Research on World Agricultural Economy
https://ojs.nassg.org/index.php/rwae

RESEARCH ARTICLE

The Contribution of Work Experience on Earnings Inequality of Migrant Workers: Decompositions Based on the Quantile Regression Equation

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Abstract: This paper aims at excavating the influence factors of earning inequality, due to the increasing contribution of earning inequality to income inequality in a rural region. The authors examine the contribution of work experience on earning inequality using survey data. Employing the quantile regression, they estimate the Mincer equation of migrant workers' earnings and decompose earning inequality by the regression-based decomposition. It has been found that the effects of work experience had been one of the most important contributors to earnings inequality, and its contribution is close to 20%. Furthermore, the authors use the same method to examine the effects on male migrant workers. The results show that work experience had a steady contribution to earning inequality.

Keywords: Earnings inequality; Work experience; Quantile regression; Shapley value

1. Introduction

According to the Migrant Workers Monitoring Survey Report, released by the National Bureau of Statistics, the number of migrant workers was 242 million in 2010, 274 million in 2014 and 288 million in 2018. In addition, the per wage of migrant workers in 2014 and 2018, was 2864 yuan and 3721 yuan respectively. Based on the statistics, the proportion of migrant workers' earnings in family income rose from 29.9% in 2010 to 39.6% in 2014, and to 41.1 in 2019. With the increasing percentage of earnings occupied in migrant workers' total income, the earning inequality has a greater impact on the overall income inequality. Therefore, the earnings difference among migrant workers should be considered carefully.

Since the American economist Mincer [1] put forward the income determination equation which links personal income with education level and work experience, the Mincer equation has become the most commonly used method for scholars to research earnings and rate of return on education. Theoretically, the factors affecting earnings or income will also have a certain impact on income in-

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Received: 20 February 2023; **Received in revised form:** 27 March 2023; **Accepted:** 31 March 2023; **Published:** 7 April 2023

Citation: Peng, J.Q., Li, J., Ma, L., et al., 2023. The Contribution of Work Experience on Earnings Inequality of Migrant Workers: Decompositions Based on the Quantile Regression Equation. *Research on World Agricultural Economy*. 4(1), 819. http://dx.doi.org/10.36956/rwae.v4i1.819

DOI: http://dx.doi.org/10.36956/rwae.v4i1.819

equality, while, these two effects are not proportional. For example, the level of education has a significant impact on the absolute level of earnings, but if the difference in education level between individuals is not large, then the impact of education on income inequality is small.

However, a large number of previous literature have shown that due to the difference in the quality of human capital, the nonagricultural probability and earnings may vary among migrant workers.

Education and work experience make up the most important part of human capital in classical theories. Because everyone's level of human capital varies, the difference in returns from education and work experience may bring about earnings inequality.

In recent years, the structure of migrant workers has also changed, and the proportion of new-generation migrant workers has steadily increased. Compared with the middle-aged and elderly migrant workers, the new generation is aggressive, and the level of education is often higher than the former, but they lack experience. The impact of these factors on earning inequality needs to be verified.

2. Literature Review

How human capital affects income distribution is an essential theme in the economy, with a large amount of literature accumulated. Zhang et al. [2] found the demand for skilled labor increased the contribution of schooling, while differences in human capital exacerbate income inequality. Gao and Yao [3] used China's rural panel data from 1987-2002 to discuss whether human capital or physical capital is more likely to affect income inequality among rural residents. They found in different income groups, the return on human capital was significantly higher than that of physical capital. While, they focused on the income inequality of rural households, and because the sources of income among rural households are varied, it needs more detailed research concerned with the impact of individual human capital on income and income inequality. Zhang [4] paid attention to the relationship between the change in human capital return and income inequality earlier, he grouped by education level and used quantile regression for comparison, which found that the return on education in high-income earners is higher than that in low-income earners. This Matthew effect of the rate of return to education deteriorated the income inequality. While, Patrinos et al. [5] believed education will reduce income inequality in mature economies and increase them in less developed economies.

A review of the previous literature reveals that human capital is an important cause of income growth and income distribution, with education and work experience being very important indicators of human capital [6]. Most of the current literature focuses on the impact of returns to education on income inequality [7], but there is still something to add about the path of the impact of work experience on wage growth and wage income inequality among migrant workers. In the long run, the returns to work experience of migrant workers in China have changed considerably and have not received a uniform conclusive conclusion [8]. Based on this, exploring the impact of work experience on wage income inequality needs to be further expanded and supplemented.

Work experience, an important component of human capital, has been further explored by many scholars for its impact on income inequality and many attempts have been made to decompose its contribution to income inequality [9-11]. Bartlett [12] decomposed the contribution of education and work experience to male wage inequality between 1939 and 1969. He found that the contribution of education was declining while the contribution of work experience was increasing, possibly due to the rise in unemployment. They found that the contribution of work experience was declining while the contribution of education and job opportunities was increasing. Chen et al. [13] used China Health and Nutrition Survey (CHNS) to measure labor earnings inequality from 1990 to 2005, proving that the contribution of work experience to earnings inequality will decline due to economic transformation and wage system reforms. Lu [14] used Chinese Household Income Project (CHIP) to study changes in urban labor income inequality from 1995 to 2013, and found that the return of experience declines continuously. The above studies all use multi-period data and compare the contributions of work experience, education and other factors in different periods to examine long-term trends. However, due to data limitations, the work experience among those studies is calculated by subtracting years of education from age. If the micro-data can obtain more effective indicators that reflect the work experience, the impact of factors such as work experience on income inequality can be more accurately examined.

It is worth noting that Xing [15] pointed out that quantile regression is different from the OLS regression based on income grouping. Using the difference in the regression results of different quantiles is not rigorous enough to explain income inequality.

3. Methodology and Data

3.1 Methodology

Due to the limitations of the classical Mincer equation, as in most studies, this paper uses the extended Mincer equation for regression testing, with earnings as the explained variable and logarithmic processing. The formula is as follows:

$$LnY = \beta_0 + \beta_1 Edu + \beta_2 Exp + \beta_3 Exp^2 + \sum_i \lambda_i x_i + \varepsilon$$

Among them, L_nY is the logarithm of the monthly salary of migrant workers. Edu and Exp represent the knowledge gained from education and experience gained from work respectively. The coefficients β_1 and β_2 represent the ratio of personal earnings increased by increasing education and work experience, which are the return rate of education and experience. Considering the non liner relationship of experience on earnings, the square term of the experience is introduced into the model, and the coefficient β_3 is usually a negative number. In addition, in order to analyze the impact of other factors on earning, control variables such as gender and location can be introduced.

Taking the estimation of the rate of return on education as an example, if the OLS is used to estimate the Mincer equation, which is mean regression, the obtained rate of return on education reflects how the average earning changes with the level of education under other conditions maintained. However, due to the skewed distribution of earnings, the estimation results from the conditional mean model are often biased. Different from OLS, quantile regression estimates how the earnings at different quantile points are determined under other conditions. Since regression estimation can be estimated on any quantile, comprehensive information about the conditional distribution of the explained variable can be obtained [16]. This article also uses quantile regression to estimate the work experience rate of return.

To verify the contribution of various factors to the overall earnings inequality, a regression based on Shapley value inequality decomposition method is needed. The development and research application of this method is mainly attributed to Shorrocks [17] and Wan [18]. The basic idea of this method is the contribution of a certain variable to inequality can be seen as the change in overall inequality when the variable is eliminated. Excluding this variable can be understood as assuming that it is equally distributed among all people. On the basis of the estimated results of the income equation, the JAVA program developed by the World Institute of Development Economics (UNU-WIDER) can be used to perform the Shapley value decomposition of the income inequality on fitted per capita income. In addition, this article also uses the method proposed by Wan [18,19] to deal with the influence of residuals and calculates the contribution of residuals by calculating the difference between the total earnings inequality index and all other explanatory variables. On this basis, simple mathematical operations are used to obtain the percentage of contribution of all explanatory variables and residuals to the inequality indicator.

This method has been widely used. Yu [20] used this method to study the impact of foreign direct investment (FDI) on China's agriculture and regional disparities in the national economy. Zhao [21] examined the impact of relationship networks as social capital on income inequality among farmers and the author decomposed that the contribution of relationship networks to income inequality among farmers reached more than 10%. Furthermore, Chen [13] also used the Shapley value decomposition to analyze the impact of education and work experience on income inequality.

3.2 Data Source

The data used in this paper come from a field survey conducted by the National Agricultural Rural Development Research Institute of China Agricultural University in 2014 on the influx of migrant workers into provinces and cities, which include Beijing, Zhejiang, Guangdong and etc. The content of the survey involves the work, income, life, and food consumption of rural migrant workers, forming cross-sectional data for studying the issues of migrant workers. A random sample was used in this research, which greatly avoided sample bias. In order to focus on the research on the human capital and earnings of migrant workers, the number of samples is 2187 after removing some outliers. The statistical characteristics of the variables are shown in Table 1.

Experience is the human capital accumulated by the labor force in the process of work. Unlike general research that uses the difference between age and age when completing education to express experience, we use the time the migrant worker enters the current industry. In the field questionnaire survey, the respondents are required to answer the time they are engaged in the current work and industry, and the number of years they have worked outside. Through comparison, it has been found that the time spent by the labor force in the industry best reflects the improvement of their own skills, which will more effectively reflect their experience in the industry. Simultaneously, the square term of experience has been introduced to examine whether the experience has diminishing returns.

Regarding education level, the number of years of education is not directly used in the survey, but is assigned to different levels of education, in which illiterate literate is rarely assigned to 1, primary school is assigned to 2, junior high school is assigned to 3, senior high school is assigned to 4, and so on. The statistical characteristics of the main variable are as follows:

Table 1. Statistical characteristics of variables.

Region	Sample Size	Monthly Salary (yuan)		Work Experience (year)		Education Level	
		Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Beijing	722	4260	1886	6.38	6.44	3.24	1.30
Zhejiang	765	3927	1983	6.73	6.54	3.36	1.42
Guangdong	700	3113	1443	5.71	4.58	3.55	1.17
Total	2187	3776	1854	6.28	5.96	3.38	1.31

The earnings inequality of the sample data is reported not only by Gini but also Theil index. Because the Theil index includes earnings inequality within and between groups, this article is grouped according to regions and industries, which can reflect the impact of regions and industries on overall income inequality.

First, it has been calculated that the overall Gini is 0.2416. In addition to removing outliers will definitely reduce the Gini, it is also necessary to understand that this relatively low Gini only reflects the earnings inequality of individual workers. This is not a concept with the Gini of the per capita income of rural households calculated by other data. Because the source of per capita household income is more diversified, the influencing factors are more complex. For example, the Gini of national residents' income in 2014 released by the National Bureau of Statistics is 0.469, which is not only the gap in household income per capita, but also the gap between urban and rural areas. Therefore, this value is higher than the calculation result in this article. What's more, some research institutions have given higher Gini estimates, which will not be repeated here. We believe the Gini of migrant workers' earnings calculated in this paper is acceptable.

Then, we group by gender, industry and region, and use the Theil index, including the zero-order Theil index GE (0) and the first-order Theil index GE (1) to measure the earning inequality. As shown in the result, whether group by gender, industry or region, the contribution of the inequality between groups to the overall inequality is far less than that of the inequality within the group.

From the results in Table 2, it can be seen that gender group has the largest contribution to the inequality between groups, and the calculation results of GE (0) and GE (1) both illustrate that their contribution is close to 20%, and the contribution of the industry group is slightly less than that of the former. The inequality between groups by region is within 10%, which indicates that there is no obvious regional difference in the income of migrant workers as a whole. Theoretically, when the labor market is well developed and labor mobility is sufficient, regional differences in earnings or income will become smaller and smaller. Therefore, the contribution of inequality between the regional group is smaller.

In the following econometric analysis, we will still consider the impact of migrant workers' gender, industry, and region on earnings in the model.

4. Quantile Regression Estimation and Inequality Decomposition

A large number of previous studies have shown that there is a positive correlation between work experience, education level and earnings. Considering that health is also an important attribute of human capital, the labor intensity that can be endured is used as an indicator of health. From low to high, it can be divided into five levels. Those who can bear the highest intensity are considered

Table 2. The result of GE (0) and GE (1).

	GE (0)				GE (1)			
	Degree of Inequality		Contribution to the overall Inequality (%)		Degree of Inequality		Contribution to the overall Inequality (%)	
	Between	Within	Between	Within	Between	Within	Between	Within
Grouped by gender	0.01850	0.07582	19.61	80.39	0.01818	0.08284	18.00	82.01
Grouped by industry	0.01679	0.07753	17.80	82.20	0.01764	0.08337	17.46	82.54
Grouped by region	0.00868	0.08564	9.20	90.80	0.00844	0.09257	8.36	91.64
Total	0.09432		100		0.10101		100	

the healthiest, and vice versa. Like Liu [22], the index of marriage was added to the income determination equation. This variable has no clear economic meaning, but rather represents personal characteristics.

The model also controls regional factors and industry factors. In order to reduce the number of variables, we do not use dummy variables representing regions or industries. Instead, we use the logarithm of the province's per capita GDP as a proxy variable for the region. We use the logarithm of the average income of various industries in 2014 released by the Migrant Workers Monitoring Survey Report as the industry proxy variable.

In order to further study the difference in the experience rate of return under different earning levels and its changing trend in the income distribution, this paper uses the quantile regression method to regress the Mincer equation. We use Stata and bootstrap (self-service method) technology to estimate the Mincer equation 10% of low income, 25% of low income, 50% of medium income, 75% of high income and 90% of high income through 400 repeated sampling. The results are shown in Table 3.

The estimated results in Table 3 show that the coefficient representing the rate of return of work experience is relatively stable in the first four quantiles, and it has declined at the highest quantile. The results also show that as the quantile rises, gender, education level, health status, and job position have an increasing influence on income. The coefficient of the square term of experience and age is negative, except that the square term of experience is not significant at the highest quantile, the others are significant.

This article uses the per capita GDP of the region to represent the different effects of the region. The results show that, except for the highest quantile, as the quantile increases, the impact of the regional per capita GDP becomes greater, that is, higher earnings can better reflect the degree of regional development. However, the influence of industry characteristics shows the opposite trend, which is also easy to understand. Because we use the average income of the industry to represent the characteristics of the industry. Naturally, there are differences between high-earing people and the average income level of the industry, and the differences keep a growing tendency.

More quantiles are selected for quantile regression in order to provide more information. For the two variables that this article focuses on, work experience and educa-

Table 3. Quantile regression results of Mincer equation.

		Q=10%	Q=25%	Q=50%	Q=75%	Q=90%
Gender		0.2130*** (0.0325)	0.2300*** (0.0186)	0.2062*** (0.0172)	0.2546*** (0.0276)	0.3435*** (0.0393)
Age		–0.0095*** (0.0014)	–0.0076*** (0.0014)	–0.0074*** (0.0010)	–0.0057*** (0.0014)	–0.0055*** (0.0019)
Education Level		0.0036 (0.0106)	0.0133 (0.0088)	0.0182** (0.0080)	0.0204** (0.0083)	0.0266** (0.0115)
Marital Status		0.1238*** (0.0304)	0.0926** (0.0264)	0.0931*** (0.0236)	0.0784*** (0.0282)	0.0909*** (0.0340)
Work Experience		0.0243*** (0.0063)	0.0264*** (0.0047)	0.0243*** (0.0039)	0.0248*** (0.0050)	0.0163** (0.0073)
Health Status		0.0133 (0.0115)	0.0139 (0.0095)	0.0302*** (0.0094)	0.0323*** (0.0101)	0.0432*** (0.0143)
Job Position		0.0700*** (0.0155)	0.0686*** (0.0114)	0.0823*** (0.0098)	0.1113*** (0.0165)	0.1246*** (0.0143)
Square term of Experience		–0.0006* (0.0003)	–0.0005** (0.0002)	–0.0004** (0.0002)	–0.0004* (0.0002)	0.0001 (0.0004)
Other Variables	Regional per capita GDP	0.3012*** (0.0725)	0.4739*** (0.0520)	0.5279*** (0.0442)	0.5651*** (0.0559)	0.5113*** (0.0753)
	Industry Average Income	1.0185*** (0.1569)	0.9311*** (0.1308)	0.8645*** (0.1100)	0.6808*** (0.1613)	0.2936 (0.1794)
Constant		–3.8850** (1.502)	–5.0495*** (1.0884)	–5.0013*** (1.1034)	–3.9005*** (1.4362)	–0.1395 (1.7717)
Pseudo R^2		0.1540	0.1954	0.2241	0.2609	0.2451

Note: ***, **, * indicate significance at the significant level of 1%, 5%, and 10%, respectively, and the values in parentheses are self-service standard errors.

tion, the coefficient of return on each quantile is demonstrated in Figure 1. Intuitively, as the quantile rises, the return on experience shows a downward trend, while the return on education, on the contrary, has some fluctuations, but generally shows an upward trend.

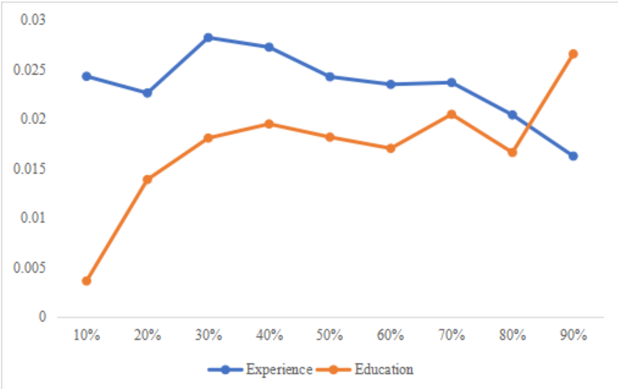

Figure 1. Experience and education return of each quantile.

The conclusion that people with higher quantiles can obtain higher education returns is similar to that of Gao and Yao [3]. Regarding the return rate of experience, contrary to the research of Liu [22], in addition to the difference in the external environment, different ways of expressing experience may also be the reason for the difference.

In order to more accurately express the contribution of various variables including professional experience to the overall earnings inequality, we use the JAVA program developed by UNU-WIDER to perform Shapley value decomposition. This article takes the decomposition result of Gini as an example to show more intuitive results.

The corresponding value to each variable is the inequality degree of the contribution of the variable obtained by decomposition. After these values are added, the overall Gini, and thus the degree of contribution of each variable to the overall earning inequality is obtained. See the brackets in the table, the value within. Among them, the contribution of the square term of the experience item is negative, indicating that this item has the effect of reducing earnings inequality.

As demonstrated in Table 4, as a whole, with the increase of the quantile, various factors such as education level, health status, and job position also contribute more and more to the earnings inequality (few low quantiles have higher contributions than high quantiles).

The contribution of work experience and the contribution of the square term of experience need to be considered comprehensively. Because the former's contribution to earnings inequality is positive and the latter is negative, the overall contribution of experience factors to earnings inequality is stable at around 20%.

As the quantile rises, the contribution of regional vari-

Table 4. Decomposition result of earnings inequality: Taking the decomposition of Gini as an example.

		Q=10%	Q=25%	Q=50%	Q=75%	Q=90%
Gender		0.03390 (27.17)	0.03622 (26.28)	0.03363 (23.57)	0.04339 (27.36)	0.06392 (36.05)
Age		0.00825 (6.61)	0.00448 (3.25)	0.00387 (2.71)	0.00201 (1.27)	0.00137 (0.77)
Education Level		0.00040 (0.32)	0.00163 (1.18)	0.00228 (1.60)	0.00272 (1.72)	0.00403 (2.27)
Marital Status		0.00658 (5.28)	0.00469 (3.40)	0.00468 (3.28)	0.00399 (2.51)	0.00497 (2.81)
Work Experience		0.02787 (22.33)	0.03615 (26.23)	0.03345 (23.45)	0.03717 (23.44)	0.02783 (15.69)
Health Status		0.00323 (2.59)	0.00344 (2.50)	0.00810 (5.68)	0.00834 (5.26)	0.01150 (6.49)
Job Position		0.01106 (8.86)	0.01075 (7.80)	0.01342 (9.41)	0.02130 (13.43)	0.02614 (14.74)
Square term of Experience		–0.00643 (–5.15)	–0.00721 (–5.23)	–0.00617 (–4.33)	–0.00594 (–3.75)	0.00530 (2.99)
Other Variables	Regional Per Capita GDP	0.01172 (9.39)	0.02253 (16.34)	0.02645 (18.54)	0.02893 (18.24)	0.02579 (14.54)
	Industry Average Income	0.02821 (22.60)	0.02515 (18.25)	0.02295 (16.09)	0.01667 (10.51)	0.00649 (3.66)
Residual (%)		48.35	42.96	40.96	34.38	26.61

Note: The degree of contribution to the inequality of estimated value is in parentheses.

ables (represented by regional per capita GDP) increases first and then decreases, showing an inverted U shape. While, the contribution of industry variables (represented by industry average income) presents a declining tendency. This decomposition result does not show that the contribution of industry factors to earnings inequality is significantly greater than that of regional factors, which seems to be inconsistent with the previous calculation of Theil index. It should be noted that the decomposition here is based on the Gini, and because of the residual contribution, it is impossible to make an intuitive comparison. In addition, we can also find that in the regression model, the coefficient of the square term is negative, and the contribution decomposition is also negative, that is, the square term of experience plays a role in reducing income inequality.

At the same time, the Shapley value is decomposed according to the estimated value of earnings, which does not include the contribution of the residual in the model, or that is the unexplained part. Generally speaking, the smaller the residual, the better the decomposition. At the 0.1 quantile point, the contribution of the residual is close to half, which means that there are factors not included in the model that affect the earnings inequality of migrant workers.

According to some typical studies in China, the model based on Mincer equation often has a low degree of fit (pseudo R^2 in quantile regression). In a general regression model, a small degree of fit is not acceptable. In this article, because the decomposition is based on the regression equation, in most cases, the degree of fit affects the explanation degree of earnings inequality. In other words, the smaller the fit, the greater the contribution of residuals to earnings inequality.

5. Further Analysis

From all samples, it can be seen that there is a significant difference in the earnings of migrant workers, which is consistent with most of the studies. The decomposition result of the Shapley value also shows that gender can explain at least 20% of the earnings inequality. At the 0.9 quantile point, gender can even contribute 36% of the earnings inequality. In all five quantiles, gender is the most important factor affecting earnings inequality.

The contribution of gender to earnings inequality is large, which reflects the phenomenon that men's earnings are significantly higher than that of women. It needs further analysis to tell whether it is discrimination in the labor market or the gender gap in human capital and other factors. According to the research of Liu[22], the return rate of education and experience of men is lower than that of women. In order to further investigate the contribution of work experience and other factors to earnings inequality, we need to test the male sample and female sample respectively. In the preliminary regression, multiple variables of the model among the female sample are not significant. In this case, we do not conduct an intuitive comparative analysis of gender. However, increasing women's earnings is an effective way to reduce earning inequality. The incompleteness in the labor market brings gender discrimination, which leads to the possibility that the work experience of female migrant workers does not have a significant impact on wage growth. Therefore, in order to better clarify the path of work experience on the wage earnings inequality, this paper further explores it only for the male sample. In this part, we only select a sample of male migrant workers and use the same method to analyze. On the basis of the original quantile regression model, the gender variable is eliminated, and other variables are used for regression. Because the female sample is excluded, there are 1119 remaining samples. The quantile regression results of the Mincer equation about earnings are presented in Table 5 as follows:

The regression results show that the explanatory variable of experience is significant, and at the highest quantile, the return on experience has dropped sharply. But the education variable is no longer significant, except at the highest quantile. The square term of experience is significant in the middle three quantiles, and its coefficient is negative. Compared with the regression results of all samples, the coefficients of work experience variables are higher except for the lowest quantile. Although it is not a direct comparison between the male sample and the female sample, the higher return to experience in the male sample can still reflect that the return to experience men is higher than that of women, which is different from previous studies. On the one hand, it may exist a change in the economic situation, or it may be a difference in the micro indicators used to express work experience. In addition, the coefficients of regional factors are lower than all samples at all quantiles, while industry factors are just the opposite, which is also a significant feature of male earnings.

It should be pointed out that the fitting degree of the male sample is obviously small, which will affect the results of Shapley value decomposition. Using the same method, this paper decomposes the earnings inequality of male migrant workers, as shown in Table 6.

Table 5. Quantile regression results of Mincer equation for male migrant workers' earnings.

		Q=10%	Q=25%	Q=50%	Q=75%	Q=90%
Age		–0.0079*** (0.0022)	–0.0064*** (0.0016)	–0.0072*** (0.0012)	–0.0079*** (0.0019)	–0.0037 (0.0036)
Education Level		0.0034 (0.0140)	0.0043 (0.0128)	0.0180* (0.0101)	0.0151 (0.0129)	0.0334 (0.0208)
Marital Status		0.1489** (0.0526)	0.0892** (0.0373)	0.1453*** (0.0291)	0.1295*** (0.0390)	0.0900 (0.0635)
Work Experience		0.0263** (0.0112)	0.0312*** (0.0065)	0.0309*** (0.0051)	0.0300*** (0.0065)	0.0250** (0.0104)
Health Status		0.0012 (0.0181)	0.0088 (0.0136)	–0.0020 (0.0146)	0.0083 (0.0144)	0.0084 (0.0286)
Job Position		0.0767*** (0.0268)	0.0903*** (0.0154)	0.0808*** (0.0191)	0.1359*** (0.0272)	0.1278*** (0.0309)
Square term of Experience		–0.0005 (0.0005)	–0.0007*** (0.0003)	–0.0006*** (0.0002)	–0.0006** (0.0002)	–0.0003 (0.0005)
Other Variables	Regional Per Capita GDP	0.2262** (0.1002)	0.2951*** (0.0738)	0.3952*** (0.0667)	0.4640*** (0.0800)	0.2595** (0.1219)
	Industry Average Income	1.2431*** (0.1977)	1.2773*** (0.1693)	1.3650*** (0.1568)	1.2753*** (0.1729)	0.8203*** (0.1990)
Constant		–4.6761** (1.8957)	–5.6222*** (1.4042)	–7.2649*** (1.4611)	–7.1911*** (1.4081)	–1.1552 (2.0636)
Pseudo R2		0.1466	0.1537	0.1875	0.1614	0.1156

Note: ***, **, * indicate significance at the significant level of 1%, 5%, and 10%, respectively, and the values in parentheses are self-service standard errors.

Table 6. The decomposition results of male migrant workers' earnings inequality: Taking the decomposition of Gini as an example.

		Q=10%	Q=25%	Q=50%	Q=75%	Q=90%
Age		0.00547 (4.80)	0.00383 (3.20)	0.00376 (2.87)	0.00541 (3.89)	0.00143 (1.17)
Education Level		0.00029 (0.25)	0.00031 (0.26)	0.00197 (1.51)	0.00169 (1.22)	0.00604 (4.95)
Marital Status		0.01429 (12.55)	0.00753 (6.29)	0.01333 (10.20)	0.01075 (7.73)	0.00798 (6.54)
Work Experience		0.04391 (38.57)	0.05320 (44.46)	0.05385 (41.19)	0.05039 (36.22)	0.05314 (43.55)
Health Status		0.00023 (0.20)	0.00192 (1.61)	0.00001 (0.01)	0.00147 (1.06)	0.00124 (1.02)
Job Position		0.01236 (10.85)	0.01486 (12.42)	0.01286 (9.83)	0.02703 (19.42)	0.03076 (25.22)
Square term of Experience		–0.00916 (–8.05)	–0.01283 (–10.73)	–0.01193 (–9.13)	–0.01081 (–7.77)	–0.00692 (–5.67)
Other Variables	Regional Per Capita GDP	0.00708 (6.22)	0.01017 (8.50)	0.01436 (10.98)	0.01763 (12.67)	0.00758 (6.22)
	Industry Average Income	0.03938 (34.59)	0.04068 (34.00)	0.04254 (32.53)	0.03557 (25.57)	0.02076 (17.04)
Residual (%)		52.04	49.60	44.92	41.39	48.61

Note: The degree of contribution to the inequality of estimated value is in parentheses.

Regardless of the difference between the Gini of the Whole sample and the sample of male migrant workers, it only compares the difference in the degree of contribution of each variable to earnings inequality. The Gini of the male migrant workers' sample is decomposed into eight explanatory variables. If the contribution of gender is evenly distributed to each variable, the contribution of each variable of the male migrant worker's sample will be higher than the same value in the whole sample. But in fact, before and after comparison, the contribution of marital status, work experience, job position, square term of experience, and industry factors in the sample of male migrant workers has increased, while the contribution of education, health status, and regional factors has declined. Among them, the contribution of health status and regional factors in the five quantiles is lower than the value of the whole sample.

The results show that, in terms of the contribution of work experience to earnings inequality, it is the most vital of all variables. Combined with the square term of work experience, the contribution of the experience factor is lower than that of the industry factor in the lowest two quantiles. In addition, it needs to be pointed out that the analysis of this article finds that education has little influence on earnings inequality. This is obviously related to the distribution of the education of the migrant workers, and the education level of them is mostly junior high school or senior high school. While, this does not mean that education is not important to earnings.

6. Conclusions and Prospect

Based on the survey data of migrant workers, this paper studies the influence of work experience and other factors on earnings inequality of migrant workers. On the basis of quantile regression, the Shapley value decomposition is used to obtain the contribution of various variables that can affect earnings to the earnings inequality, including experience. It is found that in the whole sample, gender affects the earnings inequality of migrant workers to a large extent. Furthermore, using the sample of male migrant workers, we find that the impact of experience on earnings inequality is still stable and essential.

In terms of policy, experience is different from education. The latter can reduce the earnings inequality caused by the uneven distribution of education by further implementing compulsory education and increasing education investment. But experience is related to age, occupation and other factors. Can we adjust the policy and play a role in reducing earnings inequality?

This article argues that if an individual's experience is related to age, the difference cannot be adjusted by external factors such as policy, and there is no need to adjust. However, it is necessary to minimize the differences in the experience of employees of the same age level, which requires more employment security to be provided to employees, avoiding an unnecessary change of industries or occupations, which will effectively accumulate work experience.

What's more, this article still has regrets in the following two aspects, which need to be improved in follow-up research. First, limited to the availability of data, the ability factor is not considered in the model, which will overestimate the rate of return of experience and education to a certain extent. Second, there are many factors that affect the earnings of migrant workers, which reduce the explanatory power of the classic labor theory. Because traditional theories are often based on the completely free flow of labor factors and other factors, in reality, due to the restrictions of employment systems and industry barriers, the classic Mincer equation cannot effectively explain the earnings decision of migrant workers. In specific empirical research, the fitting degree of the regression equation is often not high enough.

In addition, it needs to be explained that the employment of migrant workers is becoming more and more diversified in reality, which makes the connotation of migrant workers richer and richer and cannot be expressed by manual workers. This also requires the further expansion of the classical income determination theory.

Author Contributions

Zhiwang LV: writing—original draft preparation; Jiaqi PENG: writing—review and editing; Ling MA: methodology; Jun LI: supervision. All authors have read and agreed to the published version of the manuscript.

Funding

This research was founded by the 2115 Talent Development Program of China Agricultural University.

Data Availability

Not applicable.

Conflict of Interest

The authors declare no conflict of interest.

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