Long-term Intergenerational Human Capital Mobility: An empirical analysis in China with 3 generations

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Abstract

Most of the studies on long-term intergenerational human capital mobility is restricted to two consecutive generations based on the Becker-Tomes model, and argues that the inference will be wiped out during the third generation. However, in developing countries such as China, the ancestors play a key role in the family decision making process. Thus, this research uses a data set of China rural households, which includes three generations of data, to analyze the long-term intergenerational mobility. The results provide empirical evidence that the grandparent generation has had a direct influence on the child generation's education outcome, rather than the grandparent generation influencing the child generation through their parents. Therefore, the inference of generations on educational achievements has been underestimated by the data of two consecutive generations.

JEL Classification: J25, O14, J62

Keywords: Intergenerational Human capital mobility, China, Human capital

1 Introduction

Disparity of intergenerational human capital mobility exists widely in education, income and social status. In China, there is a social norm that the level of education changes the fortune that drives all society to pursue for high educational achievements. Thus, this research focuses on the education mobility between generations. The scope of the past research on long-term intergenerational human capital mobility has been restricted to two consecutive generations, namely parents and their children. The most cited method on measuring long-term intergenerational human capital mobility is the Becker-Tomes model, which the achievement of the child generation is influenced by the

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parent generation and the grandparents influence the child generation through influencing the patents generation. If the prediction of the Becker-Tomes model held good, the separate generation would have no influence on the human capital, in which the grandparent generation shall have no direct influence on the child generation. However, there may exist multiple channels for grandparents to influence the child generation and transform human capital independent of the parent generation. First, especially when their spouse dies, grandparent may influence children directly by living with them. Second, grand parents may give financial support through celebration presents to the grandchildren directly if their grandchildren admitted to a university, and for festival celebrations. Third, grandparents may influence children directly by making decisions for them such as choosing their names.

There is a branch of overseas studies that discuss the long-term intergenerational human capital mobility using data from two consecutive generations (Golley, 2013; Labar, 2011; Congbin, 2008; Borjas, 1992; Chetty, 2014). However, a research by Mikael (2016) pointed out that the validity of two consecutive generations' analysis relies heavily on the validity of that assumed model. Nevertheless, research on long-term intergenerational human capital mobility in China is still mainly based on the data of two consecutive generations.

In order to fill this gap, it is necessary to analyze the long-term intergenerational human capital mobility in China with 3 generations' data. We use the term "grandparents" for the first generation, "parents" for the second generation and "children" for the third generation throughout this paper. This research is interested on the following questions. First, we explore whether the grandparent generation directly influence the child generation's educational outcome. Second, we measured to what extent, can the data of two consist generations analyze the long-term intergenerational human capital mobility. For these purpose, we compared the difference between the predicted mobility and the real mobility measured obtained by two and three generations apart. Our result support that human capital mobility is under estimated by two consecutive generations' data.

This paper is organized as follows. Section 2 gives a short introduction of the background of this research. A brief description of the data set is given in Section 3, and the empirical methodology and results are shown in Section 4. Section 5 discusses the gender difference between the educational mobility. The last Section summaries the conclusion of this research and discusses the implication of the finding.

2 China traditional family structure

China is known as a country that values family. Thus, family structure has played a key role in the Chinese society.

In humanity field, there are several studies that discuss the grandparents' impact on children. One study done by Shi (1993) conclude that the grandparents play a significant role in raising the children when the parents are away for work. Chen (2000) examined how the physical condition and well-being of the elderly in families are influenced by children, and showed that retired elderly parents gain

personal satisfaction and self-esteem from taking care of their grandchildren.

Therefore, the grandparents play a significant roll in Chinese typical traditional families and have a strong influence on the young generation through several channels and for several reasons.

3 Data description

This research uses the household survey data called the Longitudinal Survey on Rural Urban Migration in China (RUMiC) from the Institute for the Study of Labor(IZA). The previous studies that used this data set focus on three different aspects of migration. The first one is regarding the relationship between remittance and migration. The second one is on the wage gap (Klaus et al. 2016; Rachel et al. 2015; Björn et al. 2014; Hartmut and Yuhao 2013; Klaus et al. 2014; Zhong et al. 2014). The last one concentrated on the well-being of migrants (Wei Huang 2015; Xin Meng and Chikako Yamauchi 2015) or education attendance of migrants' children (Massimiliano Tani 2016).

The RUMiC dataset consists of three parts: The Urban Household Survey, Rural Household Survey (RHS) and Migrant Household Survey. The survey was initiated by a group of researchers at the Australian National University, the University of Queensland and the Beijing Normal University under a support of the IZA, which provides the Scientific Use Files. The financial support for RUMiC was obtained from the Australian Research Council, the Australian Agency for International Development (AusAID), the Ford Foundation, the IZA and the Chinese Foundation of Social Sciences. The RUMiC dataset is based on a face-to-face interview, and the interviews were conducted in 2008. This paper used the RHS dataset of 2008. The sampled households were selected randomly from nine provinces in China, namely, Sichuan, Chongqing, Anhui, Hubei, Henan, Guangdong, Zhejiang, Jiangsu and Shanghai. This RHS dataset contains the information of the highest education accomplished for each household, which allows us to analyze the education mobility within the household. The reason for using RHS only rather than combining it with the Urban Household Survey is that during the Chinese Culture Revolution, the parents of urban families had been sent to rural areas and may influence the analysis of education mobility. Thus, we restricted our data by rural household data to analyze the education outcome correlation between the generations in the long term.

For all generations, we restricted the samples of households that have information for all three generations. The educational level was measured as years of schooling, which we calculated by the average years required for the highest educational degree accomplished. For the third generation, we discarded samples with age younger than 20 in order to assure that our samples have the possibility to accomplish the compulsory education (in china the compulsory education is a 9 years' education for middle school generally at age 15 or 16). With this conditions, we are left with 772 samples of households usable for our estimation.

The intergenerational human capital mobility is shown in Figure 1, and the educational achievement is presented in Figure 2. Table 1 gives the descriptive statistics for all the variables in the empirical analysis. Since the numbers of observations is almost the same across generations as shown in Figure 1, we are allowed to conduct the intergenerational mobility analysis. From Figure 2, we find that the

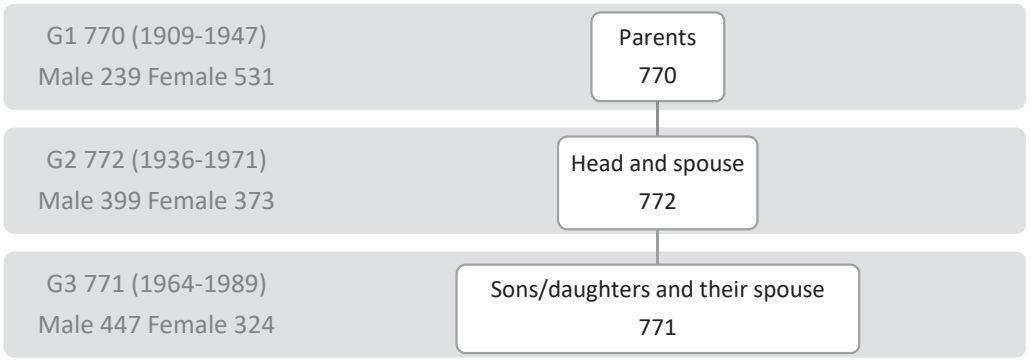
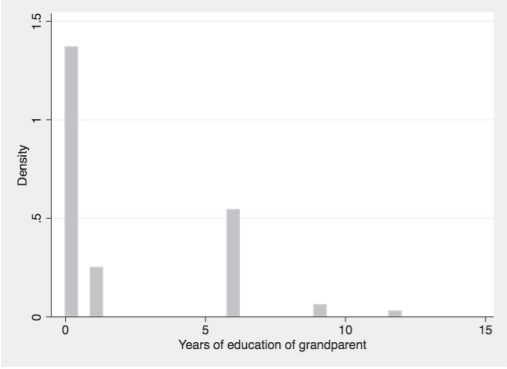
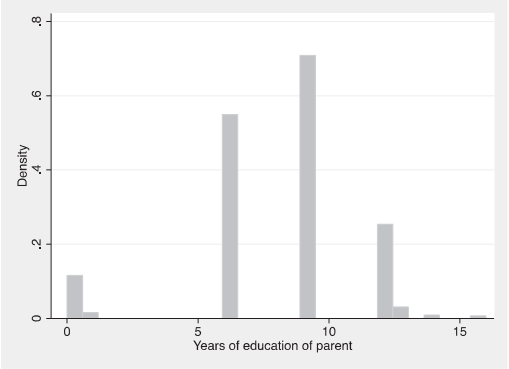


Figure 1. The generation mobility through three generations
Source: RHS 2008





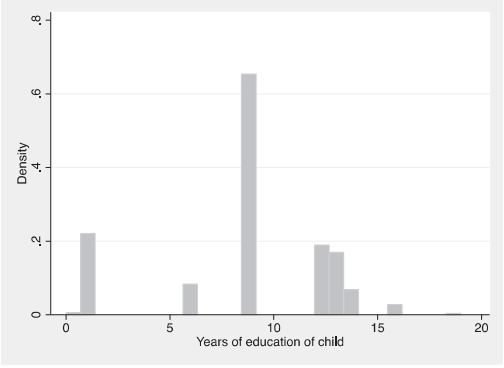


Figure 2. Educational achievement for each generation
Source: RHS 2008

Table 1. Descriptive statistics

	Grandparent		Parent		Child	
	Male	Female	Male	Female	Male	Female
Years of schooling						
Mean	3.196653	1.401501	8.822055	6.935657	8.910515	8.707692
Std. Dev.	3.354263	2.657122	2.644975	3.331366	4.188501	3.82133
Min Max	[0, 12]	[0, 12]	[0, 16]	[0, 16]	[0, 19]	[0, 16]
Observations	239	533	399	373	447	325
Age						
Mean	80.2887	80.69868	52.26065	50.32976	26.03132	24.82716
Std. Dev.	7.138215	7.053139	6.548024	6.434626	5.193468	4.772963
Min Max	[62, 97]	[62, 100]	[38, 73]	[37, 68]	[20, 45]	[20, 42]
Observations	239	531	399	373	447	324

Source: RHS 2008

educational achievement is very low for each generation. However, the years of education is still show slowly growth apparent from the grandparent generation to the child generation.

4 Methodology

As adressed before, the most cited model of intergenerational human capital mobility is the Becker-Tomes model. The Becker-Tomes model measures mobility between the two generations using the framework of first-order autoregressive process (AR(1)) of the time-series regression. The Becker-Tomes' two generation model is specified as:.

$$y_t = \emptyset y_{t-1} + \tau e_t + u_t, (1)$$

$$e_t = \lambda e_{t-1} + v_t, (2)$$

where, y is the outcome such as educational achievement, e represents endowment, u and v are the error terms, t indicates the child generation, $t-1$ indicates the parent generation, $\emptyset$ should be the estimated level of influence from parent generation, and the τ is the estimated level of endowment for child generation. Although the Becker-Tomes model has an analogy with the AR(1) process by regarding the generation as time dimension, two-generation data only allows them to include the variables of a pair of parents and their children which existed at the time of the survey. This implies that their model is boiled down to a simple cross-section model. This framework can be easily extended to the three generation case by replacing y_{t-1} by y_{t-2}, the outcome of the grandparents as long as three-generation data are available. Thus, the estimation models for the two-generation and three-generation models can be written as:

$$y_{t,i} = a + by_{t-j,i} + d'X_i + u_i, (3)$$

where $j \geq 1$, y_t is the education of the child and y_{t-j} is the education of the parents when $j=1$, and grandparents when $j = 2$, and i indicates the household i. x_i is a vector of controls including a cubic in age for generation t and generation $t-j$, and gender dummies for generation t and $t-j$, and u_i is the error term. We omit the endowment variable due to the data availability. When $j = 2$, this model allows us to measure the influence of grandparent generation on child generation. Thus, the influence of grandparent generation can be compared with that of parent generation. We estimate this model by the ordinary least squares (OLS) as was done by Becker and Tomes. Just as the Becker-Tomes' AR(1) model, we call the model with y_{it-2} AR(2) merely for our referential convenience although the analysis does not follow the case of the autoregressive model.

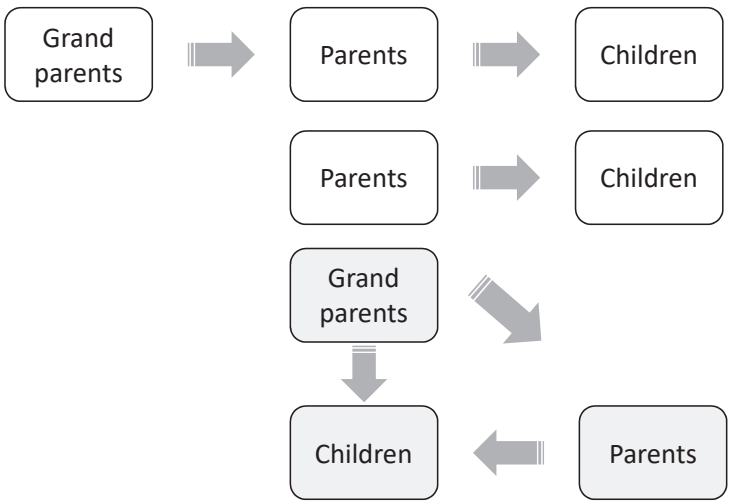


Figure 3. Intergenerational mobility in China rural area

Table 2. Intergenerational human capital mobility results from rural households

Variables	Years of schooling		
	Parent generation	Child generation	
Years of schooling of grandparents	0.110***	0.137**	
	(0.0395)	(0.0584)	
Years of schooling of parents			0.118**
			(0.0565)
Controls	yes	yes	yes
Constant	-208.0**	53.05	61.22
	(83.48)	(116.2)	(55.30)
Observations	770	769	771
R-squared	0.186	0.062	0.064
Prediction		0.01298	
		(0.11*0.118)	

Note: each columns represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Figure 3 presents the difference between the concepts of our model and Becker-Tomes' . Our model allows to examine the direct impact of grandparent generation on the outcome of child generation instead of the direct impact through the outcome of parent generation but have direct impact.

The prediction from the Becker-Tomes model is shown in the Prediction line at the level of 0.01298. Table 2 presents the intergenerational human capital mobility in two generations: (1) the education mobility from the grandparent generation to the parent generation is 0.11, the the education mobility from the grandparent generation to the child generation is 0.137, and the the education mobility from the parent generation to the child generation is 0.118; (2) the education from the grandparent to child generation is statistically significant and not equal to 0; (3) the prediction from the Becker-Tomes model of the education mobility from the grandparent to child generations is about 0.013(0.11*0.118), and almost 10 times smaller than the result from the regression, which is 0.137.

Therefore, we can conclude that the data of two consecutive generations has been under-estimated in the long-term intergenerational human capital mobility. At the same time, we can reject the hypothesis that the data of two consist generations is enough to analyze the long-term intergenerational human capital mobility.

Next, in order to interpret why our results are different from the data of two consecutive generations, we conducted two other analyses after the main regression. One is the instrumental variable model suggested by Clark (2012), and the other is AR(2) model where we extended AR(1) model by including both parents and grandparents generation in the regression.

The Clark model is an instrumental variable model using the grandparent generations' data as the instrumental variable to indicate the child generations' outcome, and is written as,

$$y_{t,i} = a + by_{t-1,i} + d'X_i + u_i, \quad (4)$$

$$y_{t-1,i} = \pi' y_{t-2,i} + \theta' X_i + \varepsilon_i \ , \quad (5)$$

where, y_t is the outcome of the child and y_{t-1} is the outcome of the parents, y_{t-2} is the outcome of the grandparents, t represent the generation and i indicates the child. x_i is a vector of controls, u_i and ε_i are the error terms.

Table 3 presents the results both from the Becker-Tomes model (OLS/AR(1) model) and the instrumental variable model. The upper portion of column (1) shows the results from the grandparents' education attendance to the parents' education attendance, and the upper portion of column (2) shows the results of parents' education attendance to children's education attendance. The lower portion from Table 3 presents the results from the instrumental variable model on education attendance for the parent generation to the child generation. The lower portion for column (1) showed the results of using the variable of "years of schooling of grandparents" as the instrumental variable to "years of schooling of parents", and the lower portion for column (2) presented the results of using the variables of both "years of schooling of grandparents" and "age of grandparents" as the instruments. From Table 3, we can conclude that for analysis regarding the relationship of education attendance between the parent generation and the child generation, the IV model is more superior than the AR(1) model, given that all of the falsification tests (endogenous test, weak iv test and over identifying test) support

Table 3. Comparing the results between the basic model and the iv-model

VARIABLES	(1) Years schooling of child	(2) Years schooling of child
OLS		
Years schooling of parent	0.110*** (0.0395)	0.118** (0.0565)
	Observations=770	Observations=771
	R-squared=0.186	R-squared=0.064
IV		
Years schooling of parent	1.295** (0.561)	1.295** (0.564)
Controls	yes	yes
Constant	161.4** (79.09)	159.1** (78.48)
Robust score chi2(1)	7.47148**	7.45565**
Robust regression F(1,758)	7.37214**	7.35635**
Test of over-identifying restrictions Score chi2(1)		0.929403 (p = 0.3350)
	Observations=771	Observations=769
Instruments		
Years schooling of grandparents	Yes	Yes
Age of grandparents	No	Yes

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 4. Comparison between grandparents and parents

VARIABLES	Years schooling of child
Years schooling of parent	0.102** (0.0499)
Years schooling of grandparent	0.127*** (0.0458)
Controls	yes
Constant	108.4 -101.6
Observations	769
R-squared	0.073

Note: Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

the IV strategy.

The AR(2) model is a model based on the AR(1) model, but includes a prior generation, and can be been written as,

$$y_{it} = a + b_1 y_{it-1} + b_2 y_{it-2} + d' x_i + \mu_i, \quad (6)$$

where y is the outcome, i is the individual household, t denotes the generation and u_{it} is the error term.

Table 4 gives the results of the AR(2) model. The results are clear in that the impact from the grandparent generation is significantly different from 0. In addition, "years schooling of grand parent" rose up 0.127 years, the education years to child generation rose by 1 year, in rural areas of China.

Therefore, we can conclude that only using two consecutive generations' data, will under estimate the long-term intergenerational human capital mobility.

5 Extended research of gender differences

We discuss the influences of gender power on intergenerational human capital mobility, in this extended research section. Table 5 shows the mobility from parent generation to child generation. Table 6 presents the mobility from the grandfathers, and Table 7 yields the mobility from the grandmothers.

From the Tables 5, 6 and 7, we find that there are some differences in mobility through elders by gender. First, females in general have a larger and positive influence on their offspring. It can be possible that most of the female elders are spending more time on taking care of their offspring. Second, male elders have an opposite influence on their offspring. This may be considered as male elders having a tendency to prefer one child among their offspring. Third, the females of the child generation tend to gain a small and non significant influence from their ancients compared with males.

Table 5. Mobility from parent generation to child generation

	Father to Son	Father to Daughter	Mother to Son	Mother to Daughter
VARIABLES	Years of education	Years of education	Years of education	Years of education
Education of parent	0.197*	-0.240*	0.238**	0.0709
	-0.109	-0.13	-0.092	-0.0933
Controls	yes	yes	yes	yes
Constant	186.7**	28.53	-70.9	212.4**
	-79.89	-92.21	-113.5	-88.21
Observations	241	158	206	166
R-squared	0.094	0.08	0.111	0.069

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 6. Mobility from grand father

VARIABLES	Education of Father	Education of Mother	Education of Son	Education of Daughter
Education of grandfather	-0.108* (0.0577)	0.211** (0.103)	-0.194* (0.0994)	0.0287 (0.131)
Controls	yes	yes	yes	yes
Constant	-159.4 (178.8)	-278.4 (364.1)	85.72 (263.4)	-405.8 (361.3)
Observations	146	93	133	106
R-squared	0.112	0.225	0.108	0.055

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table7. Mobility from grand Mother

VARIABLES	Education of Father	Education of Mother	Education of Son	Education of Daughter
Education of grandmother	0.148**	0.218***	0.357***	0.15
	-0.0657	-0.0685	-0.115	-0.0951
Controls	yes	yes	yes	yes
Constant	-302.7** (120.6)	-136.0 (142.4)	288.3 (177.6)	-241.6 (169.2)
Observations	252	279	312	218
R-squared	0.098	0.130	0.150	0.086

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

6 Conclusion

This research provided evidence that the persistence of long-term intergenerational human capital mobility in China rural area is much stronger in educational achievements across three generations than two generations. In addition, this result has been confirmed by the Instrumental Variable model and the AR(2) model that include the information of three generations rather two generations.

One possible explanation for the result of the long-term intergenerational human capital mobility in China is that the Chinese traditional family is a structure where the elderly are the decision makers, who influence the whole family and other offspring.

In the main empirical analysis and the further analysis models of the IV model and the AR(2) model, we can reject that the two consecutive generations data is adequate to analyze the long-term intergenerational human capital mobility in China. Furthermore, our results line up with other overseas studies on long-term intergenerational mobility (Lindahl 2015; Stuhler 2013).

The implication of this research is that only using two consecutive generations' data on long-term intergenerational human capital mobility should be interpreted with caution, especially those who are interested in developing countries and have similar traditional family cultures as China.

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