Preliminary Draft

Automation Biased Technology and Employment Structures in China: 1990 to 2015

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Abstract

We find that there are four significant changes in employment structures in China from 1990 to 2015. The first one is the share of routine manual jobs decreased from 56.65% to 31.58%, the second one is the share of non-employment increase from 15.85% to 30.76%, the third one is the share of routine cognitive jobs increased from 8.17% to 19.20%, and the last one is the share of non-routine jobs had no significant change. Our decomposition exercises suggest that the composition effect, the propensity effect and the interaction effect contribute to 67.6%, 66.4% and -34% to the fall in routine manual jobs, respectively. Meanwhile, these effects for the rise in routine cognitive jobs and for the increase in the not-working are 15.6%, 73.6%, 10.9%, and 6.9%, 92.8%, 0.3%, respectively. The pattern of change in employment structure and decomposition results in China are somewhat differ from those in developed countries, such as the United States. Our findings are relevant to formulate education and labor market policies to cope with the incoming AI era.

JEL Classification: J21

Keyword: Automation technology, Artificial intelligence, Employment structure

1. Introduction

Recent few decades have witnessed noticeable “polarization” of the labor market in the United States and dozens of European Union countries (Autor, Katz and Kearney, 2006 & 2008; Goos and Manning, 2007; Goos, Manning and Salomons, 2009; Michaels, Natraj and Van Reenen, 2014; Autor, 2015), which means in these countries, wage gains and employment shares mostly went to occupations at the top and bottom of the skill and income distribution, with employment in the middle part declined drastically. A principal factor that led to the increasing polarization is the disappearance of “routine” occupations (Cortes, Jaimovich and Siu, 2017), those jobs include a set of tasks following well-defined procedures that can be accomplished by machines. Previous literature (e.g., Autor and Dorn, 2013; Goos, Manning and Salomons, 2014) suggest that the decline of routine jobs is mainly caused by progress in automation technologies that could substitute for labor in routine tasks. They found that workers in America who left routine jobs sorted into non-employment and non-routine jobs.

However, employment structure change under the technological progress in developing countries may be quite different from in developed countries. Because of different initial occupational distributions, “de-polarization” effect of off-shored jobs coming from advanced countries, removal of existing entry barriers and thus new industries generated, the higher cost of information and communication technologies (ICT) capital, employment promoted by automation related productivity growth as developing countries are often price takers, more limited feasibility of automation and more challenging skills to upgrade jobs (Maloney and Molina, 2016), the growth and decline trend of routine and non-routine jobs in developing countries should be investigated specifically.

The study on how automation technologies would alter the employment structure in China deserves special attention. Firstly, China has witnessed rapid computerization in recent decades. To illustrate, from 2000 to 2015, the average number of computers in each 100 China urban households rose sharply from 9.7 to 78.5 (China Information Almanac, 2001 & 2016). Till 2017, internet users in China have reached 772 million and among them, 97.5% use smart phones to surf the internet (China Internet Network Development State Statistic Report, 2018). Working with computers and smart phones has become an essential skill in many fields.

Secondly, although China has received a large amount of off-shored jobs from advanced countries, which have made China the world factory, China's labor cost has risen drastically especially after 2003, the year Zhang, Yang and Wang (2011) identified as when China crossed the so-called "Lewis turning point", when excess supply of cheap rural labor to urban sectors came to an end. To illustrate, the average annual wage of urban employees in manufacturing industry has increased from 12671 yuan in 2003 to 59470 yuan in 2016, in transport, storage and post industry has risen from 15753 yuan to 73650 yuan (China Statistical Yearbook, 2004 & 2017), which in turn reinforce demands of industrial upgrading to substitute labor by automation technology. This led China become the world's leading market of industrial robots, the sales of which in China in 2016 came almost equal to the total sales volume of the Americas (including all countries in North and South America) and Europe together (IFR reports, 2017).

Thirdly, the demographic composition in China has experienced significant changes that may boost the adoption of automation technology. These changes include the improvement of educational attainment, the aging population and the rapid urbanization. These labor supply side factors, combined with technological development, led to the substitution effect of automation technology. Last but not least, China government has been encouraging the development of artificial intelligence (AI) by enacting incentive policies, aiming to become the world's AI innovative center by the year 2030 (Development Planning for a New Generation of Artificial Intelligence, released by China's State Council at July 2017). The thriving development of AI in China can be partly demonstrated in a report of The Economist, "imagine the perfect environment for developing AI. The ingredients would include masses of processing power, lots of computer-science boffins, a torrent of capital—and abundant data with which to train machines to recognize and respond to patterns. That environment might sound like a fair description of America, the current leader in the field. But in some respects, it is truer still of China."

The potential replacement of AI to labor in the future has become an important policy consideration. As is emphasized by the report named Artificial Intelligence, Automation, and the Economy released by the White House, facing rapid development of AI, policymakers should prepare for churning of the job market as some jobs disappear while others are created; and the loss of jobs for some workers in the short-run, and possibly longer depending on policy responses. With regard to these concerns, the historical impact of automation technology on the employment structure can also help us predict the impact of AI on future labor market. AI technology development will, in large part, turn non-routine tasks into well-defined routine problems (Frey and Osborne, 2017), by observing substitution effects of automation technology to labor in different tasks, we can dynamically adjust the range of routine jobs with the future breakthrough in AI and forecast its impacts on workers with various skills.

To investigate the effect of automation technology on employment structures in China, we follow previous literature (e.g. Autor, Levy and Murnane, 2003) and delineate occupations by their task content along two dimensions: "routine" versus "non-routine," and "cognitive" versus "manual." The occupation is routine if the tasks within it can be summarized as certain activities accomplished by following well-defined procedures. Instead, if creativity, flexibility, problem-solving, or human interaction were required, the occupation is considered non-routine. The distinction between cognitive and manual occupations is by whether they are mental or physical activities these jobs mainly cover. Thus, we group Chinese employees as either non-routine cognitive, routine cognitive, non-routine manual, routine manual, and not-working (including unemployment and not in the labor force) based on the classification and codes of occupations of China.

We find that there are four significant changes in employment structures in China from 1990 to 2015. The first one is the share of routine manual jobs decreased from 56.65% to 31.58%, the second one is the non-employment increase from 15.85% to 30.76%, the third one is the routine cognitive jobs increased from 8.17% to 19.20%, and the last one is the non-routine jobs had no significant change.

Furthermore, we decompose the change in each employment category using the framework in Cortes, Jaimovich and Siu (2017), which decompose the change in employment category across time into three components: the composition effect (effect from the composition of population demographic change), the propensity effect (effect resulting from changes in the probability for people with given demographic characteristics in different employment categories), and the interaction effect which captures the co-movement of demographic group size changes and propensity changes given demographic characteristics.

Our decomposition exercises find that from 1990 to 2015, the composition effect contributes to 67.6% of the 25.1% fall of people working in routine manual jobs, the propensity effect accounts for 66.4% and the interaction effect accounts for -34%.

For the 11% rise in the people working in routine cognitive jobs, the composition effect accounts for 15.6%, the propensity effect accounts for 73.6% and the interaction effect accounts for 10.9%.

As for the 14.9% increase in the fraction of people without working, the composition effect accounts for 6.9%, the propensity effect accounts for 92.8%, and the role of interaction effect is negligible.

Non-routine jobs changed little; non-routine cognitive jobs deceased from 13.10% to 11.15% and non-routine manual jobs increased from 6.23% to 7.31%.

These findings are quite different from what Cortes, Jaimovich and Siu (2017) found of the United States. The comparison between China and the United States is shown in Table 1. In the past 25 years, the United States experienced decline of employment in routine cognitive occupations (from 19.6% to 16.1%) as well as in routine manual jobs (from 21.0% to 15.1%) and in turn, increase in non-routine cognitive employment (from 24.7% to 28.2%) and non-routine manual employment (from 9.6% to 12.3%) as well as in not-working population (from 25.2% to 28.3%). They found out that workers in America who were crowded out from middle-wage, routine occupations sorted into low-wage, non-routine manual and non-employment categories. However, during the same period in China, the fraction of routine cognitive employment increased greatly, and the fraction of non-routine (both non-routine manual and non-routine cognitive) employment hardly undergo any change.

The rest of paper is as follows: in Section 2, we present six major factors that had great influences on China's labor market in recent decades. In Section 3, we introduce the data used in empirical analysis and present the statistical description of the change of different occupation categories in each demographic group. In Section 4, using the decomposition method proposed by Cortes, Jaimovich and Siu (2017), we decompose the change of the employment structure in China from 1990 to 2015 into composition and propensity effect and analyze how these effects vary with specific demographic groups. In Section 5, we conclude the paper and discuss the implication of our studies to the future.

2. Key Features of Labor Market in China

Recent decades have witnessed dramatic changes in both labor supply and labor demand in China. In this section, we brief six major factors that had great impacts on the Chinese labor market in past decades.

2.1 Major factors causing labor supply change

To review the main factors that reshape the labor supply structure, it's impossible to not mention the family planning policy which started as early as 1962 (Liang, 2014), and it is commonly known as one-child policy since 1979, which has resulted in great demographic shifts in China. One of the main outcomes is the growing problem of aging society. In the past 25 years, the proportion of elderly in the whole population has doubled. The share of people more than 60 years old in the whole population was 8.6% at 1990, and this number has increased to 16.1% at 2015. The share of people more than 65 years old has risen from 5.6% at 1990 to 10.5% at 2015 (China Population & Employment Statistics Yearbook, 1991 & 2016). Both these ratios now have exceeded the warning line (10% the proportion of 60 years old or above and 7% of 65 years old or above) of aging population society. The aging population problem not only aggravated the burden of young people and the society, but also shift up the average age of working population, which means the fraction of young workers in the labor market kept declining and the share of old workers rising.

Another major factor that has caused dramatically changes in the labor supply side is the increasing educational attainment, especially due to the rapid expansion of college enrollment from 1999, when the government decided to expand the college enrollment to promote economic growth and alleviate the pressure of unemployment. At 1990, the college enrollment in China was only 0.61 million; at 1998, it was 1.08 million; while at 2015, the number has climbed to 7 million. Consequently, the fraction of employed persons who got educational attainment higher than college degrees rose substantially from 5.6% at 2001 to 17.4% at 2015 (China Labour Statistical Yearbook, 2002 & 2016). The rapid increase in educational attainment, especially the rise of college enrollment raised the probability of workers in doing cognitive occupations, decreased their preferences to do manual jobs. In addition, the college graduates are facing more and more fierce competition in finding satisfying jobs. If there were not enough high-paid non-routine cognitive jobs provided, we may see these highly-educated workers sorted into routine cognitive or even manual jobs.

The substantial rise of migrant workers also accounted for a great change of the labor supply in the past 25 years. With the relaxation of household registration restrictions (Hukou system) on population mobility mainly since 1995, the year when the central government started to allow migrants to stay in cities as long as they possessed four documents: a national identification card, a temporary resident permit in cities, an employment certificate issued by the local labor bureau, and an employment card issued by the labor bureau in their origin location (Cai, Park and Zhao, 2008). From then on, a great amount of workers migrated from where they were born, mainly from less developed regions to prosperous areas, including from villages to cities, from central and western regions to eastern coastal areas. According to the 2017 Report on China’s Migrant Population Development released by China’s National Health and Family Planning Commission, by different factors that dominated the population change, we can divide China’s history after 1949 into three periods. The first period is driven by high mortality rate, from 1949 to 1969; the second one is driven by high birth rate, from 1970 to 1989; the third one is from 1990 to now, in which the increasing migration rate took the lead, while the mortality rate remained relatively stable and the birth rate steadily declined. In 1997, there were around 39 million migrant workers in cities (Meng et al., 2013) and, this number has reached 247 million at 2015, which equaled to 18% of the total population (2016 Report on China’s Migrant Population Development). Meng, Shen and Xue (2013) also argued that rural migrants’ inflow increased the rate of urban workers dropping out of the labor force or becoming unemployed as they had significantly higher reservation wages after enjoying various forms of protections and benefits in the labor market than rural workers. In addition, Feng, Hu and Moffitt (2017) found that migrants had lower unemployment rate and higher labor force participation rate than local-urban-hukou people because the majority of migrants came to cities for work, and they would return to their rural home if there were not enough job opportunities in cities. In Figure 4 of Section 3, we will give a brief comparison of migrants and local-hukou residents.

2.2 Major factors causing labor demand change

For China’s labor demand change, the automation technological development has exerted a great impact on it in the past and will keep carrying weight in the long future.

Industrial robots have been substituting assembly line workers in a great number of factories nowadays. As was reported by International Federation of Robotics (IFR), China has been so far the biggest robot market in the world regarding annual sales and regarding the operational stock at 2016. The estimated operational stock of industrial robots at 2004 in China was 7,000 of units, while this number has climbed to 340,000 at 2016. The wide adoption of industrial robots is an important contributor to the decline of routine manual employment and the rise of non-employment in labor-intensive industries in the recent decade.

Another big shock on China's labor market came from the reform of state-owned enterprises (SOEs) in late 1990s. Starting from 1995, and especially since the 1997 Fifteenth Communist Party Congress, the government began a policy of "seizing the large and letting go of the small" (in Chinese, Zhua da fang xiao), to privatize small and medium-sized SOEs while retaining control of large enterprises, as was pointed out by Feng, Hu and Moffitt (2017). According to Giles, Park and Cai (2006), from 1995 to 2001, there were an estimated 34 million workers laid off from the state sector to reduce redundant labor forces. What made things worth, as showed by a survey that 63.5% of laid-off workers did not actively pursue the jobs newly created by economic growth as they strongly believed that the state would never let them starve (Chen, 1997), thus the revised unemployment rate in urban China rose greatly from 4.4% at 1993 to 9.4% at 1997 by the calculation of Gu (1999). In addition, Yang (2000) pointed out that the re-employment rate of laid-off workers had declined sharply from 52% at 1998 to 27% in the first half year of 1999. As most of these redundant workers took routine manual jobs before, he showed that the jobless beyond age 40 were very hard to find a new job at that time, and it was almost impossible for men beyond 50 and women beyond 45 to be re-employed. As a result, urban China witnessed a great rise in non-employment rate in the late 1990s.

Job destruction mentioned above is just one-side of story, China has also experienced huge increases in cognitive occupation employment benefited from the globalization and the rapid computerization. China joined the World Trade Organization at December11, 2001, and has received a great amount of off-shored jobs from developed countries since then, especially after 2006, when China enacted policies to encourage companies to undertake more outsourcing services, mainly in information transmission, software and information technology industries, from abroad. In 2006, the contract execution amount of these services in China was only 1.4 billion dollars, while at 2015, it reached up to 96.7 billion dollars. In the meantime, the employees working on outsourcing services rose dramatically from less than 60 thousand in 2006 to more than 7 million in 2015, most of them had at least college degree and worked in routine cognitive jobs (Development Report of China's service outsourcing industry from 2006 to 2015). Also, rapid computerization in recent decades have created many cognitive jobs in offices. As is mentioned above, the average number of computers in each 100 China urban households rose sharply from 9.7 at 2000 to 78.5 at 2015 and working with computers and smart phones has become an essential skill in many fields.

These factors combined to account for a great proportion of the change on employment structures in China in recent decades.

3. Data and Descriptive Statistics

3.1 Data

Our analysis uses data from National Population Census of China in year 1990, 2000 and 2010[1], and 1% National Population Sample Survey of China in year 2005 and 2015. The Census data covered all the population in China, and the 1% National Population Sample Survey, also known as the Mini-Census, covered 1% of population in China. For 1990 Census, the publicly available data is 1% sample; for 2000 and 2010 Censuses, the publicly available data is 0.1% sample; for 2005 Mini-Census, it’s 20% sample; for 2015 Mini-Census, it’s 10% sample. They were all conducted by China’s National Bureau of Statistics. In addition to their nationwide and representative sampling, these data also have an advantage that there is hardly any other household survey in China covers so long a period from 1990 to 2015.

We focus on adult population aged 18-59 years old, as most of the Chinese

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[1] Till now, China has conducted six population censuses in 1953, 1964, 1982, 1990, 2000 and 2010. The first and second census data have been lost since they did not been imputed into the computer. The 1982 census is not used in our analysis for three main reasons: firstly, there was no question about whether those did not work were disabled or not; secondly, some parts of the data are disordered; thirdly, although the reform and opening-up policy was implemented from 1978, non-state-owned enterprises had not gotten the chance to develop rapidly until 1990s. It was since the South Talks made by Deng Xiaoping in 1992 that China started a higher stage of economic system reforming, so the employment was mainly within state-owned enterprises in 1980s, and the employment structure could be quite different from it after 1990.

workers retire when they reach the age 60. Those living in villages or those disabled are excluded. Following the literature (e.g. Autor, Levy and Murnane, 2003), we delineate occupations in China by their task content along two dimensions: “routine” versus “non-routine,” and “cognitive” versus “manual.” Thus, we group Chinese employees as either non-routine cognitive (NRC), routine cognitive (RC), non-routine manual (NRM), routine manual (RM), and not-working (including unemployment and not in the labor force) based on the classification and codes of occupations of China[2].

3.2 Descriptive statistics

Figure 1 presents the population share of each category from 1990 to 2015. In China, the share in routine manual category decreased dramatically from 57% in 1990 to 32% in 2015, which showed a same trend as in Cortes, Jaimovich and Siu (2017), which found that the fraction of the population employed in routine manual category decreased from 21% in 1989 to 15% in 2014 in the United States. However, the share of population in routine cognitive category in China increased substantially from 8% in 1990 to 19% in 2015, which is quite opposite with the trend of routine cognitive fraction change in the United States (decreased from 20% to 16%). In addition, the population share of not-working group rose greatly from 16% in 1990 to 31% in 2015, while at the same time, the not-working share just rose slightly in the United States from 25% to 28%. Besides, the population share in non-routine (both cognitive and manual) categories did not undergo a big change, remained at around 19% through 1990 to 2015, while in the United States, the fraction rose from 34% to 41%.

Figure 2 presents the fraction of male population in each category. We can see that the proportion of male employees in routine manual category rose from 57% in 1990 to 67% in 2015, which implies that more female workers left routine manual jobs than male workers. The male proportion in routine cognitive and non-routine jobs did not change much and about half of workers in these categories were males. In addition, most (nearly 70%) of the population without work were females and the proportion just changed slightly in the past 25 years.

As in Table 2, fractions of population in different categories at each education

[2] The national standard of occupation classification we use include GB/T 6565-1986 (used in 1990 census), GB/T 6565-1999 (used in 2000 census and 2005 mini-census), GB/T 6565-2009 (used in 2010 census) and GB/T 6565-2015 (used in 2015 mini-census).

level have experienced significant changes during past 25 years. The fraction of working in routine cognitive jobs increased greatly at each education level, especially for workers with college or above education. The fraction of working in routine manual jobs decreased sharply in each education level below college degree. The fraction of working in non-routine cognitive jobs dropped sharply for workers with at least secondary school degree, especially for those with at least college degree, as the college enrollment rose so greatly that high-paid non-routine cognitive jobs could not fulfill their rising preference to work. The fraction of working in non-routine manual jobs did not change much, while the fraction of people without working rose substantially in all education levels.

Some common facts among these education groups can be observed in both 1990 and 2015. For example, the fraction of working in manual jobs decreased with the rising of education level, while the tendency is opposite for the fraction change in cognitive jobs. Besides, the fraction of working in non-routine cognitive jobs dropped substantially within educational levels higher than college degrees and their fractions in routine jobs rose greatly in turn.

In addition, we create three age groups (aged 18-29 of young group, 30-49 of prime-aged group and 50-59 of old group). We find same trends of decreasing routine manual employment and increasing routine cognitive employment in the past 25 years in all age groups. For young people, the share of working in routine manual jobs decreased dramatically (from 60% in 1990 to 26% in 2015), and in routine cognitive jobs rose from 7% to 19%. Besides, the non-employment fraction doubled from 18% to 38%. For prime-aged people from 30 to 49 years old, the share of working in routine manual jobs also decreased sharply from 61% to 36%, the share in routine cognitive rose from 10% to 22%, and in not-working increased substantially from 7% to 21%. For old people, the share changes in different categories are less pronounced than previous two groups. The fraction of working in routine manual jobs decreased from 35% to 29%, in routine cognitive jobs rose from 6% to 12%, in non-routine cognitive jobs dropped from 15% to 7%, in not-working increased from 40% to 46%.

In 2015, the fraction of young people that worked in routine manual jobs was the lowest among three age groups, the fraction of primed-age group that worked in routine or non-routine cognitive jobs was the highest. For not working, the fraction of old people was the highest while of primed-aged ones was the lowest. For non-routine manual jobs, the fraction was almost the same among three groups (7-8%).

As we can see from Figure 1 that the population share of not-working group rose greatly from 16% in 1990 to 31% in 2015, and the fraction of old or young people without a job was higher than prime-aged people. Rising fraction of retirement and increased population in school maybe two major reasons for overall non-employment rise. However, for the fraction of retirement in the non-employment group, it has declined from 22% in 1990 to 15% in 2015. Actually, in China, in 1990s and early 2000s, many workers in SOEs had opportunities to retire earlier before they reached mandatory retirement age (aged 60 or 55 for men and 55 or 50 for women, generally). Some chose to retire early to let their sons took their positions. However, it is harder for workers to retire early now and the government is considering to postponed retirement age as the population aging has become a serious problem. As a result, the retirement proportion change cannot account for the sharp rise of not-working fraction from 1990 to 2015.

What's more, the fraction of schooling in the non-employment group also decreased from 22% in 1990 to 18% in 2015. Although China's university expanded the enrollment every year from 1999, the fraction of schooling in non-employment did not increase steadily from 2000. The data suggests that the rise of not-working fraction is not mainly due to the increase in the fraction of retired people or people still in school, but more likely because more people now are searching for proper jobs (unemployed) or they choose to withdraw from the labor market[3].

As is expressed in Section 2, a great amount of people migrated to other regions to work in the past 25 years, mainly flowed to more developed areas. We wonder whether they had different employment structures from other groups of people. We classified the population whose hukou were not in the same county of their permanent residences as migrant people. The results are shown in Figure 3. We can tell that the change trend from 1990 to 2015 of migrant people was almost the same with the trend of local-hukou residents. Their employment fraction in routine manual jobs decreased greatly and in routine cognitive or not-working category rose in turn.

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[3] Options in the census questionnaire for reasons of not-working included schooling, disabled (have been excluded from our analysis), did not work after graduation, lost the job because of the company, lost the job because of personal reasons, farmland lost because of acquisition by government, retirement, doing housework at home and others.

Comparing with local-hukou residents, migrant workers had a higher proportion of working in routine cognitive and non-routine manual jobs and a lower fraction in non-employment category, which shows that migrant workers preferred not to be caught into the dilemma of unemployment, so they were willing to take low-paid jobs that sometimes native workers were reluctant to do, this also explains why local-hukou residents fell faster working in routine-manual jobs than migrants. A lower non-employment rate of migrants is consistent with the results of Feng, Hu and Moffitt (2017).

In addition, with the rising of college enrollment and meanwhile, big cities like Beijing and Shanghai restricted college graduates from transferring their hukou in, many high-educated people that even work as senior executives in these cities remain possessing no local hukou. This abnormal phenomenon can partly account for why migrants' proportion of taking non-routine cognitive jobs was lower than total population's at 1990, but then rose steadily to be higher at 2015.

4. Decomposition of the employment structure change across time

4.1 Framework

Figures in Section 3 present fraction in different categories of all the population and of people in different education and age groups. On one hand, the decline of routine manual employment and the rise of routine cognitive employment and not-working people may be partially accounted for by changes in the probability for people with given demographic characteristics to work in these categories (propensity effect). These changes would indicate economic forces that change the opportunities in the labor market for specific groups of workers.

On the other hand, except for changes in different employment categories within each demographic group, China in the past 25 years has also experienced significant changes in the educational, age and gender composition of the population. Since demographic groups are different in their propensity to work in each occupation category, demographic changes would be another reason to explain the overall employment structure change (composition effect).

To investigate the relative importance of two forces, we perform a set of decompositions by the method of Cortes, Jaimovich and Siu (2017). As in Section 3, we divide people into 24 demographic groups, by their gender, age, and education.

Specifically, we have two gender groups (females and males), three age groups (18-29, 30-49, 50-59), and four education groups (primary school graduation or less, secondary school graduation, high school graduation, college or above).

The fraction of the population in each employment category *j* at time *t* is denoted as $\bar{\pi}_t^j$, this can be written as:

$$\bar{\pi}_t^j = \sum_g w_{gt}\pi_{gt}^j \tag{1}$$

where w_{gt} is the fraction of demographic group *g* in the whole population at time *t*, and π_{gt}^j is the share of individuals within demographic group *g* in employment category *j* at *t*.

The change in the fraction of people in employment category *j* can be written as:

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

The composition effect is shown in the first term, $\sum_g \Delta w_{g1}\pi_{g0}^j$, due to the change in population fraction of demographic groups over time. The propensity effect is displayed in the second term, $\sum_g w_{g0}\Delta\pi_{g1}^j$, owing to changes in the share of individuals within groups in category *j*. Their interaction effect is the third term, $\sum_g \Delta w_{g1}\Delta\pi_{g1}^j$, which captures the co-movement of demographic group size changes and propensity changes given demographic characteristics.

4.2 Decomposition of overall employment structure change

Results of the decomposition are in Table 3. We divide the past 25 years into three 10-year periods (1990-2000, 2000-2010, 2005-2015), the initial and final fractions of each category in these periods are displayed in Column (1) and (2). The total change in each category during different periods is listed in Column (3), and contributions from the composition effect, propensity effect and interaction effect are in Column (4) to (6).

From 1990 to 2015, there are four significant changes in employment structure in China. The first one is the share of routine manual jobs decreased from 56.65% to 31.58%, the second one is the share of non-employment increase from 15.85% to 30.76%, the third one is the share of routine cognitive jobs increased from 8.17% to 19.20%, and the last one is the share non-routine job had no significant change:

non-routine cognitive jobs deceased from 13.10% to 11.15% and non-routine manual jobs increased 6.23% to 7.31%.

Our decomposition exercises suggest from 1990 to 2015, the fraction of people working in routine manual jobs has fallen by 25.1%, in which the composition effect accounts for 67.6%, the propensity effect accounts for 66.4% and the interaction effect accounts for -34%. The fraction of people working in routine cognitive jobs has risen by 11%, in which the composition effect accounts for 15.6%, the propensity effect accounts for 73.6% and the interaction effect accounts for 10.9%. The fraction of people without working has risen by 14.9%, in which the composition effect accounts for 6.9%, the propensity effect accounts for 92.8%, and the role of interaction effect is negligible.

The pattern of change in each employment category for the three periods is almost the same. The fraction of non-routine cognitive decreased slightly, with a positive composition effect and negative propensity effect. The positive composition effect means demographic groups that have the highest propensity to work in non-routine cognitive category rose greatly, as the college enrollment increased sharply from 0.61 million at 1990 to 7 million at 2015. The negative propensity and interaction effect means the labor demand of non-routine cognitive occupations became increasingly insufficient (as it is hard to imagine that people became more and more unwilling to work in high-paid non-routine cognitive jobs if they had the chance), and the employment fraction in this category decreased more for the highly educated group. This result is different from in the United States, which also witnessed a positive composition effect and a negative propensity effect in non-routine cognitive occupations, but hardly any negative interaction effect, which showed that high-educated workers did not experience a greater decline than other groups of people. One possible reason of this difference is that America’s college enrollment did not undergo that sharp an increase as in China. To illustrate, the college enrollment of the United States rose from 15.3 million at 2000 to 21 million at 2010, a much less rise in proportion than China went through in the same period, and then declined to 20.2 million at 2014 (data source: National Center for Education Statistics of the United States). In following subsections, we will show that most of the decrease of highly educated people in non-routine cognitive jobs in China sorted into routine cognitive and to a lesser extent, into not-working categories.

The fraction of routine manual employment dropped greatly in all three periods, especially during 1990 and 2000. Both composition effect and propensity effect account for a large proportion of this decline, which means the share of low-educated population shrank a lot and their likelihood of working in routine manual category declined in the meantime. On one hand, the demand for routine manual workers reduced due to the development of automation technologies. On the other hand, as Cortes, Jaimovich and Siu (2017) pointed out, given the rapid increase in educational attainment, the distribution of unobserved productivity and/ or leisure preferences of those low-educated has shifted.

The fraction of routine cognitive rose substantially, especially during 1990-2000 and 2005-2015. This rise is mainly accounted for by propensity effect, which is due to partly the adoption of computers in offices from 1990s and off-shored service jobs mainly in information transmission, software and information technology industries accepted from developed countries (increased rapidly from 2006) which created a lot of routine cognitive jobs and attracted workers in routine manual category to learn and work in offices, partly the insufficient demand for non-routine cognitive workers led many college graduates flow to routine cognitive jobs.

The fraction of not-working people increased dramatically, especially during the period from 1990 to 2000. This increase is mainly resulting from propensity effect. In addition to some workers did not find proper jobs because of fierce competition or their preferences in leisure, the reform of SOEs in 1990s which led to tens of millions of employees out of work, can account for a great proportion of non-employment increase. This result is consistent with China's unemployment rate fluctuation calculated by Feng et al. (2017), that the rate rose sharply during the period of mass layoff from 1995 to 2002, reaching an average of 9.5% in the subperiod from 2002 to 2009, and that declines in labor force participation often accompany increases in the unemployment rate. What's more, they also showed that changes neither in the labor force participation rate nor in the unemployment rate are driven by demographic factors; these were structural, not demographic, shifts.

In the following subsections, we focus our analysis on changes in routine manual, routine cognitive and not-working three categories, which exhibited significant changes from 1990 to 2015.

4.3 Decline in routine manual employment

From 1990-2015, the fraction of people working in routine manual jobs has fallen by 25.1%, in which the composition effect accounts for 67.6%, the propensity effect accounts for 66.4% and the interaction effect accounts for -34%.

To determine the relative importance of each demographic group in accounting for the decline in routine manual employment, we use the method of Cortes, Jaimovich and Siu (2017) and compute the change induced by each group g, $w_{g1}\pi_{g1}^{j} - w_{g0}\pi_{g0}^{j}$ from Eq. (2), as a fraction of the total change. The results are in Table 4.A. Six demographic groups stand out as key groups that account for the bulk of the decline: female primary school graduates or less at age 18-29 and 30-49, female secondary school graduates at age 18-29, male primary school graduates or less at age 18-29 and 30-49, and male secondary school graduates under the age of 30. Changes in these six key demographic groups combined can account for 97% of the fall in routine manual employment.

Table 4.B indicates that these demographic groups contribute to both the composition and propensity effects documented in Table 3. First, these groups were shrinking in terms of their share of the population. While they represented more than 40% of the China population in 1990, they represented only 15% by 2015. Given that a large fraction of these low-educated women and men were employed in a routine manual occupation in 1990---as many as 90%, as indicated in the fourth column of the table---their reduction in the population share has implied an important reduction in the overall share of routine manual employment, even holding their propensity fixed.

Equally important, individuals within these key groups have experienced dramatic reductions in the propensity to work in routine manual jobs. For example, the fraction has fallen by about 45 percentage points for lowest-educated young women; while more than 80% worked in routine manual occupations in 1990, this figure was closer to one-third in 2015. As a result, the bulk of the propensity change documented in Table 3 is due to these six demographic groups.

Given that these key groups have experienced substantial movement out of routine manual employment, it will be interesting to ask which employment category they have transitioned into. We illustrate this in Table 4.C, by presenting the change in the share of each demographic group across employment categories. The results indicate that the dramatic decline in the probability of routine manual employment is offset primarily by increases in non-employment and, to a lesser extent, increases in routine cognitive and non-routine manual employment. Clearly individuals from these demographic groups have not benefited by transition into high-paid, non-routine cognitive occupations.

Through different sub-periods, decreases of the routine manual fraction varied greatly. As is shown in Table 3, the change of routine manual fraction during 1990-2000 period (-16.40%) accounts for 65% of the overall change (-25.06%), so we compute the change induced by each group during 1990- 2000 in routine manual employment to see the distinction of this period. The same six demographic groups stand out as key groups that account for the bulk of the decline: females and males with no higher than secondary school education in age 18-29, females and males with primary school education or less in age 30-49. Changes in these six key demographic groups combined can account for 94% of the fall in routine manual employment. Also, these demographic groups contribute to both the composition and propensity effects documented in Table 3. First, these groups were shrinking in terms of their share of the population from 41.83% in 1990 to 27.69% in 2000. What's more, individuals within these key groups have experienced sharply declines in the propensity to work in routine manual jobs. For example, the fraction of lowest-educated young women working in routine manual jobs has fallen from 81.79% in 1990 to 53.56% in 2000. In general, the overall fraction change and key groups accounting for it in routine manual occupations during 1990-2000 showed same features with during 1990-2015.

Since the key demographic groups that accounted for the decline of routine manual employment are young and prime-aged people in low-education, we can readily explain that the composition effect in these groups stems from, to a large extent, the rise of workers' educational attainment and the increasingly serious aging problem. With respect to the explanation of its propensity effect, on one hand, the widely used industrial robots in the recent decade and the reform of SOEs in late 1990s led to the decline of routine manual employment, so some routine manual workers had to leave this category and worked in non-routine manual jobs that were hard to be substituted; on the other hand, with the rising of routine cognitive employment and people's preferences on leisure, some routine manual workers flowed into routine cognitive jobs. Those workers left routine manual jobs that could not find routine cognitive jobs and did not prefer to do non-routine manual jobs became unemployed or quitted from the labor market.

4.4 Rise in routine cognitive employment

From 1990- 2015, the fraction of people working in routine cognitive jobs has risen by 11%, in which the composition effect accounts for 15.6%, the propensity effect accounts for 73.6% and the interaction effect accounts for 10.9%.

Next, we perform a similar analysis as in Section 4.3 for the change in routine cognitive employment. Table 5.A shows that the demographic groups accounting for the bulk of the rise in routine cognitive employment include females and males with some college education or above in both young and prime-aged groups, and females with secondary and high school diplomas from age 30 to 49. These six demographic groups alone account for 69% of the propensity effect.

The population shares and routine cognitive employment propensities for these groups are detailed in Table 5.B. All six groups experienced increases in their probability of working in routine cognitive jobs, half of these groups increased from approximately 10% in 1990 to about 30% in 2015.

Given that these key groups have experienced substantial movement into routine cognitive employment, we ask where they have sorted out instead. As is shown in Table 5.C, most of the share rise of routine cognitive employment came from non-routine cognitive, which means in these relatively high education groups, they can work at non-routine cognitive jobs with relatively high pays at 1990, while many of them in the same group can only work at routine cognitive jobs at 2015. As this is propensity effect, it does not reflect the rising of highly-educated population, instead this shows the rapid growth of labor demand in routine cognitive occupations and the insufficient demand of non-routine cognitive jobs for college graduates. To a lesser extent, the decline of routine manual employment in prime-aged female that have at most high school diploma account to some parts of the rise of routine cognitive employment, with reasons we discussed in Section 4.2.

4.5 Rise in non-employment

From 1990- 2015, the fraction of people without working has risen by 14.9%, in which the composition effect accounts for 6.9%, the propensity effect accounts for 92.8%.

Table 6.A shows that the groups accounting for the bulk of the rise in non-employment are females and males with some college education or above under the age 30, and females with secondary and high school diplomas from age 30 to 59. These six demographic groups alone account for 85% of the propensity effect.

The population shares and non-employment propensities for these groups are detailed in Table 6.B. All six groups experienced increases in their probability of not working, the fraction of non-employment in half of these groups increased by more than 25% from 1990 to 2015.

As is shown in Table 6.C, most of the share rise of non-employment in these key demographic groups came from non-routine cognitive, and, to a lesser extent, came from routine manual employment. For young workers with at least college degree, they have no sufficient chances to work in non-routine cognitive jobs, so most of them chose routine cognitive jobs, some young men even did more routine manual jobs than before. If they could not find a proper job, they chose to do further study for master or even Ph.D. degrees and enlarge the fraction of not-working. For prime-aged and old female workers with at most high school graduates, some of them went to routine cognitive jobs, others had no work to do without finding routine manual or cognitive jobs and reluctant to do non-routine manual jobs.

The fraction of not-working people increased mainly during the period 1990-2000, resulting from propensity effect. As is shown in Table 3, the change of not-working fraction during 1990-2000 period (10.77%) accounts for 72% of the overall change (14.90%). After computing the change induced by each group during 1990-2000 in not-working category, four demographic groups stand out as key groups: females with secondary school education from age 30 to 59 and with high school education in 30-49, males with secondary school education in age 30-49. Changes in these four key demographic groups combined can account for 61% of the rise in not-working fraction. Individuals within these key groups have experienced great increases in the propensity of non-employment. For example, the fraction of secondary school females aged 30-49 without working has risen from 9.64% in 1990 to 34.62% in 2000. During the reform of SOEs in 1990s, as is introduced in Section 2.2, most of laid-off workers did not actively pursue the jobs newly created by economic growth as they strongly believed that the state would never let them starve (Chen, 1997). In addition, the jobless beyond age 40 were very hard to find a new job at that time (Yang, 2000). As a result, urban China witnessed a great rise in non-employment in the late 1990s, especially in prime-aged or old females with no more than high school diplomas.

5. Conclusion

Existing literature (e.g., Autor and Dorn, 2013, Goos, Manning and Salomons, 2014) pointed out that the United States and Western European countries have witnessed routine-biased technological change over recent decades, which led to strong decline of the fraction of middle-skilled employment. Cortes, Jaimovich and Siu (2017) found out that workers in the United States who were crowded out from routine jobs sorted into non-routine manual and non-employment categories. However, the change of employment structure in China at the same time was quite different. The share of employment in routine manual occupations experienced sharp decline over recent 25 years, while the fraction of routine cognitive employment increased greatly, and the fraction of non-routine employment hardly undergo any change. In the meantime, the share of non-employment people rose dramatically.

By decomposing, we show that the decline of routine manual employment can be accounted for by both the composition effect, which was mainly caused by the rise of workers' educational attainment and the serious aging problem, and the propensity effect, which was due to the wide adoption of industrial robots, the reform of SOEs, and people’s increasing preferences to routine cognitive jobs. With regard to the rise of routine cognitive jobs, we find that this is primarily due to the propensity of high-educated workers to work in non-routine cognitive jobs could not be fulfilled as non-routine cognitive occupations were insufficient while the college enrollment experienced a great rise, and the increase of routine cognitive jobs attracted many routine manual employees out of their original category. What is more, if college graduates could not find a satisfying job or low-educated workers were substituted by industrial robots without finding routine cognitive or non-routine manual jobs, they became unemployed or even withdrew from the labor market, which led the fraction of not-working people increase. In addition, we find that a relatively small subset of workers who have experienced an increase in their propensity for non-employment and their propensity to work in computerized routine cognitive jobs can account for a substantial fraction of the aggregate decline in routine manual employment and the rise in routine cognitive employment and non-employment.

These findings show a different image on the impact artificial intelligence will have on the employment in China from its impact on America. As routine jobs are still principal occupation categories (routine cognitive and routine manual in total covered more than 50% of the 2015 population we analyze) in China, and it is more likely for these occupations to be computerized in the near future than non-routine jobs, so not only low-skill and low-wage workers would in high risk of computerization as Frey and Osborne (2017) predicted in America, the high-educated workers will also be easily substituted by AI technologies in China as nearly 40% of college graduates worked in routine jobs at 2015. From 1990 to 2015, the creation of both cognitive and manual non-routine jobs was stagnant. Our findings thus imply that to win the race with AI, workers with all kinds of skills in China need to reallocate to tasks requiring creative and social intelligence (these are engineering bottlenecks of AI put forward by Frey and Osborne, 2017) that are non-susceptible to computerization.

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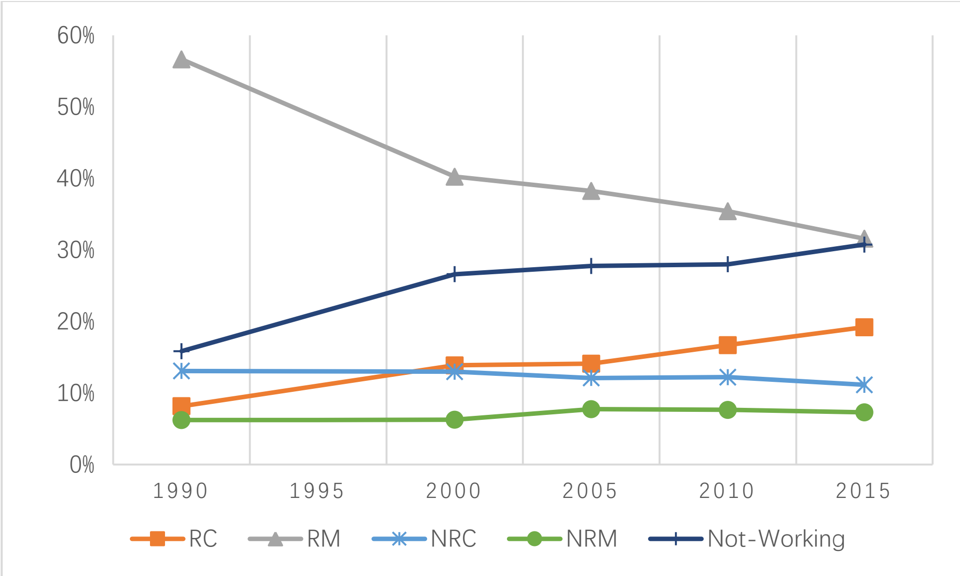

Figure. 1. Fraction of population in each employment category: 1990 to 2015

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

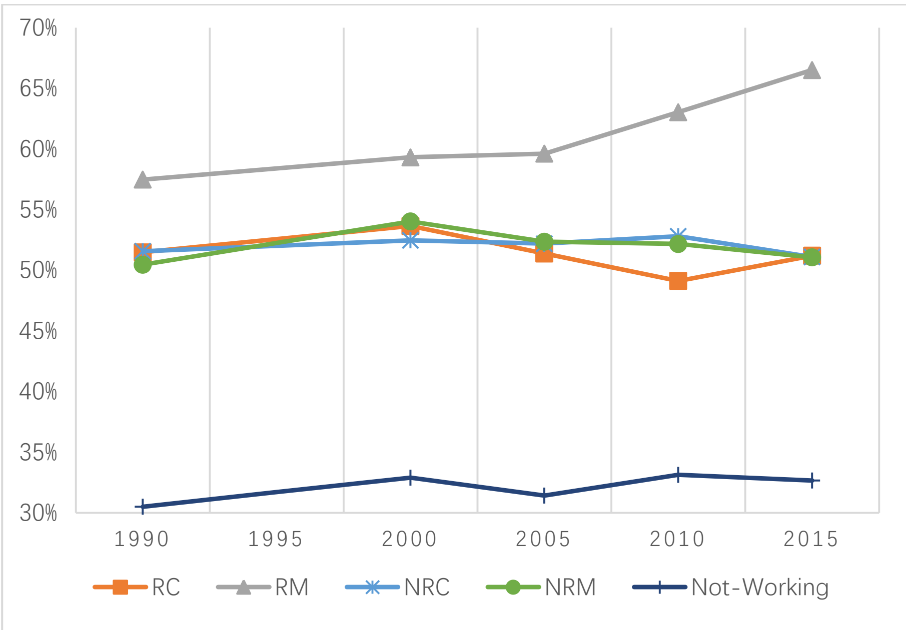

Figure. 2. The fraction of males in each employment category: 1990 to 2015

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

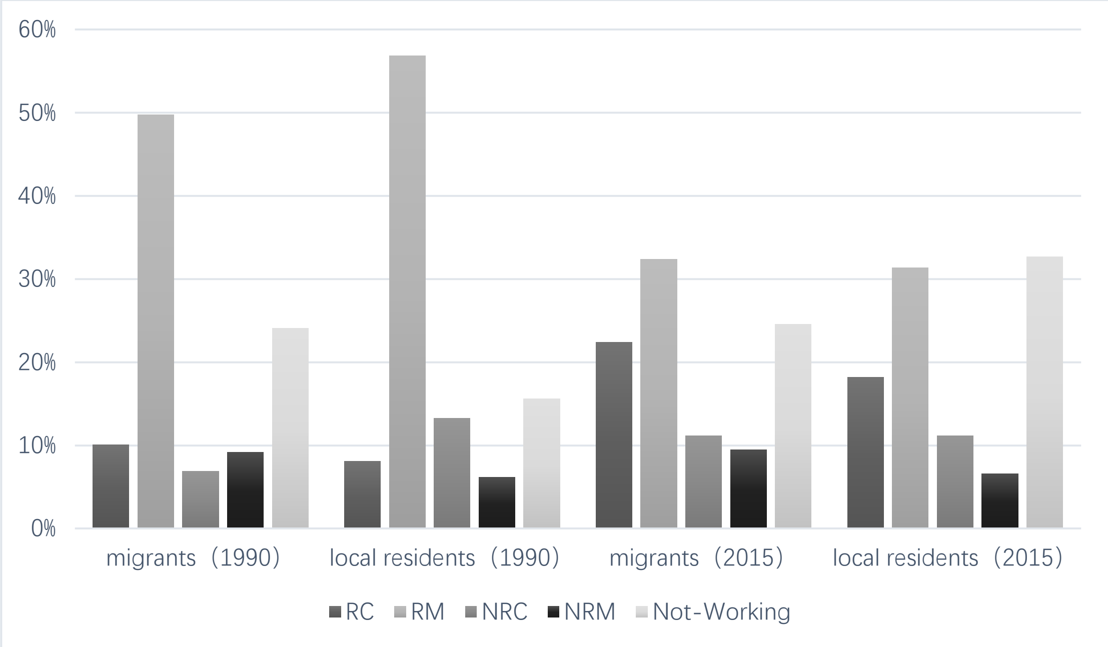

Figure.3. Fraction of migrants and local-hukou residents in each employment category: 1990 and 2015

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 1. Changes in each occupation category in China and in the United States

	China			**the United States**		
	1990	2015	Change	1989	2014	Change
Routine	64.82%	50.78%	-14.04%	40.6%	31.2%	-9.4%
Routine Cognitive	8.17%	19.20%	11.03%	19.6%	16.1%	-3.5%
Routine Manual	56.65%	31.58%	-25.07%	21.0%	15.1%	-5.9%
Non-Routine	19.33%	18.46%	-0.87%	34.3%	40.5%	6.2%
Non-Routine Cognitive	13.10%	11.15%	-1.95%	24.7%	28.2%	3.5%
Non-Routine Manual	6.23%	7.31%	1.08%	9.6%	12.3%	2.7%
Not-working	15.85%	30.76%	14.91%	25.2%	28.3%	3.1%

Sources: Data of China come from Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015. Data of the United States come from Cortes, Jaimovich and Siu (2017).

Table 2. The fraction of population in each employment category from 1990 to 2015 by education level.

		RC	RM	NRC	NRM	Not-Working
Primary School Graduates or Less	1990	3.77%	68.28%	1.44%	4.99%	21.53%
	2015	9.05%	45.48%	1.71%	7.90%	35.87%
Secondary School Graduates	1990	9.65%	65.09%	7.22%	7.28%	10.77%
	2015	15.42%	43.56%	3.68%	8.87%	28.47%
High School Graduates	1990	11.93%	40.78%	25.86%	7.12%	14.32%
	2015	22.25%	26.68%	9.81%	7.68%	33.59%
Some College Graduates or Above	1990	8.61%	5.63%	61.04%	3.30%	21.42%
	2015	27.24%	9.95%	29.56%	4.02%	29.23%

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 3 Decomposition Results

	Pre	Post	Change	Decomposition		
				Composition	Propensity	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)
1990-2000						
RC	8.17%	13.87%	5.70%	23.44%	78.41%	-1.84%
RM	56.65%	40.24%	-16.40%	43.22%	67.52%	-10.74%
Not Working	15.85%	26.63%	10.77%	-8.66%	98.91%	9.75%
No. of Obs.	2,034,153	283,144				
2000-2010						
RC	13.87%	16.70%	2.83%	11.67%	93.96%	-5.63%
RM	40.24%	35.42%	-4.82%	110.67%	6.98%	-17.65%
Not Working	26.63%	28.02%	1.39%	124.53%	-64.15%	39.63%
No. of Obs.	283,144	426,636				
2005-2015						
RC	14.11%	19.20%	5.09%	11.23%	86.26%	2.51%
RM	38.26%	31.58%	-6.67%	72.47%	48.80%	-21.26%
Not Working	27.77%	30.76%	2.99%	60.00%	59.62%	-19.62%
No. of Obs.	806,712	518,210				
1990-2015						
RC	8.17%	19.20%	11.03%	15.57%	73.56%	10.86%
RM	56.65%	31.58%	-25.06%	67.60%	66.39%	-33.99%
Not Working	15.85%	30.76%	14.90%	6.92%	92.79%	0.29%
No. of Obs.	2,034,153	518,210				

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 4.A Change in routine manual jobs by demographic group: 1990-2015

	females			males		
	18-29	30-49	50-59	18-29	30-49	50-59
Primary School Graduates or Less	**13.30%**	**20.07%**	1.58%	**10.77%**	**17.98%**	6.07%
Secondary School Graduates	**15.38%**	0.23%	-2.91%	**19.72%**	-0.50%	-6.01%
High School Graduates	6.10%	2.67%	-0.42%	6.14%	0.36%	-2.44%
Some College Graduates or Above	-0.78%	-1.27%	-0.06%	-2.27%	-3.32%	-0.39%

Note: The changes within a demographic group that can account for the majority of the total changes are highlighted in **bold font**.

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 4.B Six key demographic groups responsible for decline in routine manual jobs from 1990 to 2015

	Population share			Fraction in RM		
	1990	2015	Change	1990	2015	Change
Females of Primary School Graduates or Less						
Age 18 -29	4.25%	0.40%	-3.85%	81.79%	35.07%	-46.72%
Age 30 -49	9.54%	3.40%	-6.15%	66.79%	39.59%	-27.20%
Females of Secondary School Graduates						
Age 18 -29	8.21%	4.23%	-3.98%	63.68%	32.44%	-31.24%
Males of Primary School Graduates or Less						
Age 18 -29	3.25%	0.36%	-2.89%	89.84%	60.62%	-29.21%
Age 30 -49	7.07%	2.35%	-4.72%	85.71%	66.07%	-19.65%
Males of Secondary School Graduates						
Age 18 -29	9.51%	4.27%	-5.24%	77.98%	57.95%	-20.02%

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 4.C Employment structure change of the six key demographic groups: 1990-2015

	NRC	RC	NRM	RM	Not Working
Females of Primary School Graduates or Less					
Age 18 -29	1.28%	9.29%	6.64%	-46.72%	29.50%
Age 30 -49	0.37%	6.26%	4.21%	-27.20%	16.36%
Females of Secondary School Graduates					
Age 18 -29	-1.48%	11.00%	2.28%	-31.24%	19.44%
Males of Primary School Graduates or Less					
Age 18 -29	1.89%	6.31%	6.13%	-29.21%	14.89%
Age 30 -49	0.78%	6.04%	0.59%	-19.65%	12.24%
Males of Secondary School Graduates					
Age 18 -29	1.24%	7.83%	5.43%	-20.02%	5.52%

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 5. A Change in routine cognitive jobs by demographic group: 1990-2015

	females			males		
	18-29	30-49	50-59	18-29	30-49	50-59
Primary School Graduates or Less	-0.28%	-0.74%	0.28%	-0.35%	-0.74%	-0.14%
Secondary School Graduates	1.05%	**10.31%**	2.19%	0.36%	6.89%	3.00%
High School Graduates	1.91%	**8.53%**	1.11%	1.58%	7.27%	3.61%
Some College Graduates or Above	**9.95%**	**13.79%**	0.90%	**8.77%**	**17.40%**	3.35%

Note: The changes within a demographic group that can account for the majority of the total changes are highlighted in **bold font**.

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 5.B Six key demographic groups responsible for rise in routine cognitive jobs from 1990 to 2015

	Population share			Fraction in RC		
	1990	2015	Change	1990	2015	Change
Females of Secondary School Graduates						
Age 30 -49	7.24%	11.46%	4.22%	13.93%	18.72%	4.80%
Females of High School Graduates						
Age 30 -49	4.61%	5.48%	0.87%	14.12%	29.06%	14.95%
Females of Some College Graduates or Above						
Age 18 -29	1.24%	5.59%	4.35%	6.03%	20.98%	14.94%
Age 30 -49	0.73%	5.18%	4.45%	8.86%	30.60%	21.75%
Males of Some College Graduates or Above						
Age 18 -29	2.01%	5.21%	3.21%	7.57%	21.47%	13.90%
Age 30 -49	1.52%	5.91%	4.40%	13.68%	35.97%	22.29%

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 5.C Employment structure change of the six key demographic groups: 1990-2015

	NRC	RC	NRM	RM	Not Working
Females of Secondary School Graduates					
Age 30 -49	-9.57%	4.80%	-0.84%	-19.78%	25.39%
Females of High School Graduates					
Age 30 -49	-25.75%	14.95%	0.00%	-17.64%	28.44%
Females of Some College Graduates or Above					
Age 18 -29	-24.02%	14.94%	0.92%	-1.11%	9.27%
Age 30 -49	-38.04%	21.75%	-0.43%	3.09%	13.63%
Males of Some College Graduates or Above					
Age 18 -29	-32.14%	13.90%	1.03%	6.61%	10.60%
Age 30 -49	-36.12%	22.29%	0.06%	9.46%	4.30%

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 6. A Change in not-working by demographic group: 1990-2015

	females			males		
	18-29	30-49	50-59	18-29	30-49	50-59
Primary School Graduates or Less	-2.95%	-4.82%	-11.48%	-0.74%	1.34%	-1.85%
Secondary School Graduates	1.05%	**22.26%**	**14.35%**	-1.79%	8.02%	6.03%
High School Graduates	1.88%	**10.69%**	**11.19%**	-0.61%	4.55%	5.00%
Some College Graduates or Above	**15.46%**	5.14%	2.26%	**11.53%**	2.32%	1.20%

Note: The changes within a demographic group that can account for the majority of the total changes are highlighted in **bold font**.

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 6.B Six key demographic groups responsible for increase in not-working from 1990 to 2015

	Population share			Fraction in Non-employment		
	1990	2015	Change	1990	2015	Change
Females of Secondary School Graduates						
Age 30 -49	7.24%	11.46%	4.22%	9.64%	35.03%	25.39%
Age 50 -59	0.86%	4.12%	3.26%	62.19%	64.90%	2.71%
Females of High School Graduates						
Age 30 -49	4.61%	5.48%	0.87%	4.17%	32.61%	28.44%
Age 50 -59	0.49%	2.32%	1.83%	37.01%	79.63%	42.62%
Females of Some College Graduates or Above						
Age 18 -29	1.24%	5.59%	4.35%	41.05%	50.32%	9.27%
Males of Some College Graduates or Above						
Age 18 -29	2.01%	5.21%	3.21%	36.32%	46.92%	10.60%

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Table 6.C Employment structure change of the six key demographic groups, 1990-2015

	NRC	RC	NRM	RM	Not Working
Females of Secondary School Graduates					
Age 30 -49	-9.57%	4.80%	-0.84%	-19.78%	25.39%
Age 50 -59	-13.93%	0.12%	1.59%	9.51%	2.71%
Females of High School Graduates					
Age 30 -49	-25.75%	14.95%	0.00%	-17.64%	28.44%
Age 50 -59	-44.37%	0.38%	0.55%	0.81%	42.62%
Females of Some College Graduates or Above					
Age 18 -29	-24.02%	14.94%	0.92%	-1.11%	9.27%
Males of Some College Graduates or Above					
Age 18 -29	-32.14%	13.90%	1.03%	6.61%	10.60%

Sources: Authors' own calculations based on individuals aged 18-59, excluding those living in villages or those disabled from National Population Census of China in 1990, 2000, 2010, and 1% Mini-Census of China in 2005 and 2015.

Appendix

The classification method of different occupation categories in our analysis based on the classification and codes of occupations of China and their comparisons with the method Cortes et al. (2017) used in their analysis of the United States

	Cortes, Jaimovich and Siu (2017) (used in their analysis of the United States)	GB/T 6565-2015(used in 2015 mini-census)	GB/T 6565-2009 (used in 2010 census)	GB/T 6565-1999(used in 2000 census and 2005 mini-census)	GB/T 6565-1986 (used in 1990 census)
NRC	0010-3540：Management, Business, Science, and Arts Occupations	10100-19900： leaders of party organizations, government offices, mass and social organizations, enterprises and public institutions；20100-29900：professional and technical personnel	010-050：leaders of party organizations, government offices, mass and social organizations, enterprises and public institutions；111-290：professional and technical personnel	010-050：leaders of party organizations, government offices, mass and social organizations, enterprises and public institutions；111-290：professional and technical personnel	011-150：professional and technical personnel；211-242：leaders of government offices, party organizations, enterprises and public institutions
NRM	3600-4650: Service Occupations	30200-30299：policemen, security guards and firefighters；40300-40399： service staff of accommodation and catering；40704-40705： service staff and security guards of tourism and public visiting places ；40900-40999： service staff of water conservancy, environment protection and other public facilities；41001-41099： residents service personnel；	321-329：policemen, security guards and firefighters；431-439：service staff of catering；441-449：service staff of accommodation, tourism, fitness and entertainment places；460：health care service staff；471-478、	321-329：policemen, security guards and firefighters；431-439：service staff of catering；441-449：service staff of accommodation, tourism, fitness and entertainment places；460：health care service staff；471-478、	321-329：policemen, security guards and firefighters；431-433、499：dealers and other commercial staff；511-540：service staff, chefs and tourist guides

		41300-41399： service staff of culture, sports and entertainment industries；41400-41499： health care service staff；49900：other service staff	483-489： social and residents service personnel；490： other service staff	483-489： social and residents service personnel；490： other service staff	
RC	4700-5940： Sales and Office Occupations	30100-30199； 39900： Office Clerks； 40100-40199： wholesaling and retailing staff； 40501-40599： financial service staff； 40400-40499：information transmission, software and information technology industries staff； 40600-40699： real estate service staff； 40701-40703、40706-40799： satff of leasing, consulting, human resources, market management, conference and exhibition businesses；40801-40899：support workers of technicians	311-319、390： Office Clerks； 411-419：staff of wholesaling and retailing, leasing, market management, conference and exhibition businesses	311-319、390： Office Clerks； 411-419：staff of wholesaling and retailing, leasing, market management, conference and exhibition businesses	311-319、399： Office Clerks； 411-422： staff of wholesaling and retailing
RM	6200-9750： Construction and Maintenance Occupations, and Production, Transportation, and Material Moving Occupations	40200-40299： staff of transportation and storage industry and mail business； 41100-41199： electric power, fuel gas and water supply industries staff ； 41200-41299： repairmen and producers； 50100-59900： workers of agriculture, forestry, animal husbandry and fishery； 60100-69900： manufacturing and construction workers	331-339：staff of mail business； 421-429：staff of storage industry； 451-459：staff of transportation industry； 479-482： repairmen and producers； 511-592： workers of agriculture, forestry, animal husbandry,	331-339：staff of mail business； 421-429：staff of storage industry； 451-459：staff of transportation industry； 479-482： repairmen and producers； 511-592： workers of agriculture, forestry, animal husbandry,	331-339： staff of mail business； 551-559、599： repairmen of daily commodities； 600-699： workers of agriculture, forestry, animal husbandry and fishery； 711-997: manufacturing

			fishery and water conservancy industry; 611-993: manufacturing and construction workers	fishery and water conservancy industry; 611-993: manufacturing and construction workers	, construction and transportation workers