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The changing nature of work and earnings inequality in China

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Abstract: This paper examines the evolution of China's industrial and occupational structure in the last two decades and its impact on wage inequality. We find that non-routine cognitive and interpersonal tasks have increased, while routine cognitive tasks first increased and then declined. Occupation structural change is accompanying rising wage inequality. The wage premium for educated workers rose sharply in the 1990s and remained high thereafter. Occupations with high routine task intensity are associated with lower wages. While the return to education has become the largest contributor to wage inequality, routine task intensities have yet to play a significant role.

Key words: occupational structure, inequality, education, China

JEL classification: I32, O14, O15, P23

Figures and tables: at the end of the paper

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1 Introduction

Throughout the world, the globalization process and rapid technological change have led to dramatic changes in jobs, which, in turn, have had a profound impact on earnings inequality. This paper examines the changing nature of work in China and its consequences for earnings inequality. When an economy is transformed, the workers produce different goods and services, and the task contents of their jobs change. In their seminal work, in the context of the widespread use of computers, Autor et al. (2003) classified the tasks performed in various positions into several broad categories: routine manual, non-routine manual, routine cognitive, and non-routine cognitive tasks. They (and many follow-up studies) have shown that the task contents that workers perform are influenced by technological change. The widespread use of computers, industrial robots, and artificial intelligence in particular have replaced routine labour and have forced workers out of middle-rank occupations.

Workers with different skillsets perform differently in the labour market. For instance, the wages of educated workers can increase when the demand for skilled workers increases. Workers make adjustments (through human capital investment) in response to changes in the relative demands for labour. The adjustment process is primarily shaped by the strength of market incentives and public policies related to education, training, and migration.

China is an important case as it has experienced four decades of high growth, tremendous structural transformation, and rising inequality. In recent years, China's labour market conditions have changed significantly. Its total employment has increased more slowly than in previous decades and even declined after 2018 due to waning rural-to-urban migration and population ageing. Meanwhile, China has invested heavily in industrial robot development, and it has become one of the most active industrial robot markets. According to Cheng et al. (2019), in 2016, robot sales in China accounted for nearly 30 per cent of global sales of 294,000 units, rising from less than 1 per cent in 2000. Meanwhile, Chinese households also invest in human capital enthusiastically. The younger cohorts have become much more educated than the older ones.[1] On the other hand, technological change is redefining industries and occupations. For example, thanks to the internet, DiDi (a Chinese version of Uber) drivers have had a major impact on the taxi driver profession. These changes also have a significant impact on inequality.

Along with structural transformation, China's income inequality increased significantly in the 1990s and early 2000s (Li and Xing 2020; Ravallion and Chen 2007). Various factors have contributed to wage disparities, and the roles of these factors have changed. These include individuals' education, gender, age or experience, region, industry, occupation, and family background (such as household registration status, i.e. *Hukou*[2]). Education plays an important role, and the existing literature has estimated the returns to years of schooling or education levels. Most studies have found that education plays an increasingly important role in wage determination. However, they do not provide a deeper understanding of wage inequality. Education levels or years of formal schooling are, at best, a crude measure of skills, especially when skills are multidimensional.

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[1] In 2015, while 34 per cent of those aged 20 to 29 had tertiary degrees, only 10 per cent of those aged 40 to 49 had tertiary degrees (NBS 2016: Table 4-1).

[2] The *Hukou* system requires Chinese citizens to have household registration or *Hukou* in a specific location. Before *Hukou* reform, migration, particularly rural-to-urban migration, was strictly controlled by the *Hukou* system. With recent reforms, migration has become common but *Hukou* status in large cities is still difficult to obtain.

In this paper, we document the changing nature of work in China by examining the evolution of its occupational structure over the last two decades. We then explore the changes in earnings inequality. We find that workers' occupational structure has changed significantly and has caused inequalities between individuals with different jobs and qualities. We find that China's wage inequality has continued to rise over the last two decades. The wage premium for educated workers rose sharply in the 1990s and remained high thereafter. Education has become the largest contributor to China's wage inequality.

As mentioned earlier, and as we discuss later in the literature review, the economic literature emphasizes the distinction between different types of tasks: routine cognitive, non-routine cognitive, routine manual, non-routine manual, and non-routine interpersonal tasks. This distinction is essential as China has experienced significant structural transformation. The widespread use of computers and the internet, in particular, have fundamentally changed the relative prices of different skill types. It is well known that computers can replace routine cognitive tasks and complement non-routine cognitive and interpersonal tasks. We, therefore, construct a routine-task intensity (RTI) index based on the US (O*NET) occupational dictionary (O*NET n.d.) and assign an RTI value to individuals according to their occupation. We find that RTI has become increasingly negatively correlated with wages. The coefficient of education remains statistically significant but has declined in magnitude.

As occupation-specific task content is coded using the US occupational dictionary, we also use a corrected RTI to consider the difference in the economic development levels between the USA and China (Lewandowski et al. 2019; Lewandowski et al. 2020). We find that RTI plays an even more prominent role when using the country-specific measure, suggesting that the uncorrected RTI may have a considerable measurement error. The negative role of RTI and its magnitude are similar in two different household surveys, namely the China Household Income Project (CHIP) (China Institute for Income Distribution (n.d.) and the Chinese General Social Survey (CGSS) (NSRC n.d.). Both datasets have their pros and cons. While the CHIP is well known for its high-quality wage data and rich labour market information, its occupation variable is only at the one-digit level. By contrast, the CGSS has three-digit occupation information, which helps with matching wage data and occupational tasks.

The results of this paper are of great importance for China's educational development. Following its significant education expansion, the pattern of secondary and tertiary education development has become an urgent policy issue. For example, with nearly 90 per cent of the middle school graduates enrolling in higher level education, the government is guiding roughly an equal number of them to academic and vocational high schools. Whether this policy is justified very much depends on the returns to a different type of skill. In particular, the negative association between RTI and wages suggests that heavy investment in vocational training which emphasizes specific skills (which are easily routinized) may be unwise.

This study is also crucial for understanding the income inequality trend. For several reasons (such as stimulating domestic consumption and combating high levels of inequality), the government has placed great emphasis on enlarging the middle-income group in recent years. Our results suggest that the force of technological change has made this objective particularly challenging.

This paper is organized as follows. Section 2 summarizes the related literature, including studies on task-based models, job polarization, and China's wage or earnings inequalities. Section 3 introduces the data used for this study. Section 4 describes in detail how the sectoral and occupational structures have changed since the 1990s, with an emphasis on the most recent decades after 2000. Section 5 examines the evolution of wage inequality in China. Section 6 explores the relationship between occupational structure and wage inequality. Section 7 investigates the changes in wage inequality using the decomposition method. Section 8 uses an alternative dataset to examine the sensitivity of our empirical results and Section 9 concludes.

2 Literature and background

Economists and sociologists have recently begun to explore the relationship between job structure and wage inequality. The literature has found evidence, although mixed, that job structure can influence wage inequality through changes in between-job inequality (Mouw and Kalleberg 2010), within-job inequality (Kim and Sakamoto 2008), and job composition, or the polarization effect (Autor et al. 2003; Autor et al. 2006; Goos and Manning 2007; Goos et al. 2009).

Goos and Manning (2007) argue that technological progress increases the relative demand for well-paid skilled jobs (professional and managerial jobs, for example) and low-paid unskilled jobs, and reduces the relative demand for 'middle-rank' jobs. This is because technology can easily replace middle-rank jobs involving routine tasks but cannot replace human labour in non-routine (both highly skilled and manual) tasks (Autor et al. 2003). We conclude from these studies that job structure is an important channel through which technological forces influence the labour market. Although the above studies were on western countries (USA, UK, and other OECD countries), our paper contributes to this literature but in the context of transitional China, where the transitional feature also plays a significant role.

Our paper also reflects a growing literature on China's wage structure. Income inequality has become an eminent issue as it reached a high level in the 1990s and 2000s. Although the increase seems to have stopped, it will likely remain high (Luo et al. 2020). Wages have become increasingly important in shaping overall income inequality. During the planning economy era, region and seniority played an important role. With market reform, the wage gaps between different areas, industries, types of ownership, and demographic groups widened significantly and evolved (Knight and Song 2003; Xing 2008; 2010). Of these factors, education has played an increasingly important role. A considerable amount of effort has been made to estimate the returns to education, which increased considerably in the late 1990s and early 2000s and remained high thereafter (despite the sharp increase in education levels). The findings show that the returns to education (or skill prices) for urban China have increased continuously since the late 1980s (Zhang et al. 2005).

Several studies have quantified the contribution of different factors to wage inequality and have found that the contribution of education has been ever-increasing and has become the largest contributor. The importance of other factors, such as seniority (experience) and region, has declined. While, in the past, regional disparity was the most critical contributor to wage inequality, it has been surpassed by other factors, particularly education.

There are several reasons for the increased returns to education. First, market-oriented reform (such as ownership restructuring or privatization in the late 1990s) is closely associated with an increased return to skills. Even within state-owned enterprises, workers increasingly work in a competitive environment for wages that are determined by performance or supply-and-demand forces. Second, China's deeper integration into the world economy has increased the demand for skilled workers. Third, technological change has fundamentally changed the nature of jobs. As a developing country, China has embraced technological change enthusiastically. The declining price of computers has induced widespread use of personal computers and the internet, which can replace routine cognitive tasks in jobs and therefore influence the occupational structure.

The literature pioneered by Autor et al. (2003) has shown that occupational structure is the main channel through which technological change influences the labour market. The major advantage of the occupational approach is that it allows for a comprehensive measure of different work tasks. The skills required for performing tasks are multidimensional. By contrast, the widespread use of unidimensional education is unsatisfactory. There is significant heterogeneity for individuals with the same years of schooling or education levels. For example, college graduates can specialize in different subjects and therefore have very different career prospects. Thus, years of schooling or education levels are at best a crude measure of skills (Laajaj and Macours forthcoming; Young 2013).

Although several studies have noted the occupational (task-based) approach to understanding China's labour market, there has been little examination of the changing occupational structure. There has been even less effort to measure the changing number of different tasks performed and their linkage to wages. Ge et al. (2021) are one of the few exceptions that studied the dynamics of China's occupational structure, but they did not examine the relationship between occupational structure and wage inequality. As mentioned in the introduction, job structure can influence wage levels and wage inequality even after controlling for general skill levels. It is not an uncommon practice in research to control for occupation, industry, and ownership when examining wage determination. These characteristics are primarily auxiliary control variables, and how these characteristics affect wages is seldom reported.

3 Data

We use three datasets to explore the changing nature of work and inequality in China. First, we use the Chinese population census data for 1990, 2000, 2010, and the one per cent population survey (or the mini census) data for 2015 to examine industrial and occupational structural changes.[3] We use random samples of these census data, which cover all (31) provinces of mainland China and contain detailed industry and occupation information for a large number of individuals each year. The three-digit occupation codes, in particular, allow us to reclassify the data following the International Standard Classifications of Occupation (1988 version, or ISCO-88). We then link the occupation data to the occupational task content information to examine the changing trends in different tasks. The census data also collect detailed information such as location of residence, age, gender, and education. However, they do not have income information.

Several household surveys in China contain income and occupation information. In this paper, we mainly use the China General Social Survey (CGSS), which has several attractive features.[4] The most important is that it collects detailed (three-digit) occupation information according to the ISCO system, which allows us to assign task measures to individuals with different occupations at a more disaggregated (three-digit) level. The CGSS covers all mainland provinces, but unlike some other surveys, it only collects income information for the respondent and their spouse within a household.

[3] We accessed the census and mini census data from the National Bureau of Statistics of China but these are not yet publicly available.

[4] This survey was conducted by the National Survey Research Center at Renmin University of China (NSRC). See NSRC (n.d.).

To complement the CGSS data, we also use the China Household Income Project Survey (CHIP), which has high-quality income information.[5] Although it does not cover all provinces, it is representative of China in terms of region, population, and income distribution. Because the survey aims to evaluate China's income distribution, it collects high-quality income data (including wages) and labour market information. The data also have rich information on personal and household characteristics. We use three waves of the CHIP, namely 2002, 2007, and 2013, to study the evolution of earnings inequality. A disadvantage of the CHIP is its lack of detailed occupational data. We therefore need to explore the occupational structure and earnings inequality using a one-digit occupational code. To examine the impact of task contents (RTIs in particular) on earnings and earnings inequality, we use census data to merge the score of different tasks in each three-digit occupation. We calculate their averages within each broader classification of occupation as defined in the CHIP data, which we later link to the individual CHIP data to run earnings equations.

To focus on the labour market consequences of the changing nature of work, we examine workers' wages in both rural and urban China. The outcome variable of interest is annual earnings, which is deflated using the national consumer price index.

4 Sectoral and occupational change

4.1 Structural transformation

The nature of work has changed as the economy has experienced structural transformation. A conventional way to examine structural transformation is to study the evolution of the industrial structure or to explore the relative number of workers who produce different goods or provide different services. We use the census and mini census data to calculate the share of workers employed in different industries in 2000, 2010, and 2015, which we report in Figure 1.

A significant fact is that the agriculture industry remained the largest sector throughout the period from 2000 to 2015. However, its relative importance decreased sharply over this period. While in 2000, nearly two-thirds of the workforce were employed in agriculture, the share declined to less than 50 per cent in 2010, and to 37 per cent by 2015. These changes were associated with significant economic and societal change, as well as changes to the nature of work. As agricultural work is mainly manual and concentrated in rural areas, the reduction in employment led to rapid urbanization and an increase in the workforce of other industries. As shown in Figure 1, the share of jobs in manufacturing, construction, wholesale and retail, and other services all increased significantly. Naturally, the nature of work differs considerably across different industries and industrial upgrading is likely to lead to change in the distribution of jobs.

The quality of the workforce also changed over this period. Figure 2 reports the share of workers with tertiary degrees (including professional college, university, and graduate degrees). Agriculture workers were the least educated and their education levels changed little. All other industries had higher education levels and experienced a significant increase in education levels. Although the finance industry's share of employment was low, it had the highest education level and experienced the most significant level of growth between 2000 and 2015. In contrast, the education levels for the manufacturing, construction, and real estate industries were relatively lower and experienced a slower increase.

[5] See China Institute for Income Distribution (n.d.).

The changes in industry shares and the changing composition within industries are associated with significant wage gaps which evolved over time. Figure 3 shows the relative wages for selected industries. We calculate the cumulative growth of wages for each sector relative to the national average. It should be noted that the wage levels differed significantly at the beginning, and all increased considerably. By focusing on their relative growth, Figure 3 shows that relative wages decreased significantly for the real estate, construction, and agriculture industries. Workers in the manufacturing industry also lagged behind the average trend, but to a lesser extent. Wage levels in the finance industry increased dramatically, and the gap has only declined in recent years.

4.2 Changes in the occupational structure

The recent literature pays closer attention to the structure of occupations, enabling researchers to examine the tasks performed and to have a better understanding of how technological change has affected the labour markets. In this section, we document the changes in China's occupational structure.

Occupational structure

Table 1 reports the employment shares by one-digit occupation from 1982 to 2015. As the industrial structural transformation suggests, employment continuously shifted out of agriculture to manufacturing and service jobs. In 1990, three-quarters of the workforce had agricultural jobs, declining to 31 per cent by 2015. In contrast, service workers and market sales workers accounted for 4 per cent in 1990, increasing to 24 per cent in 2015. Manufacturing jobs (craft workers and machine operators) also accounted for 24 per cent of the workforce in 2015, compared to 11 per cent in 1990. Professional jobs (including technicians and associate professionals) increased from around 7 per cent in 1990 to 16 per cent in 2015.

It is worth mentioning that the pace of transformation in the occupational structure varied in different periods and the most significant changes happened between 2000 and 2010. In this decade, the share of agriculture-related jobs declined by 30 percentage points, accounting for three-quarters of the decline between 1990 and 2015. Accordingly, employment increased for non-agricultural jobs, especially manufacturing and service jobs. These significant changes were due to China's entry into the World Trade Organization (WTO), massive rural–urban migration, and rapid urbanization. Between 2010 and 2015, however, the pace and nature of occupational change seems to be different from the previous decade. First, manufacturing jobs declined slightly (rather than increasing). Second, service and professional jobs kept increasing, but the change was slower. The new direction of occupational change may partly reflect the penetration of technological change into the Chinese labour market.

In Table 2, we consider the occupational structure between 1990 and 2010 in rural and urban areas separately.[6] Even in urban areas, agricultural jobs accounted for one-third of the employment in 1990, followed by craft workers and those in related trades (16 per cent), technicians (13 per cent), and plant workers (9.6 per cent). By 2010, the share of agricultural and fishery workers declined to 11 per cent; meanwhile, the percentages of service and market sales workers increased to 27 per cent and plant workers to 15 per cent. Unlike for the whole sample, occupational change within urban areas between 1990 and 2000 (which was a consequence of the enterprise ownership restructuring) seems more substantial than that for the following decade. In contrast, the change in rural occupational structure was more significant in the 2000 to 2010 period than in the previous decade. Within rural areas, agricultural and fishery workers decreased by 23 percentage points

[6] The mini census of 2015 is not used because the rural–urban divide is inconsistent with former years.

between 2000 and 2010. Accordingly, service and manufacturing jobs increased dramatically. It is worth mentioning that there was massive rural–urban migration at this time, with the number of rural migrants increasing from 60 million in 2000 to 240 million in 2010 (Li and Xing 2020). Most migrants held occupations in the service and manufacturing sectors.

In Tables 1 and 2, we also aggregate the occupations into three groups, namely low-skilled (agricultural and elementary workers), mid-skilled (clerical, sales, and production workers), and high-skilled (managerial, professional, and technical workers). Our findings are different to those for developed countries. In the last two decades, especially in the ten years following China's entry into the WTO, low-skilled jobs decreased dramatically, but this trend slowed down in the most recent period.

Occupational task contents

Occupational structural change indicates that the number of tasks performed by the workforce changed. To investigate this, we merge the task contents from O*NET with the occupational structure to calculate an average score for each task, weighted by the employment share of all occupations each year. This practice relies on two assumptions: (1) that the tasks of the same occupation across countries are comparable; and (2) that the task contents within occupations do not change over time. Keeping these caveats in mind, we examine the changes to several types of tasks in Figure 4. Non-routine cognitive analytical (*nr_cog_anal*) and interpersonal (*nr_cog_pers*) tasks, routine cognitive tasks (*r_cog*), and non-routine interpersonal manual tasks increased between 1990 and 2010. However, routine manual tasks (*r_man*) and non-routine physical manual tasks (*nr_man_phys*) decreased from 1990 to 2015. These changes are consistent with our previous description of the occupational structural change. We observe that the increase in non-routine cognitive tasks continued, while routine cognitive tasks decreased slightly between 2010 and 2015.

Meanwhile, offshorable tasks increased significantly from 1990 to 2010. As a result of China's integration into the world economy following its entry into the WTO, the increase was particularly substantial between 2000 and 2010. However, offshorable tasks decreased between 2010 and 2015 because of the global financial crisis and domestic consumption growth.

We also construct an RTI index for each occupation:

$$RTI = ln\left(\frac{r\_cog + r\_man}{2}\right) - ln\left(\frac{nr\_anal + nr\_pers}{2}\right) \quad (1)$$

Between 1990 and 2000, there was a substantial increase in RTI, but a decline in the most recent period from 2010 to 2015. As mentioned earlier, because China's economic structure is different from that of the USA, the task contents will not be identical between these two countries. The last panel of Figure 4 shows the changing pattern of RTI, taking account of this difference. The results suggest only a slight increase between 2000 and 2010 and a stagnation in the following five years.

How have the share of occupations of different characteristics changed? Has there been polarization in the occupational structure, as observed in some developed countries? Figure 5 shows the change in employment share against various occupational tasks and RTI measures. The y-axis is the log change in employment share, and the x-axis is the quantiles of the three-digit occupations ranked by the level of different tasks. As the occupational employment share differs considerably, the change in employment share may not reflect the growth trend. For example, a five-percentage-point change means different growth rates for occupations whose initial shares are different. Thus, we examine the logarithm change in employment share by skill quantiles. We split the whole 1990–2015 period into three sub-periods and estimate the lowest curve between the change in employment shares and quantiles of tasks. Between 1990 and 2000, the relationship is roughly U-shaped. It is occupations at the middle range of specific tasks that experienced the lowest growth. The pattern reversed in the following two periods: an inverted U-shape relationship between employment change and task quantile became apparent. The 2000–10 period witnessed the highest employment growth in non-agricultural occupations. It was at the middle range of various task contents that occupations grew the most. The most recent period, from 2010 to 2015, exhibits a notable change. The employment shares of occupations with high non-routine manual tasks and routine cognitive tasks decreased. Correspondingly, those with low non-routine cognitive tasks also decreased.

In Figure 6, we examine the relationship between changes to occupational employment shares and RTIs. Again, we find a U-shaped relationship over the 1990–2000 period, and the shape is not symmetric. The increase in high-RTI occupations is more prominent than those with low RTI. In later periods, however, the relationships have an inverted U-shape. The decline in the employment share for high-RTI occupations is sharper in the 2010–15 period. Examining log changes produces similar results.

To examine the above relationships quantitatively, we run regressions of the change in (log) of the employment share on different tasks (instead of quintiles) and their square terms. The results in Table 3 are consistent with previous graphical patterns, and there is an inverted U-shape between the change in employment shares and RTIs. However, in most cases, the coefficients are not statistically significant.

Another way to measure the skill levels of occupations is to use wage levels. Therefore, we use the occupation log wage in the CGSS to measure the skill levels of occupations (at the two-digit occupational level). The relationship between employment change and skill level is depicted in Figure 7. The most noticeable feature is the high growth in medium–low-wage occupations in 1990–2010. The growth in high-wage occupations is also apparent. In 2010–15, low-wage occupations declined, middle-wage occupations increased, and high-wage occupations remained constant. The corresponding regression results are reported in Table 4. However, most results are insignificant. One possible reason for this is that the quadratic form is insufficient to capture the relationship between employment growth and skill levels.

Occupational structure and wages

The labour force composition of a given occupation changes over time, as do the wage levels of different occupations. Table 6 reports wages (in log) and years of schooling for different occupations (at the one-digit level) for different years. Wage levels differ considerably across occupations. Professionals, technicians, and managers earned the highest wages followed by service and manufacturing workers, and wages for agricultural and elementary occupations were the lowest. The growth rates also vary across occupations. Managerial jobs had the highest growth, while those of plant operators grew the least. Education levels also differ considerably across occupations. Professionals were the most educated, and agricultural workers were the least educated. It is worth emphasizing that although average education levels increased, those of plant workers, trades workers, and service and sales workers stagnated or even declined.

In Figure 8, we examine how occupational wage changes are associated with wage levels. With the y-axis depicting the average occupational log wage change and the x-axis being the quantile of mean log wage, a U-shaped relationship is readily observed. The low- and high-wage occupations experienced higher wage growth in rural and urban areas. Table 5 reports the corresponding regression results. The dependent variable is the log change in occupational wages, and the independent variables are the means of log wages and their squares. The results show that the U-shape is significant. When wages are aggregated at a three-digit occupation level, the results are no longer significant but the U-shaped pattern remains. These results are consistent with the patterns in Figure 5, where we find a decline in occupations with high-routine and low-non-routine tasks. They are also consistent with the apparent decline in high-RTI occupations in recent years shown in Figure 6. As medium-level wage occupations typically require high-routine tasks, a decline in their employment share and the sluggish wage growth reflect the substitution effect of technological changes.

5 Earnings inequality

5.1 Earnings distributions

We use the CGSS data to examine earnings inequalities between 2005 and 2017. Table 7 reports the summary statistics of the CGSS sample, from which we discuss urban workers first. The table shows that the labour force was ageing and getting more educated. In 2005, urban workers with tertiary degrees (professional college and college) accounted for 17 per cent of the whole urban sample. By 2015/17, the share had reached 30 per cent. The significant rise was mainly due to China's higher education expansion, which began in the late 1990s and persisted through the 2000s. Table 7 also reports the share of workers in different occupations for 2005, 2012/13, and 2015/17. It is worth mentioning that the occupational distribution does not accurately resemble that of the census data, but the changing trend is similar.

Table 8 reports the wage levels and wage inequalities in several alternative measures. Annual wages increased dramatically, by nearly four times, between 2005 and 2017. In 2005, the mean annual wage was 12,800 Yuan and, by 2017, it had reached 60,000 Yuan. We also report the means and various percentiles of the earnings distributions. All statistics significantly increased during the 2005–17 period.

Meanwhile, wage inequality increased slightly. The Gini coefficient of annual wages increased from 43 per cent in 2005 to 44 per cent in 2012/13 and to 48 per cent in 2015/17. The variance of log wages shows a similar trend. The inequality between different percentiles shows a slightly different pattern. The wage gap at the lower half of the wage distribution (P50–P10) declined (rather than increasing) between 2005 and 2012/13. This change dominated the changes in the whole wage distribution so that the wage gap between the 10th and 90th percentiles decreased. However, all inequality measures show an increasing trend in the latter period 2012/13 to 2015/17. To illustrate the evolution of the wage distribution graphically, we estimate the wage kernel densities for each year in Figure 9. The wage distribution is moving to the right and becoming more dispersed.

We also report the corresponding statistics for rural China in the last three columns of Table 7 and Table 8. In all the years considered, rural areas had significantly lower wages than urban areas, but rural wages increased significantly between 2005 and 2017 as well. Inequality, however, did not increase monotonically. In 2005, inequality was high in the Gini coefficient (50 per cent); it declined slightly between 2005 and 2012/13 and increased again thereafter. The other inequality measures show a similar trend: the percentile gap inequalities (P90–P10) and the variance of log wages kept increasing between 2005 and 2017.

As China's urbanization proceeds, the continuous increase in wage inequality has a significant implication for overall inequality in China. Many believe that China will enter the downward trajectory of the Kuznetsian curve after several decades of rapid growth. However, recent trends in rural and urban inequalities cast serious doubt on that hypothesis.

5.2 Between-group earning gaps

Existing research shows that the educational wage gap has become a significant factor in influencing wage inequality. Table 9 shows the average wages of different education groups, namely middle school graduates, high school graduates, professional college graduates, and college/university graduates. The first three columns are for urban areas and the last three for rural areas. The wage gaps between different education levels are significant for both genders in rural and urban areas. The gap between college and non-college graduates is the largest, and the gap between middle and high school graduates is relatively small.

Table 9 also shows significant wage gaps between workers of different genders. Women earn significantly less than men, and the gender gap is more prominent in rural than in urban areas. There are also significant wage gaps across age groups, regions, and individuals with the same observable but different unobservable characteristics. We do not present them to save space.

6 Wage equations and the returns to education

Many studies have estimated Mincerian wage equations for rural and urban China. We also estimate an augmented Mincerian equation, as follows:

$$ln(wage) = \beta_0 + \sum_k \beta_k * edulvl_k + \gamma X + \varepsilon \qquad (2)$$

In equation (2), *edulvl* is education level (the subscript k=1, 2, 3, and 4 represents middle school, high school, professional college, and college), and X represents other variables including gender, experience, experience squared, and region dummies. As we are interested in the role of tasks in wage determination, we control for a composite index of RTIs.

Before discussing the role of tasks, we briefly discuss the role of education in wage determination. Consistent with the summary statistics in Table 9, the regression results in Table 10 suggest that educated workers earn significantly more than less-educated workers in rural and urban China. In 2015/17, college graduates earned 0.56 log points more than high school graduates in urban areas. The college premium was significant in rural areas but lower than in urban areas. In 2015/17, college graduates earned 0.47 log points more than high school graduates in rural China. In panel B of Table 10, we use years of schooling as an independent variable. One more year of schooling is associated with a 7–9 per cent wage increase in urban areas. The schooling year coefficient is significantly lower in rural areas, around 2–4 per cent in recent years. In rural and urban China, the education gap does not show a declining trend over time despite a sharp increase in the education levels of rural and urban residents.

Our estimation procedure controls for province dummies and RTIs. As work location and occupation are correlated with education, the results indicate only a lower bound of the returns to education. They also suggest that education and occupational tasks are not correlated imperfectly.

We obtain significantly negative RTI coefficients in most cases. A one-unit increase in RTI is associated with an 8–10 per cent wage decrease in urban areas, suggesting that the urban labour markets are favourable to those who perform non-routine tasks. In contrast, the situation for those who perform routine tasks is disadvantageous. For the rural sample, the RTI coefficients are negative but smaller in magnitude than for urban areas. In 2015/17, a unit increase in RTI is associated with a 3 per cent wage decrease.

In Table 11, we consider the robustness of our results by replacing the RTI measure with a China-specific one. The results suggest that RTI has a significantly negative effect on wages, larger in magnitude than its counterparts when the RTI is uncorrected. For example, for urban areas, in 2005 a one-unit increase in RTI (which is about the difference between production workers and professionals) was associated with a 20 per cent wage decrease; this association increased to over 25 per cent in 2015/17. The RTI coefficient for rural observations also increased in absolute values but was half of the magnitudes in urban areas.

In summary, our results suggest that the rewards for different tasks in the Chinese labour markets differ significantly. The labour markets, in particular, provide higher returns to non-routine cognitive tasks but punish routine tasks, as the latter are more easily replaced by automated machines.

7 Decomposing the changes in wage inequality

The previous sections showed that wage inequality has remained high in recent years and that the occupational structure and the task contents performed by the workforce have changed significantly. How does occupational change help to shape wage inequality? In this section, we apply the methods developed by Firpo et al. (2011, 2018) to decompose the changes in the Gini coefficients of wages. The basic idea is as follows. The wage distribution is determined by the distribution of individuals' characteristics (education, experience, gender, and job tasks) and the wage differentials between groups. The traditional Oaxaca decomposition method can divide the average wage gap into two: the gap caused by the difference in personal characteristics and the gap caused by the difference in wages (or the returns to personal traits). In a similar vein, the re-centred influence function (RIF) base decomposition developed by Firpo et al. (2011, 2018) can decompose the changes in wage inequality into explained and unexplained parts. This method can also determine the contribution of each factor in shaping wage inequality.

Table 12 reports the decomposition results using a one-step RIF decomposition. First, we consider the results for urban areas. The Gini coefficient increased from 0.431 in 2005 to 0.485 in 2017. Around 70 per cent (0.0384/0.0539) of the Gini increase is due to unexplained factors or the gap between individuals of different characteristics. The returns to experience and education are the two significant factors in the rise in the Gini coefficients. The exercise which considers the two sub-periods 2005–12/13 and 2013–2015/17 suggests that the returns to education played a more substantial role in the former period than in the latter. The results are consistent with the literature which shows that increased skill prices were the major contributor to wage inequality (Knight and Song 2008; Li et al. 2007; Liu et al. 2010; Meng et al. 2010). In both periods, RTI played a minor role in shaping wage inequality. While changes in RTI distribution tended to increase wage inequality, changes in RTI prices tended to reduce it as RTI coefficients declined slightly. In the last three columns, we replace the RTI with the country-specific RTI, which played a more significant role in wage determination. Its role in changing wage inequality, however, is still minor.

In Table 13, we decompose the changes in wage inequality in rural areas between 2005 and 2017. As for urban areas, the increase in wage inequality in rural China is mainly attributable to unexplained factors and RTIs played a minor role in changing wage inequality.

8 Evidence from China Household Income Project (CHIP)

We use the CGSS in the above analysis mainly because it has detailed occupation information, but the existing research suggests that the CGSS produces higher Gini coefficients than other datasets (see Xie and Zhou 2014: Figure 1). The CHIP data are well known for the quality of their income information, and we use them to examine the robustness of our results. The corresponding results are presented in Tables A1 to A6 in the Appendix.

We emphasize the following points. First, the Gini coefficients in the CHIP are lower than those in the CGSS (see Table A1). This may be because the CGSS data have a larger share of low-educated workers. Nevertheless, similar to the CGSS, the CHIP data indicate that wage inequality has remained high or has slightly increased recently. Second, the CHIP data also suggest significant wage gaps across education groups and regions (see Table A2). The regression results of wage equations are reported in Tables A3 and A4. One more year of schooling is associated with a 7–10 per cent wage increase in urban areas. The returns are lower in rural areas at around 4 per cent. Third, the RTI coefficients are of similar magnitudes even though the RTI is averaged at the one-digit occupation level. The negative correlation between RTI and wages is larger in absolute value in urban than in rural areas. Using China-specific RTIs also produces coefficients similar to the CGSS. The CGSS and CHIP show a similar pattern in wage determination, especially the role of education and RTI, although the datasets differ in overall inequality.

We also report the decomposition results in Tables A5 and A6 in the Appendix. The exercise which considers the two sub-periods 2007–13 and 2013–18 suggests that the returns to education played a more substantial role in the former period than the latter. In both periods, the returns to RTI played a minor role in shaping wage inequality. When we consider country-specific RTI, it played a more significant role, especially in the later 2013–18 period. Although education and experience still played an important role, the RTI also explained over two-thirds of the increase in the Gini coefficient of urban annual wages. As for urban areas, the increase in wage inequality in rural China between 2013 and 2018 was mainly due to unexplained factors. Country-specific RTI has a sizeable impact on the rise in wage inequality.

9 Conclusion

China's economy has experienced record growth and significant structural change in the past four decades. Under the influence of its economic transition, integration into the world economy, and technological change, economic activities have continuously shifted out of the agricultural sector towards manufacturing and service sectors. As the number and composition of products and services produced evolved, so too did the workforce's skills and tasks. These changes are associated with a significant rise in wage inequality.

In this paper, we first documented the evolution of the occupational structure using census data. We reclassified the occupation information in the census according to ISCO-88, which allowed us to link task contents to the census data. We showed that cognitive and manual routine tasks have declined and analytical and interpersonal non-routine cognitive tasks have increased since the 1990s. We also observed an inverted U-shaped relationship between the growth of employment shares and RTIs.

We then linked the task contents to the CGSS data, which contain earnings and detailed occupation information. We showed that: (1) wage inequality increased significantly by the early 2000s and, after a period of stagnation, it increased again between 2013 and 2018; (2) education is a significant factor in wage determination; and (3) RTI is negatively correlated with wages, and the correlation has recently become more robust in both rural and urban areas. These results suggest that occupational structure is an essential channel through which technological change influences wage inequality. The RIF decomposition exercise confirmed that the wage gap between individuals with different RTIs played a significant role in increasing wage inequality in rural and urban China.

This study has two shortcomings worth mentioning. First, the occupation classification in the CHIP is only at the one-digit level, which prevents us from merging occupation information (like the task contents) at a two- or three-digit level. However, our results seem insensitive to this practice. Second, the task contents in some exercises were measured using O*NET, which relies on strong assumptions. To alleviate this concern, we also used country-specific RTIs. The pattern did not change much.

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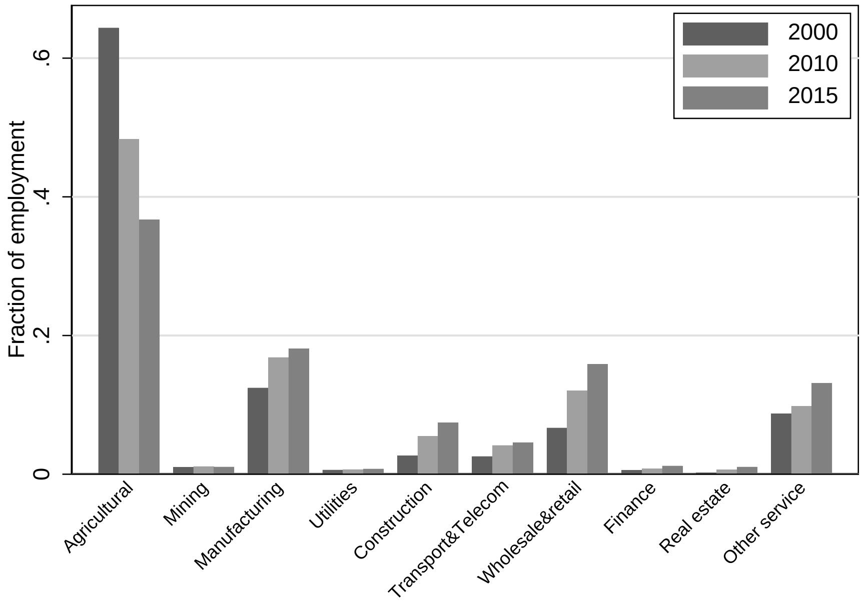
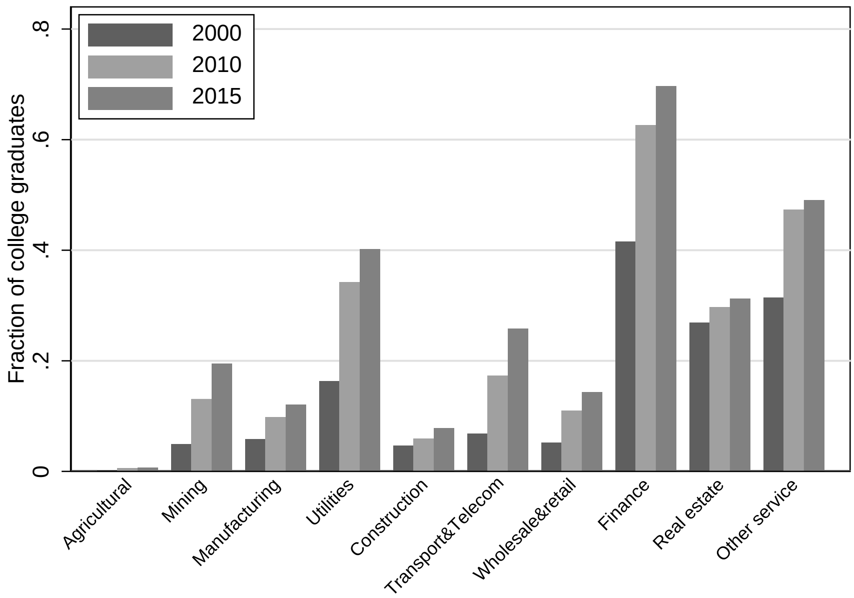
Figures and tables

Figure 1: Employment shares in different industries, 2000, 2010, and 2015



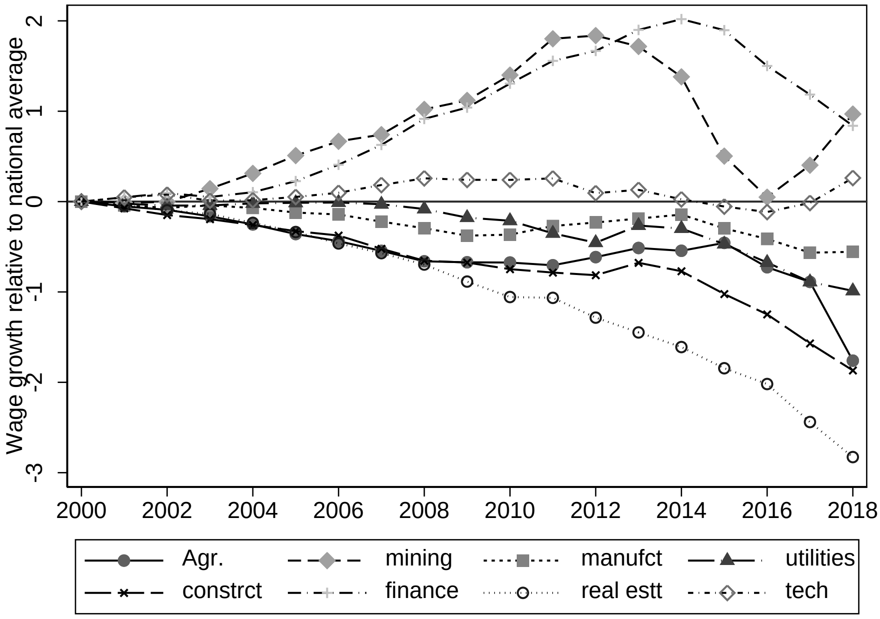
Source: author’s calculations based on NBS (2002, 2012, 2016).

Figure 2: Share of college-educated workers in different sectors



Source: author’s calculations based on NBS (2002, 2012, 2016).

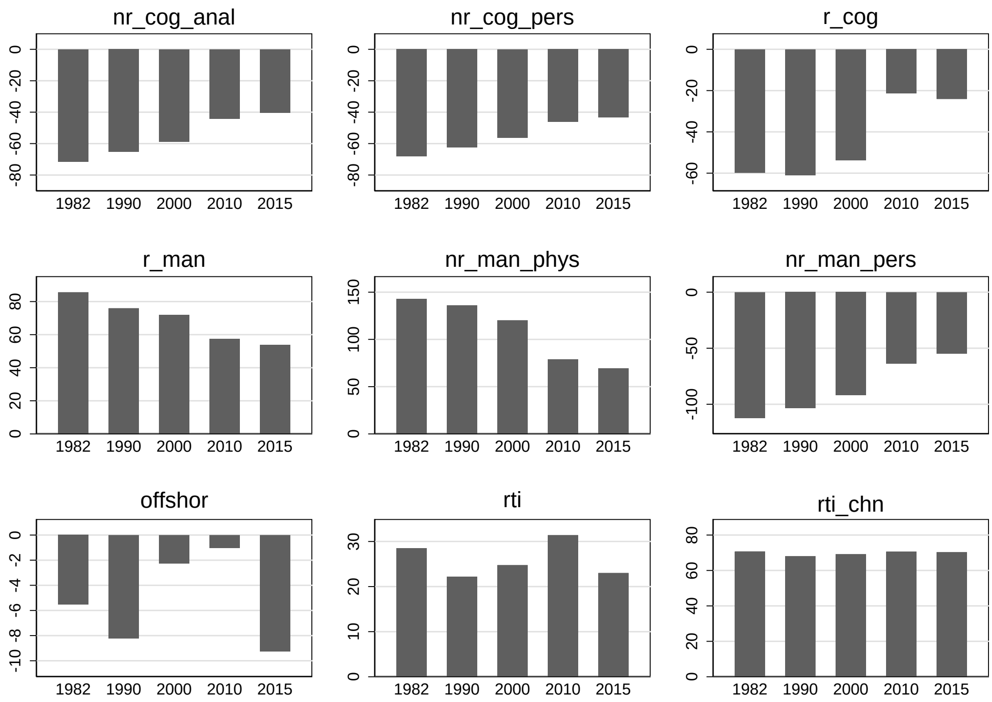
Figure 3: Cumulative relative wage growth for selected industries



Note: to produce this figure, we first calculated the cumulative changes for each industry (2000=1) and for the nation as a whole, and then obtained the relative growth by calculating the difference between each industry and the national average.

Source: author's calculations based on NBS (2004, 2008, 2019).

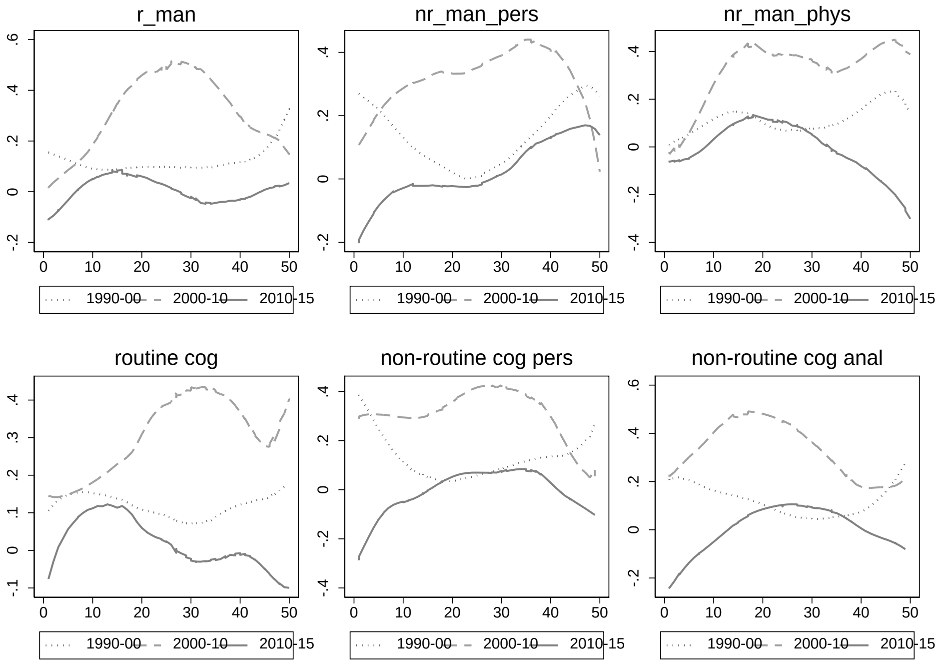
Figure 4: Task contents over time



Note: we merged the task contents with the census occupation at the three-digit level and calculated the average task contents based on the occupational structure.

Source: author's calculations based on census and mini census data for 1982, 1990, 2000, 2010, and 2015.

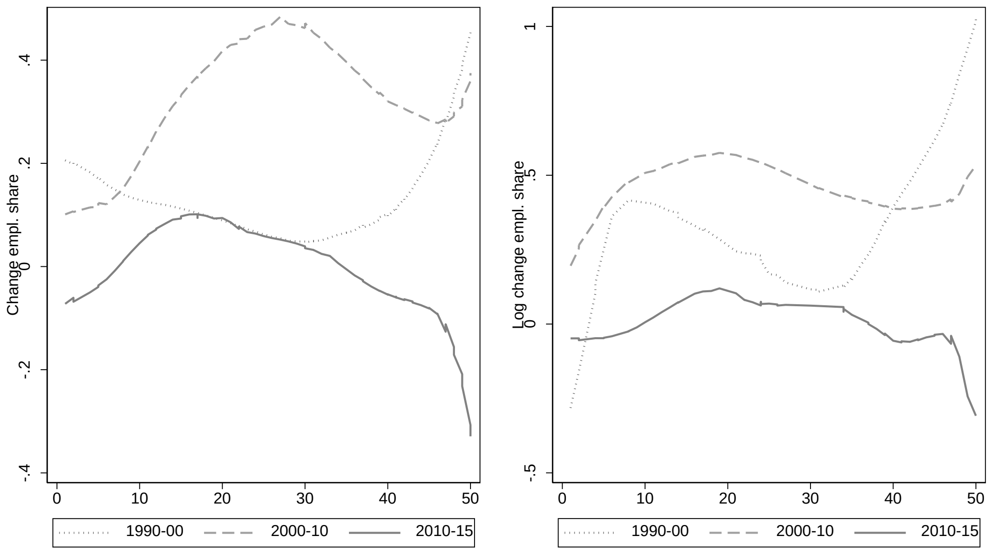
Figure 5: Changes in logarithm occupation share against task quantiles



Note: the horizontal line is for (50) quantiles of the three-digit occupations ranked by the level of different tasks; the vertical line is the log change in employment share.

Source: author's calculation of the employment share change using census data for 1990, 2000, 2010, and 2015.

Figure 6: Changes in occupation share against RTI



Note: the horizontal line is for (50) quantiles of the three-digit occupations ranked by the level of different tasks; the vertical line is the (log) change in employment share at the three-digit occupation level.

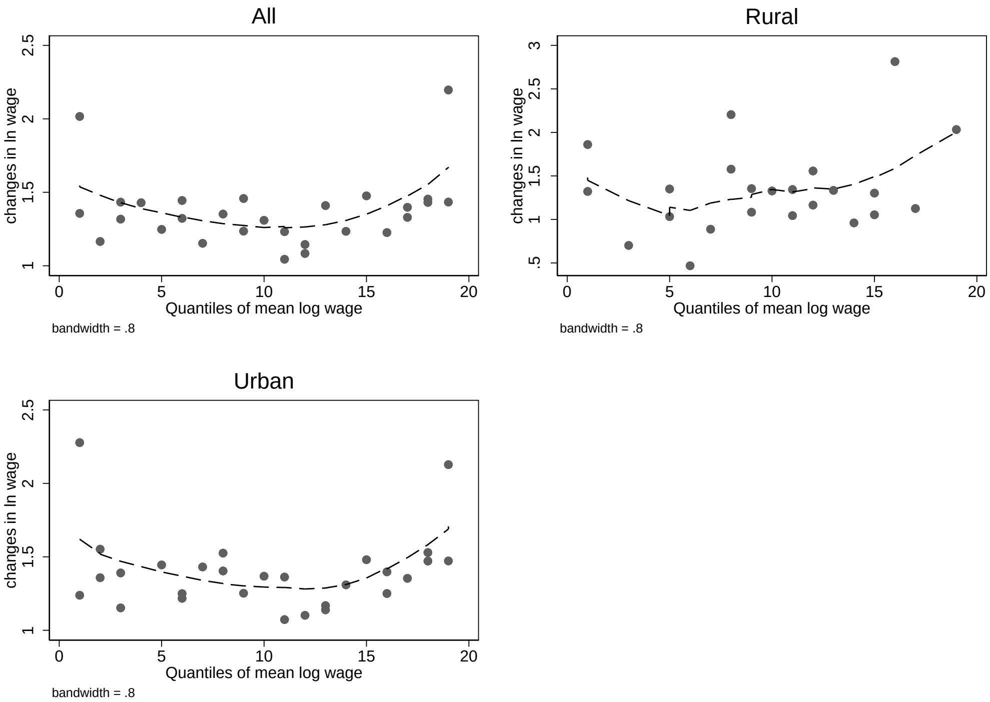
Source: author's calculation of the employment share using census data for 1990, 2000, 2010, and 2015.

Figure 7: Changes in occupation share against skills (occupational wage)

Note: the horizontal line is for (30) quantiles of the two-digit occupation ranked by the level of mean occupational wages; the vertical line is the change in employment share at the two-digit occupation level.

Source: author's calculation of mean wages using CGSS data for 2012/13 (NSRC n.d.) and employment share using census data for 1990, 2000, 2010, and 2015.

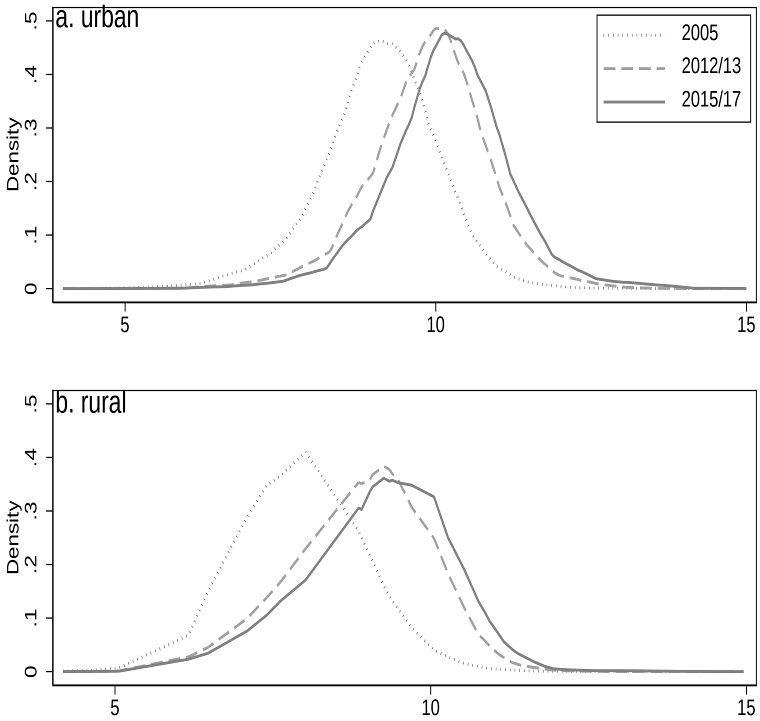
Figure 8: Occupational wage growth by wage quintiles



Note: the occupation is at two-digit level.

Source: author's calculation based on CGSS (NSRC n.d.).

Figure 9: Wage density distributions for workers in China



Source: author's calculation based on CGSS (NSRC n.d.).

Table 1: Occupational structure in China, 1982–2015

	1982	1990	2000	2010	2015
By one-digit occupation category					
Legislators, senior officials, and managers	0.46	1.20	1.76	2.34	1.78
Professionals	1.36	2.16	5.55	8.38	7.90
Technicians and associate professionals	4.09	4.86	3.99	6.40	7.68
Clerks	1.76	2.45	0.87	1.55	1.09
Service workers and market sales workers	2.37	4.16	8.47	20.00	24.48
Skilled agricultural and fishery workers	74.57	72.31	62.44	32.46	31.27
Craft and related trades workers	8.33	6.96	6.39	12.31	13.46
Plant and machine operators and assemblers	4.93	3.87	8.62	13.08	10.70
Elementary occupations	2.11	2.07	1.93	3.51	1.59
By low, mid, high skill					
Low skill (agricultural, elementary)	76.68	74.38	64.37	35.97	32.86
Mid skill (clerical, sales, production)	17.39	17.44	24.35	46.94	49.73
High skill (managerial, professional, technical)	5.91	8.22	11.3	17.12	17.36

Source: author’s calculations based on census or mini census for various years.

Table 2: One-digit occupation between 1990 and 2010, by rural and urban

	Urban			Rural		
	1990	2000	2010	1990	2000	2010
By one-digit occupation category						
Legislators, senior officials, and managers	2.80	4.07	3.63	0.55	0.57	0.61
Professionals	5.67	12.35	12.86	0.72	2.09	2.39
Technicians and associate professionals	12.50	10.06	10.07	2.54	0.90	1.42
Clerks	6.34	2.19	2.33	0.90	0.19	0.46
Service workers and market sales workers	9.09	19.65	27.37	2.12	2.80	10.05
Skilled agricultural and fishery workers	33.08	19.47	11.48	86.04	84.20	60.70
Craft and related trades workers	15.82	11.99	13.14	3.65	3.54	11.16
Plant and machine operators and assemblers	9.61	16.24	14.72	1.97	4.79	10.88
Elementary occupations	5.09	3.98	4.38	0.84	0.89	2.33
By low, mid, high skill						
Low skill (agricultural, elementary)	38.17	23.45	15.86	86.88	85.09	63.03
Mid skill (clerical, sales, production)	40.86	50.07	57.56	8.64	11.32	32.55
High skill (managerial, professional, technical)	20.97	26.48	26.56	3.81	3.56	4.42

Source: author’s calculations based on census or mini census for various years.

Table 3: Change in (log) employment share and tasks

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment share			Log change in employment share		
	1990–2000	2000–10	2010–15	1990–2000	2000–10	2010–15
nr_cog_anal	0.0337	-0.0597	-0.0186	0.0449	0.0221	0.0486
	(0.0802)	(0.101)	(0.0642)	(0.199)	(0.0616)	(0.0741)
nr_cog_analsq	-0.0391	-0.100	-0.0313	0.0144	-0.0443	-0.0882
	(0.0812)	(0.0968)	(0.0630)	(0.213)	(0.0604)	(0.0736)
nr_cog_pers	0.0938	-0.00936	-0.00924	-0.0176	-0.00397	0.00226
	(0.0911)	(0.114)	(0.0709)	(0.226)	(0.0688)	(0.0829)
nr_cog_perssq	-0.0592	-0.0600	-0.0345	-0.0619	-0.0337	-0.0364
	(0.0754)	(0.0896)	(0.0564)	(0.195)	(0.0543)	(0.0661)
nr_man_phys	-0.0781	0.0527	0.00754	-0.157	0.0363	-0.0600
	(0.0820)	(0.101)	(0.0634)	(0.197)	(0.0574)	(0.0723)
nr_man_physsq	-0.0507	-0.115	-0.0229	-0.259*	-0.151***	-0.0970*
	(0.0661)	(0.0768)	(0.0483)	(0.152)	(0.0428)	(0.0546)
nr_man_pers	0.0952	-0.0117	0.0419	-0.0555	-0.0549	0.0518
	(0.0868)	(0.107)	(0.0660)	(0.209)	(0.0642)	(0.0772)
nr_man_perssq	0.0378	-0.0855	0.0146	-0.0365	-0.0796	-0.00948
	(0.0826)	(0.104)	(0.0658)	(0.200)	(0.0631)	(0.0770)
r_cog	0.0427	0.114	-0.0374	0.0573	-0.0288	-0.0663
	(0.102)	(0.122)	(0.0766)	(0.247)	(0.0716)	(0.0898)
r_cogsq	0.00335	-0.0124	-0.00980	-0.00206	-0.0849**	-0.0368
	(0.0496)	(0.0636)	(0.0399)	(0.118)	(0.0371)	(0.0464)
r_man	-0.0426	0.101	-0.00760	-0.0469	0.0951*	-0.0300
	(0.0710)	(0.0899)	(0.0562)	(0.170)	(0.0521)	(0.0656)
r_mansq	0.0315	-0.0660	-0.00338	0.0773	-0.0822***	-0.0105
	(0.0409)	(0.0490)	(0.0307)	(0.0960)	(0.0283)	(0.0359)
offshor	-0.0153	-0.0591	-0.0441	-0.0377	-0.122*	0.0313
	(0.0799)	(0.104)	(0.0662)	(0.200)	(0.0641)	(0.0784)
offshorsq	-0.0526	-0.0599	-0.0233	-0.0573	-0.0304	-0.0147
	(0.0437)	(0.0578)	(0.0394)	(0.105)	(0.0346)	(0.0464)
rti	-0.0118	0.0556	0.000166	0.0267	0.0245	-0.0268
	(0.0644)	(0.0823)	(0.0515)	(0.154)	(0.0480)	(0.0597)
rtisq	-0.00524	-0.0138	-0.00364	-0.00897	-0.0335*	-0.0118
	(0.0223)	(0.0296)	(0.0184)	(0.0521)	(0.0173)	(0.0214)
rti_chn	0.110	0.860	0.605	-0.768	1.403***	0.273
	(0.698)	(0.785)	(0.486)	(1.628)	(0.449)	(0.560)
rti_chnsq	-0.0480	-0.578	-0.625	1.059	-1.390***	-0.534
	(0.689)	(0.777)	(0.483)	(1.629)	(0.446)	(0.557)

Notes: the dependent variable is the change in employment share (columns 1–3) and log employment share (columns 4–6). Occupation is at the three-digit level. Standard errors are in parenthesis. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level.

Source: author's calculations based on census or mini census of 1990, 2000, 2010, and 2015.

Table 4: Change in (log) employment share and occupational wage

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment share			Log change in employment share		
	1990–2000	2000–10	2010–15	1990–2000	2000–10	2010–15
mean occupational log wage (2-digit)	-5.371	10.64	13.40	-9.833	-15.90*	18.02
	(26.13)	(34.56)	(22.93)	(22.56)	(8.533)	(13.68)
mean occupational log wage square	0.275	-0.537	-0.669	0.523	0.772*	-0.871
	(1.272)	(1.682)	(1.116)	(1.098)	(0.413)	(0.662)

Note: the dependent variable is the change of employment share (columns 1–3) and log employment share (columns 4–6). Standard errors are in parenthesis. * represents statistical significance at the 10% level.

Source: author's calculations based on census 1990, 2010, and 2015, and CGSS 2012, 2013 (NSRC n.d.).

Table 5: Occupational wage growth against wage levels (dependent var.=change of log wage)

	(1)	(2)	(3)	(4)	(5)	(6)
	2-digit occupation			3-digit occupation		
	All	Rural	Urban	All	Rural	Urban
mean occupational log wage	-5.562**	-16.18*	-6.413*	-1.900	-12.89	-0.358
	(2.175)	(9.107)	(3.149)	(1.827)	(9.283)	(2.675)
mean occupational log wage square	0.279**	0.857*	0.317*	0.0918	0.684	0.0173
	(0.108)	(0.474)	(0.154)	(0.0886)	(0.481)	(0.129)

Note: the dependent variable is the change of mean log wage between 2005 and 2015/17 at the 2- or 3-digit occupation level. Standard errors are in parenthesis. * and ** represent statistical significance at the 10% and 5% level.

Source: author's calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 6: Wage levels and years of schooling by occupation

	Log annual wage			
	2005	2012/13	2015/17	2005–2015/17
Legislators, senior officials, and managers	9.22	10.38	10.50	1.29
Professionals	9.54	10.22	10.61	1.07
Technicians and associate professionals	9.55	10.27	10.51	0.97
Clerks	9.31	10.09	10.45	1.15
Service workers and market sales workers	9.09	9.75	10.02	0.93
Skilled agricultural and fishery workers	7.76	8.54	8.83	1.06
Craft and related trades workers	8.90	9.68	9.94	1.04
Plant and machine operators and assemblers	9.11	9.89	10.00	0.89
Elementary occupations	8.62	9.46	9.64	1.02
	Years of schooling			
Legislators, senior officials, and managers	9.79	12.30	11.54	1.75
Professionals	14.04	14.83	15.08	1.05
Technicians and associate professionals	12.79	13.61	13.71	0.92
Clerks	11.91	13.25	13.64	1.73
Service workers and market sales workers	10.21	10.35	10.32	0.11
Skilled agricultural and fishery workers	5.56	6.49	6.77	1.21
Craft and related trades workers	9.36	9.00	9.11	-0.25
Plant and machine operators and assemblers	9.88	9.96	9.86	-0.02
Elementary occupations	8.37	9.17	8.42	0.05

Source: author’s calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 7: Summary statistics of the CGSS data, urban and rural China

	Urban			Rural		
	2005	2012/13	2015/17	2005	2012/13	2015/17
Age	39.62	42.02	42.21	40.98	44.02	44.71
Education level						
Primary and below	0.139	0.152	0.148	0.555	0.478	0.450
Middle school	0.328	0.300	0.289	0.340	0.392	0.396
High school	0.359	0.283	0.266	0.098	0.109	0.117
Professional college	0.114	0.133	0.126	0.007	0.014	0.022
College	0.059	0.131	0.171	0.001	0.007	0.015
Female	0.539	0.507	0.506	0.524	0.504	0.503
Occupation						
Legislators, senior officials, and managers	0.116	0.094	0.124	0.043	0.023	0.047
Professionals	0.067	0.103	0.103	0.014	0.016	0.016
Technicians and associate professionals	0.082	0.114	0.132	0.007	0.011	0.022
Clerks	0.106	0.090	0.122	0.011	0.011	0.015
Service workers and market sales workers	0.210	0.200	0.191	0.022	0.057	0.065
Skilled agricultural and fishery workers	0.041	0.061	0.065	0.807	0.624	0.619
Craft and related trades workers	0.202	0.118	0.073	0.058	0.137	0.068
Plant and machine operators and assemblers	0.133	0.086	0.090	0.026	0.051	0.069
Elementary occupations	0.044	0.133	0.100	0.013	0.071	0.078

Source: author’s calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 8: Wages and wage inequality in urban and rural China, CGSS

	Urban			Rural		
	2005	2012/13	2015/17	2005	2012/13	2015/17
Annual wage (RMB)	12,816	36,477	60,297	4,398	14,622	21,429
Gini	0.4309	0.4445	0.4848	0.5000	0.4909	0.5117
Ln(Annual wage)						
Mean	9.089	9.891	10.218	7.935	8.878	9.156
Median	9.210	9.992	10.279	8.006	8.987	9.298
p10	8.006	8.946	8.928	6.908	7.378	7.689
p90	10.127	10.933	11.231	9.210	10.086	10.502
P50-10	1.204	1.045	1.351	1.099	1.609	1.609
P90-50	0.916	0.942	0.952	1.204	1.099	1.204
P90-10	2.120	1.987	2.303	2.303	2.708	2.813
Variance	0.824	0.837	0.920	0.921	1.106	1.249
Gini	0.055	0.050	0.051	0.068	0.067	0.068

Source: author’s calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 9: Annual wages (in log) by education, gender, and region

	Urban				Rural			
	2005	2012/13	2015/17	Change (2005–15/17)	2005	2012/13	2015/17	Change (2005–15/17)
Female								
Primary & below	8.264	8.917	9.311	1.047	7.543	8.245	8.482	0.939
Middle school	8.747	9.356	9.696	0.949	7.866	8.743	9.041	1.176
High school	9.077	9.757	10.002	0.925	8.091	9.023	9.220	1.129
Professional coll.	9.517	10.100	10.363	0.846	8.793	9.655	9.870	1.078
College	9.987	10.405	10.778	0.791	9.903	9.946	10.055	0.152
Male								
Primary & below	8.617	9.480	9.692	1.075	7.905	8.921	9.060	1.155
Middle school	9.051	9.781	10.103	1.052	8.402	9.309	9.507	1.105
High school	9.319	10.041	10.295	0.975	8.614	9.402	9.729	1.115
Professional coll.	9.755	10.372	10.681	0.926	9.236	9.799	10.182	0.945
College	9.906	10.644	10.992	1.086	.	10.102	10.272	

Source: author's calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 10: Earnings determination (dep. Var.=log(earnings))

	Rural			Urban		
	2005	2012/13	2015/17	2005	2012/13	2015/17
	(1)	(2)	(3)	(4)	(5)	(6)
A						
Middle school	0.235***	0.104***	0.177***	0.315***	0.146***	0.152***
	(0.0378)	(0.0226)	(0.0301)	(0.0446)	(0.0236)	(0.0275)
High school	0.430***	0.224***	0.319***	0.558***	0.321***	0.325***
	(0.0570)	(0.0343)	(0.0445)	(0.0474)	(0.0247)	(0.0290)
Professional coll.	0.949***	0.565***	0.701***	0.914***	0.571***	0.572***
	(0.184)	(0.0823)	(0.0879)	(0.0565)	(0.0287)	(0.0333)
College	2.061***	0.666***	0.786***	1.170***	0.790***	0.884***
	(0.592)	(0.119)	(0.108)	(0.0668)	(0.0298)	(0.0332)
Female	-0.458***	-0.600***	-0.507***	-0.286***	-0.391***	-0.354***
	(0.0309)	(0.0193)	(0.0253)	(0.0235)	(0.0130)	(0.0148)
Experience	0.00892	0.0135***	0.0139***	-0.000442	0.0357***	0.0395***
	(0.00561)	(0.00362)	(0.00496)	(0.00391)	(0.00224)	(0.00254)
Exp. square/100	-0.0329***	-0.0656***	-0.0648***	-0.00457	-0.0909***	-0.0989***
	(0.00934)	(0.00590)	(0.00834)	(0.00794)	(0.00457)	(0.00533)
RTI	-0.128***	-0.0130	-0.0289**	-0.0964***	-0.0769***	-0.0818***
	(0.0323)	(0.0128)	(0.0145)	(0.0127)	(0.00598)	(0.00656)
R-squared	0.259	0.351	0.305	0.335	0.402	0.397
B						
Years of schooling	0.0546***	0.0225***	0.0378***	0.0888***	0.0686***	0.0735***
	(0.00526)	(0.00350)	(0.00463)	(0.00437)	(0.00231)	(0.00257)
RTI	-0.137***	-0.0276**	-0.0431***	-0.105***	-0.0814***	-0.0899***
	(0.0319)	(0.0127)	(0.0144)	(0.0126)	(0.00599)	(0.00659)
R-squared	0.262	0.347	0.298	0.331	0.397	0.385
Obs.	3,121	8,591	5,967	3,756	11,925	9,894

Note: province dummies and a constant term are included in all regressions. Gender and experience and experience squared are included in regressions in panel B. ** and *** represent statistical significance at the 5%, and 1% level. Standard errors are in parentheses.

Source: author's calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 11: Earnings determination (dep. Var.=log(earnings)) and RTI

	Rural			Urban		
	2005	2012/13	2015/17	2005	2012/13	2015/17
	(1)	(2)	(3)	(4)	(5)	(6)
A.						
Middle school	0.225***	0.105***	0.175***	0.304***	0.145***	0.147***
	(0.0377)	(0.0226)	(0.0301)	(0.0446)	(0.0236)	(0.0274)
High school	0.411***	0.228***	0.308***	0.542***	0.298***	0.295***
	(0.0569)	(0.0344)	(0.0446)	(0.0474)	(0.0248)	(0.0290)
Professional coll.	0.920***	0.574***	0.660***	0.885***	0.495***	0.494***
	(0.183)	(0.0833)	(0.0893)	(0.0568)	(0.0295)	(0.0340)
College	1.937***	0.676***	0.731***	1.132***	0.702***	0.792***
	(0.590)	(0.120)	(0.110)	(0.0672)	(0.0310)	(0.0343)
Female	-0.458***	-0.598***	-0.509***	-0.295***	-0.389***	-0.351***
	(0.0308)	(0.0192)	(0.0253)	(0.0235)	(0.0130)	(0.0147)
Experience	0.00857	0.0135***	0.0131***	-0.00180	0.0355***	0.0382***
	(0.00560)	(0.00362)	(0.00497)	(0.00391)	(0.00224)	(0.00254)
Exp. square/100	-0.0325***	-0.0656***	-0.0637***	-0.00339	-0.0917***	-0.0982***
	(0.00931)	(0.00590)	(0.00834)	(0.00793)	(0.00456)	(0.00531)
China-specific RTI	-0.337***	-0.00905	-0.128***	-0.197***	-0.222***	-0.247***
	(0.0563)	(0.0370)	(0.0399)	(0.0233)	(0.0144)	(0.0161)
R-squared	0.263	0.351	0.305	0.337	0.406	0.402
B.						
Years of schooling	0.0528***	0.0224***	0.0352***	0.0861***	0.0589***	0.0633***
	(0.00525)	(0.00353)	(0.00468)	(0.00440)	(0.00244)	(0.00269)
China-specific RTI	-0.350***	-0.0675*	-0.183***	-0.216***	-0.244***	-0.278***
	(0.0557)	(0.0361)	(0.0387)	(0.0230)	(0.0141)	(0.0159)
R-squared	0.267	0.347	0.300	0.335	0.402	0.393
Obs.	3,121	8,591	5,967	3,756	11,925	9,894

Note: province dummies and a constant term are included in all regressions. Gender and experience and experience squared are included in regressions in panel B. ** and *** represent statistical significance at the 5%, and 1% level. Standard errors are in parentheses.

Source: author’s calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 12: RIF decomposition of Gini coefficients of wages, urban China

	Uncorrected RTI			China-specific RTI		
	2005-2015/17	2005-2012/13	2012/13-2015/17	2005-2015/17	2005-2012/13	2012/13-2015/17
Overall						
Group1 (former period)	0.4309	0.4309	0.4445	0.4309	0.4309	0.4445
Group2 (latter period)	0.4848	0.4445	0.4848	0.4848	0.4445	0.4848
Difference: Latter–former	0.0539	0.0136	0.0403	0.0539	0.0136	0.0403
Explained	0.0156	0.0089	0.0054	0.0145	0.0045	0.0072
Unexplained	0.0384	0.0047	0.0349	0.0394	0.0091	0.0331
Explained						
Middle school	0.0045	0.0033	0.0006	0.0046	0.0033	0.0006
High school	0.0137	0.0113	0.0038	0.0147	0.0117	0.0041
Professional coll.	-0.0024	-0.0052	0.0013	-0.0028	-0.0057	0.0015
College	-0.0027	-0.0025	-0.0010	-0.0064	-0.0041	-0.0023
Subtotal	*0.0131*	*0.0070*	*0.0047*	*0.0100*	*0.0052*	*0.0039*
Female	0.0005	-0.0010	-0.0001	0.0005	-0.0011	-0.0002
Experience	-0.0011	-0.0002	-0.0002	-0.0009	-0.0002	-0.0002
Exper. squared	-0.0007	-0.0016	0.0000	-0.0008	-0.0014	0.0000
RTI	0.0038	0.0046	0.0010	0.0056	0.0019	0.0036
Unexplained						
Middle school	0.0123	0.0159	-0.0030	0.0122	0.0163	-0.0034
High school	0.0189	0.0129	0.0046	0.0170	0.0123	0.0036
Professional coll.	0.0052	-0.0004	0.0071	0.0037	-0.0012	0.0063
College	-0.0014	-0.0019	0.0012	-0.0023	-0.0023	0.0001
Subtotal	*0.0350*	*0.0264*	*0.0099*	*0.0307*	*0.0251*	*0.0065*
Female	-0.0159	-0.0079	-0.0065	-0.0154	-0.0066	-0.0070
Experience	-0.0324	-0.0605	0.0274	-0.0354	-0.0558	0.0199
Exper. squared	0.0547	0.0680	-0.0124	0.0552	0.0643	-0.0085
RTI	-0.0004	-0.0012	-0.0010	-0.0108	-0.0096	-0.0011
_cons	-0.0026	-0.0200	0.0174	0.0151	-0.0082	0.0233

Source: author's calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Table 13: RIF decomposition of Gini coefficients of wages, rural China

	Uncorrected RTI			China-specific RTI		
	2005-2015/17	2005-2012/13	2012/13-2015/17	2005-2015/17	2005-2012/13	2012/13-2015/17
Overall						
Group1 (former period)	0.5000	0.5000	0.4909	0.5000	0.5000	0.4909
Group2 (latter period)	0.5117	0.4909	0.5117	0.5117	0.4909	0.5117
Difference: Latter–former	0.0117	-0.0091	0.0208	0.0117	-0.0091	0.0208
Explained	-0.0047	-0.0072	0.0000	-0.0067	-0.0146	0.0029
Unexplained	0.0164	-0.0020	0.0208	0.0184	0.0055	0.0179
Explained						
Middle school	-0.0023	-0.0020	-0.0004	-0.0024	-0.0020	-0.0004
High school	-0.0004	-0.0004	-0.0002	-0.0005	-0.0005	-0.0003
Professional coll.	-0.0008	-0.0005	-0.0005	-0.0013	-0.0008	-0.0009
College	0.0023	0.0011	0.0014	0.0018	0.0009	0.0011
Subtotal	*-0.0012*	*-0.0018*	*0.0003*	*-0.0025*	*-0.0024*	*-0.0005*
Female	-0.0049	-0.0038	-0.0009	-0.0049	-0.0038	-0.0009
Experience	-0.0001	-0.0122	0.0000	-0.0014	-0.0131	0.0000
Exper. squared	0.0051	0.0147	-0.0002	0.0060	0.0150	-0.0002
RTI_CHN	-0.0035	-0.0040	0.0008	-0.0040	-0.0104	0.0044
Unexplained						
Middle school	-0.0119	-0.0119	0.0000	-0.0116	-0.0112	-0.0005
High school	-0.0050	-0.0079	0.0032	-0.0054	-0.0084	0.0033
Professional coll.	-0.0010	-0.0013	0.0005	-0.0012	-0.0016	0.0006
College	-0.0012	-0.0011	-0.0002	-0.0012	-0.0011	-0.0002
Subtotal	*-0.0191*	*-0.0222*	*0.0035*	*-0.0194*	*-0.0223*	*0.0033*
Female	0.0180	0.0166	0.0012	0.0176	0.0161	0.0013
Experience	-0.0367	-0.2290	0.2045	-0.0565	-0.2416	0.1968
Exper. squared	0.0555	0.1552	-0.1092	0.0653	0.1587	-0.1023
RTI_CHN	0.0001	0.0007	-0.0009	-0.0248	-0.0437	0.0209
_cons	-0.0014	0.0768	-0.0782	0.0363	0.1384	-0.1021

Source: author’s calculations based on CGSS 2005, 2012, 2013, 2015, and 2017 (NSRC n.d.).

Appendix: Evidence from CHIP data

Table A1: Wages and wage inequality in urban and rural China, CHIP

	Urban			Rural		
	2002	2007	2013	2002	2007	2013
Annual wage (RMB)	9,951	19,736	26,648	3,547	13,695	17,134
US$	1,402	2,780	3,753	500	1,929	2,413
Gini	0.358	0.377	0.374	0.528	0.307	0.355
Ln(annual wage)						
Mean	8.952	9.643	9.921	7.612	8.790	9.913
Median	9.058	9.656	9.949	7.824	8.988	10.086
p10	8.051	8.731	9.019	5.858	7.300	8.854
p90	9.803	10.538	10.786	9.06	10.111	10.737
P50-10	1.007	0.925	0.931	1.966	1.688	1.232
P90-50	0.745	0.882	0.836	1.235	1.123	0.652
P90-10	1.752	1.807	1.767	3.202	2.811	1.884
Variance	0.626	0.515	0.607	1.745	1.470	0.667

Source: author’s calculations based on CHIP 2002, 2007, and 2013 (China Institute for Income Distribution n.d.).

Table A2: Annual wages (in log) by education, gender, and region

	Urban				Rural			
	2002	2007	2013	Change (02–13)	2002	2007	2013	Change (02–13)
Female								
Primary and below	8.17	8.82	9.27	1.10	7.24	8.67	9.37	2.13
Middle school	8.37	9.06	9.43	1.06	7.71	8.84	9.71	2.00
High school	8.8	9.36	9.70	0.90	7.98	9.06	9.88	1.90
Professional college	9.12	9.66	9.89	0.77	8.35	9.34	10.16	1.81
College	9.38	9.93	10.22	0.84				
Male								
Primary and below	8.75	9.28	9.72	0.97	7.22	8.66	9.76	2.54
Middle school	8.83	9.45	9.81	0.98	7.62	8.78	10.05	2.43
High school	9.03	9.65	9.99	0.96	7.94	8.92	10.11	2.17
Professional college	9.29	9.92	10.19	0.90	8.52	9.13	10.34	1.82
College	9.52	10.15	10.45	0.93				
By region								
East	9.23	9.91	10.19	0.96	8.20	9.25	10.1	1.90
Central	8.82	9.46	9.79	0.97	7.42	8.45	9.86	2.44
Western	8.9	9.37	9.79	0.89	7.17	8.41	9.75	2.58
Northeast	8.81	9.36	9.72	0.91	7.25	.	9.74	2.49

Source: author's calculations based on CHIP 2002, 2007, and 2013 (China Institute for Income Distribution n.d.).

Table A3: Wage equations for urban and rural China, annual wage

	Urban			Rural	
	(1)	(2)	(3)	(4)	(5)
	2007	2013	2018	2013	2018
Years of schooling	0.108***	0.0805***	0.0713***	0.0402***	0.0479***
	(0.00241)	(0.00280)	(0.00215)	(0.00282)	(0.00330)
Male	0.246***	0.306***	0.351***	0.361***	0.423***
	(0.0107)	(0.0143)	(0.0113)	(0.0129)	(0.0157)
Experience	0.0355***	0.0441***	0.0491***	0.0267***	0.0339***
	(0.00198)	(0.00255)	(0.00215)	(0.00214)	(0.00286)
Exper. square	-0.0529***	-0.0790***	-0.0963***	-0.0700***	-0.0866***
	(0.00448)	(0.00536)	(0.00442)	(0.00419)	(0.00541)
RTI	-0.0497***	-0.0433***	-0.0979***	-0.0114*	-0.0309***
	(0.00583)	(0.00777)	(0.00578)	(0.00656)	(0.00836)
Obs	12,994	9,595	17,362	14,838	12,886
R-squared	0.330	0.216	0.207	0.158	0.172

Source: author's calculations based on CHIP 2002, 2007, and 2013 (China Institute for Income Distribution n.d.).

Table A4: Wages and country-specific RTI

	(1)	(2)	(3)	(4)	(5)
		Urban			Rural
	2007	2013	2018	2013	2018
Years of schooling	0.0854***	0.0732***	0.0824***	0.0381***	0.0432***
	(0.00272)	(0.00321)	(0.00419)	(0.00290)	(0.00342)
Male	0.261***	0.311***	0.260***	0.367***	0.425***
	(0.0110)	(0.0153)	(0.0191)	(0.0131)	(0.0158)
Experience	0.0346***	0.0398***	0.0410***	0.0248***	0.0312***
	(0.00206)	(0.00277)	(0.00375)	(0.00229)	(0.00303)
Exper. square	-0.0556***	-0.0708***	-0.0713***	-0.0674***	-0.0831***
	(0.00465)	(0.00579)	(0.00784)	(0.00439)	(0.00564)
RTI_chn	-0.296***	-0.179***	-0.308***	-0.0412***	-0.119***
	(0.0136)	(0.0176)	(0.0230)	(0.0154)	(0.0202)
Obs	12,065	8,313	6,028	14,405	12,652
R-squared	0.359	0.228	0.247	0.161	0.176

Source: author's calculations based on CHIP 2007, 2013, and 2018 (China Institute for Income Distribution n.d.).

Table A5: RIF decomposition of Gini coefficients of urban wages

	Uncorrected RTI			China-specific RTI		
	2007–18	2007–13	2013–18	2007–18	2007–13	2013–18
Overall						
Group1 (former period)	0.377	0.377	0.373	0.377	0.377	0.373
Group2 (latter period)	0.409	0.373	0.409	0.409	0.373	0.409
Difference: Latter–former	0.032	-0.003	0.036	0.032	-0.003	0.036
Explained	0.003	0.007	0.000	0.002	-0.001	0.001
Unexplained	0.029	-0.010	0.036	0.030	-0.003	0.035
Explained						
Years of schooling	0.000	0.001	0.000	0.000	0.001	0.001
Gender	0.001	0.000	0.000	0.001	0.000	0.000
Experience	0.001	-0.001	0.000	0.001	-0.001	0.000
Exper. square	0.001	0.004	0.000	0.001	0.003	0.000
RTI	0.000	0.004	-0.001	0.000	-0.004	0.000
Unexplained						
Years of schooling	0.016	0.013	0.003	-0.013	-0.036	0.020
Gender	-0.017	-0.002	-0.015	-0.016	-0.005	-0.011
Experience	0.025	-0.011	0.038	0.032	-0.008	0.042
Exper. square	0.004	0.024	-0.023	-0.001	0.020	-0.024
RTI	-0.001	-0.009	0.005	-0.012	-0.030	0.023
_cons	0.002	-0.026	0.028	0.041	0.056	-0.015

Source: author's calculations based on CHIP 2007, 2013, and 2018 (China Institute for Income Distribution n.d.).

Table A6: RIF decomposition of rural wages

	Uncorrected RTI	China-specific RTI
Overall		
Group1 (former period)	0.353	0.353
Group2 (latter period)	0.388	0.388
Difference: Latter–former	0.035	0.035
Explained	0.002	0.004
Unexplained	0.033	0.032
Explained		
Years of schooling	0.000	0.000
Gender	0.000	0.000
Experience	-0.003	-0.003
Exper. square	0.006	0.006
RTI	-0.002	0.000
Unexplained		
Years of schooling	-0.002	0.001
Gender	-0.011	-0.009
Experience	-0.130	-0.134
Exper. square	0.068	0.071
RTI	0.011	0.033
_cons	0.098	0.071

Source: author's calculations based on CHIP 2013 and 2018 (China Institute for Income Distribution n.d.).