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Inequality and Welfare Dynamics in the Russian Federation during 1994–2015

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Abstract

The Russian Federation offers the unique example of a leading centrally planned economy swiftly transforming itself into a market-oriented economy. This paper offers a comprehensive study of inequality and mobility patterns for Russia, using multiple rounds of the Russian Longitudinal Monitoring Surveys over the past two decades spanning this transition. The findings show rising income levels and decreasing inequality, with the latter being mostly caused by pro-poor growth rather than redistribution. The poorest tercile experienced a growth rate that was more than 10 times that of the richest tercile, leading to less long-term inequality than short-term inequality. The analysis also finds that switching from a part-time job to a full-time job, from a lower-skill job to a higher-skill job, or staying in the formal sector is statistically significantly associated with reduced downward mobility and increased income growth. However, a similar transition from the private sector to the public sector is negatively associated with income growth.

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Inequality and Welfare Dynamics in the Russian Federation during 1994-2015

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I. Introduction

As living standards are rising for most countries around the world, increasingly more attention shifts toward understanding the distribution of economic gains over time. If the sole objective of economic policies is to maximize societal welfare for various population groups, a firm grasp of the trends underlying the dynamics of welfare and inequality is indispensable for cost-effective policies. Indeed, income inequality has become a key topic in public debates and has received increasing attention from various stakeholders, including policy makers, researchers, and the public.[1] Policy makers are thus keenly interested in understanding the distribution of income as well as being able to discern who benefits and who loses from (the lack of) economic growth, and to what extent.

The Russian Federation offers a particularly interesting case study for a variety of reasons. The country used to be the epitome of a centrally planned economy for almost 80 years,[2] which then underwent a radical transformation to a market-oriented economy starting in the early 1990s. This upheaval witnessed its GDP per capita plummeting by as much as 40 percent. Yet, when we plot Russia's household per capita income over the past two decades of 1994-2015, the trend displays a lop-sided V shape with a shorter line segment on the left reaching its bottom in the financial crisis year of 1998 (Figure 1). Put differently, Figure 1 shows that the economy remarkably turned around and could regain its pre-crisis income level (solid line) just within a couple years later. Russia has managed to average a steady annual GDP per capita growth rate of 2.4 percent since

[1] For instance, President Obama highlighted inequality and policies to address this issue in his 2013 speech on economic mobility and 2014 State of the Union speech (White House, 2013 and 2014). As another example, the OECD has recently published a report that focuses on inequality and mobility issues (OECD, 2018).

[2] Precisely speaking, the former Soviet Union—of which Russia was the largest and dominant member state—offered the prototype of the centrally planned economy in modern history that other socialist countries modeled after.

then, which has solidified its place among the group of upper-middle income countries (World Bank, 2017).

This economic growth process is by itself quite intriguing, and raises a number of policy-relevant questions. The egalitarian economic model as exemplified by Russia deems equality of income distribution for everyone as its highest priority, and indeed operated based on this ideal principle. But did inequality increase after Russia changed into the market economy model, which is driven by the opposite motto of free-for-all competition? Figure 1 suggests that inequality, in fact, even went down from a Gini coefficient of 0.47 in 1994 to that of 0.31 in 2015 (dashed line). Clearly, this trend appears counter-intuitive and leads to other questions. Was the trend in the short term similar to those in the medium term and in the longer term? Would poorer households suffer from less income mobility and lag even further behind richer households? If yes (or no), what are the magnitudes of the gaps between the rich and the poor? What were the factors that are associated with upward (or downward) mobility, or no mobility? These questions are pertinent not just for Russia but for other developing countries in a similar transition process as well.[3]

We aim in this paper to shed light on these policy-relevant questions. More broadly, we also aim to provide a comprehensive picture of welfare mobility and inequality for Russia over the past two decades, and we attempt to do so from new angles. First, we focus our analysis on lower-income population groups rather than those in higher income categories. For a transitional country

[3] Notably, several centrally planned economies that have been undergoing a similar transition process to a market economy, such as China, Cuba, the Lao People's Democratic Republic, the Democratic People's Republic of Korea, and Vietnam, may particularly benefit from Russia's experience. Economies with heavy government subsidies such as the República Bolivariana de Venezuela may likely share certain features with Russia's previous central economic model.

that embarked on a fast-growth transformation process like Russia, ensuring equitable growth would require special attention on the poorer population groups that may lag (further) behind.[4]

Second, we examine Russia's welfare mobility over different time windows of varying lengths. In particular, we study a 20-year time period, from 1994 to 2015, and we further divide this period into short-run and medium-run periods. The former include four periods 1994-98, 1998-2004, 2004-09, and 2009-15, while the latter include two periods 1994-2004 and 2004-15. The reason for this division is twofold: first, the major financial crisis in 1998 forms a natural dividing line for pre- and post-crisis periods, and second, we want to analyze time periods of roughly equal lengths for better comparability.[5] This detailed dissection of the time periods offers more granular analysis than previous studies, and can uncover new insights on the dynamics resulting from the country's economic growth. To our knowledge, no other study on Russia has offered such a detailed temporal breakdown as we attempt here.

Furthermore, studies of mobility and inequality have primarily focused on analysis of short-term mobility. An operational obstacle to the type of welfare dynamics analysis we provide here is the prerequisite of panel survey data, which track income or consumption of the same households (or individuals) over time. Fortunately, we can exploit multiple rounds of panel data from the Russia Longitudinal Monitoring Surveys that span over two decades from 1994 to 2015. Very few, if any, transitional countries can offer the type of long-running, nationally representative panel household survey data that Russia does.[6]

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[4] But we return to discuss top income earners in the robustness checks section.

[5] A major technical issue with any (long-running) panel survey is attrition over time; analyzing panels of varying lengths can help provide better comparison and more robust results. We also experiment with other ways to divide the time periods and discuss results in the robustness check section.

[6] As an example, the China Health and Nutrition Survey (CHNS) collects panel data and was implemented as early as 1989, but does not offer nationally representative data. A more recent panel survey, the China Family Panel Study (CFPS) provides more coverage but was started only in 2010. Alternatively, statistical techniques have recently been developed that allow the construction of synthetic panels from repeated cross sections (Dang *et al.*, 2011; Dang and

We bring several different tools to enrich our analysis. Specifically, we explicitly discuss three major aspects of mobility. The first aspect is the welfare dynamics of the different income groups—both as relative positional changes along the income distribution and growth in income levels. We provide an explicit presentation of the analytical formulae to examine these positional changes, which are simple but do not appear to have been presented elsewhere. For the second aspect of mobility, we decompose it into a growth component and a distribution component. Since mobility can be driven by either economic growth or a redistribution of society's resources (or often a mix of the two), understanding the relative contribution of each component can provide more insights into appropriate policies that ensure sustainable growth and more equality. The third aspect of mobility that we study is its linkage with inequality in the short term and in the long term. Notably, these different aspects of mobility have oftentimes been separately employed in the literature, but we combine them in an integrated manner to offer a more comprehensive picture of welfare mobility, especially for the lower-income groups.

Finally, we examine the different correlates of mobility, with a particular focus on individual employment characteristics. Almost all (i.e., 96 percent) Russians used to work for the public sector before the transformation in the 1990s thanks to the socialist ideology and economic model (Milanovic, 1998). As such, it is useful to understand whether subsequent changes in the type and sector of work are correlated with income mobility, especially since these labor transitions are amenable to policy.

Our paper is related to a few recent studies on income mobility and inequality in Russia, most notably those by Gorodnichenko, Peter, and Stolyarov (2010) and Lukiyanova and Oshchepkov

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Lanjouw, 2013), but these techniques currently focus on poverty mobility. See also Kopczuk *et al.* (2010) and Jappelli and Pistaferri (2009) for some recent examples of studies on long-term mobility in richer countries.

(2012). Yet, one major difference is that these studies examined the same data set that we investigate but over shorter periods ending in 2005. Gorodnichenko *et al.* (2010) find that inequality decreased during the 2000–2005 economic recovery, probably due to falling volatility of transitory income shocks rather than characteristics such as education, location, household composition, and age. Lukiyanova and Oshchepkov (2012), however, observe that income growth in Russia was strongly pro-poor for the same recovery period 2000-2005, but the overall reduction in cross-sectional inequality was modest. Another recent study by Novokmet, Piketty, and Zucman (2018) combines different data sources to investigate the evolution of inequality of income in Russia over a longer period than ours, but for the same time period that we analyze (i.e., 1994-2015), they found the Gini slightly increasing from 0.54 to 0.55.[7]

We find rising income levels and decreasing inequality for the country over the past two decades. We also find that decreasing inequality was mostly caused by stronger income growth for the poor (i.e., pro-poor growth), rather than their relative upward movement along the income distribution (i.e., upward mobility). In particular, for the period 1994-2015 as a whole, the poorest tercile experienced a growth rate that is more than ten times that of the richest tercile. There was also faster income growth in the second medium-term period 2004-15 than in the first medium-

[7] There are a couple key differences between Novokmet *et al.*'s (2018) study and ours. First, Novokmet *et al.* (2018) focus on the top 1 percent in the income distribution, while we focus on those not at the top but are the majority of the population. Second, while we analyze total household income, Novokmet *et al.* derive their measure of welfare based on pre-tax national income, which includes tax information that Novokmet *et al.* acknowledge is not perfect in the Russian setting. Novokmet *et al.* also exclude private and public transfers that are important income components in Russia. Indeed, private transfers are estimated to make up as much as 9 percent of household incomes during the period 1994-2000 (Kuhn and Stillman, 2004); the corresponding figure for social benefits (such as child benefits) from the government is around 5 percent during the period 2011-2015 (Rosstat, 2018). Novokmet *et al.* (2018) also assume that the RLSM can only capture the bottom 90 percent of the income distribution, which is different from Kozyreva *et al.*'s (2015) observation that the RLMS can capture 96 percent of the population. We return to more discussion in the robustness check section. More generally, another difference between the cited studies and ours is that these studies do not offer a detailed analysis for the different periods as we offer in this paper. We also employ a different analytical framework. For studies on welfare dynamics for Russia in the 1990s, see, for example, Commander, Tolstopiatenko, and Yemtsov (1999), Lokshin and Popkin (1999), Jovanovic (2001), and Lokshin and Ravallion (2004).

term period 1994-2004. Furthermore, long-term inequality is less than short-term inequality for all the different time periods under consideration. Estimation results also suggest that switching from a part-time job to a full-time job, or from a lower-skills job to a higher-skills job is statistically significantly associated with reduced downward mobility. A similar transition from the private sector to the public sector is negatively associated with income growth, but transitions to the formal sector, a full-time job, or a higher-skills job are statistically associated with higher income levels.

This paper consists of five sections. We present our analytical framework in the next section, describe the data in Section III, and offer the main estimation results in Section IV. We discuss in this section the overall trends of income and inequality (Section IV.1), short-term and medium-term mobility (Section IV.2), long-term mobility (Section IV.3), and the correlates of mobility (Section IV.4) before offering further robustness checks and further analysis (Section IV.5). We finally conclude in Section V.

II. Analytical Framework

II.1. Mobility Measures

We discuss below the different measures of income mobility that we analyze for the three aspects of mobility. While the derivations are rather simple and straightforward, it can be useful to clearly lay out the formulae and their implications (which appear not readily presented elsewhere). For a simpler discussion, we consider mobility over two years (survey rounds) and we suppress the notation indexing households (or individuals) to make the notation less cluttered in this section.

First Aspect of Mobility: Mobility for Different Income Groups

Let y_j and z_{jk} respectively represent individuals' income (consumption) and the income threshold k in year j, where j= 1 or 2, and k= 0, 1,…, K, with a higher number for k indicating a higher income threshold. As is the usual practice, both y_j and z_{jk} are expressed in logarithmic form. The minimal and maximal thresholds z_0 and z_K correspond to -∞ and +∞ respectively. Let M^{lo} represent the population's relative mobility measure of interest, where l= u (upward mobility) or d (downward mobility), and o= n (unconditional mobility) or c (conditional mobility).

We define the unconditional (probability of) upward mobility for individuals in income category k (M_k^{un}) as its probability of moving to a higher income category in the second year.

$$M_k^{un} = P(z_k \leq y_1 \leq z_{k+1} \; and \; y_2 \geq z_{k+1}) \tag{1}$$

Note that this higher income category is not just the next higher income category, but can generally include any higher income category. If we condition individuals' movement on their income levels in the first period, we can obtain the corresponding conditional version of upward mobility

$$M_k^{uc} = P(y_2 \geq z_{k+1} | z_k \leq y_1 \leq z_{k+1}) \tag{2}$$

Put differently, M_k^{un} represents individuals' unconditional upward mobility for both periods considered together (i.e., joint probability), while M_k^{uc} represents their conditional probability of upward mobility that is conditional on the fact that their income level is in income category k in the first year.

We similarly define the corresponding probabilities of unconditional and conditional downward mobility by simply reversing the inequality signs in the two equations above for individuals' income level in the second year.

$$M_k^{dn} = P(z_k \leq y_1 \leq z_{k+1} \; and \; y_2 \leq z_k) \tag{3}$$

$$M_k^{dc} = P(y_2 \leq z_k | z_k \leq y_1 \leq z_{k+1}) \tag{4}$$

Aggregating over the k income categories gives us the measure of unconditional upward or downward mobility for the whole population

$$M^{ln} = \sum_{k=1}^{K} M_k^{ln} \tag{5}$$

Further aggregating over the unconditional upward and downward mobility categories gives us the general measure of unconditional mobility for the whole population

$$M^n = M^{un} + M^{dn} \tag{6}$$

However, note that for the conditional mobility measures M^{lc}, a similar aggregation formula as that in Equation (6) does not hold because of the different conditions (denominators) in Equations (2) and (4). But if we focus on the income category k in year 1, we can have the following conditional mobility measure for this specific income category

$$M_k^c = M_k^{uc} + M_k^{dc} \tag{7}$$

To derive the measure of conditional upward and downward mobility for the whole population, we respectively use the following equation instead

$$M^{uc} = \sum_{j=k+1}^{K} P\left(y_2 \geq z_j | z_k \leq y_1 \leq z_{K-1}\right) \tag{8}$$

$$M^{dc} = \sum_{j=k}^{K-1} P\left(y_2 \leq z_j | z_{k+1} \leq y_1 \leq z_K\right) \tag{9}$$

Thus, there is no general measure of conditional mobility for the whole population that corresponds to M^n in Equation (6). A closely related, but opposite measure of mobility is immobility (i.e., individuals remain in the same income category in both periods). For the unconditional mobility measures M^{ln} or M^n defined above, we can simply subtract them from one to obtain the corresponding unconditional immobility. For the same reason as earlier discussed, we can only apply the same procedure to the conditional mobility index M_k^c in Equation (7) to obtain its corresponding conditional immobility index.

Our other measure of mobility is simply defined as the growth in income level for individuals that fall in income category *k* across the two years

$$G_k = \frac{y_{2k} - y_{1k}}{y_{1k}} \tag{10}$$

To obtain the population's relative mobility measure of interest *G*, we can similarly aggregate the quantities in the above equations over all *k* income levels as with Equation (5), taking into account the appropriate population weight for each income category k. There are two ways to calculate income growth. The first way is to calculate it for those in income category *k* in the first year, regardless of where they end up in the second year; the second way is to calculate it for those who stay in income category *k* in both years. We will show measures using both ways in the empirical analysis. Note that in the Russian context of fast economic growth as discussed later, the second measure offers a more conservative of income growth than the first, since we exclude those who moved up from the poorer terciles in calculating the growth rate for these groups.[8]

The mobility index M^O and the income growth rate *G* are also known in the literature respectively as a relative measure and an absolute measure of mobility. This is due to the former measure's focus on the positional change along the income distribution and the latter measure's focus on the change in the income levels.

Second Aspect of Mobility: Growth and Redistribution

For this aspect of mobility, we employ the Fields-Ok (1999) mobility index that can be decomposed into two components, one due to income growth, the other due to income transfer. In particular, for individual *i*, *i*= 1,…, N

[8] We also exclude those who moved down from the richer terciles in calculating the second measure, but note that in a context with more economic growth, there is more upward mobility and downward mobility.

$$M^F = \frac{1}{N}\sum_{i=1}^{N}(y_{2i} - y_{1i}) + \frac{2}{N}\sum_{i \in K}(y_{1i} - y_{2i}) \tag{11}$$

The first component on the right-hand side of Equation (11) is the growth component, and the second component the redistribution component, where K is defined only for the cases where individual i has less income in year 2 than in year 1.

Third Aspect of Mobility: Mobility and Inequality

We will use the Gini coefficient to measure inequality, and supplement it with some estimates using the $90^{th}/50^{th}$ and $50^{th}/10^{th}$ ratios of the income percentiles. We also estimate Shorrocks' (1978) mobility index, which presents a tightly-knit relationship between short-term inequality, long-term inequality, and mobility. This index is defined as follows

$$M^S = 1 - \frac{F(\bar{y})}{\sum_{t=1}^{K} F(y_t)/K} \tag{12}$$

where *F(.)* is an inequality function such as the Gini index (or the variance of log income), and $\bar{y}$ is the averaged income over K years. More intuitively, Shorrocks' mobility index suggests that more inequality in the longer term (i.e., a larger value for $F(\bar{y})$) implies less mobility, while more inequality in the shorter term (i.e., a larger value for $\sum_{t=1}^{K} F(y_t)/K$) generates the opposite result. Thus, M^S ranges between two extreme scenarios. In one extreme, M^S is 0 when individuals' income remains unchanged over time, or their averaged income over the whole period has the same inequality as the averaged inequality over each year in the period. In the other extreme, M^S equals 1 when individuals' income greatly fluctuates across periods, such that on average their averaged income over the whole period is much more equally distributed than their income in each period. Put differently, mobility can help reduce inequality in the long term.[9]

[9] See also Fields (2010) for more discussion on the concept of income mobility as an equalizer of longer-term incomes, and Jantti and Jenkins (2015) for a recent review of income mobility concepts.

In summary, a unique feature with the mobility measure M^O is that it allows further disaggregation into upward mobility and downward mobility for different income groups, while the advantages of the mobility measures M^F and M^S are respectively their disaggregation into components due to income growth and redistribution, and short-term inequality and long-term inequality. Both M^S and M^O share a common feature that they range between 0 and 1.

II.2. Correlates of Mobility

We employ an ordered logit model with individual random effects to investigate the correlates of mobility

$$y_{it}^* = \beta_l' \Delta O_{it} + \gamma_l' X_{it-1} + \eta_i + \varepsilon_{it} \quad (14)$$

where $y_{it} = j$ if $\mu_{j-1} < y_{it}^* < \mu_j$, for *j= 0,1,…, J* and $\mu_{h,h<0} = -\infty$, $\mu_0 = 0$, and $\mu_J = +\infty$. In this model, individuals can fall into any of the three mobility categories: downward mobility (*j= 0*), immobility (*j= 1*), and upward mobility (*j= 2*). The probability of falling into mobility category *j* is formally defined as

$$P(y_{it} = j|\Delta O_{it}, X_{it-1}) = \Lambda\left(\mu_j - \beta_l' \Delta O_{it} - \gamma_l' X_{it-1} - \eta_i\right) - \Lambda(\mu_{j-1} - \beta_l' \Delta O_{it} - \gamma_l' X_{it-1} - \eta_i) \quad (15)$$

where $\Lambda(.)$ is the cdf of the logistic distribution.[10] The X_{ij} variables include individual *i*'s characteristics such as age, gender, education, marital status, occupation (including work experience, qualification, being in a management position, and occupation transitions) and household characteristics (including household size and the proportion of members in different age ranges), and dummy variables indicating the urban/rural residence and nine federal regions.

[10] See, for example, Long (1997) and Greene (2018) for further discussion with the ordered logit model (with or without random effects).

The individual random effects η_i help control for unobserved individual characteristics (e.g., innate ability). We fix the values of these characteristics in the previous year to reduce possible contemporaneous issues between them and the outcomes in the current year.

As discussed earlier, we are particularly interested in individuals' occupation transitions over time (i.e., from period *t-1* to period *t*, or ΔO_{it}). We will consider these transitions for various types of occupations such as public sector versus private sector, formal work versus informal work, full-time work versus part-time work, and having an increase versus having no increase in work skills. A more detailed definition of these transitions is provided in Table 1.11, Appendix 1. To keep a reasonable estimation sample, we generally define three categories as follows: i) transition to the desirable occupation category (e.g., full-time work), ii) no transition within the desirable category (e.g., remained in full-time work), and iii) either transition to or no transition within the less desirable occupation category (e.g., part-time work). We employ the last transition as the reference category. However, data are only available since 1998 for the formal sector, and 2004 for the public sector.

To offer robustness checks and further analysis, we also employ the standard linear regression models with individual random effects to estimate income growth rate

$$y_{it} = \delta_l' \Delta O_{it} + \theta_l' X_{it-1} + \pi_i + \tau_{it} \quad (16)$$

where y_{it} is defined as individual *i*'s income in logarithm at survey year *t*. The coefficient δ_l can then be interpreted as the proportionate (percentage) change in individual *i*'s income that is associated with the occupation transitions ΔO_{it}.

III. Data Description

The Russian Longitudinal Monitoring Survey (RLMS) was initially created with funding from various sources including the G-7 countries, USAID, and the World Bank. The survey is currently managed by the Carolina Population Center, University of North Carolina, and Russia's National Research University Higher School of Economics. The ongoing panel survey started in 1994, and has been implemented every year since then, except for a break in 1997 and 1999. The RLMS collects nationally representative data on various topics including household demographics, income and consumption, occupation characteristics, and others. The sample size is between 4,000 and 6,000 households, capturing between 8,000 and 17,000 individuals for each year, which have been replenished several times due to panel attrition over time. Hardly any middle-income countries can offer such long-running and nationally representative panel data as the RLMS.

However, one data challenge with the RLMS is the considerable attrition rate over time. For example, out of the original 11,290 individuals in the 1994 round, the proportion that remains in the survey drops to 44 percent (4,917) in the 2005 round and 24 percent (2,702) in the 2015 round. We use a three-pronged approach to address attrition issues. First, we offer estimates for time periods of varying lengths. The attrition rate is far lower for shorter panels. For example, out of the original 11,290 individuals in the 1994 round, 63 percent remain in the 1998 round; the corresponding figure between the 2000 and 2004 rounds is 76 percent. Since these shorter panels and longer panels have different sample sizes due to different attrition rates, if estimation results are consistent, it will provide robustness checks on our findings. Second, we offer robustness checks that utilize econometric techniques that adjust for attrition bias (Fitzgerald *et al.*, 1998; Wooldridge, 2002). Finally, to keep reasonable sample sizes, we restrict our analysis of mobility patterns to three income categories only. To avoid any potential bias with the panel data attrition, we define these income categories using the cross-sectional data, which are nationally representative in each year. We mostly use the RLMS's panel data for analysis, but we also supplement it with analysis based on the repeated cross sections.

The main outcome variable that we analyze in this paper is total household income per capita.[11] To reduce potential mismeasurement due to outliers, we trim one-quarter of a percent of the data at both the top and the bottom of the income distribution and only keep individuals with a positive income level. But we also examine several other definitions of income, as well as consumption, for robustness checks.

IV. Estimation Results

We start in this section with a discussion of the overall trends in income and inequality over the period 1994-2015. We subsequently turn to investigating mobility in the short term and in the medium term, before examining mobility in the longer term, its decomposition into growth and distribution, and its relationship with short-term and long-term inequality.

IV.1. Overall Trends of Income and Inequality

As earlier discussed, despite a temporary decline in the late 1990s, income per capita has been rising in Russia; furthermore, this positive trend is accompanied by a continuous decrease in inequality throughout the period (Figure 1).[12] To further examine whether it is lower-income households or higher-income households that experienced more decrease in inequality, we plot in Figure 2 the $90^{th}/50^{th}$ and $50^{th}/10^{th}$ ratios of the income percentiles. The latter (red dotted line)

[11] We use only those individuals that have data at the household level and drop 124 individuals who do not have household data. We focus on household income rather than household consumption since changes to consumption items in the survey questionnaires could render the latter variable incomparable over time. For example, 14 percent of total household consumption was comprised of items that were found in 2015 only. Furthermore, comparing household consumption between 1994 and 2015, 12 percent of total household consumption in 1994 is accounted for by consumption items that are more disaggregated than 2015; the corresponding figure for 2015 compared with 1994 is 11 percent. Still, when we re-plot Figure 1 using household consumption per capita, estimation results shown in Figure 1.1 (Appendix 1) indicate similar patterns.

[12] The downward sloping trend of the Gini coefficient is consistent with the findings in other studies that use earlier data from the RLMS, including Gorodnichenko *et al.* (2010) and Denisova (2012). We also restrict our analysis to 1994, when the RLMS was first implemented. See Milanovich (1998) for a study that analyzes data from Russia for earlier periods.

started out higher than the former (green dashed line) and the distance between the two lines was largest around the crisis year, which indicates that poorer households suffered relatively more income loss during the crisis. However, poorer households have caught up with higher-income households from after around 2005, when the two lines started converging. These results are consistent with the findings in existing studies that indicate a decreasing poverty rate and increasing income growth for the bottom 40 percent of the income distribution (see, e.g., World Bank (2016)).

Can the trends differ between urban and rural areas? We further disaggregated the national trends in Figure 2 by urban and rural areas and show their combined results in Figure 1.2.[13] Rural areas exhibit lower income levels but somewhat higher inequality—both overall and for poorer households—than urban areas (Figure 1.2, Panels A and B). Indeed, all the lines representing the Gini coefficient and the 90th/50th and 50th/10th ratios for rural areas lie above those of urban areas. But similar to the national trends, inequality in urban and rural areas appears to converge over time (Figure 1.2, Panels C and D). Since the trends are qualitatively similar between urban and rural areas, we subsequently show estimates at the national level. We return to more discussion with the multiple regression analysis that controls for location and other individual characteristics in Section IV.4.

IV.2. Short-Term and Medium-Term Mobility

Figure 3 plots the mobility index M^o, using both the unconditional version (M^n) and the conditional version (M^c), for each of the four shorter periods: 1994-98, 1998-2004, 2004-09, and

[13] The population was considered as "urban" if located in cities and small towns known as "PGTs" and "rural" if located in villages. The definition was based on stratification in RLMS (see more details in http://www.cpc.unc.edu/projects/rlms-hse/project/sampling).

2009-15 by rural and urban areas. This figure suggests several interesting patterns. First, M^c is larger than M^n for both upward and downward mobility, but both indexes display rather similar trends over time. Second, (unconditional and conditional) upward mobility is stronger than downward mobility in all the periods, except for the period 2004-2009.

Figure 4 plots income growth in all four periods for the three income groups: those remaining in the poorest income tercile, the middle income tercile, and the richest income tercile. Different from the relatively stable M^n, household income grew in all the four periods. In particular, the 1994-98 crisis period saw income shrinking by around half for all the three income groups. But the other post-crisis periods witnessed positive income growth, which ranges from 15 percent to as much as 160 percent. Growth was strongest in the immediate post-crisis period 1998-2004, fell in the two subsequent periods from 2004 to 2015, reaching its lowest rate in the period 2009-15. Furthermore, income growth was strongly pro-poor, with (individuals in) the poorest tercile reaping the most.

We turn next to examining mobility in the medium term. Table 1 shows estimation results for the two indexes M^n and M^c for the two periods 1994-2004 and 2004-15, which are rather similar to the results shown earlier for short-term mobility. In particular, M^c was also stronger than M^n for both periods, but M^n hovers around 50 percent.[14] As earlier discussed, this also implies a similar rate of unconditional immobility. There was stronger unconditional upward mobility (M^{un}) than unconditional downward mobility (M^{dn}) in both periods, although conditional upward mobility (M^{uc}) was somewhat stronger than conditional downward mobility (M^{dc}).

[14] The full three-by-three transition matrixes for medium-term mobility are provided in Table 1.2 in Appendix 1.

Estimates on medium-term income growth are provided in Table 2, where we show the full three-by-three (3x3) transition matrix for the two periods. The growth rates for those that remained in the same income category over time are shown in the diagonal cells, and the growth rates for those who moved upward and downward are respectively shown in the upper-right cells and the lower-left cells. Overall, results are generally consistent with the pro-poor income growth patterns for the shorter periods discussed earlier. Indeed, the 1994-2004 period exhibited much slower growth than the 2004-15 period because the former includes the financial crisis. Yet, income growth was still pro-poor in both periods, where the poorest tercile recorded the strongest overall growth, to be followed by the middle tercile and the richest tercile in a decreasing order. For example, the overall income growth rate in the 2004-15 period for the poorest tercile is 300 percent, which is almost thrice that of the middle tercile (109 percent), and ten times that of the richest tercile (30 percent). Furthermore, even the immobile in the three income groups also had a similar, *albeit* unsurprisingly weaker, pro-poor growth pattern (as discussed earlier). For the same period, the income growth rate for the immobile in the poorest tercile is 176 percent, which is respectively almost two-thirds and more than twice higher than that of the immobile in the middle tercile and the richest tercile.

IV.3. Mobility in the Long-Term and Further Decomposition

We provide estimates on long-term mobility and income growth for the whole period 1994-2015 for Russia respectively in Table 3 and Table 4. Table 3 suggests that for both the indexes M^n and M^c, upward mobility was stronger than downward mobility in this period. Consistent with the earlier results for the short-term and the medium-term mobility, Table 4 shows that income growth was strongest for the poorest tercile and weakest for the richest tercile. In fact, the poorest tercile in 1994 experienced a growth rate of around 500 percent over the past 20 years, which is more than ten times higher than that of the richest tercile (i.e., 45 percent) in the same year (Table 4, last column). Notably, if we compare the chronic poor (i.e., the immobility in the poorest tercile) and the ever-rich (i.e., the immobility in the richest tercile), the difference in income growth would be smaller since these groups exclude the poorest who moved up and the richest who fell down. But even when we only restrict comparison to these two subgroups, the income growth rate of the chronic poor is still two and a half times higher that of the ever-rich (i.e., comparing 317 percent and 125 percent).

We graph in Figure 5 the growth rates for all the income groups in the long term, and also the medium term for comparison. This figure further confirms that growth was stronger, in a decreasing order, for the poorest tercile, the middle tercile, and the richest tercile both over the two medium-term periods and the long-term period. Figure 5 also suggests that this pro-poor growth pattern is stronger for the second medium-term period (i.e., 2004-09), and strongest for the long-term period. As discussed earlier, the consistency of stronger pro-poor growth patterns over all the periods of varying lengths reassuringly allays concerns with attrition bias.

To look more closely at the whole income distribution, we plot the growth incidence curve (GIC) for the period 1994-2015 in Figure 6. While the non-anonymous curve (solid line) displays a zigzag pattern because of the small sample size, it mostly lies above the anonymous curve (dashed line) up to approximately the 60th percentile of the income distribution. Figure 6 thus provides further supportive evidence for the earlier findings that income growth was clearly pro-poor.

Table 5 provides estimation results for the Fields-Ok index M^F. Overall, M^F indicates that, mobility patterns in Russia in the past 20 years were mostly driven by income growth rather than income redistribution. Indeed, only the crisis-related period 1994-98 (and 1994-2004) and the most recent short-term period 2009-15 saw income redistribution accounting for more than half of total mobility.[15] This result is consistent with our earlier findings that both indexes M^n and M^c remained relatively stable over time, and that it was income growth that was the driving factor behind mobility for the country. It is also interesting to note that income growth is higher for longer periods: the average income growth for the four shorter periods is 34 percent, which increased respectively, by almost twice and three times to an average growth rate of 66 percent and 95 percent for the two medium-term periods and the long-term period.

Table 6 provides estimation results for Shorrocks' mobility index M^s , short-term inequality, and long-term inequality. We estimate M^s in two different ways, using the Gini index and the variance of log income, for robustness checks. Estimation results for both methods are, however, qualitatively similar and suggest a couple of emerging patterns that are consistent with our earlier findings for the other mobility indexes.[16] First, both short-term and long-term inequality has been steadily decreasing over time for Russia, over the four shorter periods. For example, the Gini index over the short term decreased by 30 percent, from 0.44 in the 1994-98 period to 0.31 in the 2009-15 period. The corresponding decrease for the variance of log income over the same time span is even larger at more than 50 percent (i.e., from 0.76 in the 1994-98 period to 0.35 in the 2009-2015 period). There is a similar decrease in inequality for the two medium-term periods, but this is unsurprisingly smaller since inequality measures are averaged over a longer time span for the medium-term periods compared to the shorter periods. Second, long-term inequality is less than

[15] Increased minimum wages may have some moderate impacts on reducing poverty in these periods; see Calvo, Lopez-Calva, and Posadas (2015) and Kapelyuk (2015) for recent discussions on the role of higher minimum wage on poverty and inequality reduction. A recent study by Aristei and Perugini (2015) also suggests that the income growth component in the Fields-Ok index is relatively more important for income mobility for the period 2004-06 for most former centrally planned economies in Eastern Europe.

[16] We use the balanced sample for each period for the estimates in Table 6, which varies from period to period due to attrition. Another approach is to use the fully balanced sample for the whole 1994-2015 period. We provide estimation results using this approach in Table 1.3 in Appendix 1, which are largely qualitative similar to the results in Table 6.

short-term inequality thanks to mobility as discussed earlier. This result holds regardless of whether we consider the short-term periods, the medium-term periods, or the longer-term period.

IV.4. Correlates of Mobility

We turn next to examining the relationship between occupation mobility and income mobility (growth) in this section. In particular, we consider four different types of occupational transitions: public sector versus private sector, formal sector versus informal sector, full-time work versus part-time work, and higher skills versus lower skills. Since there are two job categories for each type of transition, there are four different work combinations for occupation mobility between two years. For example, an individual can remain in the job with the same level of skills in both years, or can move to the higher-skill (or lower-skill) job. To keep reasonable sample sizes, we focus on individuals' upward transition to the more desirable occupation category (e.g., a full-time job) or their immobility in (i.e., no transition from) this more desirable occupation category over time. The reference category is either individuals' downward transition to the less desirable occupation category (e.g., a part-time job) or their immobility in this less desirable occupation category over time.

Table 7 shows estimation results on income mobility for the transitions related to full-time versus part-time work for all the four shorter periods. Individual's transition to a full-time job is strongly and positively statistically associated with income mobility, as does immobility in a full-time job for all these periods except for the short-term period 1994-98. The former's impact, however, is stronger than the latter. But unlike the linear regression models, it is not straightforward to interpret the estimated coefficients in an ordered logit model. Consequently, to help with better interpretation, we graph their marginal effects for all the occupation transitions in the short-term periods in Figure 7.

A couple observations are in order for this figure. First, the transition to the more desirable job category, say full-time employment, is somewhat more strongly correlated with upward income mobility than immobility in that category. The transition to full-time employment also has stronger correlation with income mobility than other employment transitions. Second, full-time employment is statistically significantly associated with better mobility in all the short-term periods. For example, moving from part-time employment to full-time employment in this period is associated with a 5-percent increase in the probability that individuals move to a better income mobility category. However, while this result holds in all periods, for full-time employment, it is not the case with the other employment categories. For example, moving to the formal sector from the informal sector only has statistical significance in the 2009-15 period, but not in the 1998-2004 and 2004-09 periods.

The marginal effects for the medium-term and the long-term transitions in Figure 8 are generally consistent with the results for the short-term transitions, but have more statistical significance. That is, full-time employment is statistically significantly associated with better income mobility in all these periods, as does the transition to a job with a better skill level (except for the period 1994-2004). This result also holds for no transition in the formal sector. No transition within the public sector is also associated with more income mobility for the period 2004-15 (note that we only have data on the public sector from 2004). In summary, the transitions to the more desirable employment categories generally have stronger correlation, except for the transitions to the public sector in the 2004-15 period.

The percentage changes in individuals' (household per capita) income that are associated with the specified occupation transitions are shown for the short term in Table 8, Panel A, and the longer term in Table 8, Panel B. These results are qualitatively similar regardless of the time periods considered and are generally consistent with the estimation results on mobility discussed earlier. Indeed, the transition to full-time employment is associated with income growth for all short-term periods, while upward mobility skills and the transition to the formal sector are correlated with income growth in most, but not all the short-term periods. For example, moving from a part-time job to a full-time job was associated with approximately a 10-percent increase in one's income in the 1994-98, 1998-2004 and 2004-09 periods; this correlation, however, appeared to weaken over time, where it decreased to 5 percent in the most recent short-term period 2009-15 (Panel A, first row). For the medium term and longer terms, this same labor transition has a rather stable association of an 8-percent increase with income growth.

Moving to, or remaining in, a job with better skills was also associated with increased income, but the correlation was either similar or somewhat weaker than that of moving to a full-time job or to the formal sector. In particular, the association with income growth for these transitions ranged from 0 percent to 13 percent for the different periods (the association with remaining in the job with better skills was even negative in the period 1994-98, but it was marginally statistically significant at the 10 percent level). The corresponding figures for the transitions to, or immobility in, the formal sector were 0 percent to 21 percent. Finally, those who moved to or worked in the public sector actually saw a decrease ranging from 4 percent to 9 percent in their income for the different periods.

IV.5. Robustness Checks and Further Analysis

Other Definitions for Income and Consumption

As alternatives to our definition of the per capita income variable, we provide in Appendix 1, Table 1.1 a more detailed discussion of the other definitions as well as some reference to previous studies that use these definitions. For comparison, we plot household income per capita and household consumption per capita together, using both the cross sections and the balanced panel in Figure 1.3 (Appendix 1). This figure shows similar V-shaped trends over time for both variables, although the income line is somewhat lower than the consumption line in earlier years (up to 2001).[17] We further plot in Figure 1.4 (Appendix 1) other variables including household labor income per adult, household pension per capita, and individuals' labor earnings; these different definitions of incomes show qualitatively similar trends over time.[18] These results are consistent with estimates for the Gini coefficient using labor income by Calvo *et al.* (2015), who also found it to decrease by 18 percent between 2002 and 2012. Finally, we also re-estimate the mobility regressions using individuals' labor earnings and plot these results in Figures 1.6 and 1.7 (Appendix 1), which show qualitatively similar trends to Figures 7 and 8. But the magnitudes of the estimated coefficients are unsurprisingly slightly larger; for example, moving from a part-time job to a full-time job was associated with a 12-percent increase in one's labor income in the 1994-98 period.

Top Incomes

A typical issue with household survey data, including the RLMS, is that such data may not capture individuals with the top incomes. In that case, the survey data may offer a downward biased estimate of income inequality due to the survey underreporting the higher end of the income distribution (see, for example, Picketty *et al.* (2018) and Novokmet *et al.* (2018)). Yet, researchers

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[17] A recent study by Kim, Gibson, and Chung (2017) suggests that income might be underreported during this period because of the higher share of informal economy. However, we also calculated the Gini coefficient using the per capita consumption variable, which displays a similar downward trend over the period 1994-2015 (Figure 1.1, Appendix 1). This result is consistent with the finding in a recent study which shows that income inequality is similar to consumption inequality for the US (Aguiar and Bils, 2015).

[18] For example, when we re-plot Figure 1 with household income net of pension, estimation results, shown in Figure 1.5 (Appendix 1), indicate similar trends.

differ on what percentage of the top incomes the RLMS can capture, as well as the methods and auxiliary data sources that can be employed to correct for these missing values.

We employ a modelling approach to measure inequality that addresses this under-coverage issue (see Jenkins (2017) for more discussion on this approach). In particular, we obtain an inequality estimate for the poorer *p* percent in the RLMS data using non-parametric methods, and then derive an inequality estimate for the richest (*1 - p*) percent by fitting a Pareto Type I distribution to the top income observations from the same source. The adjusted Gini coefficient can then be obtained by adding together three inequality measures: one for the top incomes (i.e., the richest (*1 - p*) percent), another for the non-top incomes (i.e., the poorest *p* percent), and another between these two population groups. Using three different values of p that include 90 percent (Panel A), 95 percent (Panel B), and 97.5 percent (Panel C), we plot the results in Figure 1.8 (Appendix 1), which shows larger values for the adjusted Gini coefficients, but a reassuringly similar downward trend over time.

As a further check on whether (and how much) the RLMS missed out on the top incomes, we examine another high-quality household survey that is commonly used for (cross sectional) income and poverty monitoring purposes in Russia, the Household Budget Survey (HBS). The HBS has been conducted quarterly on an annual basis since 1987, covering 47,800 households across the country, but the micro data are only made publicly available since 2003. However, while the HBS collects detailed data on household expenditures, it does not collect data on household income. Consequently, we construct an income variable for the HBS on the basis of indirect accounting of household consumption items, where household money income is the total of household cash expenditures and financial assets (savings). We plot the income and Gini coefficient using the HBS data against those using the RLMS data in Figure 1.9, Panel A and Panel B (Appendix 1). The trends as shown by the HBS data are very similar to those based on the RLMS data.[19]

Yet, while our results apply to the majority of the population, it is possible that we may not be able to capture well the super-rich in the population, such as the top 1 percent of the income distribution. Analyzing the latter group requires more fine tuned assumptions as well as better data on the top part of the income distribution such as tax information. As such, we refer interested readers to the comprehensive studies by Novokmet *et al.* (2018) for the top 1 percent of the income distribution, and Treisman (2016) for the number of billionaires in the country.

Attrition Bias

Our estimation results are rather consistent for the different periods of varying lengths, which helps reduce concerns about potential attrition bias. But as discussed earlier, we offer further robustness checks using two popular inverse probability weighting methods that adjust for attrition: one by Fitzgerald *et al.* (1998) and the other by Wooldridge (2002). The intuition behind these methods is that, since households that drop out of the panel sample may have different characteristics from those that remain (e.g., higher education achievement or income level), we can reweight the latter by explicitly taking into account their characteristics. We apply these reweighting methods and show estimation results for the medium-term mobility and the long-term mobility in Table 1.4 (Appendix 1). Estimates using Fitzgerald *et al.*'s method are qualitatively similar to the results shown in Table 1 and Table 3, while those using Wooldridge's method display

[19] We use the unweighted HBS data because population weights are not available. Official estimates by the Russian National Statistical Agency "Rosstat" also suggest that the Gini coefficient remains stable between 1994-2015 around 0.41 (Rosstat, 2016). See also Yemtsov (2008) for discussion on other issues related to reweighting and non-response with the HBS data.

stronger upward mobility both in the medium term and the long term.[20] These results provide further supportive evidence that our estimation results are robust to attrition.

Other Robustness Checks

We examine a battery of other robustness checks and offer a brief summary of the main findings here. First, we investigate whether estimation results change if we analyze the household panel data instead of the individual panel data. We use two different definitions of a household panel: one whereby any household member remains in the panel data over time, and another whereby half or more household members remain the same over time.[21] Using both definitions offers qualitatively similar results (Appendix 1, Table 1.5). Second, we examine whether adjusting for household equivalence scale may affect our estimates. We employ two different scale adjustment methods, one by the OECD (2009) and another with a different scale parameter (i.e., using an economy-of-size parameter of 0.8).[22] Estimation results are also similar, especially for mobility in the long term (Appendix 1, Table 1.6). Third, following Gorodnichenko *et al.* (2010), who showed that accounting for differences in the cost of living between regions could reduce consumption inequality, we also make a similar adjustment. Estimation results suggest somewhat higher upward mobility in the medium term but are generally similar (Appendix 1, Table 1.7). Fourth, instead of dividing the income distributions into three terciles, we use an alternative

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[20] In fact, even if we only rely on the adjustments offered by Wooldridge's method, the finding that there was more upward conditional mobility than downward mobility in both medium-term periods is not very different from our finding that this finding holds for the long term and mostly for the short term.

[21] More precisely speaking, we analyze the panel of household heads, where we define heads according to the RLMS survey manual's recommendations: (1) the oldest working-aged male in the household, (2) if no working-aged males, then the oldest working-age female, (3) if no working-age females, then the youngest retirement-age male, (4) if no retirement-age males, then the youngest retirement-age female, (5) if no retirement-age females, then the oldest child.

[22] There is no established equivalence scale for Russia. Different equivalence scales are often applied in studies of poverty using the RLMS-HSE data (e.g., Lokshin *et al.*, 2000; Denisova, 2012).

method that defines the income thresholds based on the poverty line and the vulnerability line recently proposed by Dang and Lanjouw (2017).[23] We also find higher upward mobility in the medium term, but rather qualitatively similar results for mobility in the long term (Appendix 1, Table 1.8). Another related robustness check is to further compare results when we divide the income distributions into five quintiles for the short-term periods only, where the sample sizes are larger. We re-plot Figure 4 and show estimation results in Figure 1.10 (Appendix 1), which indicate similar pro-poor income growth patterns. Fifth, as an alternative to the Shorrocks mobility index, we apply the Fields (2010) mobility index (M^E) that essentially replaces the numerator and the denominator in Equation (12) respectively with the inequality measure of the average income in the final period and the base period, and the inequality measure in the base period. Estimation results, shown in Appendix 1, Table 1.9, suggest that mobility helps reduce long-term inequality as discussed earlier.

Finally, we examine another definition of the short-term periods, which does not use the overlapping end points. That is, the four short-term periods are 1994-98, 2000-04, 2005-09, and 2010-15. Estimation results, shown in Appendix 1, Table 1.10, remain very similar to the results discussed earlier.

V. Conclusion

We find that income has been rising and inequality has been decreasing for Russia over the past two decades, and the trends are especially strong for rural areas. We also find that decreasing inequality was mostly caused by stronger income growth for the poor (i.e., pro-poor growth), rather

[23] Since the range of the vulnerability index narrows over time (thanks to higher income levels), we use the vulnerability lines corresponding to a vulnerability index of 32 percent in the 1994-2004 period, and a vulnerability index of 12 percent in the 2004-2015 and of 11 percent in 1994-2015 periods. See Dang and Lanjouw (2017) for further discussion on the construction of the vulnerability line.

than their relative upward movement along the income distribution (i.e., upward mobility). In particular, for the period 1994-2015 as a whole, the poorest tercile experienced a growth rate that is more than ten times that of the richest tercile. There was also faster income growth in the second medium-term period 2004-15 than in the first medium-term period 1994-2004. For the short-term periods, growth was strongest in the immediate post-crisis period 1998-2004, fell in the two subsequent periods from 2004 to 2015, and reached its lowest rate in the period 2009-15. Furthermore, long-term inequality is less than short-term inequality for all the different time periods under consideration. These results are robust to different robustness checks.

While the occupational transition from the private sector to the public sector is not statistically significantly associated with income mobility, the transition to a full-time job or a higher-skills job is statistically significantly associated with reducing downward mobility. The transition to the public sector is statistically associated with lower income growth, but transition to the formal sector, a full-time job, or a higher-skills job is statistically associated with higher income levels.

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Table 1. Medium-Term Income Mobility, RLMS 1994-2015 (percentage)

	Unconditional	Conditional
Panel A: 1994-2004		
Upward mobility	29.2	39.6
Immobility	49.5	49.5
Downward mobility	21.3	36.3
Panel B: 2004-2015		
Upward mobility	27.8	39.6
Immobility	47.0	47.0
Downward mobility	25.2	38.8

Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 4941 panel individuals from the 5th and 13th rounds of the RLMS and 3719 panel individuals from the 13th and 24th rounds of the RLMS.

Table 2. Medium-Term Income Growth Rate, Russia 1994-2015 (percentage)

Panel A: 1994-2004		2004			
		Poorest tercile	Middle tercile	Richest tercile	Overall
1994	Poorest tercile	38.6	161.6	511.5	129.3
	Middle tercile	-30.5	29.8	143.7	32.0
	Richest tercile	-81.4	-30.7	26.3	-13.1
Panel B: 2004-2015		**2015**			
		Poorest tercile	Middle tercile	Richest tercile	Overall
2004	Poorest tercile	176.2	330.2	625.4	300.2
	Middle tercile	30.1	110.5	212.5	108.8
	Richest tercile	-37.7	10.7	76.0	29.6

Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 4941 panel individuals from the 5th and 13th rounds of the RLMS and 3719 panel individuals from the 13th and 24th rounds of the RLMS.

Table 3. Long-Term Income Mobility Patterns, RLMS 1994-2015 (percentage)

	Unconditional	Conditional
Upward mobility	34.5	45.7
Immobility	44.6	44.6
Downward mobility	20.9	36.7

Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 2478 panel individuals from the 5th and 24th round of the RLMS.

Table 4. Long-Term Income Growth Rate, Russia 1994-2015 (percentage)

		2015			
		Poorest tercile	Middle tercile	Richest tercile	Overall
1994	Poorest tercile	317.2	543.8	965.8	503.1
	Middle tercile	78.6	180.9	353.4	194.0
	Richest tercile	-13.1	34.0	125.4	44.9

Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 2478 panel individuals from the 5th and 24th round of the RLMS.

Table 5. Fields-Ok Mobility Index

Period	Total	Decomposition (percentage)	
		Growth	Redistribution
1994-1998	0.84	-67	167
1998-2004	1.15	81	19
2004-2009	0.79	80	20
2009-2015	0.46	40	60
1994-2004	0.80	43	57
2004-2015	0.98	89	11
1994-2015	1.32	95	5

Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights.

Table 6. Shorrocks Mobility Index and Short-Term and Long-Term Inequality (balanced sample for each period)

Period	Gini Index			Variance of Log Income			No. of observations	No. of individuals
	M^s	Short-term inequality	Long-term inequality	M^s	Short-term inequality	Long-term inequality		
1994-1998	0.18	0.44	0.36	0.41	0.76	0.45	19 120	4 780
1998-2004	0.22	0.40	0.31	0.45	0.63	0.34	25 452	4 242
2004-2009	0.18	0.35	0.29	0.38	0.47	0.29	22 956	3 826
2009-2015	0.15	0.31	0.26	0.30	0.35	0.24	27 174	3 882
1994-2004	0.27	0.39	0.29	0.51	0.60	0.29	24 111	2 679
2004-2015	0.23	0.31	0.24	0.44	0.37	0.21	23 868	1 989
1994-2015	0.34	0.33	0.22	0.58	0.42	0.17	16 680	834

Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights

Table 7. Short-Term Correlates of Mobility, Ordered Logit Model with Individual Random Effects, RLMS

	1994-1998		*1998-2004*		*2004-2009*		*2009-2015*	
	Coef	*SE*	Coef	*SE*	Coef	*SE*	Coef	*SE*
Transition variables (base - transition to part-time or no transition within part-time)								
Transition to full-time	0.312***	*0.10*	0.321***	*0.08*	0.367***	*0.09*	0.350***	*0.07*
No transition within full-time	0.054	*0.06*	0.133***	*0.05*	0.177***	*0.05*	0.179***	*0.04*
Individual Characteristics								
Age	0.005	*0.01*	-0.006	*0.01*	0.013*	*0.01*	-0.007	*0.01*
Age squared/100	-0.005	*0.02*	0.012	*0.01*	-0.014	*0.01*	0.015**	*0.01*
Male	-0.008	*0.05*	-0.066**	*0.03*	-0.061**	*0.03*	-0.041**	*0.02*
Married	-0.020	*0.06*	-0.077**	*0.03*	-0.138***	*0.03*	-0.114***	*0.02*
Education (base - less than secondary education)								
Secondary School	0.037	*0.07*	-0.027	*0.05*	0.076	*0.05*	0.007	*0.04*
Secondary + vocational	0.033	*0.08*	-0.017	*0.06*	0.010	*0.05*	0.011	*0.04*
University and higher	0.119	*0.09*	-0.024	*0.06*	0.062	*0.05*	0.000	*0.04*
Labor Market Characteristics								
Specific experience	-0.011*	*0.01*	-0.002	*0.00*	0.003	*0.00*	-0.003	*0.00*
Specific experience squared/100	0.029	*0.02*	0.004	*0.01*	0.001	*0.01*	0.009	*0.01*
Qualification (base- skilled white collar workers)								
Unskilled white collar workers	0.016	*0.06*	-0.008	*0.04*	-0.028	*0.03*	0.002	*0.03*
Skilled blue collar workers	-0.090	*0.09*	0.028	*0.05*	-0.003	*0.05*	-0.012	*0.04*
Unskilled blue collar workers	0.097	*0.08*	-0.028	*0.05*	-0.050	*0.04*	-0.012	*0.04*
Managerial position	-0.026	*0.05*	0.023	*0.04*	0.048	*0.03*	-0.052*	*0.03*
Household Characteristics								
Log of hh size	0.086	*0.06*	0.286***	*0.04*	0.216***	*0.03*	0.155***	*0.02*
Share of children aged 0-5	0.224	*0.20*	0.118	*0.15*	0.008	*0.13*	0.182*	*0.10*
Share of children aged 6-18	-0.034	*0.12*	-0.130	*0.08*	0.019	*0.08*	-0.063	*0.06*
Share of pensioners	-0.158	*0.12*	-0.158**	*0.07*	0.061	*0.06*	-0.105**	*0.05*
Type of locality (base - urban)								
Rural	0.014	*0.05*	-0.013	*0.03*	0.023	*0.03*	-0.026	*0.02*
/cut1	-1.221***	*0.30*	-1.115***	*0.20*	-0.999***	*0.18*	-1.437***	*0.14*
/cut2	1.309***	*0.30*	1.690***	*0.20*	2.174***	*0.18*	1.870***	*0.14*
/sigma2_u	0.000	*0.00*	0.000***	*0.00*	0.000	*0.00*	0.000***	*0.00*
Number of observations	6 588		13 999		18 235		30 662	
Number of individuals	3 678		5 636		7 108		11 328	
Log-Likelihood	-6 518		-13 211		-15 984		-26 087	

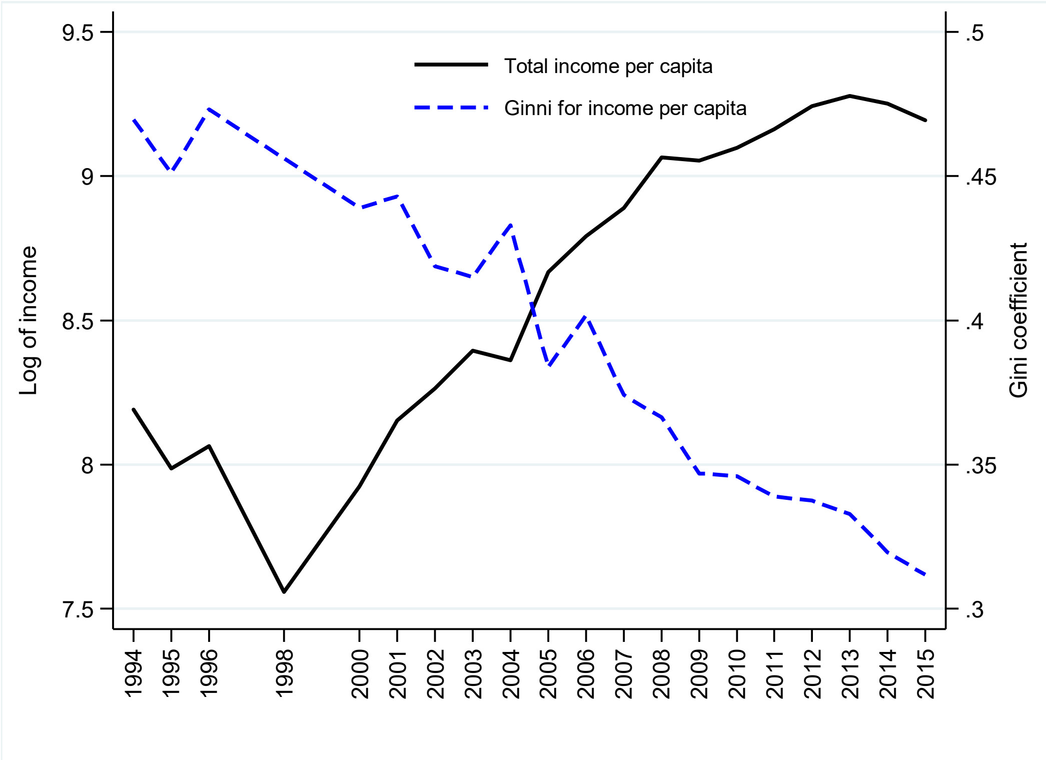
Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Robust standard errors in parentheses. The estimation sample is restricted to individuals who are 18 years old and older. Regional and time dummies are included but not showed. The dependent variable is income mobility between year *t-1* and year *t*. The terciles are defined using the cross-sectional sample for each year. Incomes are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. All control variables are measured in the reference year *t-1* except for the occupation transition variables, which are the changes between year *t-1* and year *t*.

Table 8. Labor Transitions and Income Growth, Linear Model with Individual Random Effects, RLMS 1994-2015

Occupation category	Variable	Period			
Panel A		**1994-1998**	**1998-2004**	**2004-2009**	**2009-2015**
Full-time employment	Transition to category	0.090**	0.091***	0.100***	0.053***
		(0.04)	*(0.02)*	*(0.02)*	*(0.01)*
	No transition within category	0.073***	0.096***	0.096***	0.067***
		(0.03)	*(0.02)*	*(0.01)*	*(0.01)*
Upward skills mobility	Transition to upper category	0.008	0.126***	0.102***	0.064***
		(0.05)	*(0.03)*	*(0.02)*	*(0.01)*
	No transition within category	-0.061*	0.066***	0.048***	0.037***
		(0.03)	*(0.02)*	*(0.01)*	*(0.01)*
Formal sector	Transition to category		0.214***	0.010	0.064***
			(0.07)	*(0.03)*	*(0.02)*
	No transition within category		0.131***	0.020	0.093***
			(0.04)	*(0.02)*	*(0.01)*
Public sector	Transition to category			-0.086***	-0.045***
				(0.02)	*(0.01)*
	No transition within category			-0.080***	-0.052***
				(0.01)	*(0.01)*
Panel B		**1994-2004**	**2004-2015**	**1994-2015**	
Full-time employment	Transition to category	0.089***	0.072***	0.081***	
		(0.02)	*(0.01)*	*(0.01)*	
	No transition within category	0.086***	0.078***	0.083***	
		(0.02)	*(0.01)*	*(0.01)*	
Upward skills mobility	Transition to upper category	0.078***	0.073***	0.081***	
		(0.02)	*(0.01)*	*(0.01)*	
	No transition within category	0.019	0.043***	0.041***	
		(0.02)	*(0.01)*	*(0.01)*	
Formal sector	Transition to category		0.043***	0.067***	
			(0.02)	*(0.02)*	
	No transition within category		0.069***	0.078***	
			(0.01)	*(0.01)*	
Public sector	Transition to category		-0.056***		
			(0.01)		
	No transition within category		-0.049***		
			(0.01)		

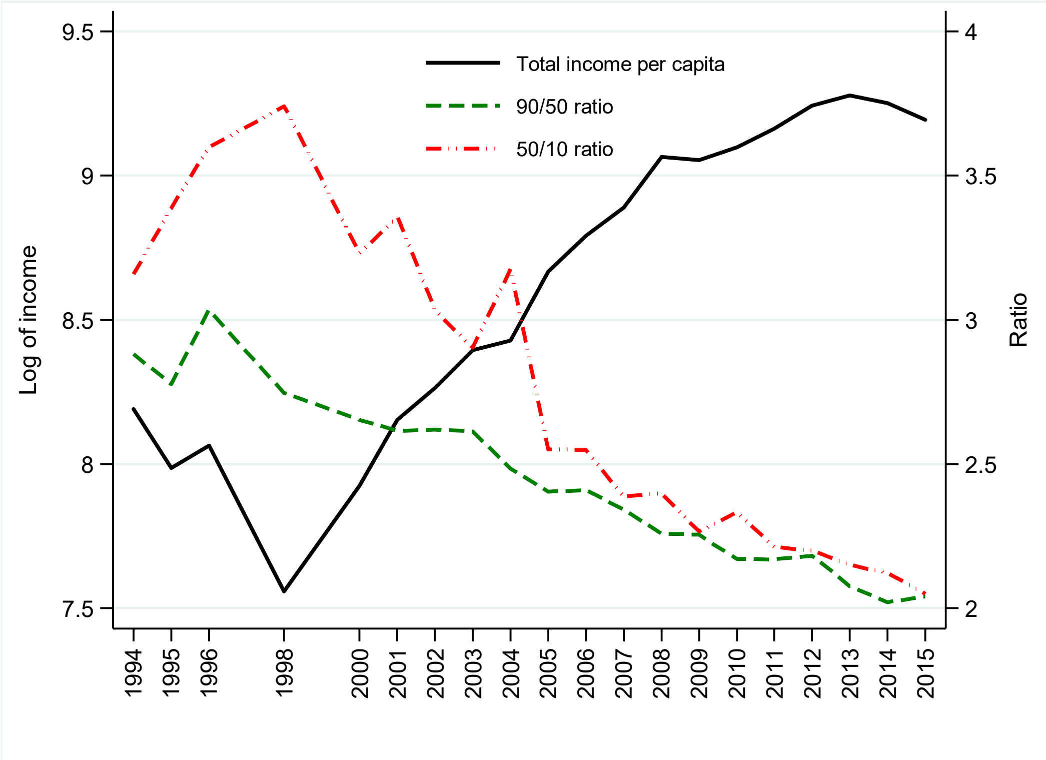
Note: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses. The estimation sample is restricted to individuals who are 18 years old and older. The dependent variable is log of household income per capita in year *t*. Incomes are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. All control variables are measured in the reference year *t-1* except for the occupation transition variables, which are the changes between year *t-1* and year *t*.

Figure 1. Trends of Income per capita and Gini Coefficients, RLMS 1994-2015



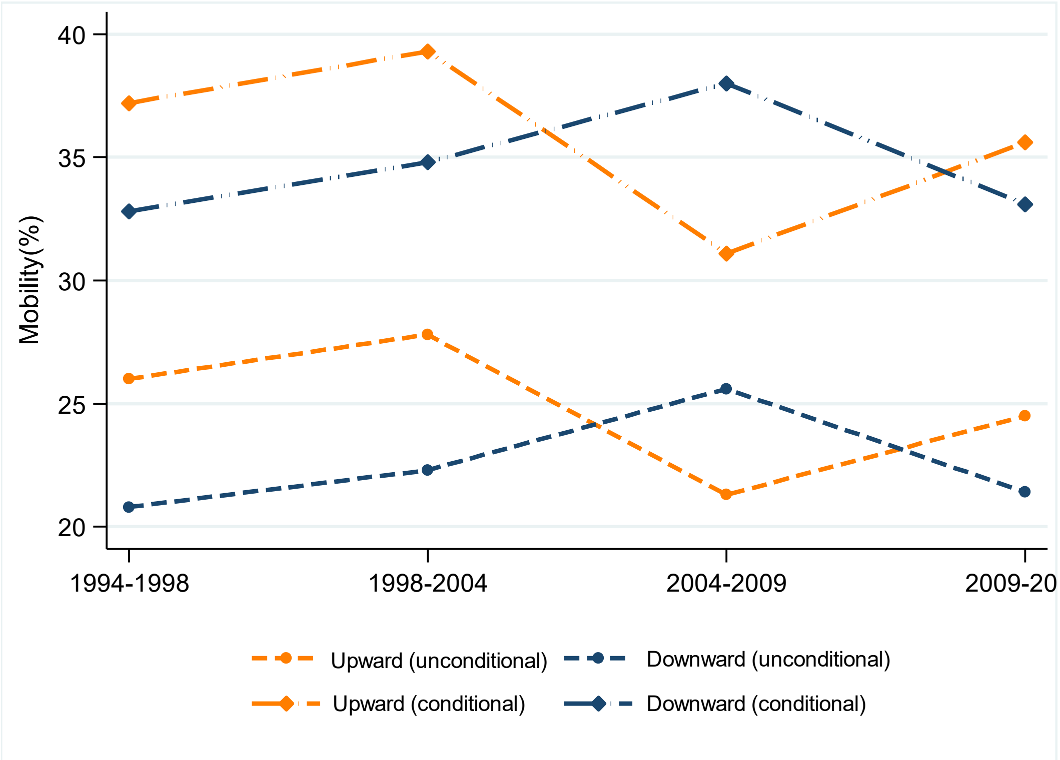
Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights. The repeated cross sections are used for each year.

Figure 2. Trends of Income per capita and Percentile Ratios, RLMS 1994-2015



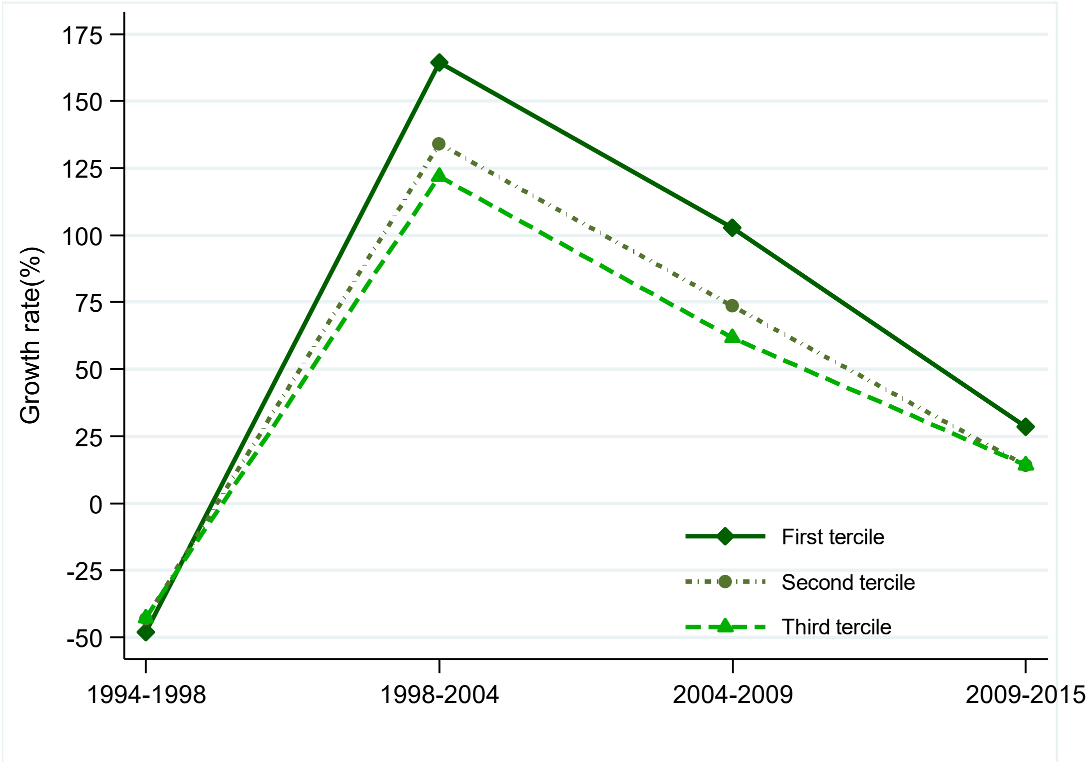
Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights. The repeated cross sections are used for each year. We remove 170 individuals in 2004 that have extremely low monthly incomes (i.e., less than 300 rubles per capita).

Figure 3. Short-Term Income Mobility, RLMS 1994-2015



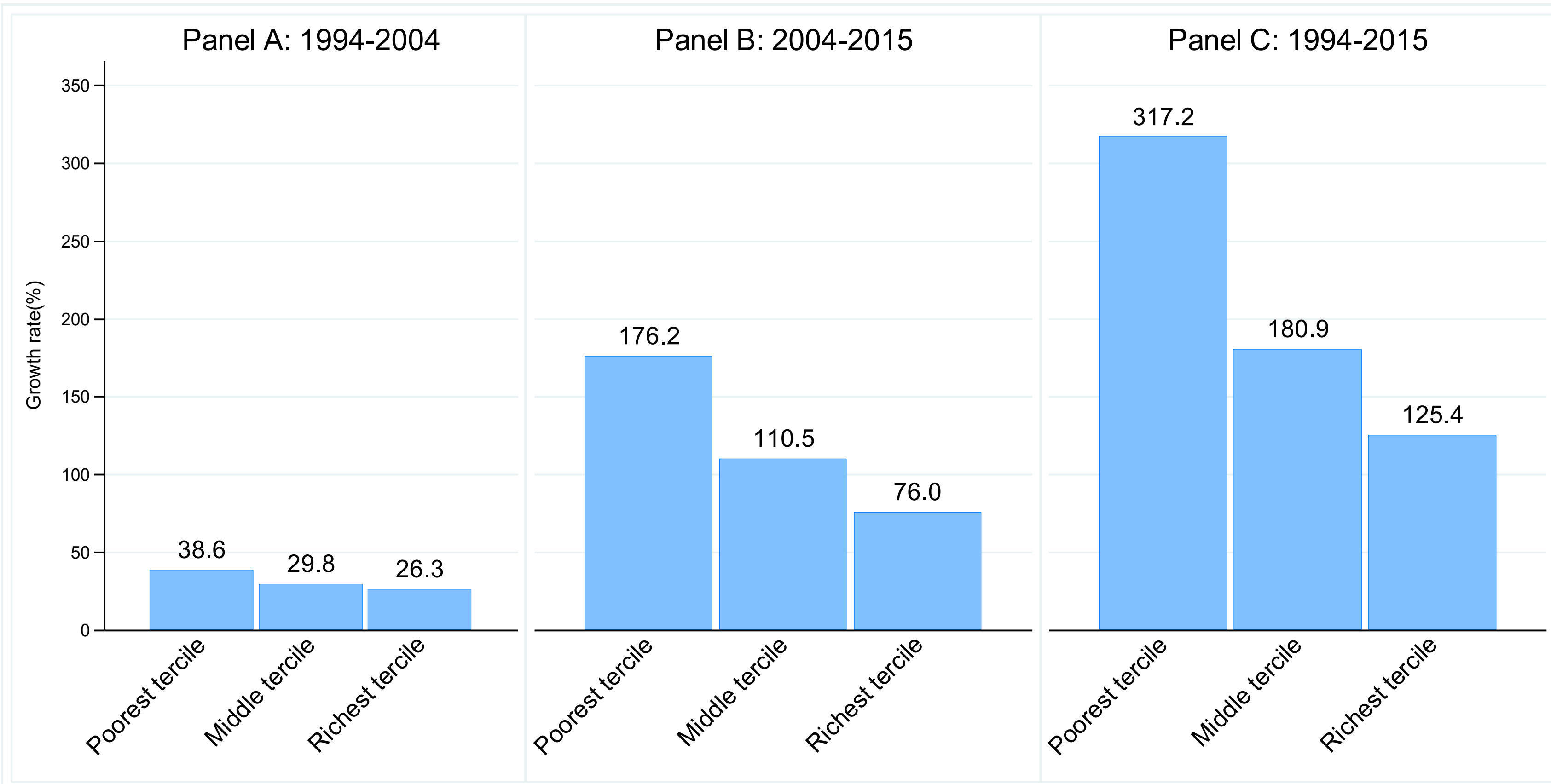
Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year.

Figure 4. Short-Term Income Growth Rate for Immobile Individuals, Russia 1994-2015



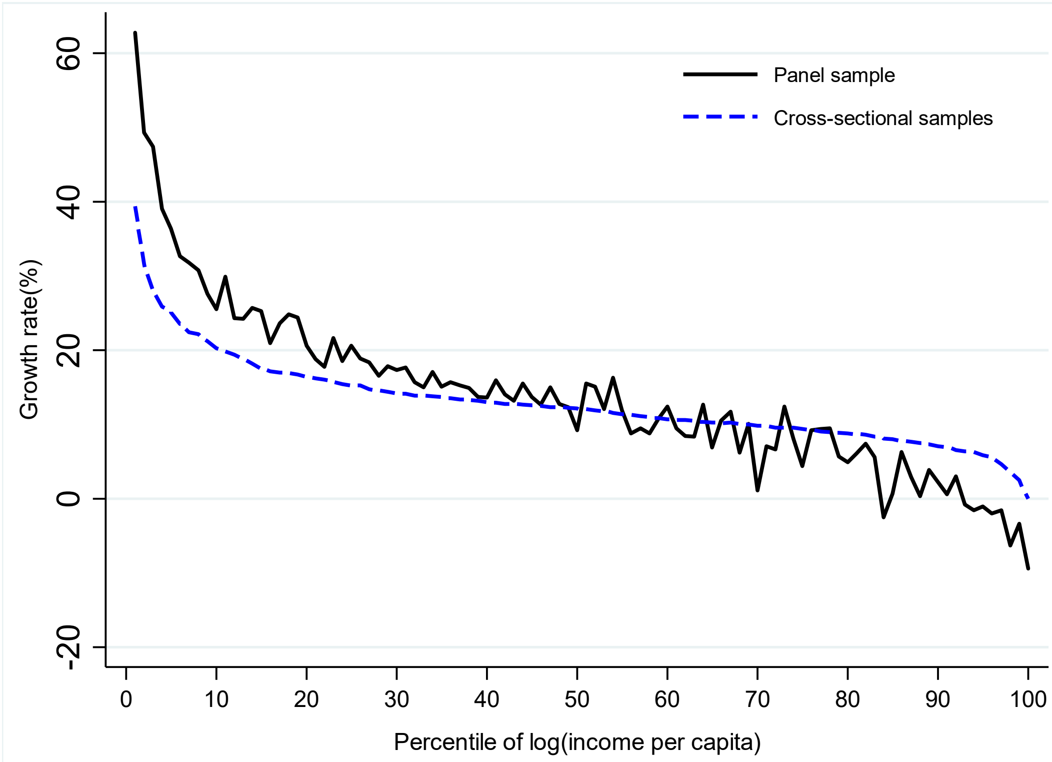
Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year.

Figure 5. Medium-Term and Long-Term Income Growth Rate for Immobile Individuals, Russia 1994-2015 (percentage)



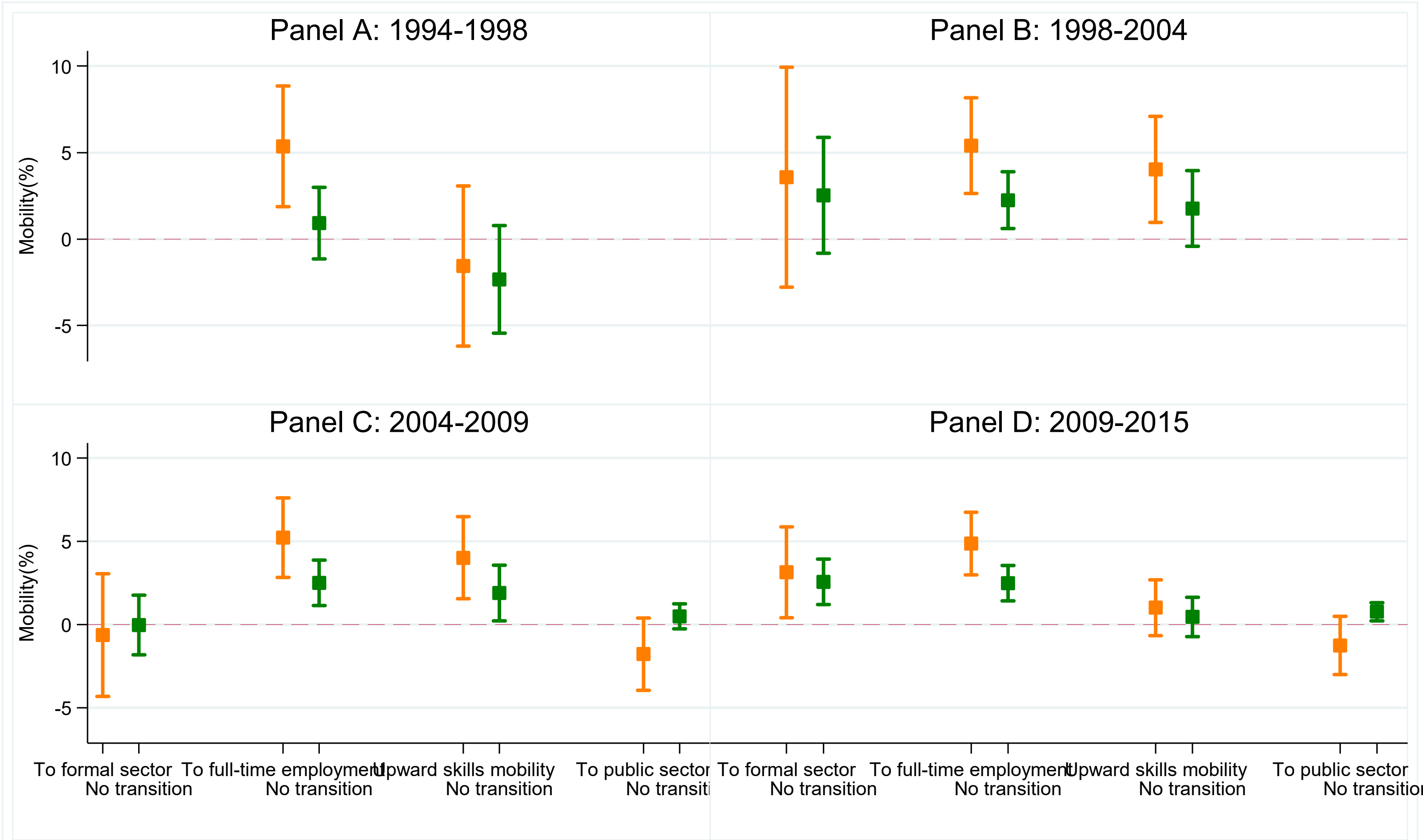
Note: Estimation results are obtained based on total household income per capita. The distribution by terciles is based on the cross-sectional sample for each year, then the tercile thresholds were assigned to panel sample. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. The exact growth rates for each income group are shown on top of the bars.

Figure 6. Growth Incidence Curves of Log of Total Household Income Per Capita, RLMS 1994-2015



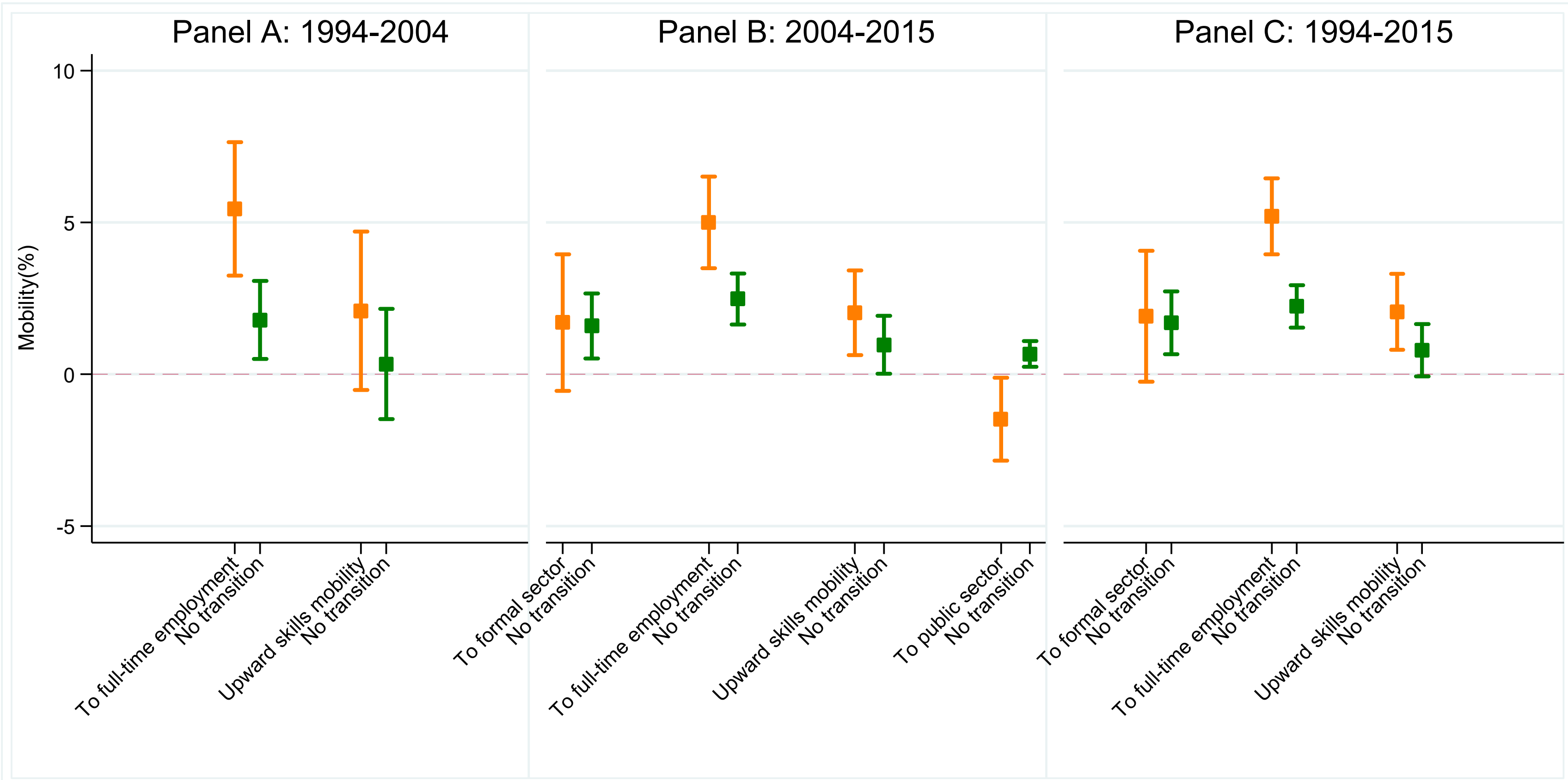
Note: Estimation results are based on log of total household income per capita. The distribution by terciles for panel individuals in the first period is based on the cross-sectional sample. Growth rate is calculated as the change in the median log of income per capita for each percentile between 1994 and 2015. All numbers are deflated with December to December regional CPIs and weighted with population weights.

Figure 7. Short-Term Correlates of Mobility, Ordered Logit Model with Random Effects, Marginal effects, RLMS 1994-2015



Note: Orange/green lines are related to 95% confidence intervals. Data on formal sector are available since 1998 and data on public sector are available since 2004. The estimation sample is restricted to individuals who are 18 years old and older. The dependent variable is income mobility between year *t-1* and year *t*. The terciles are defined using the cross-sectional sample for each year. Incomes are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. All control variables are measured in the reference year *t-1* except for the occupation transition variables, which are the changes between year *t-1* and year *t*.

Figure 8. Medium-Term and Long-Term Correlates of Mobility, Ordered Logit Model with Random Effects, Marginal Effects, RLMS 1994-2015



Note: Orange/green lines are related to 95% confidence intervals. Data on formal sector are available since 1998 and data on public sector are available since 2004. The estimation sample is restricted to individuals who are 18 years old and older. The dependent variable is income mobility between year *t-1* and year *t*. The terciles are defined using the cross-sectional sample for each year. Incomes are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. All control variables are measured in the reference year *t-1* except for the occupation transition variables, which are the changes between year *t-1* and year *t*.

Appendix 1: Additional Tables and Figures

Table 1.1. Different Definitions of Welfare in Studies on Poverty and Inequality in Russia

Description	***Definition***	***Source/paper***	***Data***
Income variable			
1.Reported total household income	***Total household monetary income (one question)***	Lukiyanova and Oshchepkov (2012)	RLMS, 2000-2005
		Ferrer-i-Carbonell and Van Praag (2001)	RUSSET,1997-1998
		Stillman (2001)	RLMS, 1994-1998
2. Total household income based on the sum of components (or disposable household income)	Household labor earning + private transfers (or net private transfers) + public transfers + capital income (+ income from home production)	Lukiyanova and Oshchepkov (2012)	RLMS, 2000-2005
		Gorodnichenko *et al.* (2010)	RLMS, 1994-2005
		Mu (2006)	RLMS, 1994-2000
		Lokshin and Ravallion (2004)	RLMS, 1994-1998
		Commander *et al.* (1999)	RLMS, 1992-1996
		Lokshin and Popkin (1999)	RLMS, 1992-1996
3. Individual labor earning (separately and aggregated at household level)	Money and payment in-kind received from primary and secondary jobs + money received from regular economic activities	Lukiyanova and Oshchepkov (2012)	RLMS, 2000-2005
		Gorodnichenko *et al.* (2010)	RLMS, 1994-2005
		Skoufias (2003)	RLMS, 1994-2000
Consumption variable			
4.Non-durable expenditures	Food, alcohol and tobacco + clothing and footwear + gasoline and other fuel expenses + rents and housing utilities + services (+consumption of home-grown food)	Gorodnichenko *et al.* (2010)	RLMS, 1994-2005
		Mu (2006)	RLMS, 1994-2000
		Stillman (2001)	RLMS, 1994-1998
		Skoufias (2003)	RLMS, 1994-2000
5. Aggregate expenditures	Non-durable expenditures + expenditures on durables (+consumption of home-grown food)	Gorodnichenko *et al.* (2010)	RLMS, 1994-2005
		Stillman and Thomas (2008)	RLMS, 1994-2000

Table 1.2. Medium-Term and Long-Term Income Mobility, RLMS 1994-2015 (percentage)

Panel A: 1994-2004		**2004**			
		Poorest tercile	**Middle tercile**	**Richest tercile**	**Total**
1994	Poorest tercile	21.7	12.2	7.4	41.3
		(0.6)	*(0.5)*	*(0.4)*	*(0.7)*
	Middle tercile	8.5	14.3	9.5	32.3
		(0.4)	*(0.5)*	*(0.4)*	*(0.7)*
	Richest tercile	3.7	9.1	13.6	26.3
		(0.3)	*(0.4)*	*(0.5)*	*(0.6)*
	Total	35.4	36.9	27.7	100
		(0.7)	*(0.7)*	*(0.7)*	
Panel B: 2004-2015		**2015**			
		Poorest tercile	**Middle tercile**	**Richest tercile**	**Total**
2004	Poorest tercile	18.1	10.6	6.3	35.0
		(0.7)	*(0.5)*	*(0.4)*	*(0.8)*
	Middle tercile	11.0	13.2	10.8	35.0
		(0.5)	*(0.6)*	*(0.5)*	*(0.8)*
	Richest tercile	4.7	9.6	15.7	29.9
		(0.4)	*(0.5)*	*(0.6)*	*(0.8)*
	Total	34.1	32.6	33.3	100
		(0.8)	*(0.8)*	*(0.8)*	
Panel C: 1994-2015		**2015**			
		Poorest tercile	**Middle tercile**	**Richest tercile**	**Total**
1994	Poorest tercile	19.9	14.7	8.5	43.1
		(0.8)	*(0.7)*	*(0.6)*	*(1.0)*
	Middle tercile	8.0	13.0	11.3	32.3
		(0.6)	*(0.7)*	*(0.6)*	*(0.9)*
	Richest tercile	5.2	7.6	11.7	24.5
		(0.5)	*(0.5)*	*(0.6)*	*(0.9)*
	Total	33.7	36.8	29.5	100
		(1.0)	*(1.0)*	*(1.0)*	

Note: Estimation results are obtained based on total household income per capita. Linearized standard errors of cell percentages are in parentheses. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 4941 panel individuals from the 5th and 13th round of the RLMS, 3719 panel individuals from the 13th and 24th round of the RLMS and 2478 panel individuals from the 5th and 24th round of the RLMS

Table 1.3. Shorrocks Mobility Index and Short-Term and Long-Term Inequality (balanced sample for the whole period 1994-2015)

Period	Gini Index			Variance of Log Income			No. of observations	No. of individuals
	M^s	Short-term inequality	Long-term inequality	M^s	Short-term inequality	Long-term inequality		
1994-1998	0.21	0.42	0.33	0.42	0.72	0.41	3 336	834
1998-2004	0.21	0.38	0.30	0.45	0.55	0.30	5 004	834
2004-2009	0.16	0.31	0.26	0.36	0.35	0.22	5 004	834
2009-2015	0.16	0.27	0.22	0.31	0.24	0.17	5 838	834
1994-2004	0.27	0.39	0.28	0.52	0.61	0.29	7 506	834
2004-2015	0.23	0.29	0.22	0.43	0.29	0.17	10 008	834
1994-2015	0.34	0.33	0.22	0.58	0.42	0.17	16 680	834

Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights

Table 1.4. Medium-Term and Long-Term Income Mobility, RLMS 1994-2015 (percentage)

	Fitzgerald approach		Wooldridge approach	
	Unconditional	**Conditional**	**Unconditional**	**Conditional**
Panel A: 1994-2004				
Upward mobility	29.1	39.4	29.7	47.6
Immobility	49.8	49.8	47.3	47.3
Downward mobility	21.0	36.1	23.0	30.8
Panel B: 2004-2015				
Upward mobility	27.5	39.1	30.6	47.3
Immobility	47.4	47.4	47.7	47.7
Downward mobility	25.1	38.7	21.7	29.6
Panel C: 1994-2015				
Upward mobility	34.4	45.7	28.4	36.3
Immobility	44.7	44.7	57.5	57.5
Downward mobility	20.9	37.1	14.1	17.2

Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with longitudinal weights, where the second survey round in each period is used as the base year. To obtain longitudinal weights we combine cross-sectional weights with the inverse dropout probabilities, which are estimated using methods suggested by Wooldridge (2002) and by Fitzgerald *et al.* (1998). Estimation sample size is 1890 and 4727 panel individuals from the 5th and 13th rounds of the RLMS, 1713 and 3555 panel individuals from the 13th and 24th rounds of the RLMS and 663 and 2371 panel individuals from the 5th and 24th round of the RLMS respectively.

Table 1.5. Medium-Term and Long-Term Income Mobility, RLMS 1994-2015 (percentage)

	All households		Households with 50% or more members	
	Unconditional	**Conditional**	**Unconditional**	**Conditional**
Panel A: 1994-2004				
Upward mobility	27.7	38.1	24.7	36.2
Immobility	48.6	48.6	51.1	51.1
Downward mobility	23.8	38.2	24.1	38.4
Panel B: 2004-2015				
Upward mobility	26.1	37.5	25.2	36.5
Immobility	47.4	47.4	47.4	47.4
Downward mobility	26.5	38.8	27.3	40.3
Panel C: 1994-2015				
Upward mobility	34.7	46.6	29.0	38.0
Immobility	44.0	44.0	51.9	51.9
Downward mobility	21.3	35.9	19.1	28.4

Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with household weights, where the first survey round in each period is used as the base year. We use panel of household heads and define heads according to RLMS recommendations as: (1) the oldest working-age male in the household, (2) if there is no working-age male, then the oldest working-age female, (3) if there is no working-age female, then the youngest retirement-age male, (4) if there is no retirement-age male, then the youngest retirement-age female, (5) if there is no retirement-age female, then the oldest child. We use two types of panel: with all households and with households that have 50% or more members in other wave. Estimation sample size is 1926 and 1055 panel households from the 5th and 13th rounds of the RLMS, 1410 and 569 panel households from the 13th and 24th rounds of the RLMS and 753 and 173 panel households from the 5th and 24th round of the RLMS respectively.

Table 1.6. Medium-Term and Long-Term Income Mobility, RLMS 1994-2015 (percentage)

	Equivalence scale		**Economies of size**	
	Unconditional	**Conditional**	**Unconditional**	**Conditional**
Panel A: 1994-2004				
Upward mobility	28.6	38.8	29.4	39.7
Immobility	49.3	49.3	48.4	48.4
Downward mobility	22.1	37.2	22.3	37.4
Panel B: 2004-2015				
Upward mobility	25.7	37.0	26.8	38.5
Immobility	47.2	47.2	46.1	46.1
Downward mobility	27.1	41.3	27.1	41.2
Panel C: 1994-2015				
Upward mobility	32.1	42.6	33.0	43.8
Immobility	44.6	44.6	43.4	43.4
Downward mobility	23.3	40.5	23.6	41.0

Note: Estimation results are based on per adult equivalent income. The OECD equivalence scale assigns a value of 1.0 to the first adult, a value of 0.7 to each additional adult (age 17 or older), and a value of 0.5 to each child (age 0-16) but does not account for the economies of size in large households. We set the economies of size equal to 0.8. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 4941 panel individuals from the 5th and 13th rounds of the RLMS, 3722 and 3719 panel individuals from the 13th and 24th rounds of the RLMS and 2477and 2475 panel individuals from the 5th and 24th round of the RLMS respectively.

Table 1.7. Medium-Term and Long-Term Income Mobility, RLMS 1994-2015 (percentage)

	Unconditional	Conditional
Panel A: 1994-2004		
Upward mobility	30.7	42.8
Immobility	47.3	47.3
Downward mobility	22.1	36.7
Panel B: 2004-2015		
Upward mobility	28.7	42.0
Immobility	46.4	46.4
Downward mobility	24.9	37.8
Panel C: 1994-2015		
Upward mobility	37.2	50.5
Immobility	40.5	40.5
Downward mobility	22.3	39.2

Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Real incomes are adjusted for regional differences in the cost-of-living by using the regional value of fixed basket of goods and services. Estimation sample size is 4939 panel individuals from the 5th and 13th rounds of the RLMS, 3715panel individuals from the 13th and 24th rounds of the RLMS and 2476 panel individuals from the 5th and 24th round of the RLMS.

Table 1.8. Medium-Term and Long-Term Income Mobility, RLMS 1994-2015 (percentage)

	Unconditional	**Conditional**
Panel A: 1994-2004		
Upward mobility	30.0	34.0
Immobility	54.8	54.8
Downward mobility	15.2	39.4
Panel B: 2004-2015		
Upward mobility	54.8	69.6
Immobility	37.8	37.8
Downward mobility	7.5	15.3
Panel C: 1994-2015		
Upward mobility	66.5	74.8
Immobility	28.4	28.4
Downward mobility	5.1	14.4

Note: Estimation results are obtained based on total household income per capita. The vulnerability index is defined as P(Y1<Z1|Z0<Y0<V0) = 0.15 yielding a yearly vulnerability line of 8152 real rubles per capita (in 2011 prices) for period 2004-2015 or about. We use this same vulnerability line for the other periods. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 4942 panel individuals from the 5th and 13th rounds of the RLMS, 3719 panel individuals from the 13th and 24th rounds of the RLMS and 2478 panel individuals from the 5th and 24th round of the RLMS.

Table 1.9. Fields' Mobility Index and Short-Term and Long-Term Equality, RLMS 1994-2015

Period	Gini Index			Theil index			No. of individuals
	M^E	Short-term inequality	Long-term inequality	M^E	Short-term inequality	Long-term inequality	
1994-1998	0.12	0.46	0.41	0.27	0.41	0.30	6 303
1998-2004	0.19	0.45	0.37	0.37	0.37	0.24	5 527
2004-2009	0.21	0.41	0.32	0.40	0.30	0.18	5 200
2009-2015	0.14	0.34	0.29	0.28	0.19	0.14	5 001
1994-2004	0.20	0.45	0.36	0.40	0.38	0.23	4 942
2004-2015	0.27	0.41	0.30	0.49	0.29	0.15	3 719
1994-2015	0.34	0.45	0.30	0.59	0.37	0.15	2 478

Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights. The mobility index M^E is calculated as defined in Fields (2010).

Table 1.10. Short-Term Income Mobility, RLMS 1994-2015 (percentage)

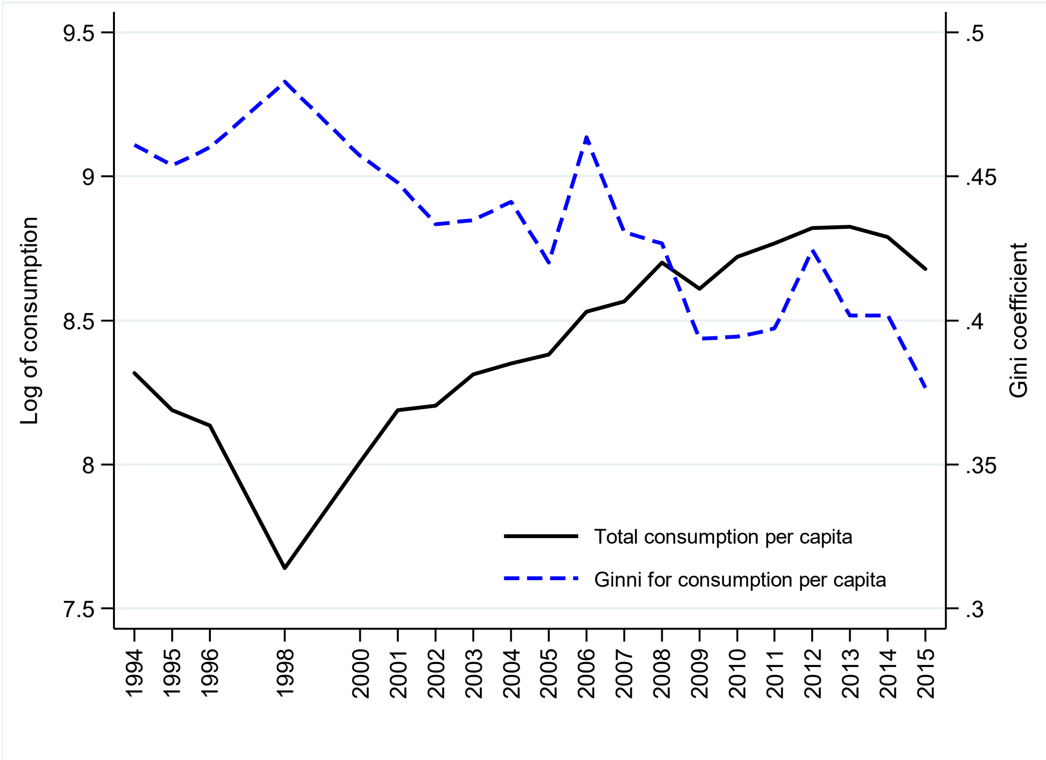
	Unconditional	Conditional
Panel A: 1994-1998		
Upward mobility	26.0	37.2
Immobility	53.2	53.2
Downward mobility	20.8	32.8
Panel B: 2000-2004		
Upward mobility	25.8	37.2
Immobility	53.2	53.2
Downward mobility	21.0	32.8
Panel C: 2005-2009		
Upward mobility	21.4	31.0
Immobility	55.7	55.7
Downward mobility	22.9	35.3
Panel D: 2010-2015		
Upward mobility	22.9	33.2
Immobility	57.3	57.3
Downward mobility	19.8	31.4

Note: Estimation results are obtained based on total household income per capita. The distribution by terciles is based on the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year. Estimation sample size is 6303 panel individuals in 1994-1998, 5901 panel individuals in 2000-2004, 5100 panel individuals in 2005-2009 and 7498 panel individuals in 2010-2015.

Table 1.11. Description of Labor Transition Variables

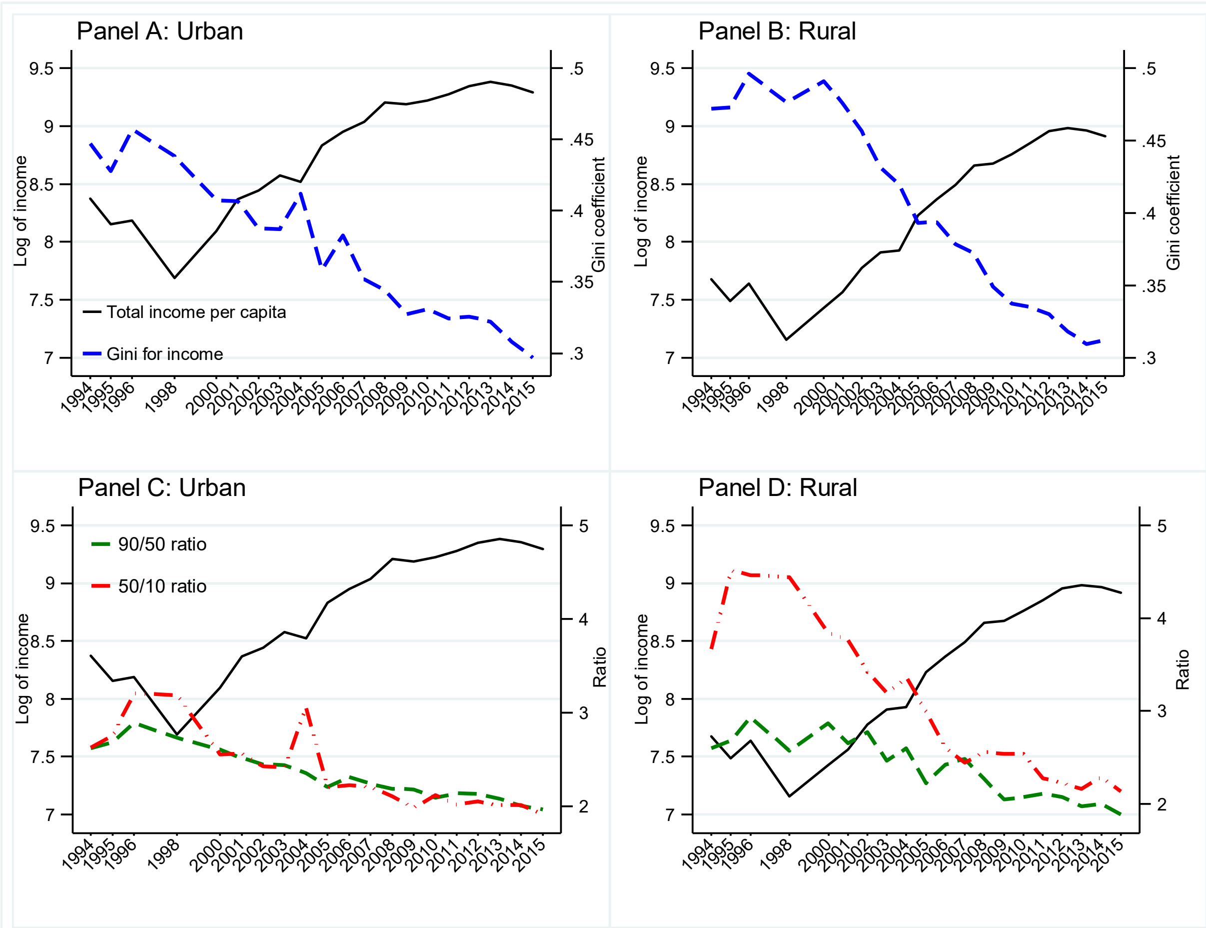
Variable	*Description*	*Data available*
Full-time/part-time employment	Workers are considered as having full-time employment if their actual work hours in the main job are more than 120 hours in the reference month. They are considered as having part-time employment otherwise.	1994-2015
Public/private sector	Workers are considered as employed in the public sector if they do not work in a foreign-owned enterprise and are employed in a state budgetary organization in education, health and social work, housing or communal services, or the public administration.	2004-2015
Formal/informal sector	Workers are considered as employed in the formal sector if they are employed officially or with a contract in the main job. They as considered as employed in the informal sector otherwise.	1998-2015
Occupational skills	All major professional groups are divided between four skill levels, where the 1st skill level is related to simple and routine work and the 4th skill level involves problem-solving and decision-making tasks according to ISCO-08 definition (International Standard Classification of Occupations in 2008, International Labour Organization, 2012).	1994-2015

Figure 1.1. Trends of Consumption per capita and Gini Coefficients, RLMS 1994-2015



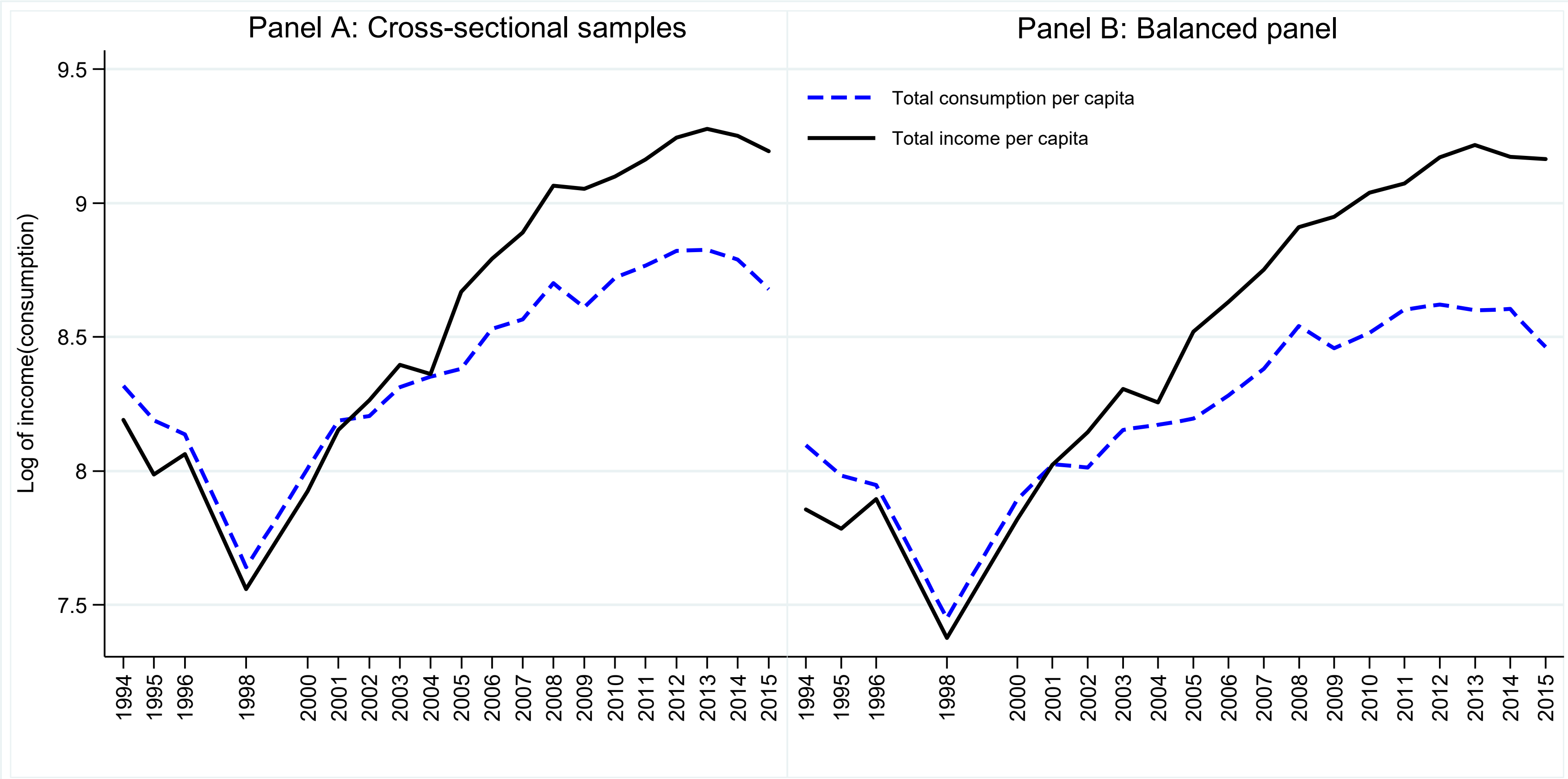
Note: Estimation results are based on total household consumption per capita using the repeated cross sections for each year. Household consumption is the total of non-durable consumption, including food, alcoholic and non-alcoholic beverages, tobacco products, clothing and footwear, gasoline and other fuel, rents and utilities, services (such as transportation, repair, health care services, education, entertainment, etc. without lumpy expenditures on housing construction, refurbishment and ritual services) and durable consumption. All consumption measures are converted to a monthly base. To keep the consumption variable consistent over time, we exclude expenditure categories that became available after 1994. All numbers are deflated with December to December regional CPIs and weighted with population weights.

Figure 1.2. Income per capita, Gini Coefficients, and Percentile Ratios for Urban and Rural Areas, RLMS 1994-2015



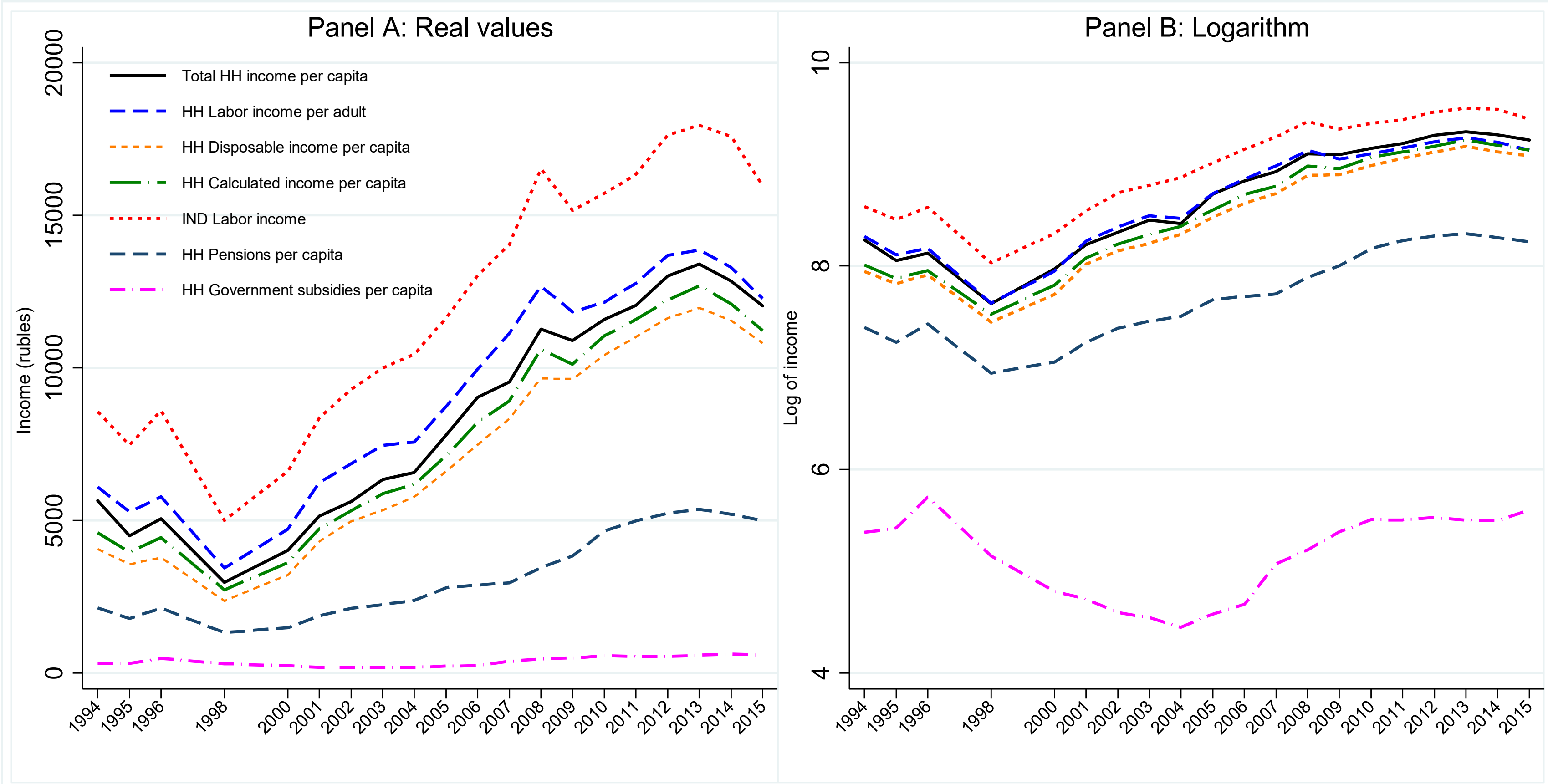
Note: Estimation results are obtained based on total household income per capita, using the repeated cross sections for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights.

Figure 1.3. Total Income and Consumption per capita, RLMS 1994-2015



Note: Estimation results are obtained based on total household income per capita and total household consumption per capita. Household consumption is constructed from non-durable consumption, including food, alcoholic and non-alcoholic beverages, tobacco products, clothing and footwear, gasoline and other fuel, rents and utilities, services (such as transportation, repair, health care services, education, entertainment, etc. without lumpy expenditures on housing construction, refurbishment and ritual services) and durable consumption. All consumption measures are converted to a monthly base. To keep the consumption variable consistent over time, we exclude expenditure categories that became available after 1994. All numbers are deflated with December to December regional CPIs and weighted with population weights.

Figure 1.4. Trends of Different Definitions of Household Income and Consumption, RLMS 1994-2015

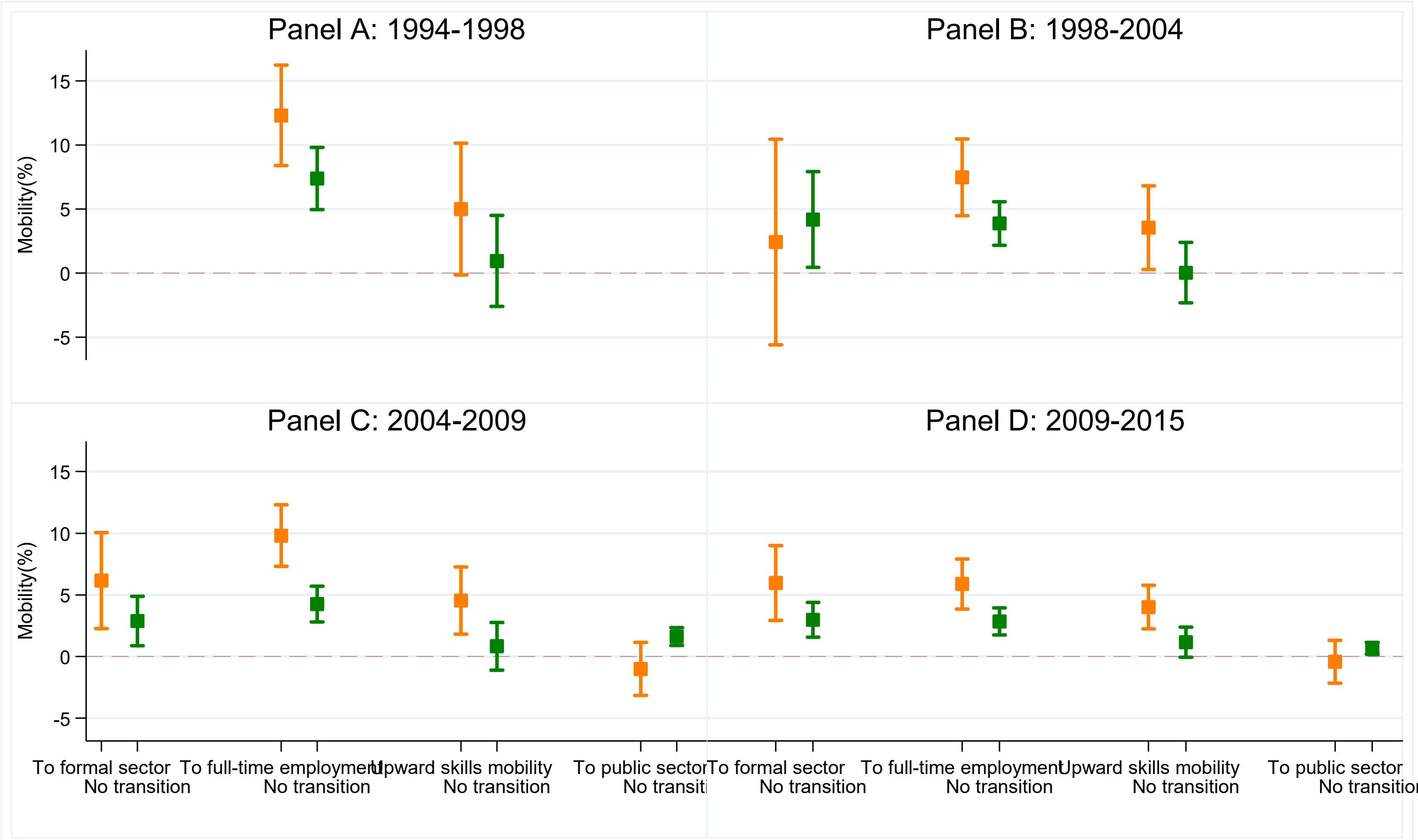


Note: We use the repeated cross sections for each year. The estimation sample is restricted to individuals who are 18 years old and older. Household labor income per adult is calculated using average household labor earnings per month. Disposable household income includes average household labor earnings, net private transfers, public transfers and financial income (see Gorodnichenko *et al.* (2010) for detailed description). Calculated household income is based on the sum of average household labor earnings, received private transfers, public transfers and financial income (see Lukiyanova and Oshchepkov (2012) for detailed description). Individual labor income includes money and payment in kind received last month from primary job and secondary job + money received last month from regular individual economic activities (see Gorodnichenko *et al.* (2010) for detailed description). Government subsidies include stipends, unemployment benefits, fuel and state child subsidies. All income measures are converted to a monthly base. To keep the income variable consistent over time, we exclude income categories that became available after 1994. All numbers are deflated with December to December regional CPIs and weighted with population weights.

Figure 1.5. Trends of Income per capita Net of Government Pensions and Gini Coefficients, RLMS 1994-2015

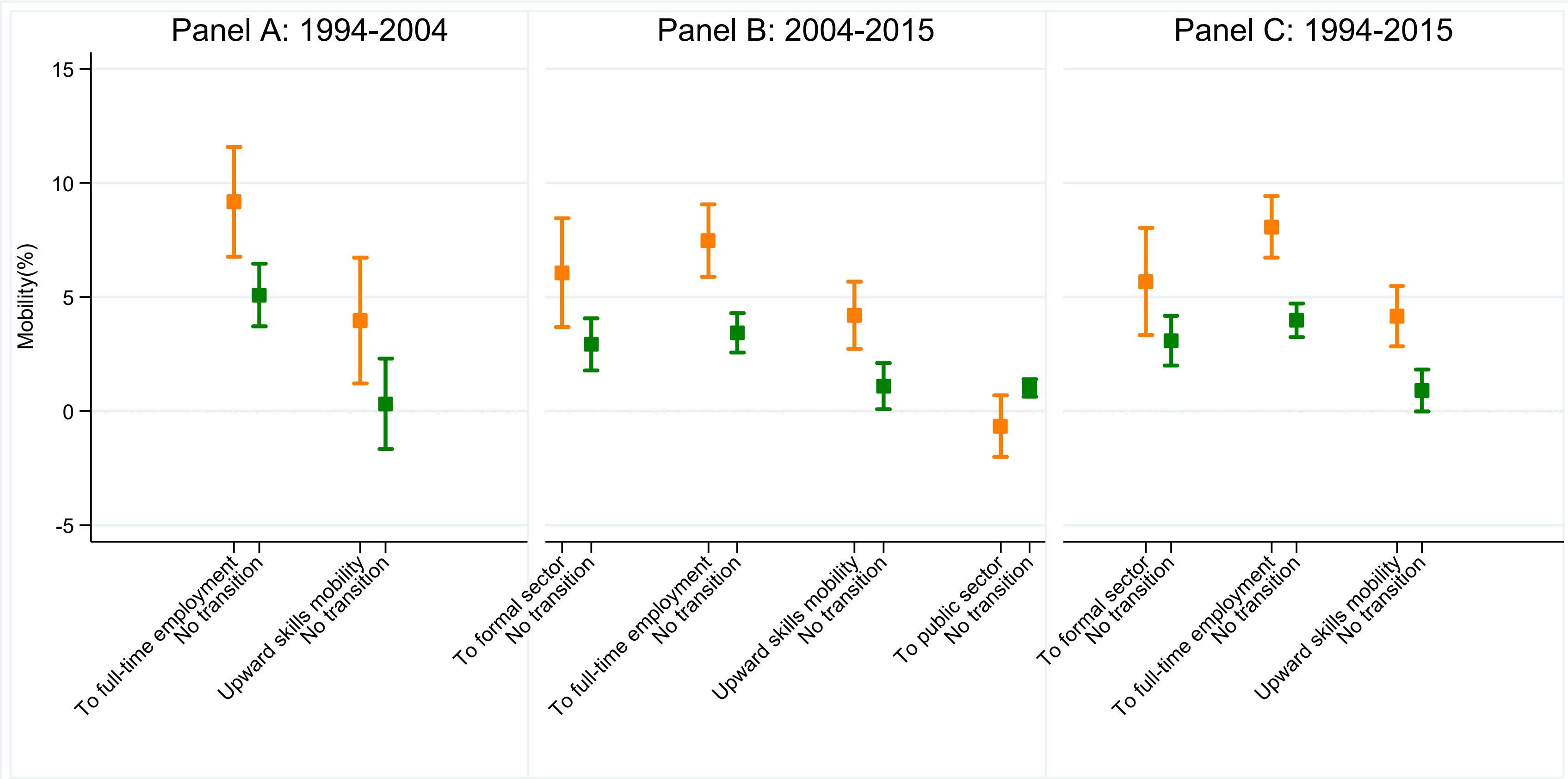
Note: Estimation results are obtained based on total household income per capita net of government pensions, using the repeated cross sections for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights.

Figure 1.6. Short-Term Correlates of Mobility, Ordered Logit Model with Random Effects, Marginal effects, RLMS 1994-2015



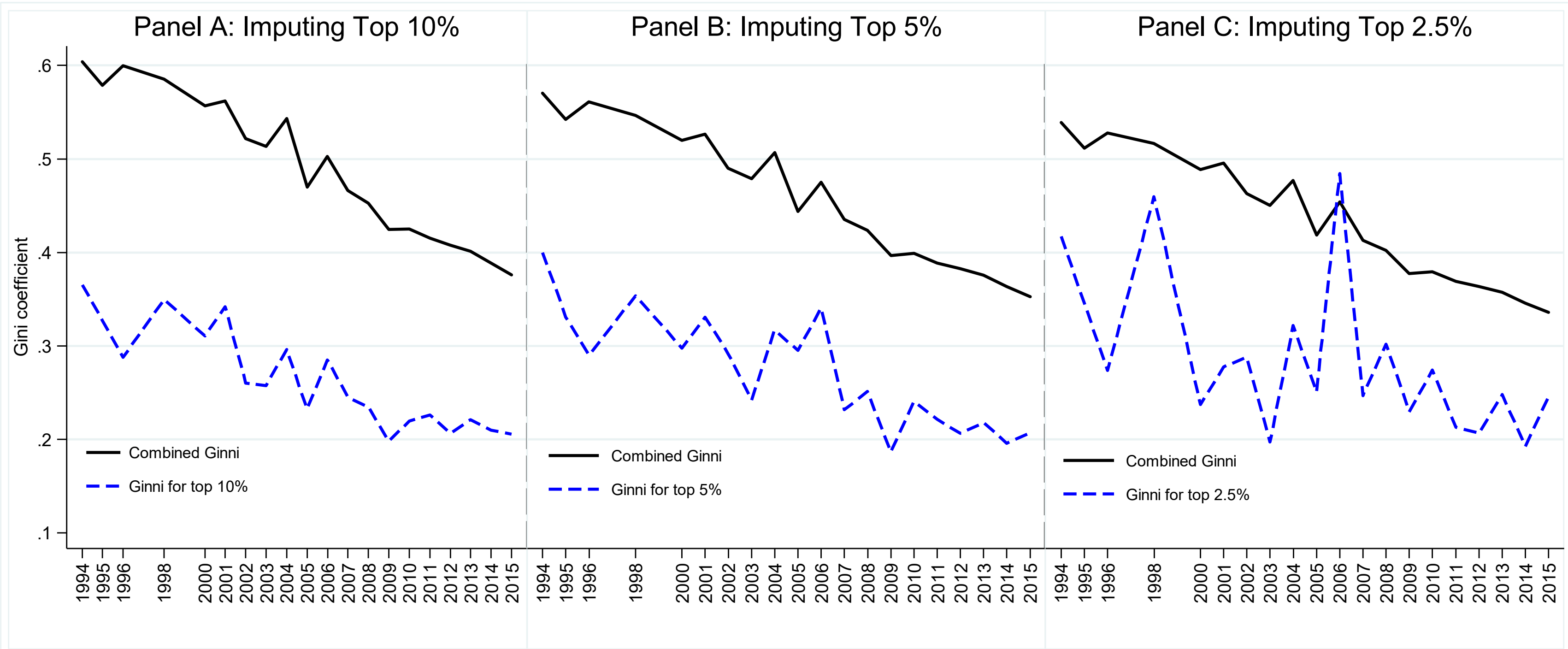
Note: Orange/green lines are related to 95% confidence intervals. The dependent variable is individual labor earning mobility between year *t-1* and year *t*. The terciles are defined using the cross-sectional sample for each year. Data on formal sector are available since 1998 and data on public sector are available since 2004.

Figure 1.7. Medium-Term and Long-Term Correlates of Mobility, Ordered Logit Model with Random Effects, Marginal Effects, RLMS 1994-2015



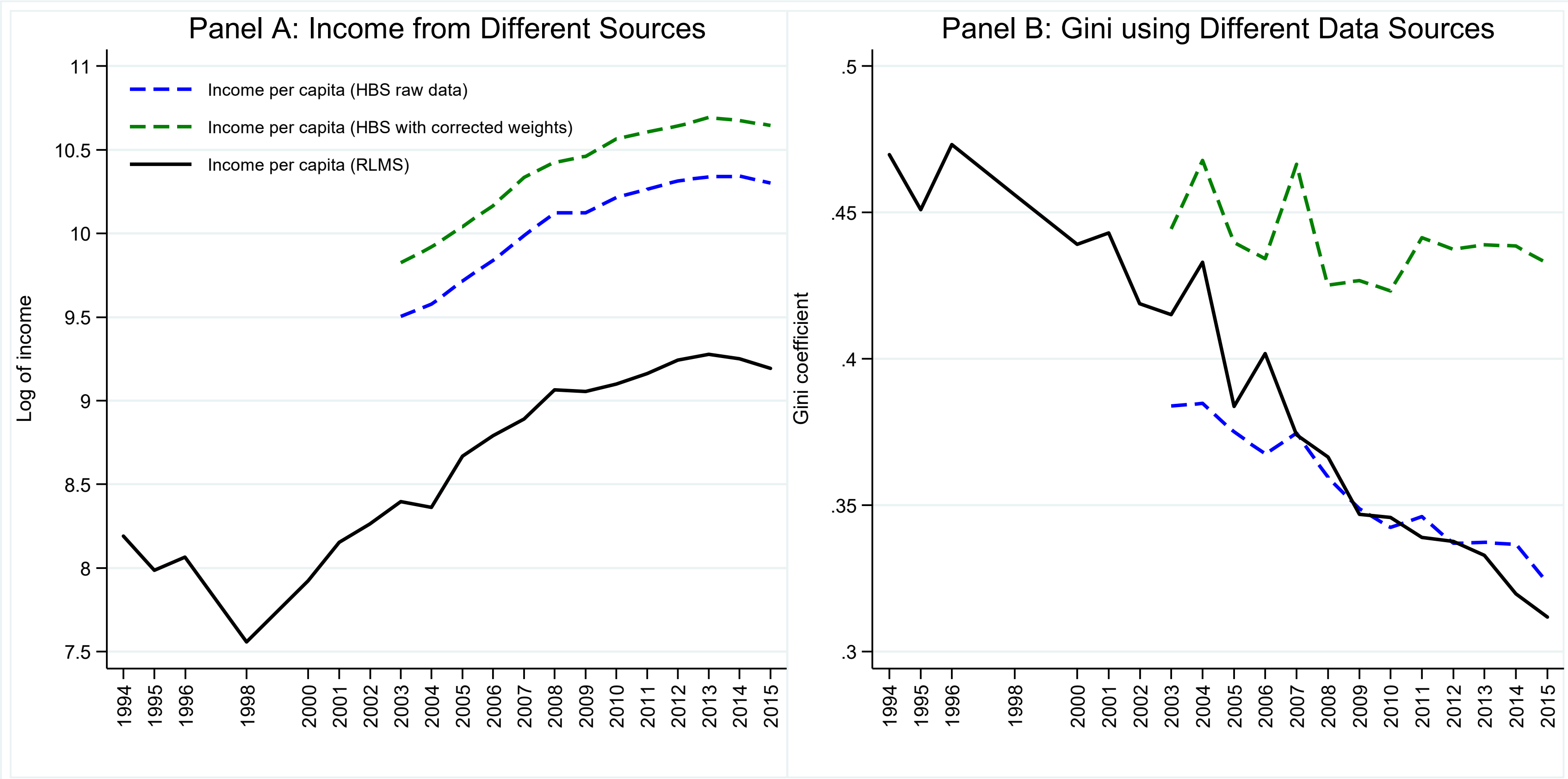
Note: Orange/green lines are related to 95% confidence intervals. The dependent variable is individual labor earning mobility between year *t-1* and year *t*. The terciles are defined using the cross-sectional sample for each year. Data on formal sector are available since 1998 and data on public sector are available since 2004.

Figure 1.8. Total inequality and inequality within top income population, RLMS 1994-2015



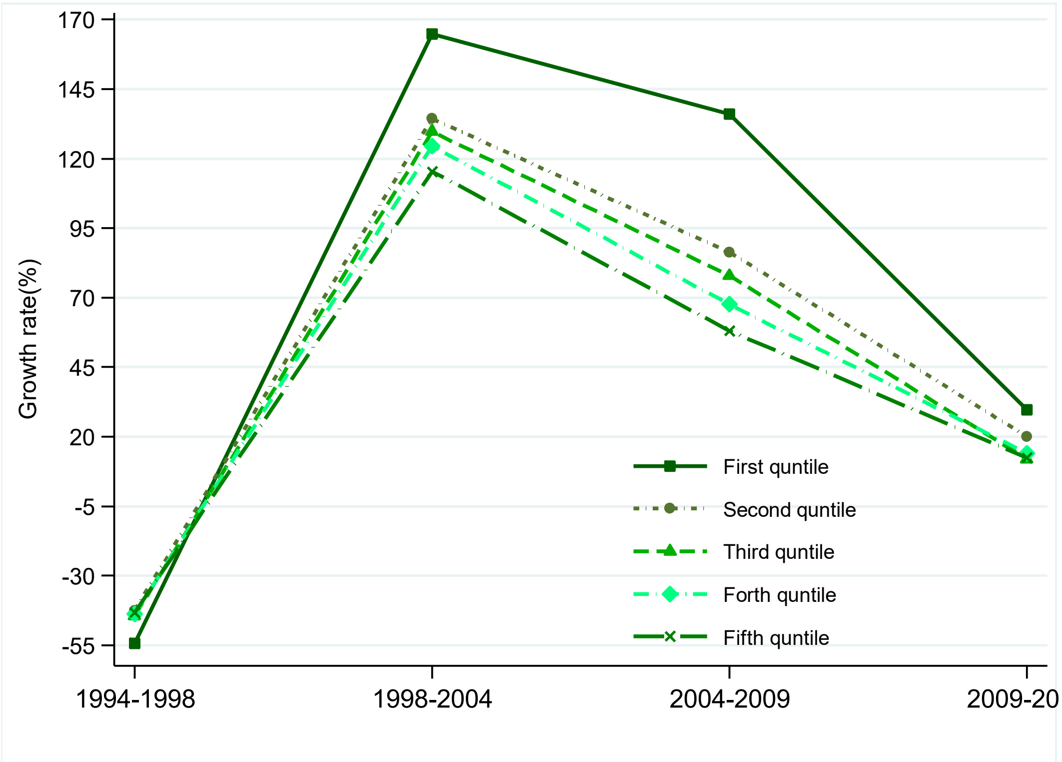
Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights. We use the repeated cross sections for each year. The combined Gini index includes top income inequality, non-top incomes inequality and inequality between these two population groups. Inequality measures are calculated for positive incomes, non-top income and between groups inequality are calculated with trimmed income data.

Figure 1.9. Income per capita and Gini index for per capita incomes in HBS and RLMS, 1994-2015



Note: Estimation results are obtained based on total household income per capita. We use the repeated cross sections for each year. Raw HBS microdata are available since 2003 (http://obdx.gks.ru/). HBS information on total monetary household income per capita collected in 4th quarter is used, RLMS refers to the 4th quarter of the same year. Corrected weights are calculated by Rosstat to adjust survey incomes to macroeconomic data. RLMS and HBS are deflated with December to December regional CPIs. RLMS incomes are weighted with population weights.

Figure 1.10. Short-Term Income Growth Rate for Immobile Individuals, Russia 1994-2015



Note: Estimation results are obtained based on total household income per capita. The distribution by 5 quantiles is based on the cross-sectional sample for each year, then the quintile thresholds are assigned to panel sample. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period is used as the base year.