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## Skill formation, employment discrimination, and wage inequality: Evidence from the People's Republic of China

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**ADB Working Paper Series**

**SKILL FORMATION, EMPLOYMENT  
DISCRIMINATION, AND WAGE  
INEQUALITY: EVIDENCE FROM  
THE PEOPLE'S REPUBLIC OF CHINA**

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**Asian Development Bank Institute**

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**Abstract**

This paper studies the impact of skill formation on employment opportunities and wages. Instead of international trade theory or technological progress theory, the paper focuses on labor “skill formation” to investigate the employment discrimination and skill wage inequality in the Chinese labor market. Based on data from the 2014 China Family Panel Studies (CFPSs), the study uses cognitive ability and noncognitive ability to measure skill formation. The empirical results show that skill formation has a positive impact on employment opportunities and wages. This result exhibits robustness in tests on monopoly industries and non-monopoly industries, except that there is a certain tendency toward wage equalization in monopoly industries. We also find employment discrimination resulting from skill differences in state-owned and non-state-owned sectors. A similar trend of wage equalization exists in state-owned sectors, while a significant trend of wage differentiation exists between high and low skills in non-state-owned sectors.

**Keywords:** skill formation, employment discrimination, skill wage inequality

**JEL Classification:** J21, J24, J71

## Contents

1.	INTRODUCTION .....	1
2.	LITERATURE REVIEW .....	2
3.	DATA SAMPLES AND VARIABLE CONSTRUCTION .....	4
3.1	Data Description .....	4
3.2	Indicator and Measurement .....	4
4.	EMPIRICAL ANALYSIS .....	8
4.1	Analysis of the Benchmark Test Results .....	8
4.2	Robustness Test .....	9
5.	HETEROGENEITY TEST .....	10
5.1	Industries with and without Monopolists .....	10
5.2	State-Owned Sectors and Non-State-Owned Sectors.....	11
6.	CONCLUSION .....	13
	REFERENCES .....	14

# 1. INTRODUCTION

Since the 1980s, with the accelerated pace of opening up to the outside world as well as capital accumulation and technological progress, the labor market of the People's Republic of China (PRC) has undergone profound structural changes, which are mainly evident in the rapid growth of the demand for high-skilled laborers, who has obtained more employment opportunities and higher wages. Meanwhile, the labor market has experienced a shortage of employment opportunities for low-educated and low-skilled laborers, making it for them difficult to enter high-wage industries and obtain relatively high wages. The reason is that laborers with different skills do not have equal employment opportunities and wages. The Chinese labor market faces double inequality in employment opportunities and wages (Sayek and Sener 2006; Mehta and Mohr 2012; Raveh and Reshef 2016).

Which factors can explain the greater employment opportunities and wage returns of high-skilled labor? Two strands of literature have tried to explain the difference: the international trade theory and technological progress theory. The factor price convergence theory, based on the HO model, predicts that developed countries export high-technology-intensive products, with a higher demand and relatively higher wages for high-skilled labor. Developing countries mainly export labor-intensive products and should provide more employment opportunities and relatively high wages for low-skilled labor. It is unlikely that the wage gap between high- and low-skilled labor will widen. The HO theory fails to explain why a skill premium also occurs in developing countries (Feenstra and Hanson 1999). The skill-biased technical change (SBTC) theory helps to explain the following: when a country appears to have skill-biased technical change, it will use more high-skilled labor in technological progress and pay higher wages. However, the question of whether there is a skill bias toward technological progress in developing countries is highly controversial, which greatly limits the explanatory power of the SBTC theory (Acemoglu 1998; Serrano and Timmer 2002).

In recent years, the rising capacity of labor has gradually become an important factor in explaining changes in employment opportunities and wages. The new human capital theory proposes a theoretical framework consisting of multiple factors, including the innate endowment of labor and the acquired environmental and individual development. Studies have proved that the cognitive and noncognitive abilities of laborers have significant effects on their job opportunities, job performance, wage levels, health behaviors, and financial decisions. Some empirical research has suggested that cognitive ability has a positive effect on income (Fryer 2011; Peng and Eunni 2011; Capatina 2014). Noncognitive ability can reduce the unemployment rate and duration of unemployment and increase the intensity of the job search, thereby increasing workers' income (Semykina and Linz 2005; Lindqvist and Vestman 2011).

However, most of the literature has ignored the relationship between skill formation and employment discrimination in the labor market and has not analyzed the importance of skill formation to the wage gap between high- and low-skilled labor and the heterogeneous effect on skill formation in different industrial sectors. Based on this, this paper uses the 2014 China Family Panel Studies (CFPSs) database and defines skill formation as consisting of two aspects: cognitive skills and noncognitive skills. We aim to clarify whether high-skilled labor has better employment opportunities and receives higher wages.

The PRC is in the process of economic and social transformation. Even though human capital is becoming increasingly important in explaining employment opportunities and wages, some inefficient institutional factors still play an important role. Immigration barriers for urban and rural households, industry barriers, administrative monopolies, and other phenomena still exist, causing inequality in employment opportunities and wage structures. In this context, this paper also answers the question of whether skill formation in industries with and without a monopolist has heterogeneous effects on the employment opportunities and wages of different-skilled laborers and on the skill formation between the state and the non-state sector. Research on these issues not only helps to provide an understanding of the skill formation of labor but also helps to view the wage gap between skilled laborers in the PRC correctly.

## 2. LITERATURE REVIEW

The widespread employment discrimination and the income gap in the labor market have attracted the attention of many researchers. Becker (1993) provided a good summary of how the neoclassical framework extends to incorporate individualism, featuring the differences in workers' characteristics. The paradigm of new structuralism that Doeringer and Piore (1971) pioneered paid more attention to the influence of structural factors, such as the market structure, social system, and cultural differences. The new human capital theory has deeply investigated individual cognitive and noncognitive abilities, such as personal preferences, personality traits, motivation, and self-esteem. Within the framework of the new human capital theory, researchers have begun to use "ability" to explain individual behavior choices and job performance, health, education, and wage levels (Heckman, Stixrud, and Urzua 2006; Hanushek 2011; Capatina 2014).

More closely related to our study, many researchers have studied the impact of cognitive and noncognitive skills on incomes and wage premiums. Most previous research on cognitive skills and wages has proved that cognitive skills can boost wages. Peng and Eunni (2011) analyzed the data from the 1984–2003 census and showed that employees receive higher wages due to the increase in the depth and breadth of their computer skills. Capatina (2014) studied wage inequality in the United States between 1980 and 2010 and found that the number of people with high cognitive skills is rising rapidly, while the number of laborers with low cognitive skills is gradually decreasing. Cognitive skills play a leading role in changes in labor wage rates. The effect of physical fitness on wages is becoming smaller and smaller. Hanushek et al. (2015) used The Program for the International Assessment of Adult Competencies (PIAAC) data to assess the impact of cognitive skills on wages and showed that, for an increment of every standard deviation of the digital skills of the labor force, the wages increase by 18%. Romero, Huertas, and Jiménez (2019) analyzed the relationship between cognitive skills and education investment returns in 13 European countries. Their empirical tests using the PIAAC database showed that an increase in the wage level will follow an improvement in the cognitive ability of the workforce. Moreover, the higher an individual's skill level, the higher the rate of return for years of necessary education.

According to the new human capital theory, noncognitive ability, as an important component of human capital, can increase wages directly through "the productivity effect" or indirectly by influencing an individual's education level, career choice preferences, and skill formation to increase the rate of education return and the rate of experience return (Heckman, Stixrud, and Urzua 2006). Semykina and Linz (2005) used the survey data of more than 2,600 Russian employees from 2000 to 2003 and

found that gender differences can lead to heterogeneous effects of noncognitive ability on wages. Noncognitive ability has a considerable influence on women's income but little effect on men's income. Lindqvist and Vestman (2011) found that higher noncognitive ability can reduce the unemployment rate and the duration of unemployment and increase the intensity of the job search, thereby increasing the wage income. This effect is more pronounced for low-skilled labor. Almlund, Duckworth, and Heckman (2011) pointed out that higher noncognitive ability can improve production efficiency, thereby boosting wages. Using data from the British Household Survey, Heineck (2011) identified a positive relationship between "openness" and wages, a negative relationship between "agreeableness" and wages, and a strong nonlinear relationship between "conscientiousness" and wages.

Some literature has also studied the influence of the interaction between cognitive ability and noncognitive ability on wage compensation. Heckman (2011) and Heckman and Corbin (2016) found that noncognitive ability can influence its self-accumulation through educational interventions; at the same time, it can increase the marginal return of human capital investment, such as education, through which it has a positive effect on wages. There is a certain level of interaction between noncognitive ability and cognitive ability. Based on data from the Colombian household survey, Acosta, Muller, and Sarzosa (2015) showed that cognitive ability can significantly influence individuals' career choices and further affect their income, while noncognitive ability has no significant effect on individual income, only influencing the labor participation rate of low-skilled labor. Based on US data, Heckman et al. (2006) found that noncognitive ability of low-skilled labor significantly influences wages and career stability, even exceeding the influence of cognitive ability.

The question that remains unanswered is whether the influence of cognitive ability and noncognitive ability on labor income is heterogeneous among different countries and regions. What are the new features of cognitive skills and noncognitive ability returns of differently skilled labor in the PRC? The answer needs to be tested with actual data. Compared with countries with mature markets, the PRC's mechanism for "nonmarket" competition may have played an important role in determining employment opportunities and wages. This paper aims not only to reveal whether high-skilled labor obtains employment opportunities and higher wage remuneration more easily but also to discover whether these advantages in the labor market are due to entering industries with a monopolist and state-owned enterprises.

Compared with the existing literature, the contribution of this paper concerns the following three aspects. First, based on the new human capital theory, this paper focuses on the perspective of laborers' skill formation and delves into the impact of laborers' own skill formation on employment opportunities and wage gaps. We answer the question of whether skill formation causes employment discrimination and wage gaps in the PRC. Second, this paper builds a reasonable measure of skill formation. We combine the CFPS database questionnaire information and define the skill formation regarding two aspects: cognitive ability and noncognitive ability. Three indicators of labor represent cognitive skills—intelligence level, word ability, and mathematics ability—and social ability, communication ability, cooperation awareness, and customer service ability represent noncognitive skills. Third, this paper considers industry heterogeneity and investigates whether there is industry heterogeneity in the impact of the employment opportunities and wage income of high- and low-skilled labor due to the difference in employment opportunities and wage determination mechanisms among different monopolistic industries and between state-owned and non-state-owned sectors. This paper also analyzes the industry heterogeneity of the effects of skill formation.



### **3. DATA SAMPLES AND VARIABLE CONSTRUCTION**

#### **3.1 Data Description**

This study used data from the 2014 China Family Panel Studies (CFPSs). The CFPS data are comprehensive large-scale sample survey data from the China Social Science Survey Center of Peking University. In 2014, it conducted a sample survey of 37,147 residents in 28 provinces and municipalities. The research subject of this paper is the labor force, with data at the individual level mainly coming from the questionnaires targeting adults. We removed the individual data with wage income of 0 or not applicable as well as the data for which the main indicators of cognitive and noncognitive ability (such as the laborers' "intelligence level," "how good is the relationship," "like trusting or doubting others," etc.) are missing. Since the research subject of this paper is the labor force, we set the age range as 18 to 65 and eliminated any samples that did not match this criterion, finally obtaining a total of 9211 samples.

#### **3.2 Indicator and Measurement**

##### **3.2.1 Skill Formation**

According to the new human capital theory, skills include cognitive skills and noncognitive skills. This study measured skill formation using the sum of cognitive ability and noncognitive ability. Drawing on the definition and scoring rules from the *Dictionary of Occupational Titles* (DOT) for each occupational skill, we defined cognitive ability in three dimensions: intelligence, verbal ability, and math ability. We determined the interviewees' intelligence according to the interviewers' judgment. The original score ranges from 1 to 7. The CFPS Adult Questionnaire provided verbal tests and math tests, the original scores of which are between 0 and 34 and between 0 and 24, respectively. The measurement of noncognitive skills generally involves multiple dimensions, such as personal relationships, self-confidence, social ability, curiosity, and trust. We used the following four indicators to measure noncognitive skills: "How good is the human relationship" indicates the interviewees' social perceptiveness; "tendency to trust (or distrust) people" reflects the interviewees' communication ability (communication); we used the respondents' "cooperativeness as a survey participant" to measure their sense of cooperation (coordination); and the respondents' "manner of dealing with people (things)" indicates their ability to serve customers (service orientation). Among them, we based the two indicators of human relationships and degree of trust on the self-rating of the interviewees. The score for "human relationship" is between 0 and 10. For "communication ability," the participants chose between "People can be trusted" and "the more careful the better." We assigned the former option the value of 1 and the latter option the value of 0. We determined the two indicators of cooperation awareness and ability to serve customers according to the "cooperativeness as a survey participant" (or "degree of anxiety to end the survey") and the "manner of dealing with people (things)."

##### **3.2.2 Employment Discrimination**

We used two indicators to measure employment discrimination. The first is "employment opportunities," referring to whether the respondent has obtained a job offer. If the respondent is currently working, the value is 1; if the respondent is in a non-working state, such as being unemployed, the value is 0. The second is job stability. The determination of the measure of workers' job stability generally uses the number of years in the current job or the number of years in the same industry or

position. The first index is flawed in the sense that the work experience that workers have accumulated in an industry may disappear once they change jobs (Vilalta-Bufi 2010). Therefore, the latter index indicates the work experience more accurately than the former. We selected the respondents' years in their main occupation to measure their job stability.

If the person's labor skill formation was higher than the average in the same industry or same occupation, we counted this person as a member of the high-skilled labor force. Otherwise, we considered the person as a member of the low-skilled labor force. Figure 1 plots the kernel density distribution of high- and low-skilled labor income in industries with and without monopolists. It shows that, in industries with monopolists, the distributions of high- and low-skilled labor wages are relatively close, indicating that there is a certain convergence trend in high–low-skilled labor wages in industries with monopolists. The skill premium is not significant. In industries without monopolists, the skewness of low-skilled labor wages is greater than that of high-skilled labor wages, and the average wage of local skilled labor is slightly lower than that of high-skilled labor, indicating that there is a certain gap between high- and low-skilled labor.

**Figure 1: Distribution of Skill Wages in Monopoly and Non-Monopoly Industries**  
(Unit: Yuan)

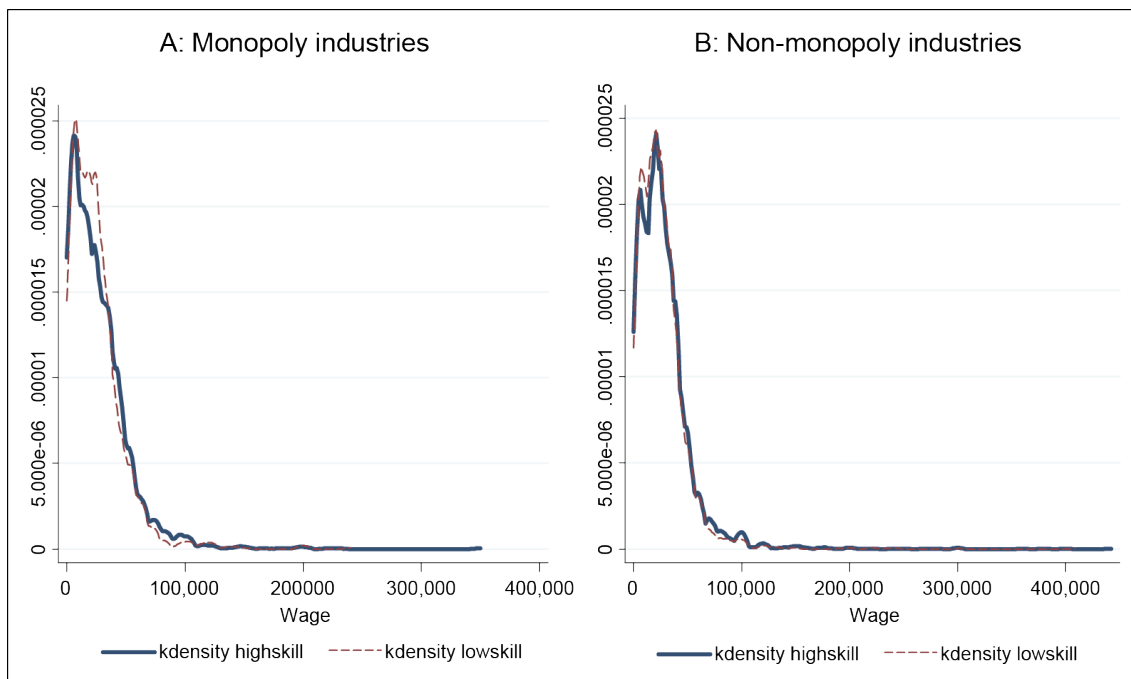
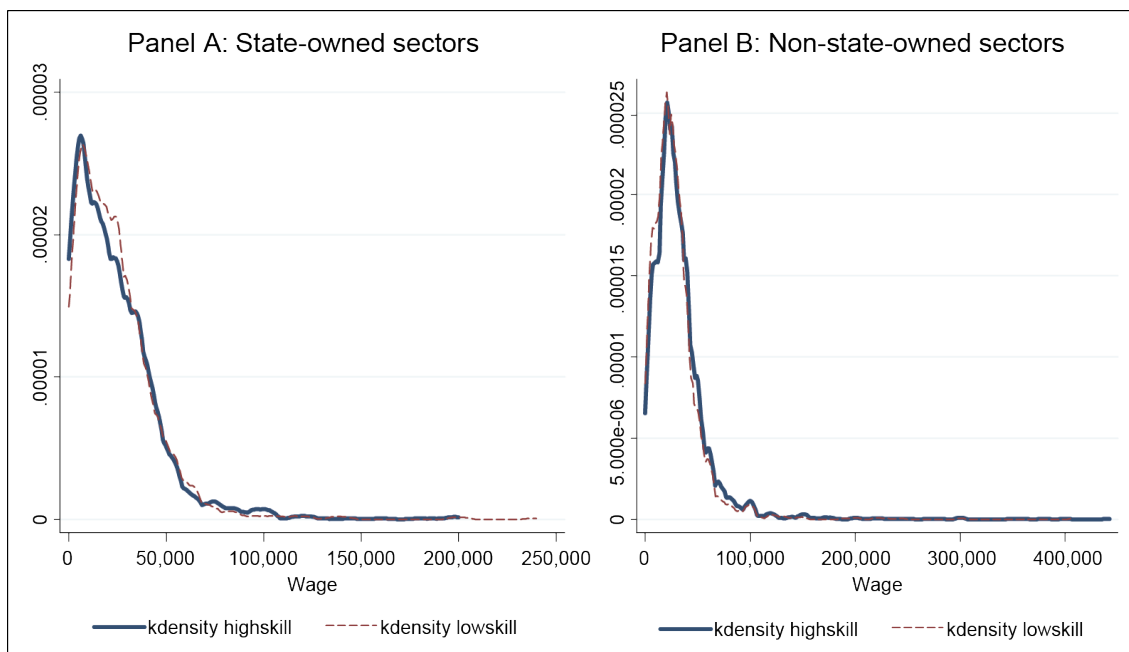


Figure 2 plots the distribution of skill wages in the state-owned sectors and non-state-owned sectors. Panel A shows that, in the state-owned sectors, there is also convergence between high- and low-skilled labor wages, and the skill premium is not significant; in Panel B, the distribution of low-skilled labor is more skewed to the right, indicating that the vast majority of low-skilled laborers are in the low-wage range, and there is a large difference in wages between high- and low-skilled laborers.

In addition, we performed a statistical analysis of the discrimination of high- and low-skilled labor employment (see Table 1). First, higher-skilled laborers have better employment opportunities and job stability than low-skilled laborers in all industries. Second, the employment opportunities and job stability of high- and low-skilled laborers

in industries with monopolists are better than those in industries without monopolists. At the same time, the employment opportunities and job stability of high- and low-skilled laborers in state-owned sectors are better than those in non-state sectors.

**Figure 2: Distribution of Skill Wages in State-Owned and Non-State-Owned Sectors**



**Table 1: Employment Discrimination Facing High- and Low-Skilled Labor**

	Industries with Monopolists		Industries w/o Monopolists	
	Job Opportunities	Job Stability	Job Opportunities	Job Stability
High-skilled labor	0.8257	5.3750	0.6727	3.1859
Low-skilled labor	0.7949	4.9960	0.6668	2.9472
	State-Owned Sectors		Non-State-Owned Sectors	
	Job Opportunities	Job Stability	Job Opportunities	Job Stability
High-skilled labor	0.8141	5.4662	0.7255	4.9102
Low-skilled labor	0.7012	4.8903	0.7110	4.8003

### 3.2.3 Model

Because of the complexity of employment opportunities and wage decisions, wages are not only under the influence of skill formation but also relate to other factors at the individual level. For this reason, we established the following measurement equations:

$$Emopp_i = \alpha_0 + \beta_0 Skillft_i + \gamma X_i + \varepsilon_i \tag{1}$$

$$\ln Wage_i = \alpha_0 + \beta_0 Skillft_i + \gamma X_i + \varepsilon_i \tag{2}$$

$Emopp_i$  represents the employment opportunities for resident  $i$ ;  $\ln Wage_i$  is the logarithm of the average monthly salary of respondent  $i$ ;  $Skillft_i$  is the skill formation of respondent  $i$ ; and  $X_i$  is a set of control variables that may influence the employment opportunities and wage income of the respondent, including the following groups:

1. We added  $Age$  and  $Age^2 / 100$ : Use  $Age^2 / 100$  to control the nonlinear effect of age on wage income;
2. Gender: The value is 1 for a male respondent and 0 for a female respondent;
3. Marital status: The value is 1 for a married respondent and 0 for a respondent who is currently unmarried, divorced, or widowed.
4. Household registration: The value is 1 for an urban household and 0 for a rural household;
5. Health: Health is an important part of laborers' human capital. With the accumulation of human capital, productivity will increase accordingly, thereby driving the growth of income and property. The value is 1 for an unhealthy respondent, 2 for a respondent with general health, 3 for a healthy respondent; and 4 for a very healthy respondent;
6. Education: The value is the number of years of education of the respondent.

To test whether skill formation is more helpful for high-skilled labor to obtain employment opportunities and a skill wage premium, we used a dummy variable,  $Skill_i$ , to distinguish high-skilled labor from low-skilled labor. For high-skilled labor,  $Skill_i = 1$ ; for low-skilled labor,  $Skill_i = 0$ . We also added interaction items of skill formation and skill dummy variables to the model. The specific regression model is as follows:

$$Emopp_i = \alpha_0 + \beta_1 Skillft_i + \beta_2 Skillft_i \times Skill_i + \gamma X_i + \varepsilon_i \tag{3}$$

$$\ln Wage_i = \alpha_0 + \beta_1 Skillft_i + \beta_2 Skillft_i \times Skill_i + \gamma X_i + \varepsilon_i \tag{4}$$

**Table 2: Variables and Descriptive Statistics**

Variable Name	Description	Sample Size	Mean	Standard Dev.	Min.	Max.
Skill formation	The sum of cognitive skills and noncognitive skills	9,211	31.8943	4.7827	11	44
Employment opportunities	The respondent's employment status: 1 if "working" and 0 if "not working"	5,663	0.6947	0.4605	0	1
Job stability	Number of years in the main occupation	5,663	3.8410	7.0250	0	51
Wage income	Logarithm of yearly wage	9,211	9.8286	1.1230	0	12.9990
Age	Age of the respondent	9,210	38.0521	12.0615	18	65
Gender	1 for men and 0 for women	9,211	0.6003	0.4898	0	1
Marital status	1 for married and 0 otherwise	9,211	0.7900	0.4073	0	1
Household registration	1 for an urban household and 0 for a rural household	9,211	0.6041	0.4890	0	1
Health level	Unhealthy=1, general health=2, relatively healthy=3, and very healthy=4	9,211	3.1592	0.8820	1	4
Educational level	Number of years of schooling	8,757	9.9683	4.1004	0	19

The interaction item  $Skillft_i \times Skill_i$  captures whether high-skilled laborers can obtain a higher wage income than low-skilled laborers. It is possible to determine respondents' skill in two ways. In this study, we regarded respondents as high-skilled labor if their skill level exceeds the average and low-skilled labor if their skill level is below the average.

## 4. EMPIRICAL ANALYSIS

### 4.1 Analysis of the Benchmark Test Results

This study first investigated whether skill formation can cause employment discrimination. Columns (1) and (2) of Table 3 report the estimated results with the predicted variable being the employment rate, and columns (3) and (4) report the estimated results with the predicted variable being job stability. The estimated coefficients of those variables composing skill formation are all significantly positive values, indicating that an improvement of the laborers' skills will help them to obtain more employment opportunities and greater job stability. The estimated coefficient of the interaction term is also significantly positive, indicating that skill formation helps to promote employment opportunities and job stability for high-skilled laborers. It is apparent that skill formation is an important factor causing employment discrimination in the PRC's labor market.

Based on models (3)–(4), we tested the relationship between skill formation and wage income. Columns (5) and (6) of Table 3 present the test results. From the estimated results, the impact of the core explanatory variables, such as skill formation and the interaction terms  $Skillft_i \times Skill_i$ , on labor wage income is significantly positive. This result indicates that, as the labor skill level increases, the wage gap between high- and low-skilled labor will widen further. This empirical result is fully consistent with the ongoing global increase in labor skills, the increase in the supply of high-skilled labor, and the simultaneous emergence of a skill premium. The empirical results can also explain the wage inequality between high- and low-skilled labor in the Chinese labor market.

The estimated coefficients of the other control variables are closer to the conclusions of the existing literature. The coefficient of age is positive, and the coefficient of  $Age^2 / 100$  is negative, showing that there is indeed an “inverted U-shaped relationship” between age and employment opportunities. Gender has a significant positive impact on employment opportunities, and this result is consistent with the facts about gender discrimination and gender wage differences in the PRC's labor market. There is also a significant positive relationship between marriage, place of registration (Hukou), health, education, and employment opportunities.

**Table 3: Benchmark Regression Results**

	Employment Rate (1)	Employment Rate (2)	Job Stability (3)	Job Stability (4)	Wages (5)	Wages (6)
Skill formation	0.0305*** (0.0182)	0.0463*** (0.0781)	0.0076*** (0.0066)	0.0035*** (0.0109)	0.0015*** (0.0023)	0.0037*** (0.0044)
Interactive item		0.0001*** (0.0947)		0.0075*** (0.0614)		0.0007*** (0.0012)
Age	0.0793*** (0.0116)	0.0798*** (0.0117)	0.0792*** (0.0114)	0.0915*** (0.0083)	0.0890*** (0.0081)	0.0876*** (0.0079)
Age squared	-0.0007*** (0.014)	-0.0007*** (0.014)	-0.0007*** (0.0014)	-0.1193*** (0.0103)	-0.1161*** (0.0099)	-0.1150*** (0.0097)
Gender	0.0112*** (0.0376)	0.0117*** (0.0377)	0.0120*** (0.0376)	0.4352*** (0.0271)	0.4366*** (0.0260)	0.4364*** (0.0256)
Marital status	0.0419** (0.0520)	0.0391** (0.0522)	0.0418** (0.0521)	0.0223** (0.0368)	0.0638* (0.0365)	0.0588** (0.0356)
Place of registration	0.0952*** (0.0390)	0.0949*** (0.0390)	0.0951*** (0.0390)	0.1099*** (0.0282)	0.1293*** (0.0273)	0.1296*** (0.0268)
Health level	0.0247*** (0.0223)	0.0253*** (0.0223)	0.0222*** (0.0224)	0.0854*** (0.0160)	0.0840*** (0.0154)	0.0877*** (0.0153)
Education level	0.0454*** (0.0051)	0.0455*** (0.0051)	0.0446*** (0.0052)	0.0351*** (0.0039)	0.0438*** (0.0035)	0.0418*** (0.0035)
Sample size	5,374	5,374	5,374	5,374	8,756	8,756
R <sup>2</sup>	0.0393	0.0395	0.1379	0.1356	0.1631	0.1631

Note: We used a probit model for the test of skill formation and employment rate. The table reports the estimated results of the marginal effects.

## 4.2 Robustness Test

The benchmark OLS regression may contain endogeneity bias due to missing variables, two-way causality, and self-selection problems. First, the model may omit the potential impact of some unobservable factors on employment opportunities and wage income; second, not only will the skill formation influence the wages directly or indirectly but the wages may in turn influence the human capital and skill composition. For example, high-income groups may invest more in human capital, and their skills may increase, while low-income groups may face insufficient investment in human capital, making it difficult to improve their skills. Therefore, there may be a reverse causal relationship between skill formation and wages. In addition, endogeneity problems and the resulting estimation bias may come from self-selection. That is to say, members of the labor force with different skills do not randomly choose an industry or a job position but actively choose the work that is the most suitable for them to gain a higher wage. High-skilled labor may enter industries or positions requiring high skills, while low-skilled labor can only choose positions requiring low skills.

Aiming to solve possible endogeneity problems, we intended to use instrumental variables and a treatment effect model. We chose the average skill formation within the occupation as the instrumental variable of skill formation. On the one hand, since different occupations have different requirements for the cognitive skills, noncognitive skills, and physical fitness of workers, although the individual skills of workers differ even within the same occupation, skill formation and occupation have strong relevance. The higher the average skill level of the internal labor force, the higher the skill level of an individual. Therefore, there is a positive correlation between the two, satisfying the correlation requirement of the instrumental variable. On the other hand, the influence of an individual's skill formation on the average skill formation within the same profession is minimal, satisfying the exogeneity requirement. For a treatment effect model, since

OLS estimation cannot effectively eliminate the “selective bias” of the sample, we used an intervention effect model to correct it.

Table 4 reports the estimation results of the instrumental variable method and the treatment effect model. We adopted 2SLS. The coefficient of the instrumental variable in the first stage is significantly positive and significant at the statistical level of 1%. The F statistic is 29.03, whereas 10 is the minimum to guarantee the validity of the instrumental variable. The first three columns of the table report the estimated results of the second stage, and it is evident that the impact of skill formation on employment opportunities and wage income is positive. The results also show that skill formation helps to promote the stability of high-skilled labor and widens the wage gap between high- and low-skilled labor. The treatment effect model also yields results similar to the previous ones. Therefore, a clear conclusion is that skill formation is the cause of employment discrimination and the wage gap in the Chinese labor market.

**Table 4: Endogenous Treatment Effect Estimation**

	IV			TE		
	Job Stability (1)	Wages (2)	Skill Premium (3)	Job Stability (4)	Wages (5)	Skill Premium (6)
Skill formation	0.0043*** (0.0026)	0.0410*** (0.0122)	0.1661*** (0.0635)	0.0038*** (0.0021)	0.0383*** (0.0112)	0.0276*** (0.0033)
Interactive item	0.0377* (0.0091)		0.0413* (0.0156)	0.0314* (0.0088)		0.0219** (0.0412)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	4,890	4,890	4,890	5,374	5,374	5,374
R <sup>2</sup>	0.1734	0.1917	0.1212	0.1864	0.1887	0.1942

Note: Job stability represents job opportunities here.

## 5. HETEROGENEITY TEST

The PRC is in the process of economic and social transformation. Since the 1990s, the wage gap between industries in the PRC has shown a gradually widening trend, and the distribution of industries' income has become polarized. Laborers with similar working conditions and skill levels experience large differences in wages and compensation when entering different industries.

During this economic transition, some noncompetitive institutional factors have played an important role in the impact of labor employment and wages. For this reason, we examined the difference in the effect of skill formation on high- and low-skilled labor in industries with and without monopolists and between state-owned and non-state-owned sectors.

### 5.1 Industries with and without Monopolists

There might be a clear wage gap between the PRC's industries with and without monopolists. The reason is the high concentration of high-income industries in the PRC's monopolistic industries. These industries with a monopolistic nature can rely on their born advantages in the seizure of resources to obtain a huge profit margin by exploiting their monopoly position and political privileges, exercising monopoly power, setting high fees, and turning raw materials into finished products. Compared with industries without monopolists, industries with monopolists in the PRC have a strong tendency to lean toward individuals in terms of profit allocation. Finally, they allocate

part of the profit to the employees in the industry, widening the wage gap between industries. As a result, the inefficiencies of workers in industries with monopolists along with monopoly prices distorting the market-oriented role of prices have a negative impact on the overall social welfare.

In accordance with the 2011 revision of the “national economic industry classification standards,” the statistical survey that we adopted, we divided 20 industry categories into two groups: industries with monopolists and industries without monopolists. The first group contains mining, electricity, heat, gas and water production and supply, transportation, warehousing and postal services, finance, water conservancy, environment and public facilities management, social security, public management and social organizations, and international organizations. The rest are in the second group.

We took “employment opportunities” as the predicted variable. The estimated coefficient of skill formation obviously differs between industries with and without monopolists. The coefficient of skill formation is evidently higher in industries with a monopolist than in industries without one. The results show that high skills are an important reason for preventing laborers from entering industries with monopolists. After adding the interaction item, the coefficient of the interaction item is also significantly positive. This result shows that, in both types of industries that we studied, high-skilled laborers have better employment opportunities. The result is also evidence of the “employment discrimination” that skill differences cause in the labor market.

Taking wage income as the predicted variable, the estimated coefficient of skill formation again obviously differs between the two types of industries. The coefficient of skill formation is noticeably higher in the industries with monopolists. The results show that high skills are still an important reason for workers to obtain high wages. After adding interaction items, the industry difference becomes very significant. In the industries with monopolists, the interaction item is negative, while, in the other group, it is positive. This result shows that high-skilled laborers within the industries with monopolists are not able to obtain higher wages, and there is a certain tendency for wage equalization within industries with monopolists.

**Table 5: Estimated Results of Industries with and without Monopolists**

	Industries with Monopolists				Industries without Monopolists			
	Employment Opportunities	Employment Opportunities	Wages	Wages	Employment Opportunities	Employment Opportunities	Wages	Wages
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill formation	0.0056*** (0.0069)	0.0104*** (0.0131)	0.0145* (0.0042)	0.0119*** (0.0081)	0.0009*** (0.0076)	0.0084* (0.0039)	0.0058*** (0.0025)	0.0054* (0.0049)
Interactive item		0.0016* (0.0037)		-0.0008* (0.0023)		0.0058* (0.0042)		0.0012* (0.0014)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	1,644	1,644	3,231	3,231	4,575	4,575	7,291	7,291
R <sup>2</sup>	0.0611	0.0611	0.2548	0.2549	0.0332	0.0332	0.1533	0.1533

## 5.2 State-Owned Sectors and Non-State-Owned Sectors

With the deepening of the PRC’s reform and opening up policies, the difference in skills of the labor force becomes increasingly able to explain the difference in wages across industries and occupations, but the institutional factors, such as ownership, are also important determinants explaining the difference in wages in different sectors. Considering the wage difference between the PRC’s state-owned and its non-state-



owned sectors, we found that there are huge differences in the mechanisms of wage determination.

Factors outside the market often determine wages in the state-owned sectors. The government determines wages, rather than enterprises, which do not have the authority to change them. At the same time, the wages between high- and low-skilled laborers within the state-owned sectors tend to equalize. This is because the determination of wages in the state-owned sectors follows the idea that the gains in human capital from skilled labor can compensate for the loss coming from overpaid unskilled labor. Therefore, there is a phenomenon of “cross-subsidization” of wages in state-owned sectors: high-skilled laborers receive less in state-owned sectors than their labor productivity, whereas low-skilled laborers enjoy higher wages in state-owned sectors. High-skilled laborers can obtain higher wages in non-state-owned sectors.

The factors in the market mainly determine wages in non-state-sectors, and employment and wages comply with the usual rules in a competitive labor market. The labor market is “divided” into two segments, and the respective supply and demand determine the labor wage rate. From the perspective of workers, high-skilled workers will obtain higher wages due to endogenous factors such as education and skills; from the perspective of externality, high-skilled laborers generate greater positive externality, which increases the demand for high-skilled laborers and enables them to obtain higher wage returns. Therefore, compared with state-owned sectors, the wage gap in non-state-owned sectors between high- and low-skilled labor is more obvious.

In this paper, we considered government agencies, state-owned institutions, research institutes, and state-owned enterprises as state-owned sectors and collective, private, and foreign enterprises as non-state-owned sectors. Taking employment opportunities as the predicted variable, although the coefficient of skill formation differs to some extent between state-owned sectors and non-state-owned sectors, the difference is not large. The result shows that the level of skills is not an important factor for the labor force to enter the state sector or the non-state sector. After adding the interaction item, the coefficient of the interaction item is not significantly different between the two sectors. This result suggests that both in state-owned sectors and in non-state-owned sectors, high-skilled laborers have better employment opportunities. The results indicate “employment discrimination” resulting from skill differences in the labor market. Taking wage income as the predicted variable, the estimated coefficient of skill formation differs significantly between state-owned sectors and non-state-owned sectors, and the skill formation coefficient in state-owned sectors is significantly higher than that in non-state-owned sectors. The results suggest that high skills are still an important factor for the labor force to obtain high wages. After adding interaction items, the difference between the two industries becomes particularly prominent. In state-owned sectors, the coefficient of the interaction term is negative, while it is positive in non-state-owned sectors. This result suggests that high-skilled labor within state-owned sectors is not able to obtain higher wages, and there is a certain tendency toward wage equalization within state-owned sectors. In non-state-owned sectors, the wage gap between high and low skills displays a widening trend.

**Table 6: Estimated Results of State-Owned and Non-State-Owned Sectors**

	State-Owned Sectors				Non-State-Owned Sectors			
	Employment Opportunities (1)	Employment Opportunities (2)	Wages (3)	Wages (4)	Employment Opportunities (5)	Employment Opportunities (6)	Wages (7)	Wages (8)
Skill formation	0.0131*** (0.0071)	0.0033* (0.0133)	0.0188*** (0.0043)	0.0144*** (0.0081)	0.0037** (0.0043)	0.00254* (0.0083)	0.0037** (0.0024)	0.0003* (0.0046)
Interaction item		0.0033* (0.0038)		-0.0014* (0.0023)		0.0004* (0.0023)		0.0013* (0.0012)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	1592	1592	3108	3108	4094	4094	6003	6003
R <sup>2</sup>	0.0817	0.0821	0.2330	0.2331	0.0312	0.0313	0.1322	0.1324

## 6. CONCLUSION

The PRC's economic development is in a period of transition. Following the adjustment of the industrial structure are structural changes in the labor market, unequal employment opportunities, and polarized wage distribution. This paper applied the new human capital theory to form a micro perspective on labor skill formation and analyzed the sources of employment discrimination and the wage gap in the PRC.

This paper used data from the 2014 China Family Panel Studies (CFPSs) to measure skill formation in terms of cognitive ability and noncognitive ability and analyzed the impact of labor skill formation on employment opportunities and wage income. The empirical results show that skill formation has a positive impact on employment opportunities and wage income. High-skilled laborers have better employment opportunities and higher wages because of their "ability." Based on a deeper investigation into industries with monopolists and industries without monopolists, further results show that, in both types of industries, high-skilled labor again has better employment opportunities. However, the wage gap in industries with monopolists is less obvious. Conversely, there is a certain tendency toward wage equalization in industries with monopolists. Based on further tests on the state-owned sectors and non-state-owned sectors, the results also indicate the "employment discrimination" that skill differences in the labor market induce. There is a certain tendency toward wage equalization in the state-owned sectors. In the non-state-owned sectors, the wage gap between high and low skills displays a widening trend.

Based on the conclusion of our empirical study, this paper has important policy implications. First, breaking down the barriers of labor mobility would help to achieve the free flow of labor, to eliminate discrimination on the basis of household registration, education, and skills in the labor market and to create a favorable social environment for free movement and fair employment opportunities. Second, this paper suggests that the government reduces the level of industry monopoly and the state protection of industries and eliminates unreasonable employment opportunities and the income gap. The state-owned sectors should further adjust the compensation mechanism, guide labor allocation according to the market mechanism, and improve the efficiency of the labor allocation. Third, the government should improve the labor skills level through education, training, social contact, and other methods. For high-skilled labor, it should pay more attention to the improvement of noncognitive abilities; at the same time, for low-skilled labor, it should provide more skills training to compensate for the cognitive lack of low-skilled labor.

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