***
		(8.64)	(8.75)		(7.57)	(7.77)
Graduate and Above		1.252***	1.241***		1.386***	1.386***
		(7.94)	(7.89)		(7.89)	(7.85)
Weekly Working Hour		0.000	-0.000			
		(0.26)	(0.37)			
Blue Collar		-0.397***	-0.331***		-0.420***	-0.367***
		(8.36)	(7.55)		(7.85)	(7.18)
Job Type						
Government		-0.164*	-0.211***		-0.212**	-0.256***
		(2.15)	(3.67)		(2.22)	(3.83)
Collective Firms		-0.003	-0.000		-0.019	-0.022
		(0.05)	(0.01)		(0.24)	(0.28)
Private Firms		0.044	0.048		-0.095	-0.104*
		(0.84)	(1.03)		(1.61)	(1.91)

Table 2 – Continued

	Log of Monthly Income			Log of Hourly Income		
	(1)	(2)	(3)	(4)	(5)	(6)
FIEs and JVs		0.349***	0.361***		0.371***	0.383***
		(3.11)	(3.47)		(2.83)	(3.24)
Self-employed		0.013	0.035		-0.130*	-0.151**
		(0.22)	(0.61)		(1.84)	(2.31)
Size of Establishment						
50-99		0.027	-0.006		0.026	-0.007
		(0.49)	(0.10)		(0.41)	(0.11)
100-499		0.127***	0.070		0.133***	0.076
		(2.89)	(1.60)		(2.65)	(1.51)
500-999		0.259***	0.173**		0.278***	0.175*
		(3.59)	(2.33)		(3.13)	(1.92)
$\geqslant$ 1000		0.350***	0.303***		0.374***	0.325***
		(5.69)	(5.44)		(5.32)	(4.89)
Satisfied with Job		0.239***	0.244***		0.278***	0.279***
		(7.07)	(7.02)		(7.04)	(6.84)
Social & Economic Status						
Middle		0.281***	0.285***		0.290***	0.292***
		(7.73)	(7.70)		(6.74)	(6.59)
High		0.606***	0.614***		0.581***	0.587***
		(9.56)	(9.53)		(8.23)	(8.11)
Constant	6.772***	5.443***	5.682***	1.289***	0.415	0.688**
	(40.87)	(19.53)	(22.63)	(7.34)	(1.33)	(2.39)
Industry Indicators	Yes	Yes	No	Yes	Yes	No
Observations	2378	2378	2378	2378	2378	2378
R^2	0.085	0.393	0.357	0.121	0.382	0.340
$\overline{R^2}$	0.073	0.377	0.350	0.109	0.366	0.333

Notes: The dependent variable is the log of real monthly income in columns (1) to (3) and the log of real hourly income in columns (4) to (6), respectively. We use the consumer price index (CPI) of 2003 as the baseline price level. Sample weights are included in all regressions to control for possible heteroscedasticity.

* p <0.1, ** p <0.05, *** p <0.01. Absolute t statistics in parentheses.

Relative to small-sized firms (with 1-49 employees), larger establishments tend to pay higher wages. This can be attributed to the fact that large firms generate higher profits that are shared with the employees in order to attract more able workers or to raise workers' motivation. In contrast to other studies, we also control for individual attitudes towards their jobs, which reflect the relationship between employees and their employers. On average, individuals who feel more satisfied with their jobs earn up to 28% higher wages than dissatisfied workers. Consistent with our expectation, people of a higher social and economic status are paid more. By comparing the results based on monthly income in columns (1)-(3) and hourly income in columns (4)-(6), we can see that the coefficient estimates are quite similar. Therefore, we only comment on the results based on hourly income in the following discussion.[8]

The first column of the table presents results based on the inclusion of only industry dummies. The R^2 is 8.5% for 2010 and reaches values of up to 14.3% across the other years, which implies that the industry affiliation can explain at most 14.3% of individual wage dispersion. After controlling for individual and other job related characteristics, as presented in columns (2) and (3), the explanatory power of the model increases substantially with the R^2 ranging in 2010 from between 35.7% and 39.3% depending on whether industry fixed effects are included. By comparing the R^2 in columns (2) and (3), we can see that industry affiliation alone explains only 3.6% of the wage variation[9], which is lower than the specification without controlling for individual and job related characteristics. Our results are similar to the findings for the case of Colombia (Goldberg and Pavcnik, 2005), but are slightly lower than those found for India (Kumar and Mishra, 2008).

Based on the full specification as presented by equation (8), we compute estimates for the average yearly wage differentials for each industry. Following Zanchi (1998), we then normalise these estimated wage premia for each industry, so that the estimates can be interpreted as the wage deviation for an average worker in one industry compared to an average worker in all other industries with identical characteristics. Table 3 reports the normalised (hourly) wage premia and shows substantial wage dispersion across sectors and years. After controlling for individual and job related characteristics, agriculture, hunting, forestry and fishing, wood and wood products, and paper products are among the low wage industries. By contrast, electricity, gas and water supply, water transport, and real estate are industries that pay the highest average wages. Industries that pay above average in all five years include inland transport, financial intermediation, and real estate activities. Those industries, which pay systematically lower wages on average through the whole sample period, are paper products and retail trade.

[8]The estimated wage premia based on these two measures are highly correlated, with Pearson correlation being 0.92 and Spearman rank correlation being 0.95, both significant at 1%.

[9]This number reaches as high as 4.4% across the other years.

Table 3: Estimated (Hourly) Normalised Wage Premia

Industry	2003	2005	2006	2008	2010
Agriculture, Hunting, Forestry and Fishing	-0.311	-0.302	-0.378	0.668	0.223
Mining and Quarrying	-0.219	-0.057	0.112	-0.230	0.287
Food, Beverages and Tobacco	0.032	0.047	0.011	0.190	-0.324
Textiles and Textile Products	-0.181	0.126	-0.170	-0.242	-0.301
Leather and Footwear	-0.061	0.762	0.309	0.528	-0.587
Wood and Wood Products	-0.285	0.242	-0.077	-0.575	-0.370
Paper Products	-0.292	-0.154	-0.223	-0.162	-0.145
Petroleum	0.154	-0.182	0.080	0.380	-0.161
Chemicals and Chemical Products	-0.096	0.078	0.008	-0.226	-0.201
Rubber and Plastics	0.161	-0.036	0.232	-0.150	-0.067
Non-Metallic Mineral	-0.134	0.170	0.312	-0.376	-0.136
Basic Metals and Fabricated Metal	-0.063	0.097	-0.129	0.010	-0.224
Machinery, Nec.	-0.240	0.135	-0.005	-0.134	0.220
Electrical and Optical Equipment	0.058	-0.367	0.313	0.117	0.127
Transport Equipment	-0.069	-0.198	-0.152	0.071	-0.231
Manufacturing, Nec; Recycling	-0.025	-0.055	0.366	0.371	-0.380
Electricity, Gas and Water Supply	0.270	0.230	0.637	0.200	-0.024
Construction	0.060	-0.095	0.034	0.065	0.129
Wholesale Trade and Commission Trade	0.028	-0.062	0.241	0.283	0.910
Retail Trade	-0.064	-0.049	-0.002	-0.017	-0.033
Hotels and Restaurants	-0.040	0.063	0.127	-0.074	-0.217
Inland Transport	0.152	0.203	0.045	0.073	0.233
Water Transport	0.246	-0.142	0.669	0.255	1.877
Other Transport Activities	0.035	0.027	0.051	-0.035	0.298
Post and Telecommunications	0.338	0.166	-0.247	0.456	-0.279
Financial Intermediation	0.120	0.137	0.351	0.414	0.447
Real Estate Activities	0.231	0.604	0.484	0.281	0.238
Renting of M&Eq; Other Business Activities	-0.150	0.227	0.066	-0.023	1.408
Public Admin and Defence	0.095	-0.170	-0.013	-0.105	-0.015
Education	0.083	-0.114	-0.224	-0.061	-0.080
Health and Social Work	0.085	-0.060	-0.232	-0.227	-0.243
Other Services	0.041	0.039	-0.175	0.103	0.084

Notes: The dependent variables are the log of real hourly income in all regressions. We include sample weights in all regressions to control for possible heteroscedasticity.

The importance of controlling for individual heterogeneity within industries in calculating accurate industry wage effects is shown by comparing the estimated wage premia and the observed wage differentials (see Appendix Table A.2). Table A.3 reports standard deviations of wage premia and observed wage differentials and shows that the observed wage differentials vary more than the estimated premia in all years, though the correlation between the two is consistently positive (see Appendix Table A.4).

Moreover, the year-to-year correlations of the estimated wage premia are quite low and are often insignificant (see Appendix Table A.5), which suggests that the ranking of industries by wage premium varies considerably over the time period. This finding is fairly different from studies on developed countries. Katz and Summers (1989), Helwege (1992) and Robertson (2000) find that the industry ranking of U.S. wage differentials was relatively constant over the years. Du Caju et al. (2010) investigate inter-industry wage inequality of eight EU countries and find significantly high correlations between 1995 and 2002. In contrast, studies on developing countries - Mexico (Robertson, 2000), Colombia (Goldberg and Pavcnik, 2005) and India (Kumar and Mishra, 2008) - find similar, low yearly correlations, which is consistent with our findings.

6 Second-stage Estimation: Globalisation and the Wage Premium

6.1 Overall Trade Effects

We explore first the effects of trade openness on industrial wage premia, specifically the effect of industry variation in total trade, import and export share in gross output on predicted average industrial wage premia obtained from the first-stage analysis. The panel structure allows us to control for time-invariant, industry-specific fixed effects. To control for common shocks to all industries we include year dummies in all regressions. We further control for a number of industry-specific, time-varying factors that might explain wage differentials across industries such as the industry-level gross fixed capital formation (GFCF), value added (expressed as shares in gross output), and employment (as share in total employment). Data of these variables are taken from WIOD. The results of these regressions are set out in Table 4.

It is perhaps not very surprising that none of the coefficients of the different trade openness variables - total trade (total exports plus total imports), and total exports and total imports separately - reported in Table 4 are significant. One potential explanation is that the measures of trade openness may be over-aggregated and may hide the impact of trade openness that operates separately through trade in intermediate or final goods. As mentioned before, the tariff rate included in the specification in column (3) is a partial policy measure of trade liberalisation which abstracts from NTBs. Again we do not find a significant effect in column (3).

Table 4: Second-stage Estimation Results: Determinants of Industrial Wage Premia in China (2003-2010)

Variables	(1)	(2)	(3)
Trade Share	0.001		
	(0.23)		
Import Share		-0.001	
		(0.07)	
Export Share		0.002	
		(0.42)	
Tariff Rate			-0.007
			(0.27)
Value Added Share	0.014	0.014	-0.018*
	(1.67)	(1.64)	(1.98)
GFCF Share	0.001	0.001	0.011
	(0.67)	(0.62)	(1.02)
Employment Share	-0.051***	-0.051***	-0.066***
	(8.06)	(7.98)	(10.69)
Year Indicators	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Observations	160	160	85

Notes: The dependent variable in all regressions is the normalised inter-industry wage premia obtained from the first-stage regressions for five years between 2003 and 2010. Trade share, import share, export share, value added share, and GFCF share denote shares of trade, import, export, value added and gross fixed capital formation in industrial gross output respectively. Employment share is the share of industrial employment in total employment. Tariff rate is the most favoured nation (MFN) weighted average rate calculated by the authors based on data from World Integrated Trade Solution (WITS). Robust standard errors are computed in all specifications to control for possible heteroscedasticity.
* p <0.1, ** p <0.05, *** p <0.01. Absolute t statistics in parentheses.

6.2 Distinguishing between Intermediate and Final Goods Trade

Recognising that trade in final goods and intermediate goods may have different impacts on labour markets and wages, we repeat the investigation of trade openness effects by separating total exports and imports into trade in intermediate and final goods for each industry. Column (1) of Table 5 reports results of this disaggregation for the full sample and shows that wage differentials are mainly affected by import and export shares of final goods with expected signs (at 1% and 5% significance level respectively). The coefficients on both intermediate import share and intermediate export share are, however, insignificant. Column (1) further reveals that the impact of import and export shares of intermediate and final goods seem to offset each other, which explains why the total trade openness indicators did not reveal systematic relationships with industrial wage premia.

An increase in imports of final goods introduces more competition in the domestic market and is likely to lower the demand for local labour which in turn will lead to lower wages (Autor et al., 2013). The wage effect of imported intermediate goods, in contrast, is more likely to be ambiguous. As with imported final goods, the stronger competition between imported and local intermediates may result in lower wages. However, increased intermediate imports also enable firms to access a larger variety of inputs at lower costs, which improves productivity and therefore allows the firm to pay higher wages (Goldberg et al., 2010). The overall wage effect of intermediate imports consequently depends on which one of these two opposite effects dominates. Our insignificant results suggest that these effects offset each other in the present context.[10]

Positive export wage premia have been observed in both developing and developed economies (e.g. Bernard and Wagner (1997) on Germany, Greenaway and Yu (2004) for the UK, and Milner and Tandrayen (2007) for some Sub-Saharan African countries). Our results are consistent with theoretical predictions in the context of relatively unskilled labour abundant China that exports increase the demand for labour in export

[10] Another explanation could be the large fraction of processing trade in China. Considering that nearly half of the intermediate imports are used for processing exports (Koopman et al., 2012), it is likely that the effect of imported intermediates is captured by processing exports. Unfortunately, the data used in this study does not allow us to differentiate processing trade from ordinary trade.

industries and in particular for relatively low-skill-intensive activities, including the assembly of final products in the export processing sector. They are also in line with new trade theories (e.g. Melitz, 2003), which emphasise selection effects of exporting and the increase in overall industry productivity induced by exit of the least-productive firms. In contrast to final exports, our results for intermediate exports indicate a negative, albeit insignificant, relationship. Exports of intermediates may be more skill-intensive than exports of assembled final goods. Any productivity enhancement effects of exporting may be biased towards skilled workers, raising their wages but lowering those of unskilled workers. In this case the net effect of expanding intermediate exports will depend on the scale of these relative wages effects and the skill-intensity of production.

Table 5: Alternative Second-stage Estimation Results: Effects of Intermediate and Final Goods Trade on Wage Premia (2003-2010)

	Full Sample	Coastal Regions	Non-coastal Regions
	(1)	(2)	(3)
Intermediate Import Share	0.001	0.000	0.006
	(0.16)	(0.02)	(0.90)
Final Import Share	-0.040***	-0.048**	-0.033***
	(3.46)	(2.66)	(2.94)
Intermediate Export Share	-0.009	-0.011	-0.008
	(1.26)	(0.99)	(1.47)
Final Export Share	0.028**	0.040***	0.007
	(2.33)	(3.58)	(0.99)
Control Variables	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Observations	160	160	160

Notes: Intermediate import share, final import share, intermediate export share, and final export share denote the respective shares in gross output respectively. Control variables include the share of value added and the share of gross fixed capital formation in gross output, and the share of industrial employment in total employment. Robust standard errors are computed to account for possible heteroscedasticity.

* p <0.1, ** p <0.05, *** p <0.01. Absolute t statistics in parentheses.

Stronger trade effects might be expected in coastal rather than non-coastal regions. We re-run therefore the regressions distinguishing between the region where individuals are from.[11] To be able to do so, we derive the predicted industry wage premia by estimating equation (8) for coastal and non-coastal regions separately. Second-stage results are presented in columns (2) and (3) in Table 5. Our general findings based on the full sample are confirmed except for the insignificant coefficients on final exports for non-coastal provinces. The coefficient estimates clearly show that effects of trade openness are greater in coastal regions. In general, these provinces are more exposed to international trade (Han et al., 2012) such that the resulting influences on the labour market are also more pronounced in coastal than non-coastal regions.

6.3 Capital Openness and the Wage Premium

Table 6 reports the estimated impact of capital openness on wage premia. The coefficient estimate of FDI share in column (1) is positive, although insignificant. In column (2), we observe a significantly positive coefficient of FUIFA, indicating that, *ceteris paribus*, a 10% increase in FUIFA share is associated with 0.15% higher average wages. The empirical results suggest that capital openness is positively associated with industrial wage premia, with increased FDI and FUIFA inflows allowing the introduction of new technology, equipment, and management methods that improve productivity and hence raise wages.

Again we repeat the analysis for coastal and non-coastal regions separately. In columns (3) and (5), we find significant effects of FDI on wage premia in both coastal and non-coastal regions, however, with opposite signs. Specifically, FDI (FUIFA) openness is positively correlated with industrial wage premia in coastal regions whereas the relationship is found to be negative (insignificantly positive) in non-coastal regions. These mixed findings explain the insignificant effects found for the whole of China in column (1). Moreover, these results also reveal that capital openness contributes to widening wage inequality between coastal and non-coastal regions.

[11] Based on the *China Marine Statistical Yearbook*, coastal regions include Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan. All other mainland provinces are considered to be non-coastal regions.

Table 6: Alternative Second-stage Estimations: The Effects of Capital Openness on the Wage Premia (2003-2010)

	Full Sample		Coastal Regions		Non-coastal Regions	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI Share	0.002		0.027***		-0.008*	
	(0.60)		(5.62)		(1.72)	
FUIFA Share		0.015**		0.021**		0.005
		(2.30)		(2.53)		(0.61)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160	160	160	160	160	160

Notes: FDI share and FUIFA share refer to the respective shares in gross output. Control variables include the share of value added and the share of gross fixed capital formation in gross output, and the share of industrial employment in total employment. Robust standard errors are computed in all specifications to control for possible heteroscedasticity.
* p <0.1, ** p <0.05, *** p <0.01. Absolute t statistics in parentheses.

6.4 Endogeneity Issues

So far, we have included industry and year fixed effects to control for unobserved industry-specific time-invariant characteristics and common macroeconomic factors, which might be correlated with industry wage premia. However, fixed effects regressions do not account for any other unobserved industry heterogeneity that affects wages and openness simultaneously. In this case, our coefficient estimates would be biased. Goldberg and Pavcnik (2005) suggest that political economy factors may give rise to such unobserved industry heterogeneity. Another possible source of endogeneity is reverse causality, which applies if average industrial wages affect a firm's production decision and in turn influences its trade behaviour. To attract a better pool of workers firms could pay higher wages, which may result in increased productivity and exporting. To address these concerns, we use an instrumental variable strategy.

Table 7: Two Stage Least Squares Second-stage Estimations: Globalisation and Wage Premia (2003-2010)

	Full Sample			Coastal Regions			Non-coastal Regions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intermediate Import Share	0.002			0.007			0.003		
	(0.17)			(0.62)			(0.29)		
Final Import Share	-0.051*			-0.067*			-0.039*		
	(1.72)			(1.87)			(1.68)		
Intermediate Export Share	-0.012			-0.008			-0.011*		
	(1.51)			(0.99)			(1.73)		
Final Export Share	0.054***			0.064***			0.024*		
	(2.86)			(3.81)			(1.69)		
FDI Share		0.008			0.032			-0.003	
		(0.37)			(1.34)			(0.25)	
FUIFA Share			0.029			0.035			0.005
			(1.43)			(1.00)			(0.37)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160	160	160	160	160	160	160	160	160

Notes: The dependent variable in all regressions is the normalised inter-industry wage premia calculated from the first-stage regressions. The endogeneous regressors are instrumented for by their own first lags. Control variables include the share of value added and the share of gross fixed capital formation in gross output, and the share of industrial employment in total employment. Robust standard errors are computed in all specifications to control for possible heteroscedasticity.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Absolute t statistics in parentheses.

For an instrument to be valid, it needs to be highly correlated with the instrumented variables but uncorrelated with the error term. Following Du Caju et al. (2011), we use the first lags of the endogenous variables as instruments. The rationale is that the current value of wages should have little impact on trade and capital openness of the last period. One might argue that using the lags of the endogenous variables as instruments is problematic if the error term or the omitted variables are serially correlated (Angrist and Krueger, 2001). However, considering that our panel only covers five years, serial correlation should not influence the validity of our instruments.

Table 7 presents the results from the 2SLS regressions. The first stage results, not reported here, indicate a highly significant and positive relationship between the openness variables and their own first lags and, additionally, with the R^2 ranging from 0.62 to 0.85. Both the under-identification and the weak identification tests suggest that our instruments are valid. In general, the results are similar to the earlier ones, though significance is lost on the capital openness variables and reduced on the final import share. Overall, however, the findings on the effects of specific types of trade on the wage premia are confirmed, as is the presence of these effects for coastal regions only.

7 Conclusions

After joining the WTO, trade and international capital inflows surged substantially in China. Meanwhile, widening wage inequality has attracted much attention. This paper investigates the effects of globalisation on industry wage dispersion in China. When studying wage differentials across industries, it is important to control for individual and firm level effects. To achieve that, we use a two-stage strategy, which uses individual household level data in the first stage to obtain estimates of the average wage for each industry that controls for differences in worker characteristics and explains the estimated industrial wage premia in terms of globalisation factors in the second stage.

The first stage regression estimates the industrial wage premium, defined as that part of the overall wage variation that cannot be explained by worker and firm characteristics but is due to industry affiliation. We find that industry affiliation explains a relatively small proportion of actual wage variations, as has been found in other studies on developing countries. The empirical results also show that men, han Chinese, white collar workers, those working in larger firms, those satisfied with their jobs and those having higher social and economic status tend to earn more than other workers.

In the second stage, the estimated, industry wage premia are regressed on globalisation-related variables. Specifically, we consider two types of measures, trade openness and capital openness. We find evidence that it is mainly greater exposure to trade in final goods (imports and exports) that drives industry wage differentials, while the effects of intermediate imports and exports are insignificant. A higher final import share is negatively associated with wage premia, which is consistent with a disciplining effect of import competition. In contrast, wage premia tend to be larger the more the industry's involvement in the exporting of final goods. This may be consistent with factor price effects of trade in traditional models or with the selection effects of exporting as found in the new trade theories. The empirical results also reveal a positive, though less robust effect of capital openness on industry wage differentials. Finally, the significant trade effects are only experienced by individuals from coastal provinces.

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Appendix

Table A.1: Mean of Key Variables

Variable	2003	2005	2006	2008	2010
Individual Characteristics					
Hourly Income (yuan)	5.8729	6.6369	7.1645	9.1311	15.2010
Female(=1)	0.4129	0.4480	0.4366	0.4358	0.4303
Age	39.0619	37.1890	36.8142	37.3292	39.2678
Han(=1)	0.9460	0.9534	0.9478	0.9414	0.9267
Urban Hukou(=1)	0.9390	0.8998	0.7995	0.8018	0.7451
Married(=1)	0.8610	0.8130	0.7739	0.7970	0.8120
Party Membership(=1)	0.2254	0.1383	0.1043	0.1540	0.1941
Education					
Below Elementary School (Reference Group)	0.0134	0.0127	0.0128	0.0133	0.0490
Elementary School	0.0716	0.0581	0.0650	0.0986	0.0863
Junior Middle School	0.2707	0.2786	0.2984	0.2658	0.2407
Senior Middle School	0.2060	0.2475	0.2146	0.1977	0.1823
Technical Secondary School	0.1473	0.1338	0.1588	0.1380	0.1041
Junior College	0.2000	0.1723	0.1588	0.1465	0.1779
College/University	0.0850	0.0921	0.0851	0.1305	0.1442
Graduate and Above	0.0060	0.0049	0.0064	0.0096	0.0154
Job Characteristics					
Weekly Working Hour	47.9741	49.0483	50.6046	50.2696	50.7234
Blue Collar(=1)	0.4370	0.5827	0.4178	0.6537	0.6961
Job Type					
Government (Reference Group)	0.0794	0.0471	0.0632	0.0309	0.0616
State-Owned Firms	0.5755	0.4288	0.3332	0.3564	0.2792
Collective Firms	0.0679	0.0921	0.0947	0.0751	0.0660
Private Firms	0.0739	0.1489	0.0764	0.2014	0.2415
FIEs and JVs[1]	0.0199	0.0352	0.0201	0.0293	0.0259
Self-employed	0.1834	0.2480	0.4124	0.3069	0.3258

Table A.1 – Continued

Variable	2003	2005	2006	2008	2010
Employer Characteristics					
Size of Establishment					
1-49 (Reference Group)	0.3561	0.3920	0.4929	0.4683	0.5170
50-99	0.1053	0.0896	0.0915	0.1018	0.1147
100-499	0.2693	0.2525	0.2114	0.1971	0.2071
500-999	0.0744	0.0642	0.0686	0.0645	0.0474
$\geqslant$ 1000	0.1949	0.2017	0.1355	0.1684	0.1139
Relations					
Satisfied with Job(=1)	0.6309	0.5270	0.6572	0.6793	0.4453
Social and Economic Status					
Low (Reference Group)	0.5440	0.5065	0.5941	0.3436	0.3358
Middle	0.4034	0.4235	0.3590	0.5850	0.5465
High	0.0526	0.0700	0.0468	0.0714	0.1177
Observations	2165	2444	2185	1877	2468

Source: CGSS (2003, 2005, 2006, 2008, and 2010).
Notes: Only employed individuals are included in our sample. We use the consumer price index (CPI) of 2003 as baseline price level.
[1] FIEs and JVs refer to Foreign-invested Enterprises and Joint Ventures.

Table A.2: Observed Industrial Wage Differentials

Industry	2003	2005	2006	2008	2010
Agriculture, Hunting, Forestry and Fishing	-0.696	-0.262	-0.710	0.909	-0.044
Mining and Quarrying	-0.334	-0.108	-0.041	-0.261	0.543
Food, Beverages and Tobacco	0.028	-0.204	0.051	0.296	-0.585
Textiles and Textile Products	-0.432	-0.242	-0.631	0.639	-0.643
Leather and Footwear	-0.567	0.070	-0.048	-0.433	-0.856
Wood and Wood Products	0.421	-0.298	-0.114	-0.658	-1.123
Paper Products	-0.532	-0.395	-0.655	-0.526	-1.110
Petroleum	0.101	-0.207	-0.033	0.011	-0.176
Chemicals and Chemical Products	-0.149	0.092	-0.146	-0.038	-0.241
Rubber and Plastics	-0.049	-0.065	-0.033	-0.516	-0.282
Non-Metallic Mineral	-0.141	-0.357	0.052	-0.772	-0.995
Basic Metals and Fabricated Metal	-0.128	-0.168	-0.237	-0.013	0.019
Machinery, Nec.	-0.409	0.074	-0.057	-0.306	0.040
Electrical and Optical Equipment	0.299	-0.329	0.259	0.093	0.476
Transport Equipment	-0.188	-0.054	-0.226	-0.121	-0.256
Manufacturing, Nec; Recycling	-0.116	-0.132	0.306	0.335	-1.162
Electricity, Gas and Water Supply	0.342	0.209	0.604	0.601	-0.251
Construction	0.096	0.227	0.249	-0.140	0.606
Wholesale Trade and Commission Trade	0.501	-0.508	0.512	-0.009	0.918
Retail Trade	-0.331	-0.053	-0.075	-0.255	-0.023
Hotels and Restaurants	-0.250	-0.203	-0.129	-0.509	-0.950
Inland Transport	0.133	0.041	-0.146	-0.008	0.580
Water Transport	0.246	-0.213	0.584	0.550	1.306
Other Transport Activities	0.074	0.014	0.146	-0.652	-0.062
Post and Telecommunications	0.453	0.298	-0.171	0.989	-0.426
Financial Intermediation	0.367	0.397	0.448	0.627	0.561
Real Estate Activities	0.595	0.767	0.344	0.002	0.176
Renting of M&Eq; Other Business Activities	-0.079	0.316	-0.062	0.627	0.447
Public Admin and Defence	0.146	0.095	0.214	-0.039	-0.087
Education	0.500	0.215	0.144	0.282	0.088
Health and Social Work	0.203	0.152	0.015	-0.043	-0.364
Other Services	-0.026	-0.078	-0.145	0.229	0.271

Source: Authors' calculation based on the CGSS database.

Notes: Observed industrial wage differentials are defined as the difference between the reported industry average wage and the employment-weighted average of all industries.

Table A.3: Standard Deviations of Wage Premia and Observed Wage Differentials

Variable	2003	2005	2006	2008	2010
Wage Premium	0.170	0.230	0.259	0.278	0.508
Observed Wage Differential	0.340	0.267	0.320	0.464	0.618

Source: First-stage estimation and authors' calculation.

Table A.4: Correlation between Wage Premia and Observed Wage Differentials

Correlation	2003	2005	2006	2008	2010
Pearson Correlation	0.706	0.481	0.777	0.583	0.773
Spearman Rank Correlation	0.720	0.358	0.723	0.578	0.838

Source: First-stage estimation and authors' calculation.
Note: All correlation coefficients are significant at 1% significance level.

Table A.5: Year-to-year Correlation of Estimated Wage Premia

	2003	2005	2006	2008	2010
2003	1.000				
2005	0.090	1.000			
2006	0.436**	0.300*	1.000		
2008	0.402**	0.049	0.218	1.000	
2010	0.156	-0.144	0.377**	0.155	1.000

Source: First-stage estimation and authors' calculation.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.