Polarization of Employment and Wages in China*

Belton M. Fleisher
fleisher.1@osu.edu
Ohio State University, & Hunan University Center for Economics, Finance, and Management Studies

William H. McGuire
wmcguire@uw.edu
University of Washington Tacoma

Yaqin Su
yaqinsu2013@gmail.com
Hunan University Center for Economics, Finance, and Management Studies

Min Qiang Zhao
kent_zhao@xmu.edu.cn
WISE, Xiamen University

Abstract

We find polarization of employment from middle-income Skilled jobs to work in the Unskilled and Self-Employment job categories using data from CHIPS 1995-2013. This redistribution of employment is consistent with the automation of routine noncognitive tasks in the skilled sector as analyzed in a number of papers on advanced economies and some work on the Chinese economy. While the Unskilled and Self-Employment jobs remain below median income, the redistribution of employment has not been associated with a commensurate polarization of labor income. We find no evidence of polarization of either employment or income at the upper end of the job-skill spectrum.

Key Words polarization; innovation; wage growth; China
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1. Introduction

Concern over rising wages (Ge & Yang, 2011) complemented by China's integration into the world economy encourages domestic efforts to develop labor-saving technology enabling the substitution of machines for routine tasks. We report evidence whether automation of routine tasks to offset rising labor costs has resulted in polarization of jobs and incomes at the lower- and higher- ends of the job-skill spectrum in China. We find evidence of employment polarization from 1995 to 2013 for jobs paying below median income in 1995, resulting in a redistribution of workers to the bottom of the wage-skill distribution. At the same time, mean income in the lowest-paying job category rose from approximately 60% to about 65% of income in the job category ranked highest in 1995.

The development of capital- and skilled-worker intensive technology in advanced economies in the later decades of the 20th century has led to polarization through two channels: (i) its adoption reduces employment of workers in routine manual and cognitive tasks, moving displaced workers to less-routine employment at the lower end of the wage spectrum; (ii) its creation increases demand for workers in higher-skilled occupations, leading to polarization at the upper end of the wage distribution. The resulting reallocation of workers to lower- and higher-skill jobs has been associated with slower wage increases for middle-skill jobs.

The use of machines capable of substituting for manual and cognitive tasks and of more- for less-skilled workers in advanced economies has received intensive analysis in recent papers by Autor & Dorn (2013), Aghion, B. Jones, & C. Jones (2016) and many previous publications that they cite, including those of Acemoglu (2010) and Acemoglu & Autor (2011). The possible impact of technology on job polarization in a broad range of developing economies is examined by Maloney and Molina (2016).

Unequal wage growth, rising income inequality and polarization in China have been studied by Khan, Schettino, & Gabriele (2017) who report that polarization of incomes has reduced the share in the benefits of China's economic growth of those who receive middle-level incomes, and that many income recipients classified as "middle class" have moved toward the lower end of the income distribution. Molero-Simarro (2017) relates the growing share of China's top incomes to the increasing importance of non-labor income's impact on inequality.

We analyze changes over the distribution of employment and associated incomes across eight employment categories over the 18-year period 1995-2013. Although there has been a substantial increase in the proportion of workers in the least-skilled job category, we find no evidence of polarization toward jobs at the upper end of the 1995 income distribution.

In addition, we develop a multinomial logit model of workers' choices among the eight job categories and nonemployment. The estimation results allow us to identify factors underlying the reallocation of employment among the categories: (i) education of the workforce; (ii) age and gender mix of the workforce; (iii) provincial real wage levels (independent of changes in human capital variables); and (iv) parameters of reduced-form utility functions. The most important contribution to the changes in employment shares has been (iii) and (iv), which we attribute to major structural changes in the demand for workers across employment categories.

The next section contains our methodology; section 3 discusses our data and summary statistics; section 4 reports the counterfactual simulations that demonstrate the relative importance of changes in economic structure versus changes in aggregate workforce characteristics on the distribution of workers across job types; and section 5 concludes.

2. Methodology: Accounting for Job Choices.

We use a multinomial logit model (MNL) of job choice to analyze changes in employment shares across eight job categories ranked according to their reported job-related incomes. The MNL estimation results are used to simulate the probabilities of worker allocation to job categories in 1995 and 2013 conditional on their age, education, gender, and a measure of provincial real wage level. We use the probabilities to construct counterfactual simulations of how employment shares would have evolved between 1995 and 2013 under two scenarios: (i) if the probability function of choosing a job in 2013 were applied to the population of 1995; and (ii) if the probability function of choosing a job in 1995 were applied to selected population characteristics of 2013. The degree to which simulated changes in the 2013 probability function applied to 1995 population characteristics match observed changes in employment shares informs us the extent to which changes in factor demand, supply, and their interactions can account for observed redistribution of workers across job categories. Conversely, applying 2013 population characteristics to the 1995 probability function provides a measure of the impact of age, gender, and provincial wage level on the distribution of workers across employment categories.

Multinomial Logit Estimation. We assume workers maximize utility by choosing a job offering the highest return to their cognitive and noncognitive skills, given the job's working conditions (e.g., safety, comfort, working hours, flexibility, etc.). Employers maximize profits by choosing workers so that the marginal cost of labor is equal to their marginal contribution to the value of output (a function of their cognitive and noncognitive skills). We take workers' skills to be predetermined, but preferences for job characteristics associated with working conditions (safety, job amenities, flexibility in work hours, and so on) may reasonably be assumed to be income elastic.

In this framework, a technology shock, e. g., substituting sophisticated machinery for workers to perform routine tasks, affects observed employment choices both directly in the impacted employment category and indirectly as displaced workers choose to work in other job categories or not to work in the market[1].We simulate these probabilities using estimation results from a multinomial logit equation. The indirect utility of choosing a choice *j* is specified as follows:

$$\begin{aligned} U_{ijt} &= \beta_{jt} + \beta_{jt}^{w} W_{ijt} + \beta_{jt}^{x} X_{it} + \varepsilon_{ijt},\ j = 1, \dots, J \\ U_{0t} &= \beta_{0t} + \varepsilon_{i0t} \end{aligned} \tag{1}$$

where individual *i* will choose occupation *j* (or to be non-employed) that provides the highest utility level in year *t*;

- *X* is a vector of individual characteristics, specifically
    - *Edu* denotes years of schooling;
    - *Age* denotes the individual's age;
    - *Female* denotes female gender;
- β_{jt}, β_{0t}, β_{jt}^{w} and β_{jt}^{x} are preference parameters that possibly change over time;
- W_{ijt} is the real wage that individual *i* would earn if choosing job *j* in year *t*.

It is fundamentally important for our research strategy that we cannot observe W_{ijt} over all *j* for each individual *i*. We observe only the employment category chosen. This limits our ability to extract information on fundamental parameters of exogenous variation in the regressors from our estimation results.[2] To accommodate this limitation, we do not attempt identify

[1] Cortes, Jaimovich, & Siu (2017) refer to the *propensity* to work in a given job. Fleisher, McGuire, Wang, & Zhao (2018) analyze the impact of wage-induced technology change on aggregate employment and wages in China over the period 1996-2007.
[2] Alternatively, we could estimate Mincer equations by occupation and province and then use the estimated equations to predict what each individual would earn if they chose another occupation. A method developed by Dahl (2002) can be used to control for non-random sorting across occupations. This approach is not feasible in our paper because of data limitation.

workers' job choices conditional on their opportunity wage structure. Rather we incorporate a variable that reflects the general wage level in provincial labor markets—an index of provincial labor scarcity. We obtain this wage variable by estimating a hedonic wage model (Mincer equation):

$$W_{ijt} = \gamma_t^x X_{it} + \eta_{p(i),t} + \upsilon_{ijt} \tag{2}$$

where X is the vector defined above, the γ terms reflect both supply and demand in the labor market as workers choose jobs while employers substitute capital for labor and adopt labor-saving technology in response to rising labor costs. The term $\eta_{p(i),t}$ is a set of dummy variables for province, year, and their interaction terms, and we define $\bar{W}_t^{p(i)} = \eta_{p(i),t}$, the normalized average wage in province $p(i)$ in year t, to represent a normalized provincial wage variable. We use this normalized provincial wage variable in our development of equation (1) because we want it to separate its effects from worker characteristics already represented in X_{it} .

By inserting $\bar{W}_t^{p(i)} = \eta_{p(i),t}$ in equation (1), the indirect utility function becomes:

$$\begin{aligned} U_{ijt} &= \beta_{jt} + \beta_{jt}^w(\gamma_t^x X_{it} + \bar{W}_t^{p(i)} + \upsilon_{ijt}) + \beta_{jt}^x X_{it} + \varepsilon_{ijt}, \qquad j = 1,\ldots,J \\ &= \beta_{jt} + \beta_{jt}^w \bar{W}_t^{p(i)} + (\beta_{jt}^w \gamma_t^x + \beta_{jt}^x) X_{it} + \beta_{jt}^w \upsilon_{ijt} + \varepsilon_{ijt} \\ &= \beta_{jt} + \beta_{jt}^w \bar{W}_t^{p(i)} + \alpha_{jt}^x X_{it} + \omega_{ijt} \\ U_{0t} &= \beta_{0t} + \varepsilon_{i0t} \end{aligned} \tag{3}$$

where $\alpha_{jt}^x = \beta_{jt}^w \gamma_t^x + \beta_{jt}^x$ and $\omega_{ijt} = \beta_{jt}^w \upsilon_{ijt} + \varepsilon_{ijt}$. α_{jt}^x are not preference parameters because they involve the γ terms. To facilitate our estimation, we assume that ω_{ijt} and ε_{i0t} follow the standard type I extreme value distribution. Equation (3) underlies estimation of the multinomial logit model that is the basis for our counterfactual simulations. To simplify the notation, we use ϕ_t to denote the set of α_{jt}^x, β_{jt}^w, β_{jt}, and β_{0t}.

From equation (3) we see that the changes in the coefficients of reduced-form utility functions capture changes in workers' utility function as well as in firms' labor demand (i.e., substitution under fixed technology and innovation-induced changes in production parameters) and their interactions.

<u>Deconstructing Changes in Employment Shares.</u> The MNL estimation results based on equation (3) provide the basis for our simulation exercise, which can show how much of the change in employment shares between 1995 and 2013 can be attributed to changes the demographic characteristics of workers, change in $\overline{W}$, and/or changes in ϕ.

To implement this deconstruction we modify the decomposition formula of Cortes, Jaimovich, and Siu (2007) by first specifying

$$\bar{\pi}_t^j(\phi_t,\overline{W}_t)=\sum_g \Pr_j(\phi_t,\overline{W}_t,X_g)\cdot f_t(X_g) \tag{4}$$

where $\bar{\pi}_t^j(\phi_t,\overline{W}_t)$ denotes the share of employment in job category *j* (including non-employment), given ϕ_t, $\overline{W}_t$ and a demographic distribution in year *t*; *g* denotes a demographic group, based on age, gender, and educational attainment; X_g is a set of demographic characteristics of group *g*; $\Pr_j(\phi_t,\overline{W}_t,X_g)$ is a fraction of individuals from the demographic group *g*, who choose job category *j* given ϕ_t and $\overline{W}_t$; and $f_t(X_g)$ denotes a population share of the demographic group *g* in year *t*.

We can decompose the total change of the employment share in job category *j* between year 0 and year *T* using the following formulation:

$$\begin{aligned}\bar{\pi}_T^j-\bar{\pi}_0^j &=\sum_g \Pr_j(\phi_T,\overline{W}_T,X_g)\cdot f_T(X_g)-\sum_g \Pr_j(\phi_0,\overline{W}_0,X_g)\cdot f_0(X_g)\\ &=\sum_g \Pr_j(\phi_0,\overline{W}_0,X_g)\cdot\left(f_T(X_g)-f_0(X_g)\right)+\\ &\quad\sum_g\left(\Pr_j(\phi_T,\overline{W}_T,X_g)-\Pr_j(\phi_0,\overline{W}_0,X_g)\right)\cdot f_0(X_g)+\\ &\quad\sum_g\left(\Pr_j(\phi_T,\overline{W}_T,X_g)-\Pr_j(\phi_0,\overline{W}_0,X_g)\right)\cdot\left(f_T(X_g)-f_0(X_g)\right)\end{aligned} \tag{5}$$

where the first component of the right-hand-side of equation (5) captures the composition effects, which focus on the changes in the population shares of the demographic group *g*. The second component captures the propensity effects, which focus on the changes in the conditional probability of choosing each job category (including non-employment), given the changes in ϕ_t and $\overline{W}_t$. The third component captures the interaction effects, which focus on the co-movement of changes in both composition and propensity.[3] The propensity effects can be further decomposed according to the changes in ϕ_t or the normalized average wages:

[3] Using the notation of equation (4), the first component of the right-hand-side of equation (5) can be expressed as $\bar{\pi}_T^j(\phi_0,\overline{W}_0)-\bar{\pi}_0^j(\phi_0,\overline{W}_0)$, and the second component can be expressed as $\bar{\pi}_0^j(\phi_T,\overline{W}_T)-\bar{\pi}_0^j(\phi_0,\overline{W}_0)$.

$$\sum_g \begin{pmatrix} \Pr_j(\phi_T, \bar{W}_T, X_g) - \\ \Pr_j(\phi_0, \bar{W}_0, X_g) \end{pmatrix} \cdot f_0(X_g) = \sum_g \begin{pmatrix} \Pr_j(\phi_0, \bar{W}_T, X_g) - \Pr_j(\phi_0, \bar{W}_0, X_g) + \\ \Pr_j(\phi_T, \bar{W}_T, X_g) - \Pr_j(\phi_0, \bar{W}_T, X_g) \end{pmatrix} \cdot f_0(X_g) \tag{6}$$

or

$$\sum_g \begin{pmatrix} \Pr_j(\phi_T, \bar{W}_T, X_g) - \\ \Pr_j(\phi_0, \bar{W}_0, X_g) \end{pmatrix} \cdot f_0(X_g) = \sum_g \begin{pmatrix} \Pr_j(\phi_T, \bar{W}_T, X_g) - \Pr_j(\phi_T, \bar{W}_0, X_g) + \\ \Pr_j(\phi_T, \bar{W}_0, X_g) - \Pr_j(\phi_0, \bar{W}_0, X_g) \end{pmatrix} \cdot f_0(X_g) \tag{7}$$

where equation (6) indicates the impact of wage changes holding the indirect utility function parameters at ϕ_0, and the impact of changing the indirect utility function parameters holding the normalized average wages at $\bar{W}_T$. Equation (7) is similar to equation (6) except that it uses a different set of the conditioning variables.

3. Data and Summary Statistics.

Our primary source of data is the CHIP urban waves conducted in 1995, 2002, and 2013. The CHIP surveys do not sample every province in China, and the coverage of provinces changes slightly year to year. We use data from provinces represented in all three waves: Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Chongqing, Sichuan, Yunnan, and Gansu. Observations with missing data or for provinces not included in all surveys are deleted. For 2013 the data we use account for approximately 66% of the total observations and 76% of all adults (those older than 15 years); for 2002, our estimation sample includes 80% of all observations and 94% of all adults; for 1995 the corresponding proportions are 75% and 94%, respectively.

The CHIP questionnaires request information on respondents' occupations and in some cases industrial sectors, which vary in number and detail among the CHIP waves. We aggregate the more detailed job categories available in the 2013 wave into seven categories we can match in the 1995 and 2002 waves (plus "Other" and "Not Working"). This aggregation has the further advantage of avoiding jobs so finely defined that they have too few observations for meaningful statistical analysis. The availability of valid answers to questionnaire items on sources of income requires us to measure wages using reported annual income, which we deflate using provincial indexes of consumer prices.

Sample statistics for the CHIPS employment categories are reported in table 1. Employment-type definitions are reported in column (1). Mean employment shares, age, school years, real income, and proportion of female respondents in each job category are reported in columns (2a) to (6c), respectively. Mean schooling affords a measure of worker cognitive skills. Age reflects important components of human-capital accumulation other than schooling, and gender reflects a mixture of employer discrimination, physical human capital, and work attitudes and tastes for tasks and working environment.

Overview of the CHIP Sample Statistics: Employment and Income Polarization. Figures 1-3 illustrate changes in employment shares and mean labor income across 7 employment categories for the periods 1995-2013, 1995-2002, 2002-2013 respectively. Observations are ranked along the horizontal axes in increasing order of their 1995 mean income, similarly to the ranking of jobs by Autor and Dorn (2013) [4]. The most striking observation is that there has been a massive shift of workers from the Skilled category, where mean income was approximately 95% of the median (Self-Employed and Clerical & Office) in 1995, to the Unskilled category, on the left tail. The unskilled employment share more than doubled between 1995 and 2013 while the share of workers in the skilled category declined to approximately one-third of its1995 level. Self-Employed is the only other category to increase its share of workers between 1995 and 2013. We find no evidence of employment-share polarization to the right tail of job categories ranked by their 1995 incomes.

The subperiods illustrated in figures 2 and 3 both display a substantial growth in the employment share of unskilled workers and a downward trend left-to-right in share growth across skill categories. The trends illustrated in figures 1-3 are consistent with those of Khan, Schettino, & Gabriele (2017) who report polarization toward the lower end of the job-income spectrum in China.

The Skilled Worker jobs include most workers classified as Operatives in the Construction, Mining, and Manufacturing sectors and are thus likely to contain a substantial portion of routine manual tasks, while Clerical/Office jobs are likely to contain routine cognitive tasks. Both types of tasks are subject to automation. The Skilled job category exhibits higher wage growth than its lower-wage adjacent job categories (Unskilled and Self-Employed) over the period 1995-2002, while from 2002 to 2013, Skilled jobs experienced lower wage growth

[4] Autor and Dorn's access to a far larger data base and catalog of occupational descriptions allow them to rank nearly 400 job types into decile bins in ascending order of mean wage, whereas our far more limited sample requires us simply to rank individual job categories, and available data preclude accurate measurement of hourly wage. Autor and Dorn's categorization of jobs into those with worker tasks that can be more readily automated follows the work of Autor, Levy, & Murnane (2003).

than the Unskilled/Service job category and somewhat higher growth than the Self-Employed category. The Clerical/Office job category exhibits a negligible change in employment share 1995-2002, but a modest decline over 2002-2013 dominates the entire 1995-2013 period.

We conjecture that the increasing income of Unskilled relative to Skilled job reflects increasing demand for services provided by workers in the Unskilled category that has buffered the downward-directed wage pressure coming from the availability automation-displaced workers in the Skilled and perhaps in the Clerical/Office categories.

Mean real income growth for Owner/Managers stands out as highest among all job categories in both 1995-2002 and 2002-2013. Our data do not permit us to separate labor and capital income for Owner/Managers. While the relatively high-income growth among Owner/Managers contributed to total-income polarization as analyzed in Khan et al. (2018), it is unclear whether Owner/Manager income growth provides evidence supporting growing returns to their ability to perform complex tasks, particularly when we note that mean school years for Owner/Managers grew by 1.37 years between 1995 and 2013 compared to 2.29 years for Clerical/Office workers and 1.27 years for Professional workers (whose mean schooling was only slightly less than 14 years in 2013).

It is critical not to interpret the soaring share of workers in the unskilled-job category as representing a decline in the abilities of workers in China to carry out specific tasks. As indicated in table 1, mean schooling increased by 1.7 years and by approximately 2 years respectively for workers in the Unskilled- and Skilled-job categories between 1995 and 2013, and annual income growth was similar to that in other job categories, with the exception of the owner/manager group.

Overview of the CHIP Sample Statistics: Schooling and Experience. Although Chinese workers were better-educated on average in 2013 than in 1995, table 1 and figure 4 reveal that over the 2002-2013 period, mean schooling of Skilled workers rose at more than double the rate of those in the Unskilled category. We attribute this divergence to changes in the worker attributes required for performing the increasingly automated tasks of Skilled jobs. Workers with less schooling evidently found their ways into Unskilled/Service jobs and into Self-Employment, where mean schooling increased by less than in any other job category 2002-2013

Workforce experience reflects the timing and accumulated amount of workers' exposure to on-the-job training. Workers in the early years of their working life will have accumulated less training on average but may have an advantage over those with more experience in a period of rapidly changing technology. Figure 5 reveals that while average workforce experience rose by about one-half year per annum during the 1995-2002 period for skilled workers, it declined sharply in 2002-2013 both absolutely and relative to all job categories except Government Agency or Enterprise Directors. We infer that jobs in the Skilled category increasingly require workers who have received recent training in the techniques needed to operate the higher-technology equipment used in more-automated production.

There was also a substantial change from rising to declining workforce experience between the 1995-2002 and 2002-2013 for Clerical/Office workers and Owner/Managers, suggesting more rapid depreciation of on-the-job acquired human capital for these groups in the later period.

4. Deconstructing Changes in Employment Shares.

We perform a simulation exercise to identify what has determined the change in the distribution of workers across employment categories. .

Marginal Probabilities for Skilled and Unskilled Workers. Before presenting the full simulation results, it is instructive to evaluate some of the marginal probabilities calculated at mean values of equation (3)'s estimation results. They are reported in table 3. To illustrate, we focus on year dummies, the provincial wage and worker education variables in the two job categories exhibiting the most dramatic employment-share shifts during 1995-2013, Skilled and Unskilled jobs in columns (7) and (8). The coefficients of year dummies shift in opposite directions, negatively for the Skilled and positively for the Unskilled, consistent with the shifting of employment shares from the Skilled to Unskilled categories. The coefficients of the provincial wage variable (taken from the hedonic wage equation (2) holding constant the individual human capital variables) indicate that the marginal probability of accepting Skilled jobs exceeded that of accepting Unskilled jobs in high-wage provinces in 1995, which is consistent with high-wage provinces' being "high-skill" provinces. This pattern disappears in the later years of the sample; the estimated provincial wage coefficients in both job categories become insignificantly different from zero in 2002 and 2013. The marginal probability of the Education variable for skilled workers increases algebraically from a significant -0.0095 to an insignificant -0.0016. For the Unskilled, the education coefficients are negative, highly significant, and greater in absolute value than for the Skilled, consistent with the growing education gap (about 0.3 years of schooling) between the skilled- and unskilled job categories over the period 1995-2013.

The Decompositions. The decomposition exercise requires simulating counterfactual changes in employment shares assuming the indirect utility function parameters (ϕ), population characteristics, and/or provincial wage levels changed independently. All simulations are performed using the Mincer equation and multinomial logit parameter estimates described above. To simulate an independent change in the demographic characteristics of the population, we simply ascribe the 1995 provincial normalized wage to individuals in the same province in 2013. We then predict these individuals' employment outcomes in 2013 using the 1995 year-specific parameter estimates from multinomial logit model. We can easily do this in reverse, ascribing the 2013 provincial normalized wages to individuals in 1995, and predicting their outcomes using the 2013 year-specific parameter estimates. We can simulate the wage counterfactual by applying the 2013 provincial normalized wage to individuals in 1995, and then predicting their employment outcomes using the 1995 parameter estimates. Again, we can just as easily do the reverse, applying the 1995 wage to 2013 individuals. Finally, we can simulate the change in ϕ independently simply by applying the 2013 multinomial logit parameters to the 1995 data, or vice versa. Decomposing the total change into composition, propensity, and interaction effects requires combining some of these strategies, as described in equation (5).

We illustrate one subset of these simulations in table 4. It is the $\Delta\phi$ component of the propensity effect in equation (7) – contribution of the change in ϕ at the initial levels of provincial wage ($\overline{W}_0$) and demographic distribution to the probability of a worker of given age and schooling being located in one of the nine job categories (including not working). The illustrated simulation is obtained by subtracting the probabilities of the observed allocation of workers in 1995 from the simulated application of the 2013 ϕ to the 1995 data sample, yielding $(\bar{\pi}_0^j(\phi_T, \overline{W}_0) - \bar{\pi}_0^j(\phi_0, \overline{W}_0))$ for workers who graduated from junior middle school. The top subset represents $\bar{\pi}_0^j(\phi_0, \overline{W}_0)$, and the bottom represents the counterfactual simulation $\bar{\pi}_0^j(\phi_T, \overline{W}_0)$.

For example, the bottom section of table 4 shows that the simulated probability for a junior middle school graduate aged 31-35 to be a Skilled worker in 1995 under the assumption that 2013 parameters (ϕ_T) applied is 0.057. The corresponding simulated probability under the assumption that the 1995 parameters (ϕ_0) applied is 0.22, a simulated 16 percentage points decrease from 1995 to 2013. A similar comparison for the Unskilled category indicates that the probability under the ϕ_0 assumption is 0.21 (top section), while the ϕ_T simulated counterfactual is 0.38, an increase of 17 percentage points between 1995 and 2013.

Table 5 summarizes results from our decomposition exercise. The first row presents the predicted changes in employment share for each category between 1995 and 2013. The second row presents simulated changes in employment shares between 1995 and 2013, given the observed change in the provincial wage variable, holding ϕ and the distribution of demographic characteristics at their 1995 levels. The third row presents changes in employment shares, given the observed change in the provincial wage variable, holding ϕ at their 2013 levels and the distribution of demographic characteristics at their 1995 levels. The fourth row illustrates the results of changes in labor-force composition of age, education, and gender (given 1995 values of ϕ and provincial wage levels). The fifth row presents changes in employment shares due to propensity effects: changes in ϕ and provincial wage levels. The sixth row presents the changes in employment share due to the interaction of the propensity and composition changes. By construction, rows 4-6 fully account for the changes in employment shares reported in row 1.

The results from the first, fourth, and fifth rows of table 5 are visualized in figure 6. The results reported in table 5 and figure 6 show that the propensity effects (fifth row of table 5) dominate the determination of the overall change (first row of table 5), and closely match the 1995-2013 time path of changes in employment-share growth, $\bar{\pi}_T^j(\phi_T, \bar{W}_T) - \bar{\pi}_0^j(\phi_0, \bar{W}_0)$, across all job categories. Another view of the relative importance of the propensity effects is provided in the seventh row of table 5, where we report the ratios (in percent) of the propensity change to employment share changes (row 5 divided by row 1). Focusing on the Skilled, Unskilled, and Self-Employed categories, we see that the ratios in row 7 are 96%, 145%, and 131%, respectively. In contrast, the composition and interaction effects do not appear very important in the determination of the overall change. In every employment category, the composition and interaction effects are smaller in absolute value than the propensity effects.

Recall from equation (5) that the propensity effects include changes in both ϕ and $\bar{W}$. The results in the second and third rows of table 5 isolate the effects of changes in the provincial wage variable ($\bar{W}$). Both of these wage counterfactual scenarios only explain a small part of the observed change in employment shares, especially when we compare them to the overall propensity effects. This suggests that the changes in the reduced form utility function parameters

ϕ are the most important determinants of the changing occupational distribution between 1995 and 2013.

5. Conclusion

Using data for 12 major provinces covered in CHIPS 1995, 2002, and 2013, we observe polarization of employment from middle-income Skilled jobs to work in the Unskilled and into Self-Employment job categories. This redistribution of employment shares is consistent with the automation of routine non-cognitive tasks in the skilled sector. While the Unskilled and Self-Employment jobs remain below median income, our finding that the redistribution of employment has not been associated with a commensurate polarization of labor income (figures 1-3) is consistent with results reported by Cheng and Wan (2015) that business income and, somewhat less so, labor income have reduced polarization of incomes in China over the period 1978-2010. In fact, mean income growth for the Unskilled has exceeded that for workers in Skilled jobs. We find no evidence of employment polarization in the right-tail of the job-category wage distribution. The employment shares of the Professional and Owner-Manager job categories, which should encompass a relatively high proportion of non-automatable tasks, declined from 16.3% of the sample in 1995 to 10.8% in 2013. It remains to be seen how recent breakthroughs in artificial intelligence and information technology will affect employment in these higher-income jobs in China.

To explain these patterns, we estimate a multinomial logit model of workers' choices among eight job categories and nonemployment. The estimation results allow us to attribute changes in workers' occupational choices (including non-employment) to underlying composition, propensity, and interaction effects. Our results suggest that sectoral demand and technological changes - rather than changes in wages or workforce age, gender, and education – played the most important role in reshaping China's occupational distribution between 1995 and 2013. More research is needed to explain why these sectoral demand and technological changes produced a lop-sided semi-polarization in China, in contrast with the experience of countries closer to the world technological frontier.

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Figure 1: Annual Growth in Mean Income and Employment Share (1995-2013)

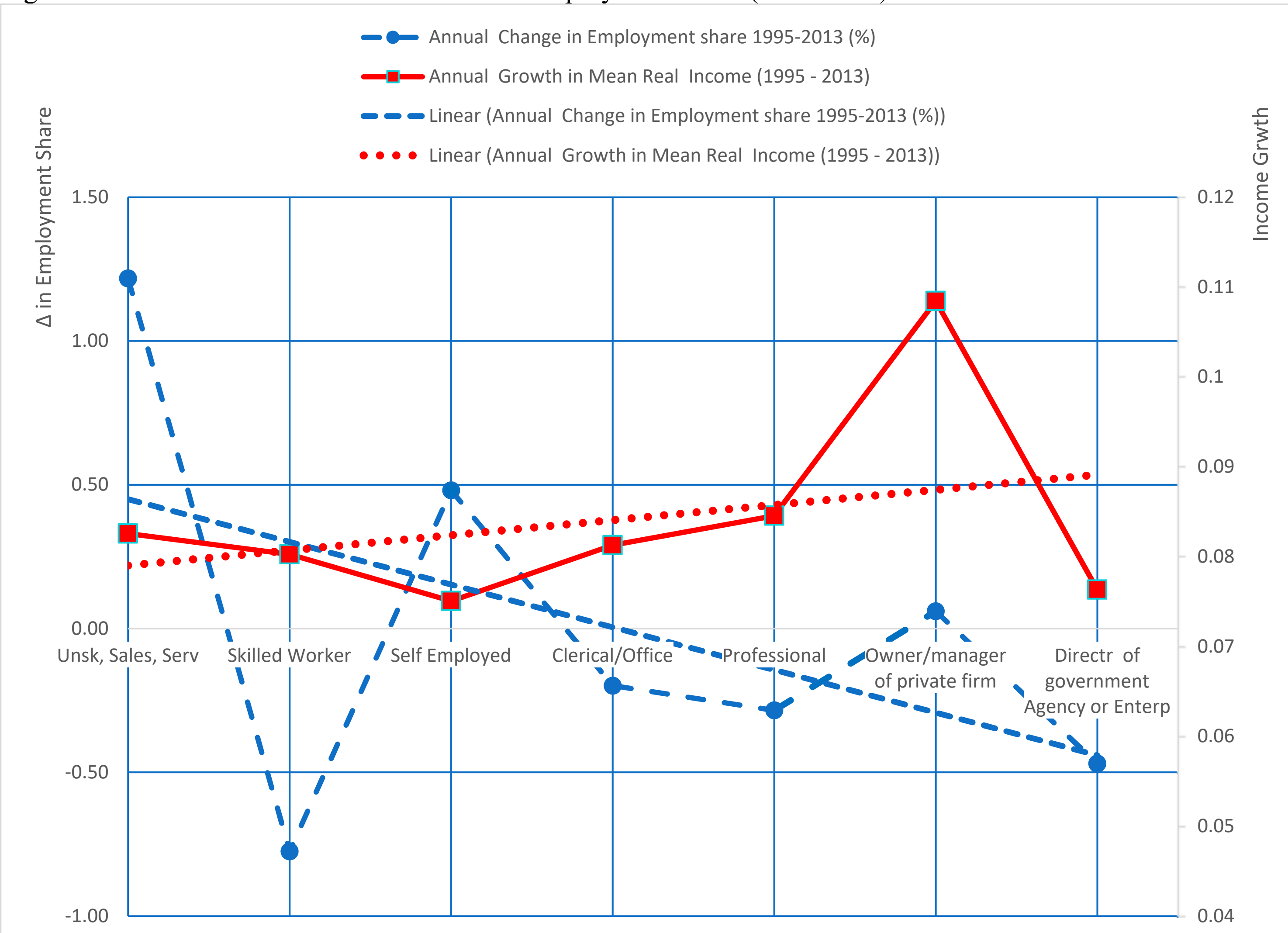

Figure 2: Annual Growth in Mean Income and Employment Share (1995-2002)

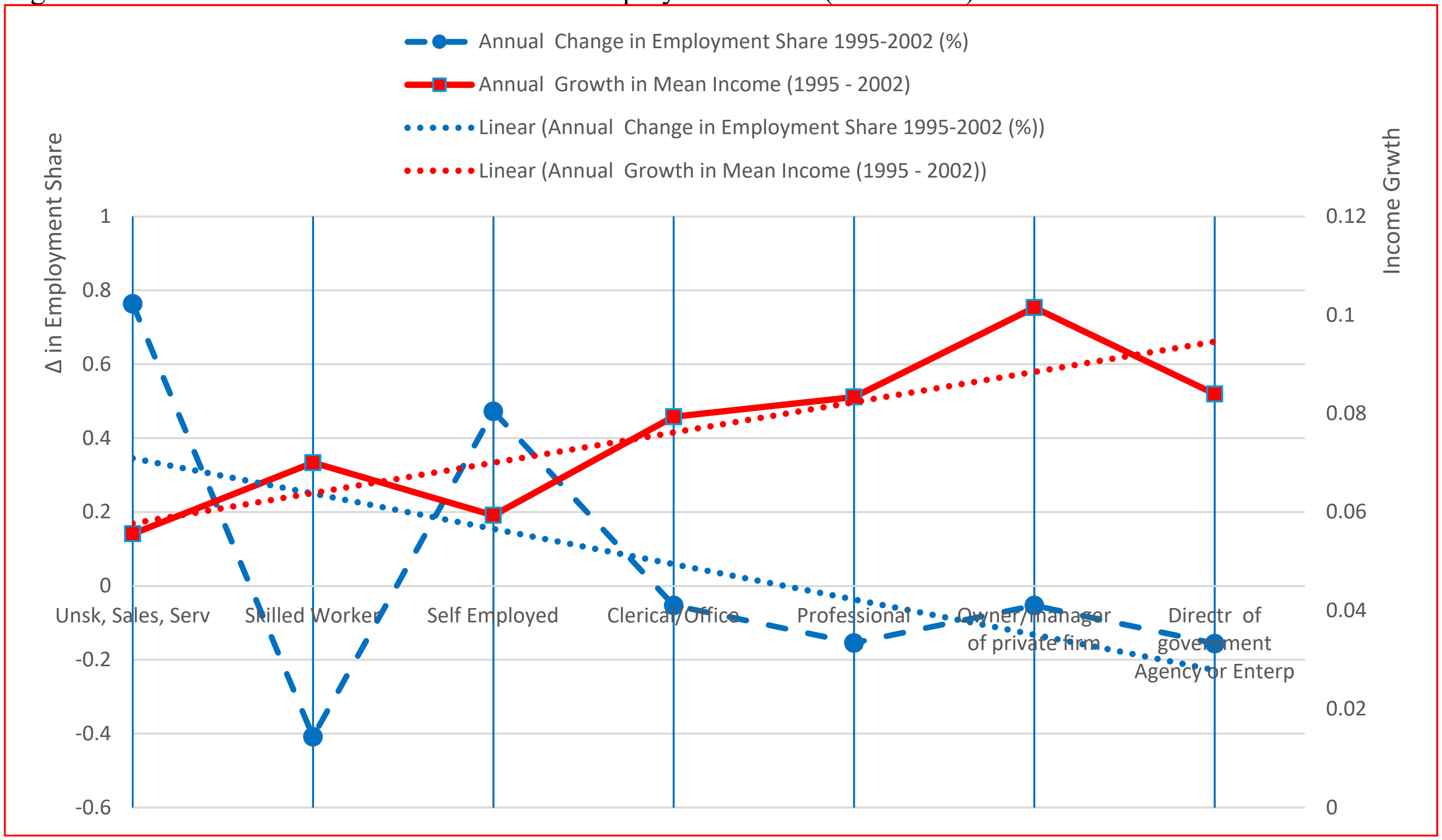

Figure 3: Annual Growth in Mean Income and Employment Shares (2002-2013)

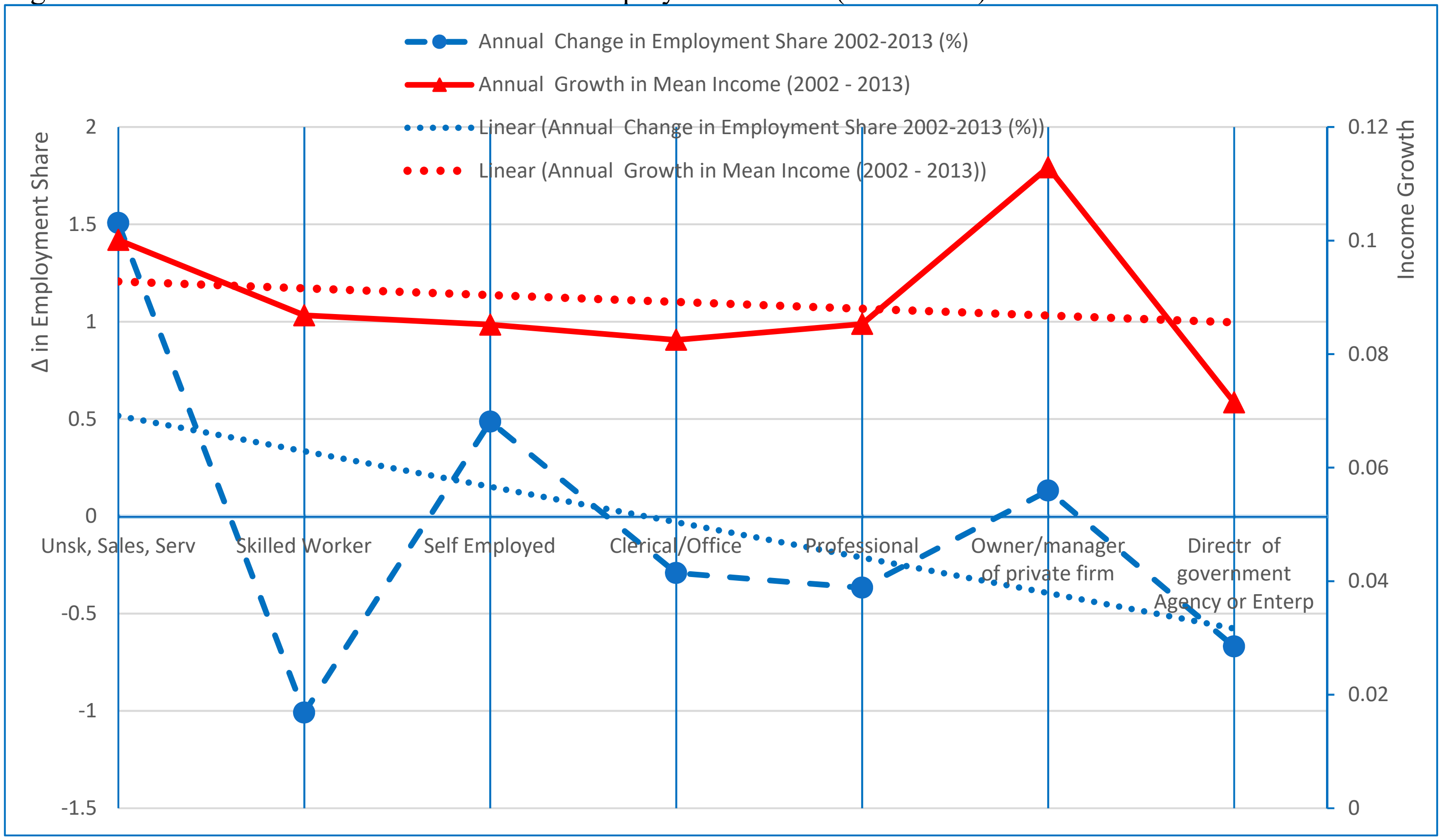

Figure 4: Annual Change in Mean Years of Education

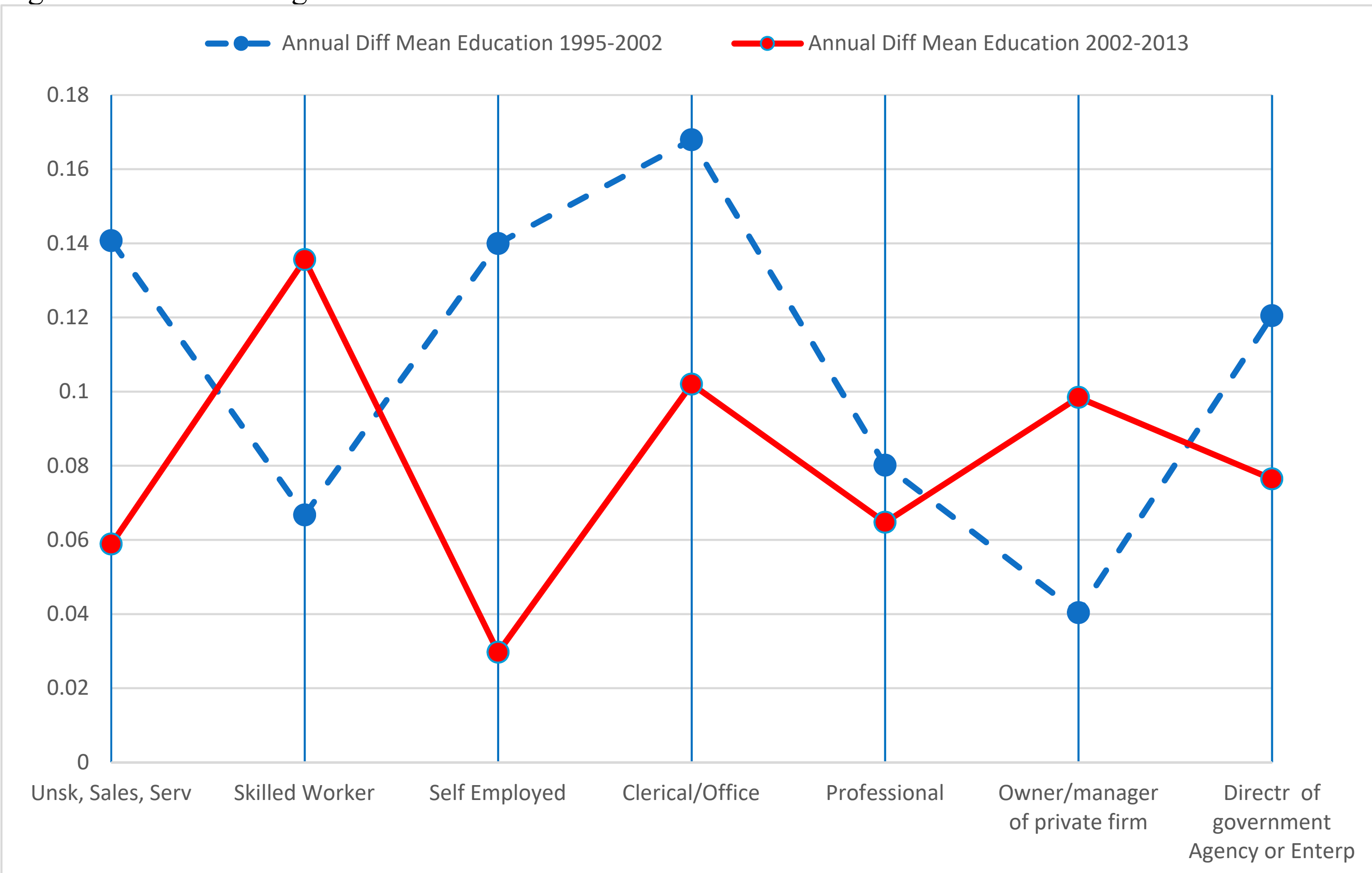

Figure 5: Annual Change in Mean Years of Work Experience

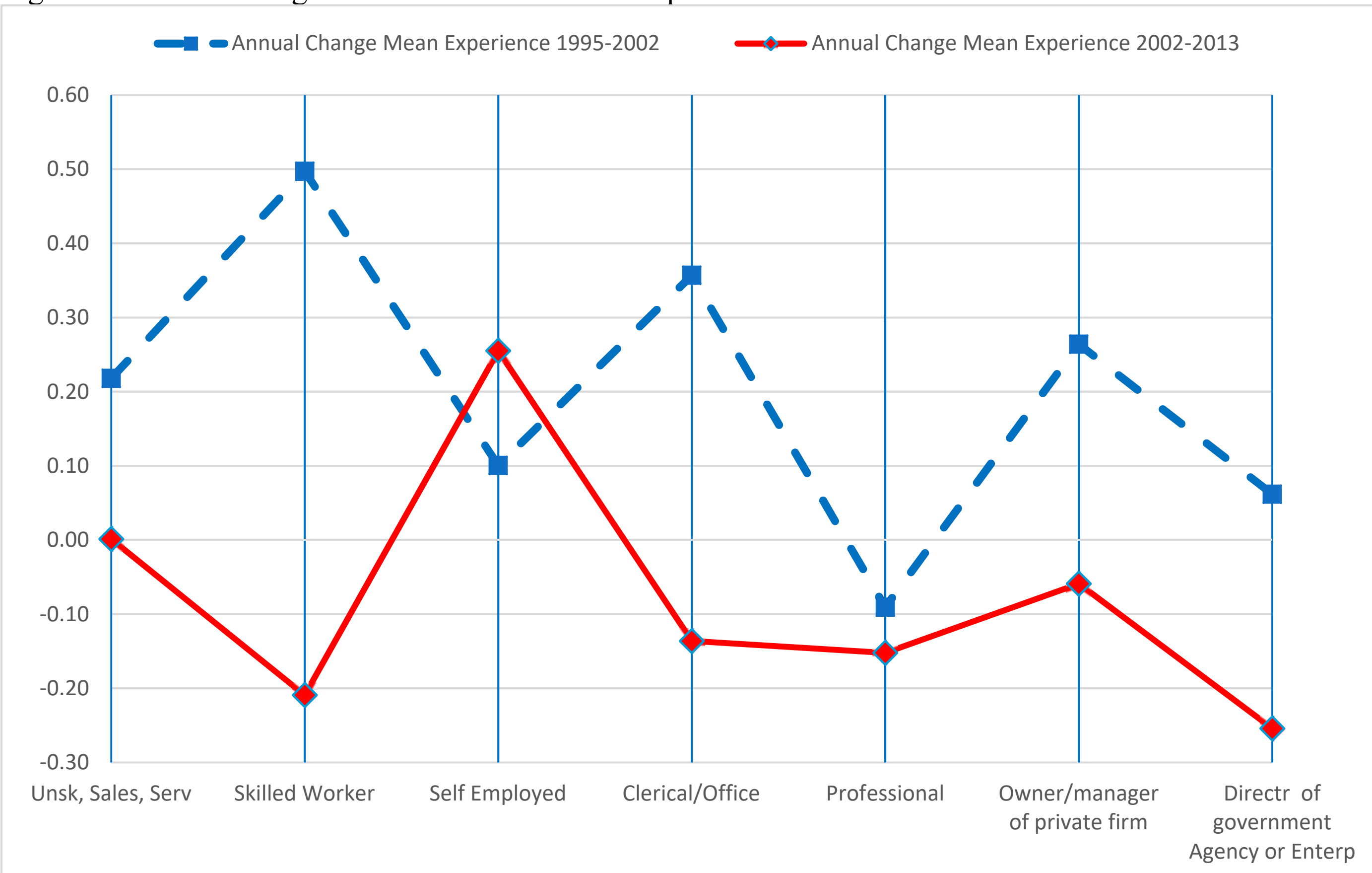

Figure 6: Summary of Job-Share Decomposition

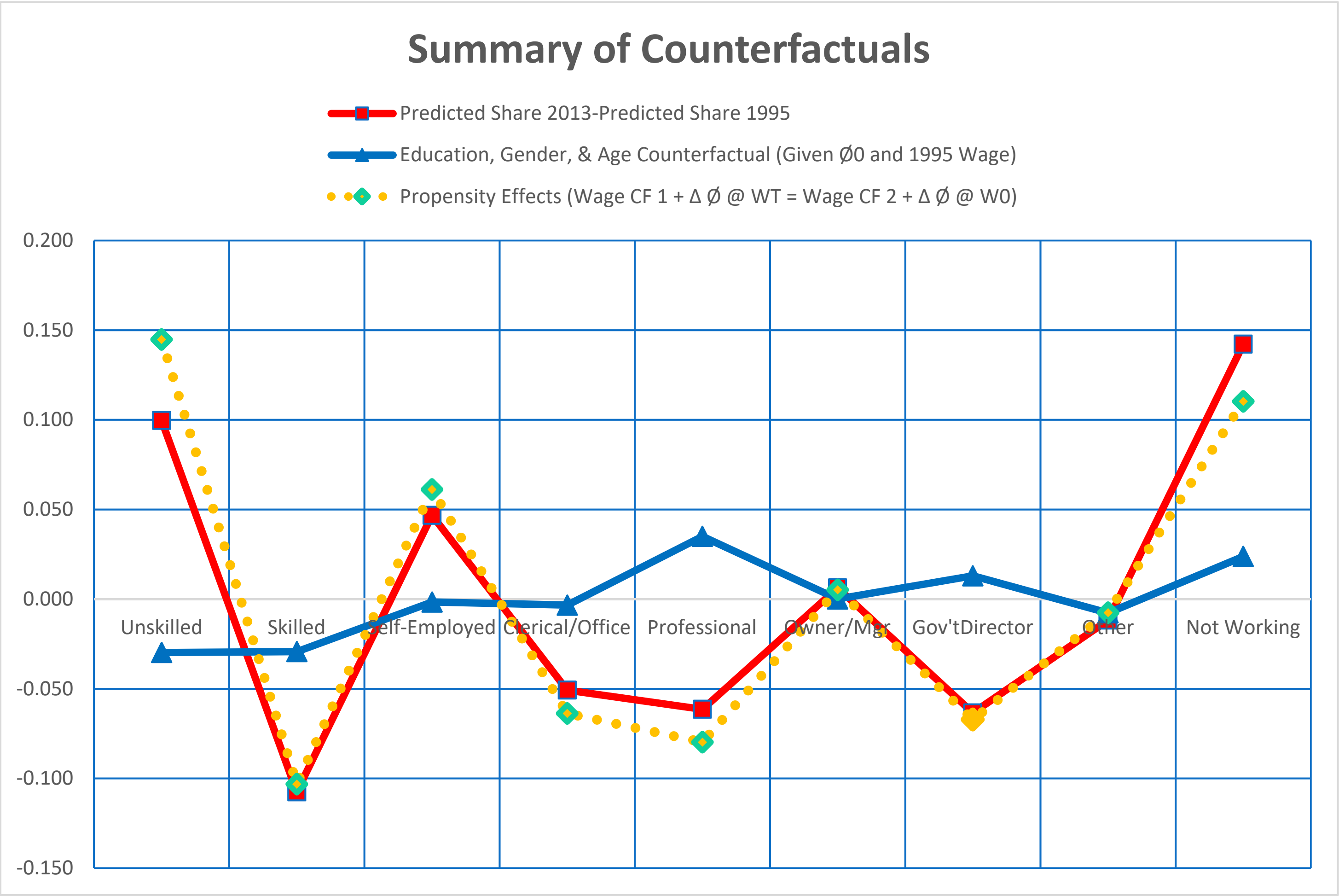

Table 1: Sample Statistics

(1)	Employment Category Share*			Mean Age			Mean School Years		
	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
	1995	**2002**	**2013**	**1995**	**2002**	**2013**	**1995**	**2002**	**2013**
Unskilled, Sales, Service	11.8%	12.9%	21.8%	37	39	40	8.93	9.92	10.59
Skilled Worker	15.3%	11.0%	4.5%	37	41	40	9.61	10.10	11.60
Self Employed	0.7%	2.5%	5.4%	39	40	43	8.22	9.19	9.59
Clerical/Office	14.7%	11.9%	9.6%	38	40	40	10.94	12.10	13.25
Professional	15.7%	12.3%	9.6%	41	40	39	12.69	13.26	14.02
Owner/Manager Private Firm	0.6%	0.3%	1.2%	41	43	43	10.69	10.88	12.10
Director Govt. Agency/Enterprise	8.3%	6.2%	1.9%	45	45	43	12.19	13.01	13.83
Other	3.7%	1.4%	2.5%	36	42	40	9.44	10.31	10.74
Not Working	29.3%	41.7%	43.5%	47	47	52	9.04	9.20	9.58

Job Category	Mean Real Income (RMB)			Proportion Female		
	(5a)	(5b)	(5c)	(6a)	(6b)	(6c)
	1995	**2002**	**2013**	**1995**	**2002**	**2013**
Unskilled, Sales, Service	1215	1781	5058	0.62	0.59	0.44
Skilled Worker	1448	2318	5822	0.39	0.29	0.29
Self Employed	1546	2304	5516	0.47	0.44	0.43
Clerical/Office	1553	2666	6550	0.51	0.51	0.46
Professional	1799	3155	7984	0.49	0.48	0.48
Owner/Manager Private Firm	1844	3684	12331	0.43	0.28	0.34
Director Govt Agency/Enterprise	2027	3566	7703	0.23	0.20	0.34
Other	1283	1678	4707	0.67	0.52	0.37
Not Working	**	**	**	0.55	0.60	0.60

Source: CHIPS 1995, 2002, & 2013 and authors' calculations. Sample sizes are 14,853, 14,646, and 9,751 in 1995, 2002, and 2013, respectively. *The share of each category in the estimation sample. **Not reported here, since we do not assume that income reported by those who report not working is a measure of their opportunity wage.

Table 2: Estimation Results Hedonic Wage Function (Equation 2)

Variables	Coefficients Standard Errors
Edu Yrs x Year 1995	60.21*** (0.00)
Edu Yrs x Year 2002	176.39*** (0.00)
Edu Yrs x Year 2013	497.21*** (0.00)
Age x Year 1995	25.94*** (0.0000)
Age x Year 2002	36.44*** (0.0000)
Age x Year 2013	57.03*** (0.0000)
Female x Year 1995	-192.88*** (0.00)
Female x Year 2002	-438.31*** (0.00)
Female x Year 2013	-1,591.58*** (0.0000)
Year 2002	-651.6176*** (0.0000)
Year 2013	-1,313.1444*** (0.0051)
Constant	111.0077* (0.0599)
Observations	29,273
R-squared	0.298

Robust p value in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: (1) Dependent variable is reported annual income *yuan*. (2) The coefficient estimates of provincial dummies and the interaction terms between year and provincial dummies are not reported.

Table 3: Marginal Probabilities from Multinomial Logit Estimation Results (Equation 3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Not Working	Owner/Manager Of Private Firm	Self-Employed	Professional	Government Director	Clerical/ Office Staff	Skilled Worker	Unskilled Worker	Other
Year 2002	0.45179***	0.00477	0.01471	0.01723	-0.01304	-0.17186***	-0.05993***	-0.17256***	-0.07112***
	(0.00000)	(0.42233)	(0.11717)	(0.43477)	(0.25130)	(0.00000)	(0.00540)	(0.00000)	(0.00000)
Year 2013	0.20665***	0.01066**	0.03506***	0.07537***	-0.03785**	-0.18194***	-0.18995***	0.07904***	0.00295
	(0.00007)	(0.02073)	(0.00026)	(0.00187)	(0.01106)	(0.00000)	(0.00000)	(0.00305)	(0.78269)
Prov. Wage. x Year 1995	-0.06567**	-0.00504	0.02277***	-0.00848	0.02836***	0.01699	0.04087*	-0.01748	-0.01230
	(0.03606)	(0.18389)	(0.00025)	(0.59840)	(0.00624)	(0.37376)	(0.07354)	(0.37136)	(0.10905)
Prov. Wage. x Year 2002	-0.10623***	0.00511**	0.00632*	0.02651**	0.02734***	0.03743***	0.01781	-0.00327	-0.01102*
	(0.00000)	(0.03070)	(0.09339)	(0.02208)	(0.00039)	(0.00719)	(0.29300)	(0.81705)	(0.07908)
Prov. Wage. x Year 2013	-0.04866***	0.00175	0.00338**	0.00466	0.01329***	0.01820***	0.00904	0.00221	-0.00388
	(0.00000)	(0.10251)	(0.04349)	(0.29310)	(0.00002)	(0.00109)	(0.12370)	(0.67673)	(0.13063)
Edu Yrs x Year 1995	-0.01903***	0.00056**	-0.00445***	0.03620***	0.01062***	0.01664***	-0.00950***	-0.02836***	-0.00267***
	(0.00000)	(0.02875)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Edu Yrs x Year 2002	-0.04351***	0.00019	-0.00312***	0.03537***	0.01207***	0.02513***	-0.00893***	-0.01618***	-0.00102*
	(0.00000)	(0.51512)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.07532)
Edu Yrs x Year 2013	-0.03759***	0.00035**	-0.00348***	0.02879***	0.01070***	0.02523***	-0.00158	-0.01958***	-0.00283***
	(0.00000)	(0.01500)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.22749)	(0.00000)	(0.00000)
Age x Year 1995	0.00987***	0.00002	-0.00058***	0.00110***	0.00102***	-0.00155***	-0.00292***	-0.00605***	-0.00091***
	(0.00000)	(0.58188)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Age x Year 2002	0.00494***	0.00003	-0.00049***	0.00040***	0.00098***	-0.00014	-0.00172***	-0.00384***	-0.00017*
	(0.00000)	(0.52203)	(0.00000)	(0.00403)	(0.00000)	(0.40299)	(0.00000)	(0.00000)	(0.05710)
Age x Year 2013	0.00980***	-0.00001	-0.00048***	-0.00046***	0.00045***	-0.00081***	-0.00259***	-0.00514***	-0.00076***
	(0.00000)	(0.54963)	(0.00000)	(0.00344)	(0.00001)	(0.00003)	(0.00000)	(0.00000)	(0.00000)
Female x Year 1995	0.05030***	-0.00177	-0.00772**	0.01038**	-0.03801***	0.00027	-0.06630***	0.03969***	0.01316***
	(0.00000)	(0.13919)	(0.02289)	(0.01388)	(0.00000)	(0.95798)	(0.00000)	(0.00000)	(0.00000)
Female x Year 2002	0.12222***	-0.00561***	-0.00772***	-0.00261	-0.04550***	0.00721	-0.10445***	0.03644***	0.00002
	(0.00000)	(0.00179)	(0.00002)	(0.56489)	(0.00000)	(0.20182)	(0.00000)	(0.00000)	(0.99474)
Female x Year 2013	0.19747***	-0.00359***	-0.00629***	0.00023	-0.01867***	-0.01456**	-0.09377***	-0.04528***	-0.01552***
	(0.00000)	(0.00020)	(0.00001)	(0.96710)	(0.00011)	(0.03745)	(0.00000)	(0.00000)	(0.00000)
Observations	46,209								

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Simulation Examples Based on Junior Middle School

Schooling Age Groups	Not Working	Owner/Manager Private Frim	Self-Employed	Professional	Government Director	Clerical/ Office Staff	Skilled Worker	Unskilled Worker	Other
				$\bar{\pi}_0^j(\phi_0, \bar{W}_0)$					
16-20	0.147	0.004	0.015	0.043	0.020	0.136	0.281	0.278	0.076
21-25	0.188	0.004	0.013	0.050	0.024	0.138	0.266	0.251	0.066
26-30	0.229	0.005	0.012	0.056	0.026	0.137	0.233	0.237	0.066
31-35	0.268	0.005	0.011	0.060	0.031	0.133	0.222	0.211	0.059
36-40	0.316	0.005	0.010	0.069	0.039	0.132	0.206	0.173	0.050
41-45	0.358	0.006	0.008	0.075	0.048	0.131	0.187	0.144	0.043
46-50	0.404	0.006	0.007	0.079	0.054	0.125	0.164	0.123	0.038
51-55	0.454	0.006	0.006	0.083	0.065	0.115	0.142	0.099	0.029
56-60	0.502	0.006	0.005	0.084	0.072	0.105	0.119	0.082	0.025
>60	0.566	0.006	0.004	0.071	0.088	0.083	0.107	0.058	0.016
				$\bar{\pi}_0^j(\phi_T, \bar{W}_0)$					
16-20	0.161	0.010	0.151	0.027	0.006	0.050	0.070	0.485	0.040
21-25	0.210	0.010	0.144	0.029	0.006	0.053	0.068	0.444	0.035
26-30	0.264	0.010	0.138	0.030	0.007	0.053	0.058	0.407	0.032
31-35	0.300	0.011	0.134	0.030	0.007	0.053	0.057	0.378	0.030
36-40	0.355	0.012	0.123	0.033	0.009	0.055	0.055	0.330	0.028
41-45	0.405	0.013	0.107	0.033	0.010	0.058	0.053	0.295	0.026
46-50	0.459	0.014	0.098	0.033	0.011	0.057	0.048	0.257	0.023
51-55	0.516	0.014	0.086	0.033	0.012	0.056	0.043	0.220	0.020
56-60	0.574	0.014	0.074	0.031	0.013	0.053	0.037	0.188	0.018
>60	0.628	0.013	0.068	0.024	0.013	0.046	0.035	0.157	0.015

Notes: $\bar{\pi}_0^j(\phi_0, \bar{W}_0)$ denotes the share of employment in job category j (including non-employment), given ϕ_0, $\bar{W}_0$ and the demographic distribution in 1995; $\bar{\pi}_0^j(\phi_T, \bar{W}_0)$ denotes the share of employment in job category j (including non-employment), given ϕ_T, $\bar{W}_0$ and the demographic distribution in 1995.

Table 5: Summary of Simulations – Shares of All Observations in Each Category (%)

	Unskilled	Skilled	Self-Employed	Clerical / Office	Professional	Owner / Manager	Government Director	Other	Not Working
(1) Predicted Share 2013-Predicted Share 1995	9.968	-10.758	4.675	-5.076	-6.142	0.627	-6.346	-1.173	14.219
(2) Wage Counterfactual 1: Effect of $\Delta\overline{W}$ (given ϕ_0 and 1995 Composition)	1.320	-6.045	-0.478	-2.756	2.125	2.015	-4.793	3.436	5.175
(3) Wage Counterfactual 2: Effect of $\Delta\overline{W}$ (given ϕ_T and 1995 Composition)	-0.241	-0.516	-2.018	-1.567	-0.248	-0.467	-0.902	0.590	5.369
(4) Composition Effects	-2.977	-2.931	-0.164	-0.338	3.496	0.009	1.297	-0.770	2.379
(5) Propensity Effects	14.484	-10.317	6.114	-6.374	-7.980	0.516	-6.717	-0.753	11.026
(6) Interaction Effects	-1.534	2.49	-1.28	1.64	-1.66	0.102	-0.925	0.35	0.814
(7) Propensity/Total (%)	145	96	131	126	130	82	106	64	78

Notes:

(i) Predicted Share 2013-Predicted Share 1995 $= \pi_T^j - \pi_0^j \equiv \sum_g \Pr_j(\phi_T, \overline{W}_T, X_g) \cdot f_T(X_g) - \sum_g \Pr_j(\phi_0, \overline{W}_0, X_g) \cdot f_0(X_g)$. (Equal to actual changes, except for data cleaning.)

(ii) Wage Counterfactual 1 $= \sum_g \left(\Pr_j(\phi_0, \overline{W}_T, X_g) - \Pr_j(\phi_0, \overline{W}_0, X_g) \right) \cdot f_0(X_g)$; Wage Counterfactual 2 $= \sum_g \left(\Pr_j(\phi_T, \overline{W}_T, X_g) - \Pr_j(\phi_T, \overline{W}_0, X_g) \right) \cdot f_0(X_g)$

(iii) Composition Effects $= \sum_g \Pr_j(\phi_0, \overline{W}_0, X_g) \cdot \left(f_T(X_g) - f_0(X_g) \right)$

(iv) Interaction Effects $= \sum_g \left(\Pr_j(\phi_T, \overline{W}_T, X_g) - \Pr_j(\phi_0, \overline{W}_0, X_g) \right) \cdot \left(f_T(X_g) - f_0(X_g) \right)$

Propensity Effects $= \sum_g f_0(X_g) \cdot \left(\Pr_j(\phi_T, \overline{W}_T, X_g) - \Pr_j(\phi_0, \overline{W}_0, X_g) \right) \cdot$

(v)

$$= \sum_g f_0(X_g) \begin{pmatrix} \Pr_j(\phi_0, \overline{W}_T, X_g) - \Pr_j(\phi_0, \overline{W}_0, X_g) \big| \underline{\Delta\overline{W} \text{ at } \phi_0 \text{ wage counterfactual 1}} + \\ \Pr_j(\phi_T, \overline{W}_T, X_g) - \Pr_j(\phi_0, \overline{W}_T, X_g) \big| \underline{\Delta\phi \text{ at } \overline{W}_T} \end{pmatrix}$$

$$= \sum_g f_0(X_g) \begin{pmatrix} \Pr_j(\phi_T, \overline{W}_T, X_g) - \Pr_j(\phi_T, \overline{W}_0, X_g) \big| \underline{\Delta\overline{W} \text{ at } \phi_T \text{ wage counterfactual 2}} + \\ \Pr_j(\phi_T, \overline{W}_0, X_g) - \Pr_j(\phi_0, \overline{W}_0, X_g) \big| \underline{\Delta\phi \text{ at } \overline{W}_0} \end{pmatrix}$$