Contents

Cristiano Perugini

Patterns and drivers of household income dynamics in Russia: The role of access to credit

Abstract

The microeconomic drivers of medium- and short-term income mobility in Russia over the period 1996–2016 are investigated using data from the Russian Longitudinal Monitoring Survey (RLMS). Focusing on the role of access to credit in triggering household income growth, the descriptive analysis suggests that high levels of mobility materialising in pro-poor patterns of growth may accompany Russia's notoriously high levels of inequality. Controlling for other personal and household characteristics, the econometric model for drivers of income mobility indicates that access to credit boosts income mobility. Complementary empirical evidence suggests that this effect may unfold through channels related to the labour market and non-labour sources of income.

Keywords: income mobility, credit access, Russia, RLMS
JEL classifications: D31, H81, J60, O15

Cristiano Perugini, orcid.org/0000-0003-4418-7340. Department of Economics, University of Perugia.
Email: cristiano.perugini@unipg.it

Acknowledgements
I thank the Bank of Finland Institute for Economies in Transition (BOFIT) for financial support under its Visiting Researchers Programme for spring 2018. Comments and suggestions by Zuzana Fungáčová, Mikko Mäkinen, Risto Herrala, Laura Solanko and the seminar participants at BOFIT are gratefully acknowledged.

1 Introduction

The aggregate growth performance of an economic system is the outcome of individual patterns. In a study of factors that exacerbate or diminish social inequality, information about these patterns can shed light on their distributional effects. In particular, turbulent economies undergoing large-scale institutional transformations are valuable in that they produce acute effects that must be addressed immediately by policymakers, as well as long-run effects that shape social and economic structures. We focus here on Russia, a country that not only experienced massive institutional change over the past three decades, but also joined the club of high income inequality countries (Mitra and Yemtsov, 2006).

The following discussion considers income mobility patterns and drivers of Russian households over various time horizons. Generally speaking, income mobility is the process of individuals changing their absolute or relative positions along the income ladder. But what shapes changes in the distribution of incomes and which factors drive the up and down movements of individuals positioned in different parts of the distribution? Russia has undergone a massive institutional and structural transformation that has greatly affected distributive patterns. In order to understand the personal and economic features favoured in Russia for a transition to higher income levels or otherwise important in preventing a slide into lower positions or poverty, we analyse data from the Russian Longitudinal Monitoring Survey (RLMS) from 1996 to 2016.

With very few exceptions, the existing literature (reviewed in section 2) focuses on periods shorter that our observation period, often emphasising the first stages of Russia's transition. Our analysis, in contrast, spans all phases of Russia's transformation to a market economy, including the years following the global financial crisis. It also allows us to shed light on the microeconomic aspects that contributed to the spectacular changes in income inequality that occurred during the first two decades of this turbulent transformation.

The novel contribution of this paper, however, is our investigation of the role of access to credit in triggering income mobility. The efficient functioning of credit markets is continuously invoked as crucial for achieving higher growth (e.g. Arestis and Demetriades, 1997; Levine, 2005). It has received much attention as a driver of distributive patterns (e.g. Galor and Zeira, 1993; Greenwood and Jovanovic, 1990; Li et al., 1998). Although the channels through which access to credit is believed to affect distributional patterns are microeconomic and unfold over time, no studies exist that explicitly consider the role of access to credit in shaping individual income mobility. Here, we explore the possibility that access to credit impacts income mobility by (i) affecting labour supply at the intensive and extensive margin; (ii) favouring better job/worker matching; and (iii) allowing households to invest in physical and financial assets that generate capital income flows.

The remainder of the paper is structured as follows. In the next section, we provide a summary of the existing studies and knowledge on income mobility in transition countries and Russia in particular. We then discuss the possible channels through which access to credit can impact income mobility, and derive a working hypothesis that we test in the subsequent empirical analysis. In section 3, we describe the dataset and the samples used in the analysis. Section 4 provides aggregate measures of income mobility for Russia over the period considered. Section 5 is devoted to illustration of the econometric methods and empirical model. In section 6, we present the results of the analysis on the drivers of income mobility and the role of credit (section 6.1), as well as explore the possible channels through which access to credit affects mobility patterns (section 6.2). Section 7 concludes.

2 Related literature and working hypotheses

It is widely acknowledged that income mobility is a multifaceted concept (Fields, 2008). Intragenerational income mobility, which is the focus of this paper, has been extensively explored both in terms of methodological/measurement issues and in empirical terms. Examples of comprehensive surveys include Atkinson et al. (1992), Maasoumi (1998), Fields and Ok (1999a), Burkhauser and Couch (2009), Jenkins and Van Kerm (2009), Jenkins (2011) and Jäntti and Jenkins (2015). Generally speaking, the literature on the microeconomic determinants of income mobility has primarily emphasised the role of demographic factors such as age and gender of individuals, as well as the size and demographic structure of the households (e.g. Shi et al., 2010). Attention has also been paid to physical and human capital endowments, labour market conditions and positions, and initial income levels (e.g. Woolard and Klasen, 2005; Castro, 2011; Marotta and Yemstov, 2011).

More recently, institutional aspects started receiving explicit consideration, especially with respect to labour market institutional settings (e.g. Ayala and Sastre, 2008; Sologon and O'Donoghue, 2011).

Despite the abundance of empirical studies for many countries and regions of the world, evidence on levels and drivers of income mobility in post-communist countries is quite limited. Only since the early 2010s a few empirical studies started to enlarge the geographical scope of European studies to the formerly centrally planned Central and Eastern European countries (GHK, 2010; Van Kerm and Pi Alperlin, 2013; Aristei and Perugini, 2015a and 2015b). Previous studies on Russia unanimously indicate higher levels of economic instability especially during the first stage of transition (Commander et al., 1999; Jovanovic, 2001). During 1994-1998, higher income growth was particularly associated with larger households, urban areas, higher levels of education and access to land, while weaker upward mobility was driven by the presence of children and elderly (Lokshin and Ravallion, 2004). For the same period, Bogomolova and Tapilina (1999) find that about 40% of households stayed in the same income quintile, while the remaining 60% split equally between those moving upwards and downwards. Lukyanova and Oshchepkov (2012) report higher and more strongly pro-poor income mobility in Russia compared to western EU countries in the period 2000–2005. Nissanov (2017), who focuses on the movements of households at the middle of the income distribution over the long run (1995–2007), find that households had a higher likelihood of staying in the same relative position compared to both rich and poor households. However, for those middle-class households moving away from their initial position, the probability of sliding into poorer groups was remarkably higher than that of climbing the income ladder. Lastly, Dang et al. (2018), using RLMS data from 1994 to 2015, show rising income levels and decreasing inequality, with the latter mostly caused by pro-poor growth rather than redistribution. They also provide evidence that income growth is favoured by switching from a part-time job to a full-time job, from a lower-skill job to a higher-skill job or by staying in the formal sector. In contrast, the transition from the private to the public sector is negatively associated with income growth.

It is somehow surprising that the relationship between access to credit and microeconomic income mobility has been almost completely disregarded. Many papers (e.g. the seminal works of Galor and Zeira, 1993) as well the extensive reviews of Sevena and Coskun (2016) and De Haan and Sturm, (2017), relate financial development to income inequality/poverty in different ways, evoking mechanisms that are inherently dynamic. Since the main channels of transmission such as access to credit allowing investments in higher education as in Galor and Moav (2004) take place over the long run or through growth patterns, the analysis is normally carried out at country level with analysis of the effects of credit market development on changes in income distribution over the long run (see e.g. Li et al., 1998; Jalilian and Kirkpatrick, 2002; Clarke et al., 2006). However, short-run impacts of credit on income mobility cannot be excluded. Based on the existing literature, we can identify at least three channels through which they might materialise.

The first channel relates access to credit to *changes in labour supply decisions by individuals or households*. Within the life cycle/permanent income literature, some contributions emphasise how labour supply can be used as an important smoothing device in the presence of liquidity constraints (Pijoan-Mas, 2006; Blundell et al., 2008). Within this framework, Rossi and Trucchi (2016) show that, since consumption can be enhanced (or smoothed) through borrowing, access to credit may decrease labour supply. Based on data for Italian young (26–35 years) male workers, they find that liquidity constraints lead to longer hours worked. This result is largely driven by the self-employed, probably due to their higher flexibility in adjusting labour supply. Bui and Ume

(2016) report a similar outcome, with credit market development increasing the intensity of labour supply but not affecting the extensive margin of participation. The effect of the liquidity constraint therefore seems limited to the intensive margin, particular age groups and individual (not household-level) labour supply decisions. However, the presence of labour market frictions and high unemployment may impose severe limitations on worker labour supply adjustments. The possible irreversibility of even temporary decisions is indeed likely to prevent rational agents to reduce their labour supply in response to having accessed credit. In contrast, as shown by extensive evidence, those households with loans/mortgages are more committed and thus more inclined to increase their participation in the labour market in view of debt repayment (Fortin, 1995; Bottazzi et al., 2007; Bottazzi, 2004; Del Boca and Lusardi, 2003; Belkar et al., 2007; Butrica and Karamcheva, 2014). This is especially the case when the institutional system and credit markets are so efficient that lenders can identify borrowers capable (or at least willing) to repay a debt and those who are not (Besley, 1995). This suggests that easier access to credit might be associated with an increase in labour supply (both at the extensive and intensive margin), and consequently to higher income mobility.

The second channel also relates to the labour market, but concerns the quality of *job/worker matching*. Bui and Ume (2016) explain how improved access to credit allows individuals to align their work effort with their productivity, i.e. they can afford to work less if their productivity and wages are low. This is not possible in the presence of liquidity constraints. Individuals need to supply more labour to fund consumption even if their productivity is low. This line of reasoning can be extended to education/skills and job matching. Access to credit can temporarily relax liquidity constraints and allow job-search efforts aimed at reducing mismatches (typically, over-education or over-qualification), normally associated to low productivity and low wages (Allen and Van der Velden, 2001; OECD, 2016; ILO, 2016). Access to credit might therefore trigger, even over the short-medium run, better matching and higher earnings and, this way, favour income mobility.

A third possible channel through which access to credit might impact on economic mobility is through other sources of household income, specifically *capital income*. It can consist of either dividends and interest/returns from trust funds or other financial assets or returns from property investments (income from rentals and leasing and potentially royalties). No evidence exists on how capital income shapes income mobility and only relatively few studies focus on how non-labour income sources influence distributive patterns (see e.g. Fräßdorf et al., 2011 and references cited therein). The existing evidence finds that non-labour incomes are relevant, especially at the top the distribution. They tend to be very volatile and important contributors to income inequality in recent decades (Atkinson, 2000; Gottschalk and Smeeding, 1997; Jenkins, 2000; Jäntti, 1997). When credit taken by households is not used up for their current needs (school fees, medical treatment, daily consumption or social expenses), which is probably the case for better off households (see Johnston and Murdoch, 2008), it can contribute to total income dynamics by generating returns from physical and financial investments. Again, this might be particularly the case when financial and credit markets are developed enough to allocate credit to agents able to employ their resources efficiently.

Based on this discussion and literature review, we formulate our working hypothesis that access to credit contributes to upward income mobility through various channels, the importance of which varies across the income distribution. Mechanisms related to labour income, in particular, may be more relevant for medium- and low-income households (for which labour is the predominant or exclusive income source), whereas the effects through non-labour income are likely to manifest at the top of the distribution. In the following, we test econometrically this working hypothesis and provide corroborative evidence on the underlying channels of transmission.

3 Data, samples and variables

The empirical analysis relies on the Russian Longitudinal Monitoring Survey (RLMS), a unique panel survey of Russian households based on the national probability sample. The database has been used extensively to analyse income mobility, income inequality and poverty dynamics in Russia (see e.g. Bogomolova and Tapilina, 1999; Jovanovic, 2001; Nissanov, 2017). The survey provides detailed information at individual and household levels, enabling *repeated cross-sectional analysis* and *longitudinal analysis*. The survey has been conducted annually since 1992 (with the exceptions of 1997 and 1999). Our analysis is restricted to the 1996–2016 period due to the change in the panel in 1994 and the high rate of attrition of the individual units sampled before 1996.

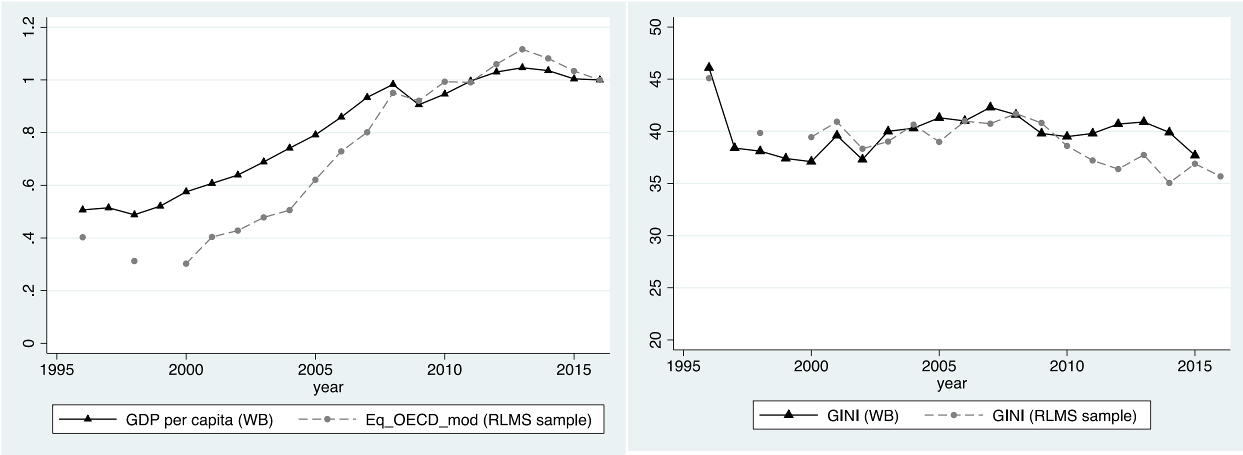
The analysis of income mobility relies on the panel component of the dataset. It is structured in two types of samples of different length: seven short-run (three-year) samples for the periods 1996–1998, 1998–2000, 2001–2003, 2003–2005, 2006–2008, 2010–2012, 2013–2015; and two medium-run (seven-year) samples for the periods 1996–2002 and 2010–2016. The time structure of the samples is intended to maximise the time coverage of the analysis while keeping the sample size reasonably large considering the attrition rate. The samples are restricted to the households that reported non-missing, non-zero and positive incomes in each year. The tails of the distributions were trimmed by dropping the 1% of the lower and top household incomes in each year. Trimming minimises the impact of extreme incomes, which can remarkably impact measures of mobility (Cowell and Schluter, 1999), and increases the consistency of our analysis across samples (Ayala and Sastre, 2008; Lukiyanova and Oshchepkov, 2012).

As non-response and attrition rates may display heterogeneous patterns and significantly vary across time, and following Lukiyanova and Oshchepkov (2012), we compare year-specific sample characteristics between the cross-section and the panel samples. Some important differences between the two samples emerge with reference to the household composition and their geographical distribution. We find good agreement, however, between the evolution of household incomes over the two periods over time, with panel samples reporting average income levels regularly 10/12% lower than in the cross-section samples. Therefore, attrition may not actually be a big problem. Further, since it is hard to estimate its potential consequences, we do not attempt to account for it.

Our income variable is *household equivalised income* (in 2010 rubles), based on self-reported total monetary income received by the household in the last 30 days (variable F14 of the RLMS), adjusted for differences in household size and composition using the modified OECD equivalence scale, which assigns a weight of 1 to the first adult in the household, 0.5 to each other member aged 14 or over, and 0.3 to children aged less than 14. This scale is widely used in the production of inequality statistics (e.g. Eurostat) and empirical analysis. Following Lukiyanova and Oshchepkov (2012), we consider alternative equivalence scales (OECD scale, Atkinson's scale) and find that the choice of the equivalence scale parameters does not significantly alter the descriptive analysis and the econometric analysis of the determinants of mobility (results available on request). The adoption of the household, rather than individual, perspective provides a richer informative set if we assume that the household is the pivotal dimension around which the decisions of the individual (e.g. parenthood, labour supply, education) are interdependently taken. In addition, we can incorporate in our analysis all income sources, the effects of demographic changes and the redistributive processes taking place within the household.

Table A1 in the Appendix reports some main characteristics of our year-by-year samples after trimming (the size of the samples used in the income mobility analysis is obviously different, depending on the number of observations observed in each specific initial and final year, see Table A2). The following diagrams (Figure 1) compare the evolution over time of average incomes and income distribution resulting from the RLMS (equivalised average income and Gini index) with corresponding measures (GDP per capita and Gini coefficients) from the World Bank's *Povcanet* database. The overall concordance of the series from the two sources indicates the RLMS data are, generally speaking, able to provide information consistent and comparable to other international data sources.

Figure 1 Average incomes and Gini index in the RLMS sample and World Bank statistics (2016=1)



Sources: Own elaborations on RLMS data and World Bank's Povcalnet database.

Our main variable of interest, access to credit, is constructed based on the information coming from two specific questions of the questionnaire. The first one asks whether the household took money on credit in the last 30 days (variable F13.11A); the second (E13.72A) whether the household spent any money in the last 30 days for payment of credit/repayment of loans. The dummy variable *credit* is coded as 1 if the household answered yes to any of the two questions, and zero otherwise. The dataset also reports the amount of credit taken and amount repaid, but the presence of many outliers prevented the use of monetary values in the analysis.

Table A1 shows that the percentage of household that had access to credit increased over time, reaching about 30% in the last available years. Starting from 2006, the questionnaire included additional information on credit access, i.e. whether the household took a line of credit in the last 12 months (F14-16). Based on this information, we create a second dummy variable for credit access (credit_12m) for our robustness checks.

As for the other drivers of income mobility, we use information regarding the head of household and household as a whole at the initial year, as well as changes over the period considered. Since head of household is not unambiguously defined in the RLMS dataset, we identify them as the breadwinner in the initial year and include controls for age, gender, education level (primary, second, tertiary), marital status and nationality (Russian or other). The inclusion of information on the head of household as controls is aimed at accounting for the social and economic status of the household.

Our major emphasis is on the role of household-level demographic and economic characteristics, given the importance we attach to complementarities and interdependences taking place at the household level. Due to the short- and medium-run periods covered, we focus primarily on initial household conditions to identify factors that represent traps or stepping-stones to income mobility.

Changes over the relevant time span in key demographic and economic features are used as controls. Based on the reference literature of similar studies (Woolard and Klasen, 1995; Aristei and Perugini, 2015a and 2015b) and on the availability of information in the RLMS data, we include in the model detailed information on the household's place of residence (region of residence and a rural/urban dummy variable), size and structure,[1] based on starting income level as well as on the labour market positions of the members, expressed as the share of components with a given attribute. This group of variables includes the share of self-employed, of unemployed, controls for a few crucial occupations (managers, professionals/technicians). Unlike other data sources, the RMLS allows controlling for the share of components with a second job and for a set of information on the employer, i.e. the percentage of components working in SMEs, public enterprises and foreign firms. As regards the variables meant to account for the evolution of household characteristics over time, we consider the change in the household size, number of children, number of components employed, disability and retirement.

4 Descriptive measures of short- and medium-run income mobility, 1996–2016

The complexity of the concept of income mobility is well depicted by the variety of possible approaches for its measurement (Fields, 2006; Jäntti and Jenkins, 2013). Here, we focus here on the dimension of mobility related to individual (household) income growth between two points in time. To this purpose, we make use of the most widely known mobility index proposed and axiomatically characterised by Fields and Ok (1999a and 199b), formally defined as:

$$FO_n(x,y) = \frac{1}{n}\sum_{i=1}^{n}\left|\ln x_i - \ln y_i\right| \tag{1}$$

where $x = \{x_1, x_2, ..., x_n\}$ and $y = \{y_1, y_2, ..., y_n\}$ are the initial and final distributions of income of a population of *n* individuals. The index is constructed as the average non-directional distance $d(x_i, y_i) = \left|\ln x_i - \ln y_i\right|$ between origin and destination income. The FO index thus focuses on the size of the fluctuations in individual incomes, irrespective of their direction (Fields and Ok, 1996).

The use of the logarithmic transformation has interesting implications in terms of social utility since, under a utilitarian approach to social welfare, FO corresponds to the per capita aggregate change in the individual social utility levels experienced in the change from *x* to *y*. The FO

[1] We classify households into four types: HT1 (A) only adult components; HT2 (A+C) adults and children; HT3 (E+A/C) elderly and adults or children; and HT4 (E) only elderly.

index is additively decomposable into two components due to income growth (or contraction) and transfers among individuals:

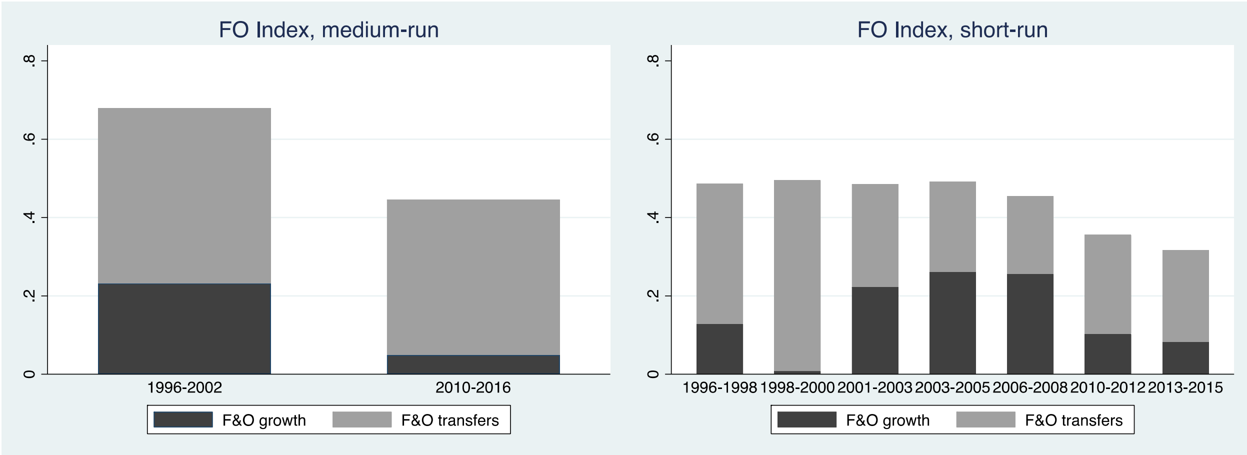
$$FO_n(x,y) = K(x,y) + T(x,y) = \frac{1}{n}\sum_{i=1}^{n}(\ln x_i - \ln y_i) + \frac{2}{n}\sum_{i \in L}(\ln x_i - \ln y_i), \tag{2}$$

where the first term *K* can be interpreted as average social utility due to growth, while *T* represents average social utility due to transfers from losers (i.e. the *L* individuals whose income declines) to gainers. $K(x,y)$ corresponds to the directional measure of mobility proposed by Fields and Ok (1999b) and is equal to the average proportional change in individual incomes, assuming $d(x_i, y_i) = \ln x_i - \ln y_i$ as a measure of distance between incomes. A positive value of this component indicates that average income movements have been welfare increasing (Burkhauser and Couch, 2009).

Table A2 in the Appendix and Figure 2 describe the levels of income mobility measured by the FO index in the different periods and its decomposition into the growth and transfer components. The data reveal that, over the medium-run, income mobility was significantly higher in the first period (1996–2002), when a higher share of mobility (around 34%) was due to the growth component. Significantly lower levels of mobility emerge for the second period (2010–2016), when the role of the growth component declines to around 10%.

The FO index for the short-run samples describes a steady level of income mobility until the late 2000s (with a more important growth component starting from 2001) and a significant decline over the last two periods. This evidence for Russia can be contrasted to the FO index calculated for other European transition countries over a similar time range. Aristei and Perugini (2015b) show that, similar to Russia, income mobility declined for all of the EU's eastern economies in the period 2008–2011 compared to 2004–2007. However, in the first period, the growth component for these countries was predominant. As in Russia, similar high levels of mobility only emerge for Bulgaria, Slovakia and Poland and only in the first period. Overall, the dynamics of the FO index (and especially of the growth component) provide a picture consistent with the macroeconomic and growth history of Russia in the last two decades, i.e. stagnation or weak growth at the end of the 1990s and after 2008 with higher growth rates in-between.

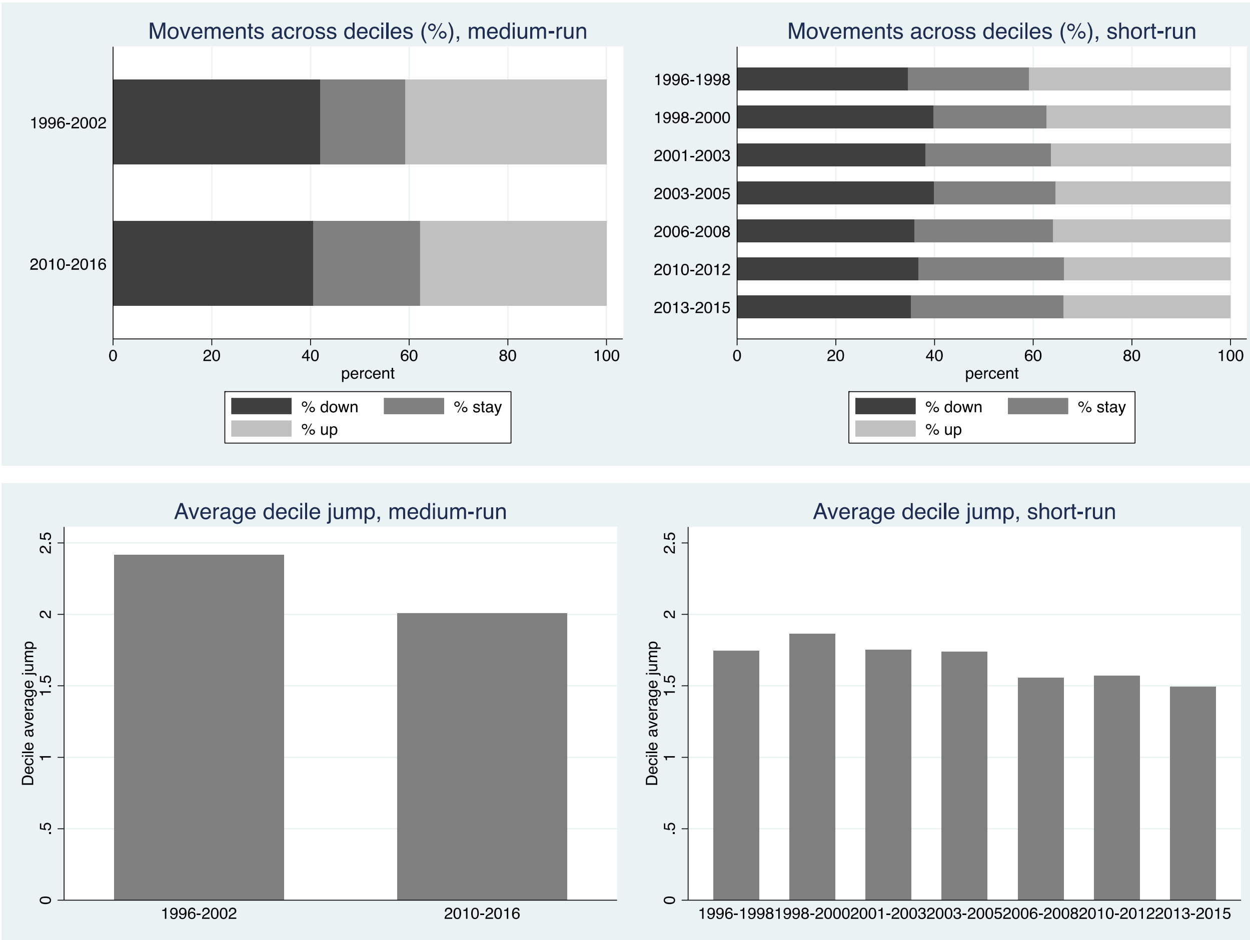
Figure 2 Absolute income mobility (Field and Ok Index) and its components, 1996–2006



Sources: own elaborations on RLMS data

In addition to the FO index, we also consider two indicators derived from transition probability matrices. For this purpose, households are assigned into income deciles of the observed initial and final distributions. Mobility is measured by movements of individuals across deciles. This two-stage relative mobility approach has the advantages of providing information on mobility in different parts of the distribution and is more robust to measurement errors (Cowell and Schluter, 1999). However, it also comes at the cost of loss of information about income changes within the groups and about the absolute income change underlying a change in income groups (Fields and Ok, 1999a). A first measure of relative mobility is simply the percentage of individuals standing in the same group (decile), as opposed to those getting ahead (*upward relative mobility*) and falling behind (*downward mobility*). Bartholomew's (1973) Average Jump index is instead a positional mobility measure defined as the number of income class boundaries (deciles) crossed by an individual (upwards or downwards), averaged over all individuals and equal to 0 in the complete immobility case.

Figure 3 Relative income mobility (average jump and movements across deciles), 1996–2006



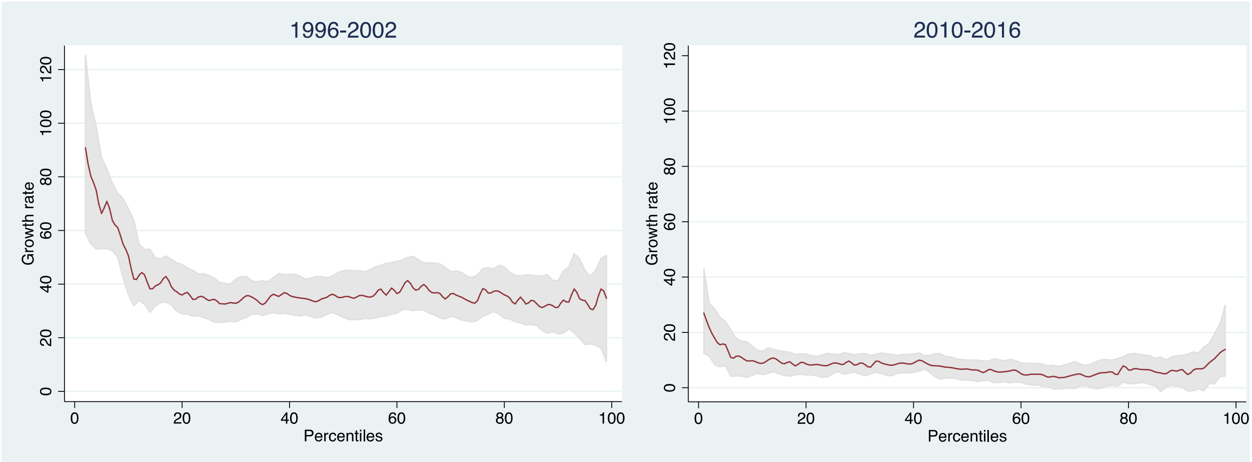
Sources: Own elaborations on RLMS data.

The information provided by the relative mobility measures (Table A2 and Figure 3) is consistent with the evidence from the FO index (higher mobility in the first medium-run period and a decrease after 2010). The top panels of Figure 3 also reveal that the increase in the share of households staying in the same decile observed for most recent periods was accompanied by a lower probability of moving upwards. This indicates that the most turbulent periods were indeed those that offered relatively better opportunities for improving the economic conditions of households.

The evidence provided so far is silent on how income growth opportunities varied across the income distribution, which is key in shedding light on the relationship between growth/mobility and income distribution patterns. Growth Incidence Curves (GICs) graphically describe the growth rate of income in different parts of the income distribution (quintiles here) between two points in time (see Ravallion and Chen, 2003).

These are provided in Figure 4 (for the medium-run samples) and in Figure A1 in the Appendix (for the short-run samples). Consistent with the decline of the Gini coefficient over time, they show that Russia’s growth patterns were predominantly pro-poor, even though the shape of the curve varies remarkably across the short-run periods. In some cases, above-average growth rates were also observed at the very top of the distribution.

Figure 4 Growth Incidence Curves (GICs), medium-run periods



Sources: Own elaborations on RLMS data.

Overall, Russia in the last two decades emerges as an economic context characterised by high levels of income inequality and high income mobility – even relative to other transition countries (see Aristei and Perugini, 2015b). The decline of the Gini coefficient over time may, at least to some extent, reflect a significant part of upward income movement occurring at the bottom of the distribution. Understanding the drivers of such movements and the role played by access to credit is the purpose of the following empirical investigation.

5 Methodology

To model the microeconomic drivers of income changes over time, we rely on the approach proposed by Fields et al. (2003). They start from a simple framework of the determinants of household income proposed by Duncan (1983) and derive a model of income changes driven by time invariant household characteristics (both observable and unobservable), base year income, time variant characteristics in the base year and changes in time-variant characteristics. As shown by Woolard and Klasen (2005), this approach is consistent with a standard household utility maximisation model with adult equivalent household income as a measure of utility dependent on household assets and the economic environment in which they are used to generate income. After some algebra, the model leads to an estimable equation of the type:

$$\Delta \ln y_i = \ln y_{i,t} - \ln y_{i,t-1} = f(\ln y_{i,t-1}, c_{i,t-1}, d_{i,t-1}, \Delta d_i, k_{i,t-1}, \Delta k_i, e_{i,t-1}, \Delta e_i), \tag{3}$$

where $y_{i,t}$ and $y_{i,t-1}$ are real household equivalised income (in initial and final year, respectively), d_i is the vector of demographic characteristics of household i (*and/or* of its head), k_i represents physical and human assets of the household (*and/or* of its head) and e_i proxies the employment status/occupation of the head of household *and/or* of the other components (as a percentage of total household size). The Δ operator refers to the change between initial and final year of the corresponding time-varying variables. For the specific aims of our analysis, we add the variable $c_{i,\ t-1}$, i.e. the dummy for household access to credit in the initial year. The dependent variable in (3) corresponds to the individual elements of the growth component of the FO mobility index in (2), and our modelling approach thus allows identifying the main drivers of individuals' proportional income changes.

As discussed in the literature (Fields et al., 2003; Woolard and Klasen, 2005; Aristei and Perugini, 2015a), the fact that initial income is reported (and not true) income in model (3) implies the possibility of measurement errors that might induce both a spurious negative correlation and attenuation bias. The standard procedure for addressing this issue is to use instrumental variable (IV) techniques to predict initial incomes, employing an additional set of identifying instruments that normally include household assets and clusters average incomes. The IV approach also allows us to control for the potential endogeneity bias due to the inclusion of initial income level among the regressors (Woolard and Klasen, 2005). However, IV estimation does not eliminate entirely the bias we would encounter using OLS, especially when the first stage fit is relatively poor. Additionally, the limited availability of instruments able to account for transitory income variations (such as information on household expenditures) exposes the IV approach to the risk of supplying upwardly biased and inconsistent estimates of the relationship between initial income and its change (Fields et al., 2003). Results obtained with the IV approach (using household ownership and household types average income as instruments) in our case are largely consistent with OLS with regard to the impact of initial income and different for certain covariates only (the results are not reported here, but available upon request). In any case, the precise estimates of the effect of initial income, although relevant, are not the primary focus of our analysis.

Our interest rather lies in correctly identifying the role of credit access, which is also at risk of being endogenous to the economic conditions of the household. We thus prefer to devote our effort to addressing this potential endogeneity issue. At the same time, to limit the threats posed by initial income measurement errors, we include in the model the initial income decile of the household rather than the reported value. Potential endogeneity of the credit access variable are addressed by means of IV. As instrumental variables, we first use a set variables constructed as the average credit access of households with similar features in terms of composition, region of residence, household head education and employment characteristics. The rationale behind the use of these variables, in the spirit of Fields et al. (2003), Woolard and Klasen(2005) and Aristei and Perugini

(2015a and 2015b), is that the behaviour of one individual household is shaped, among other things, by the behaviour of similar households defined according to a set of observable characteristics. Home ownership is also used as a possible instrument as loan collateral acts as an assurance for lenders, facilitating access to credit (see e.g. Calcagnini et al., 2015, on how collateral is positively related to the probability of obtaining a loan; or Kumarsami and Singh, 2018, who use the availability of collateral to instrument credit access by firms). As shown by the tests reported in the tables of the estimation outcomes (see detailed comments in the next section), the instruments satisfy validity conditions, indicating that the IV approach is preferable to OLS.

6 Results

6.1 Drivers of income mobility in Russia and the role of credit access

Table 1 illustrates the baseline estimation of the model described in Equation 3 for the pooled medium-run (periods 1996–2002 and 2010–2016) and short-run (1996–1998, 1998–2000, 2001–2003, 2003–2005, 2006–2008, 2010–2010, 2013–2015) samples. Columns 1 and 2 report OLS estimates, which are contrasted (columns 3 and 4) with those obtained using a IV approach to address the possible endogeneity issues of the credit access variable. As instruments, we use a dummy for home ownership and a battery of cluster average levels of credit access (by household types and household head characteristics such as occupational status, education and job position).

As shown by the tests reported in the table, the instruments satisfy validity conditions. The F-tests on the joint significance of instruments in the first stage regression reject the null hypothesis of weak instruments. Similarly, the test of overidentifying restrictions show that instruments, while significantly affecting the probability of having access to credit, are uncorrelated with the error term of the second stage regression, i.e. they are exogenous to income mobility. Comparing results from the two estimation approaches, we note that basically all variables have similar effects on income mobility in terms of signs and significance of coefficients, with differences in their size. The Wu-Hausman test comparing the IV and OLS estimates addresses toward the IV approach. For these reasons, we report only IV estimates in the following tables (OLS estimates available on request).

Results reported in Table 1 reveal that the drivers of income mobility in Russia do not differ significantly between the short- and the medium-run. Regarding the head of household's characteristics, age is negatively related (although non-linearly) to income mobility, while higher mobility is associated with being male, highly educated and married. This is consistent with the existing evidence about Russia (Nissanov, 2017), the EU and transition countries (e.g. Ayala and Sastre 2008; Aristei and Perugini, 2015a, 2015b).

Table 1 The drivers of income mobility in Russia, pooled medium- and short-run samples, OLS and IV

	Pooled OLS		Pooled IV	
	Medium-run	Short-run	Medium-run	Short-run
Initial year variables (HH)				
Age	–0.007 **	–0.008 ***	–0.007 **	–0.009 ***
	(0.003)	(0.001)	(0.003)	(0.001)
Age sq.	0.000 **	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Gender (male)	0.004	0.015 **	0.010	0.023 ***
	(0.017)	(0.007)	(0.017)	(0.007)
Sec Edu	0.066 ***	0.042 ***	0.070 ***	0.045 ***
	(0.019)	(0.008)	(0.019)	(0.008)
Ter Edu	0.122 ***	0.114 ***	0.124 ***	0.120 ***
	(0.024)	(0.010)	(0.024)	(0.010)
Married	0.101 ***	0.077 ***	0.098 ***	0.074 ***
	(0.019)	(0.008)	(0.019)	(0.008)
Russian	0.031	0.021 **	0.030	0.018 *
	(0.024)	(0.010)	(0.024)	(0.010)
Initial year variables (H)				
Credit	0.026	0.023 ***	0.179 ***	0.199 ***
	(0.018)	(0.007)	(0.053)	(0.024)
Rural	–0.077 ***	–0.038 ***	–0.079 ***	–0.038 ***
	(0.026)	(0.011)	(0.026)	(0.011)
Size	0.030 ***	0.017 ***	0.026 ***	0.011 ***
	(0.008)	(0.003)	(0.008)	(0.003)
Income Decile	–0.180 ***	–0.137 ***	–0.181 ***	–0.139 ***
	(0.004)	(0.002)	(0.004)	(0.002)
ht2 (A+C)	–0.065 ***	–0.043 ***	–0.070 ***	–0.053 ***
	(0.022)	(0.009)	(0.022)	(0.009)
ht3 (E +A/C)	–0.032	–0.028 ***	–0.021	–0.022 **
	(0.024)	(0.009)	(0.024)	(0.010)
ht4 (E)	–0.078 ***	–0.120 ***	–0.062 **	–0.113 ***
	(0.028)	(0.011)	(0.029)	(0.011)
% Self-employed	0.095	0.103 ***	0.095	0.106 ***
	(0.063)	(0.031)	(0.063)	(0.031)
% Unemployed	–0.058	0.028	–0.070	0.020
	(0.061)	(0.027)	(0.061)	(0.027)
% Manager	0.167 ***	0.266 ***	0.161 ***	0.267 ***
	(0.060)	(0.029)	(0.061)	(0.029)
% Professional	0.253 ***	0.206 ***	0.249 ***	0.204 ***
	(0.035)	(0.015)	(0.035)	(0.015)
% Second job	0.033	0.013	–0.005	–0.018
	(0.072)	(0.032)	(0.072)	(0.033)
% SME	0.048 *	0.031 ***	0.045 *	0.026 **
	(0.027)	(0.012)	(0.027)	(0.012)
% Public firms	0.138 ***	0.071 ***	0.140 ***	0.065 ***
	(0.028)	(0.012)	(0.028)	(0.012)
% Foreign firms	0.330 ***	0.260 ***	0.319 ***	0.242 ***
	(0.092)	(0.039)	(0.090)	(0.039)
Change variables (H)				
Δ size	–0.027 ***	–0.037 ***	–0.029 ***	–0.039 ***
	(0.008)	(0.005)	(0.008)	(0.005)
Δ n children	–0.001	0.028 **	–0.001	0.026 **
	(0.017)	(0.011)	(0.018)	(0.011)
Δ n unable work	–0.016	0.015	–0.018	0.016
	(0.043)	(0.020)	(0.043)	(0.020)

Δ n working	0.222	***		0.196	***	0.218	***		0.195	***	
	(0.015)			(0.007)		(0.015)			(0.007)		
Δ n retired	0.007			–0.013		0.009			–0.013		
	(0.020)			(0.011)		(0.020)			(0.011)		
Constant	1.185	***		0.684	***	0.974	***		0.713	***	
	(0.094)			(0.040)		(0.095)			(0.039)		
Region Dummies	Yes			Yes		Yes			Yes		
Year dummies	Yes			Yes		Yes			Yes		
Wu-Hausman endog. Test (F)						8.929	[0.002]		55.814	[0.000]	
Test of joint sig. of instr. (F)						8.828	[0.003]		55.898	[0.000]	
Test of overid. restr. (X2)						5.367	[0.147]		2.119	[0.548]	
Obs.	6610			36165		6566			35974		
Adj. R-Square	0.410			0.315		0.401			0.303		

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. Endogenous variable: credit. Instruments: home ownership, cluster average levels of credit access by household types and household head occupation, education and job position

As regards other demographic variables, household size increases mobility. This is as expected, since we are already controlling for different household typologies. The results unequivocally indicate that the presence of children curbs equivalent incomes growth. Similarly, households composed of elderly only have more stable incomes than households composed of adults only (the omitted category). The shares of household components in different employment conditions also affect significantly income prospects. As expected, higher mobility is associated with better occupations, while the share of unemployed in the household is not significant. Self-employment is beneficial to income growth only in the short-run. Working in small companies favours income growth, as does being employed in public and foreign firms. The controls for changes of household characteristics over time, when significant, have the expected effects. Finally, it is worth noticing that the initial income level is negatively related to subsequent growth. This convergence and pro-poor growth pattern is consistent with the descriptive evidence provided in previous sections and in previous studies on Russia (e.g. Bogomolova and Tapilina, 1999; Lukyanova and Oshchepkov, 2012) and on other countries (e.g. Fields et al. 2003; Perugini and Aristei, 2015a).

As regards our main variable of interest, the results clearly indicate that access to credit increases income mobility prospects – over both the short and medium run. However, the results obtained for distinct samples show that the effect for the pooled samples is driven by the most recent periods (see Table 2 for a summary of results and Table A3 for complete outcomes). As for the medium-run samples, credit access favours income mobility only in the period 2010–2016. Over the short-run, significant effects emerge only from 2006 onwards.

This result could be related to the institutional developments of the banking sector that occurred in Russia during the second part of the period considered. Starting from the 2000s, Russian banking authorities started to impose a number of tighter regulations aimed at increasing the strength and solidity of the banking sector. This was meant to address a number of issues emerged during the 1990s, with the first stage of financial liberalisation and bank privatisation of specialised state banks (*spetsbanki*) that led to a proliferation of financial institutions with obscure ownership structures and operating standards (Schoors, 2003). As a result, the number of banks active in Russia declined significantly during the 2000s (see Vernikov, 2017), with the shrinkage accelerating from 2012 on. This final wave of reforms, aimed at improving banking and financial market regulation, as well as financial supervision, manifested itself through extensive licence withdrawals from private banks, non-bank financial institutions, micro-lenders and other financial market operators. The Russian banking system evolved, after the first stage of transition, towards a model characterised by an intermediate level of competition (see Fungacova et al., 2010; Anzoategui et al., 2012) and a relatively high involvement of the state. Although various aspects need to be addressed (including the high concentration of banks in core regions), such trends eventually led to an overall improvement in the quality of management and conservatism in the commercial policies of banks and contributed to higher operational efficiency (see Simanovskiy et al., 2018; Solanko, 2017; Yadav, 2017). From this point of view, the results obtained from our estimations corroborate the idea that the channels of transmission from credit access to income mobility are activated by better functioning and more efficient banking and financial sectors.

Table 2 Credit access and income mobility in Russia, medium- and short-run samples, IV

	Coefficient of Credit		Obs.	Adj. R-Square
medium-run				
1996–2002	0.133 (0.165)		2366	0.492
2010–2016	0.160 (0.051)	***	4200	0.367
short-run				
1996–1998	–0.155 (0.125)		2500	0.381
1998–2000	0.113 (0.169)		2791	0.351
2001–2003	0.034 (0.132)		3368	0.329
2003–2005	0.164 (0.100)		3440	0.333
2006–2008	0.294 (0.063)	***	3982	0.269
2010–2012	0.254 (0.045)	***	5791	0.253
2013–2015	0.081 (0.046)	*	5631	0.247

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. Endogenous variable: credit. Instruments: home ownership, cluster average levels of credit access by household types and household head occupation, education and job position. Complete results available in Table A3 in the Appendix

A robustness check implemented using the alternative measure of credit access (credit_12m) provides results largely overlapping with the previous ones (see Table 3 and Table A4 in the Appendix). As this variable is available only from 2006 on, the additional analysis covers only the most recent period. Outcomes confirm the positive impact of credit access on income mobility prospect both in the medium and short run.

Table 3 Robustness check: alternative definition of access to credit (credit_12m), from 2006 on, IV

	Coefficient of credit_12m		Obs.	Adj. R-Square
medium-run				
2010-2016	0.264 (0.090)	***	4200	0.346
short-run				
pooled	0.336 (0.040)	***	20735	0.239
2006-2008	0.356 (0.076)	***	3982	0.242
2010-2012	0.450 (0.085)	***	5791	0.182
2013-2015	0.149 (0.080)	*	5631	0.237

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

Endogenous variable: credit. Instruments: home ownership, cluster average levels of credit access by household types and household head occupation, education and job position. Complete results available in Table A4 in the Appendix.

6.2 Possible channels through which credit affects mobility

In this section, we provide additional empirical evidence on possible channels of transmission through which access to credit can trigger higher income mobility. In section 2, based on the existing literature and our discussion, we envisage three possible mechanisms. The first two were related to the labour market (increase in labour supply and better worker/job matching). The third was linked to income sources other than labour.

One way to provide such descriptive evidence is to rely on the comparison of average levels of an output variable (e.g. number of hours worked) between sample units with and without access to credit. This raw difference, however, would be biased as many other characteristics could affect the gap. To control for such factors, we use simple empirical parametric models in which we include, among other explanatory variables (derived from the literature), a dummy for access to credit. For the sake of brevity, we only report here the outcomes of interest, i.e. the coefficients of the credit access variable. The full results appear in the Appendix. In all models, we use the baseline credit access variable (credit), that guarantees a larger sample size. The same estimations, replicated using credit_12m (available from 2006 onwards), provide fully consistent outcomes and are available upon request.

We first test the idea that access to credit might impact income mobility via an increase in labour supply. To this aim, we run OLS estimates on a simple model in which the dependent variable is the number of hours worked per week (by the household head or by all household components) or, alternatively, the number or the share of household components at work. The explanatory variables include information about the household head (age, gender, education, marital status, nationality, hourly wage), the household structure (size, household type, equivalised income) and the credit access dummy variable. The estimation is run on a pooled sample (1996–2006) and includes year and regional controls. A summary of the results is reported in Table 4 (complete results in Table A5 in the Appendix) and shows that access to credit is positively associated to an increase in both the intensive and the extensive margin of labour supply. In the presence of access to credit, both the household head and the household as a whole work longer hours. The presence of debt also increases the number (and share) of household members at work. This holds for both male and female components. It is consistent with the literature on the positive link between household indebtedness and labour supply (see Bottazzi et al., 2007; Del Boca and Lusardi, 2003; Belkar et al., 2007; Butrica and Karamcheva, 2014).

Table 4 Credit access and labour supply, (pooled sample 1996–2016), OLS estimates

Dep. Variable	Coefficient of credit		n. obs.	Adj. R-Square
Intensive margin				
Hours worked per week (household head)	1.168 (0.117)	***	56863	0.090
Hours worked per week (household)	7.571 (0.327)	***	58922	0.190
Extensive margin				
N. of household members employed	0.140 (0.006)	***	64249	0.166
% of household members employed	0.014 (0.002)	***	64249	0.417
N. of male household members employed	0.088 (0.004)	***	64249	0.215
N. of female household members employed	0.053 (0.004)	***	64249	0.414

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. All estimates include year and regional dummies and controls for household head (age, age squared, gender, education, marital status, nationality, hourly wage) and household characteristics (size, household type).

The same empirical model is replicated, replacing the credit variable with five interactions terms between the credit dummy and five dichotomic variables that determine to which ventile of the equivalent income distribution households belongs. This estimate helps in understanding if the effect of credit access on labour supply varies for different income groups. Results reported in Tables 5 and A5 reveal this is the case. The coefficient size declines as incomes approach the top of the distribution.

Table 5 Credit access and labour supply, (pooled sample 1996–2016), OLS estimates

Dep. Variable: Hours worked per week by the household head	Coefficient		n. obs.	Adj. R-Square
Credit * income ventile 1	0.989 (0.340)	***	58863	0.103
Credit * income ventile 2	0.917 (0.284)	***		
Credit * income ventile 3	0.884 (0.241)	***		
Credit * income ventile 4	0.896 (0.218)	***		
Credit * income ventile 5	0.554 (0.218)	**		

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

All estimates include year and regional dummies and controls for household head (age, age squared, gender, education, nationality, hourly wage) and household characteristics (size, household type, equivalised income).

The same model, run with deciles, shows similar results, with the important distinctions that the coefficient of the interaction for the top decile is not statistically significant. Overall, this descriptive evidence support the idea that an increase in labour supply is a channel through which access to credit affects income mobility. The effect is weaker or not significant for high-income households.

A second possible channel of transmission is through better labour market matching. Direct measurement of the quality of skills/education and job mismatch is *per se* a complicated task, considerably aggravated by a shortage of detailed information about occupations and job contents on one side and about workers' curricula and careers on the other. Here, we decided to rely on a variable that the literature has largely demonstrated to be positively associated to good matching, i.e. job satisfaction (see Allen and Van der Velden, 2001; Viera, 2005; Morrison et al., 2005; Badillo-Amador and Vila, 2013; OECD, 2016 and 2017).

We use this job satisfaction variable as a proxy, among other things, for the quality of matching revealed by the worker itself. The information is drawn from question J1.1 of the adult questionnaire of the RLMS in which individuals are asked to state their level of satisfaction (on a 0–5 scale) with regards to their job in general, their earnings, their work conditions and their opportunities for professional growth. This information is used to construct dummy variables coded as 1 (satisfied) if the respondent reports absolutely or mostly satisfied (points 1 or 2 on the scale), and 0 otherwise (points 1 to 3: neutral, not completely satisfied, absolutely unsatisfied). Table 6 summarises the results of a logit model aimed at identifying the effect of access to credit on job satisfaction once other possible personal, household and job characteristics are accounted for (complete results in Table A6). The results clearly indicate that credit access is associated with a higher likelihood of satisfaction with jobs, earnings, future opportunities and work conditions (the latter coefficient, however, is not statistically significant). Provided that higher satisfaction is correlated to better quality of matching (and thus higher productivity and earnings), this evidence suggests that this mechanism of transmission from credit to income mobility cannot be excluded.

Table 6 Credit access and job satisfaction, (2002–2006), logit estimates

Dep. Variable	Coefficient of Credit (odds ratio)		n. obs	Adj. R-Square
Satisfied with job in general	1.046 (0.020)	**	58148	0.046
Satisfied with earnings	1.042 (0.021)	**	58096	0.041
Satisfied with work conditions	1.015 (0.020)		58145	0.057
Satisfied with opportunities for professional growth	1.050 (0.020)	**	58112	0.046

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. Coefficients are odds ratios. All estimates include year and regional dummies and controls for household head (age, age squared, gender, education, nationality) and household characteristics (size, household type).

The third channel of transmission hypothesised in section 2 regards source of income other than labour. To test whether the empirical evidence is consistent with our conjecture, we build a model in which we include access to credit among the possible drivers of household capital income or rents. Based on question F12 of the RLMS household questionnaire, we construct a dummy variable coded as 1 if the household received property rental income from a capital investment within the last 30 days, and 0 otherwise. Again, this variable is used as a dependent variable in a model that includes, besides credit access, various characteristics of the household head and the household (see Tables 7 and A7). Results indicate that having access to credit increases the probability of having income sources other than labour. However, the effect is only significant for household sitting in the upper part of the income distribution as only the three interaction terms of credit with the top income ventiles dummies are significant. Results are confirmed if we use decile dummies, with only the top five significant. Hence, we cannot exclude that credit access can be used by better-off households for financial and real estate investments that trigger upward income mobility.

Table 7 Credit access and additional sources of incomes, (pooled sample 1996–2016), logit estimates

Dep. Variable: Any rent from property/capital income (dummy variable)	Coefficient (odds ratio)		n. obs.	Adj. R-Square
Credit	1.747 (0.120)	***	60473	0.077
Credit (v1)	0.796 (0.359)		60473	0.094
Credit (v2)	1.209 (0.313)		60473	0.094
Credit (v3)	1.565 (0.280)	**	60473	0.094
Credit (v4)	1.490 (0.183)	***	60473	0.094
Credit (v5)	1.743 (0.168)	***	60473	0.094

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. Coefficients are odds ratios. All estimates include year and regional dummies and controls for household head (age, age squared, gender, education, nationality, hourly wage) and household characteristics (size, household type, equivalised income). Complete results available upon request.

7 Conclusions

This paper investigated the microeconomic drivers of medium- and short-term income mobility in Russia. The analysis relied on the Russian Longitudinal Monitoring Survey (RLMS) for the period 1996–2016. After providing a descriptive picture of income mobility over the period considered, we modelled household income growth based on a set of demographic, economic and employment determinants referenced to both the household and the head of household.

The contribution of this paper to the existing literature is two-fold. First, it provides an extensive comparative analysis of household income mobility over time in Russia, while existing empirical literature has been limited to shorter periods. Second, it focuses on the role of access to credit in triggering household income growth. Although aspects of finance and credit markets are extensively investigated among the drivers of long-run patterns of income inequality at aggregate level, the possible impact on individual income mobility in medium- and short income growth has received little attention. Russia is a particularly interesting case in this respect as, over the period considered, credit and banking sectors evolved significantly amidst major crises and extensive reforms.

The evidence emerging from the descriptive measures of mobility shows that the high inequality of the Russian context is accompanied by high mobility. In other words, large disparities between individuals coexist with relatively widespread opportunities of changing relative positions across the income ladder. In particular, since a significant part of upward income movements occurs at the bottom of the distribution, Russia emerges as a country in which it is possible to escape the low-income trap. Such pro-poor patterns of growth are likely to have contributed significantly to the decline in the Gini coefficient over the past two decades.

The econometric analysis largely confirms the *ex-ante* expectations on factors that trigger income growth. In addition to being a young male head of household with a higher education, income prospects are also enhanced by a large household, as are increasing shares of components employed in top occupations at SMEs, state-owned or foreign firms. Conversely, the presence of children and elderly persons weakens income growth opportunities. Our outcomes indicate that access to credit is to be added to list of the factors that boost income mobility. These results are robust to changes in variables that identify access to credit and are always significant for the samples of the second half of the period considered. In view of the institutional evolution that occurred in Russia starting in the early 2000s, this suggests that access to credit access manifests as in the functioning and efficiency of banking and financial sectors. Complementary empirical evidence corroborates the idea that the beneficial effect of access to credit on upward income mobility unfolds through various channels: (i) an increase in the labour supplied by the head of the household and by the household as a whole; (ii) a better matching between jobs and workers' skills/education that positively impacts productivity and earnings; and (iii) an increase in non-labour sources of household income.

As this is the first paper dealing with such specific aspects, we are well aware of the limitations of the results obtained. They apply to only one country and rely on indirect evidence regarding the possible mechanisms of transmission from credit to individual income growth. The policy implications of this causal relationship, if confirmed, are not small, however. Functioning credit markets that can efficiently identify borrower quality can be a tool of escape from low-income and poverty traps. Indeed, such effects could even be visible over the short run.

References

Allen, J. and Van der Velden, R. (2001). Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search. Oxford Economic Papers, 53(3), 434–452.

Anzoategui, D., Martínez Pería, M.S. and Melecky, M. (2012). Bank competition in Russia: An examination at different levels of aggregation. Emerging Markets Review, 13, 42–57.

Arestis, P. and Demetriades, P. (1997). Financial development and economic growth: Assessing the evidence. Economic Journal, 107, 783–799.

Aristei, D. and Perugini, C. (2015a). The drivers of income mobility in Europe. Economic Systems, 39, 197–224.

Aristei, D. and Perugini, C. (2015b). Income mobility in the new EU member states. In: Perugini, C. and Pompei, F. (eds.), Inequalities During and After Transition in Central and Eastern Europe. Palgrave MacMillan, Basingstoke, UK.

Atkinson, A.B. (2000). The changing distribution of income: Evidence and explanations. German Economic Review, (1/1), 3–18.

Atkinson, A.B., Bourguignon, F. and Morrisson, C. (1992). Empirical Studies of Earnings Mobility (Fundamentals in Pure and Applied Economics). Harwood Academic Publishers, Chur and Philadelphia.

Ayala, L. and Sastre, M. (2008). The structure of income mobility: Empirical evidence from five UE countries. Empirical Economics, 35, 451–473.

Badillo-Amador, L. and Vila, L.E. (2013). Education and skill mismatches: wage and job satisfaction consequences. International Journal of Manpower, 34(5), 416–428.

Bartholomew, D. J. (1973). Stochastic models for social processes, 2nd Edition. Wiley.

Belkar, R., Cockerell, L. and Edwards, R. (2007). Labour force participation and household debt. RBA Research Discussion Papers rdp2007–05, Reserve Bank of Australia.

Besley, T. (1995). Savings, credit and insurance. In: J. Behrman and T. N. Srinivasan (eds.), Handbook of Development Economics, Ch. 36, Vol. III, Elsevier Science B.V., 2123–2207.

Blundell, R., Pistaferri, L. and Preston, I. (2008). Consumption inequality and partial insurance. American Economic Review, 98(5), 1887–1921.

Bogomolova, T. and Tapilina, V. (1999). Income mobility in Russia in the mid-1990s. EERC Working Paper 99/11, Economic Education and Research Consortium Russian Economic Research Program, Moscow.

Bottazzi, R., Low, H. and Wakefield, M. (2007). Why do home owners work longer hours? Working Paper10/07, IFS.

Bottazzi, R. (2004). Labor market participation and mortgage related borrowing constraints. Working Paper 04/09, IFS.

Bui, K.D. and Ume, E.S. (2016). Credit constraints and labor supply. Mimeo, Miami University.

Burkhauser, R.V. and Couch, K. (2009). Intragenerational inequality and intertemporal mobility. In: Salverda, W., Nolan, B. and Smeeding, T.M. (eds.), Oxford Handbook of Economic Inequality. Oxford University Press, Oxford, Ch. 21, 522–548.

Butrica, B. and Karamcheva, N. (2014). Does household debt influence the labor supply and benefit claiming decisions of older Americans? Netspar Discussion Paper No. 03/2014–083.

Calcagnini, G., Giombini, G. and Lenti, E. (2015). Gender Differences in Bank Loan Access: An Empirical Analysis, Italian Journal of Economics, 1, 193–217.

Castro, R. (2011). Getting ahead, falling behind and standing still. Income mobility in Chile. Estudios de Economia, 38(1), 243–258.

Clarke, G.R.G., Xu, L.C. and Zou, H. (2006). Finance and income inequality: What do the data tell us? Southern Economic Journal, 72(3), 578–596.

Commander, S., Tolstopiatenko, A. and Yemtsov, R. (1999). Channels of redistribution. Inequality and poverty in the Russian transition. Economics of Transition, 7(2), 411–447.

Cowell, F.A. and Schluter, C. (1999). Income mobility: A robust approach. In: Silber, J. (ed.), Income Inequality Measurement: From Theory to Practice. Kluwer, Dewenter.

Dang, H.A.H., Lokshin, M., Abanokova, K. and Bussolo, M. (2018). Inequality and Welfare Dynamics in the Russian Federation during 1994–2015, Policy Research Working Paper 8629, World Bank Group.

De Haan, J. and Sturm, J-E. (2017). Finance and income inequality: A review and new evidence. European Journal of Political Economy, 50, 171–195.

Del Boca, D. and Lusardi, A. (2003). Credit market constraints and labor market decisions. Labour Economics, 10(6), 681–703.

Duncan, G.J. (1983). The implications of changing family composition for the dynamic analysis of economic well-being. In: A.B. Atkinson and F.A. Cowell (eds.), Panel Data on Incomes, London: London School of Economics.

Fields, G.S. (2006). The many facets of economic mobility. In: McGillivray, M (ed.), Inequality, Poverty, and Well-Being. Palgrave Macmillan, Houndsmills: 123–142.

Fields, G.S. (2008). Income mobility. In: Blume, L. and Durlauf, S. (eds.), The New Palgrave Dictionary of Economics. Palgrave McMillan, New York.

Fields, G.S. and Ok, E.A. (1996). The meaning and measurement of income mobility. Journal of Economic Theory 71(2): 349–377

Fields, G.S. and Ok, E.A. (1999a). The measurement of income mobility: An introduction to the literature. In: Silber, J. (ed.), Handbook of Income Inequality Measurement. Recent Economic Thought. Kluwer Academic Publishers, Boston, Ch. 19, 557–598.

Fields, G.S. and Ok, E.A. (1999b). Measuring movement of incomes. Economica, 66, 455–471.

Fields, G.S., Cichello, P., Freije, S., Menendez, M. and Newhouse, D. (2003). Household income dynamics: a four country study. Journal of Development Studies, 40(2), 30–54.

Fortin, N.M. (1995). Allocation inflexibilities, female labor supply, and housing assets accumulation: Are women working to pay the mortgage? Journal of Labor Economics, 13(3), 524–557.

Fräßdorf, A., Grabka, M.M. and Schwarze, J. (2011). The impact of household capital income on income inequality – a factor decomposition analysis for the UK, Germany and the USA. Journal of Economic Inequality, 9(1), 35–56.

Fungacova, Z., Solanko, L. and Weill, L. (2010). Market power in the Russian banking industry. International Economics, 124, 127–146.

Galor, O. and Moav, O. (2004). From physical to human capital accumulation: Inequality and the process of development. Review of Economic Studies, 71, 1001–1026.

Galor, O. and Zeira, J. (1993). Income distribution and macroeconomics. Review of Economic Studies, 60, 35–52.

GHK (2010). Social mobility and intra-regional income distribution across EU member states. GHK report to the Commission, DG Regio.

Gottschalk, P. and Smeeding, T.M. (1997). Cross-national comparisons of earnings and income inequality. Journal of Economic Literature, 35, 633–687.

Greenwood, J. and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. Journal of Political Economy, 98(4), 942–63.

ILO (2016). How useful is the concept of skills mismatch? Economic and Social Research Institute for the International Labour Organisation, Geneva.

Jalilian, H. and Kirkpatrick, C. (2002). Financial development and poverty reduction in developing countries. International Journal of Finance and Economics, 7(2), 97–108.

Jäntti, M. (1997). Inequality in five countries in the 1980s: The role of demographic shifts, markets and government policies. Economica, 64, 415–440.

Jäntti, M. and Jenkins, S.P. (2015). Income mobility. In: Atkinson, A.B. and Bourguignon, F. (eds,), Handbook of Income Distribution, Volume 2A, North-Holland Elsevier, 2015, Ch. 10, 807–935.

Jenkins, S.P. (2000). Trends in UK income distribution. In: R. Hauser and I. Becker (eds.), The Personal Distribution of Income in an International Perspective, Heidelberg: Springer, 129–157.

Jenkins, S.P. and Van Kerm, P. (2009). The measurement of economic inequality. In: Salverda, W., Nolan, B. and Smeeding, T.M. (eds.), The Oxford Handbook on Economic Inequality. Oxford University Press, Oxford, 40–67.

Jenkins, S.P. (2011). Changing Fortunes: Income Mobility and Poverty Dynamics in Britain. Oxford University Press, Oxford.

Johnston, D. and Morduch, J. (2008). The unbanked: Evidence from Indonesia. World Bank Economic Review, 22(3), 517–537.

Jovanovic, B. (2001). Russian Roulette – Expenditure Inequality and Instability in Russia, 1994–1998. William Davidson Institute Working Paper No. 358.

Levine, R. (2005). Finance and growth: theory and evidence. In: Aghion, P. and Durlauf, S. (eds.), Handbook of Economic Growth. Elsevier, North-Holland, 865–933.

Li, H., Squire, L. and Zou, H. (1998). Explaining international and intertemporal variations in income inequality. Economic Journal, 108(446), 26–43.

Lokshin, M. and Ravallion, M. (2004). Household income dynamics in two transition economies. Studies in Nonlinear Dynamics and Econometrics, 8(3), Article 4.

Lukiyanova, A. and Oshchepkov, A. (2012). Income mobility in Russia (2000–2005). Economic Systems, 36(1), 46–64.

Kumarasamy, D. and Singh, P. (2018). Access to Finance, Financial Development and Firm Ability to Export: Experience from Asia-Pacific Countries. Asian Economic Journal, 32(1), 15–38.

Maasoumi, E. (1998). On mobility. In: Giles, D. and Ullah, A. (eds.), Handbook of Applied Economic Statistics. Marcel Dekker, New York, 119–175.

Marotta, D. and Yemtsov, R. (2010). Determinants of households' income mobility and poverty dynamics in Egypt. Paper presented at the 5th IZA-World Bank conference on Employment and Development, Cape Town, May 2010.

Mitra, P. and Yemtsov, R. (2006). Increasing inequality in transition economies: Is there more to come? Policy Research Working Paper Series No. 4007. New York: The World Bank.

Morrison, D., Cordery, J. and Girardi, A. (2005). Job design, opportunities for skill utilisation, and intrinsic job satisfaction. European Journal of Work and Organisational Psychology, 14(1), 59–79.

Nissanov, Z. (2017). Income mobility and the middle class in Russia, 1995–2007. Post-Communist Economies, 29(2), 250–264.

OECD (2016). Job creation and local economic development 2016. OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264261976-en.

OECD (2017). Better use of skills in the workplace: Why it matters for productivity and local jobs. OECD Publishing, Paris.

Pijoan-Mas, J. (2006). Precautionary savings or working longer hours? Review of Economic Dynamics, 9(2), 326–352.

Ravallion, M. and Chen, S. (2003). Measuring pro-poor growth. Economics Letters, 78, 93–99.

Rossi, M. and Trucchi, S. (2016). Liquidity constraints and labor supply. European Economic Review, 87, 176–193.

Schoors, K. (2003). The fate of Russia's former state banks: Chronicle of a restructuring postponed and a crisis foretold. Europe-Asia Studies, 55(1), 75–100.

Sevena, U. and Coskunb, Y. (2016). Does financial development reduce income inequality and poverty? Evidence from emerging countries. Emerging Markets Review, 26, 34–63.

Shi, X., Liu, X., Nuetah, A. and Xin, X. (2010). Determinants of household income mobility in rural China. China & World Economy, 18(2), 41–59.

Simanovskiy, A., Morozov, A. Sinyakov, A., Porshakov, A. Pomelnikova, M., Ushakova, Y., Markelov, V. and Bezdudniy, M. (2018). The 2008–2017 decade in the Russian banking sector: Trends and factors. Bank of Russia Working Paper Series wps31, Bank of Russia.

Solanko, L. (2017). The Russian banking sector – where to next? Bank of Finland Articles on the Economy, September 2017.

Sologon, D.M. and O'Donoghue, C. (2011). Shaping earnings mobility: Policy and institutional actors. European Journal of Comparative Economics, 8(2), 175–202.

Van Kerm, P. and Pi Alperin, M.N. (2013). Inequality, growth and mobility: The inter-temporal distribution of income in European Countries 2003–2007. Economic Modelling, 35(C), 931–939.

Vernikov, A. (2017). Measuring institutional change: The case of the Russian banking industry. Journal of Institutional Studies, 9(2), 119–136.

Vieira, J.A.C. (2005). Skill mismatches and job satisfaction. Economic Letters, 89(1), 39–47.

Woolard, I. and Klasen, S. (2005). Determinants of income mobility and household poverty dynamics in South Africa. Journal of Development Studies, 41(5), 865–897.

Yadav, R. (2017). Twenty five years of Russian banking system, trends and analysis. International Studies, 51(1–4), 101–117.

Appendix

Table A1 Samples and descriptive statistics

year	Obs.	Eq. income	Gini	Credit	Credit 12m
1996	3146	7149,3	0.45	0.24	-
1997	-	-	-	-	-
1998	3367	5545.4	0.40	0.23	-
1999	-	-	-	-	-
2000	3666	5368.2	0.39	0.20	-
2001	4179	7167.3	0.41	0.20	-
2002	4308	7598.3	0.38	0.18	-
2003	4350	8485.7	0.39	0.20	-
2004	4548	8974.5	0.41	0.22	-
2005	4285	11023.9	0.39	0.27	-
2006	5174	12935.6	0.41	0.25	0.25
2007	5085	14220.4	0.41	0.25	0.23
2008	4995	16878.1	0.42	0.26	0.21
2009	4996	16344.9	0.41	0.23	0.14
2010	7491	17627.6	0.39	0.25	0.18
2011	7714	17586.8	0.37	0.26	0.20
2012	8059	18813.1	0.36	0.30	0.23
2013	7809	19813.6	0.38	0.31	0.22
2014	6525	19200.6	0.35	0.33	0.18
2015	6629	18349.3	0.37	0.31	0.12
2016	6762	17748.9	0.36	0.30	0.13

Source: Own elaborations on RLMS data. Equivalent income in 2010 Russian rubles.

Table A2 Income mobility; absolute and relative descriptive measures

	N	FO index	FO growth	FO transfer	Average Jump	% Down	% Stay	% Up
medium-run								
1996–2002	2381	0.679	0.232	0.447	2.417	0.420	0.172	0.408
2010–2016	4233	0.446	0.049	0.397	2.009	0.406	0.216	0.378
short-run								
1996–1998	2512	0.487	0.129	0.358	1.747	0.346	0.246	0.408
1998–2000	2816	0.496	0.008	0.487	1.865	0.398	0.229	0.373
2001–2003	3395	0.484	0.223	0.262	1.751	0.382	0.254	0.364
2003–2005	3463	0.492	0.261	0.231	1.740	0.399	0.247	0.354
2006–2008	4001	0.455	0.256	0.199	1.558	0.36	0.28	0.36
2010–2012	5836	0.356	0.103	0.253	1.572	0.368	0.295	0.337
2013–2015	5642	0.317	0.083	0.234	1.495	0.352	0.31	0.338

Source: Own elaborations on RLMS data

Table A3 The drivers of income mobility in Russia; pooled medium– and short–run samples, IV estimates

	Medium–run		Short–run						
	96–02	10–16	96–98	98–00	01–03	03–05	06–08	10–12	13–15
Initial year variables (HH)									
Age	–0.015 ***	–0.001	0.005	–0.008 *	–0.017 ***	–0.018 ***	–0.008 **	–0.007 ***	–0.002
	(0.005)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Age sq	0.000 ***	0.000	–0.000	0.000	0.000 ***	0.000 ***	0.000 **	0.000 ***	0.000 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender (male)	0.021	0.008	0.045	0.021	–0.021	0.009	0.026	0.037 **	0.017
	(0.030)	(0.019)	(0.031)	(0.027)	(0.023)	(0.024)	(0.022)	(0.016)	(0.015)
Sec Edu	0.102 ***	0.040 *	0.037	0.032	0.056 **	0.047 *	0.067 ***	0.045 **	0.029
	(0.036)	(0.022)	(0.039)	(0.033)	(0.028)	(0.027)	(0.024)	(0.018)	(0.018)
Ter Edu	0.173 ***	0.088 ***	0.155 ***	0.120 ***	0.151 ***	0.151 ***	0.123 ***	0.106 ***	0.065 ***
	(0.045)	(0.027)	(0.049)	(0.042)	(0.035)	(0.034)	(0.030)	(0.022)	(0.022)
Married	0.156 ***	0.054 ***	0.089 **	0.137 ***	0.076 ***	0.101 ***	0.054 **	0.057 ***	0.021
	(0.035)	(0.021)	(0.035)	(0.030)	(0.025)	(0.026)	(0.022)	(0.018)	(0.016)
Russian	0.085 **	–0.015	0.051	0.018	0.085 **	0.044	–0.025	–0.002	–0.002
	(0.040)	(0.029)	(0.043)	(0.036)	(0.033)	(0.030)	(0.028)	(0.022)	(0.021)
Initial year variables (H)									
Credit	0.133	0.160 ***	–0.155	0.113	0.034	0.164	0.294 ***	0.254 ***	0.081 *
	(0.165)	(0.051)	(0.125)	(0.169)	(0.132)	(0.100)	(0.063)	(0.045)	(0.046)
Rural	–0.064	–0.068 **	–0.090 *	–0.093 **	–0.004	–0.017	–0.065 **	0.023	–0.050 **
	(0.053)	(0.028)	(0.054)	(0.045)	(0.042)	(0.039)	(0.032)	(0.024)	(0.022)
Size	0.007	0.029 ***	–0.041 **	0.015	0.022 **	0.026 **	–0.004	0.023 ***	0.012 *
	(0.017)	(0.009)	(0.016)	(0.014)	(0.011)	(0.011)	(0.011)	(0.007)	(0.007)
Income Decile	–0.235 ***	–0.145 ***	–0.199 ***	–0.170 ***	–0.147 ***	–0.158 ***	–0.141 ***	–0.116 ***	–0.102 ***
	(0.006)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)
ht2 (A+C)	–0.095 **	–0.043 *	–0.015	–0.064 *	–0.036	–0.045	–0.049 *	–0.067 ***	–0.061 ***
	(0.044)	(0.025)	(0.043)	(0.037)	(0.032)	(0.029)	(0.027)	(0.019)	(0.019)
ht3 (E +A/C)	–0.003	–0.057 **	0.018	0.010	–0.052	–0.064 **	–0.020	–0.036 *	–0.026
	(0.046)	(0.026)	(0.044)	(0.037)	(0.034)	(0.031)	(0.030)	(0.020)	(0.020)
ht4 (E)	–0.108 **	–0.036	–0.114 **	–0.026	–0.101 ***	–0.146 ***	–0.165 ***	–0.084 ***	–0.101 ***
	(0.052)	(0.034)	(0.054)	(0.038)	(0.036)	(0.037)	(0.037)	(0.026)	(0.023)
% Self–employed	0.192 **	–0.045	0.273 ***	0.153 *	0.167 **	0.290 **	0.028	0.043	–0.053
	(0.075)	(0.100)	(0.077)	(0.082)	(0.084)	(0.118)	(0.092)	(0.094)	(0.088)
% Unemployed	–0.119	0.052	–0.098	–0.000	0.317 ***	0.017	–0.006	0.195 ***	–0.101
	(0.095)	(0.077)	(0.085)	(0.087)	(0.099)	(0.075)	(0.083)	(0.065)	(0.078)

% Manager	0.116	–0.018	0.253 *	–0.263	0.255 ***	–0.010	0.002	–0.002	–0.103
	(0.138)	(0.080)	(0.146)	(0.162)	(0.091)	(0.091)	(0.090)	(0.073)	(0.083)
% Professional	0.045	0.159 **	0.196	0.166	0.325 ***	0.396 ***	0.330 ***	0.159 **	0.273 ***
	(0.130)	(0.066)	(0.148)	(0.130)	(0.093)	(0.091)	(0.073)	(0.062)	(0.079)
% Second job	0.347 ***	0.168 ***	0.260 ***	0.322 ***	0.235 ***	0.196 ***	0.227 ***	0.150 ***	0.138 ***
	(0.066)	(0.039)	(0.070)	(0.066)	(0.051)	(0.050)	(0.043)	(0.032)	(0.033)
% SME	0.053	0.055 *	–0.025	0.072	0.053	0.097 **	0.018	0.017	–0.011
	(0.055)	(0.030)	(0.060)	(0.053)	(0.045)	(0.040)	(0.037)	(0.025)	(0.024)
% Public firms	0.135 ***	0.121 ***	–0.125 **	0.044	0.162 ***	0.028	0.055	0.068 ***	0.037
	(0.052)	(0.032)	(0.056)	(0.051)	(0.041)	(0.042)	(0.035)	(0.026)	(0.026)
% Foreign firms	0.381 **	0.265 ***	0.136	0.492 ***	0.155	0.195	0.438 ***	0.451 ***	0.198 ***
	(0.165)	(0.097)	(0.227)	(0.141)	(0.111)	(0.129)	(0.101)	(0.085)	(0.076)
Change variables (H)	–0.035 **	–0.029 ***	–0.093 ***	–0.038 **	–0.053 ***	–0.020	–0.032 **	–0.036 ***	–0.044 ***
Δ size	(0.015)	(0.009)	(0.019)	(0.019)	(0.015)	(0.015)	(0.014)	(0.010)	(0.011)
	0.000	–0.003	0.166 ***	0.018	0.022	0.017	0.018	0.023	0.022
Δ n children	(0.038)	(0.018)	(0.048)	(0.044)	(0.038)	(0.036)	(0.035)	(0.027)	(0.023)
	–0.046	0.005	0.077	0.049	–0.022	0.050	–0.088	0.046	0.064 *
Δ n unable work	(0.080)	(0.048)	(0.097)	(0.079)	(0.067)	(0.060)	(0.061)	(0.043)	(0.036)
	0.228 ***	0.221 ***	0.153 ***	0.157 ***	0.156 ***	0.154 ***	0.226 ***	0.195 ***	0.233 ***
Δ n working	(0.025)	(0.018)	(0.033)	(0.032)	(0.025)	(0.023)	(0.022)	(0.017)	(0.017)
	–0.028	0.011	0.082 *	–0.008	–0.054	0.014	–0.079 **	–0.003	–0.012
Δ n retired	(0.039)	(0.022)	(0.045)	(0.047)	(0.036)	(0.039)	(0.039)	(0.025)	(0.025)
	1.469 ***	0.746 ***	0.870 ***	0.889 ***	1.104 ***	1.343 ***	1.178 ***	0.680 ***	0.571 ***
Constant	(0.190)	(0.110)	(0.185)	(0.168)	(0.142)	(0.121)	(0.113)	(0.086)	(0.081)
	–0.035 **	–0.029 ***	–0.093 ***	–0.038 **	–0.053 ***	–0.020	–0.032 **	–0.036 ***	–0.044 ***
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wu–Hausman endog. Test (F)	0.993 [0.319]	6.649 [0.009]	0.191 [0.661]	0.576 [0.447]	0.070 [0.791]	2.817 [0.093]	14.669 [0.000]	24.163 [0.000]	3.563 [0.059]
Test of joint sig. of instr. (F)	0.963 [0.326]	6.554 [0.010]	0.187 [0.665]	0.562 [0.453]	0.069 [0.793]	2.781 [0.095]	14.414 [0.000]	24.269 [0.000]	3.529 [0.060]
Test of overid. restr. (X2)	2.769 [0.250]	1.767 [0.413]	7.795 [0.100]	0.801 [0.670]	3.220 [0.200]	2.492 [0.287]	2.328 [0.312]	0.177 [0.915]	3.882 [0.143]
Obs.	2366	4200	2500	2791	3368	3440	3982	5791	5631
Adj. R–Square	0.492	0.367	0.381	0.351	0.329	0.333	0.269	0.253	0.247

Notes: Robust standard errors in parentheses. ***. ** and * denote significance at the 1. 5 and 10 percent level. respectively.

Endogenous variable: credit. Instruments: home ownership. cluster average levels of credit access by household types and household head occupation. education and job position

Table A4 Robustness check: alternative definition of access to credit (credit_12m) from 2006, IV estimates

	Medium-run	Short-run			
	10-16	pooled	06-08	10-12	13-15
Initial year variables (HH)					
Age	–0.002	–0.005 ***	–0.008 **	–0.007 ***	–0.002
	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)
Age sq	0.000	0.000 ***	0.000 **	0.000 ***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender (male)	0.009	0.031 ***	0.027	0.042 **	0.017
	(0.020)	(0.009)	(0.022)	(0.017)	(0.015)
Sec Edu	0.045 **	0.039 ***	0.066 ***	0.049 ***	0.029
	(0.022)	(0.010)	(0.024)	(0.019)	(0.018)
Ter Edu	0.096 ***	0.104 ***	0.129 ***	0.115 ***	0.069 ***
	(0.027)	(0.012)	(0.030)	(0.023)	(0.022)
Married	0.057 ***	0.049 ***	0.056 **	0.059 ***	0.022
	(0.021)	(0.009)	(0.023)	(0.018)	(0.017)
Russian	–0.020	–0.007	–0.012	–0.010	–0.001
	(0.029)	(0.012)	(0.029)	(0.024)	(0.021)
Initial year variables (H)					
credit_12m	0.264 ***	0.336 ***	0.356 ***	0.450 ***	0.149 *
	(0.090)	(0.040)	(0.076)	(0.085)	(0.080)
Rural	–0.062 **	–0.042 ***	–0.075 **	0.030	–0.053 **
	(0.028)	(0.013)	(0.032)	(0.025)	(0.022)
Size	0.028 ***	0.009 **	–0.007	0.020 ***	0.012 *
	(0.009)	(0.004)	(0.011)	(0.008)	(0.007)
Income Decile	–0.144 ***	–0.116 ***	–0.141 ***	–0.116 ***	–0.102 ***
	(0.004)	(0.002)	(0.005)	(0.004)	(0.004)
ht2 (A+C)	–0.046 *	–0.058 ***	–0.051 *	–0.068 ***	–0.065 ***
	(0.025)	(0.011)	(0.027)	(0.021)	(0.020)
ht3 (E +A/C)	–0.050 *	–0.023 **	–0.023	–0.024	–0.028
	(0.027)	(0.011)	(0.030)	(0.022)	(0.020)
ht4 (E)	–0.032	–0.103 ***	–0.162 ***	–0.072 ***	–0.097 ***
	(0.034)	(0.014)	(0.037)	(0.027)	(0.024)
% Self-employed	–0.054	0.024	0.044	0.037	–0.068
	(0.101)	(0.049)	(0.090)	(0.097)	(0.090)
% Unemployed	0.050	0.064	0.007	0.172 ***	–0.108
	(0.078)	(0.039)	(0.085)	(0.066)	(0.078)
% Manager	–0.010	–0.051	–0.015	0.003	–0.102
	(0.081)	(0.042)	(0.092)	(0.076)	(0.083)
% Professional	0.165 **	0.229 ***	0.321 ***	0.157 **	0.270 ***
	(0.067)	(0.036)	(0.073)	(0.064)	(0.079)
% Second job	0.178 ***	0.171 ***	0.231 ***	0.175 ***	0.139 ***
	(0.039)	(0.018)	(0.043)	(0.033)	(0.033)
% SME	0.043	–0.011	0.010	–0.005	–0.016
	(0.030)	(0.014)	(0.037)	(0.027)	(0.025)
% Public firms	0.110 ***	0.046 ***	0.066 *	0.049 *	0.030
	(0.032)	(0.015)	(0.035)	(0.028)	(0.027)
% Foreign firms	0.279 ***	0.281 ***	0.421 ***	0.471 ***	0.208 ***
	(0.097)	(0.044)	(0.105)	(0.094)	(0.076)

Change variables (H)										
Δ size	–0.027	***	–0.030	***	–0.033	**	–0.034	***	–0.043	***
	(0.009)		(0.006)		(0.015)		(0.011)		(0.011)	
Δ n children	–0.006		0.004		0.036		0.024		0.021	
	(0.019)		(0.014)		(0.035)		(0.027)		(0.023)	
Δ n unable work	0.003		0.035		–0.086		0.053		0.065	*
	(0.049)		(0.025)		(0.062)		(0.046)		(0.036)	
Δ n working	0.220	***	0.220	***	0.227	***	0.194	***	0.232	***
	(0.018)		(0.009)		(0.022)		(0.018)		(0.017)	
Δ n retired	0.014		–0.027	*	–0.076	*	–0.005		–0.015	
	(0.022)		(0.014)		(0.040)		(0.025)		(0.025)	
Constant	0.738	***	0.582	***	1.162	***	0.656	***	0.552	***
	(0.111)		(0.046)		(0.117)		(0.090)		(0.081)	
Region Dummies	Yes		Yes		Yes		Yes		Yes	
Year dummies			Yes							
Wu-Hausman endog. Test (F)	6.729	[0.009]	71.201	[0.000]	17.966	[0.000]	30.762	[0.002]	4.089	[0.043]
Test of joint sig. of instR. (F)	6.658	[0.009]	71.739	[0.000]	17.657	[0.000]	31.257	[0.003]	4.037	[0.044]
Test of overid. Restr. (X2)	2.497	[0.288]	1.920	[0.589]	1.360	[0.507]	0.091	[0.956]	6–625	[0.157]
Obs.	4200		20735		3982		5791		5631	
Adj. R-Square	0.346		0.239		0.242		0.182		0.237	

Notes: Robust standard errors in parentheses. ***. ** and * denote significance at the 1, 5 and 10 percent level, respectively. Endogenous variable: credit. Instruments: home ownership, cluster average levels of credit access by household types and household head occupation, education and job position.

Table A5 Credit access and labour supply (pooled sample 1996–2016), OLS estimates

	Intensive margin		H	Extensive margin			
	H head	H head	H	n work	% work	n male work	n fem work
Credit	1.168***		7.571***	0.140***	0.014***	0.088***	0.053***
	(0.117)		(0.327)	(0.006)	(0.002)	(0.004)	(0.004)
Credit * income V1		0.989***					
		(0.340)					
Credit * income V2		0.919***					
		(0.284)					
Credit * income V3		0.885***					
		(0.242)					
Credit * income V4		0.897***					
		(0.218)					
Credit * income V5		0.554**					
		(0.217)					
Age	0.405***	0.458***	–0.292***	–0.005***	–0.010***	0.011***	–0.016***
	(0.030)	(0.030)	(0.088)	(0.002)	(0.000)	(0.001)	(0.001)
Age sq.	–0.006***	–0.006***	0.000	0.000	0.000***	–0.000***	0.000***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Gender (male)	4.434***	4.216***	11.485***	0.182***	0.009***	–0.444***	0.626***
	(0.115)	(0.115)	(0.335)	(0.006)	(0.002)	(0.004)	(0.005)
Sec Edu	–0.950***	–1.265***	1.608***	0.062***	0.018***	0.034***	0.028***
	(0.193)	(0.192)	(0.533)	(0.010)	(0.003)	(0.007)	(0.006)
Ter Edu	–2.971***	–3.871***	2.026***	0.120***	0.039***	0.065***	0.056***
	(0.204)	(0.206)	(0.571)	(0.011)	(0.003)	(0.008)	(0.007)
Married	–0.369***	–0.719***	14.487***	0.331***	–0.041***	0.057***	0.275***
	(0.125)	(0.125)	(0.357)	(0.007)	(0.002)	(0.005)	(0.005)
Russian	–0.906***	–0.961***	–3.011***	–0.041***	0.006**	–0.008	–0.033***
	(0.180)	(0.179)	(0.524)	(0.010)	(0.003)	(0.007)	(0.006)
Rural	–0.221	0.084	–2.191***	–0.071***	–0.025***	–0.077***	0.006
	(0.223)	(0.222)	(0.580)	(0.011)	(0.003)	(0.008)	(0.008)
n. children	0.548***	0.807***	3.687***	0.000	–0.096***	–0.021***	0.022***
	(0.126)	(0.125)	(0.421)	(0.008)	(0.001)	(0.005)	(0.005)
ht2 (A+C)	–0.486**	–0.376*	–3.140***	–0.058***	–0.156***	0.018**	–0.077***
	(0.198)	(0.196)	(0.627)	(0.012)	(0.003)	(0.008)	(0.007)
ht3 (E +A/C)	–0.414**	–0.340**	–0.310	0.019**	–0.263***	0.024***	–0.005
	(0.164)	(0.163)	(0.492)	(0.010)	(0.002)	(0.007)	(0.007)
ht4 (E)	–0.136	0.248	–22.921***	–0.524***	–0.075***	–0.232***	–0.292***
	(0.445)	(0.441)	(0.971)	(0.019)	(0.009)	(0.015)	(0.012)
Hourly wage	–0.014***	–0.019***	–0.149***	–0.003***	–0.000***	–0.002***	–0.001***
	(0.001)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	39.172***	40.932***	68.453***	1.635***	1.012***	0.962***	0.673***
	(0.806)	(0.806)	(2.267)	(0.044)	(0.012)	(0.032)	(0.029)
Year/regional dummies	yes	yes	yes	yes	yes	yes	yes
Income ventile dummies		yes					
Obs.	56863	56863	58922	64249	64249	64249	64249
Adj. R-Squared	0.090	0.102	0.190	0.166	0.417	0.215	0.414

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

Table A6 Credit access and job satisfaction, household head (2002–2006), logit estimates

	job		earnings		conditions		opportunities	
Credit	1.046	**	1.042	**	1.015		1.050	**
	(0.020)		(0.021)		(0.020)		(0.020)	
Age	0.947	***	0.939	***	0.941	***	0.982	***
	(0.005)		(0.005)		(0.005)		(0.005)	
Age sq.	1.001	***	1.001	***	1.001	***	1.000	***
	(0.000)		(0.000)		(0.000)		(0.000)	
Gender (male)	0.993		1.084	***	0.862	***	0.968	
	(0.020)		(0.022)		(0.017)		(0.019)	
Sec Edu	1.209	***	1.160	***	1.212	***	1.244	***
	(0.036)		(0.037)		(0.035)		(0.038)	
Ter Edu	1.948	***	1.700	***	2.395	***	2.213	***
	(0.064)		(0.057)		(0.078)		(0.072)	
Married	1.196	***	1.217	***	1.104	***	1.202	***
	(0.026)		(0.027)		(0.024)		(0.026)	
Russian	1.099	***	0.999		1.080	**	1.054	*
	(0.033)		(0.031)		(0.033)		(0.031)	
Rural	0.922	**	0.898	***	0.828	***	0.939	*
	(0.032)		(0.032)		(0.029)		(0.032)	
n. children	0.997		1.028		0.968		1.010	
	(0.020)		(0.021)		(0.019)		(0.020)	
ht2 (A+C)	0.971		0.902	***	1.012		0.917	***
	(0.032)		(0.030)		(0.033)		(0.030)	
ht3 (E +A/C)	1.034		1.007		1.013		1.014	
	(0.031)		(0.031)		(0.031)		(0.030)	
ht4 (E)	1.043		0.998		1.109		1.112	
	(0.091)		(0.079)		(0.096)		(0.086)	
Constant	1.628	***	1.009		1.998	***	0.580	***
	(0.218)		(0.136)		(0.264)		(0.076)	
year/regional dummies	yes		yes		yes		yes	
Obs.	58148		58096		58145		58112	
Adj. R-Squared	0.046		0.041		0.057		0.046	

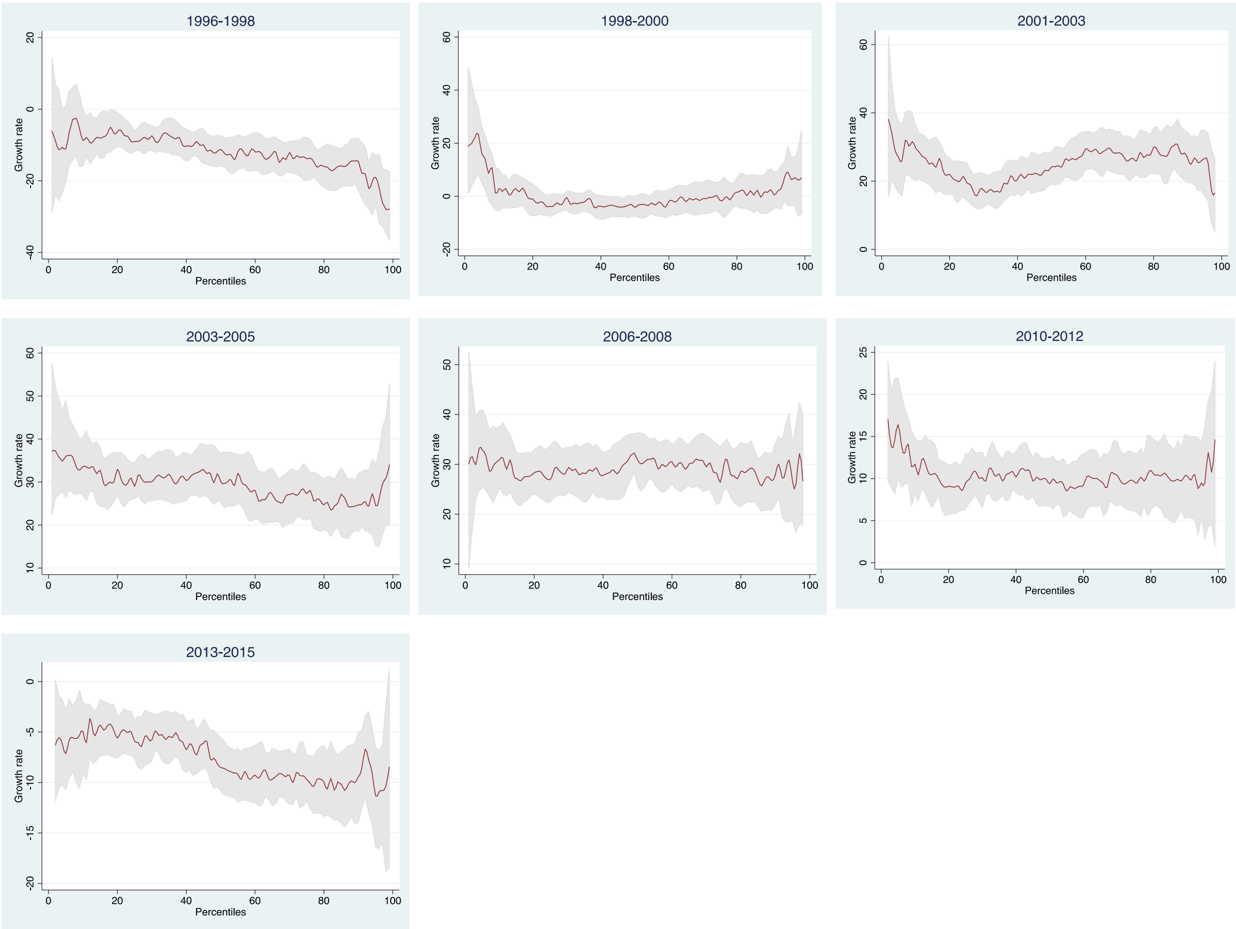
Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. Coefficients are odds ratios.

Table A7 Credit access and additional sources of incomes, (pooled sample 1996–2016), logit estimates

	rent/cap income		rent/cap income	
Credit	1.747 (0.120)	***		
Credit * income V1			0.796 (0.359)	
Credit * income V2			1.209 (0.313)	
Credit * income V3			1.565 (0.280)	**
Credit * income V4			1.490 (0.183)	***
Credit * income V5			1.743 (0.168)	***
Age	1.086 (0.024)	***	1.103 (0.026)	***
Age sq.	0.999 (0.000)	***	0.999 (0.000)	***
Gender (male)	0.805 (0.059)	***	0.771 (0.056)	***
Sec Edu	1.028 (0.130)		0.929 (0.118)	
Ter Edu	1.395 (0.182)	**	1.073 (0.142)	
Married	1.058 (0.086)		0.947 (0.077)	
Russian	1.269 (0.143)	**	1.263 (0.142)	**
Rural	0.690 (0.119)	**	0.776 (0.136)	
n. children	1.143 (0.071)	**	1.234 (0.076)	***
ht2 (A+C)	0.961 (0.108)		0.981 (0.109)	
ht3 (E +A/C)	0.962 (0.105)		1.000 (0.111)	
ht4 (E)	1.075 (0.375)		1.244 (0.436)	
Hourly wage	1.001 (0.000)	***	1.000 (0.000)	
Constant	0.000 (0.000)	***	0.001 (0.000)	***
Year/regional dummies	yes		yes	
Obs.	60473		60473	
Adj. R-Squared	0.077		0.094	

Notes: Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. Coefficients are odds ratios.

Figure A1 Growth Incidence Curves (GICs), short-run periods



Source: Own elaborations on RLMS data.