WORKING PAPER · NO. 2025-110

A Tale of Two Transitions: Mobility Dynamics in China and Russia after Central Planning

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AUGUST 2025

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August 2025
JEL No. I24, J62, P2

ABSTRACT

This paper examines intergenerational mobility in China and Russia during their transitions from central planning to market systems. We consider mobility as movement captured by changes in status between parents and children. We provide estimates of overall mobility, which involves mobility during transition to a system's steady state, as well as steady state mobility, which captures long-run mobility independent of transitional dynamics or shifts in the marginal distribution of outcomes across generations. We further decompose overall mobility into structural and exchange components. We find that China exhibits more overall educational mobility than Russia mostly due to greater structural mobility, while Russia exhibits greater steady state educational mobility. In contrast, both the overall and steady state occupational mobility is similar in China and Russia. Comparing these results to the US, we find that steady state mobility in education is substantially higher in the US and Russia compared to China, but occupational steady state mobility is comparable in all three countries.

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1 Introduction

The end of central planning and the emergence of market economies in China and Russia represents one of the major economic and social transformations of the last century. While the effects of these transitions on overall economic activity have been widely studied, there is comparatively less work on the evolution of various dimensions of inequality in these societies. This paper adds to this still nascent literature by studying intergenerational mobility dynamics in China and Russia.[1] As education and occupation are both measured discretely, we use Markov chain methods to characterize intergenerational mobility. We focus on measures that characterize mobility as movement, i.e. the extent to which children can differ from their parents.

There are many measures of intergenerational mobility that have been developed for Markov chain transition matrices (Bartholomew, 1967; Conlisk, 1990; Dardanoni, 1993; Prais, 1955; Shorrocks, 1978). Here we focus on mobility as movement between the class of parents and children. We do this as the data under our sample explore the relationship between parents who grew up and became adults under central planning and children who grew up in a market economy. Hence, the "escape" of new generations from the structures that produced parental outcomes is a natural focus for analysis. In an appendix, we consider other ways to conceptualize mobility.[2]

Operationally, for the generation of parents in our study, we trace out the way that status iterates across future generations, were the parent-child Markov transition matrix is invariant.[3] This approach produces mobility curves that illustrate how a given parent's status filters across near and distant generations. The mobility curve approach, by focusing on all future generations, avoids a limitation of some Markov chain mobility measures, such as the use of the second largest eigenvalue (Conlisk & Sommers, 1979; Shorrocks, 1978; Sommers & Conlisk, 1979), which measure mobility only after many generations have elapsed. These exercises thus should not be interpreted as forecasts. Rather, these curves reveal information about the persistence of current parental status across future generations if the current transition process linking parents to children

[1] Educational intergenerational mobility (IGM) in China is studied by Huo and Golley (2022); Xie, Dong, Zhou, and Song (2022), and in Russia by Gugushvili (2017); Roshchina (2012); Yasterbov (2016). Examples of studies on occupational IGM include Sun, Lei, and Liu (2021); Xie et al. (2022); Zhou and Xie (2019) for China, and (Bessudnov, 2016; Gerber & Hout, 2004; Gugushvili, 2017; Marshall, Sydorenko, & Roberts, 1995; Yasterbov, 2016) for Russia. Income IGM in China has been analyzed by (Congbin & Weifang, 2008; Fan, Yi, & Zhang, 2021; Gong, Leigh, & Meng, 2012; Huang, Huang, & Shui, 2021; Yan & Deng, 2022; Zhigang & Lin, 2013), and in Russia by Borisov and Pissarides (2020). Most of these papers employ variants of linear models as opposed to Markov chain models whose value we discuss below.

[2] Appendix D presents results based on classical measures from the economics literature, including intergenerational elasticity (IGE) and intergenerational correlation (IGC) derived from linear models, as well as traditional sociological measures estimated using log-multiplicative layer effect models. While some of the obtained results are consistent with our main findings, others diverge, which demonstrates the additional informational content of our measures. Appendix F provides a supplementary analysis of intergenerational mobility using memory-based measures. These measures yield the same cross-country ranking of mobility as our preferred steady-state mobility index, although memory measures per se have a different conceptual interpretation.

[3] Here we follow Blume, Cholli, Durlauf, and Lukina (2025), who propose such calculations for memory across generations.

were to remain constant. As such they constitute a way to extract the full informational content on intergenerational dependence from a given transition matrix.

We augment these calculations with some novel measures of mobility. Any study of mobility between parents and children in China and Russia during this period must account for the fact that the observed mobility is generated by an evolving dynamical system; this evolution is part of the what determines mobility. Sociology distinguishes between structural and exchange mobility (Broom & Jones, 1969; Featherman, Jones, & Hauser, 1975; Matras, 1961) for this reason. Structural mobility typically refers to mobility induced by changes in the cross-sectional distribution of outcomes. A classic example of structural mobility is the evolution of the occupational distribution resulting from movements away from agriculture. Exchange mobility refers to mobility that only depends on the probability transition function. Motivated by these ideas, we propose measures of structural and exchange mobility that naturally derive from mobility as movement. Structural mobility is measured as that mobility that is induced by the fact that the cross-sectional density is evolving. Exchange mobility is defined as the difference between overall mobility and structural mobility. Further, we propose a new measure of mobility, steady state mobility, for the mobility that is intrinsic to the mechanisms linking parents and children. Here, we follow the logic of distinguishing between economic growth induced by transition dynamics as opposed to growth that will occur in an economy near its steady state (Bernard & Durlauf, 1996; Durlauf, Johnson, & Temple, 2005). This differs from the way that exchange mobility is conventionally characterized because the measure respects that the aggregate mobility experiences of a population do depend on the cross section distribution of parental outcomes.

While the Chinese and Russian cases both involve transitions from central planning to market economies, they contain important differences. First, the Russian transition is associated with regime collapse while the Chinese transition was implemented by the same regime. Second, the Russian transition was a variant of shock therapy, while China pursued gradual reforms. Third, China and Russia started their transitions from very different initial stages of economic development. Russia was already an industrialized, urban economy, while China was poor and mostly agrarian. As a result, we will also explore ways to interpret differences between Chinese and Russian mobility patterns given these dissimilarities in their transitions.

Our study makes two important empirical contributions. First, we document the very high levels of overall mobility in China and Russia during these three decades of transition. For education, the probability of changing educational class for children is very high for China (52-53%) and for Russia (45-46%). These differences occur at different levels of education as mobility in China is driven by children who, unlike their parents complete either high school or college. For Russia, mobility is entirely due to increased college attendance. Similar results hold for occupational mobility. Overall mobility rates are closely aligned for China (57-58%) and Russia (54-57%). However, the underlying sources are very different. Chinese occupational mobility is driven by movements out of agriculture while Russian mobility is driven by shifts away from the manufacturing sector.

Second, we demonstrate these dramatic changes are largely due to structural rather than exchange mobility. Approximately 68-81% of individuals in China and 57-68%

in Russia who transitioned out of their parental educational class did so as a result of the gap between the cross-sectional distribution of parental and child educational attainment. The structural component of occupational mobility accounts for 60% of the changes in occupational classes between parents and children in China. A similar trend is observed in Russia, where structural mobility is responsible for 50% of class shifts in the father-to-child sample. In the mother-to-child sample, we observed relatively smaller structural mobility at 13%, as women in the Soviet Union already held higher positions within the occupational structure.

After accounting for the effects of structural changes, our analysis indicates that educational steady state mobility implies individuals in Russia have a higher probability of moving out of their parental class at a steady state (42%) compared to those in China (19% for father-to-child and 27% for mother-to-child samples). In contrast, the level of occupational steady state mobility is similar in China and Russia, with both countries exhibiting a probability of exiting the parental class of 50-55%.

Finally, our comparative analysis of intergenerational mobility in the transitioning societies of China and Russia, alongside the more mature United States, reveals higher levels of educational steady state mobility in the U.S. and Russia compared to China. Occupational steady state mobility is found to be quite similar across all three countries.

The paper is organized as follows. Section 2 provides a historical background for the transitions in China and Russia. Section 3 describes the data and sample construction, and summarizes the key educational and occupational variables. Section 4 defines the Markov chain mobility measures. Section 5 presents the results of the analysis of educational intergenerational mobility in China and Russia. Section 6 reports the key findings regarding occupational intergenerational mobility. Section 7 concludes.

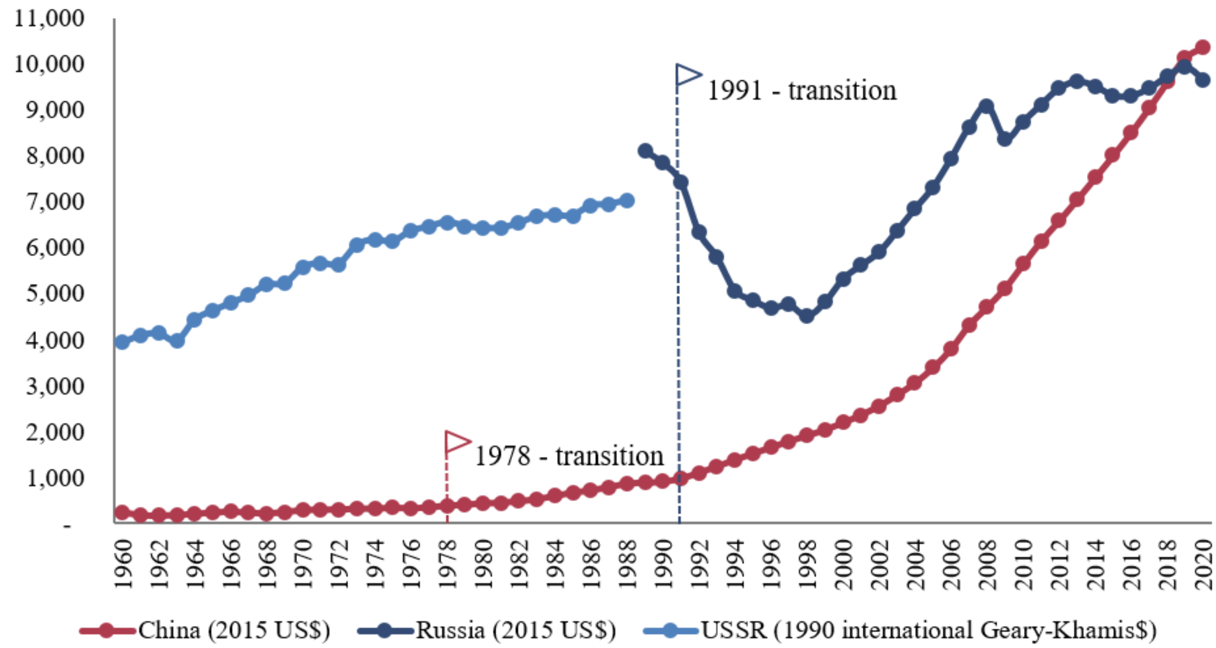
2 Historical background

Studying the two largest transition economies, China and Russia, we begin by describing the economic environment for the population cohorts to be studied and comparing the evolution and relative speed of market reforms in each country.

2.1 Initial conditions

The majority of parents in our samples were born between 1950 and 1970, with an average birth year close to 1960. In China, the Communist Revolution led the establishment of the People's Republic of China in 1949 under Chairman Mao Zedong, initiating a period of ambitious socialist central planning, including the First Five-Year Plan and the Great Leap Forward. Meanwhile, in the USSR, the communist regime had already been established for about thirty years. The country was recovering from the Second World War, and the era of Stalin was ending. In 1953, Khrushchev became the First Secretary of the USSR Communist Party, beginning "The Khrushchev Thaw," a time when stringent social repression was relaxed, and a wave of positive social, cultural, and economic reforms began.

Figure 1: Evolution of GDP per capita over time

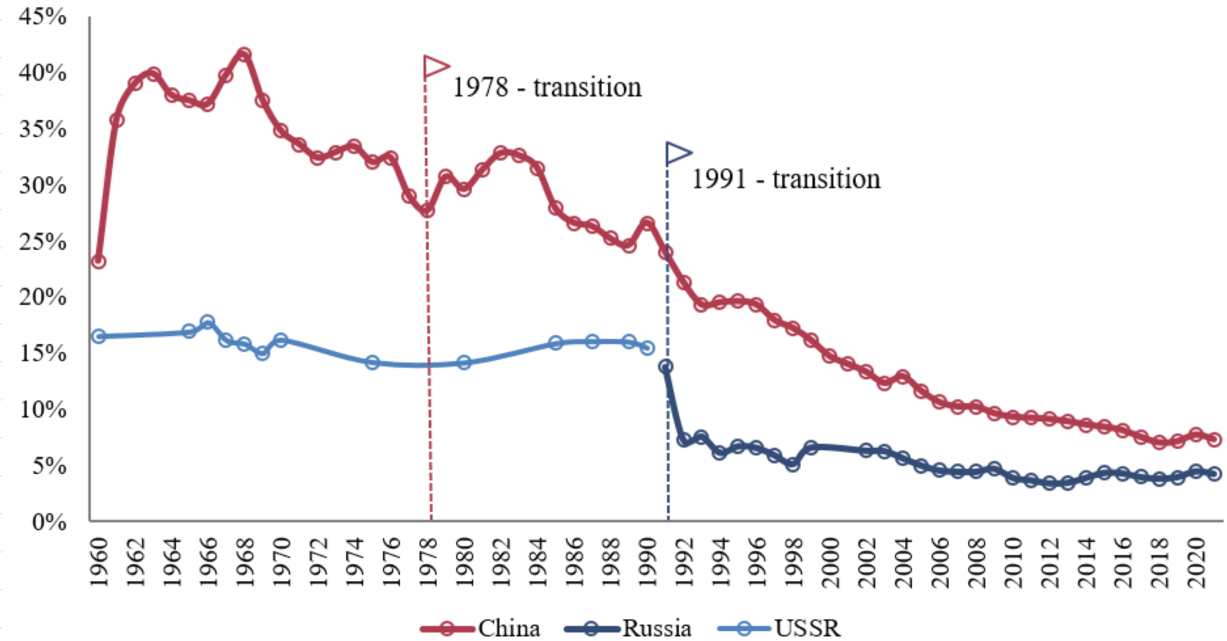


Notes: This figure illustrates the evolution of GDP per capita in China and Russia from 1960 to 2020. Red and blue flags indicate the beginning of market reforms in China and Russia, respectively. *Sources:* China and Russia - `https://ourworldindata.org`; USSR - Maddison (2006).

By the 1960s and 1970s, the communist regime in the USSR had reached a more advanced stage, with urbanization, industrialization, and educational reforms well-entrenched, unlike the active development phase in China. In contrast, during this same period, China remained primarily an agricultural, less-developed nation. The GDP per capita in the USSR was about 20 times higher than in China, and the USSR also had significantly higher annual growth rates (Figure 1). In China, the primary sector accounted for approximately 37% of GDP, while it comprised only 16% of GDP in the USSR (Figure 2). About 82% of China's population lived in rural areas (Appendix A, Figure A1), with 80% of rural workers engaged in agriculture (Appendix A, Figure A2). In comparison, only 42% of the USSR's population lived in rural areas, and merely 5% were involved in agriculture. At that time, the USSR had already developed into a mature industrialized economy that was playing a leading role globally in science and technology (Kim, 2015). The secondary industry, comprising manufacturing and construction, accounted for 74% of GDP in the Soviet Union, compared to only 35% in China (Figure 3).

Educational reforms began significantly earlier in Russia than in China. The USSR introduced a seven-year compulsory education law in 1949, while China established a nine-year compulsory education program only in 1986. By the early 1970s, the gross enrollment rate in secondary education was approximately 30% in China, compared to over 90% in the USSR (Appendix A, Figure A3). Notably, prior studies on education in the USSR highlight significant inequality in access to higher education. Gerber and Hout (1995) pointed out that after World War II, while secondary education expanded widely,

Figure 2: Evolution of the primary sector's share in GDP over time



Notes: This figure illustrates the evolution of share of primary industry in GDP in China and Russia from 1960 to 2020. Red and blue flags indicate the beginning of market reforms in China and Russia, respectively. *Sources:* China - National Bureau of Statistics (NBS) of China (`https://www.stats.gov.cn`); Russia - Federal State Statistics Service (FSSS) of Russia (`https://rosstat.gov.ru`), `https://ourworldindata.org`, `https://istmat.org`.

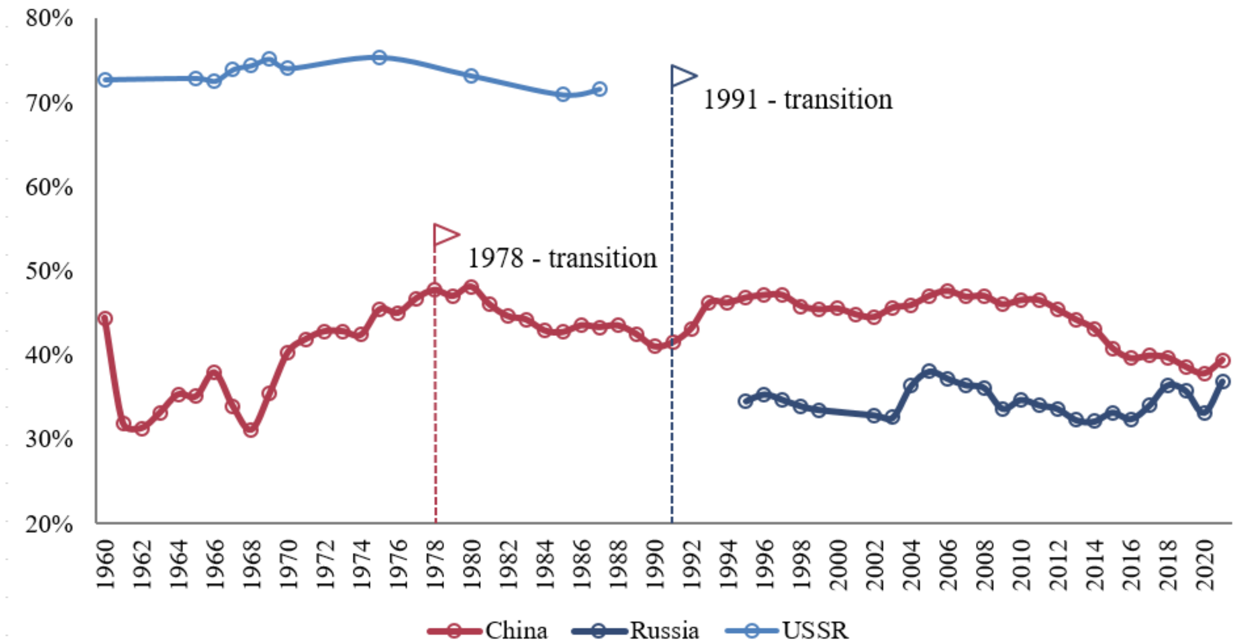
higher education did not grow at the same rate, benefiting mainly the more advantaged social classes during the Soviet era.

2.2 Market transition

In both countries, the children included in our sample were born between 1978 and 1997. The average birth year of children in the CFPS is 1987, compared to 1986 in the RLMS. This indicates that children in the Chinese sample were born shortly after the onset of China's market reforms in 1978, whereas most children in the Russian sample were born before the start of Russia's economic transition in 1991.

Among the significant structural changes, the most notable is the dramatic decline in the share of secondary industry in Russia, which dropped from around 70% in the 1980s to 35% in the 1990s, immediately following the transition (Figure 3). Sachs and Woo (1994) highlighted that the excessive reliance on heavy industry and state-sector employment during the Soviet era posed a major barrier to a successful transition. This reliance led to decreased flexibility in adapting the occupational structure to meet the growing and shifting demands of consumers for goods and services in a more market-oriented system. Bessudnov (2016) identified key changes in occupational structure resulting from the post-Soviet industrial crisis. These changes included a decrease in the share of

Figure 3: Evolution of the secondary sector's share in GDP over time



Notes: This figure illustrates the evolution of share of secondary industry in GDP in China and Russia from 1960 to 2020. Red and blue flags indicate the beginning of market reforms in China and Russia, respectively. *Sources:* China - National Bureau of Statistics (NBS) of China (`https://www.stats.gov.cn`); Russia - Federal State Statistics Service (FSSS) of Russia (`https://rosstat.gov.ru`), `https://ourworldindata.org`, `https://istmat.org`.

less skilled technical workers, an expansion of the service sector, and a stable percentage of professionals and managers within the labor force. Referring to the concept of "advantages of backwardness" from Gerschenkron (1962) and Fischer (1993), Sachs and Woo (1994) suggests that the transformation of occupational structure in China—from low-productivity agriculture to higher productivity industry—was easier than in the former USSR. In China, the share of primary industry in GDP fell from around 30% in the 1970s to 10% in the 2000s. In contrast, Russia saw a drop from 15% to 5% during the same period (Figure 2). Concurrently, employment in the agricultural sector fell from 80% to 44% in China and from 17% to 11% in Russia (Appendix A, Figure A2).

The Russian economy faced a severe crisis following the collapse of the Soviet Union. From 1991 to 1998, GDP per capita dropped by 60% (Figure 1) and only returned to pre-transition levels in 2006-2007. This "shock therapy" phase was characterized by extremely high inflation and prolonged and deep recession (Sachs & Woo, 1994). In contrast, China's transition from a planned economy to a market economy was much smoother, with no years of negative growth. In fact, the 1980s and 1990s in China were decades of rapid industrialization and economic growth. China's gradual reforms have been praised for their ex-post coherence in sequencing reforms in a way that enabled institutions and leaders to adapt gradually to a market-based system.

In 1999, China initiated a significant expansion of higher education. By the 2010s, the gross enrollment ratio for secondary education in China had reached nearly 100%, matching Russian levels (Appendix A, Figure A3). Roshchina (2012) noted that, following the market transition in Russia, there was a boom in both the demand and supply for higher education. Between 1995/1996 and 2009/2010 the number of universities increased by 50%, while the number of students rose from 2.7 to 7 million. Despite these advancements, considerable inequalities in access to higher education still exist Roshchina (2012). Unlike during the Soviet era, higher education in contemporary Russia is no longer state-funded, resulting in individuals having to cover their own educational costs. Over time, tuition fees have increased, and as a result, poorer families continue to experience substantial barriers to accessing higher education.

3 Data

3.1 Survey description

Panel data makes it possible to link the adult outcomes of a large number parent-child pairs. The data for China comes from five waves of the China Family Panel Studies (CFPS),[1] a panel survey conducted by the Institute of Social Science Survey at Peking University. The CFPS sample is nationally representative, covering 25 mainland provinces (excluding Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan) and account for approximately 95% of the Chinese population.[2] The sample size varies from 12,000 to 15,000 households, translating to about 30,000 to 37,000 individuals across different years. For Russia, the data comes from the Russian Longitudinal Monitoring Survey, a long-time panel study conducted by the National Research University Higher School of Economics (RLMS-HSE). This study has 24 annual waves available from 1994 to 2019.[3] The RLMS-HSE is the only representative micro-survey in Russia with a substantially large panel component. The data consists of both a repeated cross-sectional part, which is representative at the national level, and a panel part. The sample size for the RLMS-HSE varies from 4,000 to 8,000 households and approximately 11,000 to 18,000 individuals each year. Like the CFPS,[4] the RLMS-HSE utilizes multi-stage stratified probability sampling procedures.[5]

3.2 Sample construction

We obtain a representative sample of children from specific birth cohorts and construct variables using data from all available survey years to maximize the number of child-parent pairs. Our approach involves three key steps. First, we choose a baseline year for

[1] Namely, CFPS 2010, CFPS 2012, CFPS 2014, CFPS 2016, CFPS 2018.

[2] Since 2012, five provinces (Liaoning, Henan, Shanghai, Guangdong, and Gansu) were oversampled allowing for regional analysis at the provincial level.

[3] Except 1997 and 1999, when RLMS-HSE was not carried out.

[4] For more information on sampling procedures, please, refer to the CFPS official website `https://www.isss.pku.edu.cn/cfps/en`.

[5] For more information, please, refer to the RLMS-HSE website `https://www.hse.ru/en/rlms`.

the children's sample in each dataset that maximizes the number of parent-child pairs with valid data. This is 2018 for the CFPS, which is a short panel, and 2011 for the RLMS-HSE.

Second, from the chosen wave, we selected individuals aged 22 to 40 in the latest survey wave. This age range follows existing literature (Fan et al., 2021; Solon, 1992), and is motivated by a straightforward rationale: (a) setting the lower bound at 22 reduces the likelihood that children are still in school; (b) setting the upper bound at 40 increases the chances of finding parents for matching child-parent pairs in the data. If multiple children come from the same family, we included all of them in our sample, considering this set of observations is representative of people aged 22 to 40 at the time of the latest survey. As a robustness check, Appendix H presents results when only the eldest son in each household is included in the sample.

Third, we match these children to their parents. We obtain parental information directly from parents who are co-residents in any survey wave and indirectly from questions answered by children about non-co-resident parents. In constructing pairs, we utilize data not only from the baseline year but also trace backward and forward across survey waves to gather as much information as possible. A child-parent pair is considered valid if we find at least one parent's information on age, education, or occupation. Parents include biological parents, step-parents, and spouses of biological or step-parents. If different spouses appear across survey waves, for the CFPS, we select the spouse who appeared first; for the RLMS-HSE, we choose the spouse recorded before the child reached the age of ten. Following these procedures, our final sample includes 8,788 child-parent pairs for China and 3,718 for Russia.

3.3 Summary statistics

Table B1 in the Appendix B reports descriptive statistics for the constructed samples. In China, the average age of children in our sample is 31 at the time of the latest survey wave. The average ages of fathers and mothers are 59 and 56 years respectively. In the RLMS-HSHE sample, the average ages of children, mothers, and fathers are approximately 1-2 years older than those in the CFPS sample. The share of males among children in both samples is slightly higher (by two percentage points) than the official statistics: our CFPS sample has 53% of males compared to the 51% males reported by the National Bureau of Statistics of China (NBS) in 2018, while the RLMS sample has 48% males compared to 46% reported by the Federal State Statistics Service (FSSS) of Russia (Appendix B, Table B2). The same issue of gender bias in the RLMS-HSE sample was highlighted by Borisov and Pissarides (2020). Like Borisov and Pissarides (2020), we partially address this issue by presenting our results separately for fathers and mothers.

Table 1 indicates that parents in Russia have a significantly higher level of education compared to those in China. This is expected, as educational reforms began much earlier in the USSR than in China. In China, the gross secondary education enrollment ratio increased from around 40% in the 1980s to nearly 100% in the 2010s, while in Russia, it has remained stable over time, fluctuating between 90% and 100% (Appendix A, Figure A3). In the Chinese sample, 19% of fathers have "high school and above" education, which is slightly higher than the 11% of mothers with similar qualifications (Table 1). In contrast,

Table 1: Distribution of educational attainment

	China			Russia		
	Children	Fathers	Mothers	Children	Fathers	Mothers
Primary school and below	0.15	0.49	0.66	0.00	0.00	0.00
Middle school	0.31	0.32	0.22	0.06	0.05	0.05
High school	0.20	0.15	0.09	0.54	0.85	0.80
College and above	0.34	0.04	0.02	0.40	0.10	0.15

Notes: This table shows the distribution of educational attainment among children and their parents in our constructed samples from the China Family Panel Studies (CFPS) and the Russian Longitudinal Monitoring Survey (RLMS-HSE). Survey weights were applied to compute these shares.

Table 2: Distribution of occupational classes

	China			Russia		
	Children	Fathers	Mothers	Children	Fathers	Mothers
High skilled occupations	0.42	0.19	0.12	0.45	0.27	0.46
Middle skilled occupations	0.22	0.10	0.12	0.25	0.14	0.31
Low skilled occupations	0.36	0.72	0.75	0.31	0.60	0.24

Notes: This table shows the distribution of three major occupational classes among children and their parents in our constructed samples from the China Family Panel Studies (CFPS) and the Russian Longitudinal Monitoring Survey (RLMS-HSE). Survey weights were applied to compute these shares.

in Russia, 95% of both fathers and mothers have attained "high school and above" education. Additionally, a larger proportion of women in Russia hold a "college and above" degree. This trend of higher educational attainment among women compared to men in the USSR was documented by Titma, Tuma, and Roosma (2003). Despite these stark differences in the educational attainment of parents in Russia and China, the distribution of education among children is much more comparable between the two countries, reflecting China's significant progress in implementing educational reforms during the study period.

In our China sample, approximately 72% of fathers and 75% of mothers hold low-skilled occupations, primarily working as farmers. Among the children, the largest group (42%) holds high-skilled occupations (Table 2).[1] Similarly, in Russia, around 45% of children have high-skilled jobs, but only about 1% of parents were involved in agriculture, as shown in Figure B2 from the Appendix B. The low share of farmers among Russian parents can be attributed to the early industrialization in the USSR (1928). Notably, the occupational specialization of fathers compared to mothers is much less uniform in Russia than in China (Appendix B, Figures B1-B2). Previous studies describe the gender

[1] Our baseline occupational classification is the international ISCO-08 system used in the RLMS-HSE. To ensure comparability, we first matched the Chinese Standard Classification of Occupations (CSCO) from the CFPS to ISCO-08, and then aggregated it into three broad occupational classes.

imbalance in the distribution of occupations in the USSR under socialism, with women more prevalent in managerial and professional occupations, as well as in white-collar work (semi-professionals, clerks, sales, and services). In contrast, larger share of males than females held very top managerial positions, though this class is relatively small; and the majority of men belonged to the industrial working class, which constitutes a larger share of the class structure (Marshall et al., 1995; Titma et al., 2003). This observation is consistent with the occupational distribution in our parental sample constructed from the RLMS-HSE. According to Titma et al. (2003), the higher education levels and prevalence of women in white-collar jobs was a consequence of high male mortality during the Second World War, which pushed women into the workforce and likely motivated them to pursue higher education to avoid physically demanding labor.

Tables B3, and B4 in the Appendix B present data representativeness checks, comparing the distribution of education and occupation among children in our samples with official statistics from Russia and China. The comparison shows no significant discrepancies.

4 Markov chain mobility measures

Markov chain transition matrices are a natural way to model the conditional probability structure linking the class of parents and children given the categorical nature of our outcome variables. Markov chains allow for richer characterizations of the persistence of parental class across generations than linear measures.[1] Markov chain models have been utilized to study the intergenerational transmission of social class in sociology since Prais (1955).[2] A recent review by Song (2021) highlights the ongoing significance of these models.

To introduce the mobility measures used in this paper, consider a setting with n social classes. Let P be the transition matrix, where each entry p_{ij} represents the probability that an individual born to parents in class i transitions to class j. The dynamics of population outcomes then evolve according to:

$$\mu^t = \mu^{t-1} \cdot P, \tag{1}$$

where P is an $n \times n$ matrix of transition probabilities p_{ij}, and μ^t is the distribution of classes among every subsequent generation t. If the transition matrix is primitive,[3] as $t \to \infty$, the marginal distribution converges to what is called the invariant or steady state distribution, denoted as μ^*. Mobility measures are thus derived from the dynamics of this system as it moves to its steady state.

Considering mobility as movement, we can distinguish between "exchange" and "structural" mobility, concepts which have been widely studied in the sociology liter-

[1]Intergenerational elasticities (IGE) and intergenerational correlations (IGC) have been the workhorse statistics for assessing intergenerational persistence. Appendix D compares the proposed Markov chain measures with the traditional IGE and IGC, using several illustrative examples.

[2]For an extensive review of Markov chain mobility measures, see Boudon (1973), Dardanoni (1993), and Van de Gaer, Schokkaert, and Martinez (2001).

[3]There exists power k such that P^k is a positive matrix.

ature (McClendon, 1977; Sobel, 1983; Sobel, Hout, & Duncan, 1985).[1] This distinction is particularly important when examining educational and occupational intergenerational mobility in transition economies, such as China and Russia. Intuitively, when economies undergo structural changes (e.g., rapid development, economic transition), significant exogenous shifts in educational or occupational structures (μ^t versus μ^{t+1}, in our notation) can mechanically inflate standard mobility indices (like IGE or IGC). Consequently, conflating the trends in structural and exchange mobility might lead to misleading conclusions (Jarvis & Song, 2017).

The stabilization of the marginal distribution at μ^* over time is a key property that allows us to apply the classical definition of exchange mobility—defined as the extent of movement between classes in the absence of changes in marginal distributions (Berger & Snell, 1957). In this study, we adopt a decomposition framework from the sociology literature that distinguishes between overall, structural, and exchange mobility (also referred to as "circulation" mobility) (Broom & Jones, 1969; Featherman et al., 1975).[2] This approach originates in the work of Matras (1961).

We define *overall mobility* as the expected fraction of dynasties whose class changes from generation t to generation $t+1$:

$$OM^t(P, \mu^t, t) = 1 - \sum_i \mu_i^t \cdot P_{ii}. \tag{2}$$

Overall mobility can be decomposed into two parts: exchange and structural mobility. *Structural mobility* is defined as the part of movement that change the marginal distribution of generations across classes:

$$SM^t(P, \mu^t, t) = \|\mu^t - \mu^t \cdot P\|_{TV} = \frac{1}{2} \cdot \sum_i |\mu_i^t - \mu_i^{t+1}|. \tag{3}$$

Exchange mobility is defined residually as the part of movement that does not change the cross-sectional distribution across classes at t:

$$EM^t(P, \mu^t, t) = OM(P, \mu^t, t) - SM(P, \mu^t, t). \tag{4}$$

Structural mobility vanishes over time because as $t \to \infty$ marginal distributions converge to the steady state distribution μ^*. Therefore, at the steady state, overall mobility converges to exchange mobility. We refer to this measure as *steady-state mobility*, which is computed as:

$$SSM(P, \mu^*) = 1 - \sum_i \mu_i^* \cdot P_{ii}. \tag{5}$$

The distinction between *overall* and *steady state mobility* moves beyond the structural/exchange dichotomy in previous studies. Structural mobility and exchange mobility capture the ways that the transition affects mobility. Steady state mobility, in con-

[1] In this paper, we primarily use the "movement" definition of mobility to analyze patterns in China and Russia. However, Appendix F provides supplementary results based on memory measures, along with a detailed explanation of the conceptual differences between the two approaches to measuring intergenerational mobility.

[2] These measures are also used in Butaeva, Durlauf, and Shapoval (in progress).

trast, addresses the counterfactual question: "What level of intergenerational movement would persist across generations in the long-run once the underlying Markov process has stabilized?"

Finally, note that overall mobility OM can also be decomposed into upward and downward mobility. To achieve this, equation (2) can be estimated separately for individuals who improve their class relative to their parents, defining upward overall mobility, and for those who experience a decline in class compared to their parents, defining downward mobility.

To analyze class-specific heterogeneity in mobility patterns, we employ a well-established measure from the Markov chain literature—the mean time to exit from each initial class (Kemeny, Snell, et al., 1969):

$$MTE_i(P) = (1 - P_{ii}) \cdot \sum_{t=1}^{\infty} t \cdot P_{ii}^{t-1} \tag{6}$$

The MTE estimates how many generations, on average, it takes for descendants to exit from each social class.

5 Educational mobility

We begin by presenting the estimated educational transition matrices for China and Russia. Table 3 and Table 4 report the matrices along with 95% bootstrap confidence intervals (CIs) for the transition probabilities.[1] Several insights can be drawn from these tables. First, the point estimates of transition probabilities are similar for the father-to-child and mother-to-child samples, suggesting that the transmission of educational class from father to child and from mother to child are the same in each country. Second, in both China and Russia, the elements of transition matrices above the main diagonal are higher than those below, suggesting a greater prevalence of upward educational intergenerational mobility. This means that in both countries, most children attain higher levels of education than their parents. Third, when comparing transition probabilities across different initial parental educational levels, we find that: (a) children whose parents have a middle school education or below have around 1.6 times higher chances of surpassing their parents' education level in Russia (77-83%) compared to China (49-50%); (b) children of parents with a high school degree have a much lower chance to receive a lower degree in Russia than in China, but have a substantially higher chance of attaining a college degree or higher in China than in Russia; (c) children of parents with a college degree and above are much more likely to achieve the same level of education in China (over 90%) compared to Russia (around 60%).

Figures 4 and 5 document the evolution of educational distributions within the Markov chain framework for mother-to-child and father-to-child samples in China and Russia. Namely, the figures display the educational distribution among parents and children, as well as the steady state distribution, denoted as μ^*, following the notation in

[1] Throughout this paper, we use standard percentile bootstrap confidence intervals.

Table 3: Educational transition matrices for China

Child / Father	Middle and below	High school	College or above
Middle and below	0.51 [0.50,0.53]	0.21 [0.20,0.22]	0.28 [0.27,0.29]
High school	0.27 [0.24,0.29]	0.23 [0.20,0.25]	0.51 [0.48,0.53]
College or above	0.03 [0.01,0.05]	0.11 [0.08,0.14]	0.86 [0.82,0.89]
Child / Mother	**Middle and below**	**High school**	**College or above**
Middle and below	0.50 [0.49,0.51]	0.21 [0.20,0.22]	0.29 [0.28,0.30]
High school	0.18 [0.16,0.21]	0.16 [0.13,0.18]	0.66 [0.63,0.69]
College or above	0.02 [0.00,0.04]	0.08 [0.04,0.12]	0.90 [0.86,0.94]

Notes: This table presents the educational transition matrices for China. The numbers in brackets indicate 95% CIs, calculated from 1,000 bootstrap samples.

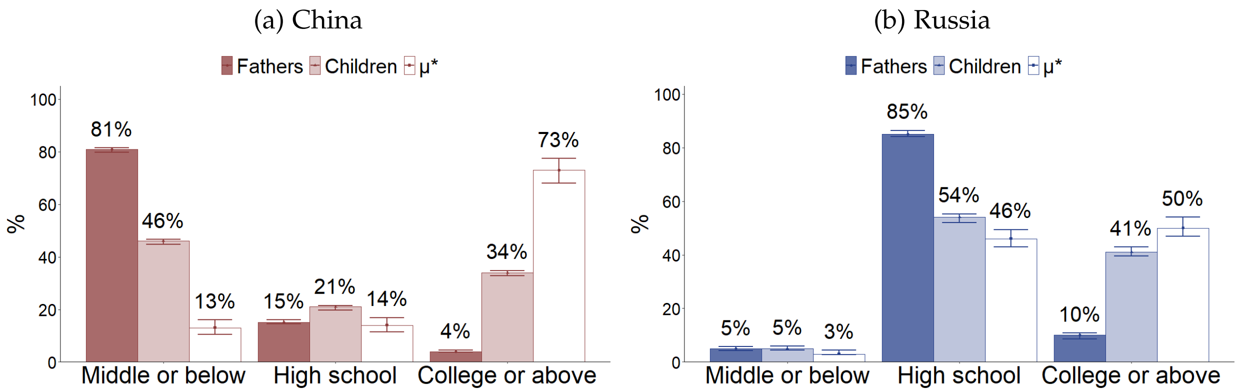
Table 4: Educational transition matrices for Russia

Child / Father	Middle and below	High school	College or above
Middle and below	0.17 [0.11,0.23]	0.70 [0.63,0.77]	0.13 [0.08,0.18]
High school	0.05 [0.04,0.06]	0.55 [0.53,0.56]	0.40 [0.39,0.42]
College or above	0.01 [0.00,0.02]	0.37 [0.32,0.42]	0.62 [0.57,0.67]
Child / Mother	**Middle and below**	**High school**	**College or above**
Middle and below	0.24 [0.18,0.30]	0.68 [0.61,0.74]	0.09 [0.05,0.13]
High school	0.05 [0.04,0.06]	0.56 [0.55,0.58]	0.39 [0.37,0.40]
College or above	0.02 [0.01,0.03]	0.37 [0.33,0.41]	0.61 [0.57,0.65]

Notes: This table presents the educational transition matrices for Russia. The numbers in brackets indicate 95% CIs, calculated from 1,000 bootstrap samples.

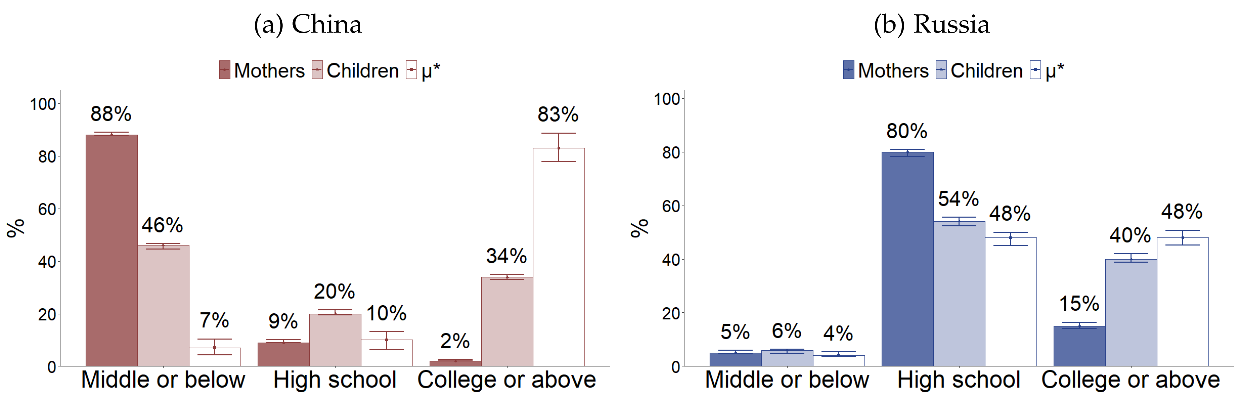
Section 4. The distributions of parental and child classes have already been presented in Section 3 (Table 1). Three more observations can be made here. First, there is minimal difference between distributional patterns from the father-to-child and mother-to-child samples in each country. Second, the steady state educational distribution μ^* in China significantly differs from the current parental and children's distributions, indicating a large number of generations between the current stage of the Markov process and the steady state. Conversely, in Russia, the steady state distribution is very similar to the children's distribution of education. Third, notably, the steady state distribution itself indicates a more favorable expected equilibrium for China compared to Russia. In China, the majority of the population (73–83%) is projected to attain a college degree or higher, whereas in Russia, the population will be nearly evenly split between those with a high

Figure 4: Distribution of educational attainment in father-to-child samples



Notes: These figures illustrate the evolution of educational distribution from fathers to children, and ultimately to the steady-state distribution μ^*, in China and Russia. Error bars indicate 95% CIs, derived from 1,000 bootstrap samples.

Figure 5: Distribution of educational attainment in mother-to-child samples



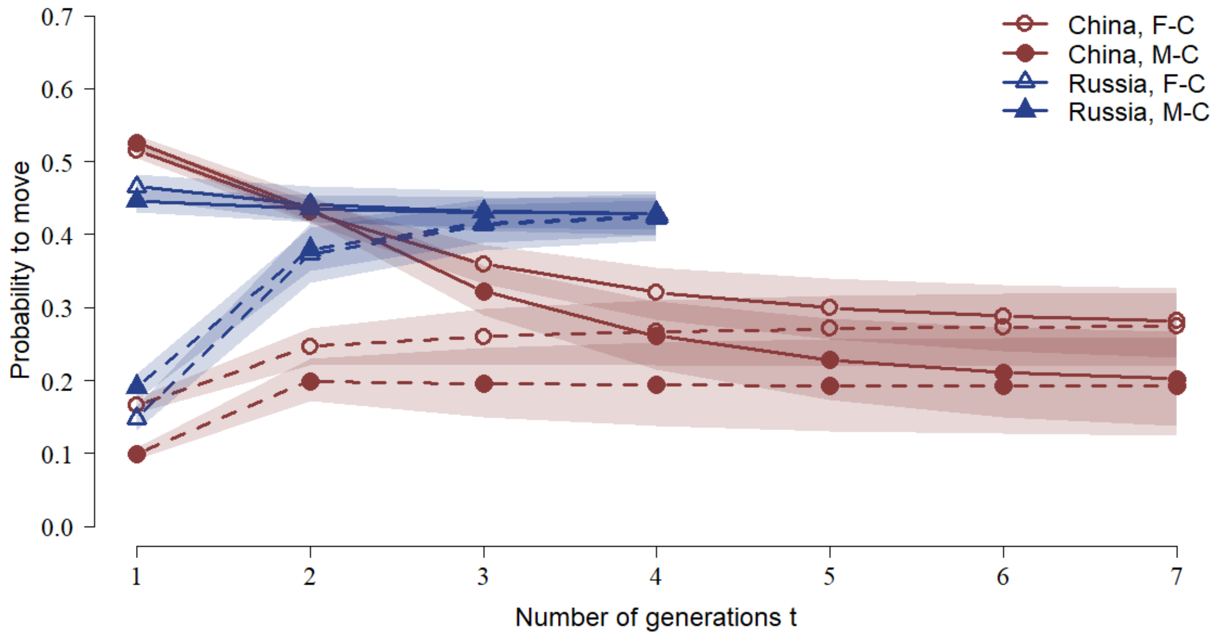
Notes: These figures illustrate the evolution of educational distribution from mothers to children, and ultimately to the steady-state distribution μ^*, in China and Russia. Error bars indicate 95% CIs derived from 1,000 bootstrap samples.

school education and those with a college degree or higher.

Next, we examine the overall, structural, and exchange mobility introduced in Section 4. Figure 6 shows that children in our constructed samples (for $t = 1$) have a higher probability of not following their parents' educational class in China ($OM^{t=1}$ is around 52-53%) than in Russia ($OM^{t=1}$ is 45-46%), reflecting the common perception of high mobility in China. From Table 5, we see that upward mobility prevails in both countries and accounts for more than 90% ($OM^{t=1}upward/OM^{t=1}$) of mobility in China and around 80% in Russia.[1] However, in both countries, most overall mobility is driven by structural changes. The probability of leaving the parental educational class due to

[1]The complete set of mobility measure estimates for each generation t, up to the steady state, is presented in the Appendix E.

Figure 6: Dynamics of overall, structural, and exchange educational mobility



Notes: This figure plots 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) 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% CIs derived from 1,000 bootstrap samples.

Table 5: Estimates of overall, structural, and exchange educational mobility measures

	Father-to-child		Mother-to-child	
	China	Russia	China	Russia
OM, t=1	0.515	0.466	0.526	0.446
OM upward, t=1	0.469	0.387	0.507	0.346
OM downward, t=1	0.046	0.079	0.019	0.100
SM, t=1	0.350	0.317	0.427	0.255
EM, t=1	0.166	0.148	0.099	0.191
SSM, t*	0.274	0.423	0.192	0.424

Notes: This table present the results on estimated movement mobility measures from eq. (2) - (5): overall mobility $OM^t(P, \mu^t, t)$, structural mobility $SM^t(P, \mu^t, t)$, and exchange mobility $EM^t(P, \mu^t, t)$.

changes in educational structure ($SM^{t=1}/OM^{t=1}$) accounts for 68% of overall mobility in the father-to-child sample and 81% in the mother-to-child sample in China. In Russia, these shares are 68% and 57%, respectively. Therefore, in each country structural mobility accounts for more than half of the overall mobility. In China, most of the parents in our sample had only middle school or lower schooling, while the subsequent generations have sharply shifted towards higher levels of education. The substantial difference in the distribution of education between parents and children is due to the timing of major educational reforms in China, including a compulsory education law in 1986 and the expansion of tertiary education in the 1990s. Only a small portion of Chinese parents in our sample benefited from these reforms. In contrast, major educational reforms started much earlier in Russia with the seven-year compulsory education law introduced in 1949 in the USSR. Figures 4 and 5 illustrate that in Russia, the major shift in educational distribution between parents and children occurs at the higher levels of education: it's a shift from predominantly high-school degrees to college and higher levels of education.[1]

From Figure 6 we can also see that current exchange mobility ($EM^{t=1}$ represented by the first points at dashed lines) is relatively small and rather similar for father-to-child sample in China and the mother-to-child sample in Russia (and vice a versa). In other words, the estimated $EM^{t=1}$ suggests that in both China and Russia the current likelihood of participating in movements not altering the educational structure is around 10-20%. We argue that a fairer cross-country comparison is provided by comparing intergenerational mobility at the steady state SSM. If societies are in their steady states, mobility is substantially larger in Russia ($SSM = EM^{t=4}$ is around 42% for both father-to-child and mother-to-child samples) compared to China ($SSM = EM^{t=7}$ is 27% in father-to-child and 19% in mother-to-child sample). This implies that under the current educational mobility patters, if the observed transition probabilities persist across future generations, Russia would become a more mobile society at the steady state than China.

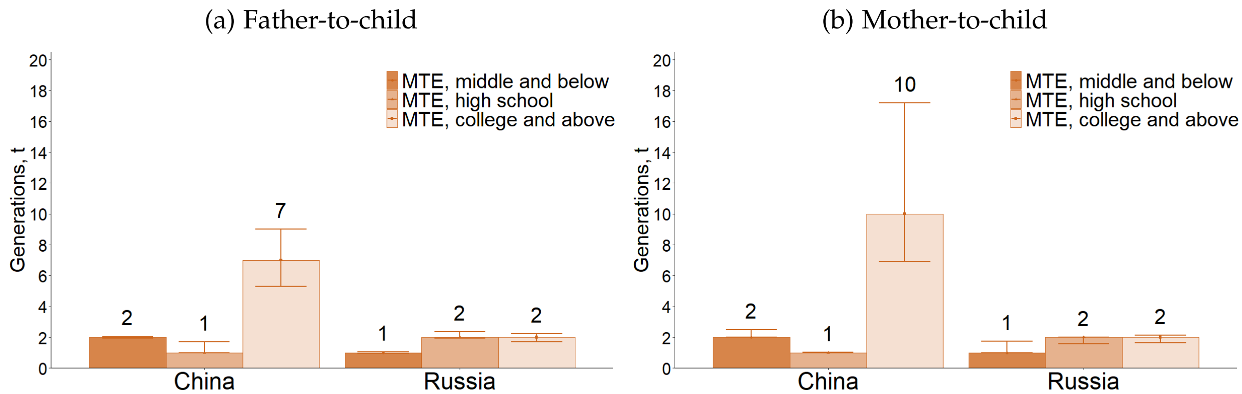
5.1 Heterogeneity

The results on the mean time to exit from each educational class, presented in Figure 7, offer insights into class-specific patterns of intergenerational mobility in China and Russia. In China, once individuals complete college, their descendants tend to remain in this class for a long time. On average, it takes 7 generations in the father-to-child sample and 10 generations in the mother-to-child sample for downward mobility to occur from this educational tier. High school graduates are the most mobile, with descendants exiting after just one generation on average. Those with "middle and below" education exhibit slightly more persistence, with an average of two generations needed to exit this class in China. In contrast, mobility in Russia is notably higher across all educational classes. The "high school" and "college and above" classes each take, on average, two generations to exit, while those with "middle and below" education exit in just one generation.

Overall, our results on educational mobility suggest that steady state exchange mobility in Russia is significantly greater than in China. At the steady state, individuals in Russia have an almost three times higher (42%) likelihood of moving to an education class different than their parents compared to China (19-27%). The overall mobility of

[1]The development of education and major educational reforms in China and Russia are discussed in more detail in Section 2.

Figure 7: Mean time to exit from each educational class



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

the current generation of parents and children $OM^{t=1}$ demonstrates an opposite pattern, but this difference is entirely due to differences in structural mobility. Therefore, the new mobility measures we introduce enable us to avoid the misleading conclusion that educational mobility is higher in China than in Russia.

5.2 Comparison to the U.S.

In this subsection, we compare intergenerational educational mobility in China and Russia with that in the United States. This comparison highlights some valuable properties of the measures proposed in Section 4 when comparing intergenerational mobility in societies that exhibit substantial structural changes with that in stable developed economies.

The examination of educational transition matrices for the U.S. reveals two main observations. First, as seen in Table 6, the point estimate of educational transition probabilities for father-to-child and mother-to-child samples are similar, just as in China and Russia. Second, upward mobility is only slightly higher than downward mobility. In the United States, children whose parents have a middle school or lower education have about a 90% chance of attaining a higher level of education, compared to around 80% in Russia and 55% in China. Additionally, there is almost no chance of achieving only a middle school or lower education if one's parents graduated from high school or above. The differences between upward and downward educational mobility that we observe in the U.S. are less pronounced in China and Russia.

Figure 8 shows that the evolution of the distribution of education is similar between mother-to-child and father-to-child samples. The distributions align with expectations for a mature, developed economy—a very low share of individuals with middle school education and below, and a substantial share with high school education and above, both among parents and children. The steady state distribution closely resembles the

Table 6: Educational transition matrices for the U.S.

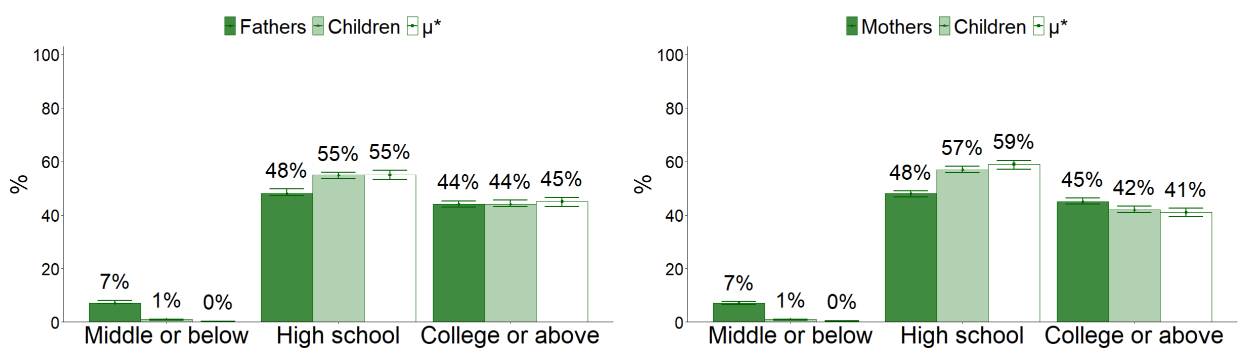
Father \ Child	Middle and below	High school	College or above
Middle and below	0.09 [0.07,0.12]	0.64 [0.60,0.69]	0.27 [0.23,0.30]
High school	0.00 [0.00,0.00]	0.70 [0.68,0.71]	0.30 [0.28,0.31]
College or above	0.00 [0.00,0.00]	0.36 [0.35,0.38]	0.63 [0.62,0.65]
Mother \ Child	**Middle and below**	**High school**	**College or above**
Middle and below	0.09 [0.06,0.11]	0.67 [0.63,0.71]	0.24 [0.20,0.27]
High school	0.00 [0.00,0.01]	0.72 [0.71,0.74]	0.27 [0.26,0.29]
College or above	0.00 [0.00,0.00]	0.39 [0.38,0.41]	0.61 [0.59,0.62]

Notes: This table presents the educational transition matrices for the U.S. The numbers in brackets indicate 95% CIs, calculated from 1,000 bootstrap samples.

Figure 8: Distribution of educational attainment in the U.S.

(a) Father-to-child.

(b) Mother-to-child.

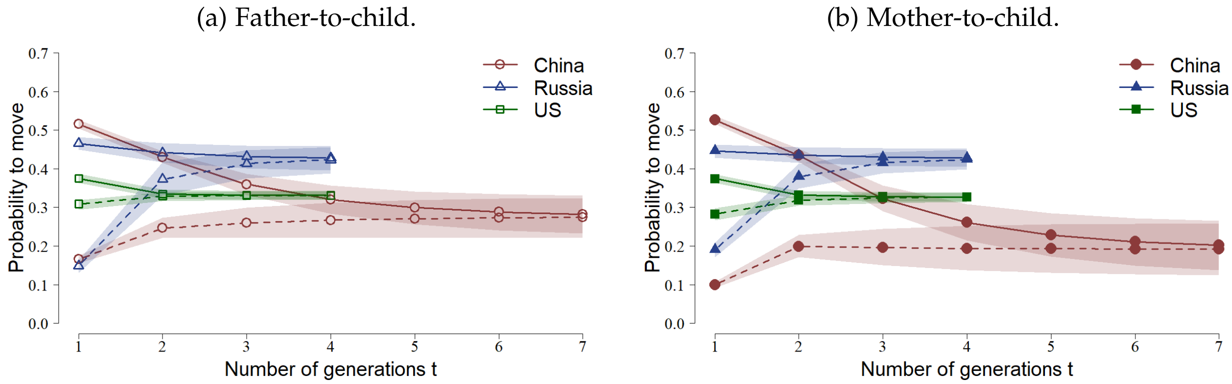


Notes: These figures illustrate the evolution of educational distribution from fathers (mothers) to children, and ultimately to the steady-state distribution μ^*, in the U.S. Error bars indicate 95% CIs, derived from 1,000 bootstrap samples.

current children's distribution, suggesting that the Markov chain process in the United States is already close to the steady state. The steady state distribution itself suggests a slightly less favorable expected equilibrium compared to Russia, but a substantially more favorable one than in China. In this equilibrium, the proportion of individuals with a college degree or higher is slightly lower than that of high school graduates.

Our results from (Figure 9) suggest that in comparison to Russia and China, in the United States children have the lowest current probability of deviating from their parents' educational class ($OM^{t=1} = 0.38$). The share of upward mobility in total overall mobility in the United States (52-56%) is also smaller than in Russia ($\sim$ 80%) and China (91-96%). In the US, the educational system was already well-developed in the parental generation, with most parents having at least a high school education. Consequently,

Figure 9: Dynamics of overall, structural, and exchange educational mobility: a comparison with the U.S.



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) 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% CIs , derived from 1,000 bootstrap samples.

fewer children changed their educational class. Compulsory education laws in the U.S. were introduced around the 1930s and all major educational reforms occurred before our parental cohorts were born. Structural mobility in the United States is substantially lower than in Russia and China, accounting for only 18-25% of overall mobility. However, for current children and parents, the probability of movements unrelated to changes in distributional structure $EM^{t=1}$ is higher in the United States ($\sim$ 30%) than in Russia and China (10-20%). At the steady state, mobility SSM is much lower in China than in the United States and Russia (Table E1, Appendix E): the probability of intergenerational changes in educational classes is 42% in Russia, 33% in the United States, and only 19-27% in China.

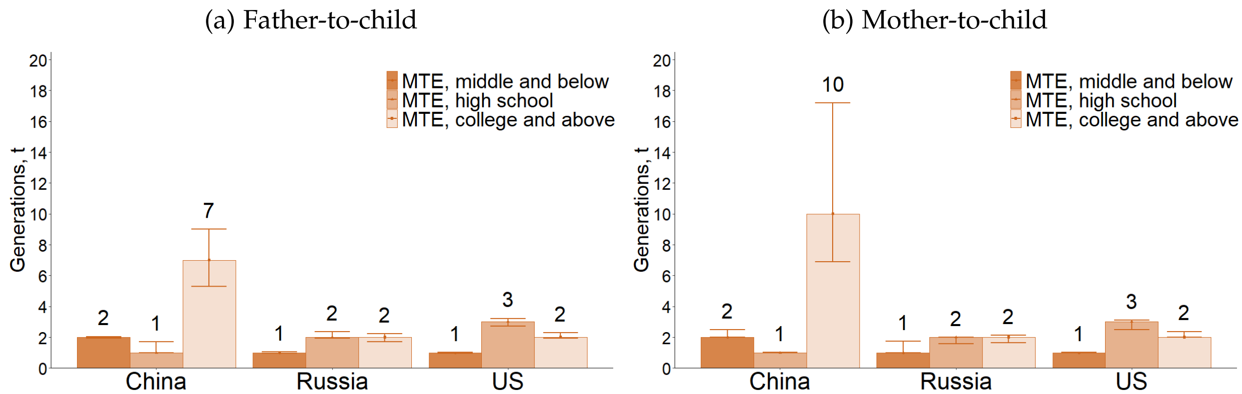
The class-specific movement measures estimated for the U.S. are similar to those observed in Russia (Figure 10). The only notable difference is that, in the U.S., the mean time to exit high school is slightly longer—averaging three generations compared to two in Russia.

Comparisons with the U.S. highlight how, by accounting for "exogenous" structural changes, we can make more accurate cross-country comparisons. Our comparative analysis of intergenerational educational mobility across the three countries shows that net of the effect of structural changes, Russia is more mobile than the United States and China. As a robustness check, we also estimate movement mobility measures based on only eldest children for all three countries, and we find very similar results (Appendix H).

5.3 Comparison to the conventional mobility measures

In Appendix F, we present the results of the additional analysis of intergenerational mobility using two sets of measures commonly applied in the literature: those typically

Figure 10: Mean time to exit from each educational class: a comparison with the U.S.



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

utilized in economics (derived from the linear models) and those used in sociology (derived from uniform and log-multiplicative layer effect models). First, the estimates of intergenerational correlation IGC in both father-to-child and mother-to-child samples, as well as intergenerational elasticity IGE in the father-to-child sample, indicate that Russia exhibits higher mobility than the United States, and both countries are substantially more mobile than China. These findings are consistent with our main results based on the steady-state exchange mobility. However, in the mother-to-child sample, the IGE suggests that the United States is more mobile than Russia, while both countries remain more mobile than China. Second, we find that our baseline results on educational mobility align with the findings from the log-multiplicative layer effect model introduced by Xie (1992). The estimate of the parameter ϕ_k from the latter indicates that both Russia and the United States exhibit significantly higher exchange mobility compared to China.

6 Occupational mobility

In this section, we analyze occupational intergenerational mobility. We start by examining occupational transition matrices and the evolution of the distribution of occupations across generations in China and Russia. Tables 7 and 8 show that point estimates of occupational transition probabilities are similar for mothers and fathers in each country, as observed previously for educational transition probabilities. However, Figures 11 and 12 reveal significant differences in occupational distributions between fathers and mothers in Russia. This discrepancy is due to gender imbalances in the USSR's occupational structure: men were primarily engaged in low-skilled labor, mainly as manufacturing workers, while women dominated high-skilled labor. As a result, the steady state distributions μ^* differ between mother-to-child and father-to-child samples in Russia (and not so much in China), resulting in gender discrepancies in occupational mobility estimates from those two samples.

Table 7: Occupational transition matrices for China

Father \ Child	Low-skilled	Middle-skilled	High-skilled
Low-skilled	0.41 [0.40,0.43]	0.22 [0.21,0.24]	0.36 [0.35,0.38]
Middle-skilled	0.24 [0.21,0.28]	0.27 [0.24,0.30]	0.49 [0.45,0.52]
High-skilled	0.24 [0.22,0.27]	0.21 [0.19,0.24]	0.54 [0.51,0.57]
Mother \ Child	**Low-skilled**	**Middle-skilled**	**High-skilled**
Low-skilled	0.44 [0.42,0.45]	0.21 [0.20,0.22]	0.35 [0.34,0.37]
Middle-skilled	0.20 [0.18,0.23]	0.28 [0.25,0.31]	0.52 [0.49,0.55]
High-skilled	0.18 [0.15,0.20]	0.22 [0.19,0.25]	0.60 [0.57,0.64]

Notes: This table presents the occupational transition matrices for China. The numbers in brackets indicate 95% CIs, calculated from 1,000 bootstrap samples.

Table 8: Occupational transition matrices for Russia

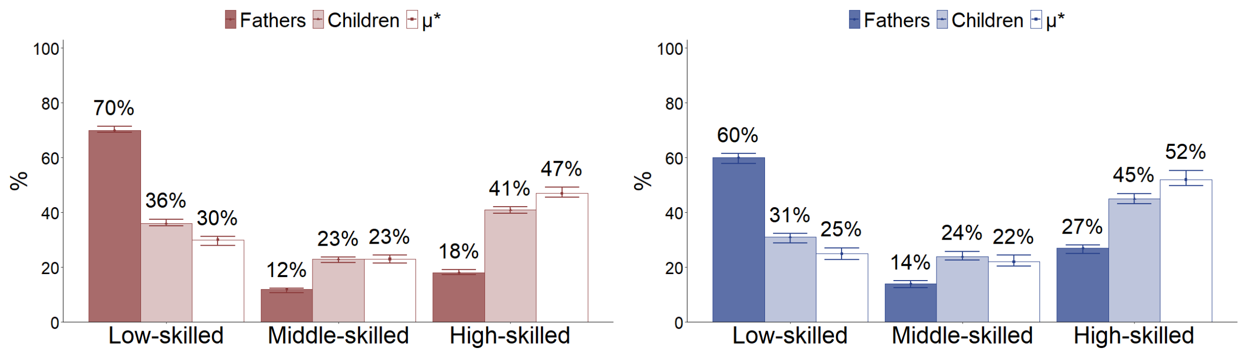
Father \ Child	Low-skilled	Middle-skilled	High-skilled
Low-skilled	0.37 [0.35,0.39]	0.26 [0.24,0.28]	0.37 [0.34,0.39]
Middle-skilled	0.29 [0.24,0.34]	0.26 [0.22,0.30]	0.45 [0.41,0.50]
High-skilled	0.17 [0.15,0.21]	0.19 [0.16,0.22]	0.64 [0.60,0.67]
Mother \ Child	**Low-skilled**	**Middle-skilled**	**High-skilled**
Low-skilled	0.42 [0.38,0.45]	0.29 [0.25,0.32]	0.30 [0.26,0.33]
Middle-skilled	0.34 [0.31,0.37]	0.30 [0.27,0.34]	0.36 [0.33,0.39]
High-skilled	0.22 [0.20,0.24]	0.18 [0.16,0.20]	0.60 [0.57,0.62]

Notes: This table presents the occupational transition matrices for Russia. The numbers in brackets indicate 95% CIs, calculated from 1,000 bootstrap samples.

The transition matrices in Tables 7 and 8 present a less striking pattern of upward mobility compared to educational intergenerational mobility. The elements above the main diagonal of the transition matrices are not that much higher than those below the main diagonal in both countries. In China, children from middle-skilled families have about a 20% chance of ending up in low-skilled occupations, while in Russia, this probability is around 30%. The likelihood of these children moving up to high-skilled occupations is approximately 50% in China and 40% in Russia. For children born into high-skilled families, the probability of holding a lower than high-skilled occupation is around 40% in both countries. Additionally, children from low-skilled families in both Russia and China have about a 60% chance of upgrading their occupational class.

Figure 11: Distribution of occupational classes in father-to-child samples

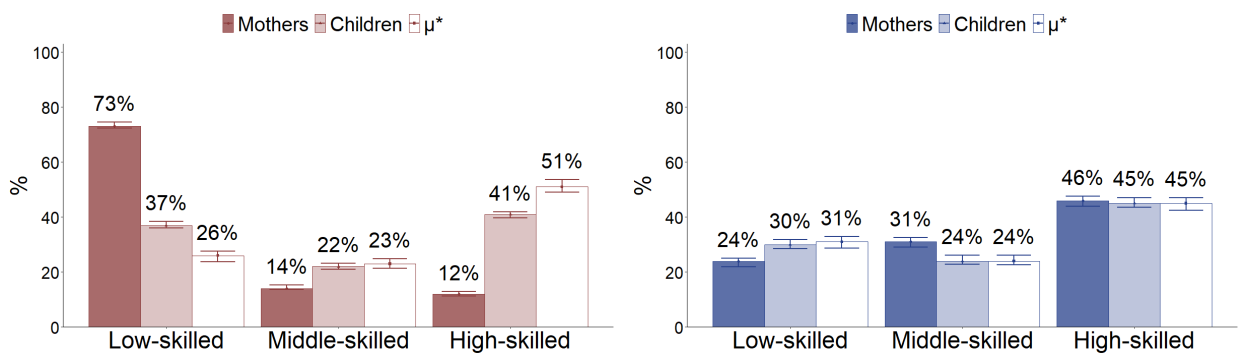
(a) China (b) Russia



Notes: These figures illustrate the evolution of occupational distribution from fathers to children, and ultimately to the steady-state distribution μ^*, in China and Russia. Error bars indicate 95% CIs, derived from 1,000 bootstrap samples.

Figure 12: Distribution of occupational classes in mother-to-child samples

(a) China (b) Russia

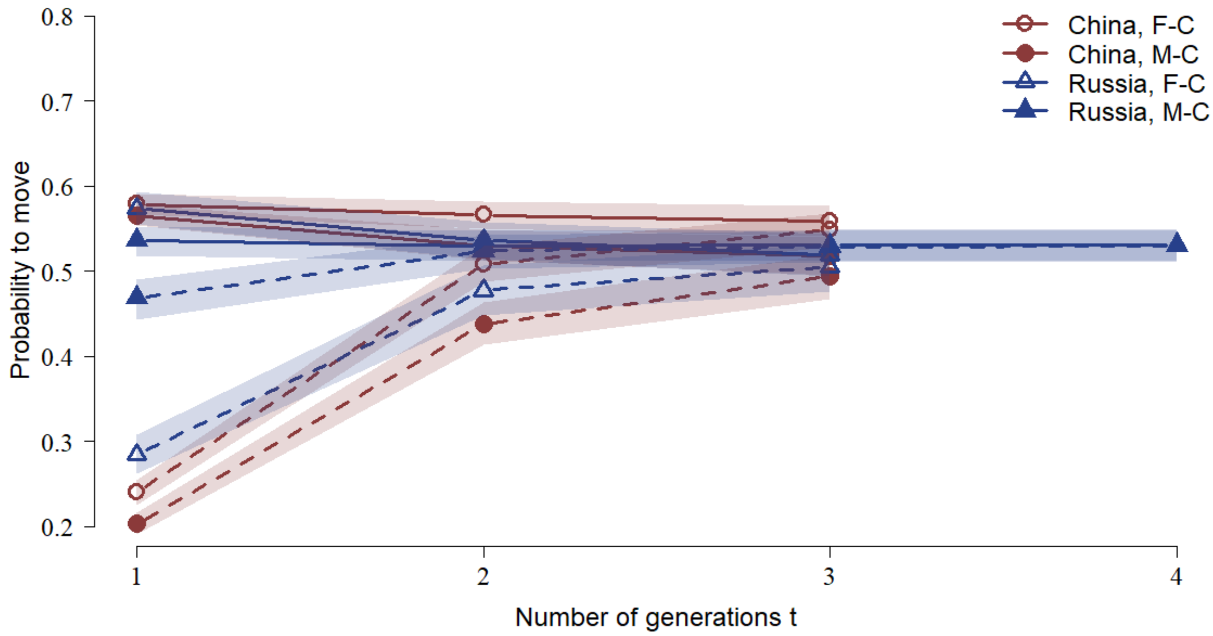


Notes: These figures illustrate the evolution of occupational distribution from mothers to children, and ultimately to the steady-state distribution μ^*, in China and Russia. Error bars indicate 95% CIs, derived from 1,000 bootstrap samples.

The comparison of the steady state occupational distributions to the current children's occupational distribution, as shown in Figures 11 and 12, suggests preliminarily that the Markov chain processes are nearing the steady state in the father-to-child samples in both China and Russia, as well as in the mother-to-child sample in China. In the mother-to-child sample in Russia, the Markov chain appears even closer and almost already at a steady state, with the steady state distribution of occupations closely matching the current children's distribution. A more rigorous analysis of the distance to the steady state is presented in the Appendix F. Notably, the steady state distribution itself indicates an equally favorable expected equilibrium for China and Russia, with both countries exhibiting comparable proportions across occupational attainment classes at

μ^*.

Figure 13: Dynamics of overall, structural, and exchange occupational mobility



Notes: This figure plots 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) 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% CIs , derived from 1,000 bootstrap samples.

Table 9: Estimates of of overall, structural, and exchange occupational mobility measures

	Father-to-child		Mother-to-child	
	China	Russia	China	Russia
OM, t=1	0.579	0.574	0.565	0.536
OM upward, t=1	0.467	0.438	0.488	0.248
OM downward, t=1	0.111	0.136	0.077	0.288
SM, t=1	0.339	0.289	0.363	0.067
EM, t=1	0.240	0.285	0.203	0.469
SSM, t*	0.549	0.504	0.494	0.530

Notes: This table present the results on estimated movement mobility measures from eq. (2) - (5): overall mobility $OM^t(P, \mu^t, t)$, structural mobility $SM^t(P, \mu^t, t)$, and exchange mobility $EM^t(P, \mu^t, t)$.

The analysis of overall, exchange, and structural occupational mobility reveals less substantial differences between China and Russia, compared to the results for educational mobility. As seen in Figure 13 and Table 9, the probability of children having a different occupation skill level than their parents $OM^{t=1}$ is slightly higher in China (57-58%) than in Russia (54-57%).[1] In China, upward mobility dominates overall mobility, accounting for around 81-86% of all class changes ($OM^{t=1}upward/OM^{t=1}$). In Russia, upward mobility accounts for 76% of overall mobility in the father-to-child sample and only 46% in the mother-to-child sample. The decomposition of overall mobility into structural and exchange mobility provides a more detailed picture. In China, the probability of movement due to changes in occupational structure ($SM^{t=1}/OM^{t=1}$) is around 60%. As previously noted, structural mobility in China is largely driven by industrialization and the shift of labor out of the agricultural sector (see Figure 2 in Section 2).[2] In Russia, for the father-to-child sample the probability is around 50%, but in the mother-to-child sample it is just 13%. The gender difference in structural mobility in Russia can be explained by the difference in occupational patterns of men and women during the Soviet era described earlier. After the collapse of the Soviet Union the industrial sector in Russia stagnated (Figure 3 in Section 2), leading to more structural mobility between fathers and their children compared to mothers. Interestingly, exchange mobility in the Russian mother-to-child sample is larger than in the father-to-child sample in Russia and in both samples in China.

In the long run, after accounting for structural changes, our key measure of occupational steady state mobility SSM is very similar for China and Russia. The likelihood of children having a different occupational skill level than their parents at the steady state is 50-55% in China and 50-53% in Russia. Conditioning on confidence intervals shown by the shaded areas in Figure 13, this difference is not statistically significant.

6.1 Heterogeneity

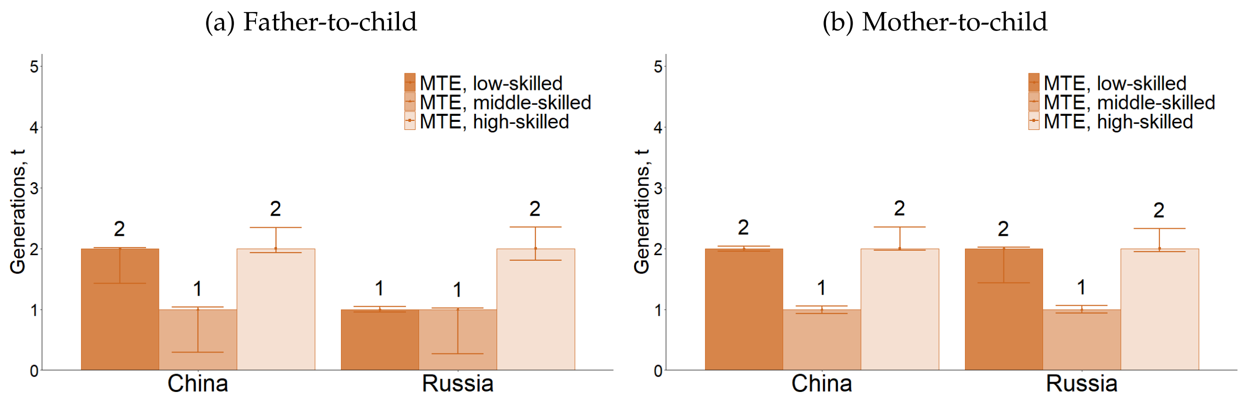
The results for class-specific movement measures (Figure 14) indicate high mobility across all occupational classes in both China and Russia, with no more than two generations required to exit any class in the Markov chain. The least "sticky" skill level, conditioning on confidence intervals, is the middle-skilled occupations in both countries, as well as the low-skilled occupation in the father-to-child sample in Russia.

Overall, the results on occupational intergenerational mobility indicate that China and Russia have comparable levels of mobility. The exchange mobility index reveals no statistically significant difference between the two countries in the likelihood of individuals deviating from their parental occupational class at the steady state. Notably, the analysis of occupational mobility shows distinctions in intergenerational mobility when comparing father-to-child and mother-to-child samples in Russia. The findings from the father-to-child sample suggest a greater level of structural mobility compared to the mother-to-child sample, which makes sense given gender imbalances in occupa-

[1]The complete set of mobility measure estimates for each generation t, up to the steady state, is presented in the Appendix E.

[2]The outflow of labor from the agricultural to the non-agricultural sector during China's market transition is also documented by Zhou and Xie (2019).

Figure 14: Mean time to exit from each occupational class



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

tional distribution that were prevalent during the Soviet era (as it was discussed in the Section 3).

6.2 Comparison to the U.S.

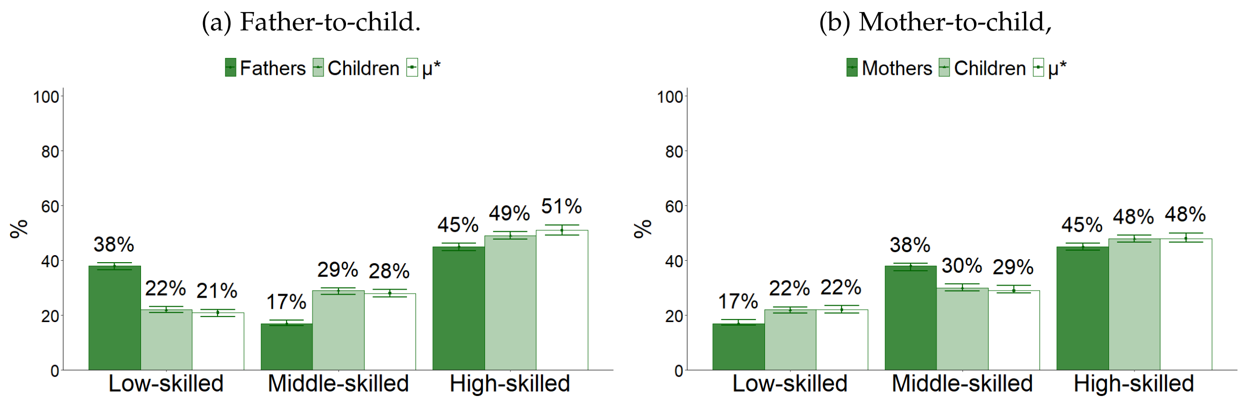
Table 10: Occupational transition matrices for the U.S.

Father \ Child	Low-skilled	Middle-skilled	High-skilled
Low-skilled	0.30 [0.27,0.32]	0.34 [0.32,0.36]	0.37 [0.35,0.39]
Middle-skilled	0.27 [0.24,0.30]	0.32 [0.29,0.35]	0.41 [0.38,0.44]
High-skilled	0.14 [0.13,0.15]	0.23 [0.22,0.25]	0.63 [0.61,0.65]
Mother \ Child	**Low-skilled**	**Middle-skilled**	**High-skilled**
Low-skilled	0.37 [0.34,0.41]	0.27 [0.24,0.30]	0.36 [0.33,0.39]
Middle-skilled	0.24 [0.22,0.26]	0.36 [0.34,0.38]	0.40 [0.38,0.42]
High-skilled	0.14 [0.13,0.15]	0.27 [0.25,0.29]	0.59 [0.57,0.61]

Notes: This table presents the occupational transition matrices for the U.S. The numbers in brackets indicate 95% CIs, calculated from 1,000 bootstrap samples.

From Table 10, it is evident that the primary patterns observed in the transition matrices for China and Russia are also found in the United States: (a) we see similar transition probabilities in the father-to-child and mother-to-child samples; (b) upward mobility is slightly greater than downward mobility although this difference is less pronounced compared to educational transition matrices.

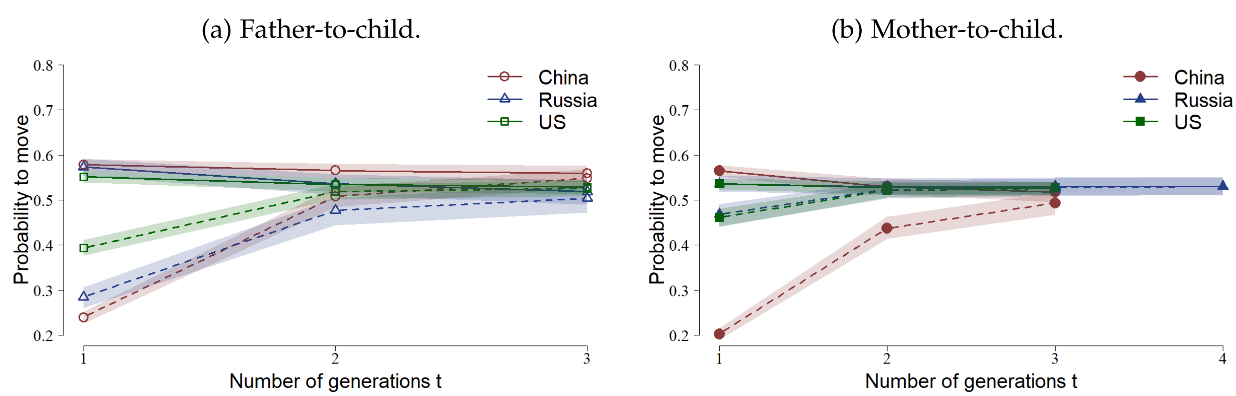
Figure 15: Distributions of occupational classes in the U.S.



Notes: These figures illustrate the evolution of occupational distribution from fathers (mothers) to children, and ultimately to the steady-state distribution μ^*, in the U.S. Error bars indicate 95% CIs, derived from 1,000 bootstrap samples.

Figure 15 illustrates the stable and high level of economic development in the United States. In China and Russia, most fathers and a significant portion of mothers in China are engaged in low-skilled labor. In the US, high-skilled labor already prevails in both the parental and children samples. The distribution of occupation in the steady state looks similar to the current children's distribution, which is suggestive of the Markov process being close to the steady state. Qualitatively, the steady state distribution in the United States is also similar to those observed in China and Russia, characterized by a higher concentration of individuals in high-skilled occupations.

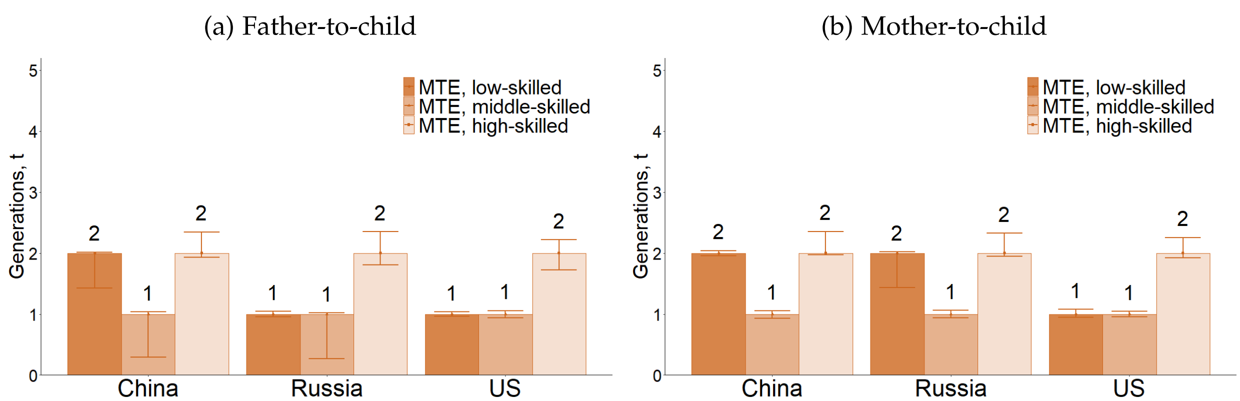
Figure 16: Dynamics of overall, structural, and exchange occupational mobility: a comparison with the U.S.



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) 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% CIs derived from 1,000 bootstrap samples.

The analysis of movement mobility measures suggests that the probability of children having a different occupational skill level than their parents $OM^{t=1}$ is pretty similar across all three countries (Figure 16).[1] Upward mobility accounts for around 50-60% of overall mobility in the United States and in the mother-to-child sample in Russia. In China and in the father-to-child sample in Russia this share is higher ($\sim$ 80%). Table E2 in Appendix E shows that the share of structural mobility $SM^{t=1}$ in overall mobility $OM^{t=1}$ in mother-to-child samples is similarly small in the United States and Russia (around 13-14%), but substantially higher in China (64%). In the father-to-child sample, the share of movement related to structural changes is substantially higher in China (59%) and Russia (50%) compared to the United States (29%). These findings align with the previously discussed differences in cross-generational occupational distributions in the three countries. In the long run, net of the effect of structural changes, our preferred measure of steady state mobility shows that the probability of intergenerational changes in occupational skill levels is similar across all three countries: 50-55% in China, 53% in the United States, and 50-53% in Russia.

Figure 17: Mean time to exit from each occupational class: a comparison with the U.S.



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

The results for class-specific movement measures in the U.S. also suggest high mobility across all occupational classes (Figure 17). Based on the mean time to exit (MTE), it takes no more than two generations to move out of any occupational skill level. Among all classes and across all three countries, the middle-skilled occupations consistently are the least "sticky"—or the most mobile.

Overall, our comparative analysis across the three countries show that using the baseline steady state exchange mobility measure all three countries exhibit similar levels of occupational intergenerational mobility. As a robustness check, we also assess occupational mobility by examining movement measures using only the eldest child sample for all three countries (Appendix H) and the results are very similar to the baseline results.

[1]See Appendix C for a comparison of transition matrices and cross-sectional distributions.

6.3 Comparison to the conventional mobility measures

Our comparisons with conventional intergenerational mobility measures from the economics literature, presented in Appendix F, indicate that occupational mobility in China exceeds that in both Russia and the United States. This conclusion is based on standard intergenerational elasticity IGE and intergenerational correlation IGC measures derived from linear models. This reveals a significant divergence between results from linear models and our baseline results using Markov chains. The parameter estimate ϕ_k from the log-multiplicative layer effect model (Xie, 1992), commonly used in sociology literature, also indicates that there is greater occupational exchange mobility in China than in both Russia and the United States within the father-to-child sample. In contrast, for the mother-to-child samples Russia exhibits greater mobility than both China and the United States even though our baseline results using Markov chain models show no statistically significant differences in steady state mobility across the three countries.

7 Conclusion

This paper studies intergenerational mobility of educational and occupational status in China and Russia during the emergence of market economies in these countries. Understanding mobility in the context of economic transition requires carefully distinguishing between structural mobility and exchange mobility. We operationalize this distinction for mobility as movement calculations. Further, we propose a new mobility statistic, steady state mobility, which captures the expected fraction of dynasties that keep experience a change in class, once transition has been completed. Together, these measures allow for a rich chacterization of Chinese and Russian mobility in the last 30 years.

For education, we find that the probability of changing educational classes for children is substantially higher in China (52-53%) than in Russia (45-46%). However, around 68-81% of the measure for China is attributable to structural change, in particular the rapid development of an educational system which led to much higher levels of educational attainment of children compared to their parents, the majority of which did not advance beyond primary education. For Russia, around 57-68% of the overall mobility also is attributable to shifts in educational structure. Decomposing overall mobility into structural and exchange components shows that for both countries, structural mobility dominates overall mobility. However, China exhibits lower mobility than Russia at the steady state, where children change educational classes with 19-27% probability in China compared to 42% in Russia.

For occupational mobility, we find that overall mobility is slightly higher in China (57-58%) than in Russia (54-57%). However, once one considers structural and exchange mobility differences, more complex patterns emerge. Changes in the marginal distribution of parents and children exhibit a common pattern for China regardless of whether one considers mothers or fathers—parents in low-skilled occupations often have children who enter high-skilled occupations. We find a similar pattern for fathers and children in Russia, but not for mothers and children. These differences reflect the nature of economic transitions in the two countries. China's structural changes mainly consisted of a transition from agriculture to industry. However, in Russia, the shift in the father and child distribution reflects the shrinking of the industrial sector after the collapse of the centrally planned economy, and gender differences in mobility findings reflect gender imbalances in the occupational structure during the Soviet era. We find that for China 60% of the overall occupational mobility is structural whereas in Russia we find relatively small structural occupational mobility in the mother-to-child sample (13% of overall mobility) compared to the father-to-child sample (50%). Our steady state mobility measure suggests that there is no statistically significant difference in the probability of intergenerational changes occupational skill levels at the steady state in both countries (50-55%).

Finally, our paper provides a comparison between intergenerational mobility in transitioning societies in China and Russia with the mature society of the U.S. We find that educational steady state mobility is substantially higher in Russia and the U.S. than in China. Occupational steady state mobility exhibits similar levels in all three societies which differs from findings using conventional measures of intergenerational mobility.

Together, these results demonstrate that the traditional sociological distinction between structural and exchange mobility is essential in understanding how the transition from central planning to a market economy has affected intergenerational mobility in Russia and China. Our analysis shows how, even with high overall mobility, in absence of further changes in the transition matrix linking parents to children, China will eventually become less mobile in education (and equally mobile in occupational skill levels) compared to Russia and the United States.

We regard these results as establishing stylized facts for the Chinese and Russian mobility process. A natural next step is the consideration of structural models of mobility that link the Markov transition probabilities to underlying mechanisms. This advance would allow for predictions about the trajectories of future mobility matrices and thereby open new channels for understanding structural, exchange and steady state mobility. It is worth noting that long term advances in our measurement calculations, of course, will be facilitated when a third generation is observed for China and Russia. Butaeva et al. (in progress) and Durlauf, Kim, Lee, and Song (2024) demonstrate how evolving Markov transition matrices can produce novel ways to think about mobility.

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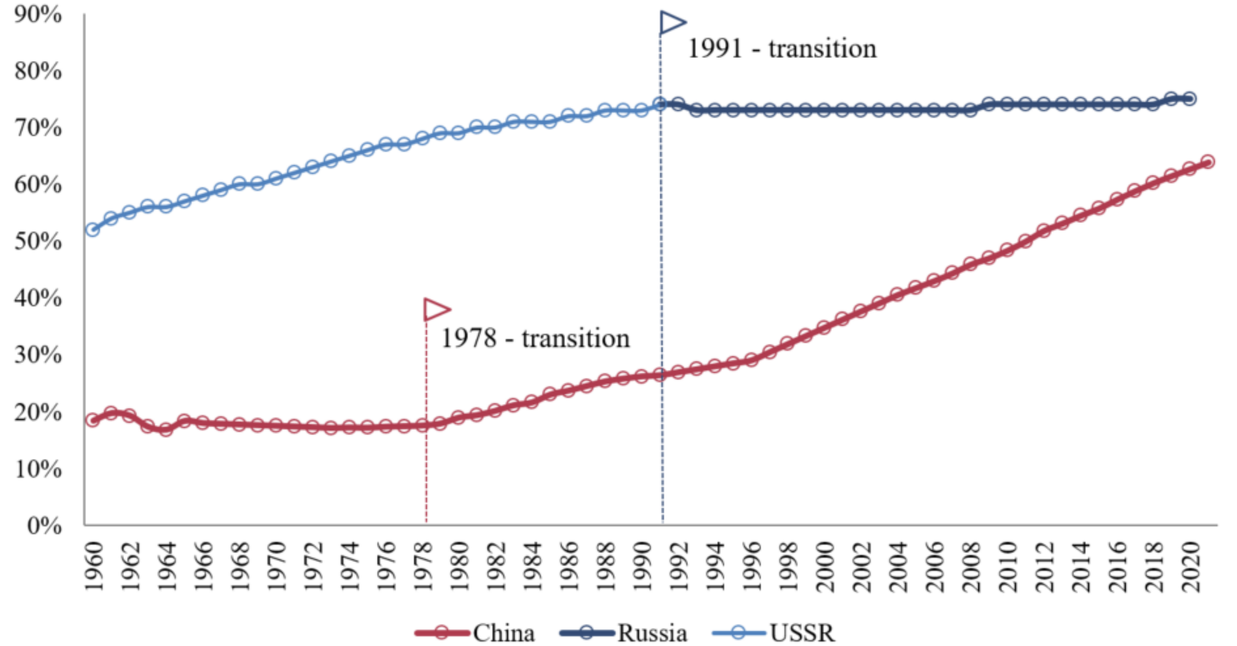
Appendix

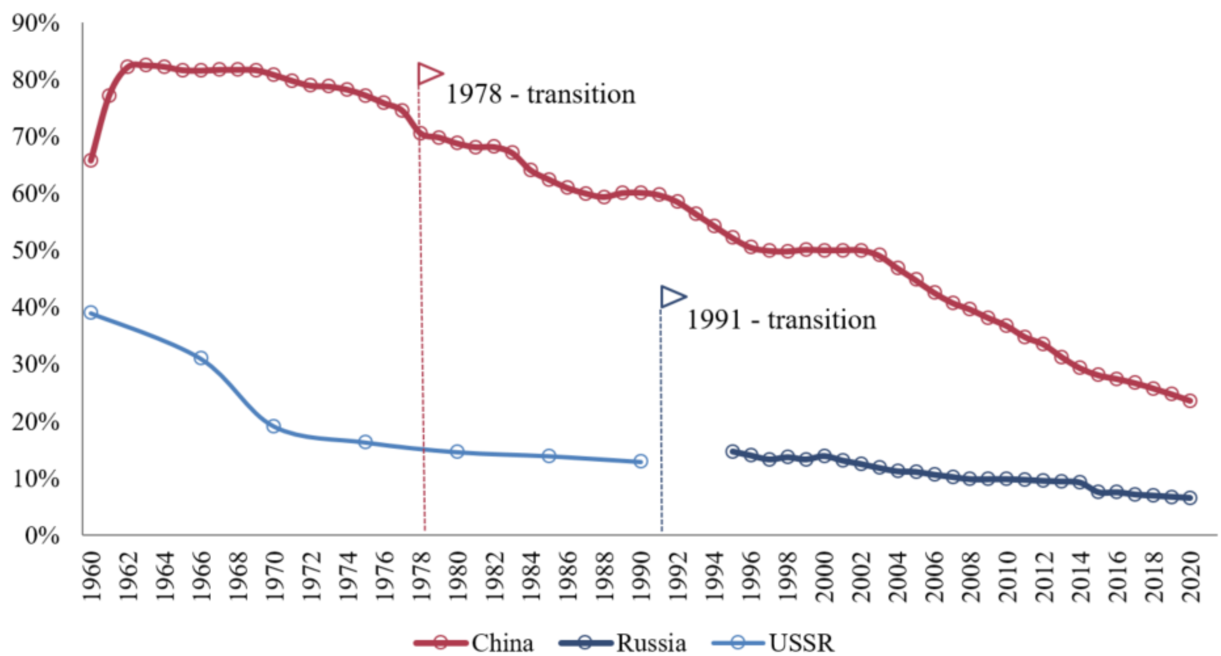
A Official statistics

Figure A1: Evolution of the urban population share over time



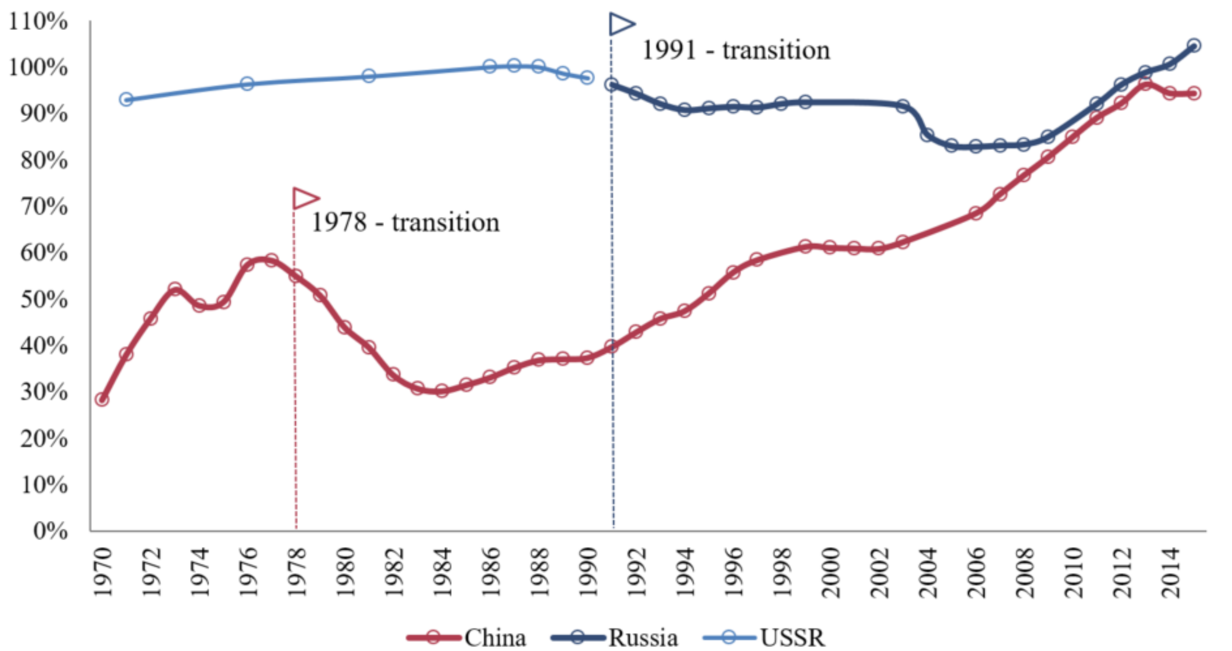
Notes: This figure illustrates the evolution of share of urban population in total population in China and Russia from 1960 to 2020. Red and blue flags indicate the beginning of market reforms in China and Russia, respectively. *Data sources:* China - National Bureau of Statistics (NBS) of China (https://www.stats.gov.cn), Xu, van Leeuwen, and van Zanden (2018); Russia - Federal State Statistics Service (FSSS) of Russia (https://rosstat.gov.ru).

Figure A2: Evolution of the employment share in the agricultural sector over time



Notes: This figure illustrates the evolution of share of workers employed in agricultural sector in China and Russia from 1960 to 2020. Red and blue flags indicate the beginning of market reforms in China and Russia, respectively. *Data sources:* China - National Bureau of Statistics (NBS) of China (https://www.stats.gov.cn); Russia - Federal State Statistics Service (FSSS) of Russia (https://rosstat.gov.ru, https://istmat.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. *Data source:* `https://ourworldindata.org`.

B Sample construction

B.1 Summary statistics

Table B1: Descriptive statistics of key sample variables

	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

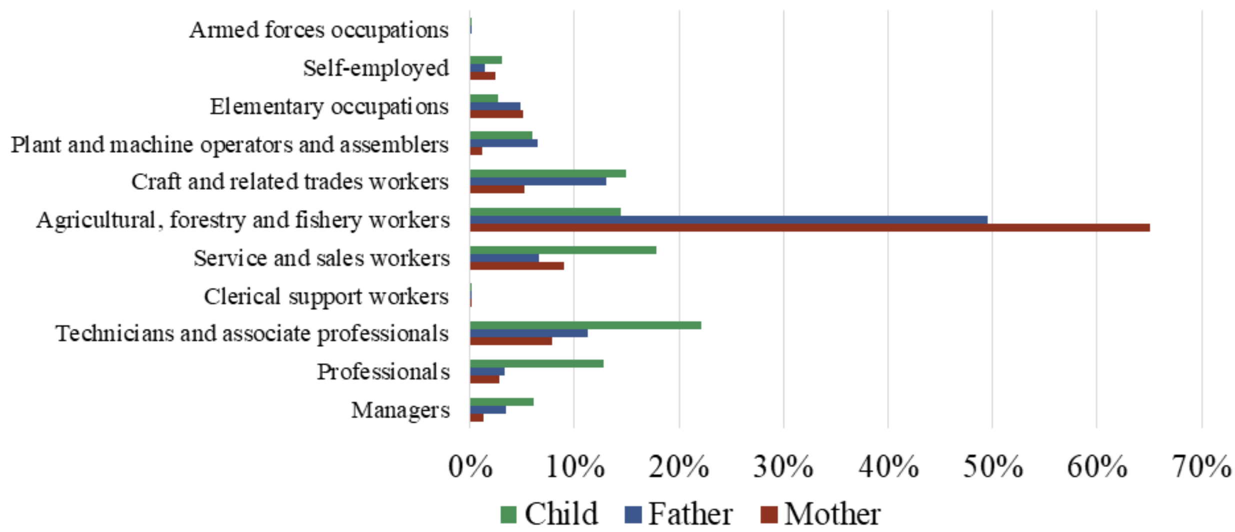
Data sources: China Family Panel Studies (CFPS), Russian Longitudinal Monitoring Survey (RLMS-HSE).

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 only applied 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 his household weight, divided by the number of individuals in each family. This standardization allows to equalize 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 only use observations on individuals who have individual survey weights.

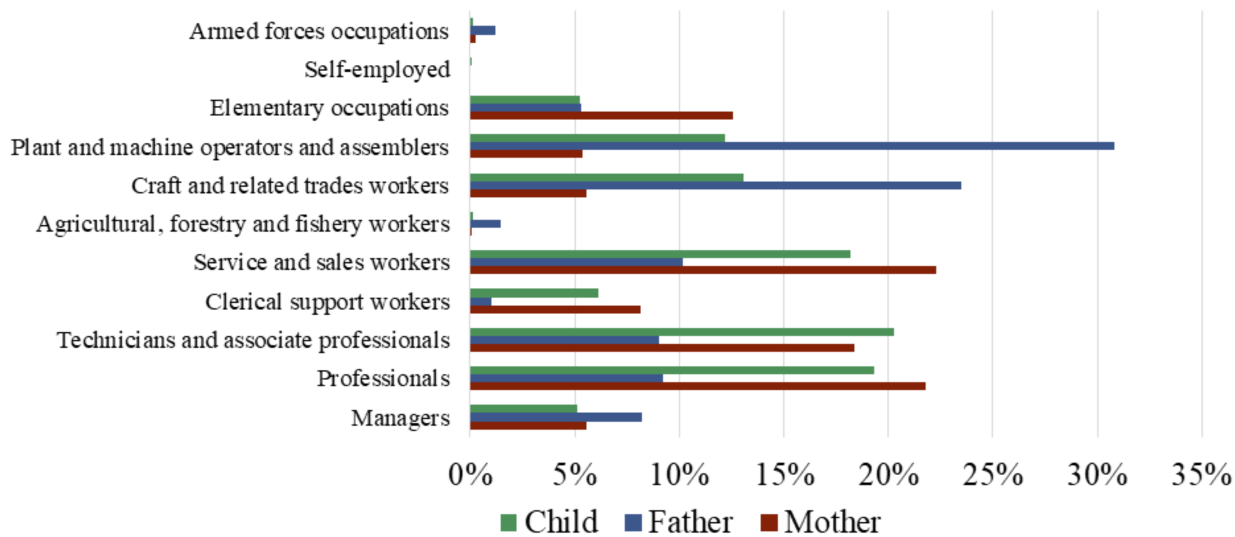
B.3 Distribution of occupational classes: detailed

Figure B1: China



Data source: China Family Panel Studies (CFPS).

Figure B2: Russia



Data source: Russian Longitudinal Monitoring Survey (RLMS-HSE).

B.4 Sample representativeness

Table B2: Gender composition

	China		Russia	
	CFPS	CSY-2019	RLMS	RSY-2019
%, Male	53%	51%	48%	46%

Notes: This table compares shares of males in our samples with the corresponding population figures reported by the National Bureau of Statistics (NBS) of China and the Federal State Statistics Service (FSSS) of Russia. *Data sources:* China Family Panel Studies (CFPS), China Statistical Yearbook (CSY) 2019 (https://www.stats.gov.cn), Russian Longitudinal Monitoring Survey (RLMS-HSE), Russian Statistical Yearbook (RSY) 2019 (https://rosstat.gov.ru).

Table B3: Distribution of educational attainment

	China			Russia		
	22-40 y.o. in 2018		Children	Among employed		Children
	Census-2015	Census-2020	CFPS	RSY-2019	RLMS-2018	RLMS
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

Notes: This table compares the distribution of educational attainment in our samples with the corresponding population figures reported by the NBS of China and the FSSS of Russia. *Data sources:* CFPS, China Census 2020, China 1% Census 2015, RLMS-HSE, RSY 2019 (https://rosstat.gov.ru).

Table B4: Distribution of occupational classes

	China		Russia		
	22-40 y.o. in 2018	Children	Among employed		Children
	Census-2015	CFPS	WEUR-2020	RLMS-2018	RLMS
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

Notes: This table compares the distribution of occupational classes in our samples with the corresponding population figures reported by the NBS of China and the FSSS of Russia. *Data sources:* CFPS, China Census 2020, China 1% Census 2015, RLMS-HSE, Yearbook ”Workforce, Employment and Unemployment in Russia 2020” (WEUR-2020) (https://rosstat.gov.ru).

C Data for the U.S.

C.1 Survey description

The data for the United States 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 China Family Panel Studies (CFPS), we designate the most recent wave (2019) as the baseline year. The final U.S. 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 U.S. sample based on the PSID data. The average age of children in the U.S. sample is 31 years, which is comparable to the average age of children in China. In contrast, the average ages of parents in

[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`.

the U.S. sample are more similar to those observed in the Russian sample. In terms of educational attainment, the U.S. sample has the highest level of education among the three countries. On average, children, fathers, and mothers in the U.S. have completed 14.0, 13.7, and 13.6 years of education, respectively.

Table C1: Distribution of educational attainment

	U.S.		
	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%

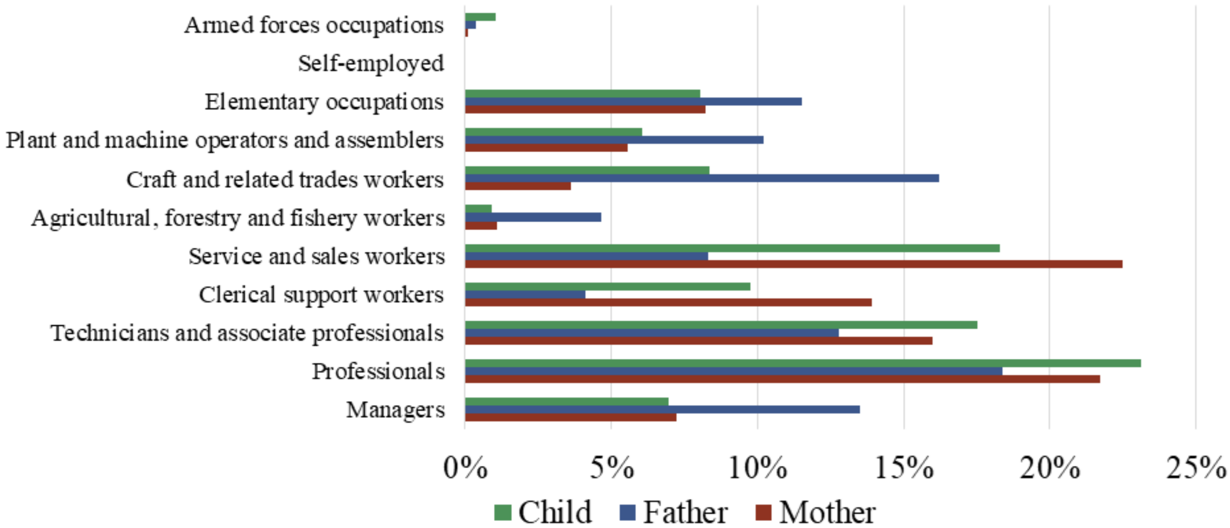
Notes: This table shows the distribution of educational attainment among children and their parents in our constructed sample from the Panel Study of Income Dynamics (PSID). Survey weights were applied to compute these shares.

Table C2: Distribution of occupational classes

	U.S.		
	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 ISCO-08 system, as used in the RLMS-HSE. 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.

Figure C1: Detailed distribution of occupational classes in the U.S.



Data source: Panel Study of Income Dynamics (PSID).

Table C3: Descriptive statistics of key sample variables

	U.S.		
	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 Education 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

Data source: Panel Study of Income Dynamics (PSID).

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

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

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 intergenerational *correlation* coefficient (IGC), defined as:

$$\rho = \beta_1 \frac{\sigma^p}{\sigma^c} \tag{D2}$$

where σ^p represents the standard deviation of the parental outcome variable SD(Y_i^p), and σ^c is the standard deviation of the child's outcome variable 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 China 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 due 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. Due to the perceived "eliteness" of the tertiary and quaternary sectors, there is significant persistence within these sectors.[1] For instance, we can assume $p_{33} = p_{44} = 0.97$. In summary, we expect that the mobility

[1]One way to rationalize this is to consider middle-class anxiety, where parents do everything possible to ensure their children don't fall below the same social class.

process will evolve according to the following Markov chain:

$$\underbrace{\begin{pmatrix}0.97\\0.01\\0.01\\0.01\end{pmatrix}^{\intercal}}_{\mu^0} \times \underbrace{\begin{pmatrix}0.01 & 0.49 & 0.49 & 0.01\\0.01 & 0.49 & 0.49 & 0.01\\0.01 & 0.01 & 0.97 & 0.01\\0.01 & 0.01 & 0.01 & 0.97\end{pmatrix}}_{P} = \underbrace{\begin{pmatrix}0.01\\0.48\\0.49\\0.02\end{pmatrix}^{\intercal}}_{\mu^1} \quad \to \quad \underbrace{\begin{pmatrix}0.01\\0.03\\0.71\\0.25\end{pmatrix}^{\intercal}}_{\mu^*} \tag{D3}$$

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.[1] This relatively low level of intergenerational persistence might suggest a highly mobile economy. However, a deeper analysis reveals that the IGE only provides 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 mostly driven 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 who 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 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

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

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 lot of important information about the mobility process may remain hidden if one considers only considers 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 & Durlauf, 1996). The latter point is illustrated in the following discussion.

Consider the following Markov chain:

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

Let's assume that the first class ($i = 1$) represents the poorest group based on income, while 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 one percent chance of improving their social class. At the same time, children of parents from classes 2 to 4 also have less than a one percent chance of descending into the poorest class. However, these probabilities are still non-zero, and as time progresses $t \to \infty$, this Markov chain will eventually converge to a steady state distribution which 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' 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 high estimate of exchange mobility $EM^{t=1} = 0.640$ mobility. The steady state mobility suggests that, after accounting for structural changes, the probability to exit one's parent's 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, China	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, China	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, China	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, China	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, China	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, U.S.	0.375	0.335	0.331	0.331	-	-	-	0.374	0.332	0.328	0.327	-	-	-
OM upward, U.S.	0.212	0.171	0.166	0.166	-	-	-	0.194	0.164	0.163	0.163	-	-	-
OM downward, U.S.	0.163	0.164	0.165	0.165	-	-	-	0.180	0.168	0.165	0.164	-	-	-
SM, U.S.	0.066	0.006	0.001	0.000	-	-	-	0.092	0.013	0.003	0.001	-	-	-
EM, U.S.	0.309	0.329	0.330	0.331	-	-	-	0.282	0.319	0.325	0.326	-	-	-

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.

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, China	0.579	0.566	0.559	0.565	0.530	0.518	-
OM upward, China	0.467	0.323	0.291	0.488	0.323	0.276	-
OM downward, China	0.111	0.242	0.268	0.077	0.207	0.242	-
SM, China	0.339	0.058	0.010	0.363	0.092	0.024	-
EM, China	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, U.S.	0.552	0.534	0.529	0.536	0.528	0.527	-
OM upward, U.S.	0.338	0.273	0.264	0.260	0.259	0.258	-
OM downward, U.S.	0.214	0.261	0.265	0.275	0.269	0.269	-
SM, U.S.	0.158	0.015	0.004	0.075	0.007	0.001	-
EM, U.S.	0.394	0.519	0.526	0.461	0.521	0.527	-

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.

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:

$$P_A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \qquad P_B = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \qquad P_C = \begin{pmatrix} p_x & p_y \\ p_x & p_y \end{pmatrix}. \tag{F1}$$

Movement mobility indices capture the frequency of changing classes in the Markov chain.[1] 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

[1]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).

a perfectly mobile society, the likelihood of a child entering a particular social class is independent of the class of their father (Prais, 1955).[1] 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.[2] 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 at every step of the transition t:

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

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 for transitioning to any given class. The process by which the distribution of transiting 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):

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

where e_i is a vector with weight 1 in class i and zeros 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.

[1]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 & Sommers, 1979; Shorrocks, 1978; Sommers & Conlisk, 1979).

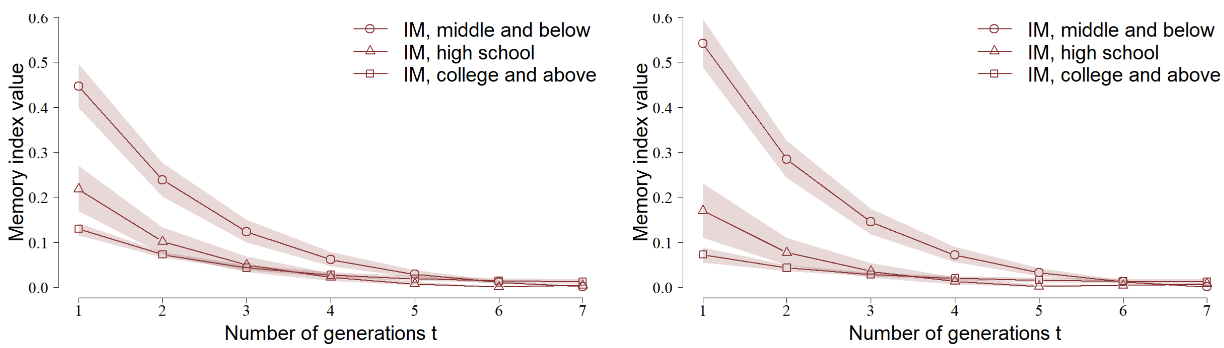
[2]We follow Blume et al. (2025).

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 7^{th} generation in China and the 4^{th} 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 China. Individual memory curves depicted on Figures F1-F2) reveal that in both Russia and China, 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 (Figures F1b) in China. The same class in the father-to-child sample in China as just as mobile as in both samples in Russia. In China, 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).[1]

Figure F1: Individual educational memory curves for China

(a) Father-to-child. (b) Mother-to-child.



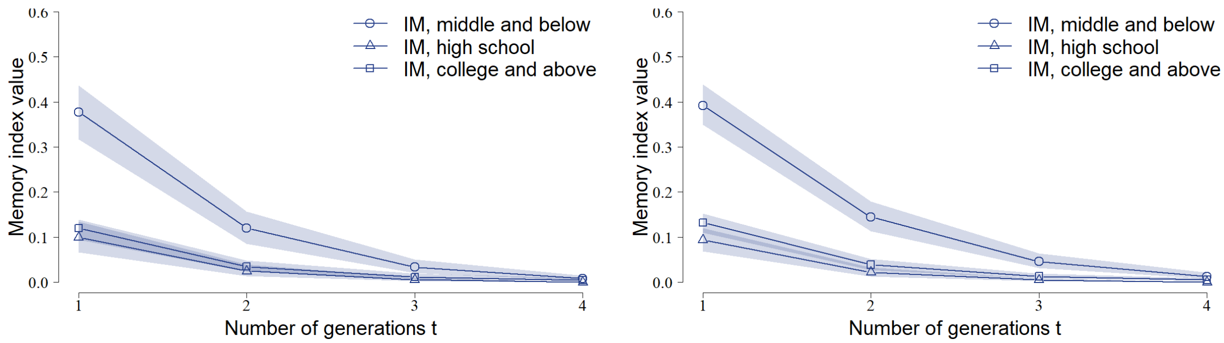
Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (a) and mother-to-child (b) samples in China. Shaded areas represent 95% CIs derived from 1,000 bootstrap samples.

The overall origin-memory disappears by the 4^{th} generation in both Russia and the United States and by the 7^{th} generation in China. The analysis of memory measures based on Figures F1, F2, and F3 suggest that in the U.S., memory disappears with the same speed across all initial classes.

[1]The full set of educational individual memory curves estimates is reported in Tables F1.

Figure F2: Individual educational memory curves for Russia

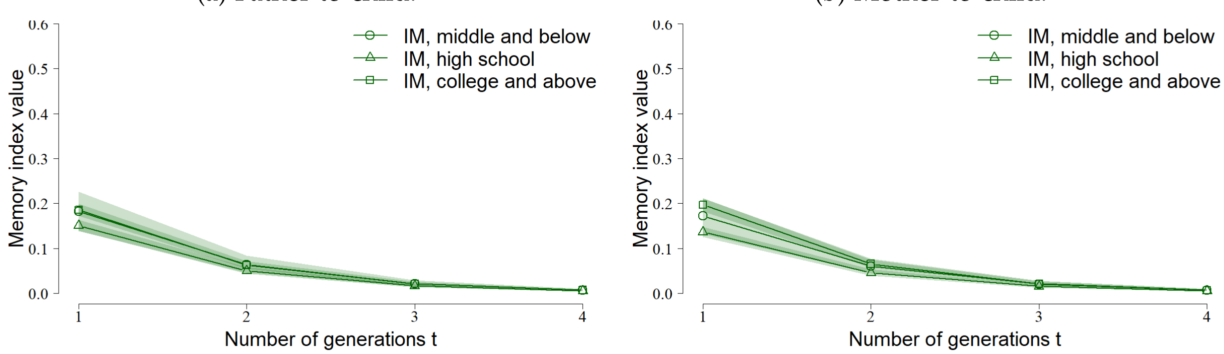
(a) Father-to-child. (b) Mother-to-child.



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% CIs derived from 1,000 bootstrap samples.

Figure F3: Individual educational memory curves for the U.S.

(a) Father-to-child. (b) Mother-to-child.



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 U.S. Shaded areas represent 95% CIs derived from 1,000 bootstrap samples.

Table F1: Measures of educational memory

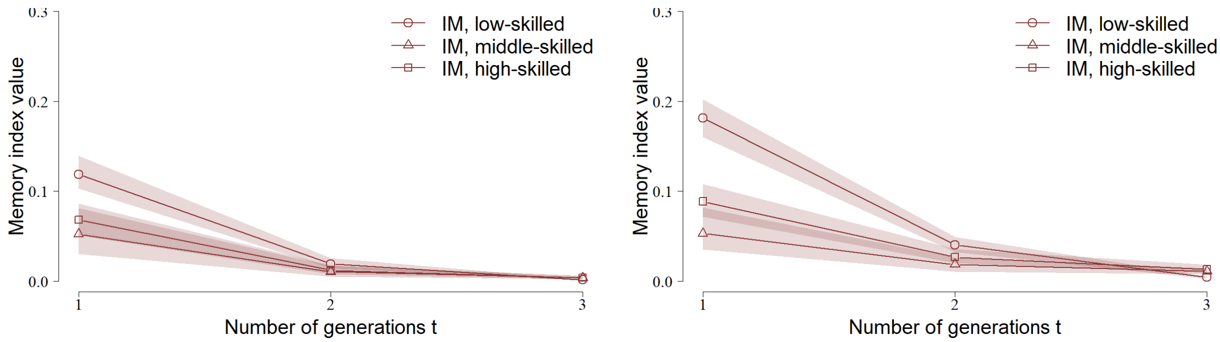
	Father-to-child							Mother-to-child						
	t=1	t=2	t=3	t=4	t=5	t=6	t=7	t=1	t=2	t=3	t=4	t=5	t=6	t=7
IM middle and below, China	0.447	0.239	0.124	0.062	0.029	0.011	0.001	0.541	0.284	0.145	0.072	0.033	0.012	0.001
IM high school, China	0.218	0.102	0.050	0.022	0.007	0.000	0.005	0.170	0.077	0.035	0.013	0.002	0.004	0.007
IM college and above, China	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, U.S.	0.182	0.064	0.022	0.007	-	-	-	0.172	0.061	0.021	0.007	-	-	-
IM high school, U.S.	0.151	0.050	0.017	0.006	-	-	-	0.137	0.046	0.016	0.005	-	-	-
IM college and above, U.S.	0.186	0.063	0.021	0.007	-	-	-	0.197	0.066	0.022	0.007	-	-	-

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

F.3 Results on occupational mobility

Figure F4: Individual occupational memory curves for China

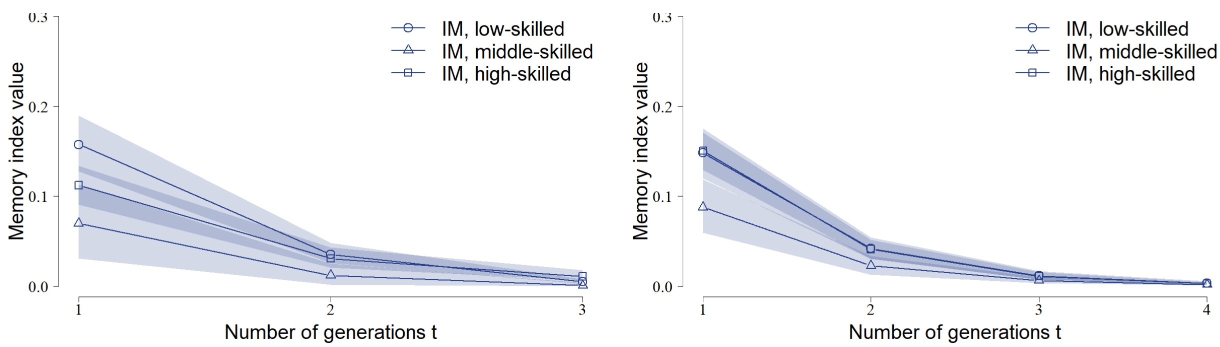
(a) Father-to-child. (b) Mother-to-child.



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 China. Shaded areas represent 95% CIs derived from 1,000 bootstrap samples.

Figure F5: Individual occupational memory curves for Russia

(a) Father-to-child. (b) Mother-to-child.

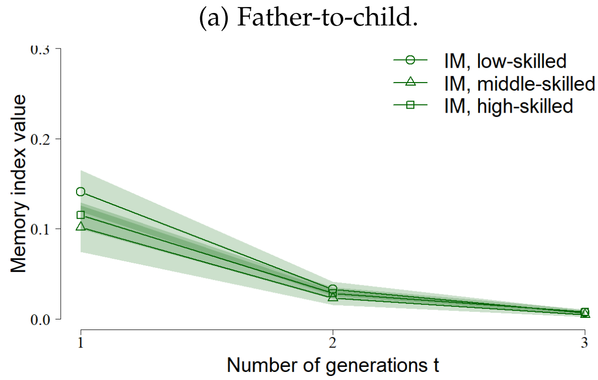


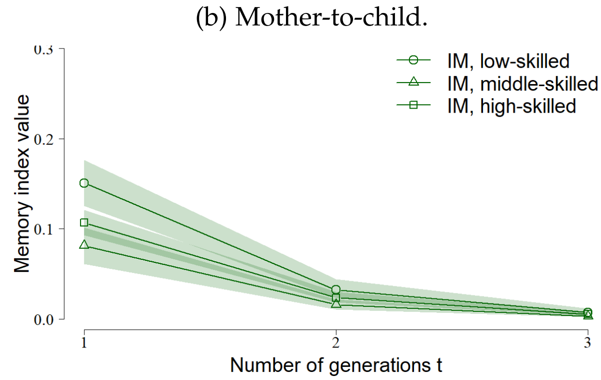
Notes: These figures plot $IM_i^t(P, \mu^*, t)$ (eq. F3) separately for father-to-child (a) and mother-to-child (b) samples in Russia. Shaded areas represent 95% CIs derived from 1,000 bootstrap samples.

The overall societal memory of occupational class origin dissipates by the 3^{rd} generation in China and in the father-to-child sample in Russia. In the mother-to-child sample in Russia, the memory fades by the 4^{th} generation. Figures F4 and F5 show that in both China 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.[1]

[1]The full set of occupational individual memory curves estimates is reported in Tables F2.

Figure F6: Individual occupational memory curves for the U.S.





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 U.S. Shaded areas represent 95% CIs derived from 1,000 bootstrap samples.

The total origin memory disappears by the 3^{rd} generation in all three countries except the mother-to-child sample in Russia, where it dissipates by the 4^{th} generation. Similarly to China and Russia, in the United States 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, China	0.119	0.019	0.002	0.182	0.040	0.004	-
IM middle-skilled, China	0.052	0.011	0.004	0.053	0.019	0.011	-
IM high-skilled, China	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, U.S.	0.141	0.033	0.007	0.151	0.032	0.007	-
IM middle-skilled, U.S.	0.102	0.023	0.005	0.081	0.016	0.003	-
IM high-skilled, U.S.	0.115	0.029	0.008	0.107	0.024	0.005	-

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

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:

$$E_{1i} = \beta_0 + \beta_1 E_{0i} + \epsilon_i, \tag{G4}$$

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

Table G1: Educational IGE and IGC

	China		Russia		U.S.	
	F-C	M-C	F-C	M-C	F-C	M-C
VARIABLES	E_{1i}	E_{1i}	E_{1i}	E_{1i}	E_{1i}	E_{1i}
	(1)	(2)	(3)	(4)	(5)	(6)
E_{0i}	0.387***	0.376***	0.254***	0.293***	0.261***	0.263***
	(0.0154)	(0.0134)	(0.0245)	(0.0216)	(0.0174)	(0.0153)
Constant	8.448***	9.252***	10.19***	9.944***	10.73***	10.60***
	(0.133)	(0.0969)	(0.440)	(0.385)	(0.248)	(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

Notes: 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 China, Russia, and the United States.

One additional year of father's schooling is associated with 0.39 more children's years of schooling in China 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 mothers-to-child pairs (IGE is equal to 0.38 in China vs. 0.29 in Russia). The two countries demonstrate divergent gender patterns. In China, 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, & Zhao, 2019). The point estimates of educational elasticities in our study are close to the existing empirical evidence on China: based on CFPS, Huo and Golley (2022) estimate that IGE of education in China 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 China and 0.18 in Russia. We can notice a sharper difference between IGEs and IGCs in Russia compared to China. The intergenerational correlations based on maternal educational attainment are higher in China (0.40) than in Russia (0.23). The results on IGC conform with the findings by Huo and Golley (2022). He estimates IGC for males in China at 0.2-0.4 and slightly larger for females, from 0.25 to 0.5.

A one 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 U.S. Our results are lower than those reported in the existing literature. Previous studies, such as Hertz et al. (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[1], 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

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 China, Russia, and the U.S. 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 fit as good as those in Xie (1992) original paper. For our analysis, we focus on comparing country-specific

[1] They use data from the U.S. Census, Panel Study of Income Dynamics (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 China	ϕ_2 Russia	ϕ_3 U.S.
(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	-	-	-

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 $\sum \phi_k^2 = 1$.

ϕ_k's from a full interaction FI_x and Hauser's (Hauser, 1978; Hauser & Schuessler, 1979) H_x level models to our results on exchange mobility.[1] 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

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

across societies, a common "topology". In 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, due to only $(R-1) \times (C-1)$ degrees of freedom, where R refers to the number of rows, and C is the number of columns. Having that 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 U.S., and substantially less in China.

G.2 Occupational intergenerational mobility

Comparison to the economist's measures

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

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

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

The estimated occupational IGEs are lower than their educational counterparts in both countries, but the relative comparisons between China and Russia (Table G4) present a similar pattern: the estimated IGEs in China (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 China in terms of the intergenerational transmission of occupations.

In the U.S., 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) claims 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 U.S. A more recent paper by Mazumder and Acosta (2015) also found a father-son intergenerational elasticity coefficient of 0.35 using a ten-year average of the Nakao-Treas Occupational Prestige measure

Table G4: Occupational IGE and IGC

	China		Russia		U.S.	
	F-C	M-C	F-C	M-C	F-C	M-C
VARIABLES	$\log(P_{1i})$	$\log(P_{1i})$	$\log(P_{1i})$	$\log(P_{1i})$	$\log(P_{1i})$	$\log(P_{1i})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P_{0i})$	0.167***	0.116***	0.248***	0.220***	0.202***	0.222***
	(0.0232)	(0.0256)	(0.0196)	(0.0169)	(0.0188)	(0.0195)
Constant	3.141***	3.327***	2.832***	2.921***	2.978***	2.896***
	(0.0828)	(0.0892)	(0.0727)	(0.0634)	(0.0705)	(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

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 China, Russia, and the United States.

and the Hauser-Warren Socioeconomic Index from PSID. Both measures resulted in very close estimates of occupational IGE. IGE comparison suggests that there is greater intergenerational mobility of occupation in China than in the U.S. 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

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

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 China	ϕ_2 Russia	ϕ_3 U.S.
(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	-	-	-

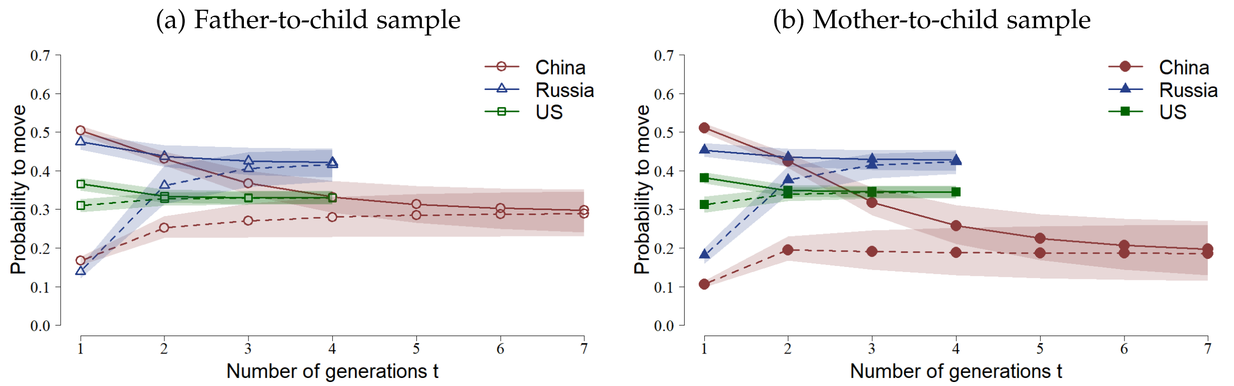
Notes: This table show the goodness-of-fit results of uniform and log-multiplicative layer effect models from Table 2 in Xie (1992), estimated from our occupational data. R is row variable (parental class), C is column variable (child's class), L is layer variable (country), L^2 is the log-likelihood 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 $\sum \phi_k^2 = 1$.

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 educational data, and again none match 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 that there is greater exchange mobility in China than in Russia and the U.S. in the father-to-child sample, while Russia shows more mobility than China and the U.S. in the mother-to-child sample.

H Elder child robustness check

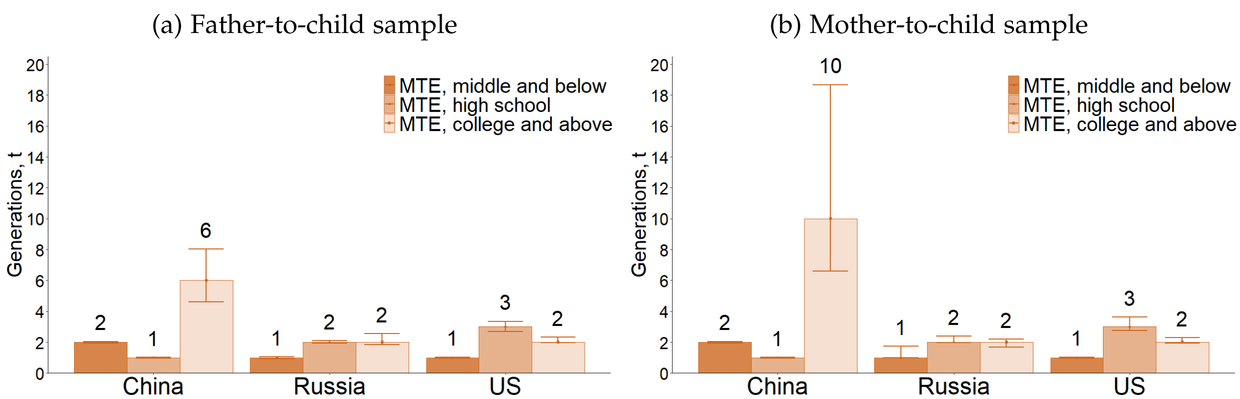
H.1 Educational mobility

Figure H1: Dynamics of overall, structural, and exchange educational mobility



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% CIs derived from 1,000 bootstrap samples.

Figure H2: Mean time to exit from each educational class

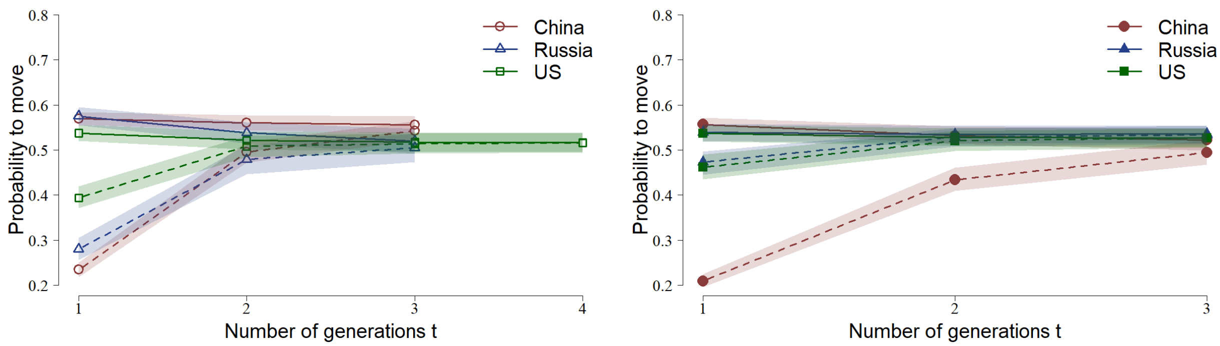


Notes: These figures display the mean time to exit MTE from each educational class, as defined in equation (6), separately for father-to-child and mother-to-child elder sibling samples. The error bars represent 95% CIs derived from 1,000 bootstrap samples.

H.2 Occupational mobility

Figure H3: Dynamics of overall, structural, and exchange occupational mobility

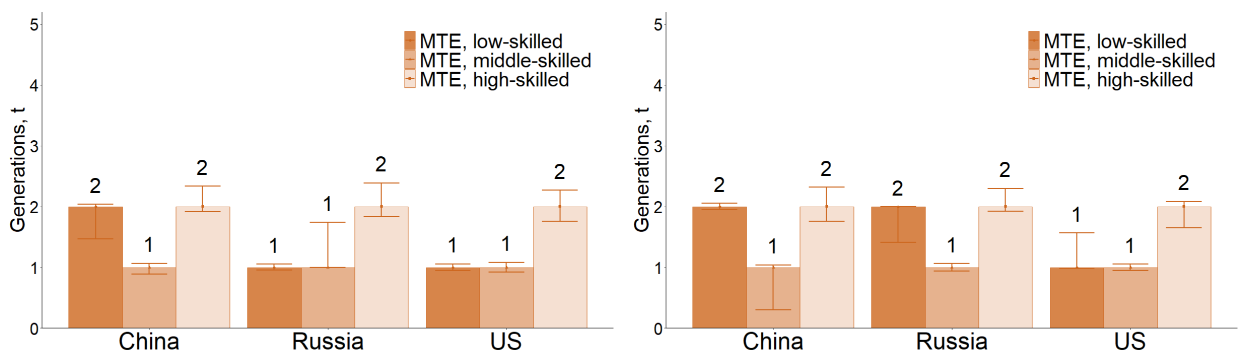
(a) Father-to-child sample (b) Mother-to-child sample



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% CIs derived from 1,000 bootstrap samples.

Figure H4: Mean time to exit from each occupational class

(a) Father-to-child sample (b) Mother-to-child sample



Notes: These figures display the mean time to exit MTE from 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% CIs derived from 1,000 bootstrap samples.