2016 Doctor's Thesis

Changes in Intergenerational Economic Mobility in Urban China

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Acknowledgements

This thesis is dedicated to my grandfather of blessed memory, whom has passed away 2 months before I had opportunity to study in Japan for Ph.D. course. He had always called me “Little Dr. Guan” with his best expectation when I was a child.

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Contents

Chapter 1 Introduction

This thesis consists three essays in intergenerational economic mobility. This thesis investigates the association between children and their parents in 3 areas: income, education and occupation.

1.1 Research Background

The Chinese economy developed rapidly, with GDP increasing 72 times[1] from 1978 to 2015 (The World Bank). However, with this economic growth, the Gini coefficient, which reflects income inequality, has increased. The Gini coefficient rose from 0.236 in 1988 to 0.376 in 2007[2] (Deng & Xue 2015). Of the increase in consumption inequality from 2003 to 2009, 59.23% is due to inequality across generations (Zhang & Xiang 2014).

A full analysis of inequality should include inequality within the same generation (intra-generational inequality) and across generations (intergenerational inequality). Since the last half of the 20th century, economists and sociologists have been concerned with the inequality issue. The former focus on intra-generational income inequality, whereas the latter focus on intergenerational social inequality. More recently, economists have proposed economic models and paid attention to developing new measurements of the associations between one generation and their offspring (Becker & Tomes 1979, Solon 1992, Mulligan 1997, Behrman 1997, Eide & Showalter 1999, Altham & Ferrie 2007). The intergenerational income mobility is always estimated by a measure called intergenerational income elasticity (IGE). The IGE is calculated using a regression of the logarithm of parental income on a child's income.

[1] In 1978, GDP was 148.38 billion U.S. dollars in 1978; by 2015, it was 10866.44 billion U.S. dollars. The data are transformed to current U.S. dollars. (from the World Bank website: databank.shihang.org/data).
[2] According to estimates from the World Bank, the Gini index was 44.28 in 2008 and 42.16 in 2012 (from the World Bank website: databank.shihang.org/data).

Higher IGE indicates lower intergenerational income mobility. Conversely, lower IGE indicates greater mobility.

How is income inequality transmitted from parents to children? Are children likely to have a similar socioeconomic status as their parents? Does the level of intergenerational mobility change over time? This thesis analyzes intergenerational mobility in urban China from an economic perspective. Most economic studies on intergenerational mobility consider income (Solon 1992, Björklund & Jäntti 1997, Solon 2002, Gong et al. 2012). When we consider the mechanism of intergenerational income mobility, the impacts of the intergenerational occupational and education transmission on income mobility cannot be ignored. This thesis investigates the association between children and their parents in 3 areas: income, education and occupation. This thesis traces changes in intergenerational economic mobility over nearly 50 years[3], so it is necessary to consider the social and economic changes that occurred during this period. Figure 1.1 shows the research background.

Economic Institutional Reform and Labor Market Reform

Economic reform and labor market changes are external factors affect intergenerational economic mobility. When the People's Republic of China was founded in 1949, national economic was under the planned economic system and public ownership that requires all enterprises be stated-owned or collectively owned. The government managed the labor market and allocated jobs to school graduates at all levels. Workers were employed in the same workplace for their whole career. Employees' income was mainly determined by a detailed wage degree system that mostly depended on employee seniority and education qualifications.

[3] Chapter 3 analyzes intergenerational income mobility from 1988 to 2007. The sample considered in chapter 4 is the children's cohort born between 1951 and 1990. Chapter 5 analyzes occupational mobility for the children's cohort born between 1948 and 1987.

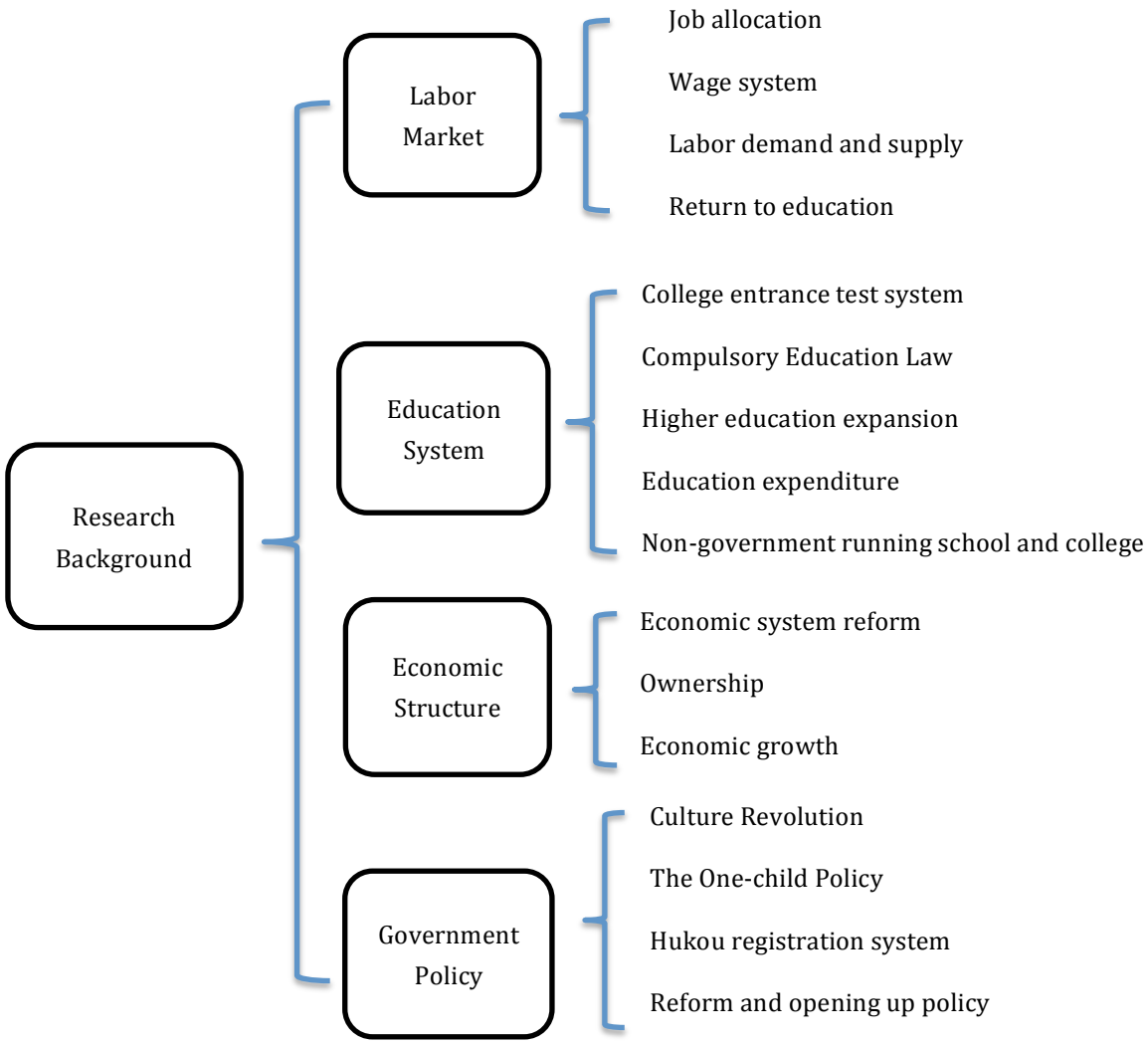


Figure 1.1 Research Background

The economic institutional reform was started in the late 1970s. The establishment of the Rural Household Responsibility System marked the launch of the reform. As a consequence, growth rates of agriculture products were accelerated up to several times higher than pre-reform era (Lin 1992). More important, the rural reform released surplus labor force in rural China (Rozelle et al. 1997). At that time, China has implemented a market economy, but urban labor market reform occurred at a slow pace. Job mobility and wage determination did not change much compared to the planned economic period.

Official statistics show that above 95 percent of urban employees were worked in the state sector or collective sector until the end of the 1980s (Meng 2000). However, the end of the extremely egalitarian wage system has enhanced labor efficiency and promoted economic growth (Knight & Song 2003).

The state-owned enterprises (SOEs) reform in the mid-1990s promoted economic growth but brought complex affects to the labor market. On one hand, it caused a large amount of laid-offs and unemployment. On the other hand, foreign enterprises and private firms created new demand of labor force, which increased private return to human capital (Ge & Yang, 2011).

Education System

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. When analyzing intergenerational mobility in education, changes in the education system must be considered. In the early years after the foundation of new China, education policies emphasized basic educational expansion as a means of nation building and economic development (Hannum, 1999).

During the Cultural Revolution, 17 million teenage urban secondary school students (born between 1946 and 1961) were sent to rural areas for re-education as part of the Up to the Mountains and Down to the Countryside Movement (Li, et al. 2010). The enrollment rate and promotion rate for primary school and middle school students have risen to 90% and 70%, respectively (Knight et al. 2011). However, the reduction of education quality and interruption of higher education have been heavily criticized. Previously, only the elite, with some exceptions, could aspire to a university education.

The "Compulsory Education Law of the People's Republic of China" was adopted in 1986 to equalize educational opportunities. Government expenditure on education was 1.41% of GDP in 1971 and steady increased to over 4% by 2012[4]. The schooling costs of primary and secondary education were mainly supported by the central government before economic reform. In the mid-1980s, the fiscal pressures were forced on local government. The fiscal decentralization leads to inequality in educational resource and education quality among different regions.

Before a serious reform on economic structures and social system in the late 1970s, very few Chinese young people (fewer than 5%) had access to college. From 1978 to 1998, the numbers of higher education student enrollment increased moderately from 0.86 million to 1.08 million. The numbers of college enrollment jumped to 5.4 million in 2006 (Bai 2006). The dramatic increase may attribute to the higher education expansion strategy enforced by the government in 1999. A growing number of college graduates improved upward educational mobility across generations. The total number of higher education graduates was 1 million in 2001 and increased to nearly 7 million in 2013, which rose by more than six times[5].

Government Policies

Since the one-child policy was carried out in the late 1970s and early 1980s by the central government in China, every pair of couples have only one child under regulations[6]. Investment in the only child, especially in the child's education, has since been the highest priority investment for almost all Chinese families. At most, the one-child policy increased educational attainment by 4%, and the opportunities to entre higher education levels increased by less than 9%

[4] Data source: China Statistics Year Book 1999-2015.
[5] Data source: China Statistics Year Book 2013.
[6] Beginning in 1981, the one-child policy was managed by the National Population and Family Planning Commission under the central government.

(Rosenzweig & Zhang 2009). The increasing numbers of higher education level graduates forced heavy employment competition to the labor market. Parents tended to invest more and more in children's education to against the employment pressure for getting a satisfying job (Wang 2005).

Moreover, the *hukou* system also affects changes in the labor market. It has been implemented in 1995. Hukou system concerned person's governmental supplement on food and other distributing resource that restricted the movement of rural labors to urban areas (Wu and Treiman 2007). The government applies *hukou* system not only as a tool of managing population, also as a tool to control urban employment (Chan & Zhang 1999). Reform and opening up policy brought large-scale foreign direct investment that increased labor demand, especially in coastal areas. However, hukou registration system restricts the migration of surplus rural labor force to urban.

1.2 Research Questions

The following is the central research question of this thesis: Are children likely to have a similar socioeconomic status as their parents? When inequality is mentioned, people may naturally think that there should be equal opportunities for human beings. However, the notion of "equal opportunity" is a too broad for economics to perfectly answer. An opportunity is a chance to obtain a good if one seeks it. When all persons are given effectively equivalent options, we say they have equal opportunities (Arneson 1989). Equality is an issue of offering equal rights for everyone no matter whose children they are, which region they comes from, what circumstances their experience in their childhood. Equal opportunity reduces the effects of inheritance, if we consider it from an intergenerational perspective. Children inherit different abilities and advantages from their parents, which directly or indirectly influence their economic and social outcomes.

In this analysis of intergenerational income mobility, IGE is estimated to illustrate I examine the intergenerational transmission of income and estimate income mobility using the IGE. It is concerned with answering the following questions: Does low-income children's income depend on their fathers' income as much as that of high-income children? Does income mobility differ in 1988 from that in 1995 and 2002? Moreover, which factors cause the observed differences in intergenerational income mobility across children's income groups over these years?

In the analysis of intergenerational educational mobility, the following questions are expected to be answer. First, how does intergenerational education mobility change over time? Second, why does the educational correlation between children and parents change over time? Third, How much does parental effect contribute to the upward mobility in children's education? Fourth, does mobility appear to exhibit gender differences? For example, does education depend more on paternal or maternal education? Does paternal or maternal education have a stronger impact on their children's education?

In the analysis of intergenerational occupational mobility, the relationship between children's occupation and their fathers' occupation is investigated among children who were born between 1948 and 1987. The following questions are expected to be answer. First, how does the occupational structure change overall across generations? Second, how does intergenerational occupational mobility change among children who were born between 1948 and 1987? Third, which factors contribute the most to changes in occupational mobility?

With these questions in mind, this thesis generates and examines alternative hypotheses as shown in table 1.

Table 1 The Hypotheses of This Thesis	
Chapter	Hypothesis
Chapter 2 Changes in Intergenerational Income Mobility	H1: Children's income is positive associated with their fathers' income. H2: The IGE is different among children's different income groups. H3: The IGE changes over years. H4: Children's education causes changes in IGE over years and across quantiles. H5: Occupational inheritance causes changes in IGE over years and across quantiles. H6: Regional difference causes changes in IGE over years and across quantiles.
Chapter 4 Changes in Intergenerational Educational Mobility	H7: Children's education attainment is positive associated with their parents' education attainment. H8: Children's education more and more depends on their parents' education over years. H9: Gender differences exist in the intergenerational educational mobility. H10: The upward intergenerational mobility of education increases over years. H11: It is easier for children with parents to receive university education. H12: The growing rate of university-educated children is more affected by educational expansion effect than parental background effect.
Chapter 5 Changes in Intergenerational Occupational Mobility	H13: Children's occupations have associations with their fathers' occupations. H14: The distance between father-child occupational associations is different over years. H15: Occupation category cells contribute differently to the overall intergenerational mobility of occupation.

1.3 Outline

The purpose of this thesis is to study trends in intergenerational economic mobility and to explore how economic status is transmitted from one generation to another to influence the income distribution for nearly half a century in urban China. To do so, the Chinese Household Income Project (CHIP) and empirical methods are used to examine the hypotheses mentioned above. This thesis

explains changes in intergenerational economic mobility in three areas: income, education and occupation.

Chapter 2 estimates the intergenerational income mobility across children's conditional income distribution in urban China from the 1980s to the 2000s. Based on CHIP data from 1988, 1995 and 2002. IGE is measured using a regression of the logarithm of a father's income on his child's income (Becker & Tomes 1979). The quantile regression approach that introduced by Koenker and Bassett (1978) is used to illustrate IGE across children's income groups.

Chapter 3 analyzes intergenerational educational mobility for parent-child pairs across 4 ten-year birth cohorts between 1951 and 1990 using data from the CHIP 2013. First, Ordinary Least Squares (OLS) regression is used to estimate intergenerational educational correlations between children and their parents. Then, a categorical data analysis is conducted and a decomposition technical approach is used to investigate educational mobility. Last, multinomial logit model is used to interpret the impact of the other explanatory variables on probabilities of children's education. The results suggest that the importance of parental education increases as time passes for both fathers and mothers; upward mobility increases while immobility decreases over time; inequality in educational opportunities shows a decreasing trend; and being male, having highly educated parents, more recent birth cohorts and growing up in the east region increase the probability of having higher education.

Chapter 4 analyzes intergenerational occupational mobility for father-child pairs among children who were born between 1948 and 1987 using data from the CHIP 2007. Children are divided into 4 birth cohorts (1948-1957, 1958-1967, 1968-1977, 1978-1987) and their occupations are classified into four categories: high white-collar workers, low white-collar workers, skilled workers and unskilled workers. Intergenerational occupational mobility is also examined using categorical data analysis. To compare mobility by children's birth cohorts,

a method based on the marginal frequency distributions is used, which is followed Deming and Stephan (1940), Altham (1970), Altham & Ferrie (2007), and Long and Ferrie (2013). Altham statistics is also used to measures the association between rows and columns in two different occupation distribution tables. Overall, the results show a declining trend in intergenerational occupational mobility. The results suggest that a large share of the change in occupational mobility is caused by the gap between the 1968-1978 birth cohort and the 1978-1987 birth cohort. A decomposition analysis indicates that children are more likely to enter high white-collar occupations than other occupations when their father has a white-collar job than when he has a skilled job.

Chapter 5 provides a brief summary of this study, states the importance of this research, gives policy implications and posts new research questions for future research.

1.4 Contributions and Limitations

To the best of my knowledge, this thesis firstly systematically analyzes the associations between children's socioeconomic status and their parents' socioeconomic status for the recent decades in urban China. This thesis offers the first detailed comparisons of intergenerational mobility in 3 areas (income, education and occupation) and traces changes in intergenerational economic mobility in urban China from the 1980s to the 2010s using the CHIP 1988 1995 2002 2007 and 2013. Unlike previous studies estimate the mobility using OLS or IV method, this thesis conducts new approaches to estimate the intergenerational economic mobility. In chapter 3, the internal transmission mechanism of intergenerational education is explored and the external effectors are analyzed. In chapter 4, we offer a new perspective on how social and economic changes influence the intergenerational transmission process. we also

decompose the intergenerational occupation transmission by the case of urban China and explore the main contributors to the occupational mobility. Based on empirical evidence, we proposal the political implications to reduce the intergenerational economic inequality.

This study focuses on the empirical evidence to examine the intergenerational economic mobility. However, due to the data limitation, measurement error and estimation bias occur. The CHIPs are lacking direct measures of long-run status, which leads to measurement error. Cross-section data cannot provide income information for a long time series to estimate permanent income. The use of single year income leads to a downward estimation bias of IGE (Solon 1992). Additionally, this survey only provides income information of children who are co-residing with their parent in the same household, which leads to a downward estimation bias in IGE (Deng et al. 2013). Although there are data limitations, it offers to achieve a meaningful comparison of intergenerational income mobility across years.

In the chapter 3 and chapter 4, we conduct categorical data analysis. we divide education into 4 levels and occupations into 4 types. However, the intergenerational mobility is not same even in the same entry of matrix. Hayhoe (1995) points out that students who comes from richer families with more social capital and cultural sources are more likely to entre key universities than students from disadvantaged families. To improve the analysis of intergenerational educational mobility requires more detailed classifications of education outcomes. Similarly, the income gap in the same type of occupations also significantly exists. Blau and Duncan (1967) carry out a most detailed investigation of intergenerational occupational mobility and finds that the intergenerational occupational movement mostly occurs in the near occupations. 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 occupation using new data is required for further research.

Chapter 2 Changes in Intergenerational Income Mobility

In this chapter, changes in intergenerational income mobility are analyzed across children's conditional income distribution in urban China from the 1980s to the 2000s. Based on CHIP data from 1988, 1995 and 2002, the IGE of father-child pairs is estimated using both ordinary least square regression and quantile regression. The results of OLS regression show that the intergenerational income mobility decreases slightly from 1988 to 1995, and then increases in 2002. The results of quantile regression suggest that low-income children's income more and more depend on their father's income, while high-income children's income tends to be less affected by their father's income over years. Results of extended analyses suggest children's educational attainment, occupation and regional differences affect intergenerational income mobility.

2.1 Literature Review

This chapter provides new evidence for the estimation of intergenerational income elasticity (IGE) in urban China. Unlike earlier studies that have examined this relationship using ordinary least squares or instrumental variables for just one or two years (Guo and Min 2008; Gong, Leigh and Meng 2012; Deng, Bjorn and Li 2013), this chapter is based on CHIP data and, using quantile regressions, estimates the IGE of 3 different years to represent the changes in intergenerational income mobility from the 1980s to the 2000s. From the results of IGE, I observe that intergenerational income inequality in urban China slightly decreases from 1988 to 2002.

Intergenerational income mobility

The quantile regression is motivated by the hypothesis that

intergenerational income mobility varies for different quantiles of children's conditional income distribution. The feature of quantile regression is that it can reveal not only the general laws but also the special laws of economic theories and economic phenomena. When distinguishing the different impacts of independent variables on dependent variables' different levels, the quantile regression can leverage its advantages. A higher IGE indicates that intergenerational income mobility is lower at that quantile of children's income distribution. Conversely, a lower IGE indicates that the mobility is greater at that quantile.

Most current studies using quantile regression suggest that the IGE is the highest in the bottom of sons' conditional earnings distribution, which indicates there is a high intergenerational persistence of low earnings (Eide and Showalter 1999, Fertig 2003, Grawe 2004, Hirvonen 2008, Bratberg 2007, Nicoletti 2008). To my knowledge, Eide and Showalter (1999) are the first to use a quantile regression approach to estimate IGE using the Panel Survey of Income Dynamics (PSID) and High School and Beyond (HSB). Their results show that the intergenerational income mobility is greater at the top quantile of sons' earnings than at the bottom. Fertig (2003) examines trend in the intergenerational earnings mobility based on data from the PSID. She notes that mobility increases for father-son pairs and that difference between the lower and upper quantiles narrows over time. A similar study in Norway shows that the higher the quantile of children's income distribution, the smaller the IGE (Bratberg et al. 2007). Hirvonen (2008) argues, using large samples of Sweden data, that children's income are more depended on parents' family for sons at the bottom quantile than sons at the top quantile. A few other studies suggest opposite results, i.e., that the IGE is higher at upper quantiles (Aydemir et al. 2009).

There is little research that estimates the IGE of China using a quantile regression approach. Previous studies on China's intergenerational income

mobility estimate the IGE in urban China using different datasets. Guo and Min (2008) estimate the IGE of urban China is 0.32 using data from the Chinese Urban Household Education and Employment Survey 2004 (UHEES). Gong, Leigh and Meng (2012) use the Urban Household Income and Expenditure Survey 1987-2004 (UHIES) to predict parents' permanent income, and they use the UHEES 2004 to estimate the IGE for father-son pairs to be 0.63. Li, Liu and Wang (2014), using the China Health and Nutrition Survey (CHNS) by IV estimate the IGE of China to be 0.83. Yuan and Chen (2013) note the trend and the mechanism of intergenerational income mobility. They argue that the IGE decreases from 1988 to 2006. Kan, Li and Wang (2014) use TS2SLS regression and structural quantile regression provide evidence for Taiwan. They argue that parents' income influences children's income through the propagation of children's income shocks, rather than by affecting the level directly. They also find that the IGE between mothers and children increases slightly, but they find no obvious trend between fathers and children. Deng, Björn and Li (2013) use the China Household Income Project (CHIP) to estimate the IGE for father-son pairs to be 0.47 in 1995 and 0.53 in 2002. They also use the quantile regression to estimate father-son, father-daughter, mother-son and mother-daughter IGE in a short paragraph in the sensitive analyses section. They argue that the IGE of children's different income distributions is not significantly different, especially for fathers and sons. However, they do not explain the reasons for the results. One motivation for writing this chapter is to explain the quantile regression results and inditify the factors that cause the differences in the IGE in children's conditional income distribution. My results show that the IGE is smaller at the lower quantiles and larger at the higher quantiles. The differences across different quantiles are obviously different from Deng's (2013) argument.

Channels of intergenerational income transmission

Assume that children's educational[7] and regional difference cause the different IGE across quantiles and years. Controlling for these factors will allow us to understand the channel of intergenerational income mobility transmission.

The use of children's education as a measurement of transmission channel is based on the human capital theory (Mincer 1974; Becker 1975 and Rosen 1978). Parental investment in their children's education can be seen as private cost of human capital investment. It used to be commonly assumed that high-income parents tend to invest more in their children's education. Herzt (2006) investigates that children of high-income parents get more education. Bowles & Ginitis (2002) introduces the correlation of parents' income and children's years of education is about 0.45. The theoretical literature proved that education as parental private human capital investment in their children affects children's income. Educational attainment is a crude measure of parental human capital investment (Bowles 1972 and Becker 1972). Glomm & Ravikumar (1992) argues that the quality of education received by children is different because parental human capital investment affects their children's learning and the effect of the investment occurs across generations. Previous empirical studies also exam how much children's education explains the correlation in intergenerational income. Eide & Showalter (1999) measures the effect of educational attainment on the IGE using the PSID. They find that accounting for children's education drops roughly 25 percentage points of IGEs. Therefore, they conclude that education is important in explaining the intergenerational mobility in income. Bowles & Ginitis (2002) finds that the effect of schooling on IQ contributes 9 percentage points to the intergenerational income transmission using data from the Armed Forces Qualification Test and the U.S. Twinsburg Study. Palomino et al. (2014) estimate the effects of educational attainment as a channel of intergenerational

[7] In general, we think genetic and ability inheritance are important channels of intergeneration transmission. Unfortunately, CHIPs do not provide micro data for measuring them. Previous studies usually evaluate the transmission channel effects using education (Glomm & Ravikumar 1992; Eide & Showalter 1999; Bowles & Ginitis 2002; Hertz 2006; Palomino et al. 2014).

income transmission channel using the PSID data. Their results show that the IGE decreases 27.4 percentage points. By quantile, the IGEs decrease between 18 and 47 percentage points.

Assume that the social and economic development varies among different regions, which affects the intergenerational income mobility. Pervious studies usually comprise regional variation in the baseline estimate model (Gong et al. 2012). However, to clarify the regional effects on the intergenerational mobility, we control regional indicator in the extend analysis part. Pekkarinen et al. (2009) conduct four estimating models to exam the regional effect by adding regional dummy variables and region fixed effects. They find that the intergenerational income mobility changes over time and to vary across regions after including a full set of cohort and region effects.

This chapter improves the research in the following two aspects. First, the main objective of this chapter is to estimate the IGE of children's conditional income distribution. Based on the estimate results, I determine the shape of IGE change over time and explain why the shape inclines or declines across children's conditional income distribution. For this purpose, I use quantile regression, a method for estimating any point in a conditional income distribution. Second, the analysis requires data for several years, which can reflect a trend over time, so I choose data from the China Household Income Project (CHIP) in 1988, 1995 and 2002. One advantage of this data set is that the samples are actual parent-child pairs. All children I select for the sample co-reside with their parents. It is reasonable to assume that the children's growth is influenced by their families' background. Moreover, the CHIP data provides individual characteristics, such as education, occupation and industry. This information is helpful for analyzing the channel of income transmitted across generations and to conduct sensitive analyses to assess the robustness of the results. One limitation of CHIP data for estimating IGE is that it is

cross-sectional data. A single-year income measurement leads to a downward bias in the estimation (Solon 1992). The results suggest that intergenerational mobility in urban China is greater.

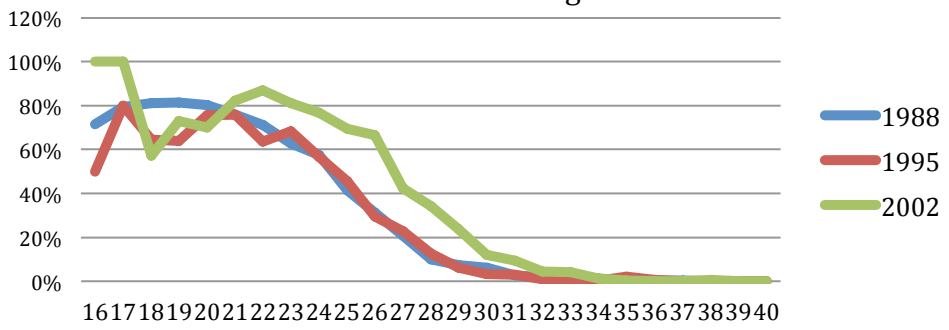
This chapter contributes new evidence for IGE in urban China over 3 decades using a quantile regression approach. Moreover, it examines the differences across children's conditional income distribution. Finally, it explains why intergenerational income mobility varies across children's income groups. The rest of this chapter is structured as follows: Section 2 describes the data, Section 3 presents the empirical model and the methodology, Section 4 reports the results and discussion, and Section 5 concludes.

2.2 Data

This analysis uses data from the Chinese Household Income Project. This project has been conducted by researchers at the Institute of Economics, Chinese Academy of Social Sciences, and data have been collected by the National Bureau of Statistics (NBS) in 1988, 1995, 2002 and 2007; the project is still running. The former designed the questionnaire and the latter carries out the fieldwork. Cross-sectional data were collected in 1988, 1995 and 2002, through interviews with different households each year. Starting in 2007, the project re-interviews the same households each of the following years. All the surveys contain rural and urban household samples. With the increasing trend of the labor force, the CHIP 2002 surveyed rural-to-urban migration. The purpose of this survey is to collect information for measuring and estimating the personal income and related economic situations. It collects rich information on households and household members, e.g., personal characteristics, employment situations, income, educational attainment, assets and debts, expenditures, and living conditions. This chapter uses CHIP data from the urban surveys in 1988, 1995 and 2002, which were representative cross-sectional surveys covering 9009

households and 31827 individuals in 1988; 6931 households and 21698 individuals in 1995; and 6836 households and 20632 individuals in 2002.

Figure 2.1 Co-residence Rate in 1988, 1995 and 2002 by Children's Age



Source: Data are from CHIP 2002. Values are calculated by the author.

There are four potential problems with the data. First, there are missing data on individual income, education, industry, and occupation. It is difficult to make sure there is no missing information in our samples. I drop the samples that are missing information on income, education or occupational information. Second, the total amount of observations is large, but after data processing, our number of observations in the regression is small—only several hundred. However, a small number of observations do not mean our samples are poor, and the results explain our hypotheses well. Third, only children who co-reside with their parents are interviewed. Figure 2.1 shows the percentage of children who co-reside with their father. We can observe from the figure that the rate varies by the children's ages. There is not a stable trend before age 22 years, and then, the trend declines. This leads to a question of whether our sample can represent the whole situation in China. Lastly, the use of annual income as a proxy for long-run income leads to measurement error. Children's and their father's income in the survey is for only one year. Children's income is measured at an earlier age, while fathers' income is measured later in their lifecycle, which leads to a lifecycle bias. Böhlmark and Lindquist (2006) argue that the use of current income as a proxy for lifetime income might lead to inconsistent parameter

estimates even when the proxy is used as a dependent variable. When estimating IGE, researchers usually use the permanent income of fathers to avoid the life-cycle bias. Unfortunately, in China, there is no suitable long panel data that can be used for this study. It is optimal to measure earnings in the middle of one's life cycle. The single-year income when one is approximately 40 years old is closest to the lifetime income (Black and Devereaux 2011). In this study's sample, the mean age of the children is approximately 24 years, and fathers' average age is approximately 53 years. Income at an earlier age leads to a downward bias in the estimation. Furthermore, income at fathers' average age is not a good proxy for permanent income. Solon (1992,1999) notes that the "noisiness" of single-year income as an indicator of long-run income causes an attenuation inconsistency in the estimation, which is similar to the errors-in-variables bias, and it alone can depress elasticity by more than 30 percent. The use of multi-year average income can reduce the bias but cannot eliminate it.

This study focuses mainly on the father-child relationship in income. The children in the sample are aged 16 to 40 years old, report positive income and provide education information. Children over 40 are excluded from the samples because the number of such children who co-reside with their parents is small; the possibility for a child over age 40 years to be interviewed in the same household as his parents is faint. Fathers in the samples are aged 31 to 60 years and report positive income. I drop samples with a generation age difference smaller than 15 years.[8] There are no direct questions on fathers' income in the survey; thus, I first select sons in the sample and then match fathers for them. The CHIP data are gathered from a household survey, and each household has a

[2] According to The Sixth National Population Census (2010). The number of children bore is collected from women aged from 15 to 64 years. It is reasonable to restrict the age gap between fathers and children to be larger than 15 years. Kan, Li and Wang (2014) exclude samples if the age difference between a parent and his child is less than 15 years. Gong, Leigh and Meng (2012) exclude samples if the age difference between a parent and his child is below 14 years.

Table 2.1 Sample Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
1988	2298				
Children's age		22.32	3.38	16	39
Children's gender		0.52	0.50	0	1
Children's income		3077	2398	511	82097
Children's years of schooling		11.22	2.17	1	16
Fathers' age		51.57	4.55	36	60
Fathers' income		5792	2620	1271	48221
Eastern		0.39	0.49	0	1
Middle		0.47	0.50	0	1
Western		0.14	0.35	0	1
1995	1011				
Children's age		23.41	3.10	16	36
Children's gender		0.59	0.49	0	1
Children's income		4978	3957	546	52122
Children's years of schooling		11.58	2.41	1	21
Fathers' age		53.07	4.24	41	60
Fathers' income		9055	5117	636	52339
Eastern		0.42	0.494	0	1
Middle		0.25	0.430	0	1
Western		0.33	0.472	0	1
2002	877				
Children's age		24.87	3.33	16	38
Children's gender		0.55	0.50	0	1
Children's income		9753	9504	500	160000
Children's years of schooling		12.83	2.34	5	19
Fathers' age		53.26	3.93	39	60
Fathers' income		12620	9030	600	100000
Eastern		0.49	0.50	0	1
Middle		0.25	0.43	0	1
Western		0.26	0.44	0	1

Notes: Income is annual income. All values are transformed to 2002 Chinese yuan using the general Consumer Price Index from the NBS. I remove outliers whose annual income is less than 500 yuan.

unique code. I use the family members' relationship[9] with the household head to match the father-child pairs. In the children sample, there are two subsamples. In one case, the second generation has a "child" relationship with the household head; then, his father maybe a "household head" or "household head's spouse" in

[9] For 1988, the relationship to the head of household is one of the following: 1, self; 2, spouse; 3, child; 4, grandchild; 5, parent; 6, grandparent; 7, other relative; 8, non-relative. For 1995 and 2002, the relationship to head of household is one of the followings: 1, self; 2, spouse; 3, child; 4, child in law; 5, grandchild; 6, parent; 7, parent in law; 8, grandparent; 9, brother or sister; 10, other relative; 11, non-relative.

the same household. In the other case, the second generation is "household head" in a household; then, his father has a "parents" relationship with him in the same household. The income variable used is total annual gross income.10 All values are transformed to 2002 Chinese yuan using the general Consumer Price Index from the NBS. I remove outlier samples whose annual income is less than 500 yuan. After data processing, the numbers of observations are 2298 in 1988, 1011 in 1995 and 877 for CHIP2002.

Table 2.1 presents the summary statistics of children's gender, age, income, years of schooling and fathers' age and income. The numbers of observations are 2298 in 1988, 1011 in 1995 and 877 in 2002. The mean age of children is approximately 24 and increases slightly each year. The subsample size of sons is a little more than daughters. The mean income of children is increasing because China's economic development promotes people's income during these twenty years. The mean income of children is lower than their father's income and the coefficient of variation is higher because one's income is lower in his earlier working years in the lifetime. Children's years of schooling increases over the years.

2.3 Methodology

Estimation of IGE

Becker and Tomes (1979) note that the influence of children's family on their income can be measured by the correlation between their income and that of their parents or grandparents. Intergenerational income elasticity (IGE) is widely used as a measurement of income transmission across generations. The

10 For 1988, the total income is not asked, so I follow the income definitions from data descriptions and add types of earnings together. The working members' income includes regular wage, floating wage, contract income, bonus, above quota wages, subsidies, other wages, hardship allowances, and other working income. Owners of private or individual enterprise income is total yearly net income before taxes. For 1995, the total income is interviewed as total annual gross income. For 2002, the total income is personal yearly total income. For 2007, the total income includes wage worker's wages, bonuses, allowances and commutations in-kind, net income for self-employed.

estimate of IGE is based on a regression of a logarithm of a father's income on his child's income.

$$\ln Y^c = \alpha + \beta \ln Y^p + \theta_1 A^c + \theta_2 A^{c2} + \varphi_1 A^p + \varphi_2 A^{p2} + \delta D + \gamma X + \mu \qquad (2.1)$$

In this equation, Y^c is children's monthly income; Y^p is fathers' monthly income; coefficient β represents the estimated intergenerational income elasticity; A^c is children's age (and $\theta_2 A^{c2}$ is its square); A^p is fathers' age (and A^{p2} is its square), D is children's gender dummy variable; X is a vector of control variables[11]; and μ is the error term, involving other factors that affect children's income but are not correlated with fathers' income. Gary Solon (1992) argues that the income variable should be represented by long-run economic status (e.g., permanent income); otherwise, the IGE will be underestimated because of measurement bias. However, due to the data limitation, I use single-year income as a proxy of fathers' long-run economic status in the estimation.

The variable of fathers' single year income has an endogeneity problem that may bias OLS estimates. To address the issue of potential endogeneity, one way is to find an instrument variable that strongly correlates with fathers' income and is uncorrelated with the error terms. Unfortunately, there is no suitable instrumental variable. Some scholars (Solon 1999; Gong, Leigh and Meng 2012) use fathers' education as the instrument variable. However, as we know, fathers' education has an independent effect on children's education, so fathers' education is not a perfect instrument variable here. An invalid instrument will generate two-stage least squares estimates that are as biased as OLS. The other way is to use fathers' income the year before the survey year. For example, when estimating the IGE of 1988, I use fathers' income before 1988—i.e., I use fathers'

[11] In the extended analyses, we control for children's years of schooling, occupation dummy variables, and regional dummy variables.

income in 1987 or earlier. However, as we know, survey data on households are often come with a rounding bias, especially when interviewers report the income of earlier years depending on their memory. A simpler way to solve the endogeneity problem is to use a fitted value as the regressor of fathers' income. However, we do not have sufficient information to calculate the fitted values of fathers' income. Few empirical papers to date have taken into account of the possibility of endogenous variables in a quantile regression framework. Thus, I do not control for the endogeneity of fathers' income. Although the results are biased, they constitute meaningful evidence to reflect the changes in IGE over the years.

Quantile Regression

Quantile regression is introduced by Koenker and Bassett (1978) and applied in labor economics, public economics, development economics and finance. It not only concerns the effect of independent variables on the average but also allows researchers to estimate the marginal effect of explanatory variables at different points in the conditional distribution. The result is estimated by minimizing a weighted sum of absolute residuals:

$$\min_{\beta \in \Re^{K}} \sum_{i \in \{i: y_i \geq x_i \beta\}} \theta \left| y_i - x_i \beta \right| + \sum_{i \in \{i: y_i < x_i \beta\}} (1-\theta) \left| y_i - x_i \beta \right| \qquad (2.2)$$

In the equation, $y_i (i = 1, \dots, I)$ is the dependent variable, $x_i (i = 1, \dots, I)$ is the K by 1 vector of explanatory variables with the first element equal to unity, β is the coefficient vector, and θ is the quantile to be estimated.

2.4 Results

This section presents basic analysis and extended analyses of intergenerational income mobility, discusses the results and provides an intergenerational comparison on the intergenerational mobility of income.

Basic Analysis

I first estimate the IGE by ordinary least squares, which estimates the conditional mean effect of father's income on child's income. Then, I apply quantile regression to estimate the different conditional distribution effects of father's income on child's income at different quantiles. This method is introduced by Koenker and Bassett (1978) and applied in labor economics, public economics, development economics and finance. Grawe (2004) argues that the separate mobility among differently achieving children might improve the understanding of the intergenerational transmission process. In this study, quantile regression provides a more detailed analysis of the relationship between father's income and child's income, and it allows a flexible analysis of the impact of father's income on child's income. Using a quantile regression method, this study describes trends in the intergenerational income mobility across children's income distribution in different years.

Table 2.2 OLS and Quantile Regression Estimates of the IGE of Children's Log Income with Respects to Fathers' Log Income

Log income of		Quantile				
Children	OLS	0.1	0.25	0.5	0.75	0.9
1988	0.420***	0.255***	0.352***	0.492***	0.580***	0.575***
Log income of fathers	[0.029]	[0.060]	[0.044]	[0.039]	[0.041]	[0.065]
1995	0.447***	0.383**	0.433***	0.476***	0.480***	0.505***
Log income of fathers	[0.038]	[0.140]	[0.053]	[0.050]	[0.047]	[0.065]
2002	0.402***	0.400***	0.423***	0.454***	0.444***	0.391***
Log income of fathers	[0.038]	[0.084]	[0.075]	[0.051]	[0.050]	[0.059]

Notes: Data are from the Chinese Household Income Project 1988, 1995 and 2002. The number of observations is 2298 in 1988, 1011 in 1995 and 877 in 2002. Standard errors are in parentheses. For the quantile regression, bootstrapped standard errors are reported. * p<0.1. ** p<0.05. *** p<0.01.

Table 2.2 reports the results for the OLS regression and the 10th, 25th, 50th, 75th and 90th regression quantiles of children's log income with respects to fathers' log income. Children's age and its square, their fathers' age and its square, and children's gender are controlled in the estimate. The first column of the table presents the OLS results of IGE in 1988, 1995 and 2002 using Equ. (2.1).

The estimated coefficient is 0.420 with a standard error of 0.029 in 1988, which indicates that a unit increase in father's income raises children's income by 42 percentage points. Then, the IGE increases to 0.447 with a standard error of 0.038 in 1995, and finally falls to 0.402 with a standard error of 0.038 in 2002 with all estimates being highly statistically significant. The change in IGE implies that the intergenerational income mobility becomes greater from 1988 to 1995, and then becomes less mobile in 2002. Children's income is more depending on their father's income. Column 2 shows the quantile regression estimates at 10th, 25th, 50th, 75th and 90th quantiles using Equ. (2.2). By years, in 1988, the IGE is 0.255 at the bottom quantile, increases to 0.580 at the 75th quantile, and finally falls slightly to 0.575 at the top quantile. The overall trend is an increase from the bottom to the top of the conditional earnings distribution. The results indicate that the intergenerational income mobility is greater in lower income groups of children, and smaller in higher income groups. In 1995, the IGE keeps increasing from the bottom quantile to the top quantile. The smallest IGE is 0.383 at the 10th quantile while the largest IGE is 0.505 at the 90th quantile. The results show that the intergenerational income mobility is smaller from children's lower income groups to higher income groups, which imply that the higher children's income is, the more associated of income with their fathers. In 2002, the IGE increases from 0.400 at the bottom quantile to 0.454 at the medium quantile then tends to decrease at the upper quantiles, with the top quantile having a point estimate of 0.391. By quantile, I find the smaller IGE is at the bottom quantile in 3 years, which suggests low-income children are less affected by their father's income than other income groups. The IGEs at the upper quantiles declines over years. It changes 0.07 with a decrease from 0.575 in 1988 to 0.505 in 2002, and it changes 0.114 with a decrease from 0.505 in 1988 to 0.391 in 2002. The quantile regression results in column 2 are therefore consistent with the hypothesis that the IGE is varies by quantile.

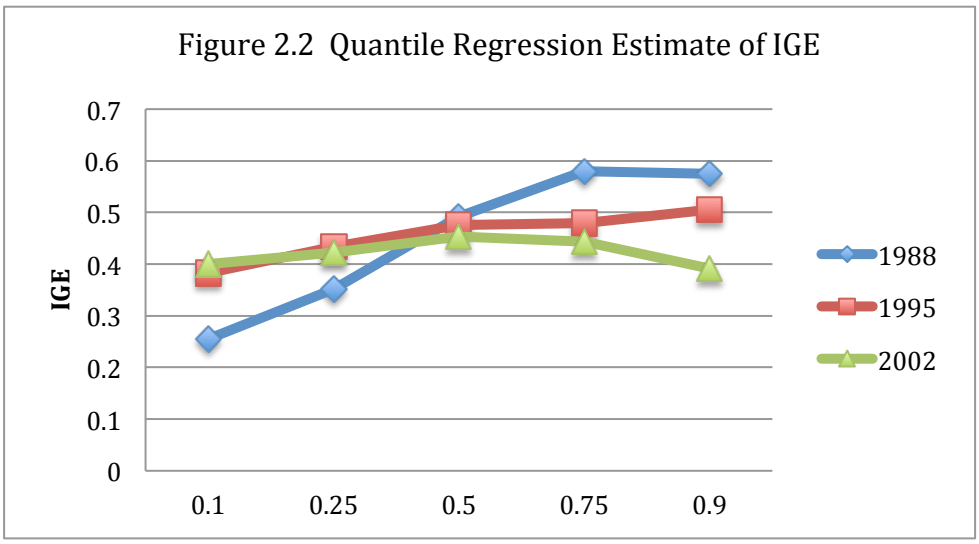


Figure 2.2 shows the shape of IGE across five quantiles in 1988, 1995 and 2002. The overall trend appears to be an increasing IGE across quantiles in 1988, which indicates intergenerational income mobility worsens from lower income groups to higher income groups. The change in IGE increases slightly in 1995 from the 10th quantile to the 90th quantile. However, this increasing trend changes in 2002; an inverted-U curve shows an increasing trend at lower quantiles and a declining trend at higher quantiles. IGE increases rapidly from the bottom quantile to the top quantile in 1988. Another obvious trend is that IGE decreases steadily at higher quantiles. At the 0.75 and 0.9 quantiles, the IGE starts at approximately 0.6 in 1988, falls to nearly 0.5 in 1995, and finally drops to 0.391 in 2002. This implies that high-income children do not depend on their father's income as much as before.

Assume that children's educational attainment, occupation and regional difference cause the different IGE across quantiles and years. Controlling for these factors will allow us to understand the channel of intergenerational income mobility transmission.

Controlling for Education

Table2.3 OLS and Quantile Regression Estimates of the IGE of Children's Log Income with Respects to Fathers' Log Income Controlling for Education Attainment

Log income of children	OLS	Quantile 0.1	0.25	0.5	0.75	0.9
Panel 1 1988						
Log income of	0.414***	0.261***	0.346**	0.476***	0.574***	0.574***
Fathers	[0.029]	[0.065]	[0.051]	[0.041]	[0.040]	[0.062]
Years of schooling	0.007	0.009	0.012**	0.012**	0.007	0.001
	[0.004]	[0.010]	[0.005]	[0.005]	[0.151]	[0.008]
% Changes in IGE	-1.45	2.35%	-1.70%	-3.25%	-1.03%	-0.17%
Panel 2 1995						
Log income of	0.435***	0.386***	0.419***	0.457***	0.474***	0.469***
Fathers	[0.038]	[0.125]	[0.045]	[0.044]	[0.052]	[0.059]
Years of schooling	0.014*	-0.001	0.015*	0.016*	0.021**	0.038***
% Changes in IGE	-2.68	0.78	-3.23	-3.99	-1.25	-7.13%
Panel 3 2002						
Log income of	0.346***	0.249*	0.363***	0.423***	0.328***	0.366***
Fathers	[0.038]	[0.120]	[0.065]	[0.039]	[0.061]	[0.059]
Years of schooling	0.079***	0.111***	0.077***	0.423***	0.077***	0.096***
% Changes in IGE	-13.93	-37.75%	-14.18%	-6.83%	-26.13%	-6.39%

Notes: Standard errors are in parentheses. For the quantile regression bootstrapped standard errors are reported. * p<0.1. ** p<0.05. *** p<0.01. Data are from the Chinese Household Income Project 1988, 1995 and 2002. The number of observations is 2298 in 1988, 1011 in 1995 and 877 in 2002.

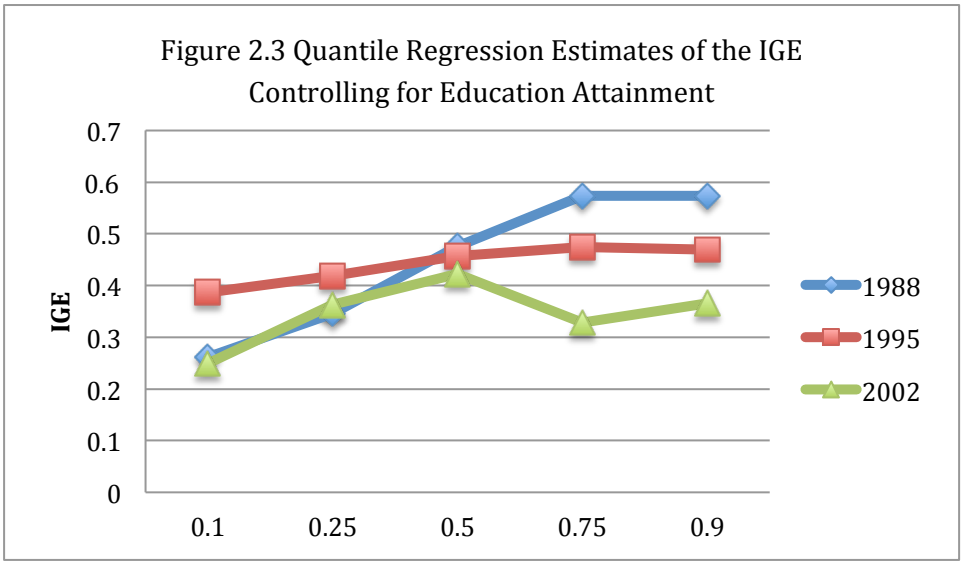


Table 2.3 represents the changes in IGEs after including a measure of children's educational attainment in equation (2.1). Previous studies proved there is a positive correlation between person's education level and his income (Mincer 1974). The educational choice of children depends on the parents' private cost of education and returns to education. There is a Chinese tradition that Chinese parents are willing to spend a large portion of their income on their children's education. In this analysis, education can be seen as parents' private investment in their children's human capital. When the determinant of education is accounted for, the OLS estimates of the IGE coefficient change in comparison to the baseline results.

Table 2.3 column 1 shows that the changes in IGE firstly increases from 0.414 in 1988 to 0.435 in 1995, then falls down to 0.346 in 2002, which have similar trend as the baseline estimates. The percentage change in IGE is below 8 in 1988 and 1995, while it obviously becomes larger in 2002, which indicates that education plays an increasingly important role in intergenerational income transmission. Panel 1 row 2 shows the coefficient of children's years of education in 1988. Controlling for education increases the IGE by 1.45 percentage points. By quantile, changes in IGEs are also small ranged between 0.17 and 3.25 percentage points. In 1995, education effect drops the IGE only 2.68 percentage points. By quantile, adding education effect changes the IGEs only by 0.78 to 7.13 percentage points. In 2002, the decreases in IGEs are significantly larger than in earlier years. The IGE drops over a third compared with the baseline estimate. Figure 2.3 shows the IGEs have the similar trend as the baseline analysis by quantiles.

How to interpret a possible change in the coefficient of fathers' income after including control variable of children's educational attainment? On one hand, assume an extreme situation that children's educational attainment is

uncorrelated with fathers' income. The original coefficient of fathers' income won't change even when the education variable is significant to explain the independent variable. On the other hand, assume children's educational attainment is strongly correlated with fathers' income. The new coefficient of father's income will drop heavily. Therefore, we can conclude that the smaller the changes in IGEs, the weaker the role of education as a transmission channel (Palomino et al. 2014).

In 1988, the regression coefficient of children's years of schooling is small that may be caused by unobvious gaps in return to education among children's different education levels. Estimation based on CHIPs shows that the income of university-educated persons is higher than primary educated persons by only 15 percentage points in 1988, while the rate increases to 82 percentage points in 2002 (Knight & Song 1993, 2008). The other potential reason may be the measurement error in children's educational attainment. CHIP 1988 does not provide individual's education years but only have individual's education level[12]. We generate children's years of schooling based on their education levels, which leads to potential measurement error. The small changes in IGEs reflect that the role of children's education as a transmission channel is weak. In 1995, the OLS regression coefficient increases and is statistically significant at the 0.1 level. In 2002, changes in IGEs drops dramatically compared to earlier years, which suggests that the role of education becomes stronger as a transmission channel. Both OLS and quantile regression coefficients of children's years schooling are significant at the 0.01 level. The largest change in IGEs is at the bottom quantile, which suggests that parental private human capital investment affects changes of IGEs largest for children's lowest income group.

[12] CHIP 1988 classified education levels to 8 categories: 1, college graduate or above; 2, community college graduate; 3, professional school graduate; 4, upper middle school graduate; 5, lower middle school graduate; 6, primary school graduate; 7, three years or more of primary school; 8, less than three years of primary school.

Controlling for Occupation

Table 2.4 OLS and Quantile Regression Estimates of the IGE of Children's Log Income with Respects to Fathers' Log Income Controlling for Occupation Persistence

Log income of children	OLS	Quantile				
		0.1	0.25	0.5	0.75	0.9
1988						
Log income of fathers	0.425***	0.271***	0.366***	0.481***	0.590***	0.616***
	[0.029]	[0.058]	[0.044]	[0.047]	[0.046]	[0.053]
% Changes in IGE	1.19%	6.27%	3.98%	-2.24%	1.72%	7.13%
1995						
Log income of fathers	0.477***	0.371***	0.456***	0.498***	0.473***	0.482***
	[0.039]	[0.099]	[0.071]	[0.047]	[0.067]	[0.062]
% Changes in IGE	7.46%	-3.13%	5.31%	4.62%	-1.46%	-4.55%
2002						
Log income of fathers	0.405***	0.300***	0.402***	0.463***	0.439***	0.412***
	[0.039]	[0.101]	[0.080]	[0.043]	[0.046]	[0.067]
% Changes in IGE	0.01%	-25.00%	-4.96%	1.98%	-1.13%	5.37%

Notes: Standard errors are in parentheses. For the quantile regression bootstrapped standard errors are reported. * p<0.1. ** p<0.05. *** p<0.01. Data are from the Chinese Household Income Project 1988, 1995 and 2002. The number of observations is 2298 in 1988, 1011 in 1995 and 877 in 2002.

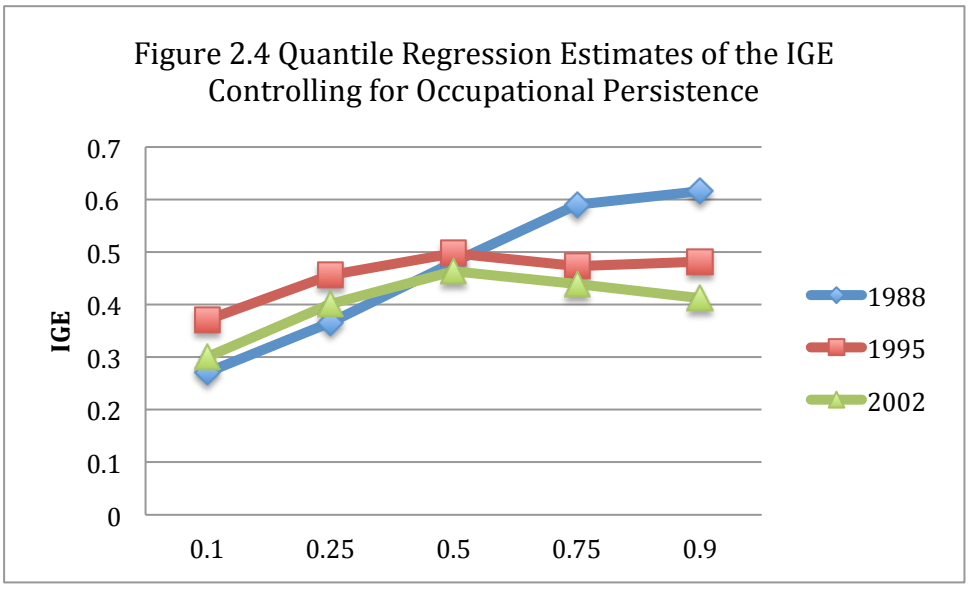


Table 2.4 shows the OLS and quantile regression estimates when controlling for occupational persistence effect. The variable of children's occupation is classified into 3 categories: white-collar work, skilled work and unskilled work[13]. we define the occupational dummy variable as 'the child works in one category and his father works in one category'. For example, if a child works in white-collar and his father works in white-collar, the dummy variable equals 1, otherwise 0; if a child works in white-collar and his father works in skilled, the dummy variable equals 1, otherwise 0. Follow this principle we generate 8 occupational dummy variables. In this analysis, occupation can be seen as a of social class transmission from fathers. When the dummy variable is accounted for, the OLS results of IGE increases slightly compared to the baseline results. The percentage increases in IGE is 1.19 percentage points in 1988, increases 7.46 percentage points in 1995 and only increases 0.01 percentage points in 2002. This implies that the influence of occupation on IGE plays an increasingly important role across years. Column 2 shows that the IGE keeps the same changing trend across quantiles compare to the baseline estimates. Occupation represents the social class of persons and has an advantage of a more stable measurement in intergenerational economic mobility. Here I perform only a rough analysis of the intergenerational occupation transmission. It is meaningful to do more detailed research, such as a more precise classification of occupations and compare the possible odds ratios. It is necessary to conduct further research on occupation associations across generations.

Controlling for Region

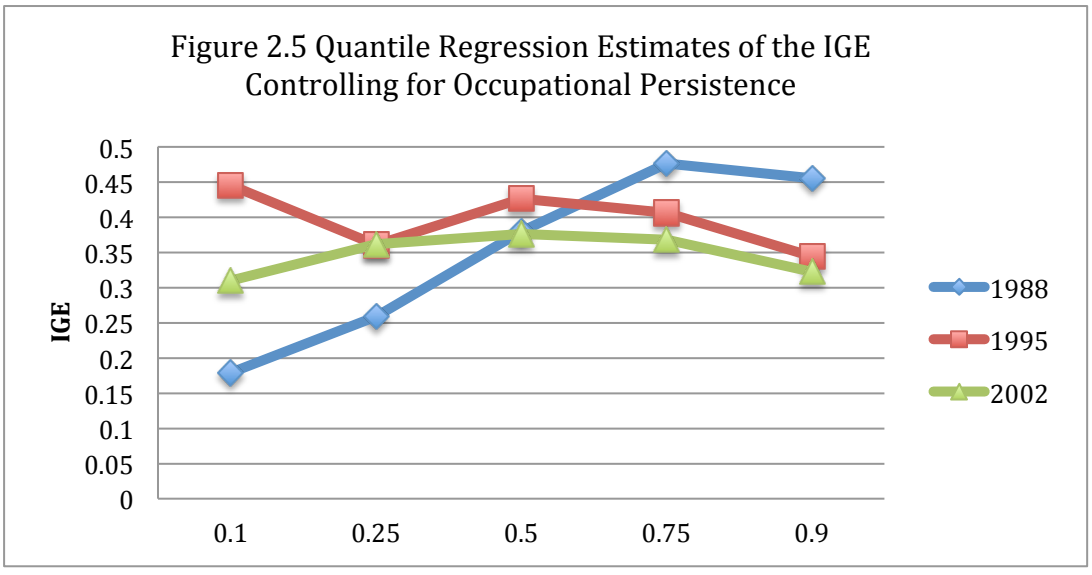
Table 2.5 shows that including regional dummy variables in the children's income equation dramatically lowers the effect of fathers' income on their children. Column 1 shows that accounting for the regional dummy variables, the

[13] The types of occupation in the three years are not same. There are 7 types of occupations in 1988; 9 in 1995; 11 in 2002. We classify all types of occupation into 3 categories: white collar, skilled and unskilled.

Table 2.5 OLS and Quantile Regression Estimates of the IGE of Children's Log Income with Respects to Fathers' Log Income Controlling for Regional Differences

		Quantile				
Log income of children	OLS	0.1	0.25	0.5	0.75	0.9
1988						
Log income of fathers	0.329***	0.179***	0.259***	0.380***	0.476***	0.455***
	[0.029]	[0.054]	[0.032]	[0.030]	[0.046]	[0.077]
% Changes in IGE	21.67%	-29.80%	-26.42%	-22.76%	-17.93%	-20.87%
1995						
Log income of fathers	0.380***	0.445***	0.361***	0.426***	0.406***	0.344***
	[0.038]	[0.111]	[0.063]	[0.054]	[0.053]	[0.056]
% Changes in IGE	14.99%	16.19%	-16.63%	-10.50%	-15.42%	-31.88%
2002						
Log income of fathers	0.330***	0.310***	0.362***	0.376***	0.368***	0.323***
	[0.038]	[0.089]	[0.071]	[0.053]	[0.047]	[0.078]
% Changes in IGE	17.91%	-22.50%	-14.42%	-17.18%	-17.12%	-17.39%

Notes: Standard errors are in parentheses. For the quantile regression bootstrapped standard errors are reported. * p<0.1. ** p<0.05. *** p<0.01. Data are from the Chinese Household Income Project 1988, 1995 and 2002. The number of observations is 2298 in 1988; 1011 in 1995 and 877 in 2002. In the CHIP data, the eastern region includes Beijing, Liaoning, Shanghai, Jiangsu, Zhejiang and Guangdong; the middle region includes Anhui, Henan and Hubei; the western region includes Shanxi, Chongqing, Sichuan, Yunnan and Gansu. All regressions include middle dummy, western dummy and a constant.



IGE drops by 21.67 percentage points in 1988, drops 14.99 percentage points in 1995 and drops 17.91 percentage points in 2002, which implies that the regional difference is an important factor that raises the IGE in China. By quantile, in 1988 and 2002, the changes in IGE are greater at the bottom of the children's conditional income distribution than at other quantiles. However, in 1995, the greatest changes in IGEs occur at the top quantile. A simple analysis on regional effects can conclude that reducing the regional inequality could lower the IGE and improve the intergenerational income mobility.

The extended analyses on intergenerational income mobility by adding control variables explore the transmission channels that affect the IGEs. The effects of regional differences are significant. However, the effects of education and occupation were not clear especially for 1988 and 1995. The investigation of the effect of occupation also has some limitations. We conduct a more detailed analysis on intergenerational occupational mobility in chapter 4. Considering these limitations, future researches are called for illustrating the channels of intergenerational income transmission.

Posttest on IGEs of each year

We are interested in determining if the association between children's income and fathers' income is greater compared to other years. The OLS results of IGEs are compared using the seemingly unrelated estimation (suest) test. If p-value is less than 0.1, we can reject the null hypothesis that the differences of coefficients of log income of fathers are the same in both years.

To carry out the suest test in Stata, first, OLS regressions of eq. (1) are run separately for each year and the results are stored, then, a 'suest' command are used to combine the results into a table, finally, a 'test' command are used to check whether the coefficients differ over years. Results are presented in Table 2.6.

Table 2.6 Seeming Unrelated Estimation on IGEs in 1988, 1995 and 2002

	1988 vs. 1995	1995 vs. 2002	1988 vs. 2002
χ^2 statistic	0.26	0.61	0.10
p-value	0.6111	0.4336	0.7459

Note: Data are from CHIP 1988, 1995 and 2002. The total number of observations is 4186. The p-value is reported to test whether the difference of coefficients of log income of fathers is significant in 1988, 1995 and 2002.

The coefficient 0.42 for 1988 was not quite significantly differently than the regression coefficient 0.447 for 1995 (p-value =0.6286). The coefficient 0.447 for 1995 was not quite significantly differently than the regression coefficient 0.402 for 2002 (p-value =0.4336). The coefficient 0.42 for 1988 was not quite significantly differently than the regression coefficient0.402 for 2002 (p-value =0.7456). Therefore, changes in intergenerational income mobility are not significantly different in each year.

Potential Bias of the Results

This research has 3 limitations. First, data limitations lead to the measurement error of income variables in this analysis. Scholars usually use permanent income, which requires a panel data source for support; however, there is no suitable Chinese data source. Why do I choose CHIP data in this analysis? Because it is similarly designed in each survey year, which can provide a comparison analysis and in this chapter I use 1988, 1995 and 2002. As we know, CHIP data are a relatively reliable dataset, which is conduced by NBS, CASS and many other foreign experts. The income data collected are more precise than predicted using an IV method even though it is single-year income. However, it cannot be ignored that the measurement error finally leads to a downward bias in the estimation. In fact, the real IGE is higher than our estimation. Second, the numbers of observations are small in this analysis. We have a large amount of data from each year's survey, but the samples used in the analysis are relatively small. This is because the questionnaire does not ask about one's parents' income. As a consequence, after matching child-father pairs,

the sample size decreases heavily. Third, I do not use the latest data in this analysis. CHIP data are updated to 2010 but I use only the data until 2002. Because after 2007, the income data of retired persons are not provided, according to our sample selection rules, I cannot use the latest data. Lastly, the analysis of the income intergenerational transfer mechanism is not deep. The functional form I have tested is also superficial. I will focus on the income transfer channels in furture research.

Moreover, this chapter analyzes only a co-residing sample. The co-residing sample leads to an underestimate of IGE. The CHIP data do not provide information about parents who do not co-reside with their children, so we cannot examine how much the co-residing sample biases the regression results. Francesconi and Nicoletti (2006) examine the co-residing sample selection bias of the UK's case, and the extent of the downward bias ranges between 12% and 39%.

Income level, housing prices, labor migration across regions and first marriage age affect the co-residence rate. First, children at the lower quantile cannot afford the housing cost of living alone while children at the higher quantile can choose to leave their family home more freely. Children who live in high housing price areas are more likely to co-reside with their parents than are in lower housing price areas. Second, there is a tendency for the labor force to move to higher income areas. We can assume that the co-residence rate of high-income children is lower than that of other quantiles. Third, children tend to leave their parents' home after marring.

The co-residence rate of children at lower quantiles is higher than that of children at top quantiles. Our baseline results show that children at higher quantiles have closer economic relationships with their father, but I cannot conclude that at which quantile the co-residence rate influences the IGE more.

International Comparison on IGEs

Table 2.7 is a summary of estimates of IGE using quantile regression in other countries. My finding in this chapter shows an opposite tendency from Row 1 to Row 6. Eide & Showalter (1999) find that the largest elasticity is 0.77 at the bottom quantile and tends to become smaller with higher the quantiles in the United States. The cases of Sweden, Norway, and Britain also show a declining trend at the lower quantiles to the upper tail of children's conditional income distribution (Hirvonen 2008; Bratbery 2007; Nicoletti and Cheti 2008). They suggest that fathers' earning is a more important explanatory variable for children's earnings at the lowest quantile and is less important at the top of children's income distribution. Canada (immigrants), Germany and the U.K. have a similar trend as urban China. Although quantile regression provides considerable cross-country evidence of IGE, it is limited explaining what causes the differences across levels of IGE. The evidence of cross-country studies does not reveal an obvious pattern of IGE across children's income distribution.

Table 2.7 Summary of estimates on intergenerational income elasticity using quantile regression

Country	Data	10th	25th	50th	75th	90th	Obs.	Authors
U.S.	PSID	0.47	0.35	0.37	0.35	0.17	469	Eide & Showalter (1999)
U.S.	PSID	0.355	0.494	0.535	0.457	0.396	354	Grawe (2004)
U.S.	OCNLS	0.275	0.248	0.261	0.157	0.005	233	Grawe (2004)
Canada	IID	0.261	0.256	0.211	0.157	0.110	47115	Grawe (2004)
Norway	DBG	0.322	0.224	0.166	0.104	0.087	23892	Bratberg, et al. (2007)
Malaysia	MFLS	0.791	0.671	0.537	0.404	0.283	153	Grawe (2004)
Canada	Census		0.183	0.177	0.271		70	Aydemir, et al. (2009)
Germany	GSEP	-0.280	-0.042	0.065	0.171	0.313	142	Grawe (2004)
U.K.	NCDS	0.344	0.455	0.579	0.703	0.814	1945	Grawe (2004)

Notes: PSID= Panel Study of Income Dynamics, OCNLS= Original Cohort National Longitudinal Survey, IID= Intergenerational Income Data, DBG= Norwegian Database of generations, MFLS= Malaysian Family Life Survey, Census=2001 Canadian Census, GSEP= German Socio-Economic Panel, NCDS= National Child Development Survey.

In this section, I estimate the IGE to be 0.42 in 1988, 0.447 in 1995 and 0.402 in 2002, showing a slightly declining trend. By quantile, the change in IGE

is smaller at the lower quantiles and decreases rapidly at the higher quantiles. I control for education, occupation and regional inequality and find these factors cause the different IGE at different quantiles.

2.5 Conclusion

This chapter finds that the IGE varies across children's conditional income distribution. We estimate the IGE using OLS and quantile regression based on CHIP data of 1988, 1995 and 2002. This paper also analyzes how IGE changes from 1988 to 2002 and what factors cause the differences across quantiles and years. This research presents the economic fact that the intergenerational economic persistence varies across children's income groups.

We find that the intergenerational income mobility that the intergenerational income mobility decreases slightly from 1988 to 1995, and then increases in 2002. We also find that by quantile, low-income children's income more and more depend on their father's income, while high-income children's income tends to be less affected by their father's income over years. Moreover, children's education level, occupation and regional differences affect intergenerational income mobility.

For the policy implications, enhancing the education level especially for lower income groups could reduce the income inequality caused by educational inequality. Previous study also shows that public education reduces income inequality more quickly than private education (Glomm & Ravikumar 1992). Greater public provision of schooling increases intergenerational earnings mobility (Mulligan 1999). The fairness of the labor market could reduce the inequality caused by different family backgrounds. Promoting balanced development between regions helps reduce intergenerational income persistence. Policies that accounte for many distributional factors and legal issues will ultimately affect the desirability of a given policy, so all the

suggestions above are given from an economic view. Future work that addresses the measurement error bias will be required.

Chapter 3 The Changes of Intergeneration Educational Mobility

In the last chapter, I estimate intergenerational income elasticity and argue that children's education attainment, occupation and regional differences are factors that affect intergenerational income mobility. In this chapter, I analyze changes in intergenerational educational mobility in urban China across 4 ten-year birth cohorts between 1951 and 1990 using data from the China Household Income Project 2013. I try to answer three questions: first, how does intergenerational education mobility change over time? Second, why does the educational correlation between children and parents change over time? Third, How much does parental effect contribute to the upward mobility in children's education?

3.1 Literature Review

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) notes 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.

If patterns of genetic transmission are similar over years, differences in intergenerational education mobility should be affect by parental human capital investment, labor market changes, education system and policies.

This chapter contributes to 3 areas of the literature. First, it describes a 40-year trend in intergenerational educational persistence in urban China. I examine whether the degree of intergenerational education mobility is currently increasing or decreasing. Second, it interprets trends in mobility based on

several different aspects, i.e., gender, region, social development, government policy and education system differences. Third, it applies estimation methods and provides a new mechanism explaining education inequality in China.

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. Riphahn (2007) argues that public policy interventions and education reforms do not significantly reduce the role of parental background in children's educational outcomes. The expansion of access to higher education can be seen as a consequence of an increase in the effect of paternal education (Chevalier, 2003). 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 Chinese Household Income Project 2002. The sample includes 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. Fan (2015) estimates an OLS regression of average parental schooling (in years) on their children's schooling; the estimated coefficients are 0.339 for the 1956-1970 cohort and 0.352 for the 1971-1985 cohort using data from the 2010 Chinese Family Panel Studies (CFPS). She also examines gender differences and finds that the coefficients are higher for girls than for boys in each cohort. The intergenerational schooling correlation also differs by region. However, she does not analyze the impacts of paternal and maternal education on that of children separately.

The rest of this chapter is structured as follows: Section 2 introduces the institutional background, Section 3 presents the empirical model and methodology, Section 4 describes the data, Section 5 reports the results and discussion, and the last section concludes.

3.2 Institutional Background

Education reform and policies have changed since the founding of the People's Republic of China in 1949. The Communist Party of China considers education a cornerstone of national renewal and social progress. From 1949 to 1952, social policies sought to address the educational deficit, emphasizing basic educational expansion as a means of achieving nation building and economic development (Hannum, 1999). In the 1950s, the government launched a nationwide, large-scale literacy campaign. Various literacy classes, popular

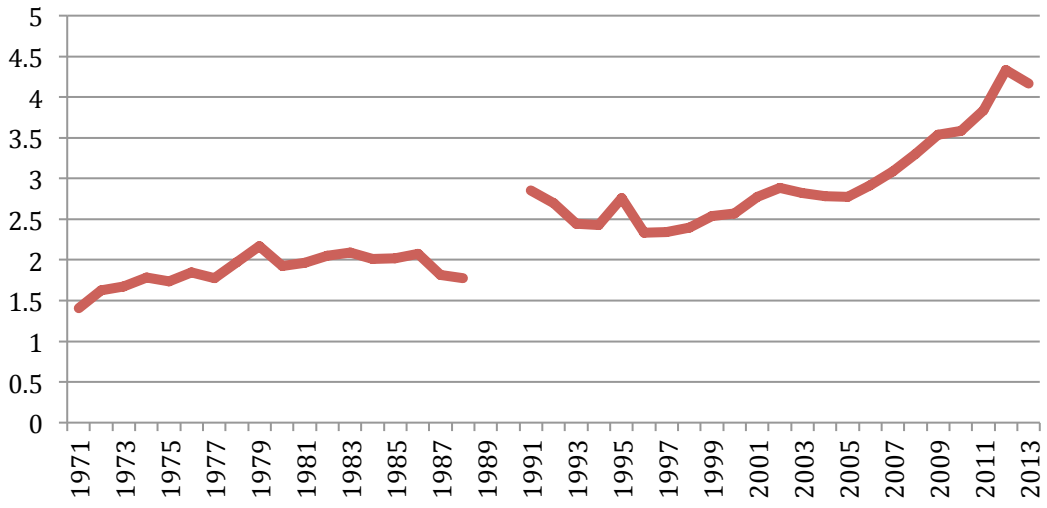
evening schools, worker and peasant schools, political schools and training schools provided educational opportunities for adults who lacked education. The illiteracy rate among adults was 80% in 1949 and declined to 52.4% by 1964 (Zhang, 2006).

With the start of the Cultural Revolution, many colleges, secondary schools and primary schools closed (Knight, 2011). Teenaged urban secondary school students were sent into rural areas for re-education as part of the Up to the Mountains and Down to the Countryside Movement. Although the reduction of education quality and the interruption of higher education were heavily criticized, the enrollment rate of children and promotion rate from primary school and middle school have risen to 90% and 70%, respectively (Knight, 2011). Meng and Gregory (2007) argued that the children whose parents at low social position and with limited education opportunity are the largest negative impact of Cultural Revolution. Based on Sato and Li's observation (2007), the upper stratum continual outperform the lower strata for educational attainment, they claim that the class discrimination during Cultural Revolution is not sustained long time, which are inadequate for making permanently influence on intergenerational educational attainment.

After the Cultural Revolution, I divide education measures and policies into the following 3 areas.

First, national and governmental public expenditures on education: (a) according to Tsang's (1996) calculations, from 1967 to 1985, total government expenditure on education averaged 2% of GNP and 7.7% of the total national budget. Figure 3.1 shows government expenditure on education as a percentage of GDP, which was 1.41% in 1971 and steady increased to over 4% by 2012. (b) The Compulsory Education Law of the People's Republic of China was adopted in the Fourth Session of the Sixth National People's Congress and promulgated on April 12, 1986. It entered into force on July 1, 1986 and held that the state would

Figure 3.1 Governemnt Expenditure on Education, total (% of GDP)

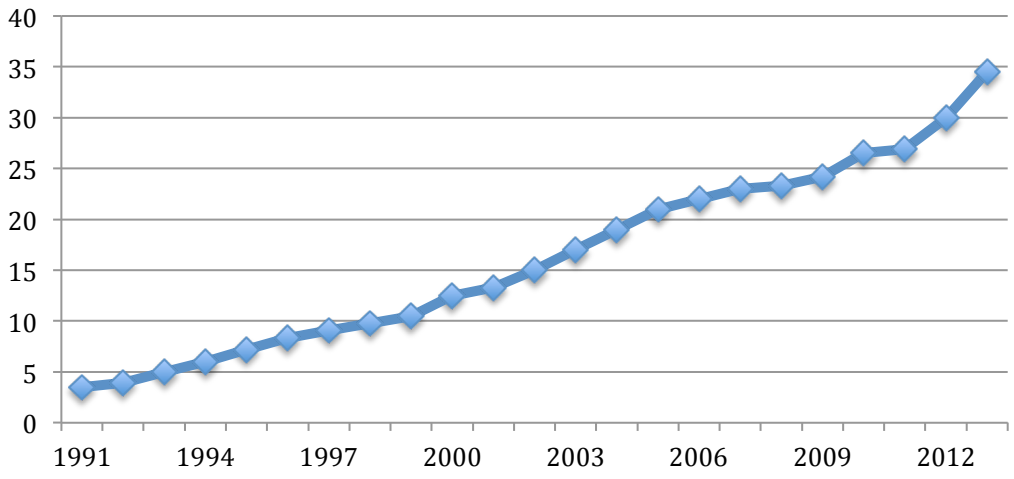


Source: China Statistics Year Book 1999-2015.

institute a system of nine years of compulsory education. The state provides free compulsory education for school age children. (c) In China, before the market reforms of the late 1990s, only very limited smart students could get university education opportunity, and the university education are consider as privilege for them which was almost free (Li & Zhang, 2010). The rapidly economy growth created high demands for high education graduates, meanwhile, as part of the traditional culture, most Chinese parents expect their children could get more higher education opportunities. Based on this background, the Chinese government expanded higher education in 1999.

Second, equal educational opportunities and educational expansion: (a) According to the Compulsory Education Law, all children reached six years old (some province in 7) must enroll in school for prescribed numbers of years compulsory education, regardless of sex, nationality or race. (b) University enrollment has increased. Figure 3.2 shows the changes in the gross enrollment rate in higher education from 1991 to 2013. During the Cultural Revolution, only members of the elite, with some exceptions, could aspire to a university education. Because of the historical reasons, Chinese higher education system was deeply influenced by the Soviet Union until late 1970s China start to

Figure 3.2 Gross Enrollment Rate of Higher Education



Source: meo.gov.cn Ministry of Education of the People's Republic of China website

implement its reform and opening-up policy. As part of the central planning economy, all higher education resources, even include the student enrollment and employment, were controlled by a highly centralized, planned system. Only very few Chinese young people (fewer than 5%) could get opportunity to access to college. Almost all higher education institutes were funded and operated by government agencies such as the Ministry of Education. Because of higher education expansion policy, the old system has changed fundamentally from late 1990s. Faced with the challenge of adapting to the needs of a market economy, an unprecedented expansion in opportunities for higher education has taken place in China since 1998. (c) In 1999, the Chinese government decided to expand higher education (Wu & Zheng, 2008). From 1978 to 1998, tertiary student enrollment improved more than 25%, increased moderately from 0.86 to 1.08 million. After higher education expanded several years, the college enrollment significant increased to 5.4 million in 2006 (Bai, 2006). (d) When the number of higher education graduates is small, it is easier for better-educated college graduates to find satisfying jobs. However, with the expansion of higher education, it has become more difficult for graduates to obtain good jobs compared with earlier graduates. The relevance of education became obvious,

and parents adjusted their investment behaviors.

Third, the impact of economic and social policies: (a) The one-child policy was an official program initiated in the late 1970s and early 1980s by the central government of China. The purpose was to limit the vast majority of family units in the country to one child for population control. In 1982, family planning was written into Article 25 of the constitution: “The state promotes family planning so that population growth may fit the plans for economic and social development.” During this period, forced sterilizations and abortions became common practice. Investment in the only child, especially in the child's education, was the highest priority for almost all Chinese families. However, the one-child policy increased schooling attainment by, at most, 4% and the probability of attending college by less than 9% (Rosenzweig & Zhang, 2009). Parents must increasingly invest in their children’s education due to market demand for educated labor and intensified competition in the labor market for better employment opportunities (Rosenzweig & Zhang, 2009). (b) Educational policies during China's early years (1949-1965) reflect a political emphasis on both economic development and social fairness. Social policies in the first years tried to address the educational deficit, emphasizing basic educational expansion as a tool of nation building and social development. Nationwide, a massive expansion occurred in basic education (Hannum, 1999). (c) The 1985 education system reform no longer defined the role of education as only ideological but as an important way to meet the skill requirements of a developing socialist market economy and as a strategic policy to promote national development (Tsang, 1996). To adapt to the demand for higher education and the need for a labor force in a market economy, an unprecedented expansion in higher education enrollment has taken place in China since 1998 (Wan, 2006). The government took college enrollment expansion as a measure against the Asian financial crisis that was triggered in July 1997. The effect of enlarging enrollment can postpone employment of school graduates and increase educational consumption to

stimulate domestic consumption and drive related industrial development.

3.3 Methodology

To explore the intergeneration educational mobility, I use both categories analysis and linear analysis.

Intergenerational educational correlations

The intergenerational education correlations can estimate using an OLS regression of parental education on children's education, or correlations coefficient method. In this chapter, we focus on the OLS method to investigate intergenerational correlations.

$$Edu^c = \alpha + \beta Edu^f + \gamma Edu^m + \mu \qquad (3.1)$$

where Edu^c is children's years of education completed, Edu^f is father's years of education completed, Edu^m is mother's years of education completed. The coefficients β and γ represent the correlation between parental education and children's education.

In the case of categorical data one is commonly looking for association between two variables. The dependent categorical variable is children's education level (E_i^c). One independent categorical variable is parental education level (E_j^p), P_{ij} is possibility when children with i education level having a father with j education level.

Decomposition of the growth of children's education level

Assume that children's education is positive correlated with his parents' education. Higher educated parents tend to have higher educated children. I see this automatism as parental background effect (Cattaneo et al., 2007). The

growth of children's education level can be decomposed into education expansion effect and parental background effect. The probability of a child with i education in birth cohort t, can be written in the following way

$$\Pr(y_i^c)_t = \sum_{j=1}^{I} \left[\Pr\left(y_i^c \middle| y_j^p\right)_t \times \Pr\left(y_j^p\right)_t \right] \qquad (3.2)$$

where y_j^p refers to parental education level, with $j = 1, 2, \ldots I$. $\Pr(y_i^c|y_j^p)_t$ measures the conditional transition rates of a child with category i education level, given his parent's with category j education levels. $\Pr(y_j^p)_t$ measures the marginal distribution of his parent's education. Applying these when considering children's birth cohort t and $t-1$, the proportional change of children's education level is

$$\Delta\ Pr(y_i^c)_t = \ Pr(y_i^c)_t - \ Pr(y_i^c)_{t-1}$$

$$= \sum_{j=1}^{I} \left[\Pr(y_i^c|y_j^p)_t \times \Pr(y_j^p)_t \right] - \sum_{j=1}^{I} \left[\Pr(y_i^c|y_j^p)_{t-1} \times \Pr(y_j^p)_{t-1} \right]$$

$$= \sum_{j=1}^{I} \left[Pr(y_i^c|y_j^p)_t - \ Pr\left(y_i^c \middle| y_j^p\right)_{t-1} \right] \times Pr(y_j^p)_t$$

$$- \sum_{j=1}^{I} \left[Pr(y_j^p)_t - Pr(y_j^p)_{t-1} \right] \times Pr\left(y_i^c \middle| y_j^p\right)_{t-1}$$

$$= \sum_{j=1}^{I} \Delta\, Pr\left(y_i^c \middle| y_j^p\right) \times Pr\left(y_j^p\right)_t + \sum_{j=1}^{I} \Delta\, Pr\left(y_j^p\right) \times Pr\left(y_i^c \middle| y_j^p\right)_{t-1}$$

$$= \lambda + \eta \qquad (3.3)$$

where λ measures the expansion of children's education that is independent of his parents' education. The second term η measures effect that

is due to the changes of parental education. $Pr\left(y_j^p\right)_t$ in λ and $Pr\left(y_i^c \middle| y_j^p\right)_{t-1}$ in η are the lights, respectively.

Multinomial Logit analysis

In analyzing educational transmission across generations, the key explanatory variable is parental education. Since I 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

$$Pr(y^c = i) = f(gender, parental\ education, birth\ cohort, region,$$

$$parental\ social\ class\ ) \qquad (3.4)$$

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.

3.4 Data

This analysis uses data from the CHIP 2013[14]. This project is conducted by researchers with the Annual Household Survey Office for Urban and Rural Integration of the National Bureau of Statistics. The CHIP 2013 sample was drawn from a larger sample from the annual NBS integration household survey

[14] In July and August 2014, the China Household Income Project conducted the 5th wave of the survey. Since the main information is 2013 income and expenditures, it is named CHIP 2013 and is consistent with the previous 4 waves. This wave of the survey was supported by the National Natural Science Fund and the National Bureau of Statistics and was organized by the China Institute for Income Distribution of Beijing Normal University.

in 2013 of 160,000 households in 31 provinces. The CHIP sample was selected by systematic sampling in three regions, eastern, central and western, and contains 15 provinces.

CHIP 2013 collects rich information on households and household members, e.g., personal characteristics, employment situations, income, educational attainments, assets and debts, expenditures, and living conditions. This paper uses the latest CHIP data from the urban survey conducted in 2013, which includes a representative cross-section of 6674 households and 19,887 individuals. The CHIP 2013 sample encompasses 15 provinces, 126 cities, and 234 counties. The CHIP 2013 data include household income, expenditures, individual demographic characteristics, labor time in 2013, job information, assets, demolition land information, and agricultural businesses. Blanden et al. (2007) argue that cross-sectional data may lead to biased estimates because of geographical inequality in educational infrastructure and missing data for children who no longer live with their parents. To address this bias, I consider the regional differences in the logit model. The CHIP 2013 provides information on children who live apart from their 'household head' parent and parents who live separately from their 'household head' child.

In this analysis, I focus on children born between 1951 and 1990. To analyze changes in intergenerational education mobility, I divide children born over these 40 years into 4 consecutive ten-year birth cohorts. The first and oldest cohort contains children born between 1951 and 1960. I disregard children born before 1951 due to increasing mortality and because I am interested in changes in intergenerational educational mobility after the founding of the People's Republic of China. The fourth and youngest cohort includes children born between 1981 and 1990 because most of these individuals had not finished their tertiary education before they were 22 years old[15]. I select children who have

[15] The average age when finishing a bachelor's degree is 22. I ignore individuals who are still attending school after they turn 23 because these students are rare.

finished schooling and are between 23 and 60 years old, with an average age of 42.

I use the relationship to the household head to create parent-child pairs[16]. These pairs are selected based on 4 parts: first, when the second generation is the household head or a spouse, his parents' information is collected using the questionnaire[17]; second, when the first generation is the household head, the children's educational information is included in the questionnaire; third, the second generation is the household head, and his parents reside with him in the same household; fourth, when the second generation has a child relationship with the household head, his parent may be either a household head or a household spouse in the same household. I drop observations with a generation age difference of less than 15 years[18]. Observations with missing information on education or parental education are also dropped. Finally, our analysis is based on a total of 13997 observations, 49.5 percent of which are for males and 50.5 percent for females.

The key explanatory variable I consider is parental 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

[16] There are 10 kinds of relationships to the household head: household head, spouse, son/daughter, parent, father/mother-in-law, grandparent, son/daughter-in-law, grandchild/grandchild's spouse/great-grandchild /great-child's spouse, sibling, and others.

[17] The questionnaire asks for basic information for parents of the household head and spouse, for example, birth year, education level, and employment status.

[18] According to the Sixth National Population Census (2010), the number of children born is collected from women aged 15 to 64. It is reasonable to restrict the age gap between fathers and children to greater than 15 years. Kan, Li and Wang (2014) exclude observations if the age difference between a parent and child is less than 15 years. Gong, Leigh and Meng (2012) exclude observations if the age difference between a parent and child is below 14 years.

level 4: university and above that includes undergraduate (bachelor's degree) and graduate (master's degree or above) studies. Table 1 lists the shares of these four education categories for children, fathers and mothers. Additional explanatory variables include children's gender, birth cohort and location of residence. 49.5 percent of the sample is comprised of sons; the others are daughters. 18.5 percent of the sample is from the 1951-1960 birth cohort, 29.7 percent from the 1961-1970 birth cohort, 29.4 percent from the 1971-1980 birth cohort, and 22.4 percent from the 1981-1990 birth cohort. I define the region variable using 3 categories: East, Central and West[19]. Descriptive statistics for the samples are presented in Table 3.1.

Table 3.1 Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Age	41.986	10.462	23	62
Male	0.495	0.500	0	1
Children's years of schooling	11.499	3.464	0	22
Fathers' years of schooling	7.041	4.450	0	20
Mothers' years of schooling	5.541	4.468	0	19
Birth cohort: 1951-1960	0.185	0.389	0	1
Birth cohort: 1961-1970	0.297	0.457	0	1
Birth cohort: 1971-1980	0.294	0.455	0	1
Birth cohort: 1981-1990	0.224	0.417	0	1
Children's education level1	0.353	0.478	0	1
Children's education level2	0.294	0.456	0	1
Children's education level3	0.169	0.375	0	1
Children's education level4	0.183	0.387	0	1
Fathers' education level1	0.751	0.432	0	1
Fathers' education level2	0.169	0.375	0	1
Fathers' education level3	0.045	0.208	0	1
Fathers' education level4	0.035	0.183	0	1
Mothers' education level1	0.838	0.369	0	1
Mothers' education level2	0.126	0.332	0	1
Mothers' education level3	0.023	0.149	0	1
Mothers' education level4	0.013	0.114	0	1
Region: East	0.414	0.493	0	1
Region: Center	0.361	0.480	0	1
Region: West	0.225	0.418	0	1

Notes: Data are from CHIP 2013. Numbers of observations: 13997. Education level1: compulsory education; education level2: upper secondary; education level3: polytechnic college; education level4: university and above.

[19] In the CHIP 2013, the East region includes Beijing, Liaoning, Shanghai, Jiangsu, Shandong and Guangdong provinces; the Central region includes Shanxi, Anhui, Henan, Hubei and Henan provinces; the West region includes Chongqing, Sichuan, Yunnan and Gansu provinces.

3.5 Results

Changes in Intergenerational Educational Correlation

Table 3.2 OLS estimates of parental education on children's education, by birth cohort

Birth cohort	Constant	Fathers' education	Mothers' education	R^2	Obs.
Children					
1.1951-1955	7.927[0.119]	0.179[0.028]	0.095[0.036]	0.085	1235
2.1956-1960	8.621[0.110]	0.171[0.025]	0.141[0.027]	0.134	1358
3.1961-1965	9.025[0.103]	0.144[0.195]	0.155[0.021]	0.144	1975
4.1966-1970	9.167[0.111]	0.187[0.184]	0.111[0.191]	0.153	2183
5.1971-1975	9.473[0.135]	0.158[0.195]	0.172[0.019]	0.147	2279
6.1976-1980	9.686[0.176]	0.232[0.023]	0.152[0.021]	0.161	1832
7.1981-1985	9.565[0.202]	0.238[0.025]	0.207[0.023]	0.203	1693
8.1986-1990	9.082[0.239]	0.239[0.029]	0.244[0.028]	0.215	1442
Sons					
1.1951-1955	8.671[0.145]	0.140[0.031]	0.059[0.049]	0.005	613
2.1956-1960	9.051[0.145]	0.175[0.031]	0.143[0.034]	0.154	670
3.1961-1965	9.663[0.150]	0.113[0.030]	0.140[0.028]	0.103	984
4.1966-1970	9.852[0.159]	0.177[0.026]	0.067[0.027]	0.104	1098
5.1971-1975	9.953[0.197]	0.143[0.028]	0.146[0.028]	0.112	1115
6.1976-1980	10.263[0.269]	0.216[0.035]	0.136[0.031]	0.132	868
7.1981-1985	9.548[0.290]	0.266[0.037]	0.169[0.035]	0.190	838
8.1986-1990	8.762[0.323]	0.283[0.039]	0.213[0.036]	0.234	745
Daughters					
1.1951-1955	7.169[0.173]	0.216[0.040]	0.140[0.051]	0.124	622
2.1956-1960	8.207[0.161]	0.155[0.039]	0.156[0.042]	0.123	688
3.1961-1965	8.416[0.138]	0.169[0.027]	0.175[0.028]	0.193	991
4.1966-1970	8.450[0.151]	0.192[0.025]	0.166[0.026]	0.220	1085
5.1971-1975	9.006[0.184]	0.173[0.027]	0.198[0.026]	0.185	1164
6.1976-1980	9.247[0.231]	0.237[0.030]	0.167[0.029]	0.184	964
7.1981-1985	9.605[0.282]	0.213[0.035]	0.241[0.032]	0.216	855
8.1986-1990	9.416[0.354]	0.189[0.042]	0.280[0.042]	0.195	697

Source: CHIP 2013.

Notes: Robust standard errors in parentheses.

Table 3.2 shows the OLS results for the effects of parental education on children's educational attainment by gender and birth cohort. For comparison purposes, I divide children who are born from 1951 to 1990 into 8 birth cohorts. Table 3.2 (panel 1, columns 3 and 4) presents the coefficients for the associations between paternal and maternal years of education on children's years of

education. The coefficient of paternal education declines from 0.179 to 0.144 over the first 3 birth cohorts and then increases from 0.158 to 0.239 in the later 4 birth cohorts. The changes in the coefficients indicate that children's education is increasingly influenced by their parents' education and that maternal education plays an increasingly important role in intergenerational educational transmission. Table 3.2 (panel 2, columns 3 and 4) presents the coefficients of paternal and maternal years of education on sons' years of education. The coefficient of paternal education fluctuates between 0.113 and 0.177 in the earlier 4 birth cohorts and then increases from 0.143 to 0.283 in the later 4 birth cohorts. The coefficient of maternal education increases from 0.059 to 0.213, and the coefficient increases especially dramatically for sons who are born after the 1980s. The coefficients of paternal education are higher than those of maternal education in each birth cohort, except in birth cohorts 3 and 5. This implies that sons' education is influenced by their fathers' education more than by their mothers' education. Table 3.2 (panel 3, columns 3 and 4) presents the coefficients of paternal and maternal years of education on daughters' years of education. The coefficient of paternal education fluctuates between 0.113 and 0.177 in the early 4 birth cohorts and then increases from 0.143 to 0.283 in the recent 4 birth cohorts. The coefficient of maternal education increases from 0.140 to 0.280, and the coefficient increases especially dramatically for daughters who are born after the 1980s. Unlike the parent-son pairs in panel 2, it is difficult to determine whether fathers or mothers are more important to intergenerational educational transmission in parent-daughter pairs. Compared with father-daughter pairs, in birth cohort 7 and 8, the coefficient of maternal education is obviously higher, which implies that maternal education has a greater impact on daughters' educational attainment.

Mobility indices

Table 3.3 Immobility, upward mobility and downward mobility of children's educational levels by parent, gender and birth cohort

	Father			Mother		
Birth cohort	Downward mobility	Immobility	Upward mobility	Downward mobility	Immobility	Upward mobility
Panel1: Children						
1951-1955	0.038	0.647	0.315	0.010	0.654	0.336
1956-1960	0.027	0.516	0.458	0.013	0.503	0.485
1961-1965	0.047	0.453	0.501	0.017	0.436	0.547
1966-1970	0.061	0.473	0.466	0.022	0.445	0.533
1971-1975	0.065	0.401	0.534	0.018	0.375	0.607
1976-1980	0.050	0.302	0.648	0.017	0.265	0.718
1981-1985	0.035	0.263	0.702	0.013	0.245	0.742
1986-1990	0.047	0.271	0.683	0.023	0.216	0.761
Panel2: Sons						
1951-1955	0.034	0.594	0.372	0.010	0.602	0.388
1956-1960	0.028	0.479	0.493	0.009	0.473	0.518
1961-1965	0.054	0.406	0.541	0.014	0.398	0.587
1966-1970	0.050	0.433	0.517	0.021	0.404	0.575
1971-1975	0.066	0.387	0.546	0.020	0.350	0.631
1976-1980	0.058	0.260	0.682	0.020	0.230	0.750
1981-1985	0.036	0.269	0.696	0.014	0.251	0.735
1986-1990	0.050	0.286	0.664	0.032	0.230	0.738
Panel3: Daughters						
1951-1955	0.042	0.699	0.259	0.010	0.706	0.285
1956-1960	0.025	0.551	0.424	0.016	0.532	0.452
1961-1965	0.039	0.500	0.461	0.019	0.473	0.508
1966-1970	0.072	0.513	0.415	0.023	0.487	0.490
1971-1975	0.064	0.414	0.522	0.016	0.400	0.585
1976-1980	0.044	0.339	0.617	0.015	0.297	0.689
1981-1985	0.034	0.259	0.708	0.012	0.240	0.749
1986-1990	0.043	0.254	0.703	0.013	0.202	0.785

Notes: Date are from CHIP 2013. All indicators take values in the interval [0,1] and they represent probabilities.

Table 3.3 presents the upward/downward mobility of children's educational levels by parent, gender and birth cohort. I categorized individual education into four categories and then compute educational transition probability matrices. The indicators are calculated as the average values of four entries below or above the main diagonal of every educational transition matrix.

The immobility ratio is calculated as the average values of all entries on the main diagonal of the transition matrices (Heineck & Riphahn, 2007). Table 3.3 (panel 1) shows that immobility in father-child pairs and mother-child pairs decline from 0.647 to 0.271 and from 0.654 to 0.216, respectively, over this period. Upward mobility increases for both father-child and mother-child pairs, and the increasing trend is more pronounced for mother-child pairs. In contrast, downward mobility does not change much over time. Table 3.3 (panel 2) shows that the immobility of father-son and mother-son pairs decreases while upward mobility increases, and downward mobility does not change much over time. The changes in upward mobility are more pronounced for mother-son pairs (0.738-0.388=0.35) than for father-son pairs (0.664-0.372=0.292). Table 3.3 (panel 3) shows that the immobility of father-daughter and mother-daughter pairs declines while upward mobility increases, and downward mobility does not change much over time. The changes in upward mobility are more pronounced for mother-daughter pairs (0.785-0.285=0.5) than for father-daughter pairs (0.703-0.259=0.444). Comparing panel 3 with panel 2, I observe that daughters' education increases at a faster rate than that of sons over time. In the most recent cohorts (cohorts 7 and 8), upward mobility for parent-daughter pairs is higher than for parent-son pairs.

Table 3.4 Distribution of Children's Education Levels by Gender and Birth Cohort

	Compulsory education	Upper secondary	Polytechnic college	University and above	Numbers of observations
Sons					
1.1951-1960	0.527	0.302	0.116	0.055	1,283
2.1961-1970	0.379	0.306	0.167	0.148	2,082
3.1971-1980	0.266	0.306	0.181	0.247	1,983
4.1981-1990	0.163	0.262	0.246	0.329	1,583
Daughters					
1.1951-1960	0.613	0.289	0.068	0.030	1,310
2.1961-1970	0.458	0.343	0.117	0.082	2,076
3.1971-1980	0.324	0.303	0.182	0.191	2,128
4.1981-1990	0.159	0.218	0.264	0.360	1,552

Source: China Household Income Project 2013.

Table 3.4 shows the distribution of children's education levels by gender and birth cohort. The percentage of daughters with university and above increased by 11 times from birth cohort 1 to birth cohort 4, from 0.03 to 0.36, and the corresponding rate for sons increased by approximately 5 times from 0.055 to 0.329. The rates of increase for sons and daughters are nearly evenly spread over all 4 birth cohorts, while daughters' education increases dramatically and surpasses sons' education in the last cohort. Similarly, the percentage of daughters with polytechnic college degrees increases by 19.6 percentage points from birth 1 to birth 4, from 0.068 to 0.264, and the corresponding rate for sons increases by 13 percentage points, from 0.116 to 0.246. Such changes are also evident for the lowest educational category, which decreases sharply by 36.4 percentage points (from 0.527 to 0.163) for sons and by 45.4 percentage points (from 0.613 to 0.159) for daughters. The information in table 4 illustrates that children's education levels increase over time and that daughters are more educated than sons in the recent birth cohort.

Table 3.5 Relative educational attainment of children, by parent, gender and birth cohort

	$[Prob(C^{UA}\|P^{UA})]/[Prob(C^{UA}\|P^{US})]$	
Birth cohort	Father	Mother
Children		
1.1951-1960	5.238	2.493
2.1961-1970	2.422	1.754
3.1971-1980	2.102	1.551
4.1981-1990	2.026	2.005
Sons		
1.1951-1960	5.831	2.750
2.1961-1970	2.035	1.911
3.1971-1980	2.106	1.191
4.1981-1990	2.129	2.078
Daughters		
1.1951-1960	4.828	2.657
2.1961-1970	3.328	1.484
3.1971-1980	2.094	1.978
4.1981-1990	1.923	1.974

Notes: Data are from CHIP 2013. Probability of 'children in 'university and above' conditional on parent in 'university and above'' divided by probability of 'children in 'university and above' conditional on parent in 'upper secondary''.

Table 3.5 presents children's relative educational attainment by fathers and mothers, gender and different birth cohort. The indicators of relative opportunities mobility show whether children have the equally observed educational attainment regardless of what backgrounds their parents have (Daouli et al, 2010). Using the same educational transition matrices as above, I compute two conditional measures of relative opportunities of education. The indicator ([Prob($C^{UA}|P^{UA}$)]/[Prob($C^{UA}|P^{US}$)]) refers to the probability that the child has completed an university and above given that his parent has completed an university and above relative to the probability that the child has completed an university and above given that his parent has completed upper secondary schooling. Table 3.5 (panel 1, row 1, column 2) shows significant inequality in educational opportunities in children's birth cohort 1. A child whose father has an university and above has a probability 5.238 times higher of attaining an university and above than a child whose father completed only upper secondary' education. This inequality declines by 2.422 times in birth cohort 2 and continues to decline slightly for subsequent cohorts. Panel 1, column 3 shows that inequality of opportunity to reach the highest educational category does not change significantly over time. Panel 2 and panel 3 show similar trends as panel 1. The significant inequality in birth cohort 1 can be partly explained by the influence of the Cultural Revolution. During the Cultural Revolution, there was no National College Entrance Examination, and the young people who could enter a college were selected based on their performance in the Up to the Mountains and Down to the Countryside Movement and recommendations.

Table 3.6 reports the results of the decomposition of cohort changes in university and aboves and polytechnic college degrees: expansion and parental effects. I assume that children's education is positively correlated with parental education. Highly educated parents tend to have highly educated children. I see this pattern as a parental background effect (Cattaneo et al. 2007). The growth of children's education can be decomposed into an education expansion effect and a

Table 3.6 Decomposition of the between cohort changes in 'university and above' and 'polytechnic college' education level: expansion and parental effects

	Decomposition of children's education			Percentage explained	
	Expansion	Parental	Cohort change	Expansion	Parental
Children of university and above					
Father	0.273	0.030	0.303	90.04	9.96
Mother	0.235	0.067	0.303	77.81	22.19
Children of polytechnic college					
Father	0.133	0.030	0.163	81.71	18.29
Mother	0.147	0.016	0.163	90.47	9.53

Source: China Household Income Project 2013

Notes: Cohort change is between 1951-1960 birth cohort and 1981-1990 birth cohort.

parental background effect. Table 3.6, panel 1 indicates that the growth in university and above increases by 30.3 percent between the earliest birth cohort (1951-1960) and the latest birth cohort (1981-1990). The total increase can be decomposed into an educational expansion effect (0.273), which indicates that a 27.3 percentage point increase can be observed even if parental education is as favorable for the earlier cohort as it eventually is for the recent cohort. The remaining 3 percent is due to the parental effect. The expansion effect explains 90.04% of the total increase, and the parental effect explains 9.96% of the total increase when the decomposition is based on paternal education. The maternal education effect is somewhat more important, as 22.19 percentage points of the total increase is attributed to the parental effect. Similar results can be observed when I decompose growth in the polytechnic college category. An expansion effect accounts for 81.71% and a parental effect for 18.29% of the total increase when the decomposition is based on paternal education, while an expansion effect accounts for 90.47% and a parental effect accounts for 9.53% of the total increase when the decomposition is based on maternal education. These figures suggest that the educational expansion effect is more important than the parental effect to the growth of higher educated children in urban China.

Multinomial Logit analysis on intergenerational educational mobility

Table3.7 Probability of children's educational level, by birth cohort, parental educational level and regional difference: marginal effects for multinomial logit estimation

	Compulsory education	Polytechnic college	University and above
Fathers' education: upper secondary	-0.174***	0.053***	0.078***
	[0.011]	[0.010]	[0.009]
Fathers' education: polytechnic college	-0.245***	0.095***	0.188***
	[0.021]	[0.020]	[0.019]
Fathers' education: university and above	-0.308***	0.078***	0.290***
	[0.021]	[0.025]	[0.026]
Mothers' education: upper secondary	-0.192***	0.077***	0.123***
	[0.014]	[0.012]	[0.011]
Mothers' education: polytechnic college	-0.269***	0.028	0.277***
	[0.037]	[0.027]	[0.032]
Mothers' education: university and above	-0.212***	-0.006	0.260***
	[0.066]	[0.034]	[0.045]
Birth cohort: 1961-1970	-0.111***	0.036***	0.065***
	[0.011]	[0.009]	[0.008]
Birth cohort: 1971-1980	-0.203***	0.065***	0.147***
	[0.011]	[0.009]	[0.008]
Birth cohort: 1981-1990	-0.289***	0.127***	0.210***
	[0.012]	[0.011]	[0.010]
Male	-0.052***	0.019***	0.030***
	[0.007]	[0.006]	[0.006]
East	-0.046***	0.014	0.058***
	[0.009]	[0.008]	[0.008]
West	-0.046***	0.001	0.015*
	[0.010]	[0.009]	[0.008]
Log likelihood	－16665.594		

Notes: Data are from CHIP 2013. Four education level categories are compulsory education; upper secondary; polytechnic college; university and above. The reference category is upper secondary for the response variable; compulsory for the explanatory variables of fathers' and mothers' education; the earliest birth cohort; and middle region for other explanatory variables.

Table 3.7 reports the marginal effects based on the multinomial logit estimation by birth cohort, parental 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 less likely children are to complete only compulsory education and the more likely they are to obtain an university and above. Having a highly educated father is correlated with an average increase in the probability of obtaining a university and above of 29 percentage points compared to a child whose father has completed only compulsory education. Since the numbers of mothers in the polytechnic college and university and above educational categories are small, we consider polytechnic college and university and above one group when interpreting panel 2. The results also reveal that a child with a highly educated mother is less likely to complete only compulsory education and is more likely to obtain an university and above compared to having a mother in the other educational categories. Panel 3 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 obtain an university and above. This pattern is consistent with the growth of educational attainment. Panel 4 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 increases the probability of obtaining an university and above by 5.8 percentage points.

We find that the importance of parental education increases over time, and this holds true for both fathers and mothers; upward mobility increases while immobility decreases over time; inequality in educational opportunity shows a decreasing trend; and being male, having highly educated parents, more recent birth cohorts and growing up in the east region increase the probability of having higher education.

Explaining the changes in intergenerational educational mobility

Understanding the channels of intergenerational transmission of education

is crucial to reduce inequality and ensure a fair personal development environment. Ultimately, reducing the education inequality aims to reduce income inequality and provide equal development opportunities for persons. How does parental education affect on their children's education? Why does intergenerational educational mobility change over years?

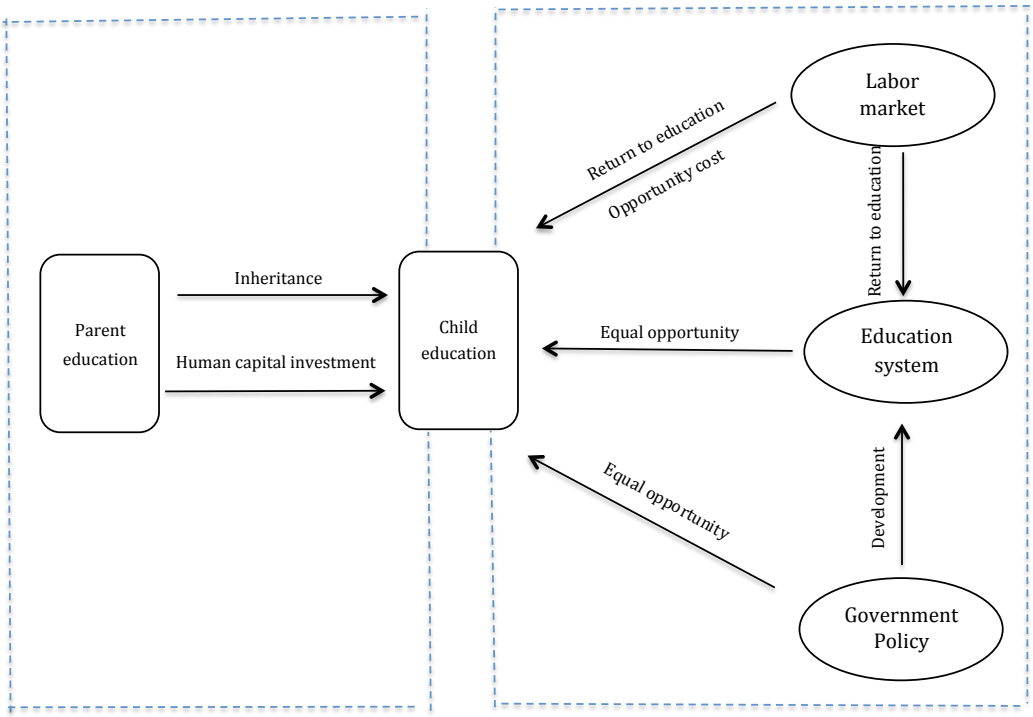


Figure 3.3 Connections among intergenerational educational transmission

The left side of figure 3.3 shows the channels of intergenerational transmission of education. Parents' education influences children's education from through two ways, one is "inheritance" and the other is "human capital investment". The high genetic inheritance measured on IQ influences children's education achievement. Bouchard and McGue's (1981) research shows that the correlation of IQ between children and their parents is from 0.42 to 0.72. The cultural inheritance influences children's education through parents' impact on children's cognitive levels. School education contributes to cognitive ability independently of genetic inheritance but individual's economic success is unrelated to the cognitive skills learned from school (Bowles et al., 2002).

I think about human capital investment in the intergenerational transmission from three aspects. First, parental human capital investment on their children's education is private costs of education. They expect private benefits from this investment. Specifically, parents expect financial support from their children because more education always brings more income for children to care for them in their older age[20]. Second, parents' education level somewhat determines their rational decision-making. More educated parents are hoping their children to receive more education because they realize the importance of education. They think about education not only as a tool to get financial benefits but also as a key to cognitive development. Third, how do parents' consider on the opportunity cost of supporting their children's or working. The opportunity cost from going to a higher-level school is the earnings children can earn if they participate in the labor market.

The right side of figure 3.3 shows the external influence on intergenerational educational mobility. I focus on three aspects: labor market, education system and government policies. First, wages in the labor market determine children's return to education and opportunity cost of giving up to find jobs but continuing education. Return to education and demand of labor force also affect education system, which further influencing the education transmission. Second, education system provides equal opportunity and balances the parental education impact for children from different families. The social cost of education guaranteed from education system is expected to balance the different private cost of education from parents. Third, government policies affect intergenerational educational mobility directly and indirectly. The government may make policy decisions to provide equal opportunities of education and balance the source allocation of education. Government policy always aims to the economic development for promoting political process. The government achieves this goal through education expenditure on the education

[20] There is a Chinese tradition called "raise children to provide against for old age".

system.

3.6 Conclusion

This chapter estimates the intergenerational educational mobility between children and their parents among children's birth cohort 1951 to 1990. The upward/downward mobility indicator shows an increasing upward trend of intergenerational mobility of education. However, the changes of regression coefficients tell us that the educational persistence from parental generation to the next generation is stronger. The relative opportunities mobility indicators show that the advantage to obtain a high degree education attainment for children with high-educated parents is weaken across years, which indicates increasing mobility in higher education level. To investigate the increasing mobility in higher education, I conduct a decomposition analysis and find that the education expansion is a greater contributor to the increasing mobility. Education expansion therefore enhances the intergenerational mobility of education. However, the effects are significantly different among different education levels. To evaluate parental effect in the educational transmission across generations still needs more work to do.

Human capital theory emphasizes differences among people as a determinant of economic outcome (Dickens & Lang, 1985). 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. It is noticed that the average educational level is low in economic development of underdeveloped areas. Teacher training that improves professional knowledge and teaching skills is an effective measure to develop education and reduce the regional inequality in education. The government should increase the education expenditure to reduce the private costs gap between poor families and rich families. Scholarship and student loans to those who have financial difficulties to finish school education are also measures to reduce the intergenerational inequality. Third, the education quality should be improved. Education explains the income inequality and productivity (Behrman & Birdsall, 1983). Although the enrolment rates at all education levels increases, poor quality of education leads students to find a job instead of going on further education. Knowledge and skills gain by better education is a key to work in certain occupation and obtain a high-income job for employees. The education quality gap between graduates from key universities and ordinary universities is likely to last in their career and future life. Secondary schools should not only teach knowledge but also provide more instructions on students' career. 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.

Chapter 4 Changes in Intergenerational Occupational Mobility

I discuss intergenerational income and educational mobility in the last chapter. We argue that education and occupation are the factors that determine one's income. Occupation is a socioeconomic characteristic and can be seen as the economic component of an individual's social class. The transmission of occupation reflects the intergenerational inequality of opportunity and the economic component of social class that exists in a society. I choose occupation as an indicator of intergenerational economic mobility because it can reflect one's life-cycle economic status. Sociologists are usually concerned with intergenerational mobility of occupation. This chapter investigates the relationship between children's occupation and paternal occupation in urban China among children who were born between 1948 and 1987 from an economic perspective. I compare children's 4-year birth cohorts using categorical analysis and Altham statistics based on the CHIP 2007 data. I find a decrease in intergenerational occupational mobility.

4.1 Literature Review

An increasing number of studies estimates intergenerational occupational mobility in developed countries. Blau & Duncan (1967) analyze the American occupation structure detailed in their book. They use a 20,000 sample of U.S. male works and find that the vertical mobility[21] is significant but the mobility occurs between quite close occupations. They argue that industrial societies provide opportunities for blue-collar workers to move into white-collar positions. They also emphasized the importance of education and training in the occupational transmission process. 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

[21] This is a sociology concept. Vertical mobility means movement up or down the socio-economic scale.

college degree. The overall intergenerational association is weaker among women than for men. Torche (2013) estimates the intergenerational occupational association is 0.349 for men who were born around 1960 based on the National Longitudinal Surveys (NLSY 79). Escobar and Izquierdo (2014) analyze changes in intergenerational mobility in Spain over the last century using data from the European Union Statistics on Income and Living Conditions (EU-SILC). They divide the International Standard Classification of Occupations into 5 categories[22]. They calculate the correlation coefficients and find that parental occupations seem to determine their children's occupations to a lesser degree. There is a strong occupational correlation between fathers and their children. However, there is no significant evidence of intergenerational occupational persistence between mothers and their children. Nevertheless, the results suggest that the effect of maternal occupation on children's occupation tends to increase over time. 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

[22] The five categories are unskilled workers; skilled agricultural, fishery and craft workers, machine operators and assemblers; service workers and shop and market sales workers; technicians, associate professionals, and clerks; and senior officials, managers, technicians and professionals.

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 affect 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.

4.2 Methodology

I estimate intergenerational occupational mobility based on categorical data analysis. 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).

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 3. 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 a1 in table A, the row a1 total is 4, but row a1 in table B is 3. This discrepancy is adjusted if every entry in row a1 of table B is multiplied by 4/3=1.333, and row a2 is multiplied by 4/7 (step 1a). A similar adjustment to column b1 and b2 corrects its frequencies[23], b1 is multiplied by 5/6.096, and b2 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

[23] 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).

Table 4.1 Fitting a Model by Interactive Proportional Adjustment of the Marginal Distributions

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

Table B Observed Frequencies			
	b_1	b_2	
a1	2	1	3
a2	6	1	7
	8	2	10

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

Step 1b: Adjust Column b1, b2			
	b_1	b_2	
a1	2.2	2.1	4.3
a2	2.8	0.9	3.7
	5.0	3.0	8.0

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

Steps 2b: Adjust Columns b1, b2			
	b_1	b_2	
a1	2.0	2.0	4.0
a2	3.0	1.0	4.0
	5.0	3.0	8.0

tables are based on odd ratios[24] 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.

Measuring the association between rows and columns

For tables with more than two rows and columns, there are several odd

[24] 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.

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 P departs from the association between rows and columns in table Q. It can be written in the following equation:

$$d(P,Q) = \left[\sum_{i=1}^{r}\sum_{j=1}^{s}\sum_{l=1}^{r}\sum_{m=1}^{s}\left|\frac{p_{ij}p_{lm}q_{im}q_{lj}}{p_{im}p_{lj}q_{ij}q_{lm}}\right|^2\right]^{1/2} \qquad (4.1)$$

$d(P,Q)$ 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).

4.3 Data

In this chapter, 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[25] (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 migrate. 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 expenditures, education attainment, household assets and debts, and living conditions.

The CHIP 2007 are used for several reasons. First, it is a well-known, reliable data set for China. It provides very detailed and reliable information for our analysis. Second, unlike the CHIP 1988, 1995 and 2002 waves, the 2007 survey records the occupations of the household head and household spouse and whether they co-reside, thus increasing our sample size. There are 5005 household heads and 4823 household spouses. Compared to using only the relationship to the household head to match father-child pairs in the individual part, we obtain extra father-child pairs. Third, this is the latest CHIP wave[26] that provides evidence over a relatively long period to observe trends in intergenerational occupational mobility. However, there are also some limitations of the CHIP 2007 data for the purposes of our analysis. Generally, it is better to collect occupational information from fathers and children at the same age over their whole life to avoid life-cycle bias. However, this survey asks their occupation information at the same time; in other words, children's occupational information is collected early in their careers based on their age, while fathers' occupational information is collected later in their careers (or retailed) based on

[25] The 2007 urban and rural surveys were conducted by the NBS, but the rural-to-urban migrant survey was conducted by a survey company.
[26] This chapter was completed in March 2016. Thus the CHIP 2007 was the latest wave until the CHIP 2013 data became public available in May 2016.

their age. There is some evidence that there are fewer occupation changes over the life cycle, which causes age-related biases (Munshi & Rosenzweg 2009, Blanden 2009).

Table 4.2 Occupation Classifications

Category	Occupations
High white-collar	1 Principals in state agencies, Party organizations, enterprises and public service unit
Low white-collar	2 Professional technicians 3 Clerk and relating personnel
Skilled	6 Manufacturing and transporting equipment manipulator and relating personnel
Unskilled	4 Commercial and service personnel 5 Agriculture, forestry, animal Husbandry, fishery and water resources producer

Notes: We ignore 7 (soldier) and 8 (other practitioner (difficult to classify)) because the numbers of them are rare and it is difficult to classify.

We examine intergenerational 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. 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. Table 4.2 shows how we classify eight occupations into four categories. “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 producers. The descriptive statistics of the sample are summarized in Table 4.3.

Table 4.3 Descriptive Statistics

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

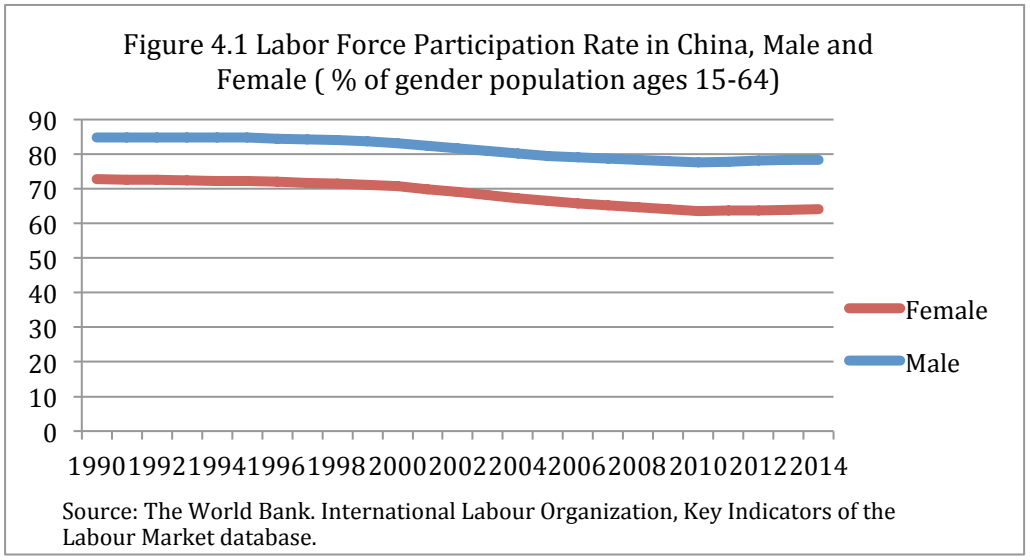
Note: Data are from CHIP 2007. Numbers of observations is 4632

In this chapter, we estimate the occupational mobility of father-child pairs. We do not consider the mother-children relationship because the female labor force participation rate of the mother's generation was low. Labor force employment patterns. Although Chinese females play an important role in economic development, they are not dynamic in many production sectors and are heavily concentrated in others. Table 4.4 and figure 4.1 show the employment differences between males and females in the labor force. Table 3 shows the employment status of urban males and females aged 45-64. Among those aged 45-49, 97.7% of males are employed, while only 73.6% of females are employed. This gender difference increases for older age groups: among those aged 50-54, 90.2% of males and 41.8% of females are employed; among those aged 55-59, 73.2% of males are employed versus 28.7% of females; among those aged 60-64, 50.9% males and only 14.7% females are employed. Figure 1 shows the labor force participation rate in China from 1990 to 2014. It shows that females participate in the labor market at lower rates than males.

Table4.4 Employment Status of Urban Male and Female, Aged 45-64 (in percentages)

	Male				Female			
Age (Birth cohort)	Employed	Retired	Household Work	Other	Employed	Retired	Household Work	Other
45-49 (1928-1932)	97.7	1.2	0	1.1	73.6	10.5	15.5	0.6
50-54 (1923-1927)	90.2	8.1	0.3	1.4	41.8	29.9	27.2	1.2
55-59 (1918-1922)	73.2	23.9	1.3	1.6	28.7	32.2	38.3	0.8
60-64 (1913-1917)	50.9	43.5	3.0	2.6	14.7	28.0	56.0	1.4

Source: 1987 One Percent Population Survey. Bauer, John et al. 1992.



We provide some empirical evidence in this section. Table 4.5 summarizes the evidence for the father-child occupational relationship in a cross-classification contingency table. There are two categorical variables based on 4 children's occupations in the rows and 4 fathers' occupations in the columns; as a consequence, 16 observed frequencies are created by multiplying the rows by the columns. For children with high white-collar jobs, for example, 77 (15.78 percent) have fathers with high white-collar jobs, 108 (8.04 percent) have

Table 4.5 Intergenerational Occupational Mobility in Urban China, Children's Birth Cohort 1948-1987, frequencies (Column Percent)

	Fathers' occupation				
Children's occupation	High white-collar	Low white-collar	Skilled	Unskilled	Row total
High white collar	77	108	70	121	376
	(15.78)	(8.04)	(4.80)	(9.01)	(8.12)
Low white collar	280	878	639	602	2399
	(57.38)	(65.38)	(43.83)	(44.83)	(51.79)
Skilled	50	149	401	174	774
	(10.25)	(11.09)	(27.50)	(12.96)	(16.71)
Unskilled	81	208	348	446	1083
	(16.60)	(15.49)	(23.87)	(33.21)	(23.38)
Total	488	1343	1458	1343	4632
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)

Notes: Data are from CHIP 2007. The numbers in parenthesis are percentage of column sum.

fathers with low white-collar jobs, 70 (4.80 percent) have fathers with skilled jobs and 121 (9.01 percent) have fathers with unskilled jobs. Among children whose fathers' have high white-collar jobs, 77 (15.78 percent) work in high white-collar jobs, 280 (58.38 percent) work in low white-collar jobs, 50 (20.25 percent) work in skilled jobs and 81 (16.60) work in unskilled jobs. Of the 1343 fathers with unskilled jobs, only 446 (33.21 percent) have children who also have unskilled jobs. Although the values in the table are helpful for understanding how much mobility has actually occurred across generations from one specific type of occupation to another, it cannot answer how mobility changes over time.

4.4 Results

Table 4.6 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 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

Table 4.6 Intergenerational Occupational Mobility in Urban China, by Birth Cohort, frequencies (Column Percent)

Panel 1 Child's Birth Cohort=1948-1957

Child	Father HW	Father LW	Father S	Father U	Row sum
HW	9 (13.24)	27 (11.74)	24 (7.23)	38 (16.74)	98 (11.44)
LW	39 (57.35)	137 (59.57)	147 (44.28)	99 (43.61)	422 (49.24)
S	7 (10.29)	35 (15.22)	96 (28.92)	33 (14.54)	171 (19.95)
U	13 (19.12)	31 (13.48)	65 (19.58)	57 (25.11)	166 (19.37)
Column sum	68 (100.00)	230 (100.00)	332 (100.00)	227 (100.00)	857 (100.00)

Panel 2 Child's Birth Cohort=1958-1967

Child	Father HW	Father LW	Father S	Father U	Row sum
HW	35 (19.13)	39 (9.18)	26 (4.74)	38 (9.13)	138 (8.77)
LW	95 (51.91)	259 (60.94)	222 (40.44)	167 (40.14)	743 (47.23)
S	25 (13.66)	63 (14.82)	167 (30.42)	67 (16.11)	322 (20.47)
U	28 (15.30)	64 (15.06)	134 (24.41)	144 (34.62)	370 (23.52)
Column sum	183 (100.00)	425 (100.00)	549 (100.00)	416 (100.00)	1573 (100.00)

Panel 3 Child's Birth Cohort=1968-1977

	Father HW	Father LW	Father S	Father U	Row sum
HW	19 (13.38)	27 (6.91)	19 (4.88)	35 (7.74)	100 (7.28)
LW	86 (60.56)	269 (68.80)	176 (45.24)	214 (47.35)	745 (54.22)
S	13 (9.15)	34 (8.70)	98 (25.19)	59 (13.05)	204 (14.85)
U	24 (16.90)	61 (15.60)	96 (24.68)	144 (31.86)	325 (23.65)
Column sum	142 (100.00)	391 (100.00)	389 (100.00)	452 (100.00)	1374 (100.00)

Panel 4 Child's Birth Cohort=1978-1987

	Father HW	Father LW	Father S	Father U	Row sum
HW	14 (14.74)	15 (5.05)	1 (0.53)	10 (4.03)	40 (4.83)
LW	60 (63.16)	213 (71.72)	94 (50.00)	122 (49.19)	489 (59.06)
S	5 (5.26)	17 (5.72)	40 (21.28)	15 (6.05)	77 (9.30)
U	16 (16.84)	52 (17.51)	53 (28.19)	101 (40.73)	222 (26.81)
Column sum	95 (100.00)	297 (100.00)	188 (100.00)	248 (100.00)	828 (100.00)

Notes: Data are from CHIP 2007. The numbers in parenthesis are percentage of column sum.

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 4.6 shows general changes in intergenerational occupational mobility in a basic cross-classification table; we also need to analyze mobility using other measures to support our hypotheses.

Table 4.7 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***	

Notes: 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.

Table 4.7 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 (Deming & Stephan (1940), 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. The difference between P and Q in their degrees of association is small in magnitude (2.89); hence, we cannot reject the null hypothesis that their associations are identical at any significance level. This suggests that even if we account for the differences in their occupational distributions, occupational mobility is similar for the P and Q cohorts.

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. This measure implies that mobility between children's occupations and their fathers' occupations is closer to independent in the 1968-1977 birth cohort than in the 1978-1987 birth cohort. The difference in magnitude between the P and Q row-column associations (13.46) becomes larger after controlling for the occupational distributions.

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. We can reject the null hypothesis that the row-column associations of P and Q equal the distance observed under independence. The difference in magnitude between P and Q in their row-column association (15.83) is statistically significant at the 5 percent level and becomes larger after controlling for the occupational distributions.

Table 4.7 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.

Table 4.8 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)	Percent of total	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

Notes: 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.

I now examine which occupational category cells contribute to the preferred mobility metric $d(P,Q)$. Table 4.8 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 association 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, I 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.

Explaining the Changes in intergenerational Occupational Mobility

Fathers' education values their sources and privileges as a socioeconomic status. It is a "social network" source to their children. Children of well-off parents not only obtain more and higher quality schooling education, but also endow their parents' experiences that affect their occupation choices (Kohn & Schooler 1969). Rytina (1992) argues that educational attainment is the main channel that occupation transmitted through. The indirect effect through education accounts for the greater part of the observed intergenerational correlation of occupation. What are the external factors that cause the changes of intergenerational occupational mobility from children's earliest birth cohort (1948-1957) to the latest birth cohort (1978-1987)? I investigate the potential reasons from three aspects: labor market, economic structure and social changes over time. The mobility changes among children's birth cohort from 1948 to 1987 experience the economic and social changes in a time span since 1964 to 2007[27].

The changes in labor market influence the occupational mobility from 3 aspects: wage system, labor force demand and job replacement policy. The economic reform since the late 1970s is a watershed of labor market. Prior to reform, urban workers employed in the state sector (even in the collective sector) and have fixed wage that based on education level and work experiences. People were guaranteed once they are employed, they won't loss jobs during lifetime. The wage system changes after the market-oriented economic reform. Meng & Kidd (1997) argue that the wage determination have a structural change that rate of return to human capital increased. Furthermore, changes in industrial wage differentials appear to play the dominant role. The changes in wage somewhat affect children's occupation choices. China carried out planned economy into market-oriented economic reform to accelerate economic growth

[27] I account samples of children who are over 16 years in the labor market. The oldest children participate in the labor market since 1964.

since the late 1970s. Industry structure adjustment changes the employment pattern in three industries over years. In 1990, the proportions are 60.1 percent in primary industry, 21.4 percent in secondary industry and 18.5 percent in tertiary industry. In 2005 the proportions are 44.8 percent in primary industry, 23.8 percent in secondary industry and 31.4 percent in tertiary industry[28]. The changes of industry structure explain that the demand of labor market also affect children's occupation choices. Another guaranteed work system is called "jieban" that children can take on their parents' job after their parents retired without any interview or exam. Prior to reform, this system was widely used to solve employment problems. Children work in the same workplaces as their parents used to, but not the same position (Bian 1994). This system largely impacts on the intergenerational mobility of occupation.

I believe the social changes affect intergenerational mobility of occupation from four aspects: reform and opening up, globalization, urbanization and one-child policy. Since the reform and opening up in 1982, Chinese government attempted a development strategy of "let some regions get rich first". This measure brings fast economic growth to the eastern coastal areas, but widen the regional gaps in economic and social development and lead to a phenomena of "rich areas becomes richer, poor areas becomes poorer". Regional economic disparity is one reason that causes the changes of occupational mobility over years. China's economic reform from planned economy to market oriented economy accompanies with globalization. Globalization is an important driving force of economic development and social changes. The development of international trade under the globalization background provides job opportunities for comparative advantage industries. In China, the globalization drives labor-intensive industry expansion, and thereby offers many unskilled job opportunities. In 1978, the rate of urbanization is only 17.9 percent with urban

[28] Data are from Information Office of the State Council of the People's Republic of China. It published a white paper on China's employment situation and policies.

population of 170 millions. In 2014, the urbanization rate increases to 54.77% with urban population of nearly 750 millions[29]. New city Migration brought by the urbanization process changes original urban labor market. They enrich the urban labor market, but also intensify the competition of employment. Long & Ferrie (2013) argue that high occupational mobility corresponded to high rate of residential mobility. However, this analysis shows the occupational mobility decreases with the rapid increase of urbanization. I assume that the one-child policy contributes more to the declining mobility than urbanization does. Parents could spend more time with their only child, which tightens the economic and social connections between two generations. This can explain the significant decreasing of intergenerational occupational mobility for children's recent birth cohort.

4.5 Conclusion

This chapter examines the intergenerational occupational mobility among children's birth cohort from 1948 to 1987. The cross-classification tables provide a comparison of intergenerational occupational mobility for children's 4 birth cohorts (1948-1957, 1958-1967, 1968-1977, 1978-1987) and show the overall occupational mobility becomes worse as time passes. The Altham statistics provides 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 change become less mobile especially when fathers have high white-collar jobs as opposed to the case fathers had skilled jobs.

Employment should be emphasized as the national development strategy

[29] Source: see the 2014 Statistics Bulletin of the National Economic and Social Development of the People's Republic of China. http://www.stats.gov.cn/tjsj/zxfb/201502/t20150226_685799.html

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 categorical data analysis, I divide occupations into 4 types, more detailed classification is necessary to investigate the associations between father's and their children's occupations. However, due to data limitation, CHIP 2007 only offers 7 types of occupations that are not essential for a more detailed analysis of intergenerational transmission. Exploring new data is required for future research.

Chapter 5 Conclusion

This chapter provides a brief summary of this study, states the importance of this research, gives policy implications and posts new research questions for future research.

The goal of this study is to investigate changes in intergenerational economic mobility in urban China over nearly half a century. The empirical evidence indicates that children are likely to have s similar socioeconomic status as their parents overall.

This study of intergenerational income persistence provides new evidence on the IGE: the IGE is 0.420 in 1988, rises to 0.447 in 1995 and then falls to 0.402 in 2002. Overall, IGE appears to increase from the bottom of children's conditional earnings distribution to the top of children's conditional earnings distribution, which indicates that the lower the children's income, the greater the intergenerational mobility. We assume that children's education attainment, occupational inheritance and regional differences affect these changes in intergenerational income mobility. An extended analysis adding these control variables supports these assumptions. To further explore intergenerational economic mobility, intergenerational educational mobility and intergenerational occupational mobility are analyzed. We re-examine children's educational attainment, which is positive correlated with their parents' educational attainment. The impact of parental education increases from the children's earlier birth cohort, 1951-1960, to the later birth cohort, 1981-1990, which implies that parental educational background is increasingly important to children's educational outcomes. Mobility also exhibits gender differences. By estimating a logit model, We find that being male, having highly educated parents, being in more recent birth cohorts and growing up in the east region increases the probability of having higher education. The analysis of intergenerational occupational mobility shows a decline among children in the

earlier birth cohort, 1948-1957, compared to the later birth cohort, 1978-1987. We also find that a large share of the change of occupational mobility is caused by the gap between the 1968-1978 birth cohort and the 1978-1987 birth cohort. A decomposition analysis indicates that children are more likely to enter high white-collar occupations than other occupations when their fathers have white-collar jobs compared to skilled jobs.

Moreover, this study depicts the structure of parental socioeconomic status, children's socioeconomic status and external conditions. Socioeconomic status refers to income, education and occupation in this study. The external conditions include the labor market, government policies and the education system. The concepts of "equal opportunity" and "inheritance" are core concepts that connect these conditions. The transmission of parental socioeconomic status to their children occurs through an inheritance process. External conditions can provide equal opportunities for children to obtain their desired socioeconomic status.

Inheritance stems from three areas: one is natural biological (e.g., physical characteristics, IQ), one is parents' consciousness (e.g., the impacts of paternal words and deeds, traditional cultures), and another is parents' decisions (e.g., human capital investment). Socioeconomic status, personal abilities and education level determine occupational status (Sewell & Hauser 1975).

Social welfare policies guarantee equal opportunities for human beings. Government policies have strong impacts on education systems, thereby offering equal opportunities for children to obtain education benefits. Government policies can also have strong impacts on labor markets, eliminating barriers to and offering equal opportunities for employment. The labor market influences the parental educational investment decision by affecting the returns to their children's education.

The findings in this study emphasize the importance of parental socioeconomic status in the children's economic inequality issues. Corak and

Piraino (2011) argue that the connections between children and their parents reflects the degree of inequality that transmits across generations, and the notion of equality of opportunity. Inequality in income and wealth cause economic instability, a range of social problems. Income inequality is a core issue concerning people's social life and national development, but education and occupation as intergenerational transmission channels also should be taken seriously. As Hannum & Buchman (2003) argues that education not only influences individual's income but also contributes to national economic development. The expansion of education is also essential to economic development since it can promote productivities of labor force. Scott (1995) also believes that Education concerns the equal distribution of wealth and higher education is a source of personal and social liberation and the expansion of higher education can effectively equalize life and social chances for individuals. The changes of occupational mobility not only illustrate the occupational transmission across generations but also reflect how social changes impact on occupations and further influence on intergenerational income inequality. The systematical analysis of intergenerational mobility on income, education and occupation offers valuable implications for policy-making.

Reducing inequality is an essential issue for national development and people's wellbeing. A higher degree of intergenerational income persistence requires substantial redistribution by the government. Two effective tools of redistribution are taxes and benefits. The international evidence suggests that greater equality confers the same benefits on a society whether it is achieved through one of these measures or the other. Progressive income taxation is probably one of the least distortionary measures to reduce inequality and to redistribute more equally the gains from growth. According the estimate of Piketty et al. (2009), the top decile income share rose from about 17 per cent in 1986 to almost 28 per cent in 2003. In general, top tax rates in many countries are over 80%, while in china are from 3 percent to 45 percent. To well

redistribution of personal wealth, the top tax rates should be raised. Moreover, the individual's capital gains are taxable at the rate of 20%, which also should be raised to balance the income gap between wage income and capital income. Inheritance tax is a direct policy tool to control the wealth transmission across generations, but has not yet been practiced. The policy objective around education, health and housing should target improving wellbeing benefits. For instance, the cost of treating major diseases may let a family be plunged into poverty. The poverty situation will influence home environment of the family's next generation and further influence their economic outcomes. After many government measures (for example, low interest rates, cheap credit, etc.) to support the housing market, the dramatic increasing housing price enlarges the wealth gap among families in different cities, which will also make a further influence on children's economic outcomes. The government must take effective measures to control the significant price-rises of housing, especially in biggest cities to reduce the regional inequality and intergenerational transmission of wealth inequality.

Government and schools should take measures to enhance the intergenerational mobility of education and occupation. The reform of structure of education should keep up with economic structure changes, and make predictions and take measures to against dismal labor market. College majors designing should fit the needs of labor market. Regional economic disparity is a tricky problem that leads to the inequality of education, which requires the government to offer preferential policies to undeveloped areas. Teacher training that improves professional knowledge and teaching skills is an effective measure to develop education and reduce the regional inequality in education. At the same time, the government should do some efforts to promote the economic activities and create more employment opportunities in the undeveloped areas. It is important to improve the intergenerational mobility in education and occupation because their gaps among children are likely to persist or expand in

children's career and future life.

This research represents a considerable advance over previous studies in the issue of intergenerational mobility in urban China. However, this thesis points to the need for additional work to improve more detailed analyses about the estimation of intergenerational mobility. For example, the definition of income in this study refers to wage and bonus. However, nowadays under the influence of expanding regional disparity, the importance of family wealth and house price cannot be ignored in the intergenerational inequality issue. The differences of economic growth and geographic concentration among cities are also factors that impact on the changes of intergenerational mobility over years. It remains to be a question how to combine those effectors in an economic approach to investigate their contributions in intergenerational transmission process. Moreover, education levels and occupation types should be more detailed classifid, which needs new data source to support. In addition, the urban migration is a notable of social change since the 1980s' economic reform. This thesis did not analyze the case of rural China and urban migration, but it provides a guide of systematic analysis and methodology for further research.

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