A Quantile Analysis of Intergenerational Income Mobility in Urban China Based on CHIP Data*

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In this paper, we estimate the intergenerational income mobility across children's conditional income distribution in urban China from the 1980s to the 2000s. Based on China Household Income Project (CHIP) data from 1988, 1995 and 2002, we examine the intergenerational income elasticity (IGE) of father-child pairs using both ordinary least square regression and quantile regression. We find that the intergenerational income mobility increases slightly from 1988 to 2002 and the overall trend of IGE appears to increase across quantiles. This finding suggests that low-income children's income does not depend on their father's income as much as high-income children's does. High-income children's income tends to be less affected by their father's income over the years. We also find that children's education attainment, occupation and regional differences are the factors that affect intergenerational income mobility.

Keywords: Income inequality, Intergenerational income elasticity, Intergenerational mobility, Quantile regression

Ⅰ. Introduction

One important driving force of the "Chinese Dream" is social fairness. Income equality is an important part of social fairness. It is necessary to study intergenerational income mobility and explore how income transmits from one generation to the next to influence income equality. This paper 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, Björn and Li 2013), this paper 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, we observe that intergenerational income inequality in urban China slightly decreases from 1988 to 2002.

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 that there is a high intergenerational persistence of low earnings (Eide and Showalter 1999, Fertig 2003, Grawe

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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 intergenerational income mobility is greater at the top of sons' earnings distribution than at the bottom. Fertig (2003) examines the trend of 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, Nilsen and Vaage 2007). Hirvonen (2008) argues, using large samples of Sweden data, that parents' family earnings are more important to sons at the bottom quantile than at the top quantile. A few other studies suggest opposite results, i.e., that the IGE is higher at upper quantiles (Aydemir, Chen and Corak 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 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 paper 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.

This paper improves the research in the following two aspects. First, the main objective of this paper 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 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.

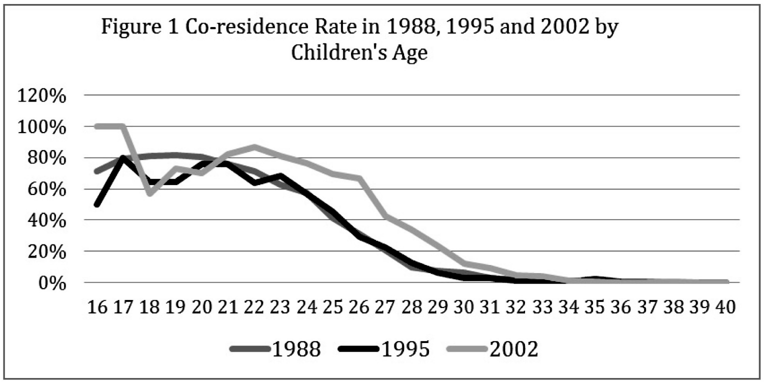
The results of our analysis suggest that the intergenerational mobility in urban China increases slightly from 1988 to 2002. The IGE varies by quantile and the lowest IGE is at the bottom quantile in each year. Children's education attainment, occupation and regional difference causes the different IGE across quantiles and years.

This paper 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 paper 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.

Ⅱ. 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 (CASS), 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 2002 survey added a survey of rural-to-urban migration. Thus, the 2002 CHIP survey includes three subsamples.[1] The purpose of this survey is to measure and estimate the personal income distribution and related economic factors in both rural and urban areas of the People's Republic of China. It collects rich information on households and household members, e.g., personal characteristics, employment situations, income, education attainment, assets and debts, expenditures, and living conditions. This paper 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.

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. We 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 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. Bohlmark 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 lifecycle 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.[2] 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 unique code. I use the family members' relationship[3] 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 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.[4] 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 1 Sample Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
1988	2298				
Children's age		22.32	3.38	16	39
Children's income		3077	2398	511	82097
Children's years of schooling		11.20	2.15	2	16
Fathers' age		51.57	4.55	36	60
Fathers' income		5792	2620	1271	48221
1995	1011				
Children's age		23.41	3.10	16	36
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		8909	5057	636	52339
2002	877				
Children's age		24.87	3.33	16	38
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

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.

Table 1 presents the summary statistics of children's 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 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.

Ⅲ. Empirical Model and Methodology

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

$$\ln Y^{child} = \alpha + \beta \ln Y^{parent} + \gamma X + \mu \qquad (1)$$

In this equation, Y^{child} is children's monthly income; Y^{parent} is fathers' monthly income; coefficient β represents the estimated intergenerational income elasticity; X is a vector of control variables[5]; 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, we use fathers' income before 1988—i.e., we use fathers' income in 1987 or earlier. However, as we know, survey data on households 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, we 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 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:

$$\min_{\beta \in \Re^K} \sum_{i \in \{i: y_i \geq x_i\beta\}} \theta |y_i - x_i\beta| + \sum_{i \in \{i: y_i < x_i\beta\}} (1-\theta) |y_i - x_i\beta| \tag{2}$$

In the equation, $y_i (i=1, \cdots, I)$ is the dependent variable, $x_i (i=1, \cdots, I)$ 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.

Ⅳ. Estimation Results

1. Basic analysis

I first estimate the IGE by ordinary least squares, which estimates the conditional mean effect of fathers' income on children's income. Then, I apply quantile regression to estimate the different conditional distribution effects of fathers' income on children'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 fathers' income and children's income, and it allows a flexible analysis of the impact of fathers' income on children'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 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 without any control variables. The first column of the table presents the OLS results of IGE in 1988, 1995 and 2002. The estimated coefficient is 0.449 with a standard error of 0.030 in 1988, which indicates that a unit increase in father's income raises children's income by 44.9 percent. Then, the IGE decreases to 0.441 with a standard error of 0.038 in 1995 and finally falls slightly to 0.429 with a standard error of 0.038 in 2002 with all estimates being highly statistically significant. The decreasing IGE implies that the intergenerational income mobility

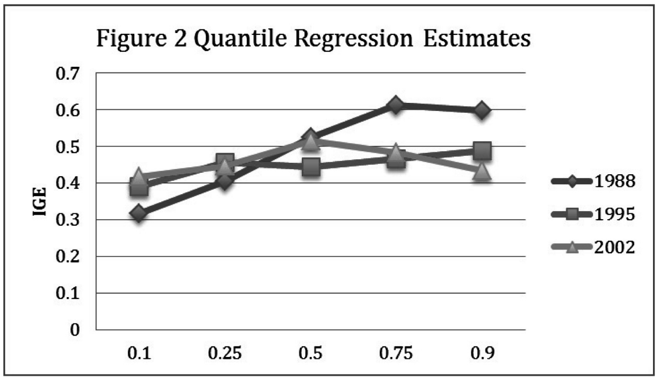
Table 2 OLS and Quantile Regression Estimates of the IGE of Children's Log Income with Respects to Fathers' Log Income

Log income of children	OLS	Quantile				
		0.1	0.25	0.5	0.75	0.9
1988	0.449***	0.317***	0.404***	0.524***	0.612***	0.597***
Log of fathers' income	[0.030]	[0.069]	[0.048]	[0.040]	[0.041]	[0.057]
1995	0.441***	0.391***	0.456***	0.444***	0.467***	0.487***
Log of fathers' income	[0.038]	[0.134]	[0.062]	[0.041]	[0.041]	[0.061]
2002	0.429***	0.416***	0.446***	0.514***	0.483***	0.435***
Log of fathers' income	[0.038]	[0.084]	[0.079]	[0.039]	[0.038]	[0.079]

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.

becomes greater over time. Children's income is lower depending on their father's income. Column 2 shows the quantile regression estimates at 10th, 25th, 50th, 75th and 90th quantiles. By years, in 1988, the IGE is 0.317 at the bottom quantile, increases to 0.612 at the 75th quantile, and finally falls slightly to 0.597 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 worse in higher income groups. In 1995, the smallest IGE is 0.391 at the 10th quantile while the largest IGE is 0.487 at the 90th quantile. The IGE is fluctuating around 0.45 between the 25th quantile and the 75th quantile. The results show that the intergenerational income mobility is greater at the bottom quantile and does not change so much at other quantiles. In 2002, the IGE increases from 0.416 at the bottom quantile to 0.514 at the medium quantile then tends to decrease at the upper quantiles, with the top quantile having a point estimate of 0.435. By quantile, we find the smallest 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 changes in IGE at the upper quantiles are larger than those at the lower quantiles across years. It changes 0.099 with an increase from 0.317 in 1988 to 0.416 in 2002, and it changes 0.162 with a decrease from 0.597 in 1988 to 0.435 in 2002. The quantile regression results in column 2 are therefore consistent with the hypothesis that the IGE is varies by quantile.

Figure 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 and 1995, which indicates intergenerational income mobility worsens



from lower income groups to higher income groups. However, this 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. The graph starts at 0.317 and maintains a high increasing speed to approximately 0.6 at the top quantile. The increasing speed slows down in 1995. It is slower in 1995 than in 1988. The change in IGE is slightly different in 2002. It increases from the bottom quantile to the median quantile then falls slightly to the top quantile. 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 0.435 in 2002. This implies that high-income children do not depend on their father's income as much as before.

2. Extended Analyses by Adding Control Variables

We assume that children's education attainment, occupation and regional difference causes the different IGE across quantiles and years. Controlling for these factors will allow us to understand the channels of intergenerational income mobility transmission.

Table 3 shows that including a measure of children's education attainment in children's income equation changes the effect of fathers' income on children's income. There is a positive correlation between children's education level and their income. The educational choice of children depends on the cost of education and the 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, we see education as parents' investment in their children's human capital. When the determinant of education is accounted for, the OLS estimates

Table3 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
1988						
Log of fathers' income	0.426***	0.258***	0.362***	0.479***	0.600***	0.580***
	[0.030]	[0.074]	[0.045]	[0.043]	[0.051]	[0.066]
Years of schooling	0.023***	0.038***	0.034***	0.023***	0.017***	0.006
	[0.004]	[0.008]	[0.005]	[0.005]	[0.005]	[0.008]
Difference in IGE	-0.023	-0.059	-0.042	-0.045	-0.012	-0.017
% Changes in IGE	-5.12	-18.61	-10.40	-8.59	-1.96	-2.85
1995						
Log of fathers' income	0.422***	0.334**	0.425***	0.423***	0.455***	0.465***
	[0.039]	[0.119]	[0.071]	[0.056]	[0.044]	[0.054]
Years of schooling	0.020**	0.023	0.026***	0.023***	0.026***	0.038***
	[0.008]	[0.019]	[0.010]	[0.008]	[0.009]	[0.015]
Difference in IGE	-0.019	-0.057	-0.031	-0.021	-0.012	-0.022
% Changes in IGE	-4.31	-14.58	-6.80	-4.73	-2.57	-4.52
2002						
Log of fathers' income	0.355***	0.268**	0.364***	0.417***	0.363***	0.331***
	[0.038]	[0.118]	[0.053]	[0.039]	[0.067]	[0.062]
Years of schooling	0.085***	0.110***	0.087***	0.078***	0.083***	0.101***
	[0.010]	[0.032]	[0.012]	[0.010]	[0.016]	[0.019]
Difference in IGE	-0.074	-0.148	-0.082	-0.097	-0.120	-0.104
% Changes in IGE	-17.25	-35.58	-18.39	-18.87	-24.84	-23.91

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.

of the IGE coefficient change in comparison to the baseline results. The IGE also maintains a decreasing trend from 1988 to 2002, which is consistent with the baseline estimates. The percentage change in IGE is approximately 5 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, Column 2 shows IGE has the same trend as the baseline analysis by quantiles. The coefficient of education decreases from 0.038 at the 10th quantile to 0.006 at the top quantile. The change in IGE is 18.61 percentage points at the bottom quantile and gradually falls to approximately 3 percentage points at the top quantile. In 1995, education influences the IGE mostly at the bottom quantile. In 2002, the IGE keeps the same changing trend as the baseline estimates. The decrease in IGE is dramatically larger in 2002 than in earlier years. By quantile, we find the greatest change at the bottom quantile in each year. This implies that the effect of education plays a more important role in the intergenerational income transmission mechanism in the low-income children groups than in other groups.

Table 4 shows the OLS and quantile regression estimates when controlling for occupational dummy variables. We classify children's occupation into 3 categories: white collar work, skilled work and unskilled work.[6] We create 2 occupational dummy variables. Letting skilled dummy=1 if child has a skilled occupation, otherwise 0; unskilled dummy=1 if child has an unskilled occupation. In this analysis, we see occupation as a of social class transmission from fathers. When the dummy variable is accounted for, the OLS results of IGE decreased slightly compared to the baseline results. The percentage decreases in IGE is 1.11 in 1988 and increases to 3.85 in 1995 and up to 5.83 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 we

Table4 OLS and Quantile Regression Estimates of the IGE of Children's Log Income with Respects to Fathers' Log Income Controlling for Occupation

Log income of children	OLS	Quantile				
		0.1	0.25	0.5	0.75	0.9
1988						
Log of fathers' income	0.444***	0.303***	0.406***	0.513***	0.605***	0.611***
	[0.030]	[0.052]	[0.046]	[0.041]	[0.045]	[0.056]
Difference in IGE	-0.005	-0.014	0.002	-0.011	-0.007	0.014
% Decrease in IGE	-1.11	-4.42	0.50	-2.10	-1.14	2.35
1995						
Log of fathers' income	0.424***	0.360**	0.432***	0.430***	0.458***	0.450***
	[0.038]	[0.119]	[0.077]	[0.044]	[0.055]	[0.060]
Difference in IGE	-0.017	-0.031	-0.024	-0.014	-0.009	-0.037
% Decrease in IGE	-3.85	-7.93	-5.26	-3.15	-1.93	-7.60
2002						
Log of fathers' income	0.404***	0.398***	0.412***	0.457***	0.428***	0.434***
	[0.038]	[0.096]	[0.070]	[0.040]	[0.059]	[0.063]
Difference in IGE	-0.025	-0.018	-0.034	-0.057	-0.055	-0.001
% Decrease in IGE	-5.83	-4.33	-7.62	-11.09	-11.39	-0.23

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. We define the occupational dummy variable as 'The child works in the same occupation category as his father'.

Table5 OLS and Quantile Regression Estimates of the IGE of Children's Log Income with Respects to Fathers' Log Income Controlling for Region Dummy Variable

Log income of children	OLS	Quantile				
		0.1	0.25	0.5	0.75	0.9
1988						
Log of fathers' income	0.359***	0.218***	0.344***	0.430***	0.534***	0.470***
	[0.030]	[0.068]	[0.036]	[0.049]	[0.039]	[0.065]
Difference in IGE	-0.09	-0.099	-0.06	-0.094	-0.078	-0.127
% Changes in IGE	-20.04	-31.23	-14.85	-17.94	-12.75	-21.27
1995						
Log of fathers' income	0.387***	0.324***	0.404***	0.434***	0.400***	0.317***
	[0.038]	[0.101]	[0.052]	[0.058]	[0.050]	[0.059]
Difference in IGE	-0.054	-0.067	-0.052	-0.01	-0.067	-0.17
% Changes in IGE	-12.24	-17.14	-11.40	-2.25	-14.35	-34.91
2002						
Log of fathers' income	0.351***	0.355***	0.379***	0.417***	0.377***	0.393***
	[0.038]	[0.099]	[0.054]	[0.041]	[0.046]	[0.047]
Difference in IGE	-0.078	-0.061	-0.067	-0.097	-0.106	-0.042
% Changes in IGE	-18.18	-14.66	-15.02	-18.87	-21.95	-9.66

Note: 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.

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.

Table 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 lowers the IGE by 20.04% in 1988, 12.24% in 1995 and 18.18% in 2002, which implies that the regional difference is an important factor that raises the IGE in China. By quantile, in 1988 and 1995, the changes in IGE are greater at the tails of the children's conditional income distribution than at the medium. However, in 2002, the changes in IGE are greater at the medium quantile than at the tails. We can conclude that reducing the regional inequality could lower the IGE and improve the intergenerational income mobility.

In this section, we estimate the IGE to be 0.449 in 1988, 0.441 in 1995 and 0.429 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. We control for education, occupation and regional inequality and find these factors cause the different IGE at different quantiles.

3. Discussion

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 we choose CHIP data in this analysis? Because it is similarly designed in each survey year, which can provide a comparison analysis and in this paper we 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, we do not use the latest data in this analysis. CHIP data are updated to 2010 but we use only the data until 2002. Because after 2007, the income data of retired persons are not provided, according to our sample selection rules, we cannot use the latest data. Lastly, the analysis of the income intergenerational transfer mechanism is not deep. The functional form we have tested is also superficial. I will focus on the income transfer channels in furture research.

Moreover, this paper 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 we cannot conclude that at which quantile the co-residence rate influences the IGE more.

Table 6 is a summary of estimates of IGE using quantile regression in other countries. My finding in this paper shows an opposite

Table 6 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.

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.

V. Conclusion

This paper 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. This provides important policy implications.

We find that the intergenerational income mobility increases slightly from 1988 to 2002 and the overall trend of IGE appears to increase across quantiles. This suggests low-income children's income does not depend on their father's income as much as high-income children's income does. High-income children's income tends to be less affected by their father's income over the years. We also find children's education level, occupation and regional differences are factors that 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. 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 account 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.

Notes

1) See the homepage of China Institute for Income Distribution. Descriptions of the CHIP surveys and key findings can be found in Griffin and Zhao (1993), Riskin, Zhao, and Li (2001), and Gustafsson, Li, and Sicular (2008)

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.

3) 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.

4) 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.

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

6) 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.

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