Social Mobility across Three Generations:
Evidence from China

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Abstract

In this paper, we propose to study social mobility across three generations in China. Using years of education as the main social status indicator, this is the first nationally representative study of three-generation mobility for China. We find significantly positive grandparent effect. We also find that paternal grandparent effect is stronger than maternal grandparent effect. Besides contributing to the long-debated grandparent effect, we will also use data to suggest possible mechanisms that such effect taking place.

1 Introduction

Social mobility research has mostly focused on two generations, namely, the correlation between parents and children (Becker and Tomes, 1979; Becker et al., 2018). The dynamic of intergenerational social mobility is modeled by a first-order autoregressive [AR(1)] process between two adjacent generations. Within this framework, the influence of the first generation’s social status (such as income and education) on their offspring will decline geometrically across the future generations. Consequently, grandparents will have no direct effect on their grandchildren; the only grandparent effect is indirect and mediated through the parents.

However, there are plausible reasons that the AR(1) assumption is not valid. First, genetic information from the grandparents may be repressed in parents and manifested again in children. Second, grandparents may also exert direct economical, educational, and cultural influence on the children. The effects are especially relevant for certain demographic groups in countries that have closely-tied
extended families. If these direct grandparent effects do exist, the results of two-generation studies under AR(1) assumption cannot be extended to multiple generations.

The explicit grandparent effects are more likely to happen in China than Western countries because, traditionally, big families with multiple generations living together are considered more successful than small families with only two generations. Although small families are pretty common at present, it is still a usual practice for the grandparents to take care of the children when the parents are busy with work. Grandparents usually consider it as a kind of pleasure instead of burden to take care of their grandchildren. Using nationally representative datasets, this paper studies three-generational social mobility in China for the first time.

Our paper can contribute to the debate about grandparent effect in mobility research: is grandparent effect on grandchildren entirely mediated through parents, or do grandparents have independent and direct effect through other channels? Previous literature has provided various methods to empirically answer these questions, which can serve as the departure point of this study.

The paper is organized as follows. Section 2 provides a literature review on the empirical studies about multigenerational social mobility. Section 3 presents the theoretical framework of intergenerational mobility. Section 4 describes the data we use. Section 5 summarizes the empirical results. Section 6 proposes a model to describe the possible mechanism for grandparent effect. Section 7 concludes.

2 Literature Review

Most of the existing multigenerational mobility studies are conducted in developed countries due to data availability. Most of them find no significant grandparent effect when parents’ effects are controlled. In an early study in the U.S., Hodge (1966) finds that besides the indirect effects through parents, the occupation of grandparents has no direct effect on the occupation of the children. This conclusion is echoed in later years. For example, using data from the Wisconsin Longitudinal Study, Warren and Hauser (1997) find that grandparents’ social status has no statistically significant impact on children’s social status once parents’ social status is controlled. Using a sample of twins, Behrman and Taubman (1985) find that grandparents’ schooling has no significant effect on children’s schooling. Erola and Moisio (2007) construct 57,585 three-generation lineages in Finland from 1950-2000 and find that the grandchildren’s social class is almost conditionally independent from the grandparents’ social class after parents’ social class is controlled. Lucas and Kerr (2013) and Peters (1992) also find no
significant grandparent effect.

However, there are still studies finding statistically significant grandparent effect with the datasets of Western countries. Chan and Boliver (2013) use data from three British birth cohort studies and find a statistically significant grandparent effect on their grandchildren class positions in terms of relative mobility patterns, after parents’ social class is controlled. Lindahl et al. (2015) find strong evidence that grandparents’ education and income directly affect children’s income in a Swedish four-generation study. Interestingly, Chan and Boliver (2014) argue that the main conclusion of “almost conditional independence” from Erola and Moisio (2007) is not supported by the results in the article. They demonstrate that the grandparent effect in social mobility in Finland is not only statistically significant, but is also of substance importance.

Researchers also try to identify the possible mechanism of grandparent effect. Møllegaard and Jæger (2015) analyze data from Denmark and find that it is grandparents’ cultural capital instead of economic and social capital that plays a positive role when grandchildren choose the academic track in upper secondary education. The results of Møllegaard and Jæger (2015) show that the possible mechanism of grandparent effect on grandchildren’s education success is carried out through the transmission of non-economic resources. The results, as the authors suggest, may be valid only in wealthy societies such as Scandinavian countries.

For the case of China, most empirical studies on multigenerational mobility focus on specific groups. Mare and Song (2014) investigate two datasets: one is genealogical data from the Qing Dynasty Imperial Lineage which contains 12 generations of Qing emperors and their relatives from the 17th to the 20th centuries; the other is population registry data which contains 10 generations of male peasants in the northeastern province of Liaoning from the mid-18th to the early 20th centuries. The former dataset contains individuals at the top while the latter contains individuals at the bottom of the society. Despite the huge differences of the two datasets, they find that men’s social positions are affected not only by the positions of their fathers but also of their grandfathers and great-grandfathers in both datasets.

Shiue (2016) uses data covering information on seven lineages of nearly 10,000 men to explore social mobility. The author finds that educational inequality is closely related to changes in mobility over time. As for grandparent effect, this paper also finds that the lineal impact of grandfathers and older generations is overshadowed by non-lineal interactions coming from higher status men in the same generation as the father. The results are consistent with the phenomenon that extended family
members usually lived together and had strong ties among each other in history. However, all the individuals of the data were living in one county of Anhui province locating in south of China.

Zeng and Xie (2014) is the only multigenerational mobility study for China with relatively nation-representative datasets we found. They used data from the 2002 Chinese Household Income Project (CHIP) to study the effect of grandparents’ education on children’s education in rural China. Because the third generation in the data is still in school, the authors can only observe the final education outcome for students who drops out. So they have to use logit models to estimate the probabilities of dropping out from schools, which in turn forces the authors to use only rural data because dropout rates are very low in urban China. Nonetheless, they not only find significant grandparent effect after controlling for parents’ education and social status, but also show that the effect exists only if the grandparents live with the children. That means the direct grandparent effect is less likely to work through genetic inheritance, and more likely to work through personal interactions. It also means the intensity of the interaction matters, since living non-coresident grandparents (who presumably also have certain level of interaction with the children) have no effect.

3 The Model

3.1 The Case of AR(1) Process

The model here follows Solon (2014) with one revision. Family $i$ contains one parent born at time $t-1$ and one child born at time $t$. The parent’s income $y_{i,t-1}$ is used for her own consumption $C_{i,t-1}$ and investment $I_{i,t-1}$ in the child’s education. The budget constraint is

$$y_{i,t-1} = C_{i,t-1} + I_{i,t-1}$$ (1)

The child’s schooling $S_{i,t}$ is a function of education investment $I_{i,t-1}$ and endowment from the parent $e_{i,t}$

$$S_{i,t} = \theta \log I_{i,t-1} + e_{i,t}$$ (2)

where $\theta$ is assumed to be positive.

In Solon (2004), the equation above describes the formation of human capital. I change it into schooling because schooling can be measured more accurately than human capital. This is the only
revision I made. The endowment follows an AR(1) process

\[ e_{it} = \delta + \lambda e_{i,t-1} + v_{it} \]  

where \( v_{it} \) is an error term which is not correlated with endowment and \( 0 < \lambda < 1 \).

The child’s income is a function of her schooling

\[ logy_{it} = u + pS_{it} \]  

where \( p \) is assumed to be positive.

The parent’s utility function is

\[ U_i = (1 - \alpha)\log C_{i,t-1} + \alpha logy_{it} \]  

\( \alpha \) is the altruism parameter because the parent cares about her child’s welfare which is represented by a function of the child’s income.

Solving the problem, we have

\[ S_{it} = \Omega_1 + (\lambda + \theta p)S_{i,t-1} - \lambda \theta p S_{i,t-2} + v_{it} \]  

where \( \Omega_1 = \delta + (1 - \lambda)\theta \left[ u + \frac{\alpha p}{1 - \alpha (1 - \theta p)} \right] \). The proof will be given in the Appendix.

We can see that \( 0 < \lambda \theta p < \lambda + \theta p \) from the assumptions of the three parameters. If the assumption of AR(1) process is true, the model predicts a negative coefficient of grandparental schooling and the magnitude of the coefficient is smaller than that of the parental schooling. The prediction of negative sign seems counter-intuitive at the first glance. It is easy to understand the prediction if we know that the influence of grandparental schooling is calculated after the influence of parental schooling is controlled. It is illustrated in figure 1. Suppose children A and B’s parents have the same schooling. However, A’s grandparent has more schooling than B’s. More schooling implies higher income, and higher income implies more investment. We can infer that A’s parent probably has lower endowment (i.e. inherited socially productive traits) because with more investment in her education, she achieved the same schooling as B’s parent. Since A only gets her endowment from her parent, the model will predict that she probably has lower endowment than B, hence less schooling.
3.2 The Case of AR(2) Process

We can model the possibility of grandparent effects with an AR(2) process of the endowments

\[ e_{it} = \delta + \lambda_1 e_{i,t-1} + \lambda_2 e_{i,t-2} + v_{it} \]  \hspace{1cm} (7)

where \( \lambda_2 \) represents grandparent effects. When it equals zero, it degrades to an AR(1) process.

Solving the same problem as the case of AR(1) process, we have the following equation

\[ S_{it} = \Omega_2 + (\lambda_1 + \theta p)S_{i,t-1} + (\lambda_2 - \lambda_1 \theta p)S_{i,t-2} - \lambda_2 \theta p S_{i,t-3} + v_{it} \]  \hspace{1cm} (8)

where \( \Omega_2 = \delta + (1 - \lambda_1 - \lambda_2)\theta \left[ u + \log \frac{\alpha p}{\alpha(1-\theta p)} \right] \). The proof will be given in the Appendix.

The sign of the coefficient of grandparental schooling is uncertain. However, if empirical evidence shows a positive coefficient of grandparental schooling, we can conclude that AR(2) process is a better assumption than AR(1) process about the dynamics of the endowments since \( \lambda_2 - \lambda_1 \theta p > 0 \Rightarrow \lambda_2 > 0 \).
4 The Data

Data used in this study are from China Health and Retirement Longitudinal Study (CHARLS). It is a nationally panel survey targeting the middle-aged and senior population carried out from 2011. The second wave data collected in 2013 are used in this paper. Households with at least one member 45 years old or above are randomly selected, and this member becomes the main respondent. Information is collected on main respondents and their spouses, together with the parents on both sides and all children of the couple regardless of where they live. Information on other family members, such as the grandchildren of the main respondents, are available if they live together with the main respondents. In the first wave data collected in 2011 and 2012, 17708 individuals who are from 10257 households and 150 counties successfully responded to the survey. This random sample is large enough to represent the whole aged population. This dataset contains detailed educational attainment information for three generations regardless of whether they live together and the fourth generation if they live in the same household. Using the information on the first three generations, nationally representative three-generation mobility can be measured for the first time for China.

Income and occupation are also used in the literature to represent social status in the research of social mobility. It may not be a problem in developed countries where income increases slowly and occupation seldom changes. However, it can be a serious problem in developing countries. China has experienced rapid economic growth for the previous four decades when both people’s income and occupation change frequently. Another issue on income is that Chinese like to make money in their leisure time. The informal income is quite unpredictable and suffers huge measurement errors. Education level is the variable which can be measured much more accurately than income level and occupation in China. Shiue (2016) also finds that educational inequality is closely related to changes in mobility over time. So we choose education attainment to represent social status for our research.

As can be seen from the Table 1, the average age of the third generation is 35 which means that most of them have finished school. So we can use schooling directly instead of estimating the probabilities of dropout like Zeng and Xie (2014). Our sample is also larger and more representative. It contains more than 20,000 observations from the whole country. Zeng and Xie (2014)’s sample contains only rural data and has only 833 households with the information of three generations.
Table 1: Sample Characteristics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Observations</th>
<th>Mean</th>
<th>Standard errors</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child’s Schooling</td>
<td>26,863</td>
<td>9.30</td>
<td>3.70</td>
<td>0</td>
<td>25</td>
</tr>
<tr>
<td>Child’s Age</td>
<td>28,546</td>
<td>34.81</td>
<td>11.81</td>
<td>0</td>
<td>81</td>
</tr>
<tr>
<td>Child’s Gender (1=Boy, 2=Girl)</td>
<td>30,221</td>
<td>1.47</td>
<td>0.50</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Finished School (1=No, 2=Yes)</td>
<td>28,404</td>
<td>1.95</td>
<td>0.21</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Father’s Schooling</td>
<td>29,166</td>
<td>5.87</td>
<td>4.32</td>
<td>0</td>
<td>21</td>
</tr>
<tr>
<td>Mother’s Schooling</td>
<td>29,534</td>
<td>3.38</td>
<td>4.05</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td>Paternal Grandfather’s Schooling</td>
<td>23,582</td>
<td>2.02</td>
<td>3.19</td>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>Paternal Grandmother’s Schooling</td>
<td>24,526</td>
<td>0.52</td>
<td>1.85</td>
<td>0</td>
<td>21</td>
</tr>
<tr>
<td>Maternal Grandfather’s Schooling</td>
<td>26,268</td>
<td>1.95</td>
<td>3.22</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>Maternal Grandmother’s Schooling</td>
<td>27,417</td>
<td>0.50</td>
<td>1.78</td>
<td>0</td>
<td>16</td>
</tr>
</tbody>
</table>

5 Empirical Analysis

5.1 Regression Equation

As illustrated in Section 3, our regression equation is

\[ S_c = \alpha + \beta_1 S_p + \beta_2 S_{pg} + \beta_3 S_{mg} + \gamma X + \epsilon \]  \hspace{1cm} (9)

\( S_c \) is the schooling of the child. \( S_p \) is the schooling of the child’s parents. Father and mother’s schooling are higher correlated, possibly because of positive assorting in marriage market. So we estimate the sum of their schooling. The same reason applies for grandparents’ schooling. \( S_{pg} \) is the schooling of the paternal grandparents. \( S_{mg} \) is the schooling of the maternal grandparents. \( X \) contains control variables which are child’s age and gender here. We distinguish the effects of paternal grandparents from that of maternal grandparents. China was a country with strong paternalism in history. The preference for sons was strong three decades ago when the third generation in our dataset were in school. Consequently, paternal grandparents were more likely to have time and money transfer to the children in our dataset than maternal grandparents. At last, we drop the observations that children are still in school.

5.2 Regression Results

The regression results are shown in table 2.

We can see that both paternal and maternal grandparents’ schooling have positive effect on the children’s schooling. The magnitude of paternal grandparent effect is about 30% higher than that of maternal grandparent effect. The results are consistent with our conjecture that grandparents prefer
Table 2: Regression Results

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Errors</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>8.815***</td>
<td>0.15</td>
<td>0.00</td>
</tr>
<tr>
<td>Age</td>
<td>-0.033***</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.467***</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>Parents’ Schooling</td>
<td>0.223***</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Paternal Grandparents’ Schooling</td>
<td>0.049***</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Maternal Grandparents’ Schooling</td>
<td>0.038***</td>
<td>0.01</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Observations: 15,463
Adjusted R-squared: 0.237

their sons’ children. Parent effect is more than four times stronger than grandparent effect. The negative sign of gender shows that girls receive less schooling than boys. The negative sign of age shows that education level increases with time. All the coefficients are statistically significant under 1% level.

5.3 Robustness

One possible concern about the regression is that most grandparents don’t have any schooling. We do the regression with positive grandparents’ schooling and show the results.

Table 3: Regression Results with Positive Grandparents’ Schooling

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Errors</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>8.165***</td>
<td>0.35</td>
<td>0.00</td>
</tr>
<tr>
<td>Age</td>
<td>-0.023***</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.250**</td>
<td>0.17</td>
<td>0.03</td>
</tr>
<tr>
<td>Parents’ Schooling</td>
<td>0.243***</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Paternal Grandparents’ Schooling</td>
<td>0.032**</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Maternal Grandparents’ Schooling</td>
<td>0.018</td>
<td>0.01</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Observations: 3,012
Adjusted R-squared: 0.231

When we limit our sample to positive grandparents’ schooling, we can still obtain positive grandparent effect. There are three differences compared to the regression results in Section 5.2. First, grandparent effect becomes weaker while parent effect become stronger. Second, the negative effect of gender becomes much weaker, which means that the education gap between girls and boys is much smaller. Third, maternal grandparent effect is not statistically significant now.
There is another method to prove the existence of grandparent effect.

The method requires three regressions. First, we regress the dad’s schooling on the paternal grandparents’ schooling and get a coefficient $\beta_1$. Then, we regress the child’s schooling on the dad’s schooling and get another coefficient $\beta_2$. At last, we regress the child’s schooling on the paternal grandparents’ schooling and get coefficient $\beta_3$. If grandparent effect does not exist, $\beta_3$ should be close to the product of $\beta_1$ and $\beta_2$. We constrain our sample with positive paternal grandparents' schooling and children who have finished education. Our regression results shows that

$$\beta_3 = 0.102 >> 0.111 \times 0.324 = \beta_1 \beta_2$$

which suggests that (paternal) grandparent effect exists.

<p>| Table 4: Regression Results of the Dad’s Schooling on the Paternal Grandparents’ Schooling |</p>
<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Standard Errors</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>10.88***</td>
<td>0.28</td>
</tr>
<tr>
<td>Age</td>
<td>-0.073***</td>
<td>0.00</td>
</tr>
<tr>
<td>Paternal Grandparents’ Schooling</td>
<td>0.111***</td>
<td>0.01</td>
</tr>
<tr>
<td>Observations</td>
<td>8,653</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.095</td>
<td></td>
</tr>
</tbody>
</table>

<p>| Table 5: Regression Results of the Child’s Schooling on the Dad’s Schooling |</p>
<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Standard Errors</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>9.662***</td>
<td>0.127</td>
</tr>
<tr>
<td>Age</td>
<td>-0.040***</td>
<td>0.00</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.436***</td>
<td>0.06</td>
</tr>
<tr>
<td>Dad’s Schooling</td>
<td>0.324***</td>
<td>0.01</td>
</tr>
<tr>
<td>Observations</td>
<td>11,434</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.187</td>
<td></td>
</tr>
</tbody>
</table>

6 The Mechanism

In this section we will propose a model to include a possible mechanism of grandparent effect. We assume that grandparents will provide education investment for their grandchildren directly. A person is assumed to live for three periods. In the first period, the person receives education investment from her parents and grandparents. In the second period, she works, consumes and makes education
investment for her child. In the third period, she makes education investment for her grandchild. In order to simplify the model, we assume that a family consists of only one parent and one child.

The maximization problem is

\[
\max_{c_t, I_t, G_{t+1}} V(I_{t-1}, G_{t-1}) = \max_{c_t, I_t, G_{t+1}} \{u(C_t) + \alpha_1 V(I_t, G_t) + \alpha_2 V(I_{t+1}, G_{t+1})\} \tag{10}
\]

subject to

\[
C_t + I_t + G_{t+1} = Y(I_{t-1}, G_{t-1}) \tag{11}
\]

where \(I\) is the investment from the parent and \(G\) is the investment from the grandparent. \(\alpha_1\) is the altruism parameter for the child and \(\alpha_2\) is the altruism parameter for the grandchild. \(Y\) is income which is a function of education investment. \(V(I_{t-1}, G_{t-1})\) is the value function of the person who was born at period \(t-1\) and has received investment \(I_{t-1}\) from her parent and \(G_{t-1}\) from her grandparent. Investments from the parent and grandparent are state variables. Consumption, investment for the child and grandchild are control variables. \(u(\cdot)\) is assumed to be increasing and strictly concave.

Combining (10) and (11), we have

\[
V(I_{t-1}, G_{t-1}) = u(Y(I_{t-1}, G_{t-1}) - I_t - G_{t+1}) + \alpha_1 V(I_t, G_t) + \alpha_2 V(I_{t+1}, G_{t+1}) \tag{12}
\]

First-order conditions are listed as follows

\[
I_{t-1} : V_1(I_{t-1}, G_{t-1}) = u'(C_t)Y_1(I_{t-1}, G_{t-1}) \tag{13}
\]

\[
G_{t-1} : V_2(I_{t-1}, G_{t-1}) = u'(C_t)Y_2(I_{t-1}, G_{t-1}) \tag{14}
\]

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Table 6: Regression Results of the Child’s Schooling on the Paternal Grandparents’ Schooling

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Standard Errors</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>11.59***</td>
<td>0.20</td>
</tr>
<tr>
<td>Age</td>
<td>-0.058***</td>
<td>0.08</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.250***</td>
<td>0.06</td>
</tr>
<tr>
<td>Paternal Grandparents’ Schooling</td>
<td>0.102***</td>
<td>0.01</td>
</tr>
<tr>
<td>Observations</td>
<td>8,480</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.07</td>
<td></td>
</tr>
</tbody>
</table>
\[ I_t : -u'(C_t) + \alpha_1 V_1(I_t, G_t) = 0 \quad (15) \]

\[ G_{t+1} : -u'(C_t) + \alpha_2 V_2(I_{t+1}, G_{t+1}) = 0 \quad (16) \]

Rewriting (13) forward one period, we have

\[ V_1(I_t, G_t) = u'(C_{t+1}) Y_1(I_t, G_t) \quad (17) \]

Plugging it into (15), we can get

\[ \frac{u'(C_t)}{u'(C_{t+1})} = \alpha_1 Y_1(I_t, G_t) \quad (18) \]

The equation depicts the relationship between the parent’s consumption and the child’s consumption.

**Lemma 1.** *The dynamics of consumption between parents and children depend on the return rates of education investment from the parents. Technically speaking,*

\[ \alpha_1 Y_1(I_t, G_t) > 1 \Rightarrow C_{t+1} > C_t \]

\[ \alpha_1 Y_1(I_t, G_t) < 1 \Rightarrow C_{t+1} < C_t \]

Similarly, rewriting (14) forward two periods, we have

\[ V_2(I_{t+1}, G_{t+1}) = u'(C_{t+2}) Y_2(I_{t+1}, G_{t+1}) \quad (19) \]

Plugging it into (16), we can get

\[ \frac{u'(C_t)}{u'(C_{t+2})} = \alpha_2 Y_2(I_{t+1}, G_{t+1}) \quad (20) \]

Rewriting the equation above backward one period to make it consistent with (18)

\[ \frac{u'(C_{t-1})}{u'(C_{t+1})} = \alpha_2 Y_2(I_t, G_t) \quad (21) \]

The equation depicts the relationship between the grandparent’s consumption and the grandchild’s consumption.
Lemma 2. The dynamics of consumption between grandparents and grandchildren depend on the return rates of education investment from the grandparents. Technically speaking,

\[ \alpha_2 Y_2(I_t, G_t) > 1 \Rightarrow C_{t+1} > C_{t-1} \]

\[ \alpha_2 Y_2(I_t, G_t) < 1 \Rightarrow C_{t+1} < C_{t-1} \]

7 Conclusions

Multigenerational social mobility gains increasing attention during the last decade. However, most datasets are limited to small samples such as twins, several big cities or rural areas. Almost all the research also focuses on three-generational mobility due to data availability. The empirical results vary across time and place. Using years of schooling as the main social status indicator, we estimate three-generational social mobility in China with a large and nationally representative dataset for the first time.

We have two useful findings. The first finding is that independent grandparent effects are positive with statistically significance. The magnitude of grandparent effects is about 20%-25% of parent effects. It contributes to the current literature on multigenerational social mobility with a better dataset. The second finding is that paternal grandparent effects are stronger than maternal grandparent effects. One possible reason is that grandparents spend more time and money on their sons’ children than their daughters’ children. One Child Policy makes millions of families with only one daughter. People nowadays are also indifferent to sons and daughters. If the reason above is right, we can foresee that paternal and maternal grandparent effects will converge. This prediction can be tested in the future with relevant datasets.

The positive grandparent effects imply that AR(2) process can model the dynamics of endowments better than AR(1) process. But is AR(2) process the right assumption? It depends on the existence of great-grandparent effects which needs an analysis of four-generation social mobility. Although Lindahl et al (2015) do a four-generation analysis, the data is limited to three big cities and the education of the fourth generation is estimated for they are still in school. As time goes on, we will have better datasets to test existence of great-grandparent effects.
References


8 Appendix

8.1 The Proof of AR(1) Case

Plugging (1)(2)(4) into (5), we have

\[ U_i = (1 - \alpha)\log(y_{i,t-1} - I_{i,t-1}) + \alpha u + \alpha \theta p \log I_{i,t-1} + \alpha \psi_{it} \] (22)

FOC w.r.t. education investment can be written as

\[ \frac{\partial U_i}{\partial I_{i,t-1}} = -\frac{1 - \alpha}{y_{i,t-1} - I_{i,t-1}} + \frac{\alpha \theta p}{I_{i,t-1}} = 0 \] (23)
Optimal investment can be obtained from equation (11)

\[ I_{i,t-1} = \frac{\alpha \theta p}{1 - \alpha(1 - \theta p)} y_{i,t-1} \]  \hspace{1cm} (24)

Substituting (12) into (2), we have

\[ S_{it} = \theta \log \frac{\alpha \theta p}{1 - \alpha(1 - \theta p)} y_{i,t-1} + e_{it} \]  \hspace{1cm} (25)

From equation (4), we have

\[ logy_{i,t-1} = u + pS_{i,t-1} \]  \hspace{1cm} (26)

Plugging (14) into (13)

\[ S_{it} = \theta \log \frac{\alpha \theta p}{1 - \alpha(1 - \theta p)} + \theta u + \theta pS_{i,t-1} + e_{it} \]  \hspace{1cm} (27)

Lagging (15) by one generation and multiplying it by \( \lambda \)

\[ \lambda S_{i,t-1} = \lambda \theta \log \frac{\alpha \theta p}{1 - \alpha(1 - \theta p)} + \lambda \theta u + \lambda \theta pS_{i,t-2} + \lambda e_{i,t-1} \]  \hspace{1cm} (28)

Subtracting (16) from (15)

\[ S_{it} - \lambda S_{i,t-1} = (1 - \lambda) \left[ \frac{\alpha \theta p}{1 - \alpha(1 - \theta p)} + \theta u \right] + \theta pS_{i,t-1} - \lambda \theta pS_{i,t-2} + e_{it} - \lambda e_{i,t-1} \]  \hspace{1cm} (29)

Combining (3) and rearranging the equation above, we can get

\[ S_{it} = \delta + (1 - \lambda) \theta \left[ u + \frac{\alpha \theta p}{1 - \alpha(1 - \theta p)} \right] + \left( \lambda + \theta p \right) S_{i,t-1} - \lambda \theta pS_{i,t-2} + v_{it} \]  \hspace{1cm} (30)

So, under the assumption of AR(1) process, \( S_{it} \) can be written as

\[ S_{it} = \Omega_1 + \left( \lambda + \theta p \right) S_{i,t-1} - \lambda \theta pS_{i,t-2} + v_{it} \]

where \( \Omega_1 = \delta + (1 - \lambda) \theta \left[ u + \frac{\alpha \theta p}{1 - \alpha(1 - \theta p)} \right] \).
8.2 The Proof of AR(2) Case

Lagging (15) by one generation and multiplying it by $\lambda_1$

$$\lambda_1 S_{i,t-1} = \lambda_1 \theta \log \frac{\alpha \theta p}{1 - \alpha (1 - \theta p)} + \lambda_1 \theta u + \lambda_1 \theta p S_{i,t-2} + \lambda_1 \epsilon_{i,t-1}$$  \hspace{1cm} (31)

Lagging (15) by two generations and multiplying it by $\lambda_2$

$$\lambda_2 S_{i,t-1} = \lambda_2 \theta \log \frac{\alpha \theta p}{1 - \alpha (1 - \theta p)} + \lambda_2 \theta u + \lambda_2 \theta p S_{i,t-2} + \lambda_2 \epsilon_{i,t-1}$$  \hspace{1cm} (32)

Subtracting (19) and (20) from (15)

$$S_{i,t} = (1 - \lambda_1 - \lambda_2) \left[ \theta \log \frac{\alpha \theta p}{1 - \alpha (1 - \theta p)} + \theta u \right] + (\lambda_1 + \theta p) S_{i,t-1} + (\lambda_2 - \lambda_1 \theta p) S_{i,t-2} - \lambda_2 \theta p S_{i,t-2} + \epsilon_{it} - \lambda_1 \epsilon_{i,t-1} - \lambda_2 \epsilon_{i,t-1}$$  \hspace{1cm} (33)

Combining (7) and (21), we have

$$S_{i,t} = \delta + (1 - \lambda_1 - \lambda_2) \theta \left[ u + \log \frac{\alpha p}{1 - \alpha (1 - \theta p)} \right] + (\lambda_1 + \theta p) S_{i,t-1} + (\lambda_2 - \lambda_1 \theta p) S_{i,t-2} - \lambda_2 \theta p S_{i,t-3} + \epsilon_{it}$$  \hspace{1cm} (34)

So, under the assumption of AR(2) process, $S_{it}$ can be written as

$$S_{i,t} = \Omega_2 + (\lambda_1 + \theta p) S_{i,t-1} + (\lambda_2 - \lambda_1 \theta p) S_{i,t-2} - \lambda_2 \theta p S_{i,t-3} + \epsilon_{it}$$

where $\Omega_2 = \delta + (1 - \lambda_1 - \lambda_2) \theta \left[ u + \log \frac{\alpha p}{1 - \alpha (1 - \theta p)} \right]$. 