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Multi-generational educational mobility in China in the twentieth century

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ABSTRACT

Two essential strategies to understand the mechanisms of intergenerational mobility are to compare mobility across countries and across time. However, for multi-generational mobility, estimates for developing countries are mostly missing, and trend studies are rare. This paper uses education to measure social status and provides nationally representative estimates of social mobility over three generations in China that are suitable for international comparison. Results show that grandparents' education positively correlates with children's education, controlling for the parents' education. This grandparent effect is comparable to what is found in Western countries, despite differences in cultures and institutions. During the sample period, the correlation between grandparent and child education is relatively stable. When exploring mechanisms, we find that the observed grandparent effect is primarily due to omitted information from the parents' generation, not direct interactions between grandparents and children.

1. Introduction

Relative intergenerational mobility measures the dependence of children's social status (relative to their peers) on the social status of family members in earlier generations.[1] The level of intergenerational mobility has important implications for human capital formation (Becker, Kominers, Murphy, & Spenkuch, 2018), economic growth (Maoz & Moav, 1999), and the preference for redistribution policies (Alesina, Stantcheva, & Teso, 2018). Most mobility studies focus on two adjacent generations (Black & Devereux, 2010; Solon, 1999; Song et al., 2020). Besides data limitations, this focus is partly driven by the possibility that the intergenerational transmission of social status may be approximated by a first-order autoregressive (AR(1)) process. If true, it means that multi-generational mobility (that is, the persistence of social status across multiple generations) can be extrapolated from mobility over two consecutive generations at a geometric rate (Solon, 2018). Recent evidence shows that the intergenerational process can substantially deviate from an AR(1) process (see Anderson, Sheppard, & Monden, 2018 for a review) and that multi-generational mobility

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[1] All mentions of mobility in this paper refer to relative mobility. Torche (2021) defines absolute and relative intergenerational educational mobility as: "Absolute mobility captures total observed change in educational attainment across generations…Relative mobility, in turn, captures the association between parents' and children's education net of any change in distribution of schooling across generations." An alternative definition of absolute mobility is the outcome (education/income) of children at a fixed point (e.g., the 25th percentile) of parent education/income distribution (Chetty, Hendren, Kline, and Saez (2014), Emran and Shilpi (2021)).

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has to be directly measured. While there have been many multi-generational mobility estimates for developed countries, evidence from developing countries is largely missing. This paper uses a nationally representative household survey to estimate three-generational educational mobility in China and establishes its trend for grandchildren born between 1950 and 1990.

Researchers have pointed to the study of diverse social institutions as a way to understand the mechanisms of social mobility (Mare, 2011). Among the proposed mechanisms of multi-generational mobility, some argue that grandparents could affect grandchildren through direct influence (Mare, 2011; Zeng & Xie, 2014) or uncles and aunts (Adermon, Lindahl, & Palme, 2021). The closer ties among extended families in China present an opportunity for international comparison, which can shed light on the theoretical discussion. Furthermore, in the past century, China has experienced World War II (1937–1945), the Civil War (1945–1949), the planned economy era (1949–1978), the Cultural Revolution (1966–1976), and the period of economic reform (since 1978). This turbulent history has created significant variations in two-generational mobility across time (Chen, Naidu, Yu, & Yuchtman, 2015; Fan, Yi, & Zhang, 2021; Xie, Dong, Zhou, & Song, 2022). We aim to answer two research questions by studying multi-generational mobility in China. First, does China, a developing country with cultures and institutions different from developed Western countries, display substantially different multi-generational educational mobility (multi-generational mobility henceforth)? Second, do the significant changes in China's two-generational mobility across birth cohorts translate into large variations in the correlation of education levels between grandparents and children?

Analyzing a nationally representative household survey, we find that the persistence of education between grandparents and children is higher than the extrapolations of the persistence between two consecutive generations. Furthermore, grandparents' education still has an economically important and statistically significant effect on children's education after controlling for parents' education (we call this the direct grandparent effect hereafter). Along the male lineage, the ratio of the direct paternal grandfather effect to the father effect is estimated to be 20%. These results show that educational mobility in China does not follow an AR(1) process.

An international comparison with existing studies shows that the direct grandparent effect in China, relative to the parent effect, is within the range of estimates from other countries. The similarity between China and Western countries is somewhat surprising, considering Chinese grandparents, relative to their Western counterparts, are more involved in their grandchildren's upbringing (Hoang & Kirby, 2020). Next, we study the time trends of intergenerational mobility up to three generations (G1 for grandparents, G2 for parents, and G3 for children) and how the trend in two-generational mobility translates into three-generational mobility. We confirm that two-generational educational persistence exhibits a pronounced U-shape for cohorts of children born between 1925 and 1990 (that is, mobility first increases, then decreases), with the lowest point appearing for children born in the mid-1950s. In the three-generation sample, the second generation is mostly born on the downslope of the U-shaped curve, and the third generation on the upslope. The decreasing educational persistence between the first and second generations partially negates the increasing persistence between the second and third generations. The resulting three-generational mobility trend is relatively stable.

When exploring mechanisms, we find potential explanations for why the direct grandparent effect in China is not stronger than what is found in developed countries. We first check whether additional information in the parents' generation, which is usually not included in previous studies, accounts for the direct grandparent effect. To this end, we include a rich set of parental characteristics and controls for the social status of uncles and aunts. The grandparent effect decreases by 63% and becomes statistically insignificant with the full set of controls. In other words, the omitted information on the second generation is an important driver of the observed direct grandparent effect because the grandparent education acts through them or as proxies for them. We then explore the possibility of grandparent effects emerging through direct interaction. We find no consistent evidence that grandparents with more direct interaction with their grandchildren have stronger direct grandparent effects. Considering these two sets of results, we conclude that direct grandparent-child interaction is not the main driver of the observed grandparent effect, which may explain why closer ties between grandparents and grandchildren in China do not result in a stronger direct grandparent effect relative to Western countries.

This study makes several contributions to the literature. First, we are the first to provide three-generational mobility estimates for China that are comparable with the international literature. Xie and Zhang (2019) study the effect of the Communist Revolution on social stratification in China. Their specification regresses G3's education on the deviation of G2's education from G1. This is not a commonly used three-generational mobility measure and cannot be readily adopted in cross-country comparisons. Zeng and Xie (2014) utilize the data from rural China and G3 children who live in the same household as G2 to estimate three-generational mobility. Their sample does not include urban China and likely suffers from the co-residency bias (Emran, Greene, & Shilpi, 2018). We show that the grandparent effect in China is within the range of estimates from other Western countries. China's unique cultural and institutional environments do not create an outlier in multi-generational education mobility. Second, we show that the drastic changes in two-generational mobility in China do not translate into equally drastic fluctuations in multi-generational mobility. Third, our exploration of mechanisms shows that the observed grandparent effect can mostly be explained by omitted characteristics of the second generation. Grandparent-child interaction does not enhance the grandparent effect.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 provides the conceptual framework. Section 4 introduces the data source and data processing procedures. Section 5 presents results on mobility measures, international comparison, mobility trends, and mobility mechanisms. Section 6 concludes.

2. Literature review

A central query in the study of multi-generational mobility involves understanding the role of social environments. The environment may affect multi-generational mobility by altering two-generational mobility. However, there is no consensus on the extent to which the environment can affect two-generational mobility. Using rare surnames to identify family lineage, Clark and various coauthors (Clark, 2013; Clark, 2014; Clark & Cummins, 2014) find that the intergenerational persistence of social status is stable across countries and through history, and call it the "universal law" of social mobility. Later studies have challenged such a "universal law" (Braun & Stuhler, 2018; Colagrossi, d'Hombres, & Schnepf, 2020; Vosters, 2018; Vosters & Nybom, 2018).

Even if the environment can change two-generational mobility, there is still the question of how two-generational mobility translates into multi-generational mobility. If the transmission of social status indeed follows an AR(1) process, multi-generational persistence would be the multiplication of two-generational persistence (that is, geometric decay). However, empirical studies often find slower-than-geometric decay of multi-generational persistence, contrary to an AR(1) process (Anderson et al., 2018). If multi-generational mobility cannot be easily extrapolated from two-generational mobility, it has to be measured and studied directly. Recent theories have pointed to direct grandparent effects as another pathway for the environment to affect multi-generational mobility (Solon, 2018).

The empirical literature tries to understand multi-generational mobility by analyzing its variation across space and time. Existing international comparisons are exclusively among Western countries. For example, in a study of 28 European nations, Colagrossi et al. (2020) find evidence against an AR(1) process for 17 out of 28 countries. Based on a comprehensive literature review of three-generational education mobility (Anderson et al., 2018), 41 of 69 studies find evidence contradicting the idea that mobility follows an AR(1) process. Studies on multi-generational mobility in developing countries are less common[2] (Kundu & Sen, 2022). Using a sample of school-aged children who co-reside with their grandparents in rural areas, Zeng and Xie (2014) provide an estimate of multi-generational mobility in China. However, completed education is not observed in their study, and the sample is not nationally representative. Our study uses a nationally representative survey with completed education to provide internationally comparable mobility measures.

To our best knowledge, only Neidhöfer and Stockhausen (2019) have considered multi-generational mobility trends. However, the countries (Germany, the United Kingdom, and the United States) included in their study exhibit little temporal variation in two-generational mobility. China's drastic change in two-generational mobility provides a more interesting case study for how changes in two-generational mobility translate into the variation in three-generational mobility.

3. Conceptual framework

A widely adopted framework to measure three-generational mobility is to estimate the following regression model:

$$y_{it} = \alpha + \beta_{-1} y_{it-1} + \beta_{-2} y_{it-2} + \varepsilon, \tag{1}$$

where y_{it}, y_{it-1}, and y_{it-2} are social status measures of the child, parent, and grandparent. The coefficient β_{-2} is sometimes interpreted as the direct grandparent effect that is not mediated by parents, presumably resulting from grandparents directly investing in children's education or from grandparents directly passing down endowments to grandchildren. However, this is not necessarily the case. For example, Becker and Tomes (1979) show that, for income, β_{-2} is negative when only the parent, not the grandparent, invests in the child's education, and the inheritance of endowments follows an AR(1) process. In Appendix 4, we show that the conclusion of the negative grandparent effect also applies to education in the Becker and Tomes (1979) model. See Goldberger (1989) for a critique of Becker and Tomes (1979) and how observed intergenerational associations can be explained without any utility-maximizing framework.

The negative grandparent effect predicted by the Becker and Tomes (1979) model is not supported by empirical studies, which mostly find null or positive grandparent effects. However, even the positive effect is not necessarily causal. For example, it may be the result that education (or income) is only an incomplete measure of social status. This argument is spelled out by the latent factor model (Braun & Stuhler, 2018; Clark, 2014) with the following two equations:

$$y_{it} = \rho e_{it} + u_{it} \tag{2}$$

$$e_{it} = \varphi e_{it-1} + v_{it} \tag{3}$$

In Eq. (2), y_{it} is still the indicator of the social status of individual i born in generation t. An unobservable endowment e_{it} determines y_{it} up to a random error u_{it} and follows an AR(1) process in Eq. (3). The unobservable endowment can be interpreted as the "true" social status, while y_{it} is the observed social status. It can be shown that, even though there is no independent grandparent effect in endowment, the estimate of β_{-2} in Eq. (1) will be positive in this model. Essentially, since e_{it-1} is inaccurately measured by y_{it-1}, y_{it-2} picks up the effect of e_{it-1}.

Currently, two empirical strategies (Neidhöfer & Stockhausen, 2019) have been adopted to determine whether the observed direct grandparent effect (β_{-2}) is causal. One is controlling for more characteristics of the second generation to address the omitted variable problem caused by incomplete status measures; the other is using the information on grandparents' direct interaction with children (for example, taking care of them, living with them, and having overlapping lifespans with them) to see if direct interaction leads to

[2] Two-generational education and income mobility in China have been estimated in many studies. For income mobility estimates, see Deng, Gustafsson, and Li (2013), Fan (2016), Fan et al. (2021), Gong, Leigh, and Meng (2012), Qin, Wang, and Zhuang (2016), Tang, Sun, and Yang (2021), and Yu et al. (2020). For educational mobility estimates, see Chen, Guo, Huang, and Song (2019), Dong, Luo, Zhang, Liu, and Bai (2019), Emran, Jiang, and Shilpi (2020), Gruijters, Chan, and Ermisch (2019), Guo, Song, and Chen (2019), Meng and Zhao (2021), Chen et al. (2015), and Xie et al. (2022). See Emran and Shilpi (2021) for a methodological discussion on intergenerational mobility of developing countries.

higher grandparent effects. Our empirical analysis adopts both approaches. Existing studies differ on whether age should be controlled for when estimating Eq. (1). For example, in the two studies that we use for international comparisons, Lindahl, Palme, Massih, and Sjögren (2015) control for age, while Neidhöfer and Stockhausen (2019) do not. We exclude age controls in the main analysis and include them as a robustness check (Appendix Table A7).

4. Data

Data used in this study are from the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative panel household survey targeting the population 45 years old and above (Zhao, Hu, Smith, Strauss, & Yang, 2014), which is labeled G2 in our study. Since the legal minimum age for marriage in China is 22 for men and 20 for women, the age group 45 and above captures the vast majority of parents whose children have completed their education. Therefore, compared to datasets that sample from the entire population, CHARLS has a higher proportion of three-generational families.[3]

Regular CHARLS started in 2011 and were collected in 2013, 2015, and 2018. A special life history survey was conducted in 2014 in-between regular survey years. The households are from 150 counties selected using a probability-proportional-to-size sampling technique from all Chinese provinces except Tibet. Our analyses utilize the 2013 sample and bring in rich family information, such as sibling characteristics and childcare by grandparents, from the 2014 life history survey.[4]

A household member who is 45 years or older is selected as the primary respondent, and her/his spouse is also interviewed when possible. Information is collected on the primary respondent and the spouse (G2), their surviving and deceased parents and parents-in-law (G1), their siblings (S2), and their surviving children (G3). To maximize accuracy, we prioritize the information reported by G2 sons and daughters over that provided by sons-in-law and daughters-in-law.[5]

The parent and grandparent effects potentially differ by biological, step-, and adoptive relationships between the generations. In CHARLS data, most non-biological parents are step-parents, many of whom came into the family after the children's childhood. The step-grandparents linked to the children through step-parents have no biological connection and likely have a lower social connection with children in the third generation. We only consider biological parents and grandparents because they exert both genetic (nature) and environmental (nurture) influences on children.[6] For example, for a child whose biological father and stepmother are interviewed, information for the mother and maternal grandparents is set as missing. Furthermore, we remove lineages with age gaps below 12 years between two consecutive generations, most likely the results of data errors. To remove outliers in age, we keep grandparents born between 1875 and 1955 and parents born between 1920 and 1960. Also, we only keep children born between 1945 and 1990 to ensure that completed education can be observed. See Appendix 1 for detailed data preparation procedures, missing data by generation, and summary statistics by biological/non-biological relationships.

We choose education as the measure of social status because it is consistently available across three generations with less measurement error than income (Black & Devereux, 2010). In addition to the years of education, standardized education (z-score) is calculated within nine birth cohorts, with the person's birth year in the middle.[7] The cohorts are gender- and generation-specific. For example, a grandfather born in 1930 is compared to other grandfathers born between 1926 and 1934.

The purpose of using standardized education is to adjust for the different scales and distributions of status measures between populations. For example, for the same cohort, fathers from a developed country may have more years of education and more variation in education than Chinese fathers. When regressing children's education on fathers' education measured by the number of years, the independent variable, father's education, is "compressed" for the Chinese sample, and coefficients from the two countries would not be comparable. A similar problem may happen when comparing two cohorts of children and parents across time in China. Standardized education can facilitate these comparisons because it is scale-independent, which is why it is commonly used in cross-country studies (Chevalier, Denny, & McMahon, 2009; Neidhöfer & Stockhausen, 2019). We choose standardized education as the preferred measure and present robustness checks using the years of education. For an in-depth discussion of the measurement of education for mobility studies, see Ahsan, Emran, Jiang, Murphy, and Shilpi (2022).

The education of later generations is regressed on that of the earlier generations. We estimate different lineage specifications

[3] China Family Panel Studies (CFPS) is another high-quality household survey for China. Fan et al. (2021) use CFPS to estimate education mobility between two generations. For children born between 1970 and 1980, controlling for quadratic age functions of children and fathers, the coefficient on fathers' standardized education is 0.458 (Fan et al., 2021, Table 2, panel G), while the corresponding estimate from CHARLS is 0.424 based on our estimation.

[4] We choose the 2013 data because we need to use the information in the 2014 life-history survey. The 2013 survey is the closest regular-year survey that can be best merged with 2014 data. We avoid adding observations from other waves (e.g., respondents who answered the 2011 and 2014 surveys but skipped the 2013 survey), which could jeopardize the statistical representativeness of the sample. See Appendix 1 for detailed data preparation procedures.

[5] Since G2 respondents report education for themselves as well as members of G1 and G3, recall errors may exist. If the recall errors are classical measurement errors, then the measurement errors in G1 education will create a downward bias in grandparent effect estimates. If the recall errors are systematic, then the direction of the bias on grandparent effects would depend on the correlation between G3 children's education (i.e., the dependent variable) and the recall error for G1's education.

[6] A large branch of the literature tried to separate nature from nurture, sometimes by comparing adoptive children with biological children. For a review of this literature, see Sacerdote (2011).

[7] Standardized education is the z-score of the person's education within the relevant cohort, which equals to the person's education, minus average education, then divided by the standard deviation of education.

because family members in the same generation may impact children independently from other family members. For example, mothers and grandmothers may have effects on female children that are independent from their male counterparts. We capture these independent impacts in some specifications by including family members separately. Alternatively, we include the average standardized education for G1 and G2 to get more parsimonious measures.

For the average standardized education measures, we calculate the cohort and gender-specific z-score before taking the average, so that education is comparable between gender and age groups. When education for one parent (or some grandparents) is missing, the average (grand) parent education takes on the value of the non-missing parent (or the average of non-missing grandparents). This procedure preserves an observation as long as education is available for at least one member in each generation.

Observations have to be dropped if standardized education is missing for one of the three generations. Specifically, observations that are missing children's standardized education, missing education for both parents, or missing education for all four grandparents are dropped from all analyses. As Table 1 and Appendix Tables A1, A3, and A5 show, G1 is the main source of missing observations. As expected, the overall missing rate is higher for households with older and less-educated parents. Without adjustment, these households will be under-represented in the study. We calculate the inverse probability of missing values by parents' years of education and age groups (every ten years) in rural and urban areas and multiply them by the survey sampling weights provided by CHARLS 2013 (Solon, Haider, & Wooldridge, 2015). The regression analyses are weighted to achieve nationally representative results.

Table 2 presents the summary statistics for the three-generation sample. Each observation is a child in G3. After the previously mentioned data cleaning, 23,789 observations remain. The number of observations will further vary depending on the analysis. The main results are the estimation of Eq. (1), controlling for children's gender when applicable. We also estimate three-generational mobility for nine-year birth cohorts to establish mobility trends. Standard errors are clustered at the level of primary sampling units (PSUs, representing village and urban neighborhoods) to account for error correlation within locations.

5. Overall measures of multi-generational mobility

In this section, we report the estimates of multi-generational mobility. The first subsection presents results on overall measures of three-generational mobility. The second subsection provides an international comparison of three-generational mobility between China and some Western countries. The third subsection presents the time trends in two- and three-generational mobility. The fourth subsection explores the mechanisms of the direct grandparent effect.

5.1. Estimating mobility across three generations

Over the three generations, education has experienced drastic growth for both men and women, and the gender gap has narrowed. Men's average years of education increase from 1.9 to 2.0 years in G1 to 6.1 years in G2, then to 8.9 years in G3. For women, the

Table 1
Missing value summary.

	Total /Remaining	Missing	% of columns (1)	Total /Remaining	Missing	% of columns (4)
	(1)	(2)	(3)	(4)	(5)	(6)
	All					
G3	26,402	217	0.8%			
G2	26,185	303	1.1%			
G1	25,882	2093	7.9%			
	23,789					
	G2 Education ≤ Median			G2 Education > Median		
G3	13,048	127	1.0%	13,044	83	0.6%
G1	12,921	1268	9.8%	12,961	825	6.4%
	11,653			12,136		
	G2 Age ≤ Median			G2 Age > Median		
G3	13,388	78	0.6%	12,704	132	1.0%
G1	13,310	498	3.7%	12,572	1595	12.7%
	12,812			10,977		
	G2 Rural Hukou			G2 Urban Hukou		
G3	20,333	172	0.8%	5759	38	0.7%
G1	20,161	1510	7.5%	5721	583	10.2%
	18,651			5138		

Notes: This table summarizes the number of observations of G3 children dropped because of missing standardized education in the three generations. Standardized education is missing if age, gender, or years of education is missing, which means the individual cannot be placed into a cohort. The initial sample is the number of children born between 1945 and 1990. In the top panel, observations missing G3, G2, and G1 information are dropped sequentially in this order. G1 and G2 standardized education is the average of members with available standardized education. Missing values may result from missing values in the raw data, non-biological relatives, and age anomalies. The bottom three panels summarize missing G1 standardized education by G2 (respondents) education, age, and rural/urban Hukou status.

Table 2
Summary statistics for three-generational mobility analysis.

	N	Mean	SD.	Min	P25	P75	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Third Generation (G3)						
Male childen's age	12,492	38.0	9.2	24.0	30.0	44.0	69.0
Female childen's age	11,297	38.0	9.2	24.0	30.0	44.0	69.0
Male childen's education	12,492	8.9	4.1	0.0	6.0	12.0	22.0
Female childen'ss education	11,297	7.6	4.6	0.0	6.0	9.0	22.0
	Second Generation (G2)						
Fathers' age	18,573	65.4	9.5	44.0	58.0	72.0	94.0
Mothers' age	21,611	64.6	9.9	44.0	57.0	71.0	94.0
Fathers' education	18,372	6.1	3.9	0.0	3.0	9.0	22.0
Mothers' education	21,550	3.2	3.8	0.0	0.0	6.0	19.0
	First Generation (G1)						
Paternal grandfathers' age	17,874	96.9	13.0	61.0	87.0	107.0	139.0
Maternal grandfathers' age	20,608	96.8	13.1	63.0	86.7	108.0	138.0
Paternal grandmothers' age	17,782	94.8	12.8	63.0	85.0	104.0	136.0
Maternal grandmothers' age	20,770	94.5	13.1	59.0	84.0	104.0	139.0
Paternal grandfathers' education	17,565	2.0	3.1	0.0	0.0	3.0	19.0
Maternal grandfathers' education	20,229	1.9	3.2	0.0	0.0	3.0	16.0
Paternal grandmothers' education	17,646	0.4	1.7	0.0	0.0	0.0	22.0
Maternal grandmothers' education	20,630	0.4	1.6	0.0	0.0	0.0	16.0

Notes: The three-generation sample is constructed from CHARLS data from 2013. Each observation is a child in G3. To be included in the sample, a child has to be born between 1945 and 1990, and standardized education has to be available for the child and at least one member of G1 and G2, respectively. Only biological parents and grandparents are included. All age variables are measured in the year 2014. All education variables are measured in years.

average years of education grow from 0.4 years in G1 to 3.2 years in G2, then to 7.6 years in G3 (Table 2). The standard deviation of education rises with its mean level. To isolate relative mobility from the change in the marginal distribution of education in each generation, we adopt standardized education (z-score) as the primary social status measure.

We first consider three-generational mobility along the male lineage (paternal grandfather, father, male child), which is common among existing studies. We regress the education of a later generation on the education of earlier generations. The results in Table 3 show that a male child's education is correlated with both the father's and, to a lesser extent, the paternal grandfather's education. We find that when the paternal grandfather's standardized education increases by one, the child's standardized education increases by 0.168 (Table 3, column (3)) when the father's education is not controlled for (i.e., the total grandparent effect) and by 0.0764 (Table 3, column (4)) when the father's education is controlled for (i.e., direct grandparent effect). The direct grandfather effect is economically substantial and statistically significant, contradicting a simple AR(1) process. An alternative and equivalent test for an AR(1) process is to see whether the product of the two-generational correlations equals the total grandparent effect (Braun & Stuhler, 2018). Our results show that the total grandparent effect (0.168, Table 3, column (3)) is much larger than the extrapolated value ($0.244 \times 0.396 = 0.097$, Table 3, columns (1) and (2)).

Table 3
Mobility across three generations along the male lineage.

Dependent Variable	Fathers' Education	Children's Education	Children's Education	Children's Education	Children's Education
Status Measures	z-score	z-score	z-score	z-score	Years
	(1)	(2)	(3)	(4)	(5)
Fathers' Education		0.396***		0.375***	0.410***
		(0.0185)		(0.0202)	(0.0187)
Paternal Grandfathers' Education	0.244***		0.168***	0.0764***	0.111***
	(0.0182)		(0.0178)	(0.0168)	(0.0207)
Constant	0.0362	0.190***	0.202***	0.188***	6.269***
	(0.0274)	(0.0188)	(0.0249)	(0.0185)	(0.115)
R-squared	0.069	0.143	0.030	0.149	0.178
Observations	9093	9093	9093	9093	9093

Notes: Column (1) presents the regression of fathers' standardized education on grandfathers' standardized education. Columns (2) to (4) present the regressions of male children's standardized education on fathers' and grandfathers' standardized education. Column (5) uses years of education as an alternative education measure. All standardized education (z-score) measures are calculated within nine birth cohorts of the same gender centered on the individual's birth year. Standard errors in parentheses are clustered at the PSU level. *** $p < 0.01$.

We conduct robustness checks using years of education (Table 3, columns (5)) as the education measure for the three generations. The direct grandfather effect relative to the father effect is similar. We also use flexible age dummies as a robustness check, and the results are essentially the same (Appendix Table A7). The analysis is conducted separately for urban and rural areas (defined by the father's hukou status), and the direct grandparent effect is stronger in rural areas (Appendix Table A8). While the main analysis focuses on biological relationships, we present results for non-biological relatives in the Appendix (Appendix Table A9.) Father and grandfather effects are smaller for non-biological fathers and grandfathers, as expected.

Information on multiple family members in each generation allows us to examine lineage and gender patterns in intergenerational mobility. In Table 4, we first reproduce the results on the male lineage (Table 4, column (1)) for comparison with other lineages. Results on the female lineage (daughter/mother/maternal grandmother) are presented in Table 4, column (2). When the mother's education is controlled for, female children's standardized education increases by 0.0775 when the standardized education of the maternal grandmother increases by 1. The ratio between the direct maternal grandmother effect and the mother effect is 0.18. In Table 4, column (3), we include two parents and four grandparents separately. All four grandparents have positive effects on children's education, although the paternal grandmother effect is not statistically significant. Compared to their female counterparts, grandfathers' and fathers' education have stronger effects on children's education. Table 4, columns (4) and (5) look at male and female children separately. We find the standardized education of that mothers, maternal grandfathers, and paternal grandmothers have stronger correlations with those of female children. In Table 4, column (6), we use the average standardized education within G1 (all four grandparents) and G2 (father and mother) as summary education measures for each generation. This is the specification that we will use for trend analysis.

5.2. *International comparison of three-generational mobility*

Our estimates can be first compared to the range estimates from meta-analyses and cross-country studies. Anderson et al. (2018) conduct a meta-analysis of multi-generational education mobility across 69 studies from various countries. They find that the ratio between G2's association with G3 and G1's association with G3 has a median of 4.10 and an interquartile range of 1.58 to 11.71 (Anderson et al., 2018, p122). Our estimate of the corresponding measure is 4.91 for the male lineage (Table 4, column (1)) and 5.59 for the female lineage (Table 4, column (2)). Our estimates for China are close to the median and well within the interquartile range from Anderson et al. (2018).

Colagrossi et al. (2020) report grandparent effects for 28 EU countries in a cross-country study. When parents' education is controlled for, the grandparent effect ranges from negative and statistically insignificant to a significantly positive value of 0.23. The point estimates of grandparent effects for Luxembourg (0.12), Bulgaria (0.13), Croatia (0.18), Hungary (0.16), Poland (0.12), Romania (0.23), Cyprus (0.17), Greece (0.16), and the UK (0.15) (Colagrossi et al., 2020, Table 8, column (1)) are all higher than the highest direct grandparent effect (0.111 from Table 3, column (5)) that we obtained for any specification.

Table 4
Gender and lineage patterns in three-generational mobility.

Dependent Variable	G3 Male	G3 Female	G3 Children	G3 Male	G3 Female	G3 Children
	(1)	(2)	(3)	(4)	(5)	(6)
Mothers' Education		0.433***	0.239***	0.198***	0.283***	
		(0.0244)	(0.0150)	(0.0178)	(0.0189)	
Fathers' Education	0.375***		0.302***	0.297***	0.307***	
	(0.0202)		(0.0164)	(0.0223)	(0.0189)	
G2 Average Education						0.483***
						(0.0235)
Paternal Grandfathers' Education	0.0764***		0.0364***	0.0447***	0.0261	
	(0.0168)		(0.0124)	(0.0147)	(0.0186)	
Maternal Grandfathers' Education			0.0378***	0.0310*	0.0479***	
			(0.0132)	(0.0166)	(0.0164)	
Paternal Grandmothers' Education			0.0147	−0.00723	0.0375**	
			(0.0116)	(0.0145)	(0.0157)	
Maternal Grandmothers' Education		0.0775***	0.0284**	0.0328**	0.0268	
		(0.0159)	(0.0136)	(0.0166)	(0.0183)	
G1 Average Education						0.105***
						(0.0249)
Constant	0.188***	0.213***	0.247***	0.233***	0.262***	0.157***
	(0.0185)	(0.0247)	(0.0173)	(0.0182)	(0.0219)	(0.0185)
R-squared	0.149	0.193	0.225	0.191	0.267	0.195
Observations	9093	9723	13,654	7175	6479	23,789

Notes: Children's standardized education is regressed on the standardized education of parents and grandparents. Columns (1) and (2) present results for the male and female lineages. Columns (3) to (5) present results with all parents and grandparents separately included for all children, male children, and female children. Column (6) uses the average standardized education (between grandparents for G1 and between father and mother for G2) to represent the education in each generation. When some grandparent or parent information is missing, the average education is calculated from available family members in each generation. All standardized education (z-score) measures are calculated within nine birth cohorts of the same gender centered on the individual's birth year. Standard errors in parentheses are clustered at the PSU level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, we focus on estimates from Neidhöfer and Stockhausen (2019) for Germany, the US, and the UK, and Lindahl et al. (2015) for Sweden. Due to data availability, these countries have received the most attention in the literature. By focusing on these two studies, we can match their education measures and lineages and achieve better comparability. Both studies use standardized education as the status measure, and their lineages have counterparts in this study. The comparison in Table 5 shows that the direct grandparent effect in China, relative to the parent effect, is lower or equal to those in the comparison countries in most cases. Therefore, we find no evidence that the direct grandparent effect is exceptionally strong in China.

5.3. Time trends in two- and three-generational mobility

The turbulent history of twentieth-century China creates drastic changes in two-generational mobility. Chen et al. (2015) find that the intergenerational persistence of education exhibits a U-shaped trend for cohorts born between 1930 and 1980. In Fig. A1 of Appendix 3, we reproduce Chen et al. (2015) results using the CHARLS data. With a larger and nationally representative dataset, we confirm that two-generational persistence does experience a pronounced U-shaped trend for cohorts born between 1925 and 1990.

We investigate how this U-shaped trend in two-generational persistence translates into mobility across three generations. If education for different generations follows an AR(1) process, then the persistence between G1-G3 would be the multiplication of the persistence between G1-G2 and G2-G3. In our case, since G2 is mostly born on the downslope of the U-shape, while G3 is mostly born on the upslope, the two trends would partially negate each other. However, the existence of the direct grandparent effect, independent of G1-G2 and G2-G3 links, complicates the analysis since its trend is unknown. In other words, given the U-shaped trend in two-generational persistence, the trend of three-generational persistence still needs to be empirically estimated.

We start by establishing the two-generational mobility trends for G1-G2 and G2-G3 in the three-generational sample. Fig. 2 uses the birth cohort of the children in G3 as the coordinate for the timeline. The average standardized education is used as the education measure for G1 and G2. Since G2 parents are mostly born before the mid-1950s, and children in G3 are born after the mid-1950s, the G1-G2 mobility trend mostly reflects the downward section of the U-shape, while the G2-G3 mobility trend mainly reflects the upward part of the U-shape. However, because S2 is included in the pooled two-generational analysis but not the three-generational analysis, the similarity between Fig. 1 and Fig. A1 is qualitative only.

Next, we investigate how the above trends in G1-G2 and G2-G3 educational persistence affect total and direct grandparent effects. Fig. 2 shows that the direct grandparent effect is relatively stable. The trends in G1-G2 persistence and G2-G3 persistence partially negate each other. The resulting trend in the total grandfather effect is mostly driven by the trend in the direct grandparent effect.

In the following subsection, we present evidence that the observed direct grandparent effect is not causal. However, it is still a useful quantity since it is closely related to the bias in extrapolating two-generational correlations (G1-G2, G2-G3) to three-generational mobility (G1-G3). Specifically, Braun and Stuhler (2018) show that any data-generating process that results in "excess persistence," i.e., the actual G1-G3 correlation being greater than what was estimated from extrapolation, will also cause a positive direct grandparent effect, and vice versa. The trend for the observed direct grandparent effect represents the evolution of the extrapolation bias over time.

Table 5
Cross-country comparison of grandparent effects as a percentage of parent effects.

	Lineage		
	Grandfather/father/son	Grandmother/mother/daughter	Grandparent/parent/child
	(1)	(2)	(3)
Germany[a]	27%	17%	29%
US[a]	14%	21%	4%
UK[a]	58%	29%	18%
Sweden[b]			27%
China[c]	19%	17%	22% (20%)

Notes: This table displays the ratio of direct grandparent effects to parent effects.
[a] The estimates for Germany, the US, and the UK are authors' calculations from Table B7, Column (3) and Table B4, columns (1), (4), (7) of Neidhöfer and Stockhausen (2019) for children born between 1960 and 1984.
[b] The estimate for Sweden is the authors' calculation from Table 8, column 2 (standardized results) of Lindahl et al. (2015) for children born between 1943 and 1992.
[c] The specifications for estimates for China, from left to right, correspond to regressions in Table 4, columns (1), (2), and (6). Birth cohorts are adjusted to match those in the comparison studies. The number in parentheses in column (3) is from a specification that controls for quadratic age functions as in the Swedish study (Lindahl et al. 2015).

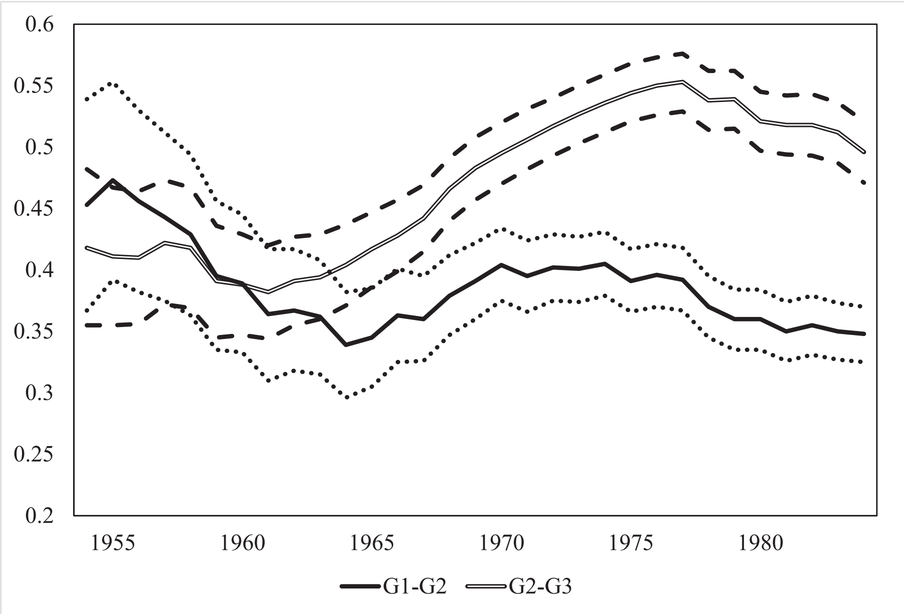

Fig. 1. Time trends in the intergenerational persistence of education between G1-G2 and between G2-G3.
The horizontal axis is the middle birth year of nine cohorts of children in G3. Each point on the line G1-G2 represents a regression coefficient of G2 average standardized education regressing on G1 average standardized education. Each point on the line G2-G3 represents a regression coefficient of G3 children's standardized education regressing on G2 average standardized education. Dashed lines represent 95% confidence intervals.

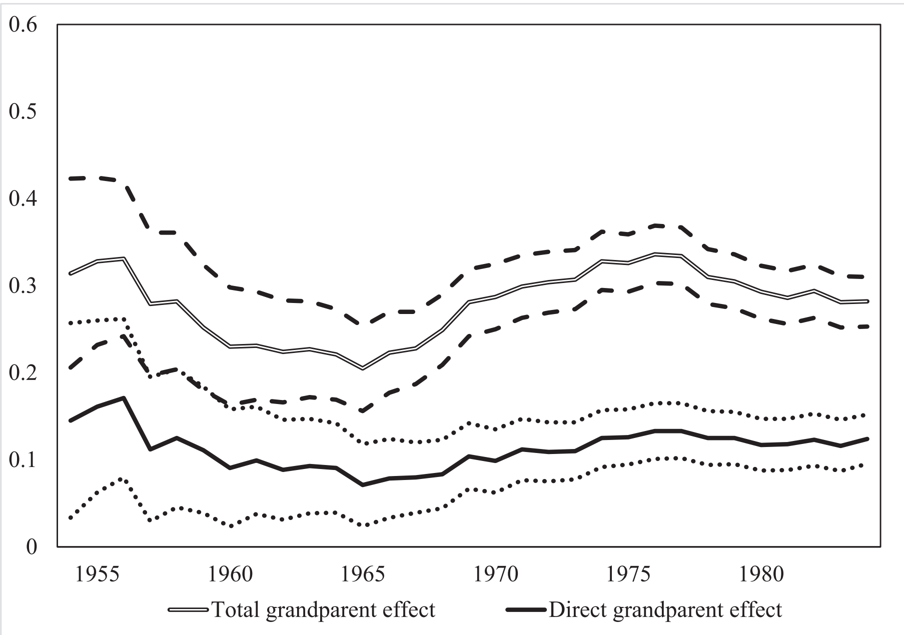

Fig. 2. Time trends of total and direct grandparent effects.
The horizontal axis is the middle birth year of nine cohorts of children in G3. The direct grandparent effect is estimated by regressing G3 children's standardized education on G1 average standardized education, controlling for G2's standardized education. The total grandparent effect is from the above regression but without controlling for G2 average education. Dashed lines represent 95% confidence intervals.

Table 6
Controlling for additional information in the second generation.

	(1)	(2)	(3)	(4)	(5)
Fathers' Education	0.385***	0.295***	0.170***	0.198***	0.130***
	(0.0175)	(0.0143)	(0.0169)	(0.0228)	(0.0206)
Mothers' Education		0.257***	0.131***	0.188***	0.0957***
		(0.0264)	(0.0158)	(0.0320)	(0.0195)
G1 Average Education	0.163***	0.101***	0.0406*	0.0687**	0.0370
	(0.0305)	(0.0256)	(0.0214)	(0.0296)	(0.0249)
Additional Parent Attributes	N	N	Y	N	Y
Uncle & Aunt Attributes	N	N	N	Y	Y
Observations	18,372	16,133	12,507	8341	7596
R-squared	0.172	0.227	0.300	0.260	0.341

Notes: Education is measured by standardized education within nine-year birth cohorts. Additional parent attributes include CCP (Chinese Communist Party) membership, Hukou status, occupation, per capita household income, and per capita household wealth. Uncle/aunt attributes include average standardized education and CCP membership per uncle and aunt. Children's gender is controlled. Standard errors in parentheses are clustered at the PSU level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4. Mechanisms: omitted variables and direct interaction

When there are omitted attributes of the second generation, grandparents' education may serve as a proxy for these missing attributes or act through them. Either way, a direct grandparent effect may be observed even though grandparents' education has no immediate causal effect on children's education. Results in Table 6 evaluate the role played by omitted second-generation attributes. We begin with only controlling for fathers' education (Table 6 column (1)), then add mothers' education (Table 6, column (2)). This simple exercise demonstrates the critical role of omitted second-generation attributes: including mothers' education alone decreases the coefficient of grandparents' education, measured by the average standardized education of four grandparents, by 38%. Using the specification with both parents' education as the baseline (Table 6, column (2)), we then include a rich set of parent attributes (Table 6, column (3)), including fathers' and mothers' CCP (Chinese Communist Party) membership, Hukou status, occupations, log per capita household income, and log per capita household wealth. These parent attributes have expected effects: party membership, urban Hukou status, non-agricultural occupations, higher household income, and higher household wealth all have positive and statistically significant correlations with children's education. After including these parent attributes, the grandparent effect decreases by 60% compared to the baseline. Alternatively, we add controls for the average standardized education of uncles and aunts and party memberships per uncle and aunt (Table 6, column (4)). Adding information on uncles and aunts reduces the direct grandparent effect by 32% from the baseline. After simultaneously including parent attributes and uncle and aunt attributes (Table 6, column (5)), the grandparent effect decreases by 63% relative to the baseline and loses statistical significance.

There are two plausible explanations for these results. The first is that grandparents do have an effect on grandchildren that is independent from their parent's education. However, such effects mostly work through other parental attributes and uncle and aunt attributes. In this case, the observed direct grandparent effect is only independent of one parent attribute (education) and not truly independent from G2's overall social status. The second interpretation is that grandparents' education serves as a proxy for G2 attributes when the latter is omitted. When G2 attributes are included, the proxy loses explanatory power. Both explanations suggest that the actual direct grandparent effect independent from G2 is not a major driver of the G1-G3 correlation.

An obvious explanation for the direct grandparent effect is that grandparents may influence children through direct interaction. Most studies that examine this potential mechanism find no evidence for it. A notable exception is Zeng and Xie (2014), who find that, in rural China, grandparents who live with their grandchildren have a stronger influence on whether children drop out of school. Here, we can examine this explanation with a nationally representative sample and completed education. Three alternative measures of direct interaction are adopted: the overlap of grandparent's and children's lifespans, whether grandparents took care of the child before age 5, and whether a grandparent co-resides with the child. Because co-residency usually happens when children are young, we restrict children to the ages of 7–24 for this analysis. To address right-censored education in this school-aged sample, we use interval regression (Billard & Diday, 2000), essentially the Tobit model with varying thresholds. In all regressions, we interact the measures of grandparent-children direct interaction with the standardized education of corresponding grandparents.

Table 7 shows that only two of the 12 interaction terms (paternal grandfather's education interacted with childcare and co-residency) are positive and statistically significant. Therefore, we do not find sufficiently strong evidence that direct grandparent-children interaction enhances direct grandparent effects. While this result is at odds with the findings of Zeng and Xie (2014), it is consistent with most other studies (for example, Braun & Stuhler, 2018; Neidhöfer & Stockhausen, 2019). It is also compatible with our previous result that the direct grandparent effect drastically decreases after controlling for detailed second-generation attributes. It seems that, although grandparents do have more interaction with grandchildren in China than in Western countries, such interaction does not translate into larger direct grandparent effects.

Table 7
Direct interaction between grandparents and children and grandparent effects.

Type of interaction:	Life-span Overlap	Childcare	Co-residency
	(1)	(2)	(3)
Interaction × Paternal Grandfather Education	0.801	0.138**	0.297*
	(0.923)	(0.0574)	(0.180)
	0.672	0.0244	−0.679**
Interaction × Maternal Grandfather Education	(0.823)	(0.0324)	(0.299)
	0.269	0.0861	0.345
Interaction × Paternal Grandmother Education	(0.724)	(0.0635)	(0.221)
	−0.253	−0.0550	0.717
Interaction × Maternal Grandmother Education	(0.682)	(0.0336)	(0.634)
Father and Mother Education	Y	Y	Y
Grandparents education	Y	Y	Y
Interaction Main Effect	Y	Y	Y
R-squared	0.213	0.225	
Observations	11,653	12,674	1149

Notes: This table presents the interaction terms of grandparent-children direct interaction and grandparent standardized education. The main effects are included but not presented here. From columns (1) to (3), the measures of grandparent-children interactions are the number of years grandparents' lives overlap with children's lives, whether grandparents took care of the child when the child was younger than five years old, and whether school-aged children live with their grandparents. Columns (1) and (2) use OLS regression and standardized education. Column (3) uses interval regression with right censoring and years of education for children still in school. Other variables in the regressions include the standardized education of parents and grandparents, measures of grandparent-children direction interaction, and children's gender. Standard errors in parentheses are clustered at the PSU level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusion

Social mobility is a topic that continues to attract the attention of scholars from a variety of disciplines. Most previous research on long-term, multi-generational mobility focuses on developed countries, and evidence from developing countries is scarce. This paper uses a nationally representative dataset to estimate the three-generational mobility of modern China that is suitable for international comparison.

We show that grandparent effects are positive and statistically significant, controlling for parent education. When such a direct grandparent effect exists, multi-generational persistence will be underestimated if it is extrapolated from two-generational persistence. An international comparison shows that the magnitudes of grandparent effects in China are in line with those in Western countries despite China's unique culture, history, and institutions. This paper also investigates the dynamics of intergenerational mobility by estimating two-generational and three-generational mobility for different birth cohorts in the children's generation. We find that a U-shaped time trend in two-generational persistence gives rise to a relatively flat time trend in three-generational persistence, which is mostly driven by the direct grandparent effect. The U-shaped two-generational persistence trend and the relatively flat three-generational persistence trend is consistent with the predictions of recent theoretical work by Nybom and Stuhler (2022).

Regarding the channels through which grandparent effects take place, results show that most of the observed direct grandparent effects can be explained by omitted information in the second generation. In other words, the observed grandparent effects either work through additional G2 attributes or proxy for these attributes. We find no evidence that direct interaction between grandparents and children increases the direct grandparent effect. These results suggest that the observed grandparent effects should not be interpreted as causal. Instead, they can only measure the bias in extrapolating multi-generational persistence from two-generational persistence.

The main limitation of this paper is the reliance on correlational analysis. As a result, the causes for spatial and temporal variations in multi-generational mobility, or the lack thereof, remain unexplained. A potentially fruitful research area is exploiting the quasi-experimental variations in historical events, such as the cultural revolution and the One-Child policy, to establish the causal pathways of grandparent effects. There has been recent progress in two-generational mobility in this direction (Meng & Zhao, 2021, Yu, Fan, & Yi, 2020), which can be extended to multi-generational mobility studies.

Declaration of Competing Interest

Jia Cao's disclosure statement: Jia Cao is supported by the Fundamental Research Funds for the Central Universities and the Research Funds of Renmin University of China (22XNF056).

Minghao Li's disclosure statement: none.

Data availability

The data used in the paper can be obtained by filing a request online at http://charls.pku.edu.cn

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Appendix A

Appendix 1. Data preparation

This appendix introduces the detailed data preparation procedures for G1, G2, and G3. We emphasize issues of missing data and non-biological relationships. The main source of education, gender, and age variables is the 2013 wave of the CHARLS survey. The regular year (2011, 2013, 2015, 2018) survey samples are designed to be nationally representative cross-sections after applying the sampling weights provided with each wave of the survey. Therefore, combining samples from multiple waves can jeopardize the representativeness of the study. For this reason, even though we process data from multiple waves, the sample is based on one wave (2013).

We choose the 2013 wave because the 2014 life-history survey attempts to collect information from all 2011 and 2013 respondents. While the 2014 wave provides rich supplementary information, it is not designed to be statistically representative, and sampling weights are not provided. Therefore, we merge the 2013 and 2014 waves but only keep observations that appear in the 2013 wave. In other words, if a household answered the 2011 survey, skipped the 2013 survey, and reappeared in the 2014 survey, it is excluded from the analysis.

In general, for repeated respondents, information that had been asked in 2011 was not asked again in later waves. Some data from the 2011 wave is carried over to the 2013 files and stored in variables starting with the letter z. For example, *ba002_1* is the birth year for G2 members collected in 2013, whereas *zba002_1* is the birth year collected in 2011. For 2011 data that is not carried over to the 2013 files, we merge them from the 2011 files. If a respondent and their family members in the 2013 wave have missing information, we try to recover it from 2011, 2014, and 2015 data.

The parent(s) in G2 answer the survey and provide information about themselves, their spouses, parents (G1), and children (G3). Both the primary respondent and the spouse (if any) are interviewed. Interviewees are asked to provide information regardless of whether family members are alive or whether they live in the same household as the interviewee. Therefore, even if a G2 member is not in the household, information for the member and their parents' is still available through the (ex-)spouse' interview. The subsections below summarize data preparation and missing observations by generation.

1.1. Data preparation for G1

The main source for G1 information is the "Parent" data file of the 2013 wave of CHARLS. The survey providers have compiled the datafile from the "Family_Information" (for non-coresident parents) and "Other_HHmember" data files of the 2013 wave for the convenience of researchers. G1 grandparents' information is provided regardless of whether they are alive (which is reported in the variable *ca001*) and whether they co-reside with G2 (which is reported in the variable *ca016*). G1 information is reported by their own children as well as their children-in-law. Data reported by the children-in-law can be used to identify G1 information when their children are not in the surveyed household (e.g., deceased or divorced). G2 respondents answer the types of their parents (G1) in the variables *ca003* (*zca003* for carried-over data). The types of parents include biological parents, adoptive parents, step-parents, relatives whom the respondent grew up with, and others. If a grandparent is not a biological parent, their entry is removed from the main three-generation analysis.

The birth year and educational attainment of G1 are in variables *ca007* and *ca009* (or carried-over variables *zca007* and *zca009*), respectively. The educational attainment is converted to the years of education based on six years for elementary school, nine years for junior middle school, 12 years for high school, 15 years for an associate degree, 16 years for a bachelor's degree, 19 years for a master's degree, and 22 years for Ph.D.

The table below shows that grandparents are the primary source of missing information in our study. The missing rate of the age variable is between 12.1% and 16.5%. The missing rate for the education variable is between 7.8% and 14.5%. The missing rates of education by G1's own age and urban/rural status (middle panel) are conditioned on not missing age and Hukou data, which are often missing together with education. Therefore, we report missing grandparent education by G2 age and Hukou status (bottom panel).

The missing rates are higher for grandfathers and paternal grandparents. Male spouses are more likely to be dead at the time of the survey since, on average, they are older and have shorter life expectancies than females. Although the survey is designed to collect information on deceased family members, the respondents are more likely to forget their information. For example, if a G2 father has passed away, the paternal grandparents' information may become missing if the mother cannot remember the education of her parents-in-law. As a result, the average education measure (which is calculated using non-missing grandparents) contains more information from the maternal grandparents and grandmothers.

The missing rates are also higher for rural areas and for older grandparents, which creates under-representation for these groups. We calculate missing rates for G2 age and education groups in rural and urban areas to address this concern. Inversed probability weights, calculated as the ratio of the number of total observations to that of non-missing observations, are multiplied by the sampling weight provided with CHARLS to adjust for both missing values and sampling probability. Weighted regressions are used in the analysis when applicable.

Table A1
Total observations, available observations, and missing rates for G1.

	Paternal Grandfather	Paternal Grandmother	Maternal Grandfather	Paternal Grandfather
Total	10,762	10,762	10,762	10,762
Age	8995	8990	9427	9460
	16.4%	*16.5%*	*12.4%*	*12.1%*
Years of education	9199	9334	9759	9922
	14.5%	*13.3%*	*9.3%*	*7.8%*

Missing education by age group and rural/urban Hukou status								
	Paternal Grandfather		Paternal Grandmother		Maternal Grandfather		Maternal Grandmother	
G1 age groups	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
60– 86	2510	732	2949	889	2869	766	3361	928
	2399	700	2889	869	2779	747	3309	906
	4.4%	*4.4%*	*2.0%*	*2.2%*	*3.1%*	*2.5%*	*1.5%*	*2.4%*
86– 113	3409	1134	3097	1042	3463	943	3217	839
	3318	1101	3051	1025	3352	913	3171	829
	2.7%	*2.9%*	*1.5%*	*1.6%*	*3.2%*	*3.2%*	*1.4%*	*1.2%*
113– 138	884	274	743	209	1078	220	865	160
	855	267	719	205	1044	209	843	156
	3.3%	*2.6%*	*3.2%*	*1.9%*	*3.2%*	*5.0%*	*2.5%*	*2.5%*
G2 age groups								
44– 60	3579	1002	3570	1001	4362	1104	4362	1104
	3432	964	3485	977	4013	1054	4093	1067
	4.1%	*3.8%*	*2.4%*	*2.4%*	*8.0%*	*4.5%*	*6.2%*	*3.4%*
61– 77	2770	970	2764	971	3373	825	3373	825
	2703	948	2732	958	2938	786	2991	802
	2.4%	*2.3%*	*1.2%*	*1.3%*	*12.9%*	*4.7%*	*11.3%*	*2.8%*
78– 94	434	168	436	168	750	158	750	158
	422	156	425	164	572	135	585	141
	2.8%	*7.1%*	*2.5%*	*2.4%*	*23.7%*	*14.6%*	*22.0%*	*10.8%*

Notes: This table summarizes missing observations for grandparents in G1. The missing values do not include those caused by merging three generations. The top panel reports the total and the available numbers of observations for the age and education variables. The bottom panel reports the total and available numbers of observations for the education variable by age group and rural/urban Hukou status. Missing rates are reported underneath the numbers of available observations in italics.

The table below summarizes G1's age and education by whether they are the biological grandparents of all family children in G3. The biological/adoptive/step relationship between G1 and G2 is recorded in the variable *ca003* (and *zca003* for carried-over data). See the subsection on G3 for identifying the relationship between G2 and G3. Results show that non-biological grandparents are older and less educated. A possible explanation is that they or their children came into the family through remarriage, and the probability of remarriage increases with age. Also, older cohorts are less educated, which explains the education difference.

Table A2
Summary of age and education for G1 by if they are biological grandparents.

Variable	Obs	Mean	Std	Min	P25	P75	Max
Age	Biological						
Paternal Grandfather	7742	92.5	13.3	60.0	83.0	102.0	137.0
Paternal Grandmother	7739	90.2	13.1	60.0	81.0	98.0	136.0
Maternal Grandfather	8465	91.9	14.5	4.0	82.0	102.0	154.0
Maternal Grandmother	8523	89.5	14.1	13.0	80.0	98.0	149.0
Years of Education							
Paternal Grandfather	7573	2.5	3.5	0.0	0.0	6.0	19.0
Paternal Grandmother	7646	0.8	2.2	0.0	0.0	0.0	22.0
Maternal Grandfather	8774	2.4	3.5	0.0	0.0	6.0	16.0
Maternal Grandmother	8931	0.8	2.2	0.0	0.0	0.0	16.0
Age	Non-biological						
Paternal Grandfather	1198	95.6	13.3	60.0	86.0	106.0	135.0
Paternal Grandmother	1185	93.2	13.2	60.0	84.0	103.0	132.0

(*continued on next page*)

Table A2 (*continued*)

Age	Non-biological						
Maternal Grandfather	961	92.2	15.9	14.0	82.0	103.0	148.0
Maternal Grandmother	935	90.2	15.9	4.0	80.0	101.0	143.0
Years of Education							
Paternal Grandfather	1099	2.0	3.2	0.0	0.0	3.0	16.0
Paternal Grandmother	1134	0.5	1.9	0.0	0.0	0.0	16.0
Maternal Grandfather	985	2.2	3.4	0.0	0.0	3.0	16.0
Maternal Grandmother	990	0.7	2.1	0.0	0.0	0.0	16.0

Notes: This table summarizes the age and education of G1 grandparents. The top panel is for grandparents who have biological relationships with all G3 children in the family. The bottom panel is for grandparents who have non-biological relationships with at least one G3 child in the family.

1.2. Data preparation for G2 (interviewees)

The main source of education, gender, and age variables for G2 is the "Demographic Background" data file of the 2013 CHARLS survey. The gender of the respondent is based on the variable *ba000_w2_3* (interviewer recorded respondents' sex, 1 = female, 2 = male). This identifies whether the information is for the mother or the father. The age information for G2 members in the household is from *ba002_1* (and *zba002_1* for carried-over data). For G2 members not in the household, their spouses provide their birth years in the variable *bf002*. Age is calculated as 2014 minus birth year. Educational attainment for G2 members in the household is based on the variables *bd001* and *zbd001* in the 2013 wave for the respondents. For G2 members not in the household, their (ex-)spouses provide their education in variable *bf004*. The educational attainment is converted to the years of education based on the same rules as for G1 education. Other G2 information that we use includes Hukou at birth and current Hukou (*bc001* and *bc010*), CCP membership (*ba006_w2_1*), average income per household member (*INCOME_PC*), and average wealth per household member (*WEALTH_PC*).

Table A3
Total observations, available observations, and missing rates for G2.

	Mothers	Fathers
Total	10,577	10,694
Age	10,577	10,694
	0.0%	*0.0%*
Years of education	10,312	10,457
	2.5%	*2.2%*

Missing standardized education by age group and rural/urban Hukou status

	Mothers		Fathers	
Age Groups	Rural	Urban	Rural	Urban
44– 60	4364	1104	3858	1040
	4238	1101	3701	1034
	2.9%	*0.3%*	*4.1%*	*0.6%*
61– 77	3373	826	3481	1037
	3269	825	3424	1037
	3.1%	*0.1%*	*1.6%*	*0.0%*
78– 94	751	159	1066	212
	720	159	1049	212
	4.1%	*0.0%*	*1.6%*	*0.0%*

Notes: This table summarizes missing observations for mothers and fathers in G2. The missing values do not include those caused by merging three generations. The top panel reports the total and the available numbers of observations for the age and education variables. The bottom panel reports the total and available numbers of observations for the education variable by age group and rural/urban *Hukou* status. Missing rates are reported underneath the numbers of observations in italics.

In the raw data, the missing rate of observations is only slightly higher for mothers than for fathers (2.5% vs. 2.2%, Appendix Table A3). After removing non-biological relationships, there are more observations with mother education (N = 21,550, Table 2) than with father education (N = 18,372, Table 2). This is because there are more non-biological fathers (Appendix Table A3) whose information is removed. Missing rate analysis by age group and rural/urban residency (table above, lower panel) shows that the missing rate is higher in the rural area but does not have a definitive pattern by age group.

In this study, we focus on biological relationships (see next subsection for how to identify non-biological children). The table below summarizes G2 parents by whether they have any non-biological children in G3. The comparison shows that parents who have non-biological children are older, possibly because the probabilities of widowhood, divorce, and remarriage increase with age. Since older cohorts have lower education levels, parents of non-biological children also have lower education levels. Therefore, removing non-biological parents places more weight on younger cohorts.

Table A4
Summary of G2 age and education by whether they have non-biological children in G3.

Variables	Obs	Mean	Std	Min	P25	P75	Max
All children biological							
Father age	8063	61.1	9.8	44.0	52.0	67.0	94.0
Father years of education	7920	6.8	4.0	0.0	3.0	9.0	22.0
Mother age	8909	60.6	10.2	44.0	52.0	67.0	94.0
Mother years of education	8845	4.2	4.3	0.0	0.0	9.0	19.0
Has non-biological children							
Father age	2323	69.8	11.8	44.0	60.0	79.0	94.0
Father years of education	2247	5.4	4.3	0.0	0.0	9.0	19.0
Mother age	1364	64.7	11.4	44.0	56.0	73.0	94.0
Mother years of education	1299	3.4	4.0	0.0	0.0	6.0	16.0

Notes: This table summarizes the age and education of parents in G2. The top panel is for parents who have biological relationships with all G3 children in the family. The bottom panel is for parents who have non-biological relationships with at least one G3 child in the family.

In the analysis of omitted variable bias, we include additional control variables in the parent generation. These variables are defined as the following. Parents' Hukou current status is measured by dummy variables indicating agricultural, non-agricultural, and unified Hukou. Parents' occupation is measured by four dummy variables indicating agricultural, manager, non-manager clerk/ worker, and self-employed. These are the longest occupations in parents' work history. Party membership is represented by a dummy variable that equals one if the individual is a member of the Chinese Communist Party. All the above variables are included separately for the mother and the father. Per capita household income and wealth are the household income and wealth of G2 divided by the household size. Income and wealth are measured at the household level. Sibling variables are defined the same as G2 variables.

1.3. Data preparation for G3

The primary data source for G3 is the "Child" data file provided by CHARLS. The survey providers compile the data in the "Child" file from the "Family Information" file of 2013 CHARLS data for the convenience of researchers.

G2 respondents provide information on their children. The biological/non-biological relationship with children (identified by the "*cat*" variable in the Child data file) may include "Not My Child," "Biological child of you and your current spouse," "Biological child of you, but not current spouse," "Biological child of the current spouse, but not yours," "Adopted or Foster," and "Others." This variable is complete for 100% of the observations. Both coresident and non-coresident children are reported, and the current residency status is reported by the variable *cb053*. The majority (74%) of children are not in the household. We define a child as coresident with G2 if they live in the same or adjacent dwelling or courtyard with the G2 respondent, regardless of whether they are economically independent.

G3 children's gender and birth years are from variables "*gender*" and "*cb051_1*", respectively. Two variables, *cb059* and *cb060*, identify children's educational attainment in and out of school, respectively. The educational attainment is converted to the number of years in school following the same rule as G1 and G2. When exploring the mechanisms of the grandparent effects, we use the information on whether grandparents interacted with the children when they were young. This information is available in the 2014 live history file from various variables with names that begin with *c034*. The table below shows that the rate of missing observations for G3 children is very low (<1%), and the limited cases of missing observations are concentrated in rural areas.

Table A5
Total observations, available observations, and missing rates for G3.

	All Children	Male	Female
Total	26,931	14,042	12,722
Age	26,931	14,042	12,722
	0.0%	*0.0%*	*0.0%*
Years of education	26,714	14,015	12,685
	0.8%	*0.2%*	*0.3%*
Gender	26,764		
	0.6%		

Missing education by age group and rural/urban Hukou status				
	Male		Female	
Age Groups	Rural	Urban	Rural	Urban
24– 39	6117	1747	5437	1651

(*continued on next page*)

Table A5 (*continued*)

Missing education by age group and rural/urban Hukou status				
	Male		Female	
Age Groups	Rural	Urban	Rural	Urban
	6111	1747	5419	1651
	0.1%	*0.0%*	*0.3%*	*0.0%*
40– 55	4135	1271	3853	1106
	4118	1271	3836	1106
	0.4%	*0.0%*	*0.4%*	*0.0%*
56– 69	568	204	508	167
	564	204	506	167
	0.7%	*0.0%*	*0.4%*	*0.0%*

Notes: This table summarizes missing observations for male and female children in G3. The missing values do not include those caused by merging three generations. The top panel reports the total and the available numbers of observations for the age and education variables. The bottom panel reports the total and available numbers of observations for the education variable by age group and rural/urban Hukou status. Missing rates are reported underneath the numbers of observations in italics.

The table below summarizes the age and education of children by their biological/non-biological relationship with parents and grandparents. A child can have a non-biological grandparent if the grandparent-parent or parent-child relationship is non-biological. The summary shows that biological children are younger and more educated than children with non-biological parents and grandparents. A possible reason is that older children are more likely to have parents that re-married, introducing step-parents into the household. Note that a child can have a non-biological parent and remain in the sample. For example, a boy can have a stepmother and remain in the grandfather-father-son regression. Similarly, a child with a non-biological grandfather still has average grandparent education calculated from the remaining grandparents.

Table A6
Summary statistics of G3 children by whether they are the biological children (grandchildren) of G2 and G1.

Variable	Obs	Mean	Std	Min	P25	P75	Max
Biological children of parents and grandparents							
Age	16,826	36.0	8.3	24.0	29.0	42.0	67.0
Years of Education	16,775	8.6	4.3	0.0	6.0	12.0	22.0
At least one parent non-biological							
Age	9300	43.3	9.7	24.0	36.0	50.0	69.0
Years of Education	9136	6.7	4.5	0.0	3.0	9.0	22.0
At least one grandparent non-biological							
Age	10,105	42.8	9.7	24.0	36.0	50.0	69.0
Years of Education	9939	6.8	4.5	0.0	3.0	9.0	22.0

Notes: This table summarizes the age and education of G3 children. The top panel is for children with only biological parents and grandparents. The middle panel is for children with at least one non-biological parent. The bottom panel is for children with at least one non-biological grandparent.

Appendix 2. Additional tables

Table A7
Mobility across three generations along the male lineage (flexible age controls).

Dependent Variable	Father Education	Children Education	Children Education	Children Education
Status Measures	z-score	z-score	z-score	z-score
	(1)	(2)	(3)	(4)
Father Education		0.394***		0.375***
		(0.0178)		(0.0193)
Paternal Grandfather Education	0.244***		0.166***	0.0740***
	(0.0178)		(0.0171)	(0.0164)
Age dummies	Y	Y	Y	Y
Constant	0.146*	0.276***	0.170**	0.249***
	(0.0875)	(0.0632)	(0.0724)	(0.0750)
R-squared	0.075	0.154	0.039	0.160
Observations	9093	9093	9093	9093

Notes: Column (1) presents the regression of fathers' standardized education on grandfathers' standardized education. Columns (2) to (4) present regressions of male children's standardized education on fathers' and grandfathers' standardized education. All standardized education measures are calculated within nine birth cohorts of the same gender centered on the individual's birth year. The control variables are age dummies (every ten years) for the grandfather, father, and child. Standard errors in parentheses are clustered at the PSU level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8
Mobility across three generations along the male lineage by father's hukou.

	Father Education	Children Education	Children Education	Children Education
	(1)	(2)	(3)	(4)
	Urban			
Grandfather	0.229***		0.0896***	0.0112
	(0.0330)		(0.0334)	(0.0284)
Father		0.346***		0.342***
		(0.0297)		(0.0323)
Constant	0.610***	0.579***	0.786***	0.577***
	(0.0502)	(0.0407)	(0.0445)	(0.0413)
R-squared	0.085	0.131	0.014	0.131
Observations	1902	1902	1902	1902
	Rural			
Grandfather	0.144***		0.113***	0.0770***
	(0.0185)		(0.0163)	(0.0160)
Father		0.265***		0.252***
		(0.0227)		(0.0241)
Constant	−0.166***	0.0457**	0.00776	0.0496**
	(0.0234)	(0.0195)	(0.0213)	(0.0195)
R-squared	0.024	0.056	0.012	0.062
Observations	7191	7191	7191	7191

Notes: Column (1) presents the regression of fathers' standardized education on grandfathers' standardized education. Columns (2) to (4) present regressions of male children's standardized education on fathers' and grandfathers' standardized education. All standardized education measures are calculated within nine birth cohorts of the same gender centered on the individual's birth year. Standard errors in parentheses are clustered at the PSU level. ** $p < 0.05$, *** $p < 0.01$.

Table A9
Mobility across three generations along the male lineage (non-biological relationships).

Dependent Variable	Father Education	Children Education	Children Education	Children Education	Children Education
Status Measures	z-score	z-score	z-score	z-score	Years
	(1)	(2)	(3)	(4)	(5)
Father Education		0.329***		0.311***	0.328***
		(0.0636)		(0.0679)	(0.0600)
Paternal Grandfather Education	0.204**		0.165**	0.101	0.146
	(0.0929)		(0.0710)	(0.0693)	(0.0945)
Constant	0.00432	−0.204***	−0.194***	−0.195***	4.971***
	(0.0775)	(0.0615)	(0.0666)	(0.0604)	(0.318)
R-squared	0.037	0.086	0.019	0.093	0.110
Observations	805	805	805	805	805

Notes: Column (1) presents the regression of fathers' standardized education on grandfathers' standardized education. The sample is for male children in G3 who have a non-biological father and non-biological grandfather. The relationship between the father and the grandfather can be biological. Columns (2) to (4) present regressions of children's standardized education on fathers' and grandfathers' standardized education. Column (5) uses years of education as an alternative education measure. All standardized education (z-score) measures are calculated within nine birth cohorts centered on the individual's birth year. Standard errors in parentheses are clustered at the PSU level. ** $p < 0.05$, *** $p < 0.01$.

Appendix 3. Time trend in two-generational mobility using pooled parent-son pairs

Previous research (Chen et al., 2015; Fan et al., 2021) has established a U-shaped trend in the intergenerational persistence of education in China, which is consistent with theoretical predictions by Nybom and Stuhler (2022). However, the U-shape has been constructed in a piecemeal fashion. Chen et al. (2015) show that education persistence exhibits a U-shaped trend in urban China with one survey, then piece together the U-shape for rural China using several surveys covering different periods. Given China's Hukou system, in which rural elites are selected into urban areas, separately studying rural and urban educational mobility is problematic (Wu & Treiman, 2004, 2007). In terms of time trends, changes in the selection process may confound changes in intergenerational mobility. Fan et al. (2021) study the time trends in education and income mobility. They find that the intergenerational persistence of these two social status measures has been rising in recent decades. However, their data does not cover the earlier half of the twentieth century.

We improve upon previous studies by establishing the trend in two-generational education persistence throughout most of the twentieth century using one dataset covering both urban and rural areas. Focusing on the time trend along the male lineage, we pool together fathers and sons from the three-generational data: the fathers are from G1 and G2, while the sons are from G2, S2, and G3.

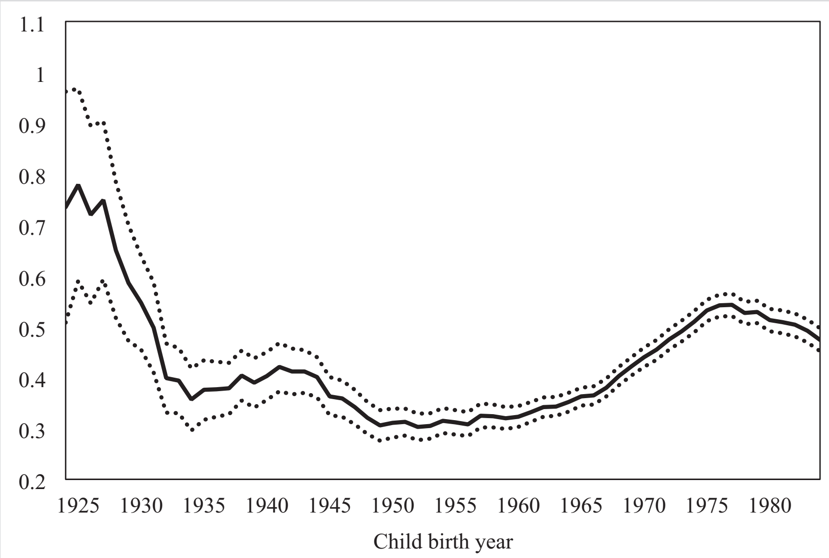

Fig. A1. Time trend in two-generational education persistence.
This figure displays the regression coefficients and 95% confidence intervals of children's standardized education when regressed on parents' average education and children's gender. The parents are from G1 and G2, while the children are from G2, S2, and G3. Each data point represents a regression within nine birth cohorts of children, and the numbers on the horizontal axis are the middle birth years of the nine-year birth cohorts.

Fig. A1 reports the coefficients of children's standardized education regressed on parents' average standardized education in a rolling window of nine birth cohorts. The intergenerational education persistence measured by the regression coefficient starts at 0.75 in the mid-1920s, reaches the lowest point of 0.3 in the mid-1950s, and increases to close to 0.54 in the late 1970s. The U-shape and the timing of the lowest point in intergenerational persistence are consistent with the findings from Chen et al. (2015). Larger sample sizes in earlier cohorts allow us to establish a distinctive downward trend that starts earlier than that in Chen et al. (2015). The early onset of the downward trend suggests that the communist regime and its policies are not the only contributing factors in the evolution of intergenerational mobility in twentieth-century China. Early events such as the demise of the Qing Dynasty and the nationalist revolution may have effects that reverberate through history. Also, intergenerational persistence reaching its lowest point in the mid-1950s cannot be interpreted as solely the result of the contemporaneous social environment. Instead, it may reflect the cumulative effects of past and contemporaneous events (Nybom & Stuhler, 2022).

Appendix 4. A Becker and Tomes (1979) style model for educational mobility

The model here closely follows Solon (2014). 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

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

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

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

where θ is assumed to be positive.

In Solon (2014), the equation above describes the formation of human capital. We change it into schooling because schooling can be measured more accurately than human capital. The endowment follows an AR(1) process

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

where v is an error term that is not correlated with endowment and $0 < \lambda < 1$.

The child's income is a function of her schooling

$$log y_{it} = u + pS_{it}$$

where p is assumed to be positive.

The parent's utility function is

$$U_i = (1-\alpha) log C_{i,t-1} + \alpha log y_{it}$$

where α 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 $\Omega_1 = \delta + (1-\lambda)\theta\left[u + \frac{\alpha p}{1-\alpha(1-\theta p)}\right]$.

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 a 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. 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 has a 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 a lower endowment than B, hence less schooling.

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