2019

IARIW-HSE

Special IARIW-HSE Conference "Experiences and Future Challenges in Measuring Income and Wealth in CIS Countries and Eastern Europe" Moscow, Russia, September 17-18, 2019

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

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Paper Prepared for the IARIW-HSE Conference
Moscow, Russia, September 17-18, 2019
Session 1: Income Inequality
Time: 9:30 – 11:00, September 17

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

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(*forthcoming, European Journal of Development Research*)

Abstract

Russia offers the unique example of a centrally planned economy swiftly transforming itself into a market-oriented economy. We offer 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. We find 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. We also find 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 income growth. However, a transition from the private sector to the public sector is negatively associated with income growth.

JEL: C15, D31, I31, O10, O57

Key words: welfare dynamics, poverty, inequality, pro-poor growth, panel data, household surveys, Russia

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I. Introduction

As living standards are rising for most countries around the world, the focus of poverty research shifts toward understanding the distribution of economic gains over time. 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 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.

Russia 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 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). The Russian economy remarkably turned around and could regain its pre-crisis income level (solid line) just a couple years later. Russia has managed to sustain a steady annual GDP per capita growth rate of 2.4 percent since 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. But did inequality increase after Russia changed into the market economy model? 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]

In this paper we 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. For a transitional country 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 time windows of varying lengths. 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 could 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. In the case of Russia, 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]

In our analysis, we explicitly discuss three major aspects of mobility. The first 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 explicit analytical formulae to examine these positional changes, which are simple but do not appear to have been presented elsewhere. Second, we decompose mobility 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 policies that ensure sustainable growth and more equality. The third aspect of mobility that we study is its linkage with inequality in the short and in the long terms. 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 focusing on individual employment characteristics. Almost all (i.e., 96 percent) Russians used to work for the public sector before the transformation in the 1990s (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.

We find rising income levels and decreasing inequality for the country over the past two decades. The decreasing inequality was mostly caused by stronger income growth for the poor (i.e., pro-poor growth), rather than their income mobility. For the period from 1994 to2015, the poorest tercile of the income distribution experienced a growth rate that is more than ten times that of the richest tercile. The income growth between 2004 and 2015 was faster compared to that during the period 1994-2004. Furthermore, the levels of long-term inequality are lower than short-term inequality for all time periods under consideration. Our estimation results 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 associated with negative income growth; transitions to the formal sector, a full-time job, or a higher-skills job are statistically associated with higher income levels.

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

A study by Novokmet, Piketty, and Zucman (2018) combines different data sources to investigate the evolution of inequality of income in Russia. They find that for the period from 1994 to 2015, the Gini either slightly increased from 0.54 to 0.55 or decreased from 0.54 to 0.52 depending on the specific correction measures. Besides these findings, there are a couple other 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 the whole distribution Second, while we analyze total household income, Novokmet *et al.* derive their measure of welfare based on pre-tax national income.[7] More generally, another difference between the cited studies and ours is that these studies offer no detailed analysis for the different periods as we offer in this paper. We also employ a different analytical framework.

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. 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. While we discuss general mobility formulae for different income categories in this section, we restrict our analysis of mobility patterns to three income categories only in our empirical work given the relatively small sample size of the panel data.

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, and a higher number for k indicating a higher income threshold. 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} be 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.

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

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

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

The corresponding probabilities of unconditional and conditional downward mobility can be obtained by reversing the inequality signs in Equations (1) and (2) for individuals' income level in the second year. Aggregating over the k income categories gives us the measure of unconditional upward or downward mobility for the whole population (M^{ln}); further aggregating over the unconditional upward and downward mobility categories gives us the general measure of unconditional mobility for the whole population (M^n).

However, for the conditional mobility measures M^{lc}, a similar aggregation formula does not hold because of the different conditions (denominators) in Equation (2). But if we focus on the income category k in year 1, the measure of conditional upward mobility for the whole population is as follows

$$M^{uc} = \textstyle\sum_{j=k+1}^{K} P\big(y_2 \geq z_j | z_k \leq y_1 \leq z_{K-1}\big) \tag{3}$$

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.[8]

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

$$G_k = \frac{y_{2k} - y_{1k}}{y_{1k}} \qquad (4)$$

To obtain the population's relative mobility measure *G*, we aggregate the quantities in the above equations over all *k* income levels, using 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. In the Russian context of fast (and positive) economic growth 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.[9]

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

$$M^F = \frac{1}{N}\sum_{i=1}^{N}(y_{2i} - y_{1i}) + \frac{2}{N}\sum_{i \in K}(y_{1i} - y_{2i}) \qquad (5)$$

The first component on the right-hand side of Equation (5) 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

$$M^s = 1 - \frac{F(\bar{y})}{\sum_{t=1}^{K} F(y_t)/K} \tag{6}$$

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. 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 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. 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.[10]

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 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

$$y_{it}^* = \beta_l' \Delta O_{it} + \gamma_l' X_{it-1} + \eta_i + \varepsilon_{it} \tag{7}$$

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 category *j* is defined as

$$P(y_{it} = j|\Delta O_{it}, X_{it-1}) = \Lambda\big(\mu_j - \beta_l' \Delta O_{it} - \gamma_l' X_{it-1} - \eta_i\big) - \Lambda(\mu_{j-1} - \beta_l' \Delta O_{it} - \gamma_l' X_{it-1} - \eta_i) \tag{8}$$

where $\Lambda(.)$ is the cdf of the logistic distribution.[11] 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. 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.

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 the transitions from the public sector to the private sector, from formal to informal work, from full-time to part-time work, and having an increase versus having no increase in work skills. A more detailed definition of these transitions is provided in Dang et al. (2018). To keep a reasonable estimation sample, we 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). The last transition is used 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

$$y_{it} = \delta_l' \Delta O_{it} + \theta_l' X_{it-1} + \pi_i + \tau_{it} \quad (9)$$

where y_{it} is defined as individual i's income in logarithm at survey year *t*. The coefficient δ_l can 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. Although post-stratification adjustments have been implemented to make the RLMS survey samples representative of the Russian population census (Kozyreva et al., 2016), we still 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 shorter panels and longer panels have different sample sizes due to attrition, 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, which is based on a survey question asking about the total income that a household received during the past 30 days. By definition, it includes other types of incomes such as capital income and labor income. Yet, the share of capital of income in the total incomes is very small, accounting for less than 3 percent in all years. On the other hand, labor income has the biggest share and can comprise more than 60 percent for some years. We also examine several other definitions of income, as well as consumption, for robustness checks.[12] To reduce effects of 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. We deflate all the income variables with the annual regional consumer price deflators indexed to 100 in December 2011. We also spatially deflate the income variables, but for robustness check purposes only.[13]

IV. Estimation Results

We start 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 and medium terms, 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

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).[14] We plot in Figure 1.2 (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. 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.

To 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 (dotted line) started out higher than the former (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 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)). Similar to the national trends, inequality in urban and rural areas appears to converge over time (Dang et al. (2018)).

We also investigate whether household composition or age effects could have played a role in the change in inequality over time; estimates respectively shown in Table 1.2 and Figure 1.3 suggest they did not. We further illustrate this point in Section IV.4 with the multiple regression analysis. Finally, we check if these results can change if we estimate the Gini index using a different data source. Figure 1.4 (Appendix 1) shows that estimates that are based on the World Income Inequality Database (WIID) offers a qualitatively similar downward-sloping trend. Estimates using the Russia Household Budget Survey (HBS)—are also similar, although the adjusted data from this same source indicates a weaker trend.[15]

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 2009-15. This figure suggests that 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. Another plot for the immobile income groups (shown in Dang et al, 2018) suggests household income grew in all the four periods, and income growth was 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 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 is at slightly less than 50 percent. For comparison, these values of M^c are smaller than the corresponding figures of almost 80 percent for the US during the two periods 1979-1988 and 1989-1998 (which uses a decile transition matrix (Jantti and Jenkins, 2015)).[16] 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}).

Estimates of the medium-term income growth are provided in Table 2 which shows the full three-by-three (3x3) transition matrix for the two periods. The growth rates for those who 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 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).

For comparison, the fastest income growth rate for all income groups for the US in the period 1989-1998 is recorded by the poorest income decile, which is less than 60 percent (Hungerford, 2011).

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 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 than that of the ever-rich (i.e., comparing 317 percent and 125 percent). 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 (see Dang et al., 2018). The non-anonymous curve mostly lies above the anonymous curve up to approximately the 60th percentile of the income distribution, which provides further evidence for the earlier findings that income growth was pro-poor.

Table 5 shows 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.[17] 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. 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. 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 qualitatively similar and suggest a couple of emerging patterns that are consistent with our earlier findings for the other mobility indexes.[18] First, both short-term and long-term inequality has been steadily decreasing over time for Russia, over the four shorter periods. For example, M^s based on 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. For comparison, this is larger than the corresponding M^s of less than 0.1 for the US over the past 50 years (Kopczuk et al., 2010).

The corresponding decrease in 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 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. 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 periods. Individual's transition to a full-time job is strongly and positively 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 4.

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 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 5 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 in 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 individual income in the 1994-98, 1998-2004 and 2004-09 periods; this correlation, however, appeared to weaken over time, decreasing to 5 percent in the 2009-15 period (Panel A, first row). For the medium and longer terms, this same labor transition has a rather stable association with an 8-percent increase in 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

We show the estimation results for a number of robustness checks and further analysis in the working paper version (Dang et al., 2018). Below we only offer a short summary of some key results.

Other Definitions for Income and Top Incomes

As discussed earlier (Section IV.1), we further plot Figure 1 using other definitions of income such as household labor income per adult, household pension per capita, and individuals' labor earnings. These income definitions show similar V-shaped trends over time (Figure 1.2, Appendix 1). We also plot this figure with household consumption per capita, using both the cross sections and the balanced panel, and obtain similar trends (results not shown). When we re-estimate the mobility regressions using individuals' labor earnings, we obtain similar results although the magnitudes of the estimated coefficients are slightly larger.[19]

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. Yet, researchers differ on what percentage of the top incomes the RLMS can capture, as well as the methods 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 details). 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. 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 1.5 (Appendix 1), which shows larger values for the adjusted Gini coefficients, but a reassuringly similar downward trend over time.

Attrition Bias

Our estimation results are 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). 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 stronger upward mobility both in the medium term and the long term (see Appendix 1, Table 1.3).[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 find similar results. 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. Second, we examine whether adjusting for household equivalence scale may affect our estimates by employing 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).[21] 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. Fourth, instead of dividing the income distributions into three terciles, we use an alternative method that defines the income thresholds based on the poverty line and the vulnerability line recently proposed by Dang and Lanjouw (2017). Another related robustness check, when we divide the income distributions into five quintiles (for the short-term periods only, where the sample sizes are larger) indicates similar pro-poor income growth patterns. Fifth, as an alternative to the Shorrocks mobility index, we apply the Fields (2010) mobility index but this index also suggests 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 (i.e., the four short-term periods are 1994-98, 2000-04, 2005-09, and 2010-15) and again obtain similar estimation results.

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 than their relative upward movement along the income distribution (i.e., upward mobility). In particular, for the period 1994-2015, 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.

Conflict of Interest Statement: On behalf of the author, the corresponding author states that there is no conflict of interest.

Notes

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[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.

[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.

[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 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.

[7] Novokmet *et al.* (2018) acknowledge that tax information is not perfect in the Russian setting, given that the share of adult submitted tax declaration between 2008-2015 account for at most 6 percent of the total adult population. They also exclude private and public transfers that are estimated to make up as much as 9 percent of household incomes during the period 1994-2000 (Kuhn and Stillman, 2004), and around 5 percent (such as social benefits) 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 (2016) estimate of 96 percent. Furthermore, the data that Novokmet et al. (2018) use for correcting incomes come from the Household Budget Survey (HBS), which are criticized for collecting incomes in the formal sector only and which are expected to be improved with the RLMS' survey design (Kozyreva et al., 2016). We return to more discussion in the robustness check section.

We also offer in Table 1.1, Appendix 1 a brief overview of some key studies on income (consumption) inequality in Russia starting from the 1990s, whose results are broadly consistent with ours for the overlapping years. For other studies on welfare dynamics for Russia in the 1990s, see, for example, Lokshin and Popkin (1999), Jovanovic (2001), and Lokshin and Ravallion (2004).

[8] Dang et al. (2018) offer more detailed discussion of these mobility measures.

[9] 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.

[10] See also Jantti and Jenkins (2015) for a recent review of income mobility concepts.

[11] See, for example, Long (1997) and Greene (2018) for further discussion with the ordered logit model.

[12] 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 indicate similar patterns.

[13] We did not include the value of imputed housing rent in household income for different reasons. The RLMS data enables us to look at household expenditure on rent. However, relatively few households have to pay market-based rents on their homes, the share of such tenants in was less than 10% between 1994-2015. A significant share of the households rent from the government and pay "social rent" instead, which is controlled and below the private market price (Hamilton et al, 2008). Furthermore, the RLMS does not ask home owners to estimate the rental value of their house. But some evidence suggests that inequality would be even lower when imputed value of housing is added to household income (Buckley and Gurenko, 1997).

[14] We also plot Figure 1 for total household income instead, and the resultant trends (Figure 1.1 in Appendix 1) are qualitatively similar. 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.

[15] 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.

[16] The full three-by-three transition matrixes for medium-term mobility are provided in Dang et al. (2018).

[17] 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.

[18] 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, which provide qualitatively similar results.

[19] We also provide a more detailed review of other definitions of income and consumption variables employed in earlier studies in the working paper version (Dang et al., 2018).

[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] 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).

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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
	Poorest tercile	317.2	543.8	965.8	503.1
1994	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	

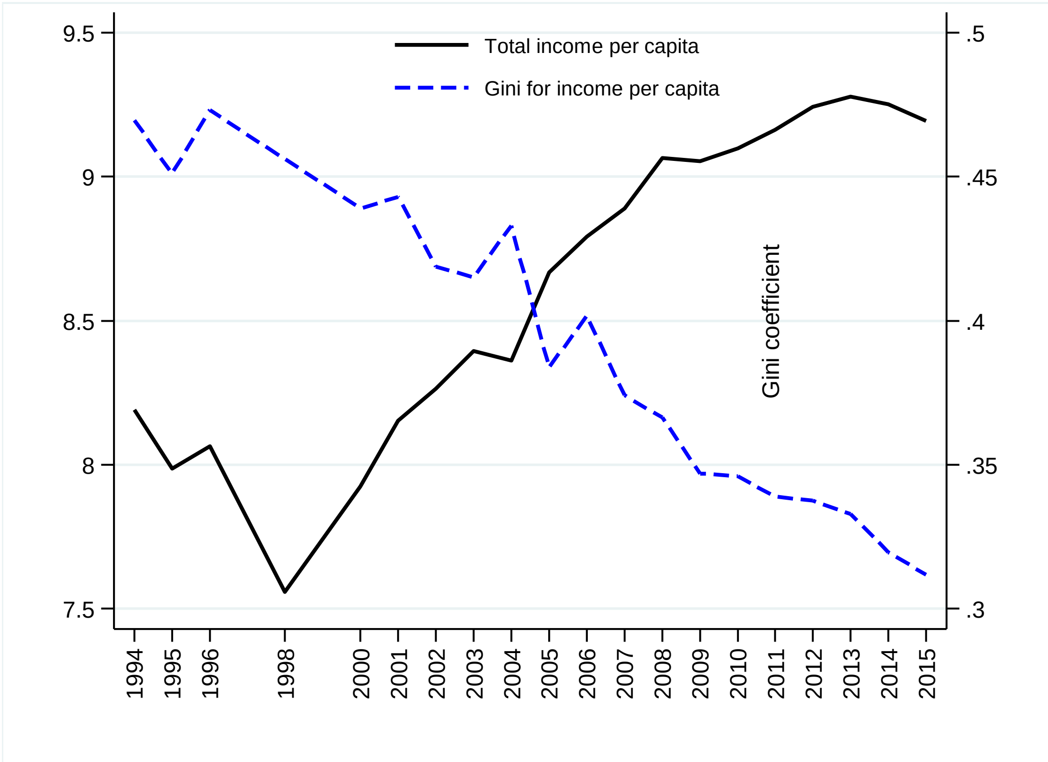
Note: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses. The estimation sample is restricted to individuals who are 18 years old and older. Regional and time dummies are included but not showed. The dependent variable is income mobility between year *t-1* and year *t*. The terciles 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)		

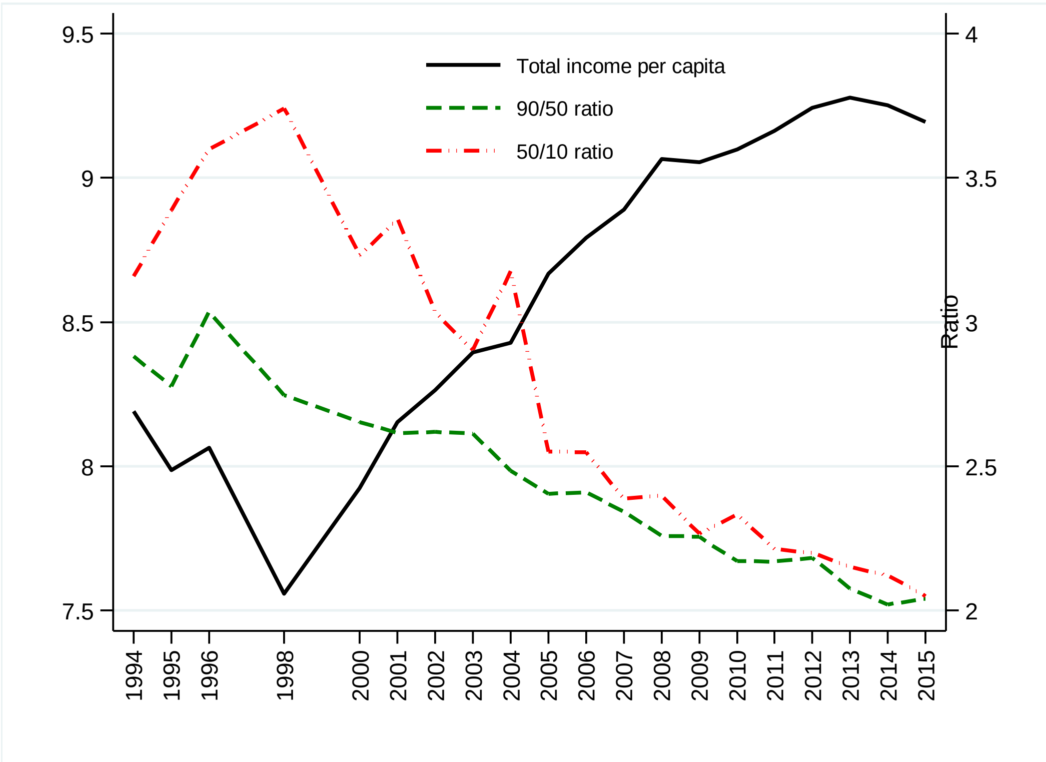
Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Robust standard errors in parentheses. The estimation sample is restricted to individuals who are 18 years old and older. The dependent variable is log of household income per capita in year *t*. Incomes are deflated with December to December regional CPIs and 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



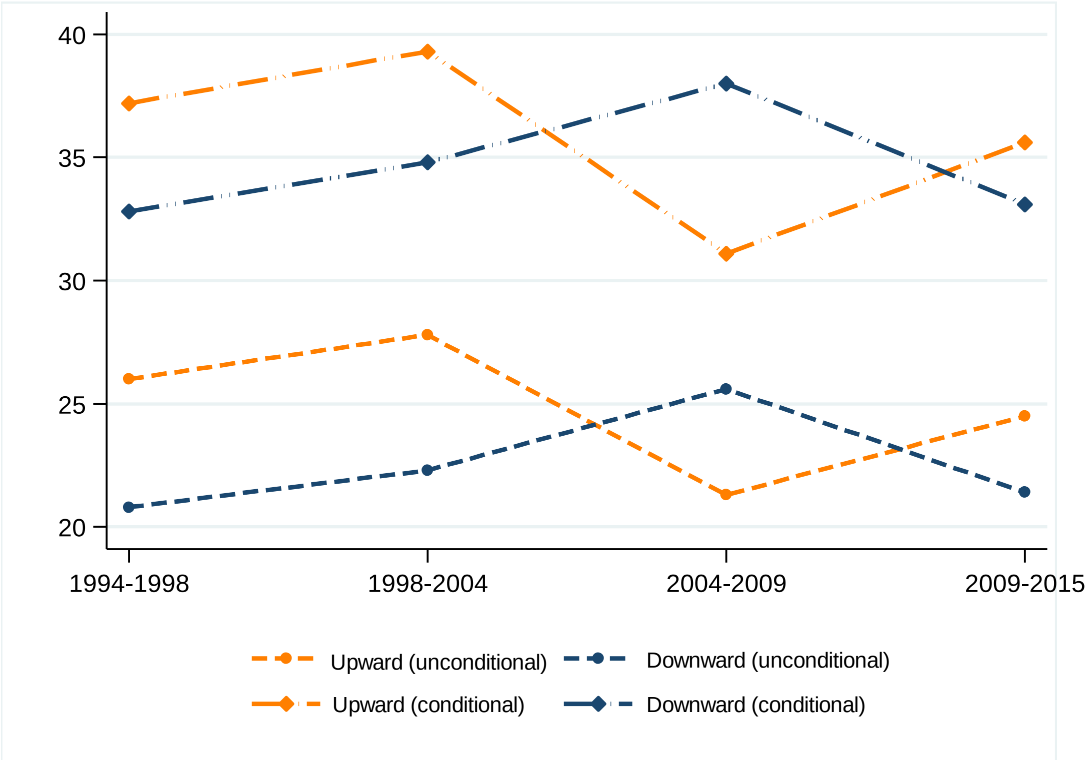
Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights. The repeated cross sections are used for each year.

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



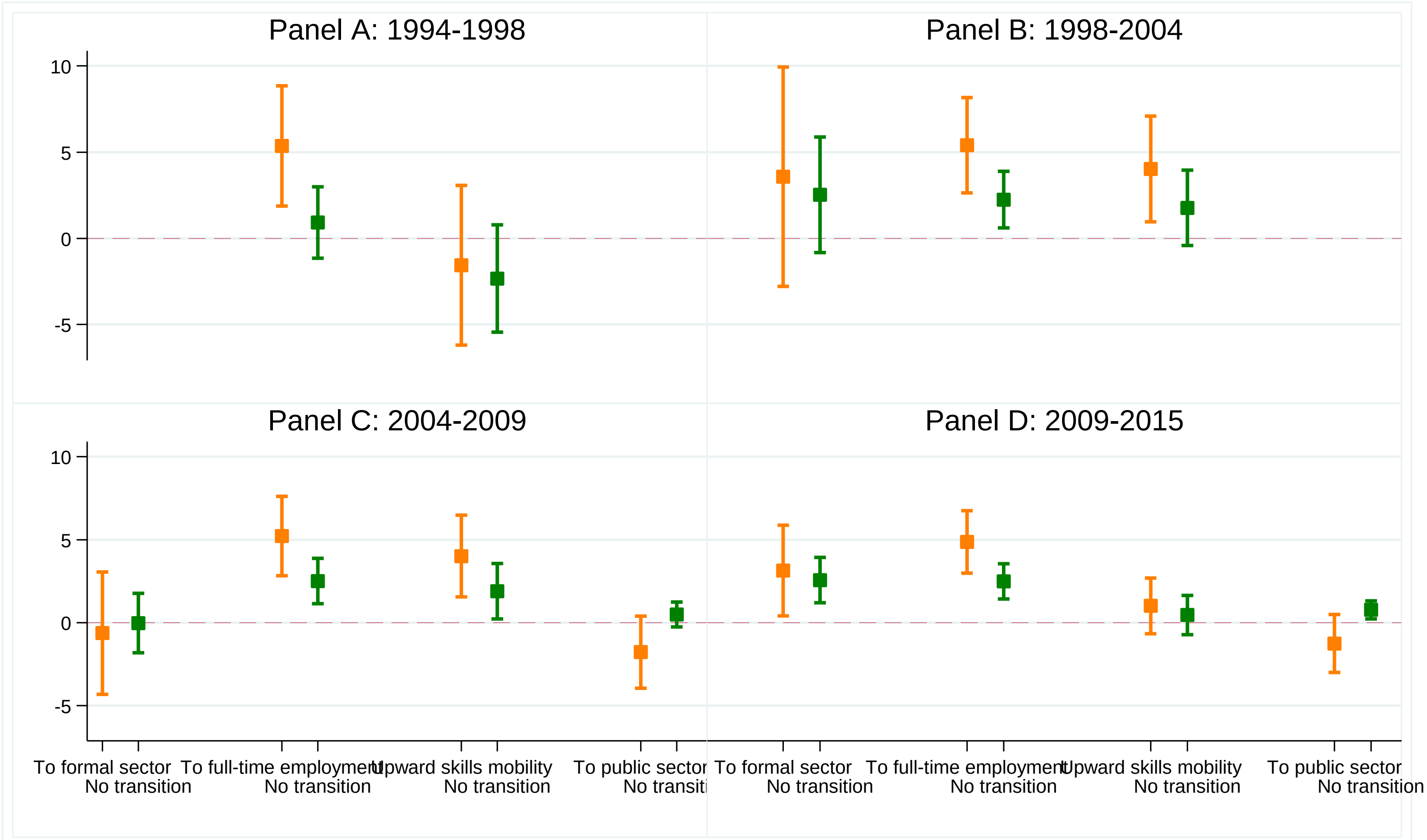
Note: Estimation results are obtained based on total household income per capita. All numbers are deflated with December to December regional CPIs and weighted with population weights. The repeated cross sections are used for each year. We remove 170 individuals in 2004 that have extremely low monthly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

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



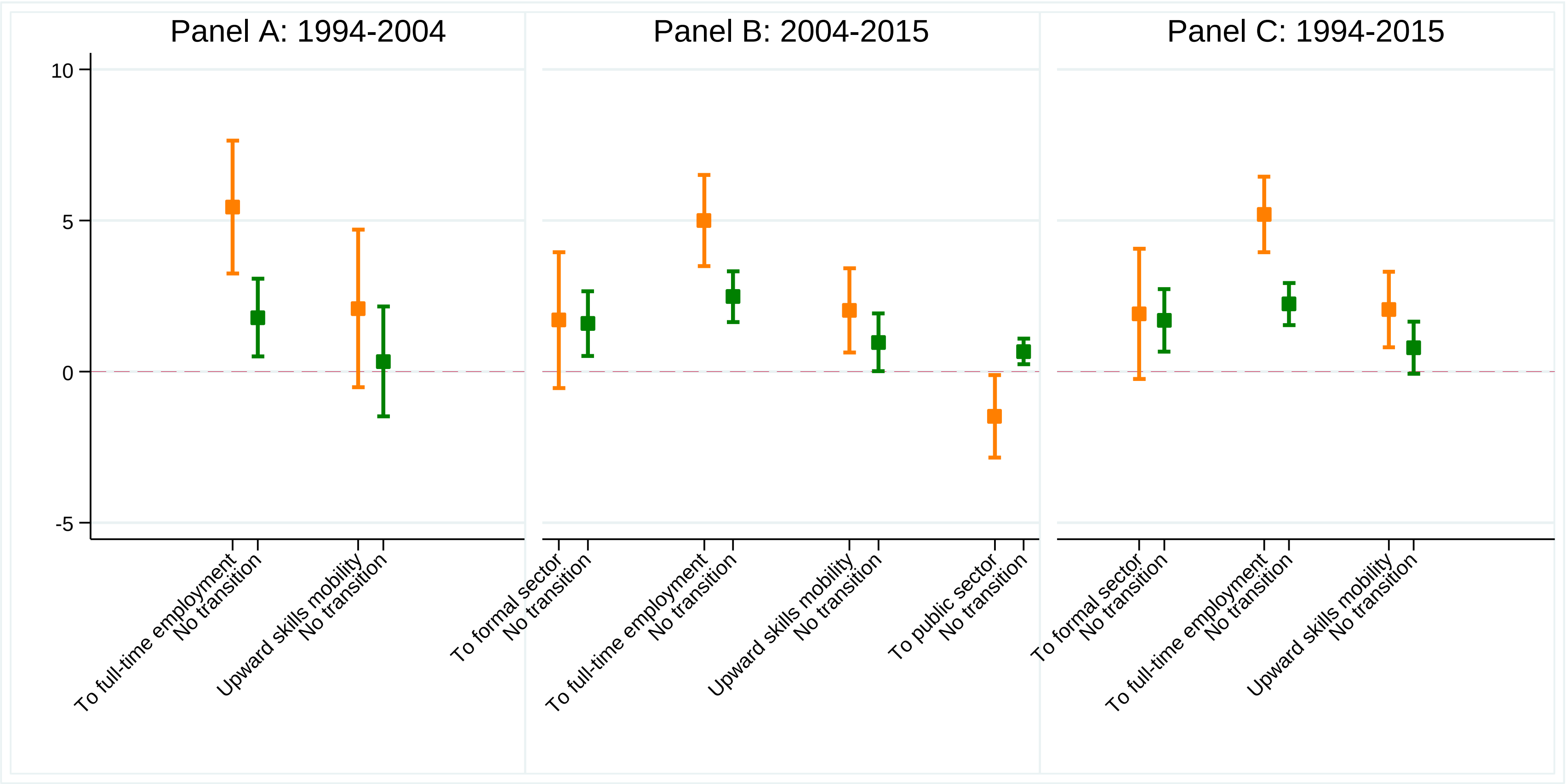
Note: Estimation results are obtained based on total household income per capita. The terciles are defined using the cross-sectional sample for each year. All numbers are deflated with December to December regional CPIs and weighted with population weights, where the first survey round in each period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

Figure 4. Short-Term 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 5. 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. Overview of Some Key Studies on Income (Consumption) Inequality in Russia Starting from the 1990s

№	Authors	Data	Welfare indicator	Main findings
1	Milanovic (1998)	RLMS 1993-1995	Per capita disposable income and consumption expenditure	Gini for income - 0.48, Gini for consumption - 0.5
2	Commander et al. (1999)	RLMS 1992-1996	Per capita and household incomes deflated using regional CPIs	Gini for per capita income rose from 0.43 to 0.48, Gini for household income - from 0.48 to 0.51
3	Flemming and Micklewright (2000)	RLMS 1992-1996	Per capita household income deflated using regional CPIs	Gini rose from 0.43 to 0.48
4	Gorodnichenko et al. (2010)	RLMS 1994-2005	Individual labor earnings deflated using regional CPIs and regional value of fixed basket of goods and services	Gini declined from 0.48 to 0.41
5	Lukiyanova and Oshchepkov (2011)	RLMS 2000-2005	Per adult household income based on individual and household incomes and deflated using regional CPIs	Gini declined from 0.41 to 0.37 (based on individual incomes), and from 0.39 to 0.37 (based on household incomes)
6	Denisova (2012)	RLMS 1994-2009	Per adult disposable income/consumption expenditure deflated by regional subsistence level	Gini for income declined from 0.46 to 0.35, Gini for consumption – from 0.48 to 0.42
7	Checchi et al. (2018)	LIS 2000-2013	Per adult disposable income/consumption expenditure	Gini for income dropped from 0.41 to 0.33, Gini for consumption remained at 0.4 in 2004-2013
8	Novokmet et al. (2018)	Rosstat, RLMS (in 1994-2015 only), unofficial sources, 1980-2015	Pretax national income, fiscal income, self-reported survey incomes	<u>1980-1993</u>: Gini for national and fiscal incomes rose from 0.28 to 0.46, Gini for HBS income – from 0.27 to 0.39 <u>1994-2015</u>: Gini for national income increased from 0.54 to 0.55, Gini for fiscal income decreased from 0.54 to 0.52, Gini for HBS income – from 0.41 to 0.45, Gini for RLMS income decreased from 0.53 to 0.4

Table 1.2. Actual and Re-Weighted Changes of Inequality, RLMS 1994-2015

Period	**Change in Gini coefficient**		**Share of the changing household structure in the total change of Gini**
	Actual	**Counterfactual**	
1994-2004	-3.7	-3.1	15.4
	(0.60)	*(0.62)*	*(5.49)*
2004-2015	-12.1	-12.2	-0.8
	(0.48)	*(0.48)*	*(0.30)*
1994-2015	-15.8	-15.3	3.4
	(0.50)	*(0.54)*	*(0.63)*

Note: Estimated are obtained using the Peichl, Pestel, and Schneider's (2012) decomposition method. Bootstrapped standard errors in parentheses (500 replications). Results are based on total household income per capita and are displayed as percentages, i.e. they were multiplied by 100. For all periods, the actual growth rates of the Gini coefficient are not statistically different from those based on the counterfactual re-weighted data, which indicate that inequality would have decreased as much as they did regardless of the changes in household composition. Only 3% of the decrease in income inequality can be explained by changes in household size in 1994-2015.

Table 1.3. 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.

Figure 1.1. Trends of Total Household Income and Gini Coefficients, RLMS 1994-2015

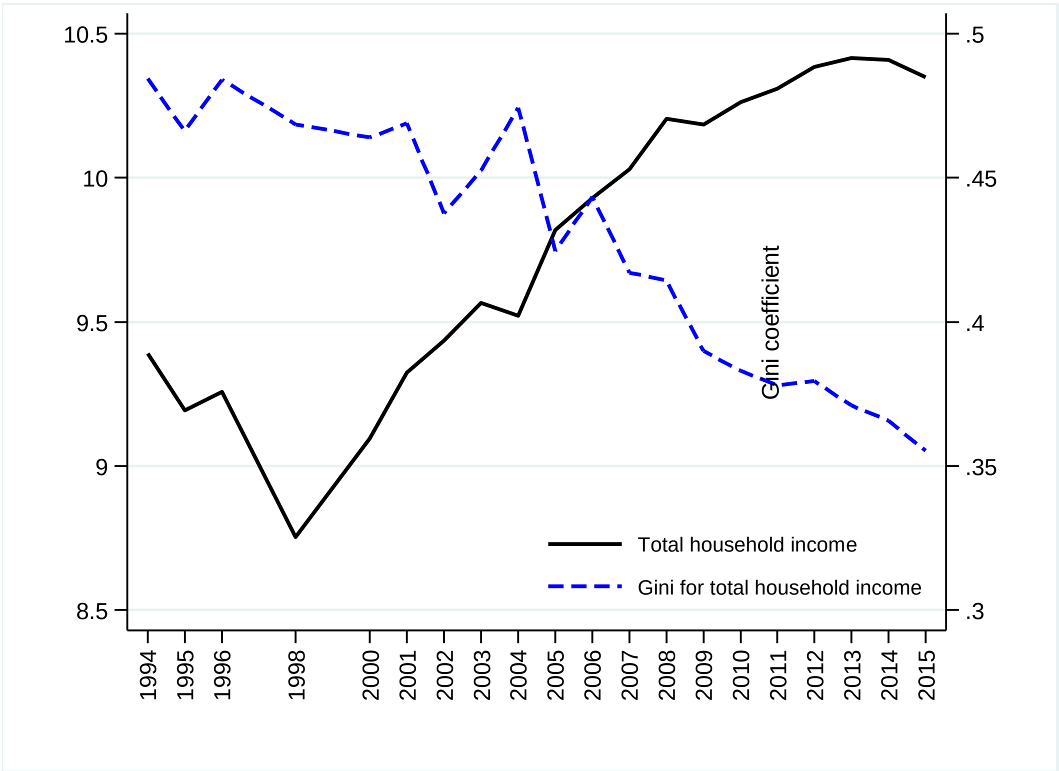
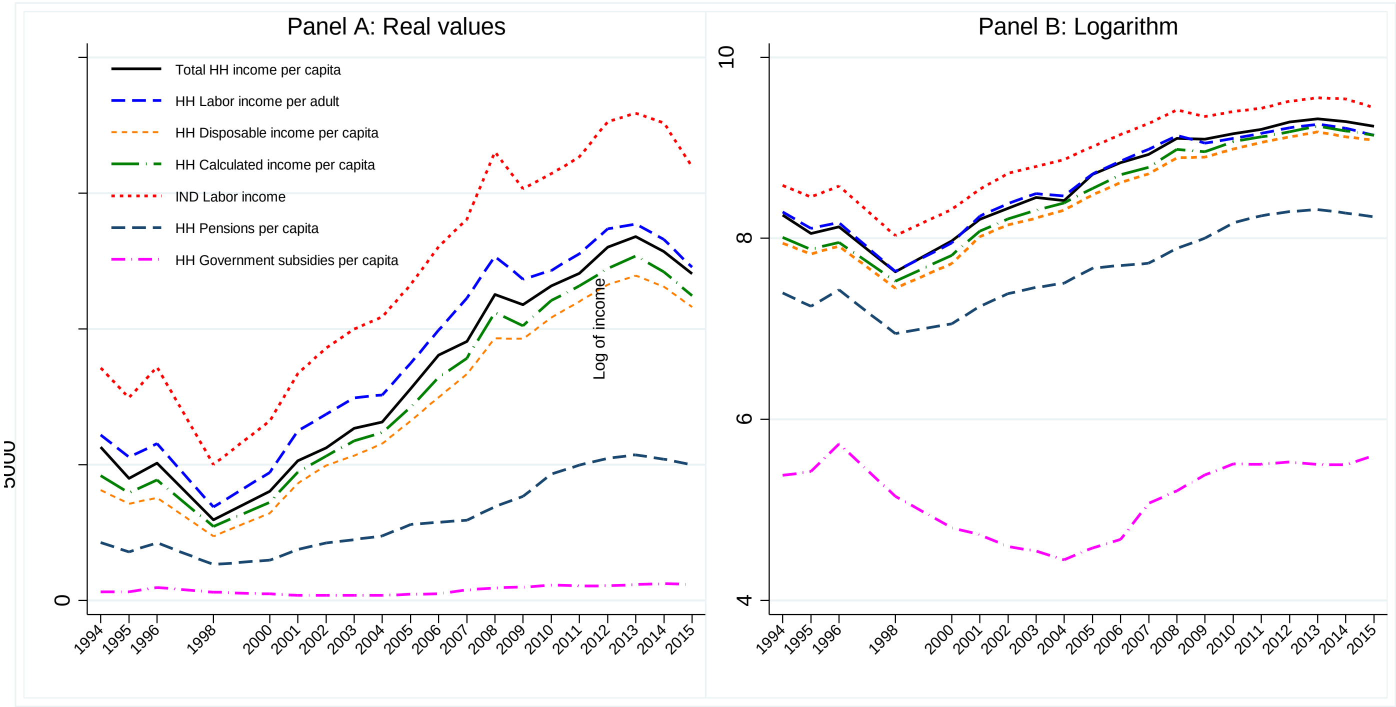
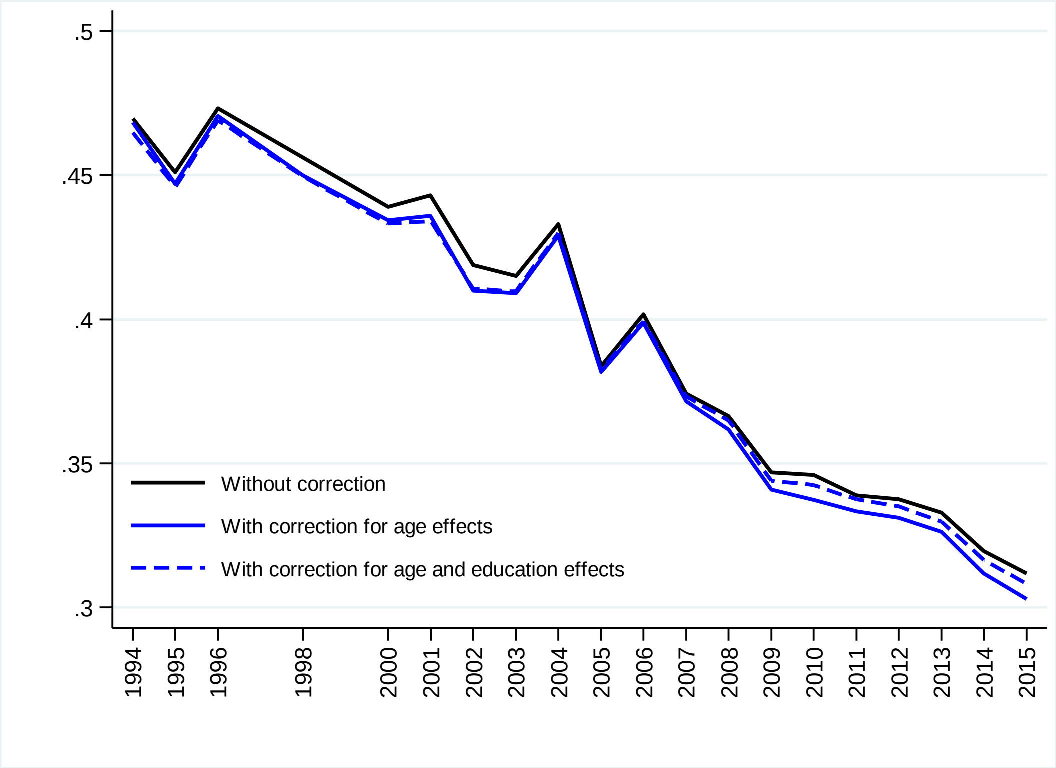


Figure 1.2. Trends of Different Definitions of Household Income, RLMS 1994-2015



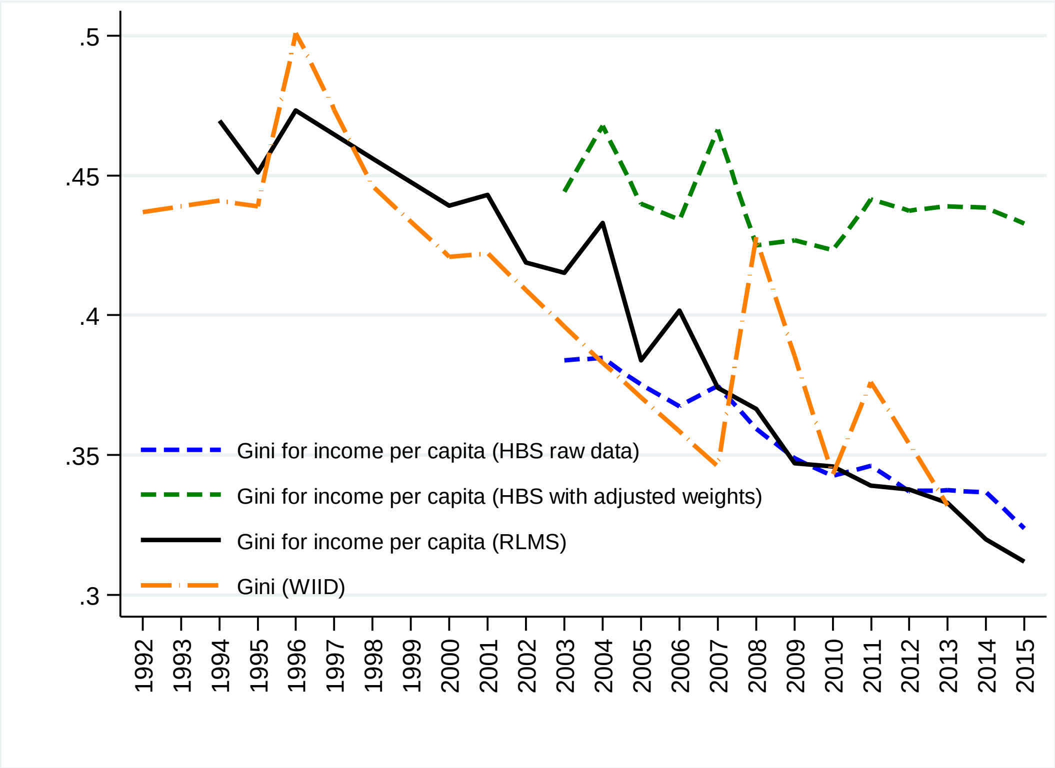
Note: We use the repeated cross sections for each year. The estimation sample is restricted to individuals who are 18 years old and older. Household labor income per adult is calculated using average household labor earnings per month. Disposable household income includes average household labor earnings, 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 1.3. The Impact of Age Adjustment on Income Inequality, RLMS 1994-2015



Note: The RLMS's nationally representative cross-sectional sample is used for each year. Estimates are obtained using Almas and Mogstad (2012) regression-based decomposition. Figure 1.3 compares the original Gini coefficients with those adjusted by age, either with or without control for education effects.

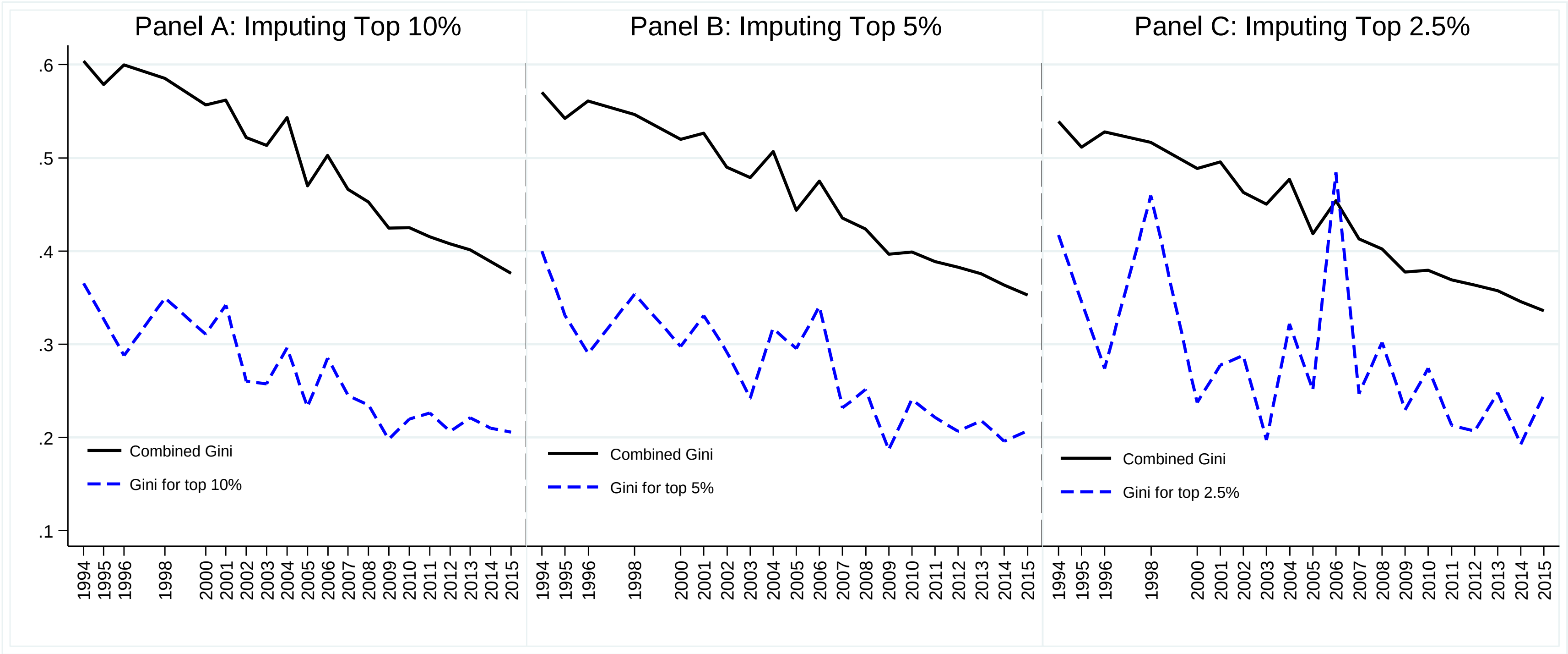
Figure 1.4. Trends of Gini Index Using HBS, RLMS and WIID Data, 1992-2015



Note: HBS results refer to total monetary household income per capita collected in 4th quarter. Adjusted weights are calculated by Rosstat to make the survey data consistent with national accounts data. RLMS results refer to total household income per capita and are weighted with population weights. RLMS and HBS are deflated with December to December regional CPIs. WIID results refer to net/gross household income per capita in 1993-1998, 2000-2001, 2004, 2007, 2010 and 2013, to household equivalized income in 1992, 2008, 2011 and refer to consumption in 1999, 2005, 2006 and 2009, 2012.

Data source: The Household Budget Survey (HBS) is conducted by Rosstat, and the raw HBS microdata are available since 2003 (http://obdx.gks.ru/). Russia Longitudinal Monitoring Survey microdata are available since 1994 annually, except 1997 and 1999 (https://dataverse.unc.edu/). World Income Inequality Database (WIID) is available from 1992 to 2013 (https://www.wider.unu.edu/project/wiid-world-income-inequality-database).

Figure 1.5. 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.