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What caused the wage convergence between urban natives and migrants in China?

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Abstract

In the Chinese labor market, the wage gap between urban natives and rural-urban migrants has narrowed 17% from 2002 to 2013. This research focuses on wage convergence and seeks to underpin the reasons. I utilize the Chinese Household Income Project (CHIP) survey dataset and employ Juhn, Murphy, and Pierce (1991) decomposition method to undertake the analysis. I find three main factors that caused the closing wage gap: reduced discrimination (74.45%), favorable wage structure (31.24%), and improvement in job characteristics of migrants (24.56%). But the differentials in schooling quality widen the wage gap by 45.00%. This study further explores the wage gap trends in different skill groups and finds that low-skilled migrants benefit more than high-skilled from the labor market.

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1 Introduction

Since the reform and opening in the 1980s, China's industrialization and urbanization have continued to improve. More and more rural laborers flooded into cities and became the driving force for the urbanization. However, migrants[1] cannot enjoy the same treatment as urban natives[2] in terms of employment, salary, and social insurance. Wage gap between urban natives and migrants has aroused extensive attention(Yao, 2016).

In previous studies, many researchers have examined causes of the cross-sectional wage gap. Deng (2007), Ma (2012), Yu and Sun (2017) used the Oaxaca-Blinder model (Oaxaca, 1973; Blinder, 1973) and the FFL model (Firpo et al., 2009) to undertake the decomposition. They found that both discrimination and human capital differentials affect the wage gap. Some researchers also paid attention to job characteristics. Ma (2018) discussed the impact of labor market segmentation by industry sectors on the wage gap. However, the effect of discrimination differs among these studies. Besides, the wage gap has narrowed 17% from 2002 to 2013, but few researchers focused on it.

This paper uses the Chinese Household Income Project (CHIP) survey datasets and employs Juhn, Murphy, and Pierce (1991, below denoted as JMP) decomposition method to analyze the wage convergence. The method provides a way to show the effect of unobserved skills on wage gap explicitly (Yun, 2009). The contributions this paper made are as follows: First, it explores reasons caused the wage convergence between migrants and urban natives in the 2000s. Second, it investigates how eliminating discrimination affect the wage gap. Third, it measures unobserved schooling quality impact on the wage gap. Forth, it discusses the wage gap trends in different skill groups.

I find three main factors caused closing wage gap: the elimination of discrimination accounts for 74.45%, favorable wage structure accounts for 31.24%, and migrants' improvement in job characteristics accounts for 24.56%. However, differentials in schooling quality increased the wage gap by 45.00%. I also find that low-skilled migrants benefit more from the labor market.

2 Data and Samples

I use two-period survey data from the Chinese Household Income Project (CHIP) for analysis. These data are gained from CHIP conducted by the Economic Institute of Chinese Academy of Social Sciences and Beijing Normal University in 2003 and 2014 (CHIP2002 and CHIP2013), which include information on the personal and job characteristics of urban natives and migrants. The sample contains 12 provinces in 2002 and 15 in 2013, including the eastern, central, and western regions of China.

I employ some treatments to deal with samples: Firstly, according to relevant regulations on retirement age in China, I select males aged 16-60 and females aged 16-55. Second, the

[1] The Chinese labor market is segmented by Household Registration System (Huko in Chinese language). "Migrants" is used to refer to individuals who possess Huko from rural area but live in cities for working or living purposes.

[2] "Urban natives" is used to refer to individuals who possess Huko of an urbanized area, meaning they have legal residence and working permit in the area.

Table 1: Data description

	2002				2013			
	Urban Natives		**Migrants**		**Urban Natives**		**Migrants**	
Variable	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Log hourly earnings	1.500	0.731	0.867	0.677	2.656	0.753	2.434	0.684
Male	0.549	0.498	0.598	0.491	0.560	0.496	0.573	0.495
Education(year)	11.506	2.854	8.473	2.781	12.393	3.101	9.847	2.946
Work experience(year)	22.919	10.010	18.738	10.687	22.101	11.122	20.073	10.951
Education level								
Less than high school	0.288	0.453	0.754	0.431	0.244	0.430	0.612	0.485
High school	0.396	0.489	0.198	0.399	0.320	0.466	0.229	0.421
College and above	0.316	0.465	0.048	0.214	0.436	0.496	0.149	0.356
Region								
East	0.429	0.495	0.453	0.498	0.435	0.496	0.463	0.499
Central	0.306	0.461	0.265	0.442	0.367	0.482	0.360	0.480
West	0.265	0.441	0.282	0.450	0.198	0.398	0.177	0.382
Occupation								
White collar	0.535	0.499	0.178	0.383	0.485	0.499	0.234	0.424
Blue collar	0.341	0.474	0.326	0.382	0.244	0.429	0.366	0.482
Service personnel	0.124	0.329	0.496	0.500	0.271	0.444	0.400	0.490
Industry								
Manufacturing	0.279	0.448	0.134	0.340	0.156	0.363	0.216	0.411
Construction	0.034	0.182	0.091	0.288	0.043	0.199	0.102	0.303
Wholesale, retail & catering	0.101	0.301	0.212	0.409	0.135	0.342	0.254	0.435
Service	0.102	0.301	0.266	0.440	0.134	0.341	0.158	0.365
Finance, education, health, & culture	0.182	0.386	0.065	0.247	0.224	0.417	0.099	0.299
Public sector	0.110	0.312	0.033	0.178	0.127	0.334	0.022	0.147
Others	0.192	0.393	0.199	0.400	0.181	0.385	0.149	0.356
Enterprise property								
State owned & state controlled	0.387	0.492	0.195	0.396	0.489	0.500	0.125	0.330
Collective	0.079	0.270	0.105	0.307	0.049	0.215	0.049	0.216
Private	0.042	0.201	0.166	0.372	0.271	0.444	0.449	0.498
Individual	0.041	0.198	0.297	0.457	0.090	0.286	0.271	0.445
Foreign&joint venture	0.026	0.160	0.017	0.130	0.034	0.182	0.029	0.168
Other shared	0.425	0.281	0.220	0.415	0.067	0.247	0.077	0.253
Observations	6966	6966	1104	1104	5142	5142	858	858

Note: Work experience is calculated by “age - schooling years - 6.”

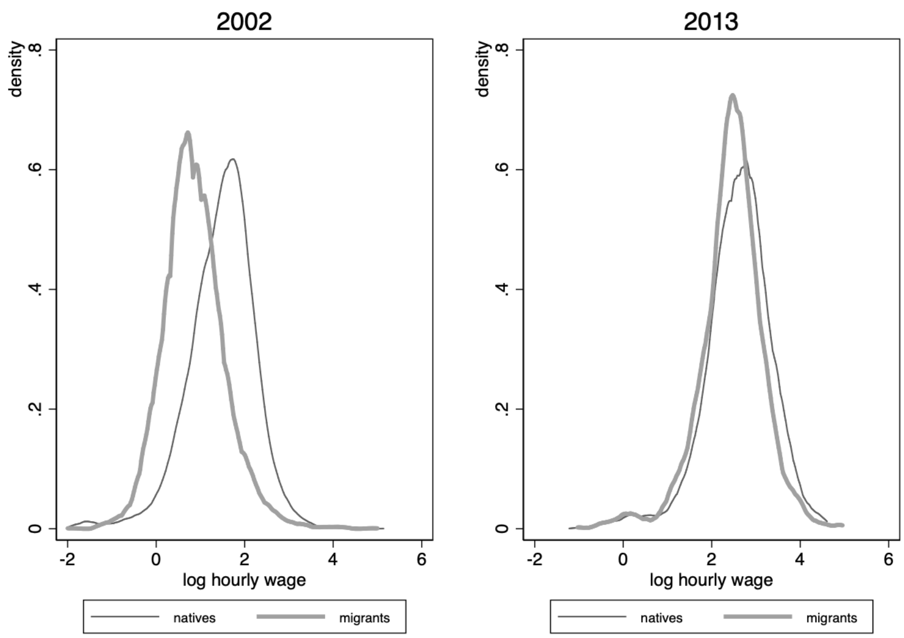

Figure 1: Wage distribution of urban natives and migrants

subjects of analysis are limited to the labor force population. Third, I remove self-employed observations[3], urban natives who have changed their Huko[4], and missing values. After this selection process, the sample includes 6966 urban natives and 1104 migrants in 2002, while 5142 urban natives and 858 migrants in 2013.

When comparing the change of the estimated kernel density curve (Figure 1), the gap between migrants and local urban residents reduced from 2002 to 2013. It shows that the wage gap narrowed in this period. Additionally, the density of high-wage groups is higher for local urban residents than for migrants in both two years. It indicates that there are more high wage workers in urban natives than migrants.

Table 1 shows the associated descriptive statistics. The wage gap narrowed from 0.633 to 0.222 log points in the 2000s. Differentials in average education years and work experience have decreased between migrants and urban natives. Changes in job characteristics are also visible, and migrants have improved their job positions. For instance, migrants who are in the manufacturing, FEHC (finance, education, health, and culture) industries and white-collar occupations increased by 8.2%, 3.4%, and 5.6%, respectively. But most migrants are still working in lower-pay job positions, such as blue-collar occupations, service personnel, and wholesale and retail sectors. In terms of enterprise property, the majority of urban natives work in state-owned or state-shared firms, while migrants gather in the individual or private firms. Primarily, migrants employed by private firms rose to 44.9% from 16.6% during the 2000s.

Table 2 shows the detailed descriptive statistics of different education groups and experience

[3]Self-employed observations include self-employed individuals, private business owners, etc.
[4]Huko means the Chinese Household Registration.

Table 2: **Detailed descriptive statistics**

Panel A: Wage gaps in education groups and experience levels			
	Wage gap in 2002	Wage gap in 2013	Wage gap differentials
Education groups			
Less than high school	0.464	0.020	-0.444
High school	0.379	0.051	-0.328
College or above	0.419	0.224	-0.195
Experience levels			
0-10 years	0.447	0.143	-0.304
10-20 years	0.551	0.197	-0.354
20-30 years	0.680	0.295	-0.385
>30 years	0.884	0.292	-0.592
Panel B: Educational attachment in experience levels			
	Urban natives	Migrants	Education gap
2002			
0-10 years	13.64	10.46	3.18
10-20 years	12.66	8.85	3.80
20-30 years	11.21	7.46	3.75
>30 years	9.69	5.78	3.91
2013			
0-10 years	14.63	12.51	2.12
10-20 years	13.63	10.30	3.33
20-30 years	12.06	8.75	3.31
>30 years	9.96	7.54	2.42

levels. The wage gap converged most in the less than high school group, while least in the college or above group. Since the quality of schooling in college is greater than in primary school, that may slow down the wage convergence in high skilled groups. This issue will be further discussed in Section 4.2. Wage convergence performance also differs in work experience levels. The wage gap of more than 30-years experience workers converged almost twice as that of young workers. The result is consistent with the above when I check the education attachment in a given experience level (Table 2 Panel B). The average schooling years of older workers are less than ten years, which means almost all of them are low-skilled. In contrast, young workers have more than 12 schooling years. It also illustrates that the wage gap of low skilled workers converged more in the 2000s.

3 Analytical Framework

3.1 OLS model

The estimations based on OLS are requested to explore the wage gaps between urban natives and migrants. The OLS analysis is expressed by equation(1).

$$y_{gi} = \mathbf{x}_{gi}\boldsymbol{\beta}_g + u_{gi} \tag{1}$$

In equation (1), y is the logarithm of the average hourly wage. g means group, which represents urban natives and migrants. $\mathbf{x}$ describes the factors (e.g., education, experience years, occupations, industries, ownerships) which affect wage, u is a random error item.

Here, education is a dummy variable that contains less than high school, high school, and college or above. Experience is a continuous variable. Since the experience years are not reported in the CHIP datasets, this study calculates it by using "age - education years - 6" (Gupta et al., 2006). Hence, the regression utilizes the experience years and a square of experience years instead of age. Also, six kinds of industries—manufacturing; construction; wholesale, retail, and catering; service; finance, education, health, and culture industries; public sector; and others—are utilized to construct the category variable. Occupation is also a category variable that includes white-collar, blue-collar, and service personnel. Enterprise property contains collective, private, individual, foreign, and other shares.

3.2 JMP decomposition method

I use a technique developed by Juhn et al. (1991) in their analysis of trends in black-white wage differentials to assess the effects of wage inequality on the native-migrant pay gap. This technique allows decomposing the wage gap into a portion due to individual characteristics differentials and a portion due to changes in the overall level of wage inequality.

JMP decomposition method is widely used in the wage gap trend analysis filed. Juhn et al. (1993) apply the decomposition methodology to the second moment of income distribution. Blau & Kahn (1997) use this method to panel data to analyze how a falling gender wage gap occurred despite changes in wage structure unfavorable to low-wage workers in the 1980s. They further define "gender-specific" factors and "wage structure" effect based on the decomposition results. However, the JMP decomposition method has to rely on strong assumptions such as OLS estimates of one group (base group) are unbiased, while those of the other group are biased (Yun, 2009). To release the assumptions, Gupta et al. (2006) anchor the pooled wage regression analysis rather than the base group's regression.

Following JMP's notation, suppose that I have for urban native workers i and migrant workers j. The wage equation of urban natives is:

$$y_{ui} = \mathbf{x}_{ui}\boldsymbol{\beta}_u + \theta_{ui}\sigma_u, E\left[\theta_{ui}|\mathbf{x}_{ui}\right] = 0, \tag{2}$$

where y_{ui} is the log of wages, x_{ui} is a vector of explanatory variables, β_u is a vector of coefficients, θ_{ui} is a standardized residual(i.e.,with mean zero and variance one), and σ_u is the residual standard deviation of urban natives' wages (i.e., level of urban natives' residual wage inequality).

Table 3: **Ordinary Least Squares regression results**

	2002		2013	
Variables	**Urban natives**	**Migrants**	**Urban natives**	**Migrants**
Male	0.125***	0.285***	0.179***	0.317***
	(0.0155)	(0.0386)	(0.0198)	(0.0467)
Experience	0.039***	0.030***	0.032***	0.028***
	(0.0029)	(0.0063)	(0.0034)	(0.0087)
Experience square	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Education level				
High school	0.215***	0.274***	0.180***	0.0869
	(0.0201)	(0.0485)	(0.0270)	(0.0584)
College	0.408***	0.598***	0.507***	0.327***
	(0.0254)	(0.0919)	(0.0317)	(0.0812)
Region				
Central	-0.401***	-0.255***	-0.258***	-0.136***
	(0.0177)	(0.0449)	(0.0214)	(0.0501)
West	-0.296***	-0.319***	-0.184***	-0.132**
	(0.0183)	(0.0437)	(0.0255)	(0.0629)
Occupation				
Blue workers	-0.201***	0.063	-0.193***	-0.107*
	(0.0194)	(0.0607)	(0.0280)	(0.0651)
Service personnel	-0.316***	-0.116**	-0.185***	-0.184***
	(0.0290)	(0.0471)	(0.0273)	(0.0668)
Industry				
Construction	-0.053	0.159**	0.099**	0.267***
	(0.0413)	(0.0735)	(0.0493)	(0.0822)
WRC	-0.112***	-0.028	-0.133***	0.043
	(0.0298)	(0.0589)	(0.0351)	(0.0710)
FEHC	0.164***	-0.017	0.012	0.016
	(0.0222)	(0.0807)	(0.0291)	(0.0882)
Service	-0.240***	-0.091*	-0.139***	0.076
	(0.0279)	(0.0545)	(0.0333)	(0.0769)
Public	0.046*	-0.158	-0.116***	-0.100
	(0.0269)	(0.1060)	(0.0343)	(0.1630)
Enterprise property				
Collective	-0.312***	0.056	-0.098***	-0.010
	(0.0284)	(0.0696)	(0.0455)	(0.1180)
Private	-0.245***	0.143**	-0.130***	-0.024
	(0.0378)	(0.0631)	(0.0256)	(0.0747)
Individual	-0.498***	-0.040	-0.196***	-0.056
	(0.0391)	(0.0556)	(0.0389)	(0.0834)
Foreign	0.158***	0.331**	0.225***	0.321**
	(0.0470)	(0.1453)	(0.0534)	(0.1475)
Other share	-0.081***	-0.089	-0.250***	-0.324***
	(0.0272)	(0.0569)	(0.0411)	(0.1103)
Constant	1.072***	0.619***	2.250***	2.179***
	(0.0429)	(0.0977)	(0.0560)	(0.1410)
Observations	6,966	1,104	5,142	858
R-squared	0.2982	0.2513	0.2261	0.1551

Note: ***, ** and * are significant at the 1%, 5% and 10% levels. Standard errors are in parentheses.
WRC: Wholesale, retail and catering
FEHC: Finance, education, health and culture

According to the JMP decomposition method assumption, I assume that the returns to individual characteristics are the same for both urban natives and migrants and construct an auxiliary wage function for migrants.

$$y_{mj} = \mathbf{x}_{mj}\beta_u + \theta_{mj}\sigma_u, E\left[\theta_{mj}|\mathbf{x}_{mj}\right] \neq 0, \tag{3}$$

Using this auxiliary wage equation, wage gap could then be decomposed as follows:

$$\begin{aligned}
\overline{D_{ij}} &= \overline{y_{ui}} - \overline{y_{mj}} \\
&= \mathbf{x}_{ui}\widehat{\boldsymbol{\beta}}_u + \overline{\overline{\widehat{\theta}}}_{ui}\widehat{\sigma}_u - \left(\mathbf{x}_{mj}\widehat{\boldsymbol{\beta}}_u + \overline{\overline{\theta}}_{mj}\widehat{\sigma}_u\right) \\
&= \left(\mathbf{x}_{ui} - \mathbf{x}_{mj}\right)\widehat{\beta}_u + \left(\widehat{\theta}_{ui} - \widehat{\theta}_{mj}\right)\widehat{\sigma}_u,
\end{aligned}$$

here, $\left(\mathbf{x}_{ui} - \mathbf{x}_{mj}\right)\widehat{\beta}_u$ represents the effect of observed characteristics differentials, similarly $\left(\widehat{\theta}_{ui} - \widehat{\theta}_{mj}\right)\widehat{\sigma}_u$ is the effect the unobserved skill gap. Then, taking the average over individuals, I obtain the following:

$$\begin{aligned}
\overline{D} &= \overline{y}_u - \overline{y}_m \\
&= \left(\overline{\mathbf{x}}_u - \overline{\mathbf{x}}_m\right)\widehat{\beta}_u - \overline{\overline{\widehat{\theta}}}_m\widehat{\sigma}_u.
\end{aligned}$$

Based on the framework above, let's consider the wage convergence from 2002 to 2013. Let year 0 refer to 2002 and year 1 refer to 2013. Then, wage gap in the year 0, $\bar{D}_0$ is

$$\overline{D}_0 = \left(\overline{\mathbf{x}}_{u0} - \overline{\mathbf{x}}_{m0}\right)\widehat{\beta}_{u0} - \overline{\overline{\widehat{\theta}}}_{m0}\widehat{\sigma}_{u0}. \tag{4}$$

Wage gap in the year 1, $\bar{D}_1$ is

$$\overline{D}_1 = \left(\overline{\mathbf{x}}_{u1} - \overline{\mathbf{x}}_{m1}\right)\widehat{\beta}_{u1} - \overline{\overline{\widehat{\theta}}}_{m1}\widehat{\sigma}_{u1}. \tag{5}$$

The wage convergence in urban natives and migrants from year 0 to year 1 would then be

$$\begin{aligned}
\overline{D}_1 - \overline{D}_0 = &\left(\triangle\overline{\mathbf{x}}_1 - \triangle\overline{\mathbf{x}}_0\right)\widehat{\boldsymbol{\beta}}_{u1} + \triangle\overline{\mathbf{x}}_0\left(\widehat{\boldsymbol{\beta}}_{u1} - \widehat{\boldsymbol{\beta}}_{u0}\right) \\
&+ \left(\triangle\overline{\overline{\theta}}_1 - \triangle\overline{\overline{\theta}}_0\right)\widehat{\sigma}_{u1} + \triangle\overline{\overline{\theta}}_0\left(\widehat{\sigma}_{u1} - \widehat{\sigma}_{u0}\right),
\end{aligned} \tag{6}$$

here, $\triangle\overline{\mathbf{x}}_t = \overline{\mathbf{x}}_{ut} - \overline{\mathbf{x}}_{mt}$, $\triangle\overline{\overline{\hat{\theta}}}_t = -\overline{\overline{\hat{\theta}}}_{mt}$(t=0,1). Since $\overline{\overline{\hat{\theta}}}_{ut}$ should be zero according to the assumption of JMP, that is, OLS estimates of urban natives are unbiased. The JMP method explains wage differentials in terms of differences in characteristics (both changes in characteristics and skill prices) and in terms of differences in residuals. The residual gap is further specified in terms of the standard deviation of the residuals and standardized residuals.

The first term of equation(6) measures "observed skill gap effect," reflects the contribution of changing native-migrant differences in observed characteristics. The second term is "observed skill price effect" that calculates the wage convergence caused by changes in the coefficients of the observed characteristics. "Skill price" means the value of skills in the labor market. The third term is the "unobserved gap effect" , which measures the effect of changing differences in the relative wage positions of urban natives and migrants after controlling for observed characteristics. It gives the contribution of unobserved skill gaps and unobserved discriminations. The fourth term stands "unobserved skill price effect," which reflects the effect of differences in residual inequality between the two years.

4 Results

4.1 The factors caused closing wage gap

This study implements the JMP decomposition method by using human capital specification and full specification. In the human capital specification, I use X as explanatory variables, a vector including sex, education, experience, a square of experience, and region variables. In the full specification, I add the explanatory variables in vector X, which are dummy variables for occupation, industry, and enterprise property.

Table 4 shows the decomposition results. Human capital specification results are reported in column 1. The observed skill gap effect narrowed the wage gap by 16.80% (0.0691/0.4113), which represents the effect of changes in human capital gap. In contrast, the unobserved gap effect contributes the bulk (76.51%) of convergence, which is the effect of unobserved individual skill gaps and discrimination.

Job characteristics may play an essential role in affecting the wage gap (Ma, 2018), but excluded in the human capital specification. I thus add job characteristics in the full specification to further analyze the wage gap trend. Column 2 shows the results. The contribution of observed skill gap effect rises to 37.22% (0.1531/0.4113), but that of unobserved gap effect reduces to 31.58% (0.1299/0.4113). It means that changes in job characteristics contribute a lot to closing the wage gap, which is 24.56%. In detail, changes in occupations account for 12.50%, changes in industries account for 6.22%, and changes in enterprise properties account for 5.84%. Vocational training and public policies helped migrants break the job-hunting barriers, so the proportion of migrants who work in high-paying jobs increased and drove up migrants' earnings.

The observed skill price effect narrowed the wage gap by 31.24% (0.1285/0.4113), which shows wage structure benefit migrants to converge the gap during the 2000s. Changes in returns to job characteristics closed the wage gap by 0.1464 log points, accounting for 35.59%. Differences in returns to occupations, industries, and enterprise properties contribute 4.67%, 12.69%, and 18.23%, respectively. It shows that migrants are floating down with the favorable wage structure. Particularly the development of private or individual firms raises migrants' wages.

Unobserved gap effect accounts for 31.58%, but it contains the effects of both unobserved individual skill gaps and discrimination. To figure out these effects, I employ a proxy variable to estimate the "effective" education years of migrants. The disaggregated analysis presented below is designed to shed further light on this issue.

Table 4: JMP decomposition results

	(1)HC Specification	(2)Full Specification	(3)Adjusted Specification
Wage convergence	-0.4113	-0.4113	-0.4113
	(0.0308)	(0.0293)	(0.0293)
Observed skill gap effect	-0.0691	-0.1531	-0.1531
	(0.0143)	(0.0197)	(0.0097)
Male	0.0048	0.0042	0.0042
	(0.0035)	(0.0026)	(0.0026)
Education	-0.0241	-0.0155	-0.0155
	(0.130)	(0.0066)	(0.0166)
Experience	-0.0510	-0.0423	-0.0423
	(0.0116)	(0.0070)	(0.0070)
Region	0.0012	0.0016	0.0016
	(0.0085)	(0.0089)	(0.0089)
Occupation		-0.0514	-0.0514
		(0.0082)	(0.0082)
Industry		-0.0256	-0.0256
		(0.0075)	(0.0075)
Enterprise property		-0.0240	-0.0240
		(0.0105)	(0.0105)
Observed skill price effect	-0.0279	-0.1285	-0.1285
	(0.0135)	(0.0186)	(0.0186)
Male	-0.0009	-0.0008	-0.0008
	(0.0009)	(0.0008)	(0.0008)
Education	-0.0132	0.0249	0.0249
	(0.0122)	(0.0134)	(0.0134)
Experience	-0.0160	-0.0096	-0.0096
	(0.0037)	(0.0036)	(0.0036)
Region	0.0021	0.0036	0.0036
	(0.0016)	(0.0026)	(0.0026)
Occupation		-0.0192	-0.0192
		(0.0068)	(0.0068)
Industry		-0.0522	-0.0522
		(0.0103)	(0.0103)
Enterprise property		-0.0750	-0.0750
		(0.0175)	(0.0175)
Schooling quality effect			0.1851
			(0.0183)
Education return gap effect			-0.0082
			(0.0026)
Discrimination effect			-0.3062
			(0.0431)
Unobserved gap effect	-0.3147	-0.1299	
	(0.0332)	(0.0321)	
Unobserved skill price effect	0.0004	0.0002	-0.0004
	(0.0047)	(0.0046)	(0.0018)

Note: Standard errors are in parentheses.
HC: Human Capital

4.2 Schooling quality and discrimination

Since the educational wage differential is the most natural differential for looking at the wage gap (Juhn et al. 1991), I assume that the unobserved skill gap is accounted for entirely by differences in the quality of schooling. Based on the method Juhn et al. (1991) developed, this study uses the education of urban natives at a given level of schooling as a proxy for the "effective" schooling of migrants. Empirically I calculated this term as follows. For both urban natives and migrants, I estimate the returns to education independently for less than high school, high school, and college or above groups. Then I get "effective" schooling for migrants by finding the level of urban natives' schooling that gave the same level of earnings at a given level of migrants' schooling.

The log-wage equations for urban residents and migrants are:

$$y_{uit} = \mathbf{x}_{uit}\boldsymbol{\beta}_{ut} + u_{uit}, E\left[u_{uit}|\mathbf{x}_{ui}\right] = 0, \tag{7}$$

$$y_{mjt} = (\mathbf{x}_{mjt}*)\boldsymbol{\beta}_{ut} + u_{mjt}, E\left[u_{mjt}|\mathbf{x}_{mj}\right] \neq 0, \tag{8}$$

where $\mathbf{x}_{mjt}* = \mathbf{x}_{mjt} + q$ is a matrix that includes the quality-adjusted education level for migrants. q is the differential between "effective" schooling and actual schooling. The other characteristics in $\mathbf{x}$ remain the same as the full specification. The changes in wage gap between urban natives and migrants from year 0 to year 1 would then be:

$$\begin{aligned} \overline{D}_1 - \overline{D}_0 = {} & \left(\triangle\overline{\mathbf{x}}_1 - \triangle\overline{\mathbf{x}}_0\right)\widehat{\boldsymbol{\beta}}_{u1} + \triangle\overline{\mathbf{x}}_0\left(\widehat{\boldsymbol{\beta}}_{u1} - \widehat{\boldsymbol{\beta}}_{u0}\right) \\ & + \left(\triangle\overline{q}_1 - \triangle\overline{q}_0\right)\widehat{\beta}_{u1} + \triangle\overline{q}_0\left(\widehat{\beta}_{u1} - \widehat{\beta}_{u0}\right) \\ & + \left(\triangle\overline{\overline{\widehat{\theta}}}_1 - \triangle\overline{\overline{\widehat{\theta}}}_0\right)\widehat{\sigma}_{u1} + \triangle\overline{\overline{\widehat{\theta}}}_0\left(\widehat{\sigma}_{u1} - \widehat{\sigma}_{u0}\right), \end{aligned} \tag{9}$$

The first and second terms are observed skill gap effect and price effect, which are the same as the full specification. The third term and fourth term represent the effect of changes in schooling quality at a fixed price and the effect of the shift in education returns at the fixed schooling quality gap. The fifth term shows the effect of changes in discrimination. After "correct" the schooling level for migrants, the unobserved gap $\left(\triangle\overline{\overline{\widehat{\theta}}}_1 - \triangle\overline{\overline{\widehat{\theta}}}_0\right)$ reflects different treatments in other characteristics, that is discrimination.

The last column in Table 4 shows the decomposition results. Schooling quality gap widens the wage gap by 45.00% (0.1851 log points). It illustrates urban residents enjoy higher schooling quality than migrants that slowdown the wage convergence. On the other hand, the effect of changes in discrimination narrowed the wage gap by 0.3062 log points, accounting for 74.45%. Eliminating discrimination plays a crucial role in closing the wage gap.

4.3 Greater close in low skilled workers

This section aims to analyze the wage convergence in different skill groups: less than high school, high school, and college or above. The observations in each group are 4629, 4820,

Table 5: Wage gaps in different skill groups

	Less than high school	High school	College
Wage gap in 2002	0.4643	0.3790	0.4188
	(0.0290)	(0.0499)	(0.0888)
Wage gap in 2013	-0.0310	0.0514	0.2276
	(0.0385)	(0.0563)	(0.0630)
Wage convergence	-0.4953	-0.3276	-0.1912
	(0.0449)	(0.0768)	(0.1018)
Observations	4629	4820	4621

Note: Standard errors are in parentheses.

and 4621. As Table 2 already showed, the wage gap narrowed most in the less than high school group. Low skilled migrants' average earnings are even higher than urban natives' in 2013. Table 5 gives a more detailed description of standard errors.

I adopt the JMP decomposition method under the full specification for the three groups. Three main findings as follows base on the results reported in Table 6. First, changes in differentials of observed skills help to narrow the wage gap in all groups but have the most significant impact on the low-skilled group. It indicates that low-skilled migrants raise their earnings more by improving job characteristics. Second, the observed price gap effect also contributes most to the low-skilled group. Because of the public policies' protection, wage structure benefits low-skilled migrants more than high-skilled. The Chinese state council issued several policies to solve migrants' employment problems and safeguard migrants' legitimate rights, making them enjoy profitable returns to skills. Third, the changes in human capital characteristics affect high-skilled workers more than low-skilled. Both work experience years and the returns to experience are more effective in the college than in the less than high school group. It shows that the Law of Compulsory Education issued in 2006 and the development of vocational education for migrants have a fundamental impact on closing the wage gap for high skilled migrants.

Migrants improved job positions, enjoyed favorable wage structures, and increased human capital stocks. Besides, low skilled workers are over-demand in the 2000s(Liu, 2016). Therefore, low-skilled migrants benefit more than high-skilled.

5 Conclusions

By using the Chinese Household Income Project survey data CHIP2002 and CHIP2013, this paper has investigated the reasons for the native-migrant wage convergence in the 2000s. I find that eliminating discrimination against migrants affect the wage gap most, and the

Table 6: **JMP decomposition results of different skill groups**

	Less than high school	High school	College
Observed skill gap effect	-0.2402	-0.1680	-0.1201
	(0.0329)	(0.0395)	(0.0879)
Male	0.0031	0.0100	0.0057
	(0.0054)	(0.0063)	(0.0069)
Experience	-0.0777	-0.0443	-0.0802
	(0.0185)	(0.018)	(0.0304)
Region	-0.0134	-0.0285	0.0662
	(0.0080)	(0.0213)	(0.0337)
Occupation	-0.0614	-0.0372	-0.0205
	(0.0185)	(0.0138)	(0.0268)
Industry	-0.0373	-0.0342	-0.0484
	(0.0151)	(0.0125)	(0.0332)
Enterprise property	-0.0536	-0.0337	-0.0429
	(0.0166)	(0.0193)	(0.0347)
Observed skill price effect	-0.1473	-0.1187	-0.0985
	(0.0297)	(0.0296)	(0.0354)
Male	0.0012	-0.0030	-0.0013
	(0.0023)	(0.0037)	(0.0033)
Experience	-0.0665	-0.0133	-0.0408
	(0.0209)	(0.0212)	(0.0188)
Region	0.0133	0.0125	-0.0056
	(0.0051)	(0.0085)	(0.0058)
Occupation	-0.0133	-0.0063	-0.0113
	0.0071	(0.0066)	(0.0136)
Industry	-0.0232	-0.0177	-0.0469
	(0.0142)	(0.0112)	(0.0185)
Enterprise property	-0.0587	-0.0909	0.0073
	(0.0146)	(0.0200)	(0.0293)
Unobserved gap effect	-0.1032	-0.0453	0.0270
	(0.0521)	(0.0805)	(0.1007)
Unobserved skill price effect	-0.0046	0.0044	0.0004
	(0.0066)	(0.0145)	(0.0101)
Observations	4629	4820	4621

Note: Standard errors are in parentheses.

wage growth for low-skilled migrants lead to the wage convergence.

From 2002 to 2013, the wage gap between urban natives and migrants decreased by an average of 0.4113 log points. In this paper, I employ the JMP decomposition method to ascertain the determining factors for the wage convergence. The result shows that the elimination of discrimination against migrants mainly narrows the wage gap, accounting for 74.45%. Improvements in job characteristics and favorable wage structure contribute 24.56% and 31.24%. But differentials in schooling qualities widen the wage gap by 45.00%. This study also finds that due to the labor supply and demand factors favor low-skilled migrants, the wage gap converged more in the low-skilled group.

Several policy implications this research made are as follows. First, employment equality laws and "equal pay for equal work" policy are immediate priorities to continue eliminating the discrimination. Second, it is essential that develop vocational education, strengthen vocational training, and give employment guidance for not only migrants but also low-skilled urban natives. Last but most important, reducing the human capital differentials between these two groups is a fundamental mission in the long term.

References

Blau F. D. & Kahn L. M. (1997) "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s" *Journal Labor Economics* **15(1)**, 1-42.

Blinder A. S. (1973) "Wage Discrimination: Reduced Form and Structural Estimates" *The Journal of Human Resources* **8(4)**, 436-455.

Deng Quheng (2007): "Earing Differential between Urban Residents and Rural Migrants: Evidence from Oaxaca-Blinder and Quantile Regression Decomposition" *Chinese Journal of Population Science* **2**, 8-16.

Firpo S. and Fortin N. M. and Lemieux T. (2009) "Unconditional quantile regressions" *Econometrica* **77(3)**, 953-973.

Gupta N. D., Oaxaca R., & Smith N. (2006) "Swimming Upstream, Floating Downstream: Comparing Women's Relative Wage Progress in the United States and Denmark" *Industrial and Relations Review* **59(2)**, 243-266.

Hu Fengxia & Ye Rensun (2019) "The Wage Gap between Migrant Workers and Urban workers and Their Convergence–Based on the Empirical Study of CHIP Data", *Population and economics* **232**, 31-41.

Juhn C., Murphy K., & Pierce B. (1991) "Accounting for the slowdown in the black-white wage convergence in Kosters M" (Ed) Workers and their wages. AEI Press.

Juhn C., Murphy K., & Pierce B. (1993) "Wage inequality and the rise in returns to skill" *Journal of Political Economy* **101(3)**, 410-442.

Liu xiaoying (2016) "Analysis of double lag effect of labor demand structure and industrial upgrading" *Journal of Zhengzhou University* **49**, 57-60.

Ma X. (2012) “Industrial Segregation in Labor Market: An Empirical Study on the Wage Gaps between the Monopoly Industry and Competitive Industry”. *Chinese Labor Economics* **7**, 44-82.

Ma X. (2018) “Labor market segmentation by industry sectors and wage gaps between migrants and local urban residents in urban China”. *China Economic Review* **47**, 96-115.

Maurer-Fazio M. & Dinh N. (2004) “Differential rewards to, and contributions of, education in urban China’s segmented labor markets” *Pacific Economic Review* **9(3)**, 173-189.

Meng Xin & Jansen Zhang (2001) “The Two Tier Labor Market in Urban China: Occupational Segregation and Wage Differentials between Urban Residents and Rural Migrants in Shanghai,” *Journal Comparative Economics* **29(3)**, 485—504.

Oaxaca R.L. (1973) “Male-Female Wage Differentials in Urban Labor Markets” *International Economic Review* **14(3)**, 693-709.

Oaxaca R.L. & Ransom M.R. (1994) “On discrimination and the decomposition of wage differentials” *Journal of Econometrics* **61**, 5-21.

Xing Chunbing (2008) “The Wage Gap between Migrant Workers and Urban Residents” *Management World* **5**, 74-86.

Yao Xianguo & Yu Ling (2006) “The Occupational Stratification of Migrant Workers and Human Capital Constraints” *Journal of Zhejiang University* **36**, 16-22.

Yun, Myeong-Su (2009) “Wage differentials, discrimination and inequality: A cautionary note on the Juhn, Murphy and Pierce Decomposition Method.” *Scottish Journal of Political Economy* **56(1)**, 114-122.

Yu Xiao & Sun Yue (2017) “The Wage Differences between Urban and Rural Migrant workers: Based on the Quantile Regression Analysis of the National Monitoring Data of Migrants in 2015” *Chinese Population Research* **1**, 84-97.