

Butaeva, Kristina; Chen, Lian; Durlauf, Steven N.; Park, Albert

Working Paper

A tale of two transitions: Mobility dynamics in the People's Republic of China and Russia after central planning

ADB Economics Working Paper Series, No. 807

Provided in Cooperation with:

Asian Development Bank (ADB), Manila

Suggested Citation: Butaeva, Kristina; Chen, Lian; Durlauf, Steven N.; Park, Albert (2025) : A tale of two transitions: Mobility dynamics in the People's Republic of China and Russia after central planning, ADB Economics Working Paper Series, No. 807, Asian Development Bank (ADB), Manila, <https://doi.org/10.22617/WPS250383-2>

This Version is available at:

<https://hdl.handle.net/10419/336519>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/3.0/igo/>

APPENDIXES

A Tale of Two Transitions: Mobility Dynamics in the People's Republic of China and Russia After Central Planning

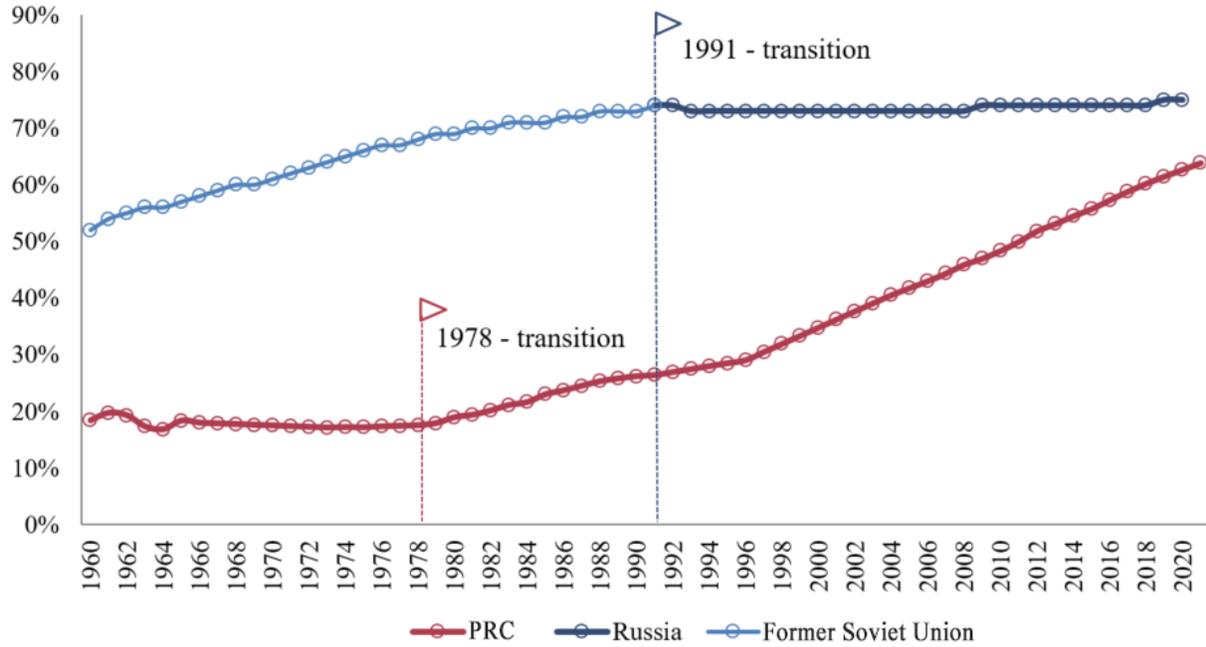
Kristina Butaeva, Lian Chen, Steven N. Durlauf, and Albert F. Park

ADB Economics Working Paper No. 807

October 2025

A OFFICIAL STATISTICS

Figure A1: Evolution of the Urban Population Share over Time

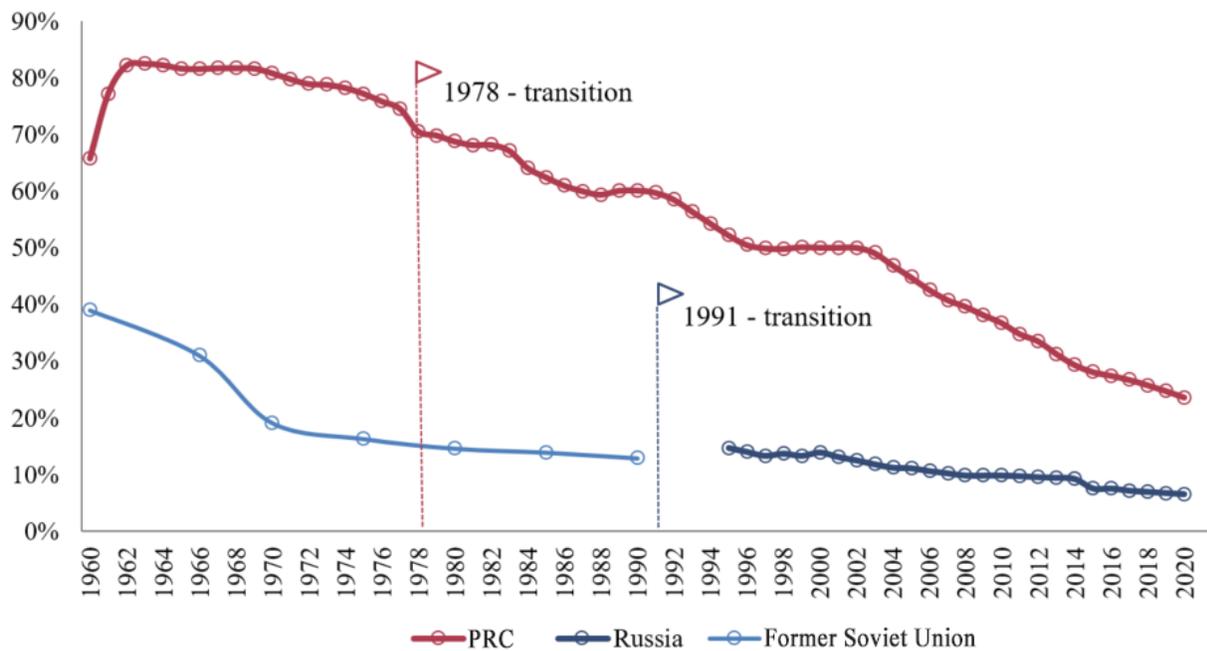


PRC = People's Republic of China.

Notes: This figure illustrates the evolution of the share of the urban population in the total population in the PRC and Russia from 1960 to 2020. Red and blue flags indicate the beginning of market reforms in the PRC and Russia, respectively.

Sources: Federal State Statistics Service of the Russian Federation; National Bureau of Statistics of China; Xu, van Leeuwen, and van Zanden (2018).

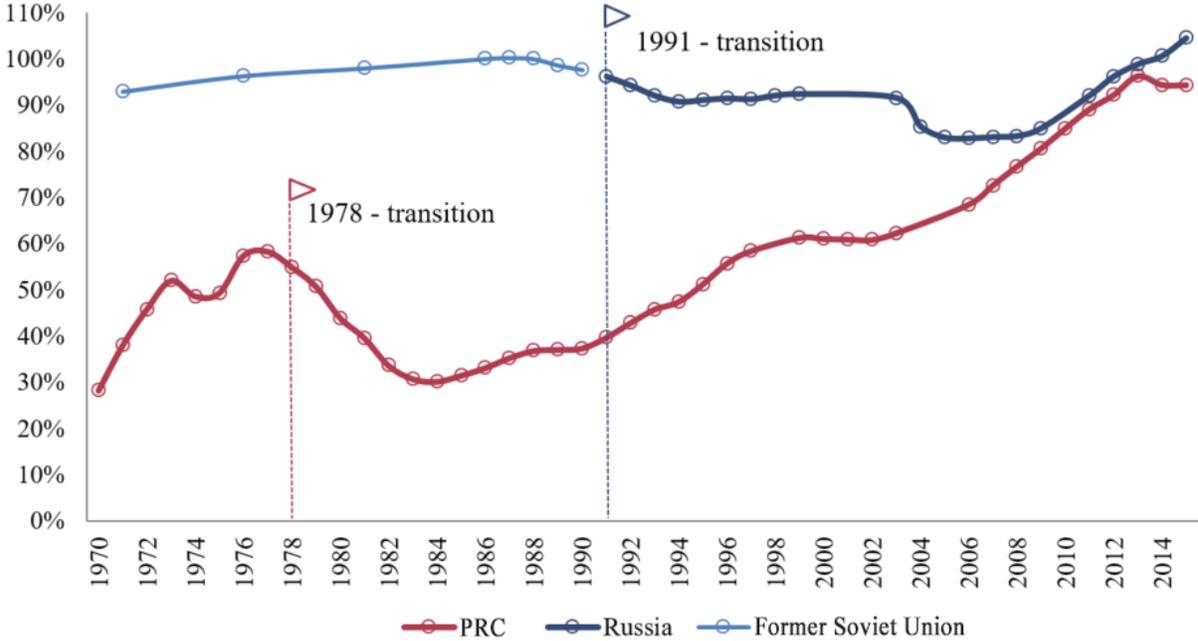
Figure A2: Evolution of the Employment Share in the Agriculture Sector over Time



Notes: This figure illustrates the evolution of the share of workers employed in the agriculture sector in the PRC and Russia from 1960 to 2020. Red and blue flags indicate the beginning of market reforms in the PRC and Russia, respectively.

Sources: Исторические материалы. www.istmat.org; Federal State Statistics Service of the Russian Federation; National Bureau of Statistics of China; Our World in Data. www.ourworldindata.org.

Figure A3: Evolution of the Gross Enrollment Ratio for Secondary Education over Time



Notes: This figure illustrates the evolution of the gross enrollment ratio for secondary education, defined as the number of individuals enrolled in secondary education expressed as a percentage of the population of the official secondary school-age group.

Source: Our World in Data. www.ourworldindata.org.

B SAMPLE CONSTRUCTION

B.1 Summary Statistics

Table B1: Descriptive Statistics of Key Sample Variables

	People's Republic of China			Russia		
	Obs.	Mean	SD	Obs.	Mean	SD
Male	8,788	0.53	0.50	3,718	0.48	0.50
Child's age	8,788	31.01	5.33	3,718	32.76	4.66
Father's age	8,365	58.50	8.01	3,404	60.38	7.24
Mother's age	8,293	56.40	7.41	3,632	58.34	7.00
Child's educational level	8,787	10.40	4.34	3,717	13.39	2.23
Father's educational level	8,446	6.55	4.33	3,317	12.26	1.60
Mother's education level	8,487	4.40	4.46	3,615	12.45	1.73
Father's age is missed	8,788	0.05	0.21	3,718	0.08	0.28
Mother's age is missed	8,788	0.06	0.23	3,718	0.02	0.15
Child's educational level is missed	8,788	0.00	0.01	3,718	0.00	0.02
Father's educational level is missed	8,788	0.04	0.19	3,718	0.11	0.31
Mother's educational level is missed	8,788	0.03	0.18	3,718	0.03	0.16
Child's primary job is missed	8,788	0.09	0.29	3,718	0.11	0.32
Father's primary job is missed	8,788	0.18	0.39	3,718	0.18	0.39
Mother's primary job is missed	8,788	0.21	0.41	3,718	0.12	0.32

SD = standard deviation.

Sources: China Family Panel Studies; Russian Longitudinal Monitoring Survey.

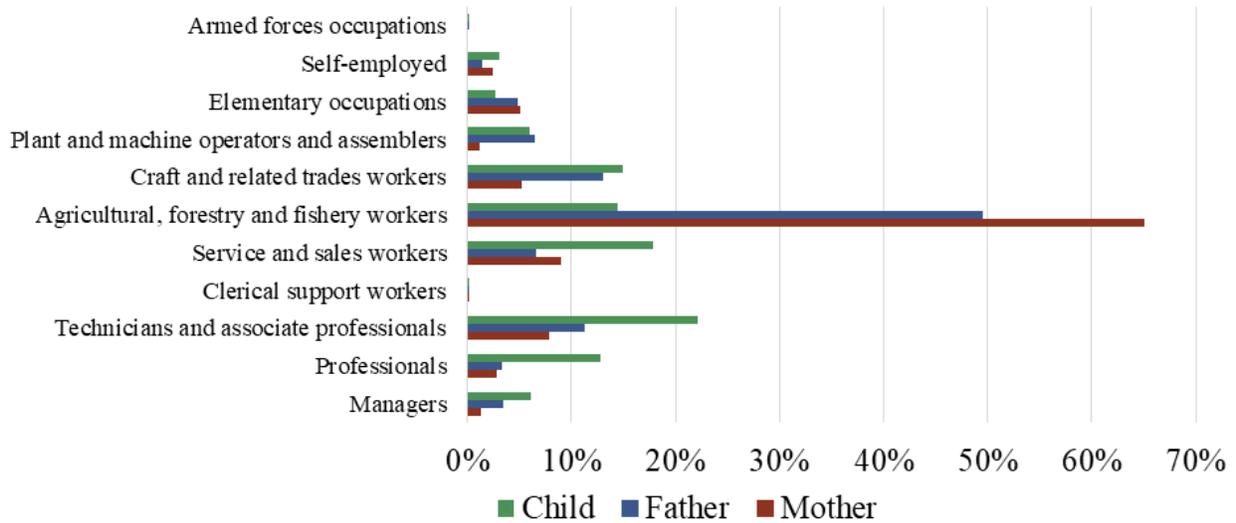
B.2 Survey Weights

To calculate nationally representative statistics, we apply survey weights. In CFPS, every household has a household weight, but individual weights are applied only for gene members of households, who were initially sampled in 2010, and newborns in the follow-up surveys. To keep more observations in our child–parent pairs, we assign for every individual their household weight, divided by the number of individuals in each family. This standardization allows us to equalize the chances of being sampled for individuals from households of a different size. In the RLMS-HSE, every wave consists of a representative sample of this year and a panel part. All households and household members from a representative sample have sample weights. The panel part consists of individuals who were in the representative sample at some year, but then left it because they moved to some other living address. The RLMS-HSE keeps tracking those

individuals and households but does not assign them survey weights. For our analysis, we use only observations on individuals who have individual survey weights.

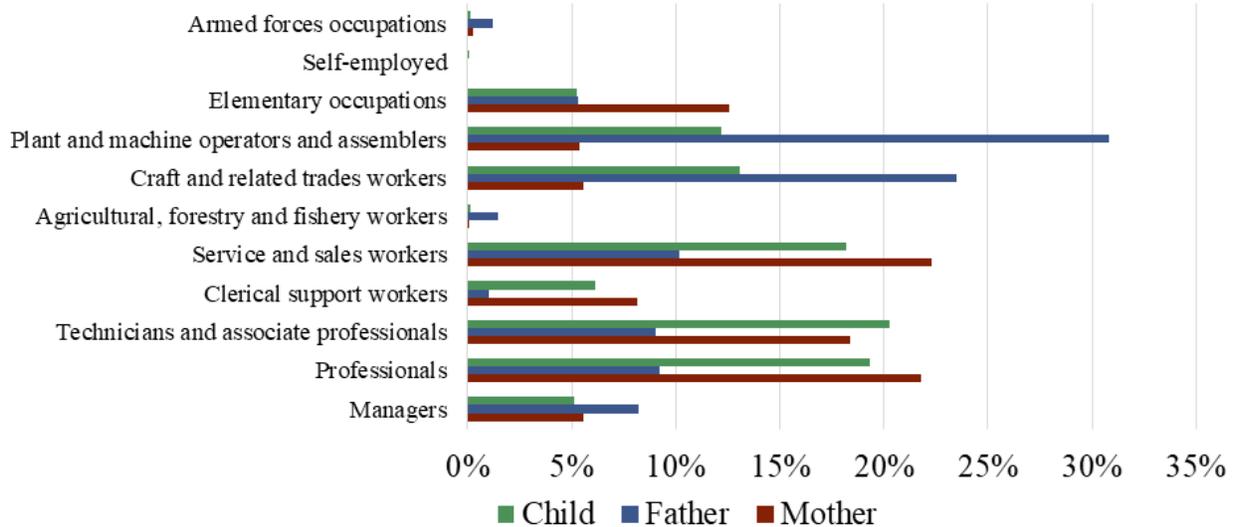
B.3 Distribution of Occupational Classes: Detailed

Figure B1: People’s Republic of China



Source: China Family Panel Studies.

Figure B2: Russia



Source: Russian Longitudinal Monitoring Survey.

B.4 Sample Representativeness

Table B2: Gender Composition

	People's Republic of China		Russia	
	CFPS	CSY 2019	RLMS-HSE	RSY 2019
% male	53%	51%	48%	46%

CFPS = China Family Panel Studies, CSY = China Statistical Yearbook, RLMS-HSE = Russia Longitudinal Monitoring Survey - Higher School of Economics, RSY = Russian Statistical Yearbook.

Notes: This table compares shares of males in our samples with the corresponding population figures.

Sources: Federal State Statistics Service of the Russian Federation; National Bureau of Statistics of China.

Table B3: Distribution of Educational Attainment

	People's Republic of China			Russia		
	22–40 y.o. in 2018		Children	Among employed		Children
	Census 2015	Census 2020	CFPS	RSY 2019	RLMS-HSE 2018	RLMS-HSE
Middle school	0.52	0.48	0.38	0.04	0.05	0.05
High school	0.22	0.20	0.20	0.62	0.64	0.54
College and above	0.26	0.32	0.42	0.34	0.31	0.41

CFPS = China Family Panel Studies, CSY = China Statistical Yearbook, RLMS-HSE = Russia Longitudinal Monitoring Survey - Higher School of Economics, RSY = Russian Statistical Yearbook.

Notes: This table compares the distribution of educational attainment in our samples with the corresponding population figures.

Sources: Federal State Statistics Service of the Russian Federation; National Bureau of Statistics of China.

Table B4: Distribution of Occupational Classes

	People's Republic of China			Russia		
	22–40 y.o. in 2018		Children	Among employed		Children
	Census 2015	CFPS	WEUR 2020	RLMS-HSE 2018	RLMS-HSE	
High-skilled	0.54	0.45	0.44	0.45	0.45	
Middle-skilled	0.20	0.23	0.20	0.20	0.24	
Low-skilled	0.26	0.32	0.36	0.35	0.32	

CFPS = China Family Panel Studies, RLMS-HSE = Russia Longitudinal Monitoring Survey - Higher School of Economics, RSY = Russian Statistical Yearbook.

Notes: This table compares the distribution of occupational classes in our samples with the corresponding population figures reported by the National Bureau of Statistics of China and the Federal State Statistics Service of Russia.

Sources: Federal State Statistics Service of the Russian Federation; National Bureau of Statistics of China.

C DATA FOR THE UNITED STATES

C.1 Survey Description

The data for the US are drawn from the Panel Study of Income Dynamics (PSID), a longitudinal household survey initiated in 1968 by the University of Michigan.¹ The PSID is one of the longest-running household panel studies globally. The original sample includes approximately 18,000 individuals residing in 5,000 households and is designed to be nationally representative, with an intentional oversampling of low-income families. Since its inception, the PSID has continuously followed all families, tracking them irrespective of geographic relocation. Our analysis utilizes all available waves of the PSID from 1968 through 2019 and includes both sample and non-sample individuals. Consistent with our approach to the CFPS, we designate the most recent wave (2019) as the baseline year. The final US sample comprises 8,042 child–parent pairs. Across survey years, wave-to-wave response rates range from 81.4% to 98%. Notably, in 2019, 3,232 individuals were traced back to the original 1968 sample.²

C.2 Survey Weights

In the PSID, the sample includes both sample individuals, who are assigned longitudinal and cross-sectional weights, and non-sample individuals, who are assigned only cross-sectional weights. Non-sample individuals are typically spouses, partners, or other household members residing with sample persons. In the early waves of the survey, non-sample individuals comprised a relatively small proportion of the total sample. For instance, in 1969, only 537 out of 17,212 individuals (approximately 3.1%) were non-sample persons. However, their share has grown substantially over time. By 2019, non-sample individuals constituted 26.9% of the total PSID sample (7,029 out of 26,084 individuals). As a result, excluding non-sample individuals from the analysis in recent waves would significantly reduce the sample size and statistical power. To address this issue, the PSID provides two types of weights: longitudinal weights, which are non-zero only for sample persons, and cross-sectional weights, which are available for both sample and non-sample individuals. To maximize the number of observations in our analysis of parent–child pairs and to ensure national representativeness, we employ the cross-sectional sampling weights provided by the PSID.

C.3 Summary Statistics

Table C3 presents summary statistics for the constructed US sample based on the PSID data. The average age of children in the US sample is 31 years, which is comparable to the average age of children in the PRC. In contrast, the average ages of parents in the US sample are more similar to those observed in the Russian sample. In terms of educational

¹ For more information, see <https://psidonline.isr.umich.edu>.

² Further details are available in the PSID User Guide: <https://psidonline.isr.umich.edu/Guide/documents.aspx>.

attainment, the US sample has the highest level of education among the three countries. On average, children, fathers, and mothers in the US have completed 14.0, 13.7, and 13.6 years of education, respectively.

Table C1: Distribution of Educational Attainment

	United States		
	Child	Father	Mother
Primary school and below	0.2%	2.4%	2.0%
Middle school	0.9%	5.1%	5.0%
High school	57.1%	48.4%	47.9%
College and above	41.8%	44.1%	45.2%

Notes: This table shows the distribution of educational attainment among children and their parents in our constructed sample from the Panel Study of Income Dynamics. Survey weights were applied to compute these shares.

Source: Authors' calculations.

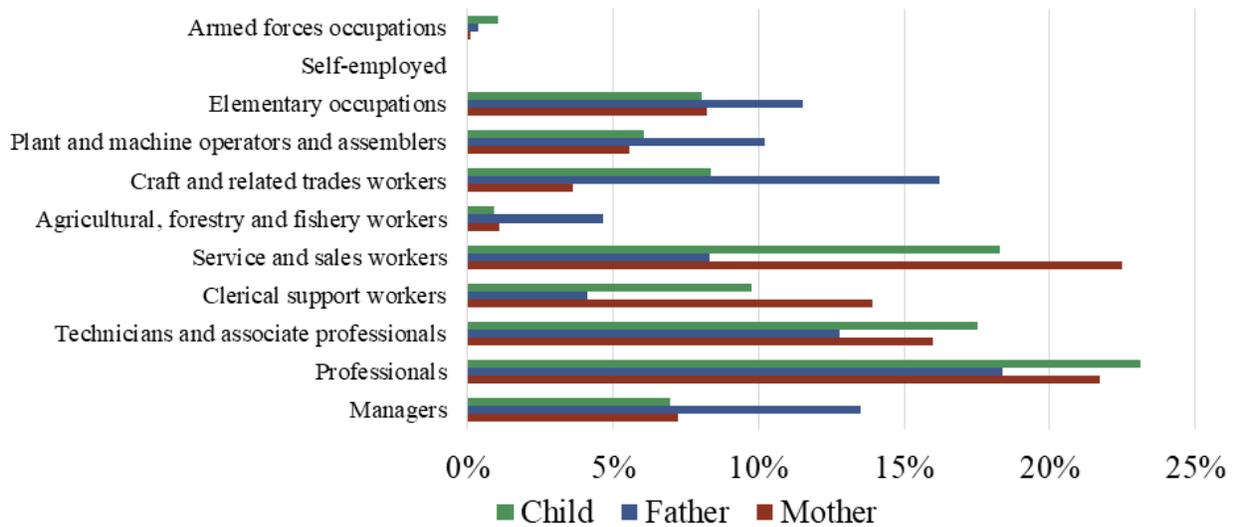
Table C2: Distribution of Occupational Classes

	United States		
	Child	Father	Mother
High-skilled occupations	48.0%	44.9%	45.0%
Middle-skilled occupations	29.6%	17.3%	37.6%
Low-skilled occupations	22.5%	37.9%	17.4%

Notes: This table shows the distribution of three major occupational classes among children and their parents in our constructed sample from the Panel Study of Income Dynamics (PSID). Our baseline occupational classification is the international International Standard Classification of Occupations (ISCO)-08 system, as used in the Russian Longitudinal Monitoring Survey. To ensure comparability, we first mapped the 2010 Census Occupational Classification from the PSID to ISCO-08, and then aggregated it into three broad occupational classes. Survey weights were applied to compute these shares.

Source: Authors' calculations.

Figure C1: Detailed Distribution of Occupational Classes in the United States



Source: Panel Study of Income Dynamics.

Table C3: Descriptive Statistics of Key Sample Variables

	United States		
	Obs.	Mean	SD
Male	8,042	0.47	0.50
Child's age	8,042	31.34	5.30
Father's age	3,990	60.10	7.92
Mother's age	5,150	56.88	7.71
Child's educational level	7,878	13.97	2.55
Father's educational level	6,607	13.46	3.01
Mother's educational level	7,279	13.67	2.87
Father's age is missed	8,042	0.50	0.50
Mother's age is missed	8,042	0.36	0.48
Child's educational level is missed	8,042	0.02	0.14
Father's educational level is missed	8,042	0.18	0.38
Mother's educational level is missed	8,042	0.09	0.29
Child's primary job is missed	8,042	0.23	0.42
Father's primary job is missed	8,042	0.23	0.42
Mother's primary job is missed	8,042	0.19	0.39

Source: Panel Study of Income Dynamics.

D COMPARISON TO LINEAR MODELS

Research on intergenerational mobility largely focuses on estimating the persistence of socioeconomic status between parents and children using linear regression models. These models link the outcome of a child from family i , Y_i^c to the outcome of their parent Y_i^p via

$$\log(Y_i^c) = \beta_0 + \beta_1 \log(Y_i^p) + \varepsilon_i, \quad (\text{D1})$$

where β_1 is an intergenerational *elasticity* (IGE). Economists typically study income IGEs, and sociologists focus on estimating the persistence of occupation. Another widely used measure is the intergenerational *correlation* coefficient (IGC), defined as:

$$\rho = \beta_1 \frac{\sigma^p}{\sigma^c} \quad (\text{D2})$$

where σ^p represents the standard deviation of the parental outcome variable $\text{SD}(Y_i^p)$, and σ^c is the standard deviation of the child's outcome variable $\text{SD}(Y_i^c)$.

The categorical nature of our data makes the Markov chain formulation of intergenerational links the natural one. Of course, this does not preclude the calculation of a regression coefficient. Regression models have in fact been used to study educational mobility in the PRC by Huo and Golley (2022) and for educational and occupational mobility in Russia by Gugushvili (2017). In this appendix, we show how linear approximations to the Markov chain formulation can lead to lost information.

Consider an economy comprising four major sectors. The first three sectors are from the standard classification: primary, secondary, and tertiary. The fourth sector, quaternary, refers to economic activities related to the intellectual or knowledge-based economy. In this economy, over 97% of the population works in the primary sector, while each of the remaining sectors accounts for only 1% of the workforce in period $t = 0$ (before a structural change). This scenario might capture a pre-industrial society. Consistent with our main focus, we study the impact of economic transition owing to structural changes, resulting from various reforms. This impact is illustrated by the transition dynamics described below. Assume that productivity and wages, or perceived “eliteness,” are monotonically increasing from the primary sector to the quaternary sector. After rapid industrialization and market reforms in period $t = 1$, there are many job opportunities emerging in the secondary and tertiary sectors. This influx attracts workers, particularly those from lower sectors. In our model, this is represented by a high speed of mixing between first, second, and third classes, with transitional probabilities denoted by $p_{12} = p_{13} = p_{22} = p_{23} = 0.49$. Here, p_{ij} indicates the probability that a child of a parent in the i^{th} sector works in the j^{th} sector. Owing to the perceived “eliteness” of the tertiary and quaternary sectors, there is significant persistence within these sectors.³

³ One way to rationalize this is to consider middle-class anxiety, whereby parents do everything possible to ensure their children do not fall below the same social class.

For instance, we can assume $p_{33} = p_{44} = 0.97$. In summary, we expect that the mobility process will evolve according to the following Markov chain:

$$\underbrace{\begin{pmatrix} 0.97 \\ 0.01 \\ 0.01 \\ 0.01 \end{pmatrix}^T}_{\mu^0} \times \underbrace{\begin{pmatrix} 0.01 & 0.49 & 0.49 & 0.01 \\ 0.01 & 0.49 & 0.49 & 0.01 \\ 0.01 & 0.01 & 0.97 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.97 \end{pmatrix}}_P = \underbrace{\begin{pmatrix} 0.01 \\ 0.48 \\ 0.49 \\ 0.02 \end{pmatrix}^T}_{\mu^1} \rightarrow \underbrace{\begin{pmatrix} 0.01 \\ 0.03 \\ 0.71 \\ 0.25 \end{pmatrix}^T}_{\mu^*} \quad (\text{D3})$$

where entry (i, j) is the p_{ij} defined above.

The equation (D3) illustrates how the dynamics of mobility in this economy change over time. An estimate of the standard intergenerational elasticity IGE is 0.20.⁴ This relatively low level of intergenerational persistence might suggest a highly mobile economy. However, a deeper analysis reveals that the IGE provides only a “snapshot” of the current mobility levels for parents at $t = 0$, denoted as μ^0 , and their children at $t = 1$, denoted as μ^1 . This high level of mobility is primarily attributable to the short-term impact of reforms that facilitate opportunities for children whose parents work in the primary sector. Numerically, this result is driven mostly by the distribution of probabilities in the first row of the transition matrix $P(1, j) = \{0.01, 0.49, 0.49, 0.01\}$, which is applied to the majority of the probability mass concentrated in sector one at period $t = 0$, $\mu_1^0 = 0.97$.

The short-term effects of reforms that caused structural changes results in a temporary increase in absolute mobility. However, this increase is not indicative of the true “inheritance” of the occupational class across generations in this society. As previously discussed, the estimated IGE could be misleading. In contrast, the proposed measures based on Markov chains provide a more comprehensive view of mobility, taking into account the full dynamics of the mobility process until it reaches its steady state. Using our “movement” measures, we can decompose the overall mobility. The estimate of the overall mobility from eq. (2) for $t = 1$, $OM^{t=1} = 0.966$, indicates that 96.6% of dynasties will change their job sector in the first step of the transition, confirming high mobility between current parents and children, as seen in a low IGE . The estimates of exchange mobility $EM^{t=1} = 0.006$ from eq. (4) and structural mobility $SM^{t=1} = 0.960$ from eq. (3) indicate that, among 96.6% of dynasties that change their class, the vast majority (96%) were involved in movements associated with temporary shifts in the distributional structure (from $\mu^0 = \{0.97, 0.01, 0.01, 0.01\}$ to $\mu^1 = \{0.01, 0.48, 0.49, 0.02\}$) driven by structural reforms. When the system stabilizes at the steady state, the remaining steady state mobility is $SSM = 0.053$, suggesting that only 5.3% of dynasties would move net of the effect of structural changes. Therefore, our movement concept implies that, once the effects of reforms fade away (and in the absence of any new structural changes), this economy is in fact a low-mobility society instead of the high-mobility “snapshot” captured by IGE . This distinction is crucial, especially when comparing multiple economies at different stages of their development or with and without ongoing economic shocks, like the two transition economies and one developed

⁴ This estimate is derived from a simulated dataset based on the transition dynamics described above.

economy covered in our empirical analysis. The memory concept, introduced in Appendix F, suggests that achieving equality of opportunities in this society would take approximately 113 generations, as indicated by the estimate $t^* = 113$. This implies a very low level of intergenerational mobility. Individual memory curves $IM^{t=1} = \{0.46, 0.46, 0.26, 0.72\}$ from eq. (F3) identify that class 4 is the slowest class and class 2 is the fastest class in this Markov chain.

This illustrative example suggests that a great deal of important information about the mobility process may remain hidden if one considers only *IGE* or *IGC*. We can highlight three main advantages of the proposed set of measures. First, these measures enable us to assess the current level of mobility by integrating the full range of information regarding potential mobility dynamics from time $t = 1$ to time t^* , thereby accurately capturing the potential changes in mobility dynamics within the Markov process. Second, the proposed steady state mobility measure helps distinguish between the mobility driven by changes in marginal structures—which may stem from exogenous transformations in the economy—and pure exchange mobility that persists at the steady state. This distinction is particularly important when studying intergenerational mobility in transition economies. Finally, unlike linear models, Markov chain models provide valuable instruments for analyzing cross-class heterogeneity in intergenerational mobility trends. This capability is especially useful for identifying bottlenecks in the mobility process, including poverty traps (Bernard and Durlauf, 1996). The latter point is illustrated in the following discussion.

Consider the following Markov chain:

$$\underbrace{\begin{pmatrix} 0.03 \\ 0.32 \\ 0.32 \\ 0.33 \end{pmatrix}^T}_{\mu^0} \times \underbrace{\begin{pmatrix} 0.997 & 0.001 & 0.001 & 0.001 \\ 0.001 & 0.333 & 0.333 & 0.333 \\ 0.001 & 0.333 & 0.333 & 0.333 \\ 0.001 & 0.333 & 0.333 & 0.333 \end{pmatrix}}_P = \underbrace{\begin{pmatrix} 0.03 \\ 0.32 \\ 0.32 \\ 0.33 \end{pmatrix}^T}_{\mu^1} \rightarrow \underbrace{\begin{pmatrix} 0.25 \\ 0.25 \\ 0.25 \\ 0.25 \end{pmatrix}^T}_{\mu^\infty} \quad (D4)$$

Let us assume that the first class ($i = 1$) represents the poorest group based on income, whereas the fourth class is the richest ($i = 4$). In this example, it is evident that the poorest class has limited communication with the other classes, as seen in the transition matrix from (D4). Children of parents from the poorest class have less than a 1% chance of improving their social class. At the same time, children of parents from classes 2 to 4 also have less than a 1% chance of descending into the poorest class. However, these probabilities are still non-zero, and, as time progresses $t \rightarrow \infty$, this Markov chain will eventually converge to a steady state distribution that maintains equal representation of classes in the population ($\mu^* = \{0.25, 0.25, 0.25, 0.25\}$). In a linear model, the coefficients of *IGE* and *IGC* for this example are $IGE = IGC = 0.29$, suggesting a relatively high degree of intergenerational mobility. These measures indicate low persistence of income class because 97% of the probability mass in the distribution of current parents ($\mu^{t=0}$) and children ($\mu^{t=1}$) are nearly evenly distributed between classes 2, 3, and 4, for which the transition matrix shows significant mobility (the probability to move between classes 2, 3, and 4 is 33.3%). Our proposed measure of overall mobility also fairly captures a large amount of movements $OM^{t=1} = 0.647$ between current parents' and children's classes, with an estimating probability of changing class equal to 64.7%. In this example,

we find a low estimate of structural mobility $SM^{t=1} = 0.007$ and a high estimate of exchange mobility $EM^{t=1} = 0.640$ mobility. The steady state mobility suggests that, after accounting for structural changes, the probability of exiting one's parents' income class in the steady state is 50.1% ($SSM = 0.501$). However, if we consider the proposed measures of memory, it becomes clear that this society experiences very slow progress toward achieving equal opportunities: it takes 514 generations to reach steady state ($t^* = 514$). Moreover, the class-specific measures of individual memory curves $IM^{t=1} = \{0.75, 0.25, 0.25, 0.25\}$ immediately highlight the bottleneck for the mobility process: it takes three times longer for individuals from the poorest class to mix with members of other classes compared to individuals from the other three classes. While one might argue that quantile regression could yield similar results, it is important to note that quantile regression is not commonly employed in the literature on intergenerational mobility. First, researchers need to recognize its potential application. Second, to find the slowest income class using quantile regression, the researcher should also make a correct prior guess on the definition of class boundaries. In contrast, our t^* measure of convergence time to the steady state directly reveals the potential existence of a poverty trap and clearly indicates that the Markov process is very slow. Then, both IM or quantile regression elasticity coefficients might be used for uncovering the potential bottlenecks to mobility.

E MOVEMENT MEASURES: DETAILED RESULTS

Table E1: Estimates of Overall, Structural, and Exchange Educational Mobility Measures over Generations t

	Father-to-child							Mother-to-child						
	t=1	t=2	t=3	t=4	t=5	t=6	t=7	t=1	t=2	t=3	t=4	t=5	t=6	t=7
OM, PRC	0.515	0.430	0.360	0.320	0.299	0.288	0.282	0.526	0.435	0.322	0.261	0.228	0.211	0.202
OM upward, PRC	0.469	0.326	0.237	0.188	0.162	0.148	0.140	0.507	0.365	0.239	0.171	0.135	0.115	0.105
OM downward, PRC	0.046	0.103	0.123	0.132	0.137	0.140	0.142	0.019	0.070	0.083	0.090	0.094	0.096	0.097
SM, PRC	0.350	0.183	0.100	0.053	0.029	0.015	0.008	0.427	0.235	0.126	0.067	0.035	0.019	0.010
EM, PRC	0.166	0.247	0.260	0.267	0.271	0.273	0.274	0.099	0.199	0.196	0.194	0.193	0.192	0.192
OM, Russia	0.466	0.442	0.432	0.428	-	-	-	0.446	0.435	0.430	0.429	-	-	-
OM upward, Russia	0.387	0.260	0.227	0.218	-	-	-	0.346	0.251	0.226	0.220	-	-	-
OM downward, Russia	0.079	0.182	0.205	0.211	-	-	-	0.100	0.185	0.204	0.209	-	-	-
SM, Russia	0.317	0.068	0.018	0.005	-	-	-	0.255	0.056	0.015	0.004	-	-	-
EM, Russia	0.148	0.373	0.413	0.423	-	-	-	0.191	0.380	0.416	0.424	-	-	-
OM, US	0.375	0.335	0.331	0.331	-	-	-	0.374	0.332	0.328	0.327	-	-	-
OM upward, US	0.212	0.171	0.166	0.166	-	-	-	0.194	0.164	0.163	0.163	-	-	-
OM downward, US	0.163	0.164	0.165	0.165	-	-	-	0.180	0.168	0.165	0.164	-	-	-
SM, US	0.066	0.006	0.001	0.000	-	-	-	0.092	0.013	0.003	0.001	-	-	-
EM, US	0.309	0.329	0.330	0.331	-	-	-	0.282	0.319	0.325	0.326	-	-	-

PRC = People's Republic of China, US = United States.

Notes: This table reports estimates of the overall mobility $OM^t(P, \mu^t, t)$ from eq. (2), exchange mobility $EM^t(P, \mu^t, t)$ from eq. (4), and structural mobility $SM^t(P, \mu^t, t)$ from eq. (3). Steady state mobility $SSM(P, \mu^*)$ from eq. (5) is represented by the final (rightmost) point estimate of exchange mobility.

Source: Authors' calculations.

Table E2: Estimates of Overall, Structural, and Exchange Occupational Mobility Measures over Generations t

	Father-to-child			Mother-to-child			
	t=1	t=2	t=3	t=1	t=2	t=3	t=4
OM, PRC	0.579	0.566	0.559	0.565	0.530	0.518	-
OM upward, PRC	0.467	0.323	0.291	0.488	0.323	0.276	-
OM downward, PRC	0.111	0.242	0.268	0.077	0.207	0.242	-
SM, PRC	0.339	0.058	0.010	0.363	0.092	0.024	-
EM, PRC	0.240	0.508	0.549	0.203	0.437	0.494	-
OM, Russia	0.574	0.536	0.519	0.536	0.529	0.530	0.530
OM upward, Russia	0.438	0.303	0.269	0.248	0.264	0.267	0.268
OM downward, Russia	0.136	0.233	0.250	0.288	0.265	0.263	0.263
SM, Russia	0.289	0.059	0.015	0.067	0.006	0.002	0.000
EM, Russia	0.285	0.477	0.504	0.469	0.524	0.529	0.530
OM, US	0.552	0.534	0.529	0.536	0.528	0.527	-
OM upward, US	0.338	0.273	0.264	0.260	0.259	0.258	-
OM downward, US	0.214	0.261	0.265	0.275	0.269	0.269	-
SM, US	0.158	0.015	0.004	0.075	0.007	0.001	-
EM, US	0.394	0.519	0.526	0.461	0.521	0.527	-

PRC = People's Republic of China, US = United States.

Notes: This table reports estimates of the overall mobility $OM^t(P, \mu^t, t)$ from eq. (2), exchange mobility $EM^t(P, \mu^t, t)$ from eq. (4), and structural mobility $SM^t(P, \mu^t, t)$ from eq. (3). Steady state mobility $SSM(P, \mu^*)$ from eq. (5) is represented by the final (rightmost) point estimate of exchange mobility.

Source: Authors' calculations.

F MEMORY MEASURES

F.1 Memory Measures

Formally, the distinction between “movement” and “memory” measures we use can be understood as follows. Consider three elementary transition matrices:

$$P_A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \quad P_B = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad P_C = \begin{pmatrix} p_x & p_y \\ p_x & p_y \end{pmatrix}. \quad (\text{F1})$$

Movement mobility indices capture the frequency of changing classes in the Markov chain.⁵ In this context, an example of the transition matrix P_A would represent a perfectly immobile society, while a matrix P_B would be considered perfectly mobile. In contrast, the “memory” concept focuses on the idea of “equality of opportunity”: in a perfectly mobile society, the likelihood of a child entering a particular social class is independent of the class

⁵ For instance, classic measures of movement include the share of mobile individuals, which is calculated as the sum of the off-diagonal elements of the transition matrix (Matras, 1961), or the count of class boundaries crossed during the transition process, as proposed by Bartholomew (1967).

of their father (Prais, 1955).⁶ This concept is illustrated by a matrix P_C , which features similar rows, indicating a similar distribution of probabilities of transitioning to any class from any original class. Both concepts of mobility can be analyzed by exploring the limiting properties of the Markov chain.

Under the memory concept, we are interested in measuring how quickly a society can achieve “equality of opportunities” within a Markov chain framework.⁷ In this context, societal “memory” refers to the time it takes for a particular society to reach a state in which an individual’s social class is not determined by their family background. We study the evolution of social classes as defined by the initial distribution μ^0 at every step of the transition t :

$$\mu^t = \mu^0 \cdot P^t \quad \rightarrow \quad \mu^* = \mu^0 \cdot P^\infty \quad (\text{F2})$$

In the steady state, the descendants of parents from the initial distribution μ^0 will face a limiting transition matrix P^∞ where each row matches μ^* . This means that all descendants of parents from the initial classes represented by μ^0 will have the same probabilities of transitioning to any given class. The process by which the distribution of transitioning probabilities becomes independent of origin is commonly referred to as “mixing” in the probability literature. Mobility measures under this framework aim to capture the speed at which a Markov chain converges to the steady state.

We employ the measure t^* , which defines a number of generations until the transition matrix reaches the steady state, as our baseline measure of mobility within the memory concept. In words, t^* indicates how quickly a society reaches the steady state where under the limiting transition matrix P^∞ all classes have an identical distribution of probabilities for transitioning to any other class, regardless of the starting class μ_i^0 .

In addition, we consider “class-specific” memory measures. For that, we employ individual memory curves introduced in Blume et al. (2025):

$$IM_i(P, \mu^*, t) = \| e_i \cdot P^t - \mu^* \|_{TV} = \frac{1}{2} \cdot \sum_{k=1}^n |P_{ik}^t - \mu_k^*|, \quad (\text{F3})$$

where e_i is a vector with weight 1 in class i and 0s in other classes. This measure describes the evolution of the “class-specific” deviation of the current “lottery”—which we refer to as each row of the transition matrix, as it defines the chances of reaching any class from every initial class i —from the steady state. By plotting these curves for different initial class i , we can illustrate the varying rates of memory decay depending on an ancestor’s specific class.

F.2 Results on Educational Mobility

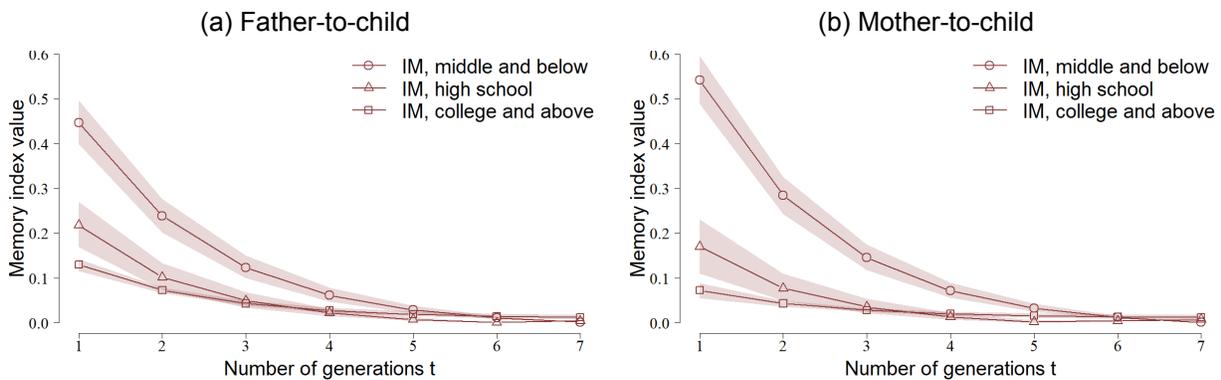
By comparing t^* (the largest number on the x -axis in Figures F1 and F2), we see that the overall memory of origin disappears by approximately the seventh generation in the PRC

⁶ Classic mobility indices related to this memory concept are measures of the speed of the convergence of the transition matrix based on its eigenvalues (Conlisk and Sommers, 1979; Shorrocks, 1978; Sommers and Conlisk, 1979).

⁷ We follow Blume et al. (2025).

and the fourth in Russia. Therefore, if the observed transition probabilities persist across future generations, Russia would reach a steady state—where a descendant’s class is unrelated to the class of the initial parent (representing equality of opportunity)—almost twice as fast as in the PRC. Individual memory curves depicted in Figures F1-F2) reveal that, in both Russia and the PRC, family dynasties originating from the “middle school and below” educational class are the least mobile. Notably, the lower educated class is substantially less mobile in the mother-to-child sample (Figure F1b) in the PRC. The same class in the father-to-child sample in the PRC is just as mobile as in both samples in Russia. In the PRC, memory fades more quickly for those originating from the “college and above” class, and in Russia “high school” and “college and above” classes have similar memory (conditioning on confidence intervals).⁸

Figure F1: Individual Educational Memory Curves for the People’s Republic of China



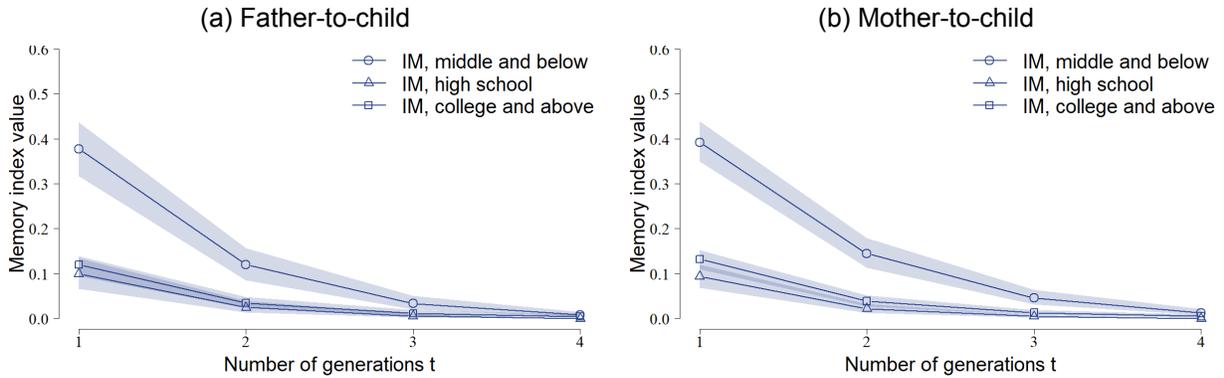
Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (a) and mother-to-child (b) samples in the People’s Republic of China. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors’ calculations.

The overall origin-memory disappears by the fourth generation in both Russia and the US and by the seventh generation in the PRC. The analysis of memory measures based on Figures F1, F2, and F3 suggests that, in the US, memory disappears with the same speed across all initial classes.

⁸ The full set of educational individual memory curves estimates is reported in Table F1.

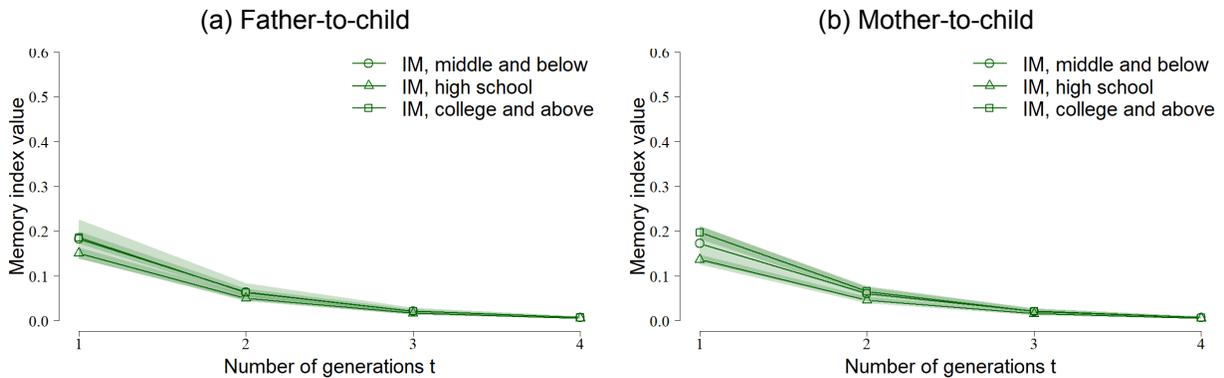
Figure F2: Individual Educational Memory Curves for Russia



Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (a) and mother-to-child (b) samples in Russia. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors' calculations.

Figure F3: Individual Educational Memory Curves for the United States



Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (a) and mother-to-child (b) samples in the United States. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors' calculations.

Table F1: Measures of Educational Memory

	Father-to-child							Mother-to-child						
	t=1	t=2	t=3	t=4	t=5	t=6	t=7	t=1	t=2	t=3	t=4	t=5	t=6	t=7
IM middle and below, PRC	0.447	0.239	0.124	0.062	0.029	0.011	0.001	0.541	0.284	0.145	0.072	0.033	0.012	0.001
IM high school, PRC	0.218	0.102	0.050	0.022	0.007	0.000	0.005	0.170	0.077	0.035	0.013	0.002	0.004	0.007
IM college and above, PRC	0.130	0.073	0.043	0.028	0.019	0.015	0.012	0.073	0.043	0.028	0.020	0.016	0.014	0.012
IM middle and below, Russia	0.378	0.120	0.034	0.008	-	-	-	0.392	0.145	0.046	0.013	-	-	-
IM high school, Russia	0.100	0.025	0.005	0.000	-	-	-	0.094	0.022	0.005	0.000	-	-	-
IM college and above, Russia	0.120	0.035	0.011	0.005	-	-	-	0.132	0.039	0.013	0.005	-	-	-
IM middle and below, US	0.182	0.064	0.022	0.007	-	-	-	0.172	0.061	0.021	0.007	-	-	-
IM high school, US	0.151	0.050	0.017	0.006	-	-	-	0.137	0.046	0.016	0.005	-	-	-
IM college and above, US	0.186	0.063	0.021	0.007	-	-	-	0.197	0.066	0.022	0.007	-	-	-

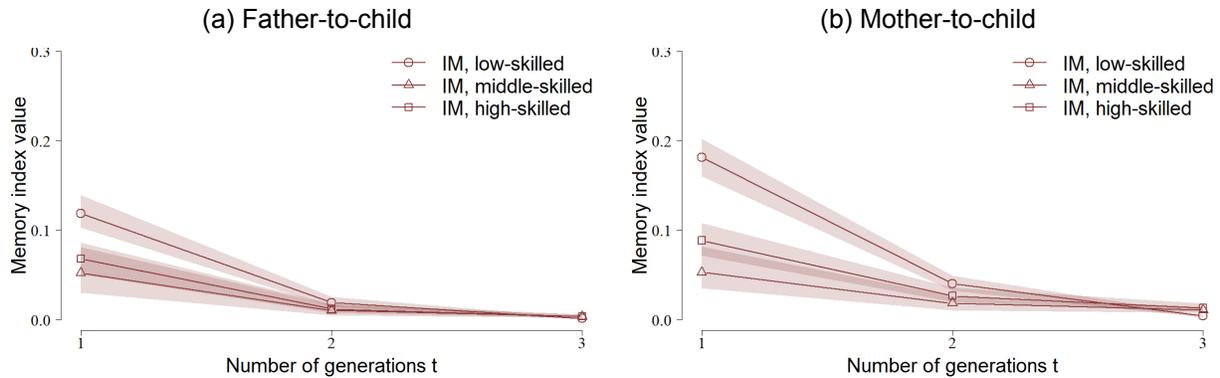
PRC = People's Republic of China, US = United States.

Notes: This table reports estimates of the individual memory measure $IM_i^t(P, \mu^*, t)$ from eq. (F3).

Source: Authors' calculations.

F.3 Results on Occupational Mobility

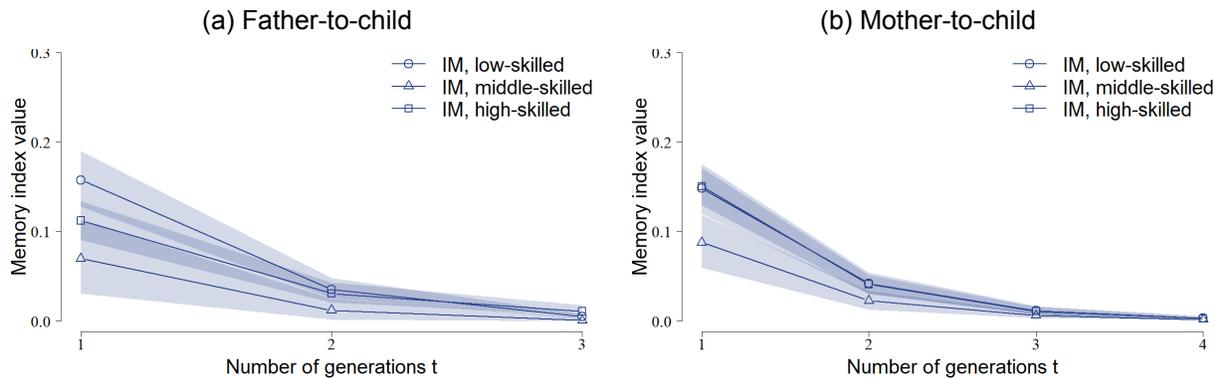
Figure F4: Individual Occupational Memory Curves for the People’s Republic of China



Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (left panel) and mother-to-child (right panel) samples in the People’s Republic of China. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors’ calculations.

Figure F5: Individual Occupational Memory Curves for Russia



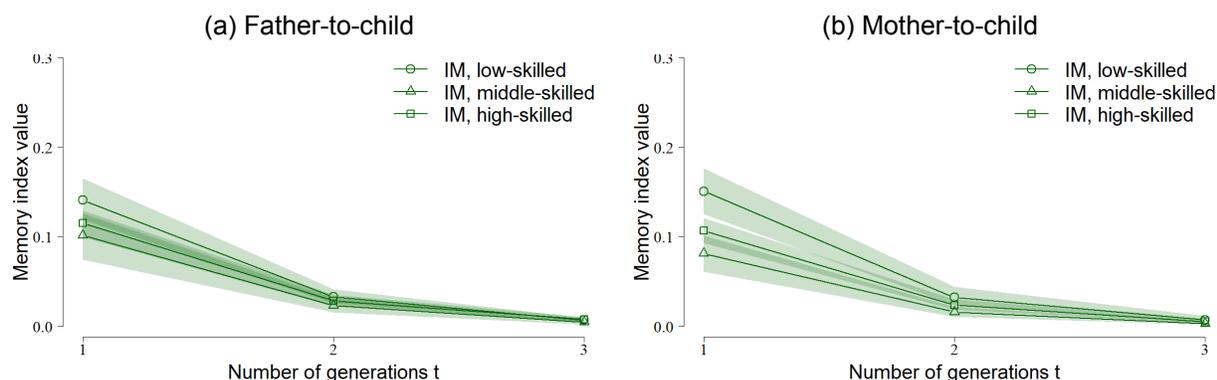
Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (a) and mother-to-child (b) samples in Russia. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors’ calculations.

The overall societal memory of occupational class origin dissipates by the third generation in the PRC and in the father-to-child sample in Russia. In the mother-to-child sample in Russia, the memory fades by the fourth generation. Figures F4 and F5 show that, in both the PRC and Russia, family dynasties originating from the “low-skilled” occupational class are the least mobile. In Russia, dynasties from “high-skilled” families in the mother-to-child sample are the least mobile as well. In both countries, the origin memory fades faster for those originating from the “middle-skilled” class.⁹

⁹ The full set of occupational individual memory curves estimates is reported in Table F2.

Figure F6: Individual Occupational Memory Curves for the United States



Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (a) and mother-to-child (b) samples in the United States. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors' calculations.

The total origin memory disappears by the third generation in all three countries except the mother-to-child sample in Russia, where it dissipates by the fourth generation. Similarly to the PRC and Russia, in the US dynasties originating from the “low-skilled” class exhibit the least mobility (Figure F6).

Table F2: Measures of Occupational Memory

	Father-to-child			Mother-to-child			
	t=1	t=2	t=3	t=1	t=2	t=3	t=4
IM low-skilled, PRC	0.119	0.019	0.002	0.182	0.040	0.004	-
IM middle-skilled, PRC	0.052	0.011	0.004	0.053	0.019	0.011	-
IM high-skilled, PRC	0.068	0.012	0.004	0.089	0.027	0.013	-
IM low-skilled, Russia	0.158	0.036	0.005	0.148	0.042	0.012	0.003
IM middle-skilled, Russia	0.070	0.012	0.001	0.088	0.023	0.006	0.002
IM high-skilled, Russia	0.112	0.031	0.011	0.151	0.041	0.011	0.003
IM low-skilled, US	0.141	0.033	0.007	0.151	0.032	0.007	-
IM middle-skilled, US	0.102	0.023	0.005	0.081	0.016	0.003	-
IM high-skilled, US	0.115	0.029	0.008	0.107	0.024	0.005	-

PRC = People's Republic of China, US = United States.

Note: This table reports estimates of the individual memory measure $IM_i^t(P, \mu^*, t)$ from eq. (F3).

Source: Authors' calculations.

G RESULTS ON THE CONVENTIONAL MOBILITY MEASURES

G.1 Educational Intergenerational Mobility

Comparison to the Economist's Measures

In this subsection, we document the intergenerational education elasticities and correlations. We estimate IGEs as $\hat{\beta}_1$ from the regression:

$$E_{1i} = \beta_0 + \beta_1 E_{0i} + \epsilon_i, \quad (\text{G4})$$

where E_{1i} is the child's years of schooling and E_{0i} is the parent's years of schooling.

Table G1: Educational Intergenerational Elasticity and Intergenerational Correlation

Variable	PRC		Russia		US	
	F-C E_{1i} (1)	M-C E_{1i} (2)	F-C E_{1i} (3)	M-C E_{1i} (4)	F-C E_{1i} (5)	M-C E_{1i} (6)
E_{0i}	0.387*** (0.0154)	0.376*** (0.0134)	0.254*** (0.0245)	0.293*** (0.0216)	0.261*** (0.0174)	0.263*** (0.0153)
Constant	8.448*** (0.133)	9.252*** (0.0969)	10.19*** (0.440)	9.944*** (0.385)	10.73*** (0.248)	10.60*** (0.217)
Observations	8,445	8,486	3,317	3,615	6,584	7,248
R-squared	0.162	0.167	0.033	0.051	0.132	0.118
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1						
Correlations	0.402	0.409	0.182	0.227	0.364	0.344

PRC = People's Republic of China, US = United States.

Note: This table reports estimates from the linear model specified in eq. (G4) for father-to-child (F–C) and mother-to-child (M–C) samples in the PRC, Russia, and the US.

Source: Authors' calculations.

One additional year of father's schooling is associated with 0.39 more children's years of schooling in the PRC and 0.25 more children's years of schooling in Russia (Table G1), which suggests a larger intergenerational mobility in Russia. A similar pattern is observed in mother-to-child pairs (IGE is equal to 0.38 in the PRC vs 0.29 in Russia). The two countries demonstrate divergent gender patterns. In the PRC, the estimated IGE between mothers and children is 0.01 lower than that between fathers and children, whereas the Russian IGE between mothers and children is 0.04 higher than that estimated from father–children pairs. This echoes the literature emphasizing the importance of maternal education on child development (eg., Cui, Liu, and Zhao, 2019). The point estimates of educational elasticities in our study are close to the existing empirical evidence on the PRC: based on CFPS, Huo and Golley (2022) estimate that IGE of education in the PRC ranges for different age cohorts from around 0.2 to 0.4 for males, and from 0.3 to 0.55 for females.

The estimates of intergenerational correlations between fathers and children are 0.40 in the PRC and 0.18 in Russia. We can notice a sharper difference between IGEs and IGCs in Russia compared to the PRC. The intergenerational correlations based on maternal educational attainment are higher in the PRC (0.40) than in Russia (0.23). The results on IGC conform with the findings by Huo and Golley (2022). They estimate IGC for males in the PRC at 0.2-0.4 and slightly larger for females, from 0.25 to 0.5.

A 1-year increase in parental years of schooling is associated with an average increase of 0.26 in children’s years of schooling for both father-to-child and mother-to-child pairs in the US. Our results are lower than those reported in the existing literature. Previous studies, such as Hertz, Jayasundera, Piraino, Selcuk, Smith, and Verashchagina (2008) and Couch and Dunn (1997), estimated educational intergenerational elasticity from the PSID at around 0.46. In a later study by Hilger (2015), employing multiple datasets,¹⁰ educational elasticity coefficient was estimated at around 0.4. The difference in our results might be explained by the fact that we consider younger birth cohorts of children in comparison to the studies mentioned.

Comparison to the Sociologist’s Measures

Table G2: Levels Matrix for a Model of the Common Pattern of Educational Mobility

	Middle and below	High school	College or above
(a) Father-to-child sample			
Middle and below	4	2	1
High school	3	3	4
College or above	1	4	3
(b) Mother-to-child sample			
Middle and below	3	2	2
High school	2	1	2
College or above	1	1	3

Source: Authors’ calculations.

We also compare the results on exchange mobility to the log-multiplicative layer effect model introduced by Xie (1992). This model, commonly used in sociology, measures the strength of dependencies between categorical variables. Specifically, it restricts variation in the origin-destination association across transition matrices to be the log-multiplicative product of a common association pattern and a matrix-specific deviation parameter. Table G3 replicates a set of six models from Table 2 of Xie (1992) using our educational data for the PRC, Russia, and the US. According to the *BIC* statistics, only a cross-nationally heterogeneous levels model H_l in the father-to-child sample is better than the saturated model, for which $BIC = 0$, and none of our models

¹⁰They use data from the US Census, the PSID, the National Longitudinal Survey of Youth 1979 and 1997 (NLSY79 and NLSY97), the Occupational Change in a Generation 1973 survey (OCG73), and the General Social Survey (GSS).

Table G3: Goodness-of-Fit Results of Uniform and Log-Multiplicative Layer Effect Models: Education

Model	Description	L^2	df	p	BIC	ϕ_1 PRC	ϕ_2 Russia	ϕ_3 US
(b) Father-to-child sample								
NA	Null association between R and C , given L	4,158.80	12	0.000	4,041	-	-	-
FI_0	Cross-nationally homogeneous full two-way R and C interaction	118.89	8	0.000	40	-	-	-
FI_x	Cross-nationally log-multiplicative full two-way R and C interaction	76.46	6	0.000	18	0.686	0.424	0.592
H_0	Cross-nationally homogeneous levels model (Table G2)	119.45	9	0.000	31	-	-	-
H_x	Cross-nationally log-multiplicative levels model (Table G2)	76.46	7	0.000	8	0.686	0.424	0.591
H_l	Cross-nationally heterogeneous levels model (Table G2)	22.06	3	0.000	-7	-	-	-
(b) Mother-to-child sample								
NA	Null association between R and C , given L	4,659.16	12	0.000	4,541	-	-	-
FI_0	Cross-nationally homogeneous full two-way R and C interaction	158.14	8	0.000	79	-	-	-
FI_x	Cross-nationally log-multiplicative full two-way R and C interaction	92.31	6	0.000	33	0.723	0.405	0.559
H_0	Cross-nationally homogeneous levels model (Table G2)	186.49	10	0.000	88	-	-	-
H_x	Cross-nationally log-multiplicative levels model (Table G2)	101.34	8	0.000	22	0.703	0.422	0.572
H_l	Cross-nationally heterogeneous levels model (Table G2)	90.01	6	0.000	31	-	-	-

PRC = People's Republic of China, US = United States.

Notes: This table show the goodness-of-fit results of uniform and log-multiplicative layer effect models from Table 2 in Xie (1992), estimated from our educational data. R is row variable (parental class), C is column variable (child's class), L is layer variable (country), L^2 is the log-likelihood ratio chi-square statistic with the degrees of freedom reported in column df and the p -value in column p . $BIC = L^2 - (df)\log(N)$, where N is the total number of observations. The ϕ parameters are normalized so that $\sum \phi_k^2 = 1$.

Source: Authors' calculations.

has as good fit as those in Xie (1992)'s original paper. For our analysis, we focus on comparing country-specific ϕ_k 's from a full interaction FI_x and Hauser's (Hauser, 1978; Hauser and Schuessler, 1979) H_x level models to our results on exchange mobility.¹¹ Parameters ϕ_k define the ordering of the strength of association between origins and destinations across countries. It should be described in more detail how we construct the levels matrix for the H_x model. A levels matrix is a matrix that aims to represent a common pattern of social mobility across societies, a common "topology." In Xie (1992),

¹¹For more details on other models as well as for the general settings please refer to Xie (1992).

a six-levels 7×7 matrix introduced in Erikson, Goldthorpe, and Portocarero (1982) was used to analyze occupational mobility in England, France, and Sweden. In our analysis, we examine 3×3 matrices and therefore might have up to four levels in our levels matrix, given only $(R - 1) \times (C - 1)$ degrees of freedom, where R refers to the number of rows and C is the number of columns. With this in mind, our approach involves solving an optimization problem to search for a 3×3 matrix filled with integers from 1 to 4 that minimizes the BIC statistics in the H_x model (262,144 possible combinations need to be estimated). Therefore, this approach already guarantees the lowest possible *BIC* in the H_x model for our cross-country data. Estimated levels matrices are presented in Table G2. The results from the estimated ϕ_k are close to our conclusions from point estimates for cross-country comparison of exchange mobility: for both father-to-child and mother-to-child samples ϕ_k , estimates suggest more educational intergenerational mobility in Russia than in the US, and substantially less in the PRC.

G.2 Occupational Intergenerational Mobility

Comparison to the Economist's Measures

We estimate the occupational elasticity coefficient (IGE) as $\hat{\beta}_1$ from the specification:

$$\log(P_{1i}) = \beta_0 + \beta_1 \log(P_{0i}) + \epsilon_i, \quad (\text{G5})$$

where P_{1i} is child's and P_{0i} is parent's Standard International Occupational Prestige Scale (SIOPS) (Ganzeboom and Treiman, 1996), also known as Treiman's (Treiman, 1977) prestige scores.

Table G4: Occupational Intergenerational Elasticity and Intergenerational Correlation

Variable	PRC		Russia		US	
	F-C $\log(P_{1i})$ (1)	M-C $\log(P_{1i})$ (2)	F-C $\log(P_{1i})$ (3)	M-C $\log(P_{1i})$ (4)	F-C $\log(P_{1i})$ (5)	M-C $\log(P_{1i})$ (6)
$\log(P_{0i})$	0.167*** (0.0232)	0.116*** (0.0256)	0.248*** (0.0196)	0.220*** (0.0169)	0.202*** (0.0188)	0.222*** (0.0195)
Constant	3.141*** (0.0828)	3.327*** (0.0892)	2.832*** (0.0727)	2.921*** (0.0634)	2.978*** (0.0705)	2.896*** (0.0730)
Observations	6,357	6,138	2,693	2,942	4,782	4,857
R-squared	0.022	0.011	0.057	0.065	0.047	0.052
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1						
IGC	0.149	0.106	0.239	0.254	0.218	0.228

PRC = People's Republic of China, US = United States.

Notes: This table reports estimates from the linear model specified in eq. (G5) for father-to-child (F-C) and mother-to-child (M-C) samples in the PRC, Russia, and the US.

Source: Authors' calculations.

The estimated occupational IGEs are lower than their educational counterparts in both countries, but the relative comparisons between the PRC and Russia (Table G4) present a similar pattern: the estimated IGEs in the PRC (0.17 for father-to-child and 0.12 for mother-to-child sample) are lower than those in Russia (0.25 for father-to-child and 0.22 for mother-to-child sample). Unlike the educational results, which are lower than those found in the literature, our occupational elasticities agree with Gugushvili (2017), who find intergenerational associations in social class (but not occupations per se) at around 0.23 in contemporary Russia.

After taking into account the variance in the distribution of occupation among parents and children, we found the same result from the IGCs: Russia is a less mobile society compared to the PRC in terms of the intergenerational transmission of occupations.

In the US, a 1% percent rise in the occupational score of a parent is associated with a 0.20% increase (for the father-to-child sample) or 0.22% increase (for the mother-to-child sample) in a child’s occupational prestige score. These estimates are lower than those reported in the existing literature. Hauser and Warren (1997) claim the existing studies report father–son correlations in occupational class (typically measured by Socioeconomic Status Index—SEI) between 0.35 and 0.45 in the US. A more recent paper by Mazumder and Acosta (2015) has also found a father–son intergenerational elasticity coefficient of 0.35 using a 10-year average of the Nakao-Treas Occupational Prestige measure and the Hauser-Warren Socioeconomic Index from the PSID. Both measures resulted in very close estimates of occupational IGE. IGE comparison suggests there is greater intergenerational mobility of occupation in the PRC than in the US and Russia. Even after correction for the difference in variability of occupation among parents and children, the IGC analysis reveals the same result.

Comparison to the Sociologist’s Measures

Table G5: Levels Matrix for a Model of the Common Pattern of Occupational Mobility

	Low-skilled	Middle-skilled	High-skilled
(a) Father-to-child sample			
Low-skilled	2	4	1
Middle-skilled	4	1	1
High-skilled	1	1	2
(b) Mother-to-child sample			
Low-skilled	2	2	3
Middle-skilled	3	2	3
High-skilled	3	2	2

Source: Authors’ calculations.

Table G6 shows Xie (1992)’s uniform and log-multiplicative layer effect models estimated based on our occupational data. The common topology levels matrices for Hauser’s H_x level models, estimated by minimizing the *BIC* statistics, are presented in Table G5. According to the *BIC* statistics, the model’s fits are better than those for

Table G6: Goodness-of-Fit Results of Uniform and Log-Multiplicative Layer Effect Models from Xie (1992): Occupation

Model	Description	L^2	df	p	BIC	ϕ_1 PRC	ϕ_2 Russia	ϕ_3 US
(a) Father-to-child sample								
NA	Null association between R and C , given L	699.81	12	0.000	585	-	-	-
FI_0	Cross-nationally homogeneous full two-way R and C interaction	86.36	8	0.000	10	-	-	-
FI_x	Cross-nationally log-multiplicative full two-way R and C interaction	64.47	6	0.000	7	0.427	0.638	0.641
H_0	Cross-nationally homogeneous levels model (Table G5)	87.98	10	0.000	-8	-	-	-
H_x	Cross-nationally log-multiplicative levels model (Table G5)	64.94	8	0.000	-12	0.425	0.638	0.642
H_l	Cross-nationally heterogeneous levels model (Table G5)	20.36	6	0.002	-37	-	-	-
(b) Mother-to-child sample								
NA	Null association between R and C , given L	1,043.30	12	0.000	929	-	-	-
FI_0	Cross-nationally homogeneous full two-way R and C interaction	84.49	8	0.000	8	-	-	-
FI_x	Cross-nationally log-multiplicative full two-way R and C interaction	83.41	6	0.000	26	0.587	0.544	0.599
H_0	Cross-nationally homogeneous levels model (Table G5)	90.32	11	0.000	-15	-	-	-
H_x	Cross-nationally log-multiplicative levels model (Table G5)	90.14	9	0.000	4	0.578	0.566	0.588
H_l	Cross-nationally heterogeneous levels model (Table G5)	90.14	9	0.000	4	-	-	-

PRC = People's Republic of China, US = United States.

Notes: This table show the goodness-of-fit results of uniform and log-multiplicative layer effect models from Table 2 in Xie (1992), estimated from our occupational data. R is row variable (parental class), C is column variable (child's class), L is layer variable (country), L^2 is the log-likelihood ratio chi-square statistic with the degrees of freedom reported in column df and the p -value in column p . $BIC = L^2 - (df)\log(N)$, where N is the total number of observations. The ϕ parameters are normalized so that $\sum \phi_k^2 = 1$.

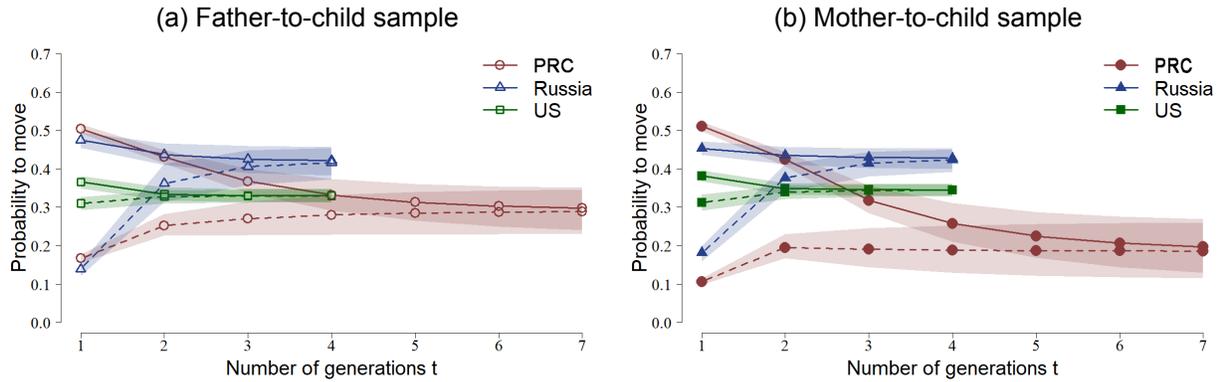
Source: Authors' calculations.

educational data, and again none matches the fit of the Xie (1992) paper. The full interaction FI_x and Hauser's H_x level models fit slightly better for the father-to-child sample compared to the mother-to-child sample. The comparison of ϕ_k implies there is greater exchange mobility in the PRC than in Russia and the US in the father-to-child sample, while Russia shows more mobility than the PRC and the US in the mother-to-child sample.

H ELDER CHILD ROBUSTNESS CHECK

H.1 Educational Mobility

Figure H1: Dynamics of Overall, Structural, and Exchange Educational Mobility

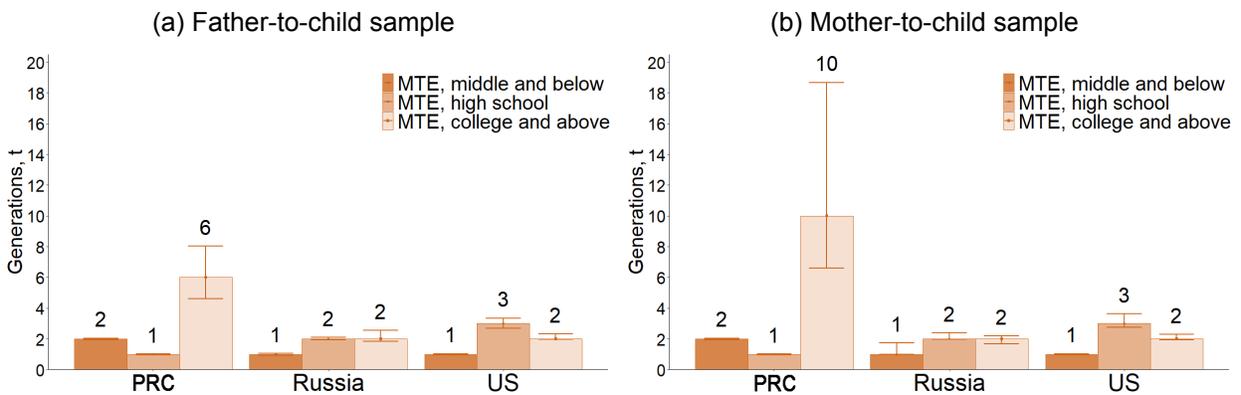


PRC = People's Republic of China, US = United States.

Notes: These figures plot overall mobility $OM^t(P, \mu^t, t)$ (solid lines), exchange mobility $EM^t(P, \mu^t, t)$ (dashed lines), and structural mobility $SM^t(P, \mu^t, t)$ (the vertical distance between solid and dashed lines) for father-to-child (F-C) and mother-to-child (M-C) elder sibling samples. Steady state mobility $SSM(P, \mu^*)$ is represented by the final (rightmost) point on each mobility curve, where overall mobility equals exchange mobility. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors' calculations.

Figure H2: Mean Time to Exit Each Educational Class



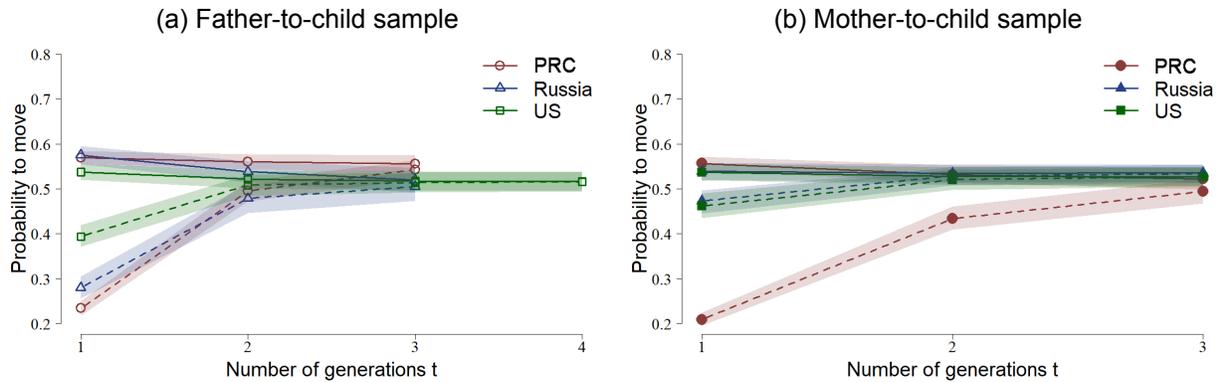
MTE = mean time to exit, PRC = People's Republic of China, US = United States.

Notes: These figures display mean time to exit MTE each educational class, as defined in equation (6), separately for father-to-child and mother-to-child elder sibling samples. The error bars represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors' calculations.

H.2 Occupational Mobility

Figure H3: Dynamics of Overall, Structural, and Exchange Occupational Mobility

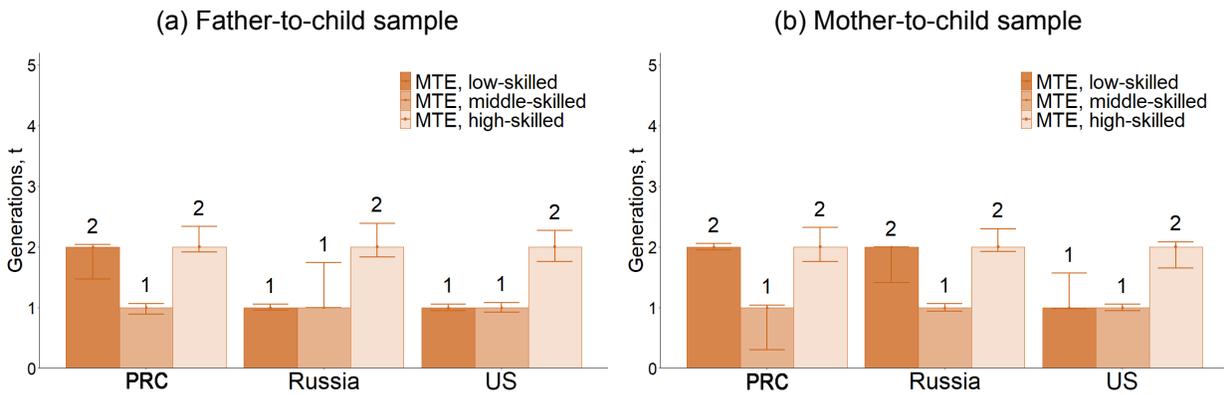


PRC = People's Republic of China, US = United States.

Notes: These figures plot overall mobility $OM^t(P, \mu^t, t)$ (solid lines), exchange mobility $EM^t(P, \mu^t, t)$ (dashed lines), and structural mobility $SM^t(P, \mu^t, t)$ (the vertical distance between solid and dashed lines) for father-to-child (F-C) and mother-to-child (M-C) elder sibling samples. Steady state mobility $SSM(P, \mu^*)$ is represented by the final (rightmost) point on each mobility curve, where overall mobility equals exchange mobility. Shaded areas represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors' calculations.

Figure H4: Mean Time to Exit Each Occupational Class



PRC = People's Republic of China, US = United States.

Notes: These figures display the mean time to exit MTE each occupational class, as defined in equation (6), separately for father-to-child and mother-to-child elder sibling samples. The error bars represent 95% confidence intervals derived from 1,000 bootstrap samples.

Source: Authors' calculations.