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Sustainable Development of the Rural Labor Market in China from the Perspective of Occupation Structure Transformation

Zhiyuan Ma ^{1,2,3} , Yunli Bai ^{1,2,*}  and Linxiu Zhang ^{1,2,3} 

¹ Key Laboratory of Ecosystem Network Observation and Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; mazy.18b@igsrr.ac.cn (Z.M.); linxiu.zhang@unep-iemp.org (L.Z.)

² United Nations Environment Programme-International Ecosystem Management Partnership (UNEP-IEMP), Beijing 100101, China

³ University of Chinese Academy of Sciences, Beijing 100049, China

* Correspondence: baiyl.11b@igsrr.ac.cn; Tel.: +86-010-64889833

Abstract: This study analyzes the structural transformations of the occupations of all off-farm rural laborers in China over the period 2007–2022. The changes in the rural labor market are mainly reflected in the decrease in the share of routine manual laborers from 66.59 percent to 52.77 percent, and the increases in the shares of non-routine cognitive and non-working laborers by 4.48 and 10.73 percentage points from 2007 to 2022, respectively. By adopting decomposition analysis, which improves the definition of occupational classification based on information on sub-sectors in industries and job contents using a dataset with a nationally representative sample covering 2000 rural households, the results show that both composition effect and propensity effect play important roles in the decrease in routine manual occupations; the composition effect dominates the changes in the non-routine cognitive occupation category, while the propensity effect is the main driver of the increasing trend in the non-working group. The economic model further illustrates the results of decomposition analysis. These findings imply that the government should further improve education in rural areas and pay greater attention to female and low-education-attainment groups among rural laborers. This study provides a reference for policies aimed at promoting the sustainable development of the rural labor market.



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1. Introduction

Off-farm employment has been the primary form of employment and one of the key drivers promoting common prosperity in China [1]. The proportion of rural laborers employed off-farm increased from 33.9 percent in 2000 to 74.9 percent in 2015 [2]. The per capita wage income accounted for 42.24 percent of the per capita disposable income of rural households in 2023 [3]. The increase in wages played an important role in promoting common prosperity in China by narrowing the income gap between rural and urban areas and within rural areas [4,5].

However, rural laborers encounter pressures to sustain their off-farm employment. Industrial upgrading and technological improvements have put forward high requirements for worker's skills, which poses challenges to rural laborers, especially the low-skilled ones [6–8]. There is still a large amount of surplus labor force in the agricultural sector that needs to engage in off-farm employment and the risk of large-scale unemployment among them cannot be ignored [9]. Additionally, the economic downturn in China, the uncertainty of globalization, and the occurrence of emergencies have further intensified employment pressures [10–13] and have brought the development of sustainability of the rural labor market into increasingly challenging surroundings. These pressures are unfavorable for stabilizing the off-farm employment of rural laborers.

In fact, the labor market in China has experienced a structural transformation in off-farm occupations with the change in the macro-economic situation. Since the 1950s, there has been a declining trend in the demand for routine employees in the manufacturing industry globally [14], which has led to changes in the off-farm occupation structure. Studies on the transformation of occupation structure in urban China show a significant decrease in the proportion of routine occupations due to technological progress [8]. However, little is known about the occupation transformation of all off-farm rural laborers in China, including migrants to cities, local off-farm employment, and non-working groups.

It is important and urgent to investigate the transformation of the occupations of all off-farm rural laborers in China due to three facts. First, according to our data, 40 percent of off-farm-employed rural laborers worked within their hometowns. This indicates that such a large group would be excluded from the analysis of off-farm occupation transformation if we only used data from urban areas. Second, compared to urban laborers, rural laborers in China are more vulnerable in the labor market due to their low education attainment and skills [11,15,16]. The evolution of their off-farm occupations is an important indicator to determine whether they can catch up or win the race against technological progress, which is important to China's common prosperity. Third, the statistics on the unemployment rates in China only cover urban areas [3], and thus fail to inform us about the changes in the non-working group among the rural laborers.

Therefore, this study aims to investigate the transformation of occupations of all off-farm rural laborers in China. To achieve the goal, we used data from five recent waves of the China Rural Development Survey (CRDS) conducted between 2008 and 2023 based on a nationally representative sample covering 2000 households in 100 villages in 50 townships from 25 counties across 5 provinces.

This study has three potential contributions to the literature. First, it focuses on the occupational transformation of all off-farm rural laborers in China from 2007 to 2022, which updates the occupational transformation of rural laborers and enriches the existing literature. Second, the dynamic transformation of rural laborers who were not working is fully documented, which contributes to a better understanding of the transformation of the rural labor market in China. Finally, the definition of the occupational category was classified according to information on the sub-sector of industries and job contents, which is more precise compared with previous studies.

The rest of the paper is organized as follows: Section 2 reviews the literature and presents the hypotheses. Section 3 introduces the methodology. Section 4 depicts the evolution of occupation structure among off-farm rural laborers. Section 5 presents the results of the decomposition analysis of China's rural labor market. Section 6 presents and discusses the results of empirical analysis. Section 7 concludes with the implications.

2. Literature Review and Hypotheses

There are internationally recognized classification criteria and analytical methods used to document occupation structure transformation. Autor and Dorn [17] and Cortes et al. [18] categorized occupations into four groups using a methodology that transfers all the 3-digit census occupation codes from different years to a common coding system [19]. Based on the study by Autor et al. [20], scholars delineated occupations through two dimensions: cognitive jobs versus manual jobs, and routine jobs versus non-routine jobs based on job content [18,21,22]. The difference between the cognitive and manual groups depends on the extent of mental or physical activity in the job content of the occupation. As for the routine group and the non-routine group, the occupation is classified into the routine group if the job content of the occupation can be summarized as a group of specific activities accomplished by following well-defined instructions. The occupation is classified into the non-routine group if the job content of the occupation requires flexibility, creativity, problem-solving, or human interaction. Therefore, employed workers can be classified into four groups: non-routine cognitive, routine cognitive, routine manual, and

non-routine manual. The decline in routine occupations has been well documented in many countries [14,21,23–26].

In terms of analytical methods, decomposition analysis is widely used in existing research on employment structure [27,28]. For example, Cortes et al. [18] found that routine occupation employed 40.5 percent of the working-age population in the United States in 1979 but the fraction declined, reaching a level of 31.2 percent in 2014 based on the Monthly Current Population Survey (CPS) data. The decline in routine employment in the United States was mainly driven by the propensity effect [29].

In the context of China, the classification criteria for occupation are not consistent. Referring to Abel and Deitz [30] and Foote et al. [31], Tang et al. [32] analyzed China's skill-based development in employment structure and simply categorized occupations into two groups based on the level of skills: manufacturing workers in routine jobs with low skills were regarded as low-skilled workers, while research and development personnel and technicians with professional skills were regarded as high-skilled workers. Cheng et al. [7] divided China's manufacturing workers into three groups based on the degree to which their jobs involved a manual, routine, or abstract task. The latest research has documented important occupation transformation in China following the current international classification criteria [8] after comparing the International Standard Classification of Occupations used by Autor and Dorn [17] with GB/T 6565, the Chinese national standard of occupation classification, which does not present the job content for each occupation.

The existing research on the occupational structure in China has primarily focused on urban areas. Cheng et al. [7] focused on the manufacturing sector and described the adoption of robots by China's manufacturers using both aggregate industry-level and firm-level data. Yu et al. [33], Xu et al. [34], and Wang et al. [35] analyzed the impact of industrial robot application and found that the introduction of robots has led to an increase in wages for non-routine occupations, therefore widening the wage gap between non-routine and routine occupations. Ge et al. [8] analyzed China's occupational dynamics from 1990 to 2015 using nationally representative samples from the population census, and the mini-census excluding villages. They found that the share of routine occupations decreased from 64.82 percent to 50.78 percent from 1990 to 2015, including a dramatic decrease in routine manual occupations from 57 percent in 1990 to 32 percent in 2015, consistent with trends in the United States. Besides, the non-working group share nearly doubled—from 16 percent to 31 percent. According to their decomposition results, both the composition effect and propensity effect played important roles in the declining share of routine manual occupations, while only the propensity effect was an important determinant in the rising share of non-working laborers. Compared to non-routine manual and cognitive jobs, routine jobs were more easily replaced by technology [8], threatening the sustainable development of the rural labor market and workers' career sustainability.

Based on the existing research findings, we proposed the following hypotheses:

Hypothesis 1 (H1). *There is a declining trend in the share of routine manual occupations in the rural labor market, with both the composition effect and propensity effect playing important roles.*

Hypothesis 2 (H2). *There is a rising trend in the share of the non-working group in the rural labor market, with the propensity effect dominating the change.*

3. Methodology

3.1. Sampling and Data Collection

The data used in this study are from the five recent waves of the China Rural Development Survey (CRDS) conducted in 2008, 2012, 2016, 2019, and 2023 (The survey is also known as "One Hundred Village Survey" as it covers 100 sample villages). It is a tracking survey; however, it is not a balanced panel data due to sample attrition. The initial survey in 2005 used a stratified random sampling procedure to select a nationally representative sample covering 2000 households in 100 villages in 50 townships from 25 counties across 5 provinces.

The stratified random sampling procedure in the 2005 survey took a five-step approach. First, five provinces were selected from each of China's major agro-ecological zones from a list of provinces arranged in descending order of gross value of industrial output (GVIO). Jiangsu, Sichuan, Shaanxi, Hebei, and Jilin were selected. Second, within each sample province, counties were ranked and divided into five quintiles in descending order according to their per capita gross industrial output, and one county was randomly selected from each quintile. Third, within each county, two townships were selected, one from each of the following two groups: a "more well-off" group and a "poorer" group. Fourth, within each township, two villages were selected following the same procedure. The survey teams selected 20 villages in each province (1 province $\times$ 5 counties $\times$ 2 townships $\times$ 2 villages). Finally, the survey team randomly selected 20 households from each sample village. Due to budget constraints in the 2005 survey, of the 20 households in each village, trained enumerators interviewed 8 households one-on-one using a questionnaire, while the remaining 12 households were interviewed in small groups. In the five follow-up surveys conducted in 2008, 2012, 2016, 2019, and 2023, all 20 sample households in each sample village were interviewed one-on-one by trained enumerators using questionnaires. In this study, we used the data collected in 2008, 2012, 2016, 2019, and 2023, since in these years, all households were interviewed using questionnaires.

Detailed information on the household members was collected in each survey wave. For the purpose of this study, we drew on information from two survey modules. The first one is the individual demographic characteristics module, including age, gender, and years of schooling. The second one is the individual off-farm employment module. This module collected rich information on each household member aged 16 years and above, including their participation in off-farm employment, sub-industry and occupation of off-farm employment, job content of current occupation, as well as working destination.

There is no retirement for China's rural laborers. Following Zhang et al. [2], we defined rural laborers as those aged between 16 and 64 years old who finished formal schooling, are non-retirees, or have not exited the labor market due to health-related reasons. We focused on rural laborers with off-farm employment or those who were not working. With this criteria, the numbers of individuals included for analysis in the study were 2293, 3017, 2918, 2857, and 3138 from the five rounds of surveys conducted in 2007, 2011, 2015, 2018, and 2022, respectively.

3.2. Definition of Variables

3.2.1. Occupation Classification

The occupation classification variable is used to reflect the occupation categories of rural laborers. It is a categorical variable including the non-routine cognitive category, non-routine manual category, routine cognitive category, routine manual category, and the non-working group.

We adopted the occupation classification of laborers in China used by Ge et al. [8], which has no major differences from the existing literature focused on the United States [17,36]. We first classify occupations into manual and cognitive groups based on the extent of the mental versus physical activities of the job content. Then, occupations are categorized into a routine group if the job content can be summarized as a set of specific activities accomplished by following well-defined procedures. If the occupations demand more flexibility, creativity, problem-solving, or human interaction, they are categorized into a non-routine group. For example, manufacturing and construction workers and delivery men are classified into the routine manual category; office clerks and wholesale and retail staff are classified into the routine cognitive category; chefs, barbers, and nannies are classified into the non-routine manual category; and teachers, doctors, and government staffs are classified into the non-routine cognitive category.

We then make the following adjustments to the occupation classification using specific information on the employment sub-industry and job content collected during the survey. First, we classify managers in enterprises into the non-routine cognitive occupation category.

Second, we move security personnel and cleaning workers from the non-routine manual occupation category to the routine manual occupation category considering that their detailed tasks are relatively more routine. Third, we move staff working in information technology industries from the routine cognitive occupation category to the non-routine cognitive occupation category.

For non-working rural laborers, we define them as those who neither farmed nor conducted off-farm work across the whole year.

3.2.2. Independent Variables

We controlled for individual characteristics, household characteristics, village characteristics, province dummy variables, and year dummy variables in the model.

Specifically, the individual characteristics include *gender*, *age*, *age square*, *education*, *marriage*, *CPC member*, and *certificate*. The household characteristics include *lead*, *labor*, *child*, and *elder*. The village characteristics include *size*, *income*, *distance*, and *distance square*. Table 1 shows the definitions and descriptive statistics of these variables.

Table 1. Description of variables.

Variable	Definition	Mean	Std.	Min	Max
Occupation classification	Occupation category (1 = NRC, 2 = NRM, 3 = RC, 4 = RM, 5 = NW)	3.730	1.364	1	5
Gender	Gender (1 = men, 0 = women)	0.578	0.494	0	1
Age	Years	38.13	12.77	16	64
Age square	The square of age	1616.453	1027.645	256	4096
Education	Years of schooling	9.094	3.355	0	22
Marriage	Married or not (1 = yes, 0 = no)	0.753	0.431	0	1
CPC member	CPC member or not (1 = yes, 0 = no)	0.102	0.303	0	1
Certificate	Whether they have skills certificates (1 = yes, 0 = no)	0.253	0.435	0	1
Lead	Whether they have village leaders in the household (1 = yes, 0 = no)	0.128	0.334	0	1
Labor	Number of laborers in the household	3.056	1.150	1	8
Child	Whether there is a child (0–15) in the household (1 = yes, 0 = no)	0.595	0.491	0	1
Elder	Whether there are elders (65+) in the household (1 = yes, 0 = no)	0.394	0.489	0	1
Size	Village population (thousands)	1.828	1.242	0.161	9.1
Income	Natural Logarithm of per capita income of the village	8.886	0.703	6.918	11
Distance	Distance from the village to the town (km)	5.547	5.168	0	35
Distance square	The square of the distance	57.479	119.789	0	1225

Data Source: China Rural Development Survey.

3.3. Model Specification

The dependent variable occupation classification is a categorical variable; therefore, we adopt a multinomial logit model to find the determinants of occupation classification of rural laborers. The model specification is as follows.

$$Occupation\ Classification_{it} = \alpha + \beta I_{it} + \delta H_{it} + \chi V_{it} + \lambda P_{it} + \rho T_t + \varepsilon_{it}$$

where i indicates the i th rural laborer, t indicates the t th year; $Occupation\ Classification_{it}$ is the dependent variable; I_{it} , H_{it} , V_{it} are the individual, household, and village characteristics shown in Table 1, respectively; α is a constant; β , δ , χ , λ , and ρ are the parameters to be estimated; and ε_{it} is the error term. The province dummy variable P_{it} is added to identify the influence of economic development and regional differences on occupation classification. The year dummy variable T_t is included to control the time trend, which affects the dependent variable.

4. Transformation of the Occupation Structure

4.1. Overall Changes in the Occupation Structure

Our data show that the transformation of occupations of off-farm rural laborers has clear trends. The proportion of off-farm rural laborers engaged in routine occupations decreased continuously from 74.18 percent in 2007 to 60.80 percent in 2022 (Table 2, Row 1, Columns 1 and 5). However, the share of off-farm rural laborers engaged in non-routine

occupations exhibited an upward trend, with bumps and butts, over the same period: it was 16.92 percent in 2008 and slightly declined to 16.74 in 2012 then climbed up to 19.96 percent in 2016 before dropping slightly to 19.57 in 2022 (Row 4).

Table 2. Occupational transformation of off-farm rural laborers in China.

		Fraction and Total Employment in Each Category (%)					Change
		2007 (1)	2011 (2)	2015 (3)	2018 (4)	2022 (5)	2007–2022 (6)
(1)	Routine Job	74.18 (1.701)	71.99 (2.172)	65.97 (1.925)	64.27 (1.836)	60.80 (1.908)	−13.38 (0.207)
(2)	Routine Cognitive Job	7.59 (0.174)	8.05 (0.243)	8.67 (0.253)	8.44 (0.241)	8.03 (0.252)	0.44 (0.078)
(3)	Routine Manual Job	66.59 (1.527)	63.94 (1.929)	57.30 (1.672)	55.83 (1.595)	52.77 (1.656)	−13.82 (0.129)
(4)	Non-Routine Job	16.92 (0.388)	16.74 (0.505)	18.95 (0.553)	19.96 (0.570)	19.57 (0.614)	2.65 (0.226)
(5)	Non-Routine Cognitive Job	8.46 (0.194)	8.39 (0.253)	11.24 (0.328)	11.80 (0.337)	12.94 (0.406)	4.48 (0.212)
(6)	Non-Routine Manual Job	8.46 (0.194)	8.35 (0.252)	7.71 (0.225)	8.16 (0.233)	6.63 (0.208)	−1.83 (0.014)
(7)	Non-Working	8.90 (0.204)	11.27 (0.340)	15.08 (0.440)	15.79 (0.451)	19.63 (0.616)	10.73 (0.412)
(8)	Total	100.00 (2.293)	100.00 (3.017)	100.00 (2.918)	100.00 (2.857)	100.00 (3.138)	0.00 (0.845)

Notes: The number of rural laborers (in thousands) in each category is shown in parentheses.

When examining the evolution of specific occupations, we found that the decrease in the share of routine manual occupations was the major contributor to the reduction in the proportion of rural laborers engaging in routine occupations. Specifically, the share of off-farm rural laborers engaged in routine manual occupations decreased by 13.82 percentage points (Row 3). This finding is similar to the trend found by Ge et al. [8] using national census data from 2000 to 2015. However, the proportion of off-farm rural laborers engaged in routine manual occupations in our study is much higher than that in the study by Ge et al. [8], which focused on the labor force in urban areas, including both local natives and migrants. This difference may result from the fact that engaging in routine manual jobs is one of the characteristics of rural laborers' off-farm employment. Compared with the dramatic change in the proportion of off-farm rural laborers in routine manual jobs, their share in routine cognitive occupations remained relatively consistent (Row 5).

The evolution of two specific categories of non-routine occupations shows different patterns. The share of off-farm rural laborers in non-routine cognitive occupations showed an upward trend from 2007 to 2022, increasing by 4.48 percentage points (Row 5). However, their share in non-routine manual occupations decreased by 1.83 percentage points during the same period (Row 6).

The proportion of non-working rural laborers increased from 2008 to 2022, rising from 8.9 percent in 2008 to 19.63 percent in 2022 (Row 7). Compared with the urban areas in China, Ge et al. [8] found that the proportion of non-working laborers increased from 27 percent in 2000 to 31 percent in 2015, while the non-working share rose from 25 percent to 28 percent in the United States over the same period [18]. The upward trend observed in our research is consistent with the national census data, but the proportion is only about half of the latter, which defined the non-working group as the labor force not working for income for over an hour in the last week [37]. Our findings indicate that nearly 1/5 of rural laborers had no work, neither in the agricultural nor in the non-agricultural sectors, in 2022.

To sum up, the transformation of the off-farm rural labor market is mainly reflected in the increased share of non-routine cognitive and non-working laborers, and the decreased share of routine manual laborers, which aligns with China's overall reduction in demand for low-skilled routine employees in the manufacturing industry, and reflects the growing number of new-generation rural workers with higher education attainment [38].

4.2. Transformation of Occupation Structure by Demographic Characteristics

4.2.1. Transformation of Occupation Structure by Gender

Our data show similar trends but different shares of the fractions of males and females in each occupation category from 2007 to 2022 (Figure 1).

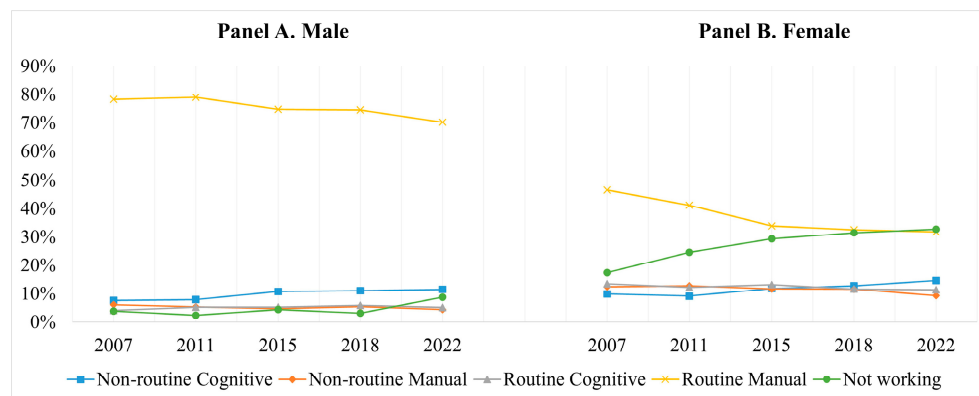


Figure 1. Occupational transformation of off-farm rural laborers by gender.

The share of both male and female off-farm rural laborers engaged in routine manual occupations decreased, but at different rates, in 2007–2022. It was 78.21 percent for males in 2007, which was 1.68 times that of females, at 46.62 percent. By 2022, the proportion of males in routine manual occupations had declined to 70.25 percent, 2.21 times that of females, at 31.81 percent. This implies a widening gender gap in the share of off-farm rural laborers in routine manual occupations.

There were different trends in the shares of male and female off-farm rural laborers engaged in routine cognitive occupations in 2007–2022. For males, the share increased from 4.14 percent in 2007 to 5.87 percent in 2018, with a slight decrease between 2011 and 2015, and then declined to 5.2 percent in 2022. In contrast, the share of females engaged in routine cognitive occupations exhibited the opposite trend by 2018; it decreased from 13.52 percent in 2007 to 12.2 percent in 2011, then increased to 13.19 percent in 2015. This was followed by a 1.5 percentage point decline in 2018. Similar to males, the share of females in routine cognitive occupations decreased from 2018 to 2022 but the decrease rate was much lower than that among males.

There were decreasing trends, with some rebounds, in the proportions of both male and female off-farm rural laborers engaged in non-routine manual occupations from 2007 to 2022. The proportion of males in non-routine manual occupations decreased from 6.14 percent in 2007 to 4.74 percent in 2015, then increased to 5.43 percent in 2018. This was followed by a decline of 1.05 percentage points from 2018 to 2022. The proportion of females in non-routine manual occupations was 12.46 percent in 2007, which was 2.02 times that of males; it increased to 12.78 percent in 2011 and then declined continuously to 9.32 percent in 2022.

The trends of both males and females in non-routine cognitive occupations increased from 2007 to 2022. It was 7.59 percent for males in 2007, which was 2.37 percentage points less than that of females. This then increased continuously to 11.46 percent in 2022, 3.26 percentage points less than that of females. These findings reflect that females are more likely to have postgraduate education that benefits them in obtaining non-routine cognitive jobs. It implies a widening gender gap in the share of rural laborers in non-routine cognitive

occupations. Compared with the consistent trend among males, the increasing trend among females showed a slight descent, declining 0.83 percentage points in 2007–2011.

The share of non-working male and female rural laborers increased at different rates during the same period. It climbed from 17.44 percent to 32.73 percent for females in 2007; this was much more than for males, which increased by 4.78 percentage points. By 2022, nearly 1/3 of females were working in neither farming nor off-farm jobs, indicating that females faced more difficulty in achieving sustainable employment. From 2018 to 2022, the share of non-working males increased much more dramatically than before 2018. These findings reveal gender inequality and high employment pressures among rural laborers.

There are huge gender differences in the non-working share of females and the routine manual share of males. Gender differences remain the fundamental form of labor market discrimination and have always attracted great attention from scholars. Existing research indicates that there are still unequal employment opportunities for males and females in China and other countries. In sectors such as manufacturing and construction, the ratio of male employees is significantly higher than that of female employees. Men are more distributed in the manual labor-intensive industry, while women are more distributed in the tertiary industry. Sectoral segregation in the employment of different genders is increasing [39], which means that gender differences are becoming increasingly evident. With the widening gender gap resulting from the structural transformation of the labor market, Li et al. [40] found that females were more severely discriminated against and more likely to lose their jobs. Additionally, some female rural laborers chose to quit off-farm jobs and remain unemployed to take care of their family members [41].

4.2.2. Transformation of Occupation Structure by Educational Attainment

Rural laborers with different educational attainment experienced disparate transformations of occupations (Table 3).

Table 3. Occupational transformation of off-farm rural laborers by educational attainment.

Educational Attainment		Year	Routine Cognitive (%)	Routine Manual (%)	Non-Routine Cognitive (%)	Non-Routine Manual (%)	Non-Working (%)
(1)	Primary school and below	2007	4.02	72.99	2.87	8.24	11.88
(2)		2011	2.03	75.15	3.78	6.54	12.5
(3)		2015	3.6	66.61	3.11	9.49	17.18
(4)		2018	2.71	66.27	1.66	9.04	20.33
(5)		2022	3.09	59.19	1.96	5.75	30.01
(6)	Junior high school	2007	6.12	71.57	4.65	9.37	8.29
(7)		2011	6.17	67.84	4.78	9.69	11.52
(8)		2015	7.09	63.19	5.39	8.94	15.39
(9)		2018	7.2	61.14	5.61	9.47	16.59
(10)		2022	5.68	62.6	6.03	8.3	17.39
(11)	Senior high school	2007	12.09	55.77	17.58	6.87	7.69
(12)		2011	13.75	53.67	14.69	8.66	9.23
(13)		2015	11.21	50.96	16.29	5.43	16.11
(14)		2018	11.46	50.49	17.09	6.99	13.98
(15)		2022	11.78	45.42	18.88	5.98	17.94
(16)	College and above	2007	25.86	16.38	47.41	4.31	6.03
(17)		2011	27.75	23.44	34.93	3.35	10.53
(18)		2015	20.55	25.46	42.94	3.07	7.98
(19)		2018	19.27	24.58	45.81	3.35	6.98
(20)		2022	18.09	22.66	42.83	3.74	12.68

For rural laborers with primary school education and below, the overall share of off-farm rural laborers engaged in each occupation category decreased, while the share of those not working increased. The share of those engaged in routine cognitive occupations

decreased, with rebounds from 2007 to 2022. Specifically, it declined from 4.02 percent in 2007 to 2.03 percent in 2011, increased to 3.6 percent in 2015, then declined to 2.71 percent in 2018. This was followed by a 0.38 percentage point increase in 2022 (Rows 1–5, Column 1). The share of those engaged in routine manual occupations increased from 72.99 percent in 2007 to 75.15 percent in 2011 and then declined continuously to 59.19 percent in 2022 (Rows 1–5, Column 2). The share of rural laborers in non-routine cognitive occupations increased from 2.87 percent in 2007 to 3.78 percent in 2011, declined to 1.66 percent in 2018, and then increased slightly to 1.96 percent in 2022 (Rows 1–5, Column 3). The share that was engaged in non-routine manual occupations declined from 8.24 percent in 2007 to 6.54 percent in 2011, and increased to 9.49 percent in 2015, followed by a continuous decline to 5.75 percent in 2022 (Rows 1–5, Column 4). The share of those not working showed steadily increasing trends from 11.88 percent to 30.01 percent in 2007–2022 (Rows 1–5, Column 5). These findings indicate that the increase in the non-working group is the main driver of the occupational transformation of rural laborers with education levels at primary school and below.

For rural laborers with junior high school education, the trends in occupational transformation were quite different from those of laborers with primary school education and below, with increasing shares of laborers in non-routine cognitive occupations and non-working laborers but decreasing shares of laborers in other occupation categories. The share of those with non-routine cognitive occupations and those not working showed steadily increasing trends, from 4.65 percent to 6.03 percent (Rows 6–10, Column 3) and 8.29 percent to 17.39 percent (Rows 6–10, Column 5), respectively, in 2007–2022. Comparatively, the share of those engaged in routine cognitive occupations increased from 6.12 percent in 2007 to 7.2 percent in 2018, followed by a 1.52 percentage point decline in 2022 (Rows 6–10, Column 1). The share of off-farm rural laborers in routine manual occupations showed the opposite trend, decreasing from 71.57 percent in 2007 to 61.14 percent in 2018, followed by a 1.46 percentage point increase in 2022 (Rows 6–10, Column 2). Unlike the trends for laborers engaged in routine occupations, the share of those in non-routine manual occupations increased from 9.37 percent in 2007 to 9.69 percent in 2011, declined to 8.94 percent in 2015, then increased to 9.47 percent in 2018, followed by a 1.17 percentage point decrease in 2022 (Rows 6–10, Column 4).

For the group of laborers with senior high school education, the overall trends in occupational transformation were similar to those of laborers with junior high school education, but with different patterns at different periods and different shares in each occupation category. For example, the share of those engaged in routine cognitive occupations increased from 12.09 percent in 2007 to 13.75 percent in 2011, then decreased to 11.21 percent in 2015, followed by a 0.57 percentage point increase in 2022 (Rows 11–15, Column 1). The share of those engaged in routine manual occupations decreased steadily from 55.77 percent in 2007 to 45.42 percent in 2022 (Rows 11–15, Column 2), then decreased from 17.58 percent in 2007 to 14.69 percent in 2011, followed by a 4.19 percentage point increase in 2022 for those engaged in non-routine cognitive occupations (Rows 11–15, Column 3). The share of those not working increased from 7.69 percent in 2007 to 16.11 percent in 2015, then decreased to 13.98 percent in 2018, followed by a 3.96 percentage point increase in 2022 (Rows 11–15, Column 5).

For those with college education and above, the trends in occupational transformation differed from those with junior and senior high school education. Specifically, the share of those engaged in routine manual occupations increased from 16.38 percent in 2007 to 25.46 percent in 2015, then decreased to 22.66 percent in 2022 (Rows 16–20, Column 2), exhibiting an overall increasing trend, which was opposite to those with junior and senior high school education. The share of those engaged in non-routine cognitive occupations decreased from 47.41 percent in 2007 to 34.93 percent in 2011, then increased to 45.81 percent in 2018, followed by a 2.98 percentage point decrease in 2022 (Rows 16–20, Column 3), exhibiting an overall decreasing trend that also differed from those with junior and senior high school education. For those engaged in routine cognitive and non-routine manual

occupations, as well as those not working, the trends in occupational transformation were similar to those with junior and senior high school education.

Additionally, certain trends were observed across education groups during this period. For example, the proportion of off-farm rural laborers engaged in routine manual jobs decreased with the rise in educational attainment. The proportion of rural laborers with college degrees or above in manual jobs was significantly lower than those of rural laborers with other educational attainment, both in routine and non-routine manual jobs. Conversely, the proportion of off-farm rural laborers engaged in either routine cognitive jobs or non-routine cognitive jobs increased with the rise in educational attainment.

4.2.3. Transformation of Occupation Structure by Age Groups

We then examined occupational transformations based on the three age groups referred by Ge et al. [8]: 16–29 years for the young group, 30–49 years for the middle-aged group, and 50–64 years for the old group.

For the young age group, the overall share of those engaged in cognitive occupations and those not working increased with the decline in manual occupations. Specifically, the share of those engaged in routine cognitive occupations increased from 12.45 percent in 2007 to 15.25 percent in 2022, with a slight drop in 2018–2022 (Table 4, Rows 1–5, Column 1). The share of those engaged in non-routine cognitive occupations showed steadily increasing trends from 6.67 percent in 2007 to 23.05 percent in 2022 (Rows 1–5, Column 3). The share of those not working increased from 11.06 percent in 2007 to 18.71 percent in 2015, then decreased to 16.8 percent in 2018, followed by a 2.09 percentage point increase in 2022 (Rows 1–5, Column 5). Although the overall share of those engaged in manual occupations decreased, there were different evolution patterns between routine and non-routine occupations. The share of those engaged in routine manual occupations decreased steadily from 55.78 percent in 2007 to 33.62 percent in 2022 (Rows 1–5, Column 2). However, the share of those engaged in non-routine manual occupations decreased from 14.04 percent in 2007 to 9.74 percent in 2015, then increased to 10.75 percent in 2018, followed by a 1.56 percentage point decrease in 2022 (Rows 1–5, Column 4). These findings indicate that, in the past 15 years, young rural laborers in China have shifted from manual occupations to cognitive occupations or to not working.

Table 4. Occupational transformation of off-farm rural laborers based on age group.

Age Group	Year	Routine Cognitive (1)	Routine Manual (2)	Non-Routine Cognitive (3)	Non-Routine Manual (4)	Non-Working (5)
(1) 16–29	2007	12.45	55.78	6.67	14.04	11.06
	(2) 2011	13.67	51.22	7.09	12.57	15.44
	(3) 2015	14.27	45.56	11.72	9.74	18.71
	(4) 2018	16.13	39.52	16.8	10.75	16.8
	(5) 2022	15.25	33.62	23.05	9.19	18.89
(6) 30–49	2007	3.76	78.68	8.78	4.39	4.39
	(7) 2011	5.01	72.9	8.23	6.59	7.26
	(8) 2015	6.93	65.84	9.71	7.4	10.11
	(9) 2018	8	61.69	10.51	8.38	11.42
	(10) 2022	9.16	57.07	12.11	7.2	14.46
(11) 50–64	2007	3.92	64.46	12.95	3.31	15.36
	(12) 2011	2.82	70.16	11.9	3.02	12.1
	(13) 2015	2.48	60.1	13.58	4.8	19.04
	(14) 2018	2	61.38	9.25	5.38	22
	(15) 2022	2.32	57.12	8.52	4.36	27.69

For the middle-aged group, the most significant transformation of occupation was the declining share of those engaged in routine manual jobs. Of these, 78.68 percent engaged in

routine manual occupations in 2007, but this dropped continuously, reaching 57.05 percent in 2022 (Rows 6–10, Column 2). With this trend, the shares of those engaged in other occupations and those not working increased during the same period. For example, the share of those in routine cognitive occupations increased steadily from 3.76 percent in 2007 to 9.16 percent in 2022 (Rows 6–10, Column 1). Although the share of those engaged in non-routine cognitive occupations decreased from 8.78 percent in 2007 to 8.23 percent in 2011, it subsequently increased to 12.11 percent in 2022 (Rows 6–10, Column 3). The share of those not working showed a continuously increasing trend from 4.39 percent to 14.46 percent in 2007–2022 (Rows 6–10, Column 5).

The old age group was more likely to exit the labor market, while the share of those not working increased dramatically from 2007 to 2022; the share of those not working in 2022 was 27.69 percent, which was 1.8 times that in 2007 (Rows 11–15, Column 5). The share of those engaged in routine cognitive, routine manual, and non-routine cognitive occupations decreased by 1.7, 7.34, and 4.42 percentage points from 2007 to 2022, respectively (Rows 11–15, Columns 1–3).

These findings indicate that the increasing proportion of non-routine cognitive jobs and the decreasing proportion of routine manual jobs were mainly driven by occupational changes within the young and middle-aged groups, while the increasing proportion of the non-working group was mainly driven by occupational changes within the old age group.

4.2.4. Transformation of Occupation Structure by Working Destination

There were similar trends, but different shares, of rural laborers working within and outside their home counties in each category from 2007 to 2022 (Figure 2).

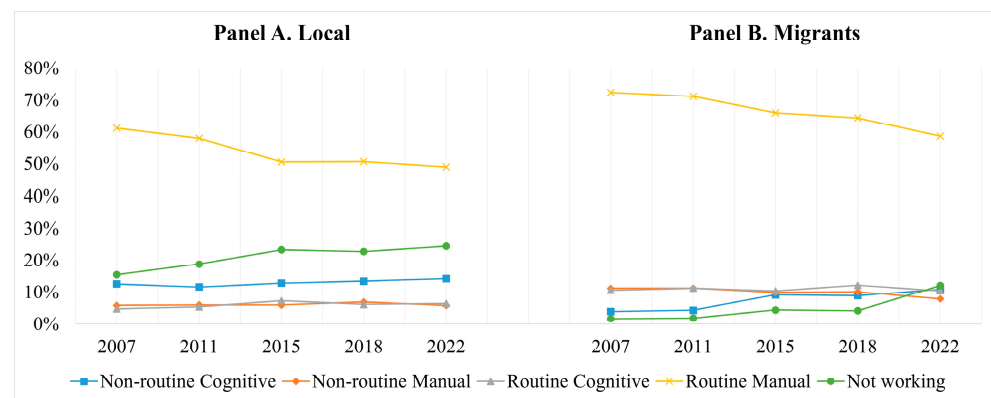


Figure 2. Occupational transformation of off-farm rural laborers by working destination.

Off-farm rural laborers engaged in routine manual occupations and working within or outside their home counties showed decreasing trends from 2007 to 2022; 61.18 percent worked within their home counties in 2007. This was 11.26 percentage points less than those working outside their home counties. The proportion then decreased continuously to 48.95 percent in 2022, 9.72 percentage points less than those working outside their home counties. Compared with the consistent trend of those working outside their home counties, the decreasing trend of those working within their home counties showed a slight descent, increasing by 0.12 percentage points in 2015–2018.

The trends of changes in the shares of off-farm rural laborers engaged in routine cognitive occupations were not obvious for those who worked within their home counties and those who worked outside their home counties in 2007–2022. It increased from 4.79 percent in 2007 to 7.31 percent in 2015, then declined to 6.16 percent in 2018, followed by a 0.3 percentage point increase in 2022 for those who worked within their home counties. Similar to those working within their home counties, the share of off-farm rural laborers engaged in routine cognitive occupations and working outside their home counties increased from 10.61 percent in 2007 to 11.25 percent in 2011, decreased from 11.25 percent in

2011 to 10.42 percent in 2015, and then increased to 12.23 percent in 2018, followed by a 1.78 percentage point decline in 2022.

The share of off-farm rural laborers engaged in non-routine manual occupations showed different trends between those who worked within their home counties and those who worked outside their home counties from 2007 to 2022. For those who worked within their home counties, it increased from 5.88 percent in 2007 to 6.94 percent in 2018, followed by a 1.11 percentage point decline in 2022. For those who worked outside their home counties, it decreased from 11.24 percent in 2007 to 7.86 percent in 2022.

There were different patterns in the increasing trends in the shares of off-farm rural laborers in non-routine cognitive occupations who worked within their home counties and those who worked outside their home counties from 2007 to 2022. It was a V-shaped transformation for those who worked within their home counties, decreasing from 12.61 percent in 2007 to 11.64 percent in 2011, then increasing to 14.29 in 2022. However, it followed an S-shaped pattern for those who worked outside their home counties, with slightly faster growth in 2011–2015.

The share of non-working rural laborers increased among both those who worked within their home counties and those who worked outside their home counties, with different rates in the same period. It was 15.55 percent in 2007 for those who worked within their home counties and increased to 24.47 percent in 2022, with a little fast growth before 2015. However, it was 1.72 percent in 2007 for those who worked outside their home counties and increased to 12.16 percent in 2022, with slightly faster growth after 2018.

There were narrowing gaps in the share of rural laborers in each category of occupation between those who worked within their home counties and those who worked outside their home counties. For example, the share of off-farm rural laborers engaged in non-routine cognitive occupations and working within their home counties was 3.16 times that of those working outside their home counties in 2007 but decreased to 1.32 times in 2022. The share of non-working rural laborers within their home counties was 9.04 times that of those working outside their home counties in 2007 but decreased to 2.01 times in 2022.

5. Decomposing Changes in Occupation Structure

5.1. The Framework of Decomposition

Following Cortes et al. [18], decomposition analysis contains three effects: Composition effect caused by the composition of population demographic changes, propensity effect owing to the change in the probability of people with specific demographic characteristics being classified into different occupation categories, and interaction effect due to the co-movement of the size of demographic group changes and probability changes.

Our data show that China's rural labor market experienced declining trends in routine manual occupations and increasing trends in non-routine cognitive occupations and non-working laborers. This may be partly due to the propensity effect, that the chances of rural laborers with different demographic characteristics engaging in each occupation category changed because of economic, technological, unobserved productivity, and leisure preference variations in specific groups [8]. Moreover, the composition of China's population has significantly changed in terms of age, gender, and education attainment since the beginning of the twenty-first century [42]. Since the chances of different groups of rural laborers working in these occupation categories differ, the composition effect may play an important role in the structural transformation of the rural labor market.

We classified rural laborers into 24 demographic groups based on their ages, genders, and education attainments. Combined with the current education system in China and the age range of our sample, we constructed three age groups (16–29 years old, 30–49 years old, and 50–64 years old), two gender groups (males and females), and four education groups (primary school and below, junior high school, senior high school, and college and above). There were 24 groups in total (3 age groups $\times$ 2 gender groups $\times$ 4 education groups).

To estimate propensity and composition effects, we specified the fraction of rural laborers in each category j at time t as $\bar{\pi}_t^j$, which can be written as:

$$\bar{\pi}_t^j = \sum_g w_{gt} \pi_{gt}^j \quad (1)$$

where w_{gt} represents the proportion of group g in the total sample at time t , and π_{gt}^j is the proportion of individuals in category j within group g at time t .

The equation for the change in the proportion of rural laborers in category j from time 0 to time 1 can be expressed as:

$$\bar{\pi}_1^j - \bar{\pi}_0^j = \sum_g w_{g1} \pi_{g1}^j - \sum_g w_{g0} \pi_{g0}^j = \sum_g \Delta w_{g1} \pi_{g0}^j + \sum_g w_{g0} \Delta \pi_{g1}^j + \sum_g \Delta w_{g1} \Delta \pi_{g1}^j \quad (2)$$

Obtained by calculating the formula, the term $\sum_g \Delta w_{g1} \pi_{g0}^j$ is the above-mentioned composition effect caused by the change in the proportion of the 24 demographic groups. The second term $\sum_g w_{g0} \Delta \pi_{g1}^j$ represents the propensity effect because of the changes in the proportion of individuals in the groups classified in category j . The term $\sum_g \Delta w_{g1} \Delta \pi_{g1}^j$ represents the interaction effect, reflecting the co-movements of composition and propensity effects.

5.2. Overall Decomposition

The remaining analyses focused on routine manual occupations, non-routine cognitive occupations, and non-working rural laborers since these groups experienced significant variations in 2007–2022.

The results of the decomposition analyses are presented in Table 5. The fraction of routine manual occupations reduced by 13.82 percentage points, from 66.59 percent in 2007 to 52.77 percent in 2022 (Row 2, Columns 1–3). The composition, propensity, and interaction effects accounted for 56.38, 71.63, and −28.01 percent of this overall declining trend, respectively (Row 2, Columns 4–6). Both the composition effect and the propensity effect played important roles in the share of the decrease in routine manual occupations, supporting hypothesis 1. These findings indicate that the main factors driving the reduction in the share of routine manual occupations are diverse, including changes in education attainment, opportunities in the rural labor market for specific groups of rural laborers caused by economic or technological forces, and the distribution of unobserved productivity and leisure preferences within the groups.

Table 5. Decomposition results.

		Pre (%)	Post (%)	Change	Decomposition (%)		
		(1)	(2)	(3)	Composition (4)	Propensity (5)	Interaction (6)
(1)	Routine Cognitive Jobs	7.59	8.03	0.44	93.83	108.29	−102.12
(2)	Routine Manual Jobs	66.59	52.77	−13.82	56.38	71.63	−28.01
(3)	Non-Routine Cognitive Jobs	8.46	12.94	4.48	180.77	−0.24	−80.53
(4)	Non-Routine Manual Jobs	8.46	6.63	−1.83	152.40	−11.20	−41.20
(5)	Non-Working	8.90	19.63	10.73	17.88	85.96	−3.85

The share of off-farm rural laborers engaged in non-routine cognitive occupations rose by 4.48 percentage points, from 8.46 percent in 2007 to 12.94 percent in 2022 (Row 3, Columns 1 and 2). This finding is different from that of Ge et al. [8] who found a 1.95 percentage point decrease for workers in cities and towns, including both local natives and migrants. The composition, propensity, and interaction effects accounted for

180.77, −0.24, and −80.53 percent of this overall increasing trend, respectively (Row 3, Columns 4–6). Obviously, the composition effect dominated the change in this occupation category. An explanation for the increased share of this occupation category is the rapid improvement in rural education in recent decades, which has led to growth in the proportion of rural laborers with high educational attainment and a significant decline in the fraction of lowly educated ones.

The share of the non-working group increased by 10.73 percentage points, from 8.90 percent in 2007 to 19.63 percent in 2022 (Row 5, Columns 1 and 2). The composition, propensity, and interaction effects made up 17.88, 85.96, and −3.85 percent, respectively (Row 5, Columns 4–6). Apparently, the propensity effect was the main driver of the increasing trend, while the other two effects played a slightly weaker role, providing support for Hypothesis 2.

5.3. Decomposition of the Decline in Routine Manual Occupations

The four key demographic groups that were responsible for most of the declines in the shares of routine manual occupations include both females and males with junior high school education aged between 16 and 29 years old, and males with junior high school and primary school education and below aged between 30 and 49 years old. The changes in these four groups accounted for 141.03 percent of the decline in the share of rural laborers engaged in routine manual occupations (Table 6).

Table 6. Fractions of changes in routine manual jobs by demographic group (%).

		Females			Males		
		16–29 (1)	30–49 (2)	50–64 (3)	16–29 (4)	30–49 (5)	50–64 (6)
(1)	Primary school and below	8.86	1.10	−13.81	12.67	19.33	−5.23
(2)	Junior high school	30.52	5.76	−12.15	65.15	26.03	−27.10
(3)	Senior high school	7.45	−2.67	−2.14	13.81	−1.03	−7.40
(4)	College and above	−2.05	−1.53	0.00	−4.43	−10.44	−0.69

We then identified the composition and propensity effects of these four groups. Both composition effect and propensity effect accounted for a large proportion of this decline. Population share is the fraction of demographic group g in the whole sample at time t , w_{gt} . Fraction in the routine manual is the share of individuals within demographic group g working in the routine manual category at t , π_{gt}^{RM} . In terms of the share of the total sample, it decreased from 49.54 percent in 2007 to 23.10 percent in 2022 for these four groups. Because over 93 percent of lowly educated rural laborers were engaged in routine manual jobs in 2007 (Table 7, Row 2, Column 4), its reduction in the population share implies a decline in the overall share of routine manual occupations, even holding their propensity steady.

Table 7. Four key groups responsible for the declining share of routine manual occupations.

		Population Share			Fraction in Routine Manual		
		2007 (%) (1)	2022 (%) (2)	Change (3)	2007 (%) (4)	2022 (%) (5)	Change (6)
(1)	Females with junior high school education Aged 16–29	10.77	2.04	−8.73	42.11	15.63	−26.48
(2)	Males with primary school education and below Aged 30–49	6.45	4.21	−2.25	93.24	79.55	−13.69
(3)	Males with junior high school education Aged 16–29	15.48	3.38	−12.10	73.80	71.70	−2.10
(4)	Aged 30–49	16.83	13.48	−3.35	89.90	85.58	−4.32

Individuals within these four key groups experienced dramatic reductions in the propensity to work in routine manual jobs as well. For example, the fraction of females with junior high school education and aged between 16 and 29 years old changed most, decreasing from 42.11 percent to 15.63 percent (Row 1, Columns 4 and 5), while the fraction of males with primary schooling education and below aged between 31 and 49 years old decreased from 93.24 percent to 79.55 percent (Row 2, Columns 4 and 5). As a result, the bulk of the propensity change documented in Table 5 is due to these four demographic groups.

We further analyzed the occupation categories to which these four key groups transferred after ending their routine manual jobs. According to the changes in the shares of these four key demographic groups in the occupation categories, the decline in the propensity of routine cognitive occupations was primarily offset by the increase in the non-working group (Table 8, Columns 2 and 5). Most of the rural laborers sorted into routine cognitive categories were mainly engaged in the retail industry, which was severely hit by COVID-19 [43]. Apparently, rural laborers in these demographic groups have not benefited from the transition to high-paid non-routine cognitive occupations.

Table 8. Occupation structure changes of the four key groups responsible for the decline in routine manual jobs (%).

		Non-Routine Cognitive (1)	Routine Cognitive (2)	Non-Routine Manual (3)	Routine Manual (4)	Non-Working (5)	Total (6)
(1)	Females with junior high school education Aged 16–29	−4.16	−26.48	9.67	4.47	16.51	0
(2)	Males with primary school education and below Aged 30–49	1.59	−13.69	−1.94	3.87	10.18	0
(3)	Males with junior high school education Aged 16–29	2.09	−2.10	1.04	−1.82	0.79	0
(4)	Aged 30–49	1.03	−4.32	−2.11	2.37	3.03	0

Since the four key groups responsible for the reduction in the share of off-farm rural laborers engaged in routine manual occupations are the young and middle-aged people with low education, the composition effect of these groups was largely due to the improvement in workers' education attainment and the aggravation of population aging. As for the propensity effect, the widespread application of automation technology in recent decades, such as computer software and robots in manufacturing, led to a decrease in the proportion of rural laborers engaged in routine manual occupations and was unfavorable to the sustainability of low-skilled workers' off-farm employment. Some of the rural laborers left routine manual jobs to engage in non-routine manuals that were hard to replace with the application of technology. Workers who left routine manual employment but could not find other proper jobs were unemployed or withdrew from the labor market [8].

5.4. Decomposition of the Increase in Non-Routine Cognitive Employment

Table 9 shows that the four key demographic groups accounting for the bulk of the rising share of rural laborers engaged in non-routine cognitive occupations included females and males with a college education and above and aged between 16 and 49 years old (Row 4, Column 1, 2, 4, and 5). These four demographic groups accounted for 85.43 percent of the total change.

Table 9. Fractions of changes in non-routine cognitive occupations by demographic group (%).

		Females			Males		
		16–29	30–49	50–64	16–29	30–49	50–64
(1)	Primary school and below	0.71	0.90	−2.73	0.00	−3.18	−0.34
(2)	Junior high school	−1.11	7.34	2.50	−1.51	−10.23	5.05
(3)	Senior high school	−7.22	10.37	2.25	2.51	−4.80	6.44
(4)	College and above	21.52	30.25	2.85	14.49	19.17	4.72

We then identified the composition and propensity effects of these four groups. The composition effect accounted for a large proportion of this increase while the propensity effect played a negligible role; therefore, we only focused on the composition effect.

The shares of different groups of off-farm rural laborers engaged in non-routine cognitive occupations, and the propensities of these groups, are shown in Table 10. These four demographic groups made up only 4.97 percent of China’s population in 2007 but tripled to about 14.79 percent in 2022. The improvement in the educational attainment of the rural labor force promoted the increase in non-routine cognitive employment. The results of the propensities of non-routine cognitive occupations have little value because the composition effect dominated the increasing share of non-routine cognitive occupations.

Table 10. Four key groups responsible for the increased share of non-routine cognitive occupations.

		Population Share			Fraction in Non-Routine Cognitive		
		2007 (%) (1)	2022 (%) (2)	Change (3)	2007 (%) (4)	2022 (%) (5)	Change (6)
Females with college education and above							
(1)	Aged 16–29	2.18	4.14	1.96	42.00	45.38	3.38
(2)	Aged 30–49	0.31	3.19	2.88	57.14	48.00	−9.14
Males with college education and above							
(3)	Aged 16–29	1.74	3.86	2.11	45.00	37.19	−7.81
(4)	Aged 30–49	0.74	3.60	2.86	64.71	37.17	−27.54

5.5. Decomposition of the Increase in the Non-Working Group

The four key demographic groups accounting for the bulk of the rising share of rural laborers in the non-working group were females aged 30–64 years old with junior high school education and below. These four key groups accounted for 73.62 percent of the total change (Table 11).

Table 11. Fractions of changes in non-working rural laborers by demographic group (%).

		Females			Males		
		16–29 (1)	30–49 (2)	50–64 (3)	16–29 (4)	30–49 (5)	50–64 (6)
(1)	Primary school and below	−4.61	9.86	23.51	0.78	3.43	5.39
(2)	Junior high school	−12.67	20.23	20.02	−7.38	3.64	5.44
(3)	Senior high school	1.98	3.80	5.31	−0.39	2.08	4.35
(4)	College and above	6.28	4.94	0.30	3.27	0.59	−0.11

The population proportion and propensities of the non-working category for these four key groups are presented in Table 12. These four key groups experienced increases in both probability and fraction of the non-working group. They made up 14.83 percent of China’s population in 2007 but doubled to about 28.65 percent in 2022. Additionally, except for females aged between 50 and 64 with primary school education and below, the

fraction of non-working laborers in the other three key groups increased by more than 16 percentage points from 2007 to 2022 (Column 6).

Table 12. Four key groups responsible for the increased share of non-working rural laborers (%).

		Population Share			Fraction in Non-Working		
		2007 (%) (1)	2022 (%) (2)	Change (3)	2007 (%) (4)	2022 (%) (5)	Change (6)
Females with primary school education and below							
(1)	Aged 30–49	3.84	4.94	1.10	14.77	32.90	18.13
(2)	Aged 50–64	2.53	7.20	4.67	41.38	49.56	8.18
Females with junior high school education							
(3)	Aged 30–49	7.37	11.06	3.69	9.47	25.94	16.47
(4)	Aged 50–64	1.09	5.45	4.36	28.00	45.03	17.03

Most of the increase in the share of the non-working category in these four key demographic groups was derived from the decrease in the shares of the other three categories rather than the routine manual category. For females aged between 30 and 49 years old with junior high school and primary school education and below, the decrease in the propensity of routine cognitive jobs led to an increase in the share of non-working laborers (Table 13, Rows 1 and 3, Columns 2 and 5). As mentioned above, most individuals classified into the routine cognitive category were engaged in jobs in the retail industry, which was hit severely by the COVID-19 pandemic. Moreover, females were more likely to be excluded from the labor market because of gender inequality [44]. For females aged between 50 and 64 years old with junior high school and primary school education and below, the propensity of non-routine jobs declined, including both non-routine cognitive jobs and non-routine manual jobs. The non-routine occupations require more flexibility, creativity, problem-solving, or human interaction compared with the routine category [8], and usually have relatively higher requirements for educational attainment. Thus, they were more likely to be eliminated from non-routine occupations and the non-working group.

Table 13. Occupation structure changes of the 4 key groups responsible for the increase in the not-working rural labor (%).

		Non-Routine Cognitive (1)	Routine Cognitive (2)	Non-Routine Manual (3)	Routine Manual (4)	Non-Working (5)	Total (6)
Females with primary school education and below							
(1)	Age 30–49	0.77	−18.02	0.31	−1.20	18.13	0
(2)	Age 50–64	−3.84	1.89	−7.29	1.06	8.18	0
Females with junior high school education							
(3)	Age 30–49	8.27	−31.27	1.00	5.53	16.47	0
(4)	Age 50–64	−5.08	2.01	−10.74	−3.23	17.03	0

6. Results and Discussion of Multivariate Analysis

Decomposition analysis is a descriptive analysis method; therefore, we further establish an empirical model to find the determinants of occupation classification. The results of the multinomial logit model are presented in Table 14. Columns 1–4 represent the non-routine cognitive, non-routine manual, routine cognitive, and routine manual categories that rural laborers belong to, respectively. The reference group is the non-working group.

Table 14. The determinants of occupation classification.

Variables	Non-Routine Cognitive	Non-Routine Manual	Routine Cognitive	Routine Manual
	(1)	(2)	(3)	(4)
Gender	−0.045 *** (−7.698)	−0.049 *** (−7.885)	−0.057 *** (−10.633)	0.351 *** (38.083)
Age	0.004 ** (2.516)	−0.006 *** (−4.612)	0.000 (0.086)	0.027 *** (9.698)
Age square	−0.000 (−0.643)	0.000 ** (2.477)	−0.000 (−1.497)	−0.000 *** (−9.297)
Education	0.028 *** (25.279)	−0.007 *** (−8.057)	0.010 *** (10.461)	−0.029 *** (−17.401)
Marriage	−0.015 ** (−2.560)	−0.016 ** (−2.388)	−0.015 ** (−2.076)	0.032 *** (2.781)
CPC member	0.122 *** (16.639)	0.003 (0.273)	0.007 (0.757)	−0.102 *** (−5.925)
Certificate	0.048 *** (7.404)	−0.007 (−0.898)	0.011 ** (2.205)	−0.030 *** (−2.803)
Lead	0.031 *** (5.352)	0.012 ** (2.208)	−0.000 (−0.003)	−0.027 *** (−2.640)
Labor	−0.004 (−1.433)	−0.001 (−0.530)	0.001 (0.379)	0.002 (0.626)
Child	0.005 (0.927)	−0.020 *** (−3.307)	−0.006 (−1.088)	−0.024 ** (−2.452)
Elder	−0.003 (−0.580)	0.007 (1.219)	0.001 (0.145)	0.002 (0.265)
Size	−0.001 (−0.383)	−0.000 (−0.068)	0.009 *** (3.522)	−0.006 (−1.010)
Income	−0.002 (−0.293)	0.006 (0.806)	−0.005 (−0.931)	0.003 (0.288)
Distance	0.002 * (1.670)	−0.002 (−1.544)	−0.004 *** (−2.848)	0.006 ** (2.407)
Distance square	−0.000 (−1.041)	0.000 (1.273)	0.000 ** (2.232)	−0.000 ** (−2.058)
Province dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	14,223	14,223	14,223	14,223

Note: z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Marginal effects are reported. Data source: China Rural Development Survey.

The results show that individual characteristics were highly correlated with the occupation categories of rural laborers. Males were 35.1 percentage points more likely to do routine manual jobs than not work, while females were more likely to do non-routine jobs and routine cognitive jobs. Compared with the non-working group, rural laborers were more likely to do non-routine cognitive jobs as age increased. The relationship between age and the probability of doing non-routine manual jobs was U-shaped, while the relationship between age and the probability of doing routine manual jobs formed an inverted U-shape. With an increase in the years of schooling, rural laborers were more likely to do cognitive jobs compared to not working, and were also less likely to do manual jobs. Married rural laborers were more likely to do routine manual jobs compared to not working, while unmarried rural laborers were more likely to do non-routine jobs and routine cognitive jobs. Rural laborers with CPC membership were more likely to do non-routine cognitive jobs compared to not working but were less likely to do routine manual jobs. Rural laborers with skills certificates were more likely to do cognitive jobs compared to not working, and were less likely to do routine manual jobs. Consistent with the results of the descriptive analysis, there are huge gender differences in the routine manual category. Men were more distributed in the manual labor-intensive industry, while women were more distributed in the tertiary industry [39]. The conclusion that the probability of participating in cognitive

jobs increases with an increase in years of schooling is consistent with the descriptive analysis results.

For the household characteristics, the variables leader and child were significantly correlated with occupation categories of rural laborers. Specifically, rural laborers with a village leader in the household were more likely to do non-routine jobs and less likely to do routine manual jobs compared to not working. If there was any child aged between 0 and 15 years old in the household, the rural laborers were less likely to do manual jobs compared to not working.

Few village characteristics were significantly correlated with occupation categories of rural laborers. With the increase in the village population, rural laborers were more likely to do routine cognitive jobs compared to not working. Compared to the non-working group, rural laborers were more likely to do non-routine cognitive jobs with increasing distance from the village to the town. The relationship between the distance from the village to the town and the probability of doing routine cognitive jobs was U-shaped, while the relationship between the distance from the village to the town and the probability of doing routine manual jobs formed an inverted U-shape.

7. Conclusions and Implications

Using nationally representative data from rural China, this study analyzed the structural transformation of occupations of all off-farm rural laborers in China, including migrants to urban areas, local off-farm employees, and non-working groups over the period covering 2007–2022, and further identified the three effects using analysis of decomposition.

From 2007 to 2022, the changes in the rural labor market were mainly reflected in the decrease in the share of routine manual laborers and the increase in the shares of non-routine cognitive and non-working laborers. The share of rural laborers in routine manual occupations decreased by 13.82 percentage points, the share of rural laborers in non-routine cognitive occupations increased by 4.48 percentage points, and the share of non-working rural laborers increased by 10.73 percentage points.

The composition effect, propensity effect, and interaction effect played different roles in the changes in occupations and non-working of rural laborers in China. Both the composition effect and propensity effect played important roles in the decrease of the share of routine manual occupations. The composition effect dominated the change in the non-routine cognitive occupation category while the propensity effect was the main driver of the increasing trend in the non-working group.

The four key demographic groups accounting for most of the decline in the share of routine manual occupations included both females and males with junior high school education and aged between 16 and 29 years old, and males with junior high school and primary school education and below and aged between 30 and 49 years old. Females and males with college education and above and aged between 16 and 49 years old were responsible for most of the increase in the share of non-routine cognitive occupations, and females aged 30–49 years old with junior high school education and below accounted for the bulk of the rising share of rural laborers in the non-working group.

The multivariate analysis further illustrated the results of the decomposition analysis. Compared with female rural laborers, males had a higher probability of working in routine manual jobs. Compared with the non-working group, rural laborers were more likely to do non-routine cognitive jobs as age increased. The relationship between age and the probability of doing non-routine manual jobs was U-shaped, while the relationship between age and the probability of doing routine manual jobs formed an inverted U-shape. With the increase in education level, the probability of rural laborers working in cognitive jobs increased.

The government needs to take effective measures to promote sustainable development of the rural labor market in response to the recent changes in the off-farm occupation structure. Our findings imply that the government should strengthen education for rural laborers to increase the possibility of benefiting from the transition to high-paid occupations.

Attention should also be paid to females and low-education-attainment groups of rural laborers, focusing on occupation changes and wage increases and providing support to sustain their off-farm jobs.

Although this study captures the transformation of off-farm occupations for all the off-farm rural laborers in China and identifies the three decomposition effects, we acknowledge some limitations in our work. First, the decomposition method cannot provide a causal explanation of structural transformation because it is a descriptive analysis. The causes of the transformations of off-farm occupations should be explored and advanced methods should be adopted in future studies. Second, subsequent research is needed to further explore the impact of the structural transformations of occupations of off-farm rural laborers on their wage income.

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