Using Education and Occupation to Measure Intergenerational Mobility in Urban China

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This paper investigates the relationship between children's and fathers' education and occupation in urban China among children who were born between 1948 and 1987 from an economic perspective based on the Chinese Household Income Project (CHIP) 2007 data. We examine intergenerational educational and occupational mobility in urban China among children born from 1948 to 1987 (aged 20 to 59) and divide children into 4 birth cohorts (1948-1957, 1958-1967, 1968-1977, 1978-1987). We find that children with higher educated fathers have significant advantages to complete higher education level. Multinomial logit estimation indicates that the higher paternal education, the more likely children completed higher education levels. Being a male, in more recent birth cohort and living in the east significantly reduce the probability of being in the lowest educational category and increases the probability of being in the highest educational category. The cross-classification tables provide a comparison of intergenerational occupational mobility for children's 4 birth cohorts and show the overall occupational mobility becomes worse as time passes. A decomposition analysis shows that in more recent years, the intergenerational occupational changes become less mobile especially when fathers have high white-collar jobs as opposed to the case fathers have skilled jobs.

Keywords: Categorical data analysis, Intergenerational mobility, Intergenerational inequality, Multinomial logit analysis

Ⅰ. Introduction

According to Mincer (Mincer 1958), A positive correlation exists between one's education and income levels. Chinese parents are traditionally willing to consume on children's education and expecting a good future of children. Therefore, education can be seen as a parental investment in their children's human capital. Occupation is a socioeconomic characteristic and can be seen as the economic component of an individual's social class. The transmission of education and occupation reflects the intergenerational inequality of opportunity and the economic component of social class that exists in a society.

Children's educational attainment appears to be affected by genes, parental education, human capital investment, government education policies and other factors. Plomin et al. (2001) note that inherited genes affect the intergenerational transmission of ability. According to Hertz et al. (2007), there is a strong intergenerational association between the level of parental schooling and the level of the child's schooling. Daouli et al. (2010) argue that children's educational outcomes are to some extent influenced by parental human capital.

Intergenerational educational mobility has been discussed for many years. Previous studies provide both theoretical and empirical evidence on the connections between children's education and parental education. Cattaneo et al. (2007) find that parental education is the main predictor of children's education: the higher the parents' education, the better the average school performance and the higher the children's education. Huang (2013) argues that high intergenerational educational persistence is an indicator of educational inequality and a barrier to equal opportunities in the labor market and beyond. He finds that household assets interact with parental education to affect children's educational attainment. Wang (2005) notes that parents tend to invest more in their children's education to meet the demand for well-educated workers and intensified competition in the labor market for better employment. Regional differences are environmental variables that are becoming more important for explaining educational inequalities (Daouli et al., 2010).

Previous cross-country studies show that intergenerational education mobility differs among groups. For example, Blanden et al. (2007) find that intergenerational education mobility is higher among whites than among blacks. Black females have higher intergenerational education mobility than males, while the poorest students have the lowest intergenerational education mobility. Riphahn (2007) estimates the intergenerational transmission of educational attainment in Germany and finds that a more recent birth cohort share attained advanced educational degrees, and there is a positive trend in upward intergenerational mobility and a negative trend in downward intergenerational mobility for cohorts born from 1940 through 1978. Daouli et al. (2010) estimate intergenerational educational transmission among Greek women and find that upward mobility and maternal educational background are important. The results of a probit model show that the influence of parental education seems to weaken over time. In Malaysia, at least two-thirds of the impact of parental education on their children's schooling transmission appears to be a consequence of parental schooling. Family environments have significant positive effects on children's schooling. The level of maternal education has a stronger impact on daughters' education, while paternal education has a stronger impact on sons' education (Turcotte, 2011). Hertz et al. (2007) estimate intergenerational educational persistence in 42 countries. They find that the intergenerational education transmission decreased for children who were born from the 1930s to the 1970s. They argue that differences across countries may depend on geography and institutional system. The differences also imply that intergenerational education transmission is not only the result of genetic inheritance but also of the returns to educational investment, parents' human capital investment in children, public policy and household economic resources, as well.

Little research estimates intergenerational education mobility in China from an economic perspective. Most previous studies of education from economic perspectives discuss the returns to education (e.g. Brown & Park, 2002, Cai et al., 2002, Luo, 2007). Previous studies on China's intergenerational education mobility estimate correlations in urban China using different datasets. Sato and Li (2007) examine the determinants of intergenerational correlations in education in rural China. The data sources they use are from a rural survey, the CHIP 2002. The samples include three generations of citizens who completed their educations from before 1949 to the beginning of the 2000s. They focus on the impact of family class status on offspring's education and find that family class status, which is generally believed to have become irrelevant after the 1980s, remains important in intergenerational educational transmission. Golley and Kong (2013) estimate the intergenerational pattern of educational attainment among children born between 1941 and 1990 using the 2008 Rural-Urban Migration in China and Indonesia Survey. They find that the intergenerational correlation is lower in rural and migrant populations than in urban populations.

An increasing number of studies estimate intergenerational occupational mobility in developed countries. Torche (2011) analyzes the intergenerational occupational mobility across education levels and finds that among men, the intergenerational status association is substantial among those with less than a college degree. The overall intergenerational association is weaker among women than for men. Mazumder and Acosta (2015) estimate intergenerational occupational mobility using data from the Panel Study of Income Dynamics (PSID). They pay particular attention to addressing measurement error. They argue that intergenerational occupational mobility is overstated when using a single year of the fathers' occupation compared to a 10-year average centered on the mid-career occupation. They show that estimated intergenerational persistence is approximately 15 to 20 percent higher when using a 10-year average than when using a single-year measure of occupational prestige. In this paper, we use the single-year paternal occupation status because most of fathers were engaged in the same occupations under the planned economy.

Previous studies in economics and sociology use different measures to estimate the rate of intergenerational occupational mobility. Since our data are categorical, we estimate intergenerational occupational mobility using categorical data analysis. We compare contingency tables with paternal categorical occupations arrayed across one dimension and children's categorical occupations arrayed across the other. Altham and Ferrie (2007) discuss two tools to compare contingency tables generated by categorical data using two characteristics. One method is to adjust the marginal frequencies of tables with different row and column totals. The other method is to measure the associations between rows and columns and to determine how they differ across the two tables. Long and Ferrie (2013) compare intergenerational occupational mobility in Great Britain and the United States since 1850. They estimate occupational mobility using a methodology to compare two-dimensional matrices from different datasets. Azam (2013) compares intergenerational occupational mobility across birth cohorts in India. He also decomposes the distance in associations between rows and columns to determine how much and in which odds ratios the associations differ across birth cohorts.

For China, earlier studies of intergenerational occupational mobility argue that parental status does not directly affect their children's occupational status. Lin and Bian (1991) note that since the mid-1970s, several large-scale surveys have been conducted on status attainment in China. Their major finding is that parental status does not directly affect their children's occupational status but does so indirectly through education. They apply a basic Blau-Duncan model using a survey of 1000 employed adults in Tianjin, China. They find evidence of intergenerational occupational persistence (the paternal work unit affects his son's work unit). Paternal status directly affects sons' work units but not those of daughters. Blau and Ruan (1990) compare Tianjin, China and the urban United States and find that the transmission of occupational status in Tianjin is much less pronounced than in the urban United States. Moreover, paternal occupational status does not improve their sons' achievement. More recently, Wu and Treiman (2007) analyze the effect of parental and family background on occupational mobility in China using data from the 1996 national probability samples of Chinese men from both urban and rural areas. They argue that occupational inheritance and mobility are important aspects of intergenerational social reproduction and need further careful investigation. They pay particular attention to the effects of the hukou system on occupational mobility. In their analysis of rural and urban Chinese men between 20 and 55 years old, they find a high rate of downward mobility into agriculture for rural men compared to other countries but no downward mobility for urban men. They estimate multinomial conditional logit models to investigate how the hukou system affects the process of intergenerational occupational mobility and find that men with rural hukou are disadvantaged in obtaining higher-status occupations. Emran and Sun (2015) estimate intergenerational occupational mobility in rural China and focus on occupational mobility from agricultural to non-farm occupations. They use rural survey data from the CHIP 1988 and 2002. They find that intergenerational persistence in occupation is significant, although children are no longer likely to be farmers like their parents by 2002. For daughters with farmer parents, the probability of being in a non-farm occupation increased from 0.09 in 1988 to 0.43 in 2002; for daughters with both parents in non-farm occupations, the probability of being in a non-farm occupation was 0.71 in 1988 and 0.73 in 2002. The results are similar for sons. Using a probit regression, they find that the intergenerational link between parents and children in non-farm occupational participation disappears by 2002 both for daughters and sons.

The rest of this paper is structured as follows: section 2 presents the empirical model and the methodology, section 3 describes the data, section 4 reports the results and section 5 concludes and gives policy implications.

Ⅱ. Methodology

I estimate intergenerational mobility of education and occupation based on categorical data analysis.

1. Multinomial Logit Analysis

We analyzing educational transmission across generations, the key explanatory variable is parental education. Since We code education information into categorical variables, the estimated coefficients have to be interpreted relative to a reference category. Other explanatory variables include categorical indicators of children's gender, birth cohort, region of residence, and parental social class. A multinomial logit model can be used when all regressors are case specific, which allows for differences in each covariate's marginal effect across categories. The baseline model can be written as follows

$$pr(y^{c}=i)=f(\textit{gender, parental education, birth cohort, region, parental social class}) \quad (1)$$

The estimated coefficients do not have a direct interpretation as marginal effects. They describe the ratios of the probability of choosing one outcome category over the probability of choosing the reference category.

Intergenerational occupational mobility can be calculated by analyzing of two contingency tables, with fathers' categorical occupations arrayed across one dimension and children's categorical occupations arrayed across the other.

A categorical variable has a measurement scale consisting of a set of categories. Categorical scales are pervasive in the social sciences and are used to measure attitudes and opinions. For social and health a science, that's common for categorical variables, however, the categorical variables are not limited in these areas (Agresti 2007). Single categorical variable data could be summarized by counting each category observation numbers. For each category, the probabilities could be evaluated by measuring sample's proportion. For example, if two categorical variables are identified as X and Y, we could define 'I' as the numbers of categories in X, and 'J' for categories in Y. Based the assumption as above, an 'I' rows times 'J' columns matrix could be developed, the row means the categories of X and columns means categories of Y, all possibilities of 'I' and 'J' combinations are displayed in this matrix, which called contingency table (Agresti 2007).

2. Adjusting Marginal Frequencies of Different Contingency Tables

Comparing mobility across different places or periods in different contingency tables has several ways. I use the method that based on the marginal frequency distributions, as Deming and Stephan (1940), Altham (1970), Wickens (1989), Altham and Ferrie (2007), Long and Ferrie (2013) introduced in their articles.

It is most simply to illustrate the interactive proportional fitting algorithm in a two-way contingency table. Suppose fathers and children works in either of two occupations (1 or 2). A contingency table that describes the mobility in period A has the elements $\{a_{11}, a_{21}, a_{12}, a_{22}\}$, where the first subscript is fathers' occupation and the second is children's occupation. We can write it in the matrix form $A=\begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix}$. The mobility of intergenerational occupation can be measured by the probability of being in the off diagonal: $M_A=(a_{12}+a_{21})/(a_{11}+a_{21}+a_{12}+a_{22})$, whereas the immobility can be measured by the probability of being in the main diagonal. How to compare the mobility of two square contingency tables with different rows and columns total? We can do comparison analysis by adjusting the marginal frequencies of one square contingency table to match for the other.

Consider we have 2×2 contingency table A with elements {3,1,2,2} and 2×2 contingency table B {2,1,6,1} as shown in table 1. The mobility of Table A is $M_A=3/8$ and $M_B=7/10$. The marginal frequencies in table A disagree badly with table B, so it is not clear whether the difference in mobility results from this difference or from some more fundamental such as differences between A and B in the amount of human capital necessary to get job 1. But the different marginal frequencies in the two tables can be fixed. Consider row a_1 in table A, the row a_1 total is 4, but row a_1 in table B is 3. This discrepancy is adjusted if every entry in row a_1 of table B is multiplied by 4/3=1.333, and row a_2 is multiplied by 4/7 (step 1a). A similar adjustment to column b_1 and b_2 corrects its frequencies[1], b_1 is multiplied by

Table 1 Fitting a Model by Interactive Proportional Adjustment of the Marginal Distributions

Table A Observed Frequencies	b_1	b_2	Row
a_1	3	1	4
a_2	2	2	4
Column	5	3	8

Table B Observed Frequencies	b_1	b_2	Row
a_1	2	1	3
a2	6	1	7
Column	8	2	10

Step 1a: Adjust Row a1, a2	b_1	b_2	Row
a_1	2.7	1.3	4.0
a_2	3.4	0.6	4.0
Column	6.1	1.9	8.0

Step 1b: Adjust Column b1, b2	b_1	b_2	Row
a_1	2.2	2.1	4.3
a2	2.8	0.9	3.7
Column	5.0	3.0	8.0

Step 2a: Adjust Row a1, a2	b_1	b_2	Row
a_1	2.0	2.0	4.0
a_2	3.0	1.0	4.0
Column	5.1	2.9	8.0

Step 2b: Adjust Columns b1, b2	b_1	b_2	Row
a_1	2.0	2.0	4.0
a2	3.0	1.0	4.0
Column	5.0	3.0	8.0

Note: The adjustment factor of step 1a is 4/7; adjustment factor of step 1b is 3/1.094.

5/6.096, and b_2 is multiplied by 3/1.094 (step 1b). Because all the entries in each row have been changed following the same way, no row-column dependencies are introduced and the independence in the table is not compromised. The rows and columns totals are still required another round of adjustment. Finally, we get the adjusted contingency table B' with elements {2.0, 2.0, 3.0, 1.0}, the mobility $M_{B'}=5/8$. Then, we could calculate the difference between A and B' (3/8 − 5/8). We can conclude that the difference in occupational mobility does not because of differences in the occupation distributions between the two periods.

There may be a possible that the difference in mobility of A and B is 0 ($M_A - M_{B'} = 0$). We measure the associations between rows and columns in tables are based on odd ratios[2)] or cross-product ratios. For A, it is $a_{11}a_{22}/a_{12}a_{21}$ and can be arrange to give $(a_{11}/a_{12})(a_{21}/a_{22})$, the ratio of (1) the odds that children of occupation 1 fathers get occupation 1 rather than occupation 2 to (2) the odds that children of occupation 2 fathers get occupation 1 rather than occupation 2. If there is perfect mobility, the ratio would be 1 corresponds to independence of children's occupation and his fathers' occupation. The more the cross-product ratio exceeds one, the greater the relative advantage of having the same occupation with their fathers.

3. Measuring the Association between Rows And Columns

For tables with more than two rows and columns, there are several odd ratios or cross-product ratios. Altham (1970) suggests a measure that the sum of the squares of the differences between the logs of the cross-product ratios in tables. Suppose we have two square tables P and Q, both of them have r rows and s columns, it measures how much the association is present between rows and columns in table departs from the association between rows and columns in table Q. It can be written in the following equation:

$$d(P,Q)=\left[\sum_{i=1}^{r}\sum_{j=1}^{s}\sum_{l=1}^{r}\sum_{m=1}^{s}\left|\frac{p_{ij}p_{lm}q_{im}q_{lj}}{p_{im}p_{lj}q_{ij}q_{lm}}\right|^2\right]^{1/2} \qquad (2)$$

$d(P,Q)$ tells us how much between the row-column associations in table P and table Q. We can use a classical testing method, likelihood-ratio χ^2 statistic G^2 with $(r-1)(s-1)$ degrees of freedom to test whether the matrix Θ with elements $\theta_{ij}=\log(p_{ij}/q_{ij})$ is independent. If we can reject the null hypothesis that matrix Θ is independent, then we accept the hypothesis that $d(P,Q)\neq 0$ so the degree of association between rows and columns differs between table P and Q (Long and Ferrie 2013).

$d(P,Q)$ does not tell us the in which table the association is stronger. But we can use a new matrix J with no associations (all elements are ones) to replace P or Q, then calculating $d(P,J)$ and $d(Q,J)$. If $d(P,Q)>0$ and $d(P,J)>d(Q,J)$, it means that the mobility is greater in table Q. If $d(P,Q)>0$ but $d(P,J)\approx d(Q,J)$, it means that table P and Q have row-column associations that are the same distance from the row-column association observed under independence, but that table P and Q differ in how they differ from independence (Long and Ferrie 2013).

Ⅲ. Data

In this paper, estimates are based on CHIP 2007 that was initiated by a team of researchers at Australian National University and Beijing Normal University and was conducted by the China National Bureau of Statistics[3)] (NBS) and supported by the Institute for the Study of Labor (IZA). The CHIP 2007 provides cross-sectional data and involves 3 parts: urban, rural and rural-urban migrant. The urban survey covers 5005 households and 14692 individuals; the rural survey, 8000 households and 31791 individuals; and the migration survey, 4974 household and 15449 individuals. It collects rich information on households and household members, e.g., personal characteristics, employment status, income and

Table 2 Descriptive Statistics of father-child Pairs on Education

	Mean	Std. Dev.	Min	Max
Age	41.208	10.370	20	59
Male	0.491	0.500	0	1
Birth cohort: 1948-1957	0.185	0.389	0	1
Birth cohort: 1958-1967	0.297	0.457	0	1
Birth cohort: 1968-1977	0.294	0.455	0	1
Birth cohort: 1978-1987	0.224	0.417	0	1
Children's education level1	0.270	0.478	0	1
Children's education level2	0.290	0.456	0	1
Children's education level3	0.271	0.375	0	1
Children's education level4	0.169	0.387	0	1
Fathers' education level1	0.496	0.432	0	1
Fathers' education level2	0.410	0.375	0	1
Fathers' education level3	0.049	0.208	0	1
Fathers' education level4	0.045	0.183	0	1
Region: East	0.494	0.493	0	1
Region: Center	0.304	0.480	0	1
Region: West	0.203	0.418	0	1

Note: Data are from CHIP 2007. Numbers of observations: 8433. Education level1: compulsory education; education level2: upper secondary; education level3: polytechnic college; education level4: university and above.

expenditures, education attainment, household assets and debts, and living conditions.

We examine intergenerational educational and occupational mobility in urban China among children born from 1948 to 1987 (aged 20 to 59) and divide children into 4 birth cohorts (1948-1957, 1958-1967, 1968-1977, 1978-1987). The four birth cohorts ensure comparability of intergenerational occupational mobility trends over 40 years. The key explanatory variable I consider is fathers' education. In the questionnaire, there are 9 levels of education into which to categorize an individual's educational attainment. I define education using 4 categories: education level 1: compulsory education, which includes those never schooled (including informal education such as literacy courses), elementary school, and junior middle school; education level 2: upper secondary, which includes senior middle school, vocational senior secondary school/technical school and specialized secondary school; education level 3: polytechnic college; education level 4: university and above that includes undergraduate (bachelor's degree) and graduate (master's degree or above) studies. Table 2 lists the shares of these four education categories for children and fathers. Additional explanatory variables include children's gender, birth cohort and location of residence. Descriptive statistics for the samples are presented in Table 2.

There are eight kinds of occupations in the questionnaire. To reduce the sparseness of the mobility table, we classify these occupations into four categories: high white-collar workers, low white-collar workers, skilled workers and unskilled workers. "High white collar" comprises principals of state agencies, Party organizations, enterprises and public service units. "Low white collar" comprises professional technicians, clerks and related personnel. "Skilled" comprises manufacturing and transportation equipment operators and related personnel. "Unskilled" comprises commercial and service personnel; agriculture, forestry, animal husbandry, fishery and water resources

Table 3 Descriptive Statistics of Father-child Pairs on Occupation

Variable	Mean	Std. Dev.	Min	Max
Male	0.563	0.496	0	1
Children's occupations: High white-collar	0.081	0.273	0	1
Children's occupations: Low white-collar	0.517	0.500	0	1
Children's occupations: Skilled	0.167	0.373	0	1
Children's occupations: Unskilled	0.234	0.423	0	1
Fathers' occupation: High white-collar	0.105	0.307	0	1
Fathers' occupation: Low white-collar	0.290	0.454	0	1
Fathers' occupation: Skilled	0.315	0.464	0	1
Fathers' occupation: Unskilled	0.290	0.454	0	1
Birth cohort: 1948-1957	0.185	0.388	0	1
Birth cohort: 1958-1967	0.340	0.474	0	1
Birth cohort: 1968-1977	0.297	0.457	0	1
Birth cohort: 1978-1987	0.179	0.383	0	1

Note: Data are from CHIP 2007. Numbers of observations is 4632

producers. The descriptive statistics of the sample are summarized in Table 3.

Ⅳ. Results

1. Analysis on Intergenerational Educational Mobility

We first use cross-classification tables to compare the changes in intergenerational educational mobility by children's birth cohorts and then estimate marginal effects to indicate the impact of parental education, birth cohort and regional on the probabilities of alternative outcome of children's education level.

Table 4 presents intergenerational educational mobility in cross-classification tables by children's birth cohorts: 1948-1957 (panel 1), 1958-1967 (panel 2), 1968-1977 (panel 3), 1978-1987 (panel 4). This table provides a comparison of intergenerational educational mobility among the children of 4 birth cohorts. The row sum of row 1 and row 2 in each panel shows that children with lower education levels (compulsory education level and upper secondary education level) decline over years. Conversely, the row sum of row 3 and row 4 in each panel shows that children with higher education levels (polytechnic college education level and university and above education level) increases over years and keeps an increasing trend from fathers' lowest education level to highest education level, which indicates that education expansion from children's earlier birth cohort to later birth cohort and children with high-educated fathers are more likely to have higher education levels. Column 1 in each panel shows the percentage of education levels of children whose fathers have compulsory education level. We find that the percentage of first two education categories decreases over years, and the percentage of last two education categories increases over years. The changes indicate that the education levels of children with lower educated fathers increase over years. A similar trend can also be found in column 2 in each panel. The percentage of children whose fathers have compulsory education level completed university and above education increases by 4.53 times from children's birth cohort 1949-1957 to birth cohort 1978-1987. The percentage increases by 12.33 times for children whose fathers have the highest education level. This result implies that children with higher educated fathers have significant advantages to complete higher education level.

Table 4 Intergenerational Educational Mobility in Urban China, by Birth Cohort, frequencies (Column Percent)

Panel 1 Child's Birth Cohort=1948-1957						Panel 2 Child's Birth Cohort=1958-1967					
Child	Father				Row sum	Child	Father				Row sum
	Edu1	Edu2	Edu3	Edu4			Edu1	Edu2	Edu3	Edu4	
Edu1	212 (13.24)	26 (4.76)	1 (1.56)	3 (4.05)	242 (10.65)	Edu1	85 (5.86)	13 (1.56)	1 (1.15)	3 (3.75)	102 (4.17)
Edu2	1194 (75.14)	405 (74.18)	45 (70.31)	51 (68.92)	1695 (74.57)	Edu2	1089 (75.10)	553 (66.55)	49 (56.32)	33 (41.25)	1724 (70.42)
Edu3	126 (7.93)	82 (15.02)	12 (18.75)	14 (18.92)	234 (10.29)	Edu3	155 (10.69)	161 (19.37)	21 (24.14)	18 (22.50)	355 (14.50)
Edu4	57 (3.59)	33 (6.04)	6 (9.38)	6 (8.11)	166 (4.49)	Edu4	121(8.34)	104 (12.52)	16 (18.39)	26 (32.50)	267 (10.91)
Column sum	1589 (100.0)	546 (100.0)	64 (100.0)	74 (100.0)	2273 (100.0)	Column sum	1450 (100.0)	831 (100.0)	87 (100.0)	80 (100.0)	2448 (100.0)
Panel 3 Child's Birth Cohort=1968-1977						Panel 4 Child's Birth Cohort=1978-1987					
	Father				Row sum		Father				Row sum
	Edu1	Edu2	Edu3	Edu4			Edu1	Edu2	Edu3	Edu4	
Edu1	43 (4.84)	21 (1.90)	0 (0.00)	1 (0.63)	65 (2.84)	Edu1	2 (0.78)	9 (0.92)	0 (0.00)	0 (0.00)	11 (0.77)
Edu2	551 (62.05)	521 (47.19)	46 (33.82)	47 (29.56)	1165 (50.94)	Edu2	135 (52.33)	383 (39.08)	15 (12.30)	7 (10.77)	540 (37.89)
Edu3	168 (18.92)	328 (29.71)	45 (33.09)	52 (32.70)	593 (25.93)	Edu3	79 (30.62)	357 (36.43)	49 (40.16)	22 (33.85)	507 (35.58)
Edu4	126 (14.19)	234 (21.20)	45 (33.09)	59 (37.11)	464 (20.29)	Edu4	42 (16.28)	231 (23.57)	58 (47.54)	36 (55.38)	367 (25.75)
Column sum	888 (100.0)	1104 (100.0)	136 (100.0)	159 (100.0)	2287 (100.0)	Column sum	258 (100.0)	980 (100.0)	122 (100.0)	248 (100.0)	1425 (100.0)

Note: Data are from CHIP 2007. Edu1: compulsory education; Edu2: upper secondary; Edu3: polytechnic college; Edu4: university and above.

Table 5 Probability of children's educational level, by birth cohort, fathers' educational level and regional difference: marginal effects for multinomial logit estimation

	Compulsory education	Polytechnic college	University and above
Fathers' education: upper secondary	-0.043*** [0.005]	0.085*** [0.010]	0.043*** [0.008]
Fathers' education: Polytechnic college	-0.062*** [0.006]	0.131*** [0.023]	0.163*** [0.021]
Fathers' education: University and above	-0.046*** [0.009]	0.115*** [0.023]	0.202*** [0.023]
Birth cohort: 1961-1970	-0.052*** [0.007]	0.036*** [0.010]	0.065*** [0.008]
Birth cohort: 1971-1980	-0.058*** [0.007]	0.131*** [0.012]	0.139*** [0.010]
Birth cohort: 1981-1990	-0.078*** [0.007]	0.205*** [0.015]	0.184*** [0.013]
Male	-0.025*** [0.005]	0.028*** [0.008]	0.055*** [0.007]
East	-0.009* [0.009]	0.009 [0.010]	0.005 [0.008]
West	0.001 [0.006]	0.039*** [0.012]	0.012 [0.008]
Log likelihood	−7971.702		

Note: Data are from CHIP 2007. Robust standard errors in parentheses. * p<0.1. ** p<0.05. *** p<0.01. The reference category is upper secondary for the response variable; compulsory education for the explanatory variables of fathers' education; the earliest birth cohort; and middle region for other explanatory variables.

Table 5 reports the marginal effects based on the multinomial logit estimation by birth cohort, fathers' educational level and region. As the logit model is non-linear, the estimated coefficients cannot interpret directly, therefore estimate marginal effects were estimated to indicate the impact of parental education, birth cohort and regional on the probabilities of alternative outcome of children's education level. The values in panel 1 indicate that the higher paternal education, the more likely children are to educated university and above. Having a highly educated father is correlated with an average increase in the probability of obtaining a university and above of 20.2 percentage points compared to a child whose father has completed only compulsory education. Panel 2 tells us that the later a child is born, the less likely is he to complete only compulsory education and the more likely he is to complete an university and above education level. Panel 3 shows the gender and regional impacts on the probability of children's educational level. Being a male significantly reduces the probability of being in the lowest educational category and increases the probability of being in the highest educational category relative to being a female. Living in the eastern region significantly reduces the probability of only completing compulsory education level and increases the probability of completing university and above education level.

2. Analysis on Intergenerational Occupational Mobility

Table 6 presents intergenerational occupational mobility in cross-classification tables by children's birth cohorts: 1948-1957 (panel 1), 1958-1967 (panel 2), 1968-1977 (panel 3), 1978-1987 (panel 4). This table provides a comparison

Table 6 Intergenerational Occupational Mobility in Urban China, by Birth Cohort, frequencies (Column Percent)

Panel 1 Child's Birth Cohort=1948-1957						Panel 2 Child's Birth Cohort=1958-1967					
Child	Father				Row sum	Child	Father				Row sum
	HW	LW	S	U			HW	LW	S	U	
HW	9 (13.24)	27 (11.74)	24 (7.23)	38 (16.74)	98 (11.44)	HW	35 (19.13)	39 (9.18)	26 (4.74)	38 (9.13)	138 (8.77)
LW	39 (57.35)	137 (59.57)	147 (44.28)	99 (43.61)	422 (49.24)	LW	95 (51.91)	259 (60.94)	222 (40.44)	167 (40.14)	743 (47.23)
S	7 (10.29)	35 (15.22)	96 (28.92)	33 (14.54)	171 (19.95)	S	25 (13.66)	63 (14.82)	167 (30.42)	67 (16.11)	322 (20.47)
U	13 (19.12)	31 (13.48)	65 (19.58)	57 (25.11)	166 (19.37)	U	28 (15.30)	64 (15.06)	134 (24.41)	144 (34.62)	370 (23.52)
Column um	68 (100.0)	230 (100.0)	332 (100.0)	227 (100.0)	857 (100.0)	Column sum	183 (100.0)	425 (100.0)	549 (100.0)	416 (100.0)	1573 (100.0)
Panel 3 Child's Birth Cohort=1968-1977						Panel 4 Child's Birth Cohort=1978-1987					
	Father				Row sum		Father				Row sum
	HW	LW	S	U			HW	LW	S	U	
HW	19 (13.38)	27 (6.91)	19 (4.88)	35 (7.74)	100 (7.28)	HW	14 (14.74)	15 (5.05)	1 (0.53)	10 (4.03)	40 (4.83)
LW	86 (60.56)	269 (68.80)	176 (45.24)	214 (47.35)	745 (54.22)	LW	60 (63.16)	213 (71.72)	94 (50.00)	122 (49.19)	489 (59.06)
S	13 (9.15)	34 (8.70)	98 (25.19)	59 (13.05)	204 (14.85)	S	5 (5.26)	17 (5.72)	40 (21.28)	15 (6.05)	77 (9.30)
U	24 (16.90)	61 (15.60)	96 (24.68)	144 (31.86)	325 (23.65)	U	16 (16.84)	52 (17.51)	53 (28.19)	101 (40.73)	222 (26.81)
Column sum	142 (100.0)	391 (100.0)	389 (100.0)	452 (100.0)	1374 (100.0)	Column sum	95 (100.0)	297 (100.0)	188 (100.0)	248 (100.0)	828 (100.0)

Note: Data are from CHIP 2007. HW: high white-collar; LW: low white-collar; S: skilled U: unskilled.

of intergenerational occupational mobility among the children of 4 birth cohorts.

For the oldest birth cohort, 1948-1957, 13.24 percent of children born to fathers with high white-collar jobs end up in the same high white-collar occupations. This percentage is approximately 14 in other panels, except panel 2 reaches 19 percent. We do not find significant trends in the transmission of high white-collar jobs. Similarly, in column 1 of each panel, we find no indication that children born to fathers with high white-collar jobs end up in other occupations. However, the percentage of children whose fathers have high white-collar jobs in other occupations gradually declines from the earliest cohort to the most recent cohort. This suggests that children whose fathers do not have high white-collar jobs find it increasingly difficult to find high white-collar jobs. Column 2 of each panel presents the percentage of sons whose fathers work low white-collar jobs in each occupation. In panel 1, 59.57 percent of children work in the same low white-collar occupation as their fathers; this percentage increases to 60.94 in panel 2, continues to increase to 68.8 in panel 3 and reaches 71.72 in panel 4. However, the percentages of children whose fathers have low white-collar jobs that end up in high white-collar and skilled jobs decline over time. Row 2 in each panel shows that the percentages of sons with low white-collar jobs whose fathers work in other occupations also decline over time. For example, the percentage of children with low white-collar jobs whose fathers also have low white-collar jobs (row 2 of column 2) in each panel is higher than those for children with low white-collar jobs whose fathers have other occupations (row 2, columns 1, 3, 4). These figures suggest that the persistence of low white-collar jobs increases over time. Occupational persistence also exists among skilled children who have skilled fathers. Column 3 in each panel presents the percentage of children in each occupation whose fathers worked in skilled occupations. There are no significant trends in children' occupation among those who have skilled fathers. However, we find that the percentage of unskilled children who have skilled fathers increases over time. The sum of row 3 shows that the share of children in skilled occupation increases from the early birth cohort to the recent birth cohort. In each panel, the percentage of skilled children with skilled fathers is higher than those whose fathers are in other occupations. Among children whose fathers have unskilled jobs, the percentage of children in the same unskilled category increases over time but decreases in the high white-collar category. The increasing row sum suggests inflows into unskilled occupations. Table 6 shows general changes in intergenerational occupa-

Table 7 Summary Measures of Mobility in Children's different birth cohorts

	M	M'	$d(P,J)$	$d(Q,J)$	$d(P,Q)$
1. 1948-1957 (P)	65.11	64.60	8.58***		6.73
1958-1967 (Q)	61.54	62.44		11.13***	
2. 1958-1967 (P)	61.54	61.27	11.13***		2.89
1968-1977 (Q)	61.43	61.40		10.07***	
3. 1968-1977 (P)	61.43	58.22	10.07***		13.46
1978-1987 (Q)	55.56	57.92		21.72***	
4. 1948-1957 (P)	65.11	60.67	8.58***		15.83**
1978-1987 (Q)	55.56	58.43		21.72***	

Note: M is total mobility (percent off the main diagonal). M' is total mobility using the marginal frequencies from the other table. * $p<0.1$. ** $p<0.05$. *** $p<0.01$. Significance levels for the likelihood ratio χ^2 statistic G^2.

tional mobility in a basic cross-classification table; we also need to analyze mobility using other measures to support our hypotheses.

Table 7 presents summary measures of occupational mobility among children's birth cohorts. We use 4 panels to compare the difference between one period and the following period and between the earliest and the latest birth cohorts. M is a simple measure of total mobility. The higher the value of M, the lower the intergenerational occupational persistence. From panel 4, we find that mobility is 65.11 for the earliest birth cohort, 1948-1957, which declines to 55.56 for the latest birth cohort, 1978-1987. M' is the mobility after adjusting the cross-classification table so that the categories have the same marginal frequencies. We transform the table by multiplying rows and columns by arbitrary constants based on the marginal frequency distributions (Altham 1970, Wickens 1989, Altham & Ferrie 2007, Long & Ferrie 2013).

In panel 1, column 1, the simple mobility gap between 1948-1957 birth cohort (*P*) and 1958-1967 birth cohort (*Q*) is 3.57 percentage points (65.11-61.54). If total mobility is measured using adjusted mobility (M’) the *P* (65.11 versus 62.44) or *Q* (64.60 versus 61.54) distributions of occupations indicate that the gap in total mobility between the two birth cohorts falls from 3.57 percent to 2.67 or 3.06 percentage points. If *P* had the *Q* occupational distribution but the underlying association between rows and columns actually seen in *P* (64.60), and the *Q* had the *P* occupational distribution but the underlying association between rows and columns actually seen in *Q* (62.44), then *P* would actually have had higher total mobility than *Q* (64.60-62.44). The Altham statistic for the 1948-1957 birth cohort is 8.58 and that for the 1958-1967 birth cohort is 11.13, which are both significant at the 1 percent level. It is possible to reject the null hypothesis that the association between rows and columns is the same as it would have been under independence. This measurement implies that mobility between children's occupations and their fathers' occupations is slightly closer to independent in the 1958-1967 birth cohort than in the 1948-1957 birth cohort, which is consistent with the simple mobility measurement. Panel 1, column 5 presents the underlying association between children's occupations and their fathers' occupations apart from that induced by differences in occupational distributions. (We can reject the null hypothesis that the association between rows and columns is the same as that under independence). The difference between *P* and *Q* in their degrees of association is small in magnitude (6.73); hence, we cannot reject the null hypothesis that their associations are identical at any significance level. This suggests that even if we account for differences in their occupational distributions, occupational mobility is similar for the *P* and *Q* cohorts.

Panel 2 compares mobility between the 1958-1967 birth cohort (*P*) and the 1968-1977 birth cohort (*Q*). Column 1 shows that the difference in simple mobility between *P* and *Q* is very small. If total mobility is measured using adjusted mobility (M’) for either the *P* (61.54 versus 61.40) or *Q* (61.27 versus 61.43) distributions of occupations, it is difficult to evaluate the period in which mobility is greater. The Altham statistic for *P* is 11.13 and that for *Q* is 10.07, which are both significant at the 1 percent level. The small difference between and implies that the association between children's occupations and their fathers' occupations is slightly closer to independent in the 1968-1977 birth cohort than in the 1958-1967 birth cohort.

Panel 3 compares mobility between the 1968-1977 birth cohort (*P*) and the 1978-1987 birth cohort (*Q*). Column 1 shows that the difference in simple mobility between *P* and *Q* is 5.87, which is larger than in panels 1 and 2. If mobility is measured using adjusted mobility (M') for either the *P* (61.43 versus 57.92) or *Q* (58.22 versus 55.56) distributions of occupations, the difference between *P* and *Q* falls to 3.51 or 2.66

percentage points. The Altham statistic for Q (21.72) is approximately twice that for P (10.07), and both are significant at the 1 percent level. We can reject the null hypothesis that the associations between rows and columns are the same as would be observed under independence.

Panel 4 compares mobility between the earliest birth cohort, 1948-1957, and the most recent birth cohort, 1978-1987, over a longer period. M declines by 9.55 percentage points, and M' declines by 5.11 percentage points (using Q marginal frequencies) or 6.68 percentage points (using P marginal frequencies). The results indicate that intergenerational occupational mobility worsens over time. The Altham statistic for Q (21.72) is approximately 1.5 times larger than that for P (8.58), but both are significant at the 1 percent level.

Table 7 provides measurements of the distance between the row-column associations among children of different birth cohorts. I find that large shares of the differences are caused by the gaps between the 1968-1978 birth cohort and the 1978-1987 birth cohort (panel 3). However, it is not clear which kind of occupational transmission causes these differences in mobility. It is necessary to apply a decomposition analysis to identify the factors making the greatest contributions to the differences between the row-column associations over time.

I now examine which occupational category cells contribute to the preferred mobility metric $d(P,Q)$. Table 8 shows the components of $d(P,Q)$ that have contributed to three-quarters of the difference between P and Q. There is a total of 144 such odds ratios for a 44 table for P (1948-1957 birth cohort) and Q (1978-1987 birth cohort). However, because of symmetry, only 36 of these are unique. Here, we only list the main 8 components that account for three-quarters of the difference between the associations. The first entry, [(HH)(HS)]/[(SH)(SS)], is the relative advantage when entering high white-collar work rather than skilled work when a father had a high white-collar job rather than skilled job. In the recent cohort, the 1978-1987 birth cohort, the children of fathers with high white-collar jobs are 140 times more likely to enter high white-collar occupations than skilled work who are the sons of skilled workers. In the 1948-1957 birth cohort, the odds ratio was only 5.14 to 1, so the advantage of having a father with high white-collar job rather than a skilled job in making this move (into high white-collar rather than skilled work) was 27 times greater in 1978-1987 cohort than in 1948-1957 cohort. This odds ratio contrast only accounts for 17 percent of the difference between the associa-

Table 8 Components of d(P,I), d(Q,J), and d(P,Q) for Child's Birth Cohort 1948-1957 Versus 1978-1987

Contrast	d(P,I)	Odds ratio	d(Q,I)	Odds ratio	d(P,Q)	Percentof otal	Cumulative percent
1. [(HH)(HS)]/[(SH)(SS)]	3.28	5.14	9.88***	140	6.61***	17.44	17.44
2. [(HH)(HU)]/[(SH)(SU)]	1.26	1.88	7.67***	46.38	6.42***	16.45	33.89
3. [(HH)(HL)]/[(SH)(SL)]	0.69	1.41	6.18***	21.93	5.48***	11.98	45.87
4. [(LH)(LS)]/[(SH)(SS)]	2.25	3.09	7.13***	35.29	4.87***	9.46	55.33
5. [(LH)(LU)]/[(SH)(SU)]	1.72**	2.36	5.45***	15.29	3.74**	5.58	60.91
6. [(SH)(SS)]/[(UH)(US)]	3.05***	0.22	6.57***	0.04	3.51*	4.92	65.83
7. [(LH)(LL)]/[(SH)(SL)]	0.38	1.21	3.78**	6.62	3.40*	4.61	70.44
8.[(HH)(HL)]/[(UH)(UL)]	1.02	0.60	2.09**	2.85	3.11***	3.86	74.30

Note: First element of each pair is father's occupation, second is son's. H: High white-collar, L: Low white-collar, S: Skilled and unskilled, U: Unskilled. * p<0.1. ** p<0.05. *** p<0.01. Significance levels for the likelihood ratio χ^2 statistic G^2.

tion in P and the association in Q. The first three entries present the likelihood that the children of fathers with high white-collar jobs were to enter high white-collar occupations compared to the children of fathers in skilled work were to enter other occupations. Moreover, this trend appears increasingly obvious in the youngest birth cohort compared to in the oldest birth cohort. These three entries explain nearly one-half of the difference in the association between P and Q. The fourth, fifth and seventh entries show that the children of fathers who worked low white-collar jobs are more likely to enter high white-collar occupations than are the sons of fathers with skilled jobs are to enter other occupations. These three contrasts explain nearly 20 percent of the difference in the association between P and Q. The odds ratio is less than 1 in the sixth entry, which indicates that a child entering a high white-collar occupations rather than skilled work is at a disadvantage when their fathers are engaged in skilled work compared to unskilled father. Overall, We find that children are more likely to enter high white-collar occupations than other occupations when their fathers have white-collar jobs than when their fathers have skilled jobs.

V. Conclusion

This paper examines the educational and intergenerational occupational mobility among children's birth cohort from 1948 to 1987. We find that education levels of children with lower educated fathers increase over years. This result implies that children with higher educated fathers have significant advantages to complete higher education level. Multinomial logit estimation indicates that the higher paternal education, the more likely children are to educated university and above. Being a male, borning in later birth cohort and living in the east significantly reduces the probability of being in the lowest educational category and increases the probability of being in the highest educational category. The cross-classification tables provide a comparison of intergenerational occupational mobility for children's 4 birth cohorts and show the overall occupational mobility becomes worse as time passes. The Altham statistics provide measurement of analyzing the distance between the row-column associations among children's different birth cohorts and shows that a large part of the differences are caused by the gaps between 1968-1978 birth cohort and 1978-1987 birth cohort. A decomposition analysis shows that in more recent years, the intergenerational occupational changes become less mobile especially when fathers have high white-collar jobs as opposed to the case fathers had skilled jobs.

Human capital theory emphasizes differences among people as a determinant of economic outcome. The intergenerational education persistence transmits the educational inequality from the parental generation to children's generation. Government should take measures to against the intergenerational transmission of inequality. First, the direction of education reform should fit the needs of the labor market. The development of education not only means increasing person's schooling years but also needs to fit the demand of labor market. Otherwise it is a waste of education resources. Particularly, the education reform should not only focus on expanding the higher education but also developing vocational education because economic development needs high level skilled workforce to improve productivity and competitiveness. Second, the regional differences in education level and intergenerational mobility require the government offers preferential policies to undeveloped areas. Teacher training that improves professional knowledge and teaching skills is an effective measure to develop education and reduces the regional inequality in education. The government should increase the education expenditure to reduce the private costs gap between poor families and rich families. Finally, government should create job chances for school graduates. Otherwise, the expansion of higher education will be a heavy burden to the labor market if the government cannot provide suitable employment chances.

Employment should be emphasized as the national development strategy because it concerns people's livelihood and the stability of society. Promoting the tertiary industry is efficient for expanding employment. The government should encourage entrepreneurship and private small/medium enterprises to create job opportunities. Improving the occupational mobility is an effective measure to enhance the intergenerational mobility of occupation. For example, active labor market policies to increase re-employability such as re-training schemes can not only reduce unemployment but also increase the personal occupational mobility. The government and schools should consider the demand of positions in the labor market to design majors and provide career instructions for students' first job.

In the CHIP 2007, occupations are classified into 7 types that are not essential for a more detailed analysis of intergenerational transmission. To examine the intergenerational mobility of education and occupation using new data is required for further research.

Notes

1) After adjusting row a1, a2, fitting the columns in step 1b do not alter the row sums that had been adjusted in step 1a. In general, the agreement of one set of marginal frequencies is lost when others are adjusted. How to solute this problem? We can use proportional adjustment again to readjust the expected frequencies and make the defective marginal distribution back to agreement. After several rounds adjustment, the inaccuracies become less than any desired value as the estimates converge (Wickens 1989).

2) The odds ratio begins with a different way to present the probability of an event, known as the odds. The odds of any event are calculated by taking the ratio of the probability of the event occurring to the probability of not occurring (Wickens 1989). The odds are nonnegative, it can equal any nonnegative number.

3) The 2007 urban and rural surveys were conducted by the NBS, but the rural-to-urban migrant survey was conducted by a survey company.

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