Breaking out of poverty traps:
Internal migration and interregional convergence in Russia[1]

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Abstract

We study barriers to labor mobility using panel data on gross region-to-region migration flows in Russia in 1996-2010. Using both parametric and semiparametric methods and controlling for region-to-region pairwise fixed effects, we find a non-monotonic relationship between income and migration. In richer regions, higher income results in lower migration outflows. However, in the poorest regions, increase in income results in *higher* emigration. This is consistent with the presence of the geographical poverty traps: potential migrants want to leave the poor regions but cannot afford to finance the move. We also show that economic growth and financial development have allowed most Russian regions to grow out of poverty traps bringing down interregional differentials of wages, incomes and unemployment rates.

Keywords: labor mobility, poverty traps, liquidity constraints

JEL classification: J61, R23.

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1. Introduction

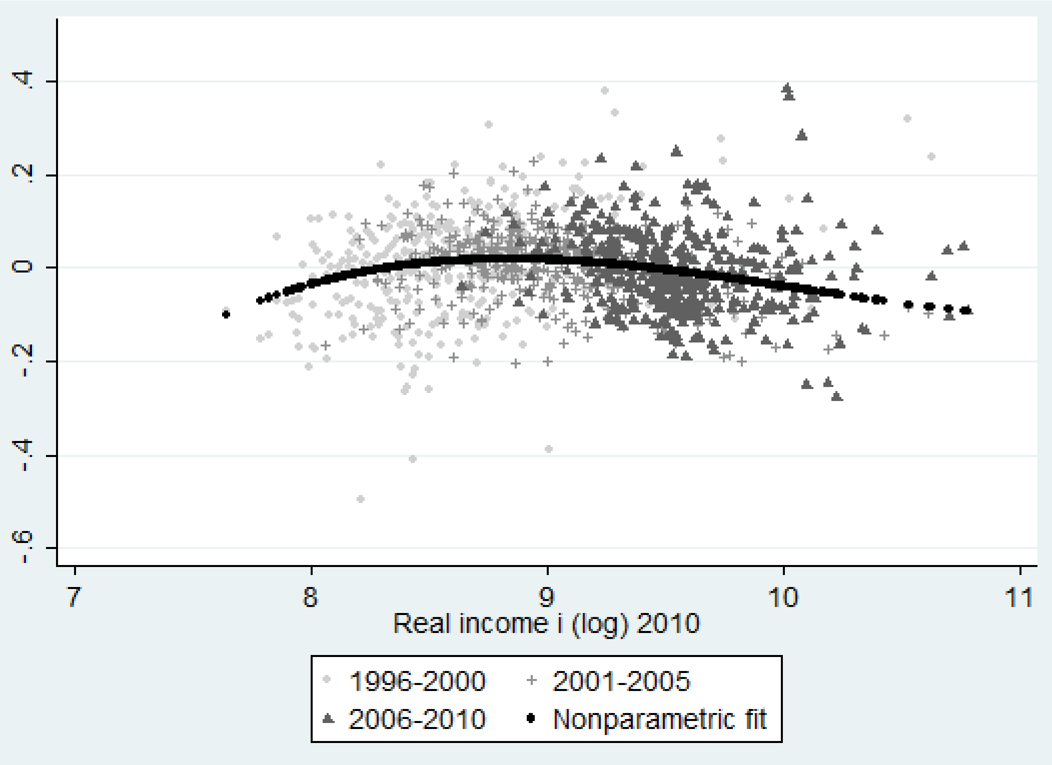
This paper is an empirical study of the barriers to labor mobility and of resulting geographical poverty traps. Labor mobility is one of the most important issues in economic development in terms of its impact on human welfare. Large differentials – both within and between countries – in incomes, living standards, productivity, public goods and other development outcomes imply high individual and social returns to migration (Human Development Report, 2009). However, the very fact that these differentials persist implies there are also substantial barriers to labor mobility. These barriers may be especially high for people with low earnings and assets. If financial markets are not developed, potential migrants with low incomes are locked in geographical poverty traps. Even though they are more likely to benefit from mobility they do not have cash to pay for the move.

Empirical analysis of such geographical poverty traps is a challenging task. By definition, we do not observe the actual costs of mobility for those potential migrants who cannot and therefore do not move. In order to quantify the barriers to mobility, we need to estimate the change of migration in response to change in external circumstances that allows breaking out of poverty traps at least for some potential migrants. The most obvious example of such an exogenous change is a substantial increase of income (keeping the moving costs constant). Such an increase in income should allow breaking out of poverty traps and therefore should result in higher migration outflows.

On the other hand, there is another effect of income on migration that works in the opposite direction. Controlling for income at destination, a higher income at home decreases the economic returns to migration. Therefore, in the presence of the poverty traps we should expect a non-monotonic (hill-shaped) relationship between income and migration outflows. For very low incomes, migrants are locked in poverty traps, so that we should find a positive effect of income on migration. For sufficiently high incomes there are no poverty traps so that the impact of income on migration is negative (due to lower incentives to leave).

In this paper we study interregional migration in Russia in 1996-2010 and do find such a non-monotonic relationship (see Figure 1). As we argue below, Russia offers a unique setting for an empirical study of barriers to migration and geographical poverty traps. First, due to the Soviet legacies, Russia started the transition from a command economy to market with a large potential for interregional migration. Second, while incomes of potential migrants were low in 1990s, they have grown substantially during 2000s (according to the IMF data, Russia's GDP per capita in constant prices grew by 80% between 1996 and 2010). As Figure 1 shows, in 1990s, many Russian regions where on the increasing branch of the non-monotonic curve. This is consistent with the presence of geographical poverty traps. In 2000s the growth in incomes was sufficient to move most regions over the peak of the relationship onto the decreasing branch. Poverty traps are no longer important; the effect of economic returns to migration dominates.

Figure 1. The non-monotonic relationship between income at the origin and interregional migration flows in Russia in 1996-2010.



Note: Vertical axis: residuals from the semiparametric model of log migration from region *i* to region *j* in a given year (equation (5) below), i.e. the differences between the logarithm of observed migration and the estimated parametric part of the specification. Horizontal axis: log real income in the origin region *i* in 2010 rubles. The graph shows the results of a semiparametric estimation controlling for region-to-region pairwise fixed effects, year dummies, income at destination and time-varying characteristics of regions *i* and *j* (including population, unemployment, provision of public goods, real estate market indicators etc.). The specification is described in Section 6.3. The dark dots represent the non-parametric fitted value of the relationship between migration and income in the origin region. The light dots, crosses and triangles are the actual observations for different periods (1996-2000, 2001-05, and 2006-10, respectively) averaged out for each value of the income at the origin region.

Our analysis allows quantifying the barriers to mobility that result in the emergence of the poverty traps. The peak in Figure 1 corresponds to the threshold of about $3000 per year. Our analysis implies that poverty traps are present only in those regions and years where and when the income is below this threshold.

We obtain this estimate using annual data on the gross migration flows between Russian regions in 1996-2010. Figure 1 shows the results of semiparametric specification where we estimate the non-parametric relationship between income at the origin region and migration flows controlling for region-to-region pairwise fixed effects, year dummies, income at destination, and time-varying characteristics of both origin region and destination region including population, provision of public goods, real estate market indicators and others. Controlling for pairwise fixed effects allows to take into account the distance between origin and destination and other time-invariant variables that can affect informational, cultural, or psychic costs of migration from region *i* to region *j* (e.g. due to historical affinity or differences in terms of language, religion, culture, or climate). Also, controlling for pairwise fixed effects automatically allows to control for regional fixed effects – e.g. region *i*'s cultural or psychic propensity to move or region *j*'s attractiveness to migrants.

In addition to the semiparametric estimation we also use parametric methods. We allow for a piece-wise linear and for a quadratic relationship between income and migration. In these specifications the relationship is also non-monotonic and hill-shaped. Moreover, both parametric methods deliver similar estimates for the peak of the relationship: about $3000 per year.

While the relationship between migration and income is non-monotonic for income at origin, there is no such relationship between migration and income at destination. This is intuitive: income at destination has nothing to do with poverty traps. A higher income at destination is associated with higher migration. Our other results are also predictable: migrants tend to go from regions with high unemployment and worse public goods to regions with low unemployment and better public goods.

We also run the estimations separately for subsamples of pairs of regions distant from and close to each other. We find that the non-monotonic relationship is driven by the long-distance migration rather than migration to nearby regions. This is intuitive as costs of migration are likely to be increasing with distance. We also provide additional evidence using the data on financial development of Russian regions. Unfortunately, these data are only available since 2001 (and some of the series start only in 2004). We find that financial development relaxes the financial constraints to mobility. In particular, the interaction term between the level of financial development and income has a negative effect on migration outflows. In financially developed regions, higher income is more likely to have a negative rather than positive impact on migration. In order words, poverty traps are less likely to emerge in the regions with more developed financial markets.

While the idea of the financial constraints and poverty traps in migration is not new (see Section 2 for the survey of the related literature), our paper is the first one to provide a direct quantitative estimate of parameters of the poverty traps using both semiparametric and parametric methods and panel data on gross migration flows.

Why is Russia in 1990s and 2000s a good testing ground for a study of migration and geographical poverty traps? It is a large and diverse country with a substantial potential for geographical labor reallocation. The initial allocation of population and physical capital at the beginning of transition was far from the spatial equilibrium in a market economy – thus creating a large potential for geographical labor reallocation. Before 1990s, Soviet industrialization policies often pursued political or geopolitical rather than economic goals. Even when they reflected economic realities, decision-making was distorted substantially by central planning, price controls and subsidies. Also, the allocation of production was intended to serve a different country – the Soviet Union (or even the whole socialist bloc) rather than Russia. This is why transition to market started out with an exogenous allocation of labor that was not driven by market forces. Not surprisingly, the transition had to involve moving millions of people across Russian regions. In 1995-2010 (see Figure 12 in the Appendix), some Russian regions lost tens of percents of their population due to migration with others gaining tens of percents. However, as our analysis shows that migration could have been even higher if not for the poverty traps.

The fact that initial allocation of factors of production was exogenous to the market equilibrium is one of our arguments why income and other right-hand side variables are not endogenous to migration flows. The other argument is that the average annual migration rate has only been the level of 0.5-1.0% of total population and therefore could hardly affect incomes and other socio-economic variables in the origin and destination regions. Finally, we also run regressions with lagged independent variables, as those are unlikely to be endogenous to current migration.

The rest of the paper is structured as follows. In the next Section, we discuss related literature. Section 3 provides a general background on the evolution of interregional differentials and interregional migration in Russia. We show that interregional differentials were high in 1990s when incomes were low and many regions were locked in geographical poverty traps. Moreover, these differentials were increasing rather than decreasing until early 2000s. Then, as incomes grew and geographical poverty traps became irrelevant, interregional convergence took place. Now, the interregional differentials are comparable to those in Europe. Section 4 describes a simple model of migration with heterogeneous workers and financial constraints. By aggregating migration decisions of individual workers we show that the relationship between the average income in the region of origin and the migration flow from this region is non-monotonic (namely, inverted-U-shaped). In Section 5, we discuss our empirical specifications and describe the data. In Section 6 we discuss the main empirical results. We compare the magnitudes of the parameters of poverty traps that we estimate through different parametric and semiparametric specifications; we find that three different methodologies provide strikingly similar results. In Section 7 we discuss additional evidence including regressions for subperiods and subsamples as well as regressions with proxies for financial development. Given that these variables are only available for a much shorter period of time, we present these results as additional evidence rather than include it into the main empirical section. In Section 8, we conclude and discuss avenues for further research.

2. Related literature

As the literature on internal migration is very large, in this Section we focus only on two strands of literature: first, the general equilibrium theory of spatial reallocation of labor, second, the papers that study the relationship between migration and income in the origin region (and the effect of liquidity constraints on migration).

Moretti (2011) provides a comprehensive survey of the general equilibrium models of spatial labor reallocation. In these models (starting from Rosen, 1979, and Roback, 1982) labor allocation, wages and rents are jointly determined endogenously taking into account incentives to move, equilibria in local labor markets and local real estate markets. More recent models (see also Klein, 2010) expand the theory to the case of heterogeneous skills and preferences of potential migrants. Depending on the assumptions on the elasticity of land supply, on firm entry, and on the production technology, the general equilibrium may have very different property in terms of response of wage to migration and the division of surplus between workers, firm owners and land owners. In our paper, we consider a partial equilibrium model. However, our analysis is consistent with the general equilibrium model in Kline (2010) who assumed that wages are determined by technology and do not depend on migration; also, supply of land is elastic so the returns to migration is appropriated by workers rather than by landowners. Our paper–both the model and the empirical exercise– belongs to the literature with workers' heterogeneity in terms of their skills (and therefore wages at home and at destination regions). We should emphasize that in the presence of financial constraints and therefore poverty traps, the spatial equilibrium may be different from the long-run general equilibrium described in the models above. In equilibrium with financial constraints, workers may be strictly better-off in regions with higher wages, better amenities and lower rents but end up in the regions with lower utility because they cannot finance the move.

The general theory of spatial labor allocation usually either focuses on the long-term equilibrium spatial allocation thus neglecting the migration costs – or takes a reduced-form view of these costs. If these costs do not depend on income, then the convergence to the long-term equilibrium proceeds in an intuitive way: migrants move from locations with lower wages, poorer amenities and expensive real estate to those with higher wages, better amenities and cheaper real estate. However, once we take into account potential migrants' financial constraints, the relationship between income and migration outflows may become non-monotonic – as suggested in the seminal paper by Banerjee and Kanbur (1981). An increase in income decreases the incentives to move but relaxes the financial constraints. In our paper, we develop these insights from Banerjee and Kanbur into a simple model of migration decisions of heterogeneous migrants under financial constraints.

Hatton and Williamson (2005) and Williamson (2006) argue that poverty traps and non-monotonic relationship between income and outgoing migration is not a new phenomenon but has been important for the long-distance migration in the last 200 years. In the times where there were no visa restrictions, poverty was a binding constraint on emigration. Williamson (2006) writes: "In fact, ever since 'free' mass migration started two centuries ago it has always been true that the richer of the poor regions, and the richer within poor regions, are the first to make the long distance move to the richest regions." This directly implies an inverse-U-shaped relationship between income of the sending country and migration flows. Williamson refers to such a non-monotonic relationship as the "Emigration Life Cycle" (Williamson, 2006, Figure 2). de Haas (2009) and Human Development Report

(2009) argue that financial constraints and poverty traps remain important for the modern international migration as well.

Andrienko and Guriev (2004) study internal migration in Russia in 1990s and show that in about 30% poorest regions of Russia (hosting about 30% of Russia's population) the potential outgoing migrants are indeed locked in a poverty trap. For these regions, an increase in income would result in relaxing the liquidity constraints and *higher* rather than lower outmigration. Our paper is different from Andrienko and Guriev in several respects. First, we extend the dataset to 2000s. This allows understanding the effect of overall economic growth and financial development (which took place in 2000s) on poverty traps. We find that most regions did break out of poverty traps in 2000s. Therefore the regional poverty traps were not just an artifact of certain unexplained Russia-specific factors but were indeed driven by low income and lack of financial development in 1990s. The very same regions that experienced a positive relationship between income and migration outflows, broke out of poverty traps and now have a negative relationship between income and migration. Second, the larger size of the dataset (our panel expands from 6 to 15 years) allows for additional evidence based on estimates for subperiods and subsamples of regions (e.g. short-haul vs. long-haul migration), as well as regressions with proxies for region-level financial development that were not available in 1990s. Finally, unlike Andrienko and Guriev (2004) we use both parametric and semiparametric methods. We find that both parametric and semiparametric methods provide the same quantitative estimates of the income threshold of the poverty trap.

Gerber (2006) analyzes the determinants of net (rather than gross) migration rates in 77 Russian regions. He finds that the positive effect of wages on net immigration is increasing over time. The importance of poverty traps in the early years of transition would weaken the positive effect of wages on net immigration. Indeed, in a poor region an increase in wages would result in increase in both immigration and outmigration (the latter due to overcoming the binding financial constraints). In later periods, as poverty traps became less important, the latter effect disappeared so the positive effect of wages became stronger.

McKenzie and Rapoport (2007) find a similar non-monotonic relationship between wealth and probability to migrate from Mexico to the US migration in communities with small migration networks. However, they show that liquidity constraints become less important for communities with larger networks. They use survey data and estimate linear model of probability to migrate with quadratic term for wealth and the interactions of wealth with migration network. Angelucci (2012) also finds the importance of financial constraints for Mexican migrants.

Phan and Coxhead (2010) analyze inter-provincial migration and inequality in Vietnam. They establish the importance of liquidity constraints for some provinces using semiparametric estimates for the impact of income in the sending province on migration. Michálek and Podolák (2010) analyze a relationship between socio-economic disparities and internal migration in Slovakia. They show that there are significant regional disparities in wage and unemployment in 1996-2007. However internal migration is relatively low. The authors suggest that the reason is liquidity constraints. Horváth (2007) finds similar results for internal migration of Czech population in 1992-2001 – most migration takes place between richer regions.

Golgher et al. (2008) and Golgher (2012) find that poor migrants in rural areas in Brazil have a limited range of options whether and/or where to migrate and are partially trapped in their home regions. The authors show that in the poor parts of Brazil there are substantial barriers to long-haul migration (even though short-haul migration is possible).

Djajic et al. (2013) consider international migration and show that the relationship between the source-country wage and emigration pressure is also hill-shaped. They test this inverted-U relationship for three different skill groups of migrants separately and find strong statistical evidence of it for low-skilled migrants.

Bazzi (2013) uses data on migration from Indonesian villages and uses rice price shocks and rainfall shocks as instruments for potential migrants' income. He does find a positive effect of agricultural income on migration outflows thus confirming the importance of liquidity constraints. Moreover, he shows that this effect is stronger in villages with a greater number of small landholders; this is also consistent with the importance of financial constraints as the small landholders are more likely to be willing to migrate but unable to finance the move.

Several recent papers use individual and household-level data. Beam et al. (2010) show the importance of financial constraints for the migration decision in the Philippines using randomized experiment at the household level. Beegle et al. (2011) follow a panel of individuals in Tanzania for 13 years and track the impact of mobility on their consumption. They find large returns to migration and therefore argue that there are substantial exit barriers for certain categories of potential migrants. They however find no evidence of the role of financial constraints. Abramitzky, Boustan and Eriksson (2012) study the effect of wealth on the decision to migrate, either internally or internationally, during the Age of Mass Migration (1850-1913) using data on 50 thousand Norwegian men. They estimate binary and multinomial logit models of migration choice. They explain the migration decision with various household characteristics including household assets. They do not find the evidence of liquidity constraints. In their data, parental wealth discourages migration. Apparently, wealth influenced the migration process through its effect on opportunities in the source country, rather than through the use of family resources to finance migration costs which were rather low. However, they suggest that today migration costs are much higher and liquidity constraints may be more important. Dustmann and Okatenko (2013) find positive relationship between individual migration propensities and individual assets in sub-Saharan Africa and Asia regions. Mendola (2008), Sharma and Zaman (2013) establish the importance of the budget constraints for the external migrants from Bangladesh, McDonald and Venezuela (2012) find the same for migrants from the Philippines.

Our work is also related to the literature on wage arrears in Russia in 1990s. Several papers use individual-level data on 1990s Russia to show that firms may strategically use and even aggravate employees' financial constraints through wage arrears and in-kind wages. Earle and Sabirianova (2002) show that Russian firms in 1990s did practice extensive wage arrears: a typical worker in 1995 faces half a year in overdue wages in 1995 and nine months in wage arrears in 1998). Earle and Sabirianova show that wage arrears were at least in part strategic decisions of employers. Friebel and Guriev (2005) find that these practices were more likely to take place in towns with higher monopsony power of employers. Furthermore, controlling for other determinants of mobility, the migration from such towns in mid-1990s was lower.

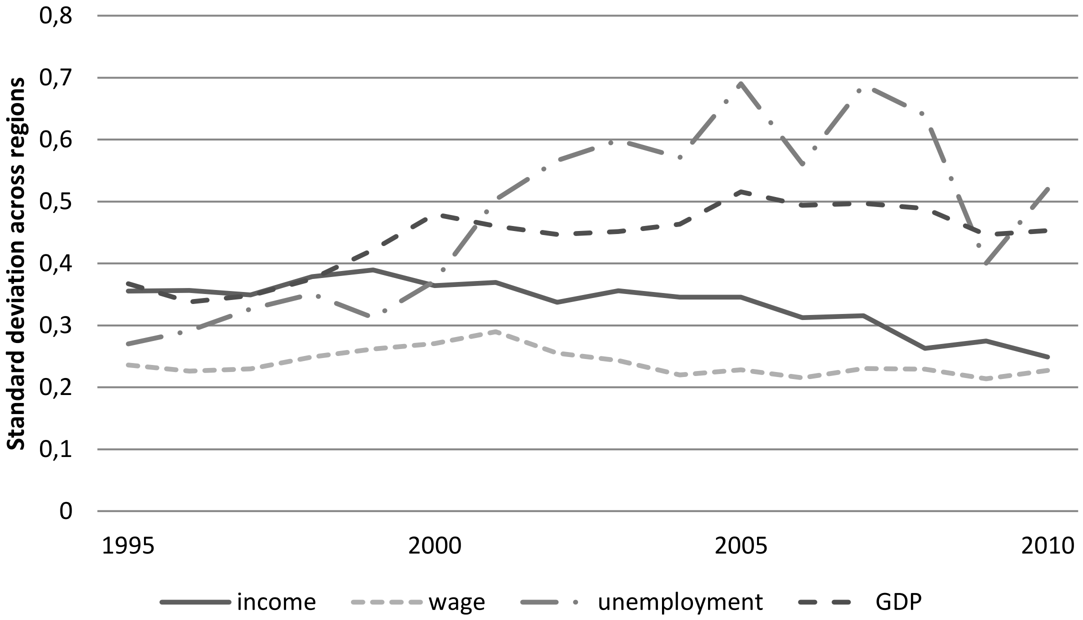
Our analysis of the relationship between migration and convergence is related to the literature on the decreasing internal migration rates in the US. Molloy, Smith and Wozniak (2011) provide an extensive survey of this literature and conclude that there is still no convincing explanation of the phenomenon. In particular, they show that the slowdown is not due to developments in demographics, labor and housing market. They conjecture that the reason may be that the potential for interregional migration is lower today than decades before – because of the completion of the "multidecade adjustment processes" or because of higher efficiency of working from home or because of more uniform geographical distribution of demand for skills.

We contribute to the literature in several ways. First, we use a major quasi-natural experiment of transition from command economy where the original allocation of labor was exogenous and different from the long-run market equilibrium. This creates a potential for migration and alleviates important endogeneity concerns. Second, our paper studies panel data on gross migration flows thus controlling for many important determinants of migration by including pairwise fixed effects and characteristics of both sending and receiving regions. Third, we use both parametric and semiparametric methods that produce similar quantitative estimates of barriers to mobility. Fourth, we document the change in external factors that allow migrants to overcome these barriers and break out of the regional poverty traps.

3. Interregional differentials, convergence and migration in Russia

In this section we discuss the basic trends in interregional differentials and migration in Russia. Figure 2 presents the interregional differentials in logarithms of incomes, wages, unemployment and GDP per capita. We use logarithms to make these differentials comparable across variables. This Figure shows that there was no convergence in GDP per capita, incomes, wages and unemployment rates in 1990s. If anything, the interregional differentials were increasing rather than decreasing. The situation changed dramatically in 2000s. Interregional differences in unemployment rates declined sharply in 2005-10. The convergence in incomes and wages started even earlier (around year 2000). The magnitude of convergence in 2000s is large: interregional dispersions of real incomes, real wages and unemployment rates declined by a third. As we argue below the fact that there is convergence in incomes and wages and no convergence in GDP per capita is consistent with falling barriers to mobility.

Figure 2. Differences between Russian regions in terms of logarithms of real incomes, real wages, unemployment, and real GDP per capita.[4]



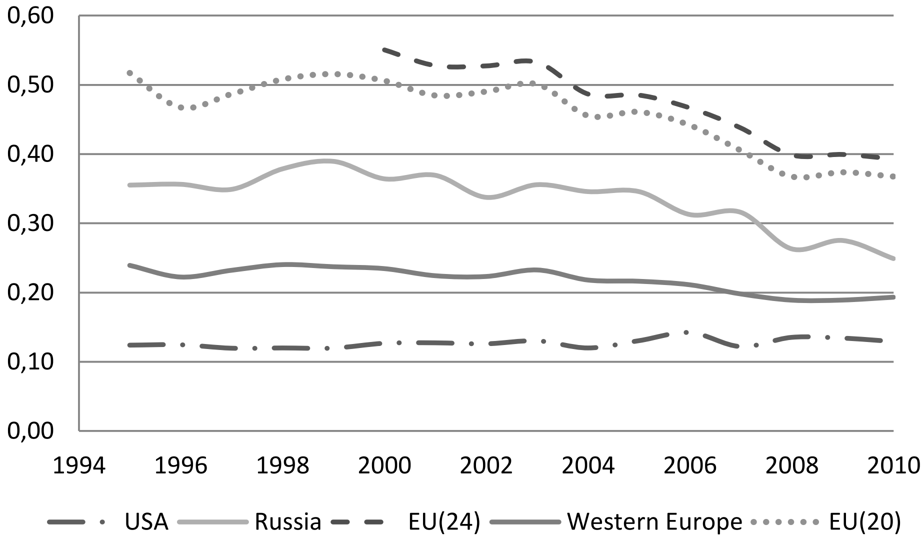
Note: The graph shows $\sqrt{\frac{1}{P}\sum_{i=1}^{N} P_i \left(X_{it} - \bar{X}_t \right)^2}$, where X_{it} is the log of real income (or real wage, or unemployment, or real GDP per capita) in region *i* in year *t*, and $\bar{X}_t$ is the population average log of real income (or real wage, or unemployment, or real GDP per capita, respectively) in year *t*. *P* and P_i are population of Russia and of region *i*, respectively.

Source: Rosstat's official data, authors' calculations.

Are these interregional differences still large compared to other countries? It turns out that while recent convergence in incomes did not make Russia as uniform as the US or Western Europe, differences in incomes between Russian regions are lower than the differences between subnational NUTS-2 units in the EU-24 (Figure 3). This is quite striking given that EU also had a decade of fast convergence.

[4]We calculate population-weighted measures of interregional differences in order to make our results internationally comparable. The results for the unweighted measures are very similar (available upon request).

Figure 3. Russian convergence in the international perspective: population-weighted standard deviation of logarithm of real income across subnational units in Russia, Europe and the United States.



Note: The graph shows $\sqrt{\frac{1}{P}\sum_{i=1}^{N} P_i\left(X_{it}-\bar{X}_t\right)^2}$, where X_{it} is the log of real income in region *i* in year *t*, and $\bar{X}_t$ is the average log of real income in year *t*. *P* and P_i are population of Russia and of region *i*, respectively.

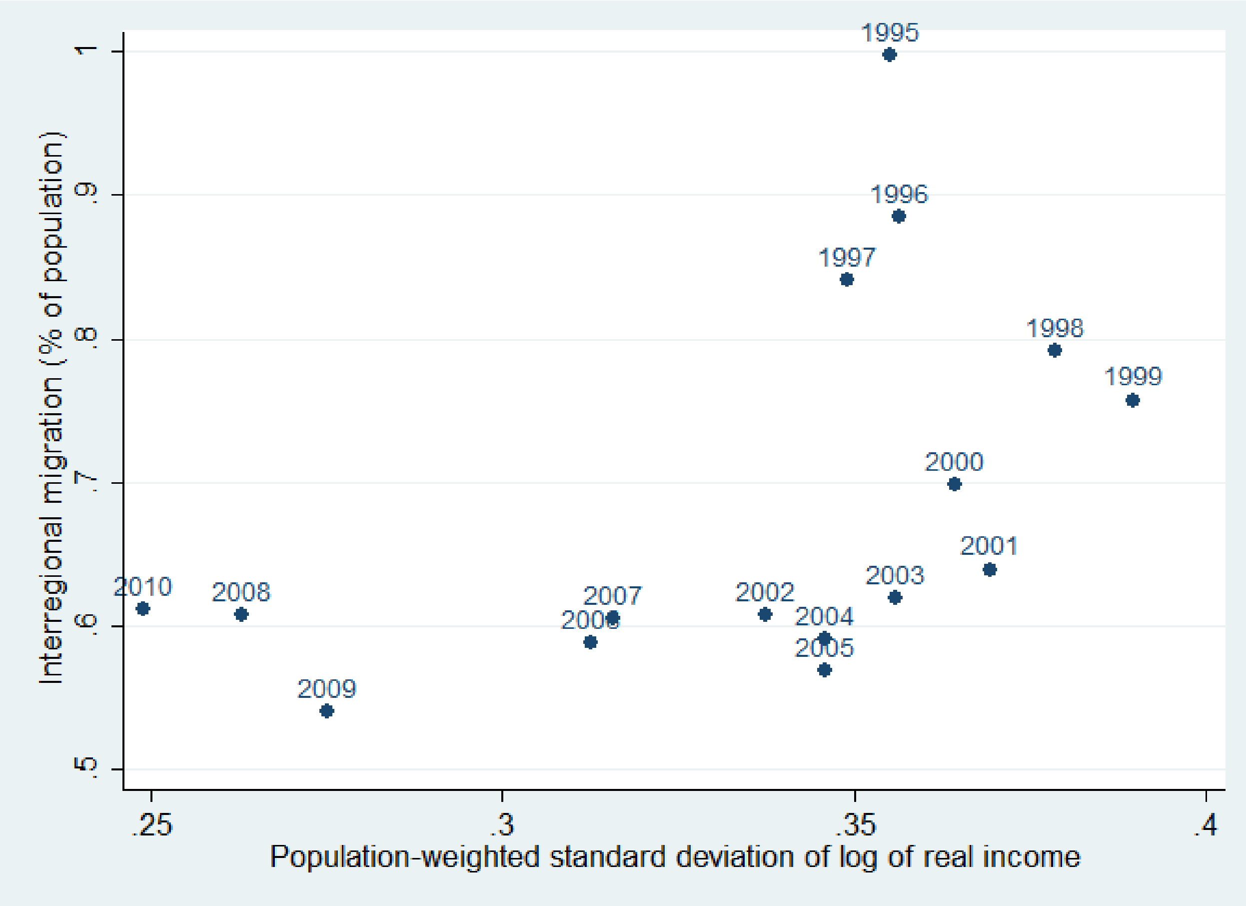
For the EU and Western Europe the unit of observation is NUTS-2 region (NUTS is the Nomenclature of Territorial Units for Statistics, a hierarchical system for collecting regional statistics in the EU). Average size of a NUTS-2 region is about 2.5 million people, average size of a Russian region is 1.8 million people.

EU (20): Belgium, Czech Republic, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Latvia, Lithuania, Netherlands, Austria, Poland, Portugal, Romania, Slovakia, Finland, Sweden, United Kingdom. EU (24): all European Union countries except Malta, Cyprus, Luxemburg. For EU (20) and EU (24) we consider only those NUTS-2 units for which data are available for every year. Western Europe: Austria, Belgium, Germany, Ireland, Greece, France, Italy, Netherlands, Portugal, Finland, Sweden, United Kingdom.

Data sources: Rosstat's official data, authors' calculations, Statistics Database of European Commission, Eurostathttp://epp.eurostat.ec.europa.eu (we use disposable income deflated to purchasing power standard based on final consumption per capita), US Census Bureau www.census.gov.

The interregional convergence in incomes in Russia was taking place along with the decreasing migration (Figure 4). This is consistent with the view that the lack of convergence in 1990s was explained by the high barriers to mobility. While many poor regions' residents were willing to migrate to richer regions, they were not able to as they simply were too poor to pay for the move. As the financial markets were underdeveloped, they also could not borrow to finance the move. In 2000s the situation changed: as Russians' incomes grew and Russia's financial markets developed, barriers to mobility and therefore poverty traps disappeared. Lower barriers to mobility resulted in the convergence between wages and incomes. Indeed, as the barriers to mobility decreased, a threat of mobility became more credible. The convergence in wages and incomes reduced the incentives to migrate – and the migration rates did decrease as well.

Figure 4. Interregional migration rates and interregional differences in real incomes.



Note: Population-weighted standard deviation of log of real income is $\sqrt{\frac{1}{P}\sum_{i=1}^{N} P_i\left(X_{it}-\bar{X}_t\right)^2}$, where X_{it} is the log of real income in region *i* in year *t*, and $\bar{X}_t$ is the population average log of real income in year *t*. *P* and P_i are population in Russia and region *i*, respectively.

4. A simple model of geographical poverty traps

In this section we develop a simple model with heterogeneous workers that captures the intuition for a non-monotonic relationship between average income at the region of origin and aggregate migration flows.

In the origin region (we will refer to the origin region as the "region i"), there is a continuum of workers. Workers vary in their skills and therefore incomes *y* in the origin region. The cumulative distribution function of income *y* is $F(y-y_m)$, where y_m is an exogenous parameter. The function F is normalized so that $Ey=y_m$ (i.e. the average income in the region is exactly y_m). We assume that the distribution F has a finite support $[y^L,y^H]$.

Each worker may move to the destination region ("region j"). For simplicity we assume that the income at destination *Y* is not correlated with the income at origin.

There are two periods. In the first period, a potential migrant earns income *y* in her home region and then decides whether to move or to stay. In the second period, her income depends on the first period's decision: either *y* if she stays in the origin region or *Y* if she moves to the destination region. Migration is costly: in order to move, the migrant has to pay *C* in cash. We assume that this cost is sufficiently small relative to the income at destination: $C<Y/2$.

Therefore, there are three possible outcomes:

1. If $y<C$, the migrant does not have cash to move. She stays in the home region, and receives y in the first period and in the second period. Her total payoff is therefore $2y$.
2. If $y\geq C$, the migrant may choose to migrate.
    a. If she migrates, she pays the cost C and in the second period she receives Y. Her total payoff is $y-C+Y$.
    b. If she stays, then in the second period she receives y. Her total payoff is $2y$.

Comparing cases 2a and 2b, we immediately find that the potential migrant prefers to migrate if $y-C+Y>2y$ (for simplicity we assume that in case of indifference over payoffs, the migrant stays put). Therefore migration takes place if and only if $y\geq C$ *and* $y<Y-C$.

As the income at origin y is distributed with the c.d.f. $F(y)$, the number of migrants is

$$M=F(Y-C)-F(C).$$

As we assumed above that $C<Y/2$, we have $Y-C>C$, so at least some people migrate.

Let us now carry out comparative statics with regard to a change in average income in the origin region y_m that we model as a shift of the whole income distribution. The analysis above implies

$$M'(y_m) = - f(Y-C-y_m) + f(C-y_m)$$

where $f=F'$ is the density function.

Now we can fully solve the model and find the impact of income on migration $M'(y_m)$ for all constellations of parameters. The solution depends on whether $Y-C-y^H$ is above or below $C-y^L$ (see Table 1). Let us discuss the intuition behind the results presented in the Table 1 for the case where $Y-C-y^H<C-y^L$. If the average income is very small $y_m< C-y^H$, then nobody can afford to migrate including the richest workers with $y=y_m+y^H<C$. As the income is growing further, at least some rich workers are both able to move $y_m+y^H>C$ and willing to move $y_m+ y^H< Y-C$. In this case, an increase in income results in higher migration. Further increase in income results in an ambiguous effect on migration: on one hand side, a greater number of poor workers are breaking out of poverty traps but fewer rich workers are willing to move. When average income increases further and $y_m + y^L$ exceeds C, the impact of income on migration is certainly negative: even the poorest workers are out of poverty traps and lower willingness to migration results in lower migration. Finally, when $y_m + y^L$ exceeds Y-C, migration comes down to zero as no workers are interested in migration.

For the second case, where $Y\text{-}C\text{-}y^H > C\text{-}y^L$ the analysis is similar with one major difference. There is a range of incomes when the poorest workers are already out of poverty traps $y_m + y^L > C$ and the richest workers are still poor enough to be interested in migration $y_m + y^H < Y\text{-}C$. In this range, all workers are both able and willing to migrate. Thus everybody migrates and the marginal effect of the change of income is trivial.

Table 1. Relationship between average income and migration for different levels of income in a region.

Case 1: $Y\text{-}C\text{-}y^H<C\text{-}y^L$		Case 2: $Y\text{-}C\text{-}y^H>C\text{-}y^L$	
Parameters	Outcome	Parameters	Outcome
$y_m< C\text{-}y^H$	$M'(y_m)=0$, $M=0$, nobody can migrate	$y_m< C\text{-}y^H$	$M'(y_m)=0$, $M=0$, nobody can migrate
$C\text{-}y^H<y_m< Y\text{-}C\text{-}y^H$	$M'(y_m)>0$	$C\text{-}y^H<y_m< C\text{-}y^L$	$M'(y_m)>0$
$Y\text{-}C\text{-}y^H<y_m< C\text{-}y^L$	$M'(y_m)$ may be either positive or negative[5]	$C\text{-}y^L<y_m< Y\text{-}C\text{-}y^H$	$M'(y_m)=0$, $M=1$, everybody migrates
$C\text{-}y^L<y_m< Y\text{-}C\text{-}y^L$	$M'(y_m)<0$	$Y\text{-}C\text{-}y^H<y_m< Y\text{-}C\text{-}y^L$	$M'(y_m)<0$
$Y\text{-}C\text{-}y^L<y_m$	$M'(y_m)=0$, $M=0$, nobody wants to migrate	$Y\text{-}C\text{-}y^L<y_m$	$M'(y_m)=0$, $M=0$, nobody wants to migrate

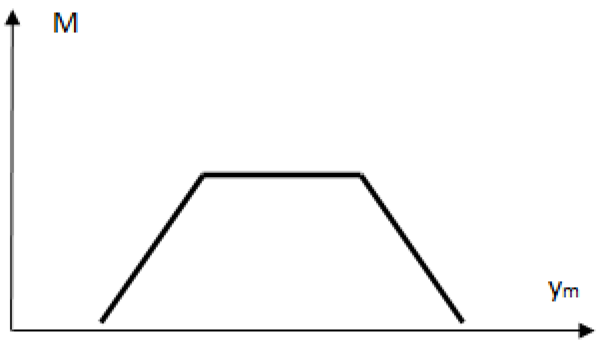
In both cases, the relationship between average income in the origin region and the migration flow is non-monotonic. As the whole income distribution moves to the right, first M increases, then stays constant (in the Case 2) or its monotonicity is not determined (in the Case 1), then M certainly decreases. This result is similar to Proposition 1 in Bazzi (2013) whose model also takes into account the impact of migration costs on heterogeneous workers' willingness and ability to migrate.

The Figure 5 illustrates the relationship for the Case 2 ($Y\text{-}C\text{-}y^H>C\text{-}y^L$). In the Case 1 ($Y\text{-}C\text{-}y^H<C\text{-}y^L$), the middle range of the graph is flat only if the distribution is uniform: in this case, as the average income y_m increases, the number of migrants who break out of the poverty trap and

[5] If the distribution is uniform, $M'(y_m)=0$

emigrate equals exactly the number of people who lose their willingness to migrate. If the distribution is not uniform, the middle range of the graph does not have to be flat.

Figure 5. Migration as a function of the mean income at origin for the case of the uniform distribution of incomes at origin (for the case $Y\text{-}C\text{-}y^H > C\text{-}y^L$).



Also, the decreasing and increasing parts of the relationship may be non-linear (they are precisely linear only for the uniform distribution). But the model predicts with certainty that there is an increasing part for low y_m (for $y_m < \min\{C\text{-}y^L, Y\text{-}C\text{-}y^H\}$), and there is a decreasing part for high y_m(for $y_m > \max\{C\text{-}y^L, Y\text{-}C\text{-}y^H\}$).

Notice that we follow Kline (2010) in making two important assumptions. First, wages in the destination region are driven by productivity and do not depend on the migration decisions. Second, the supply of real estate in the host region is perfectly elastic; therefore rents also do not depend on migration. Both assumptions are realistic in the context of Russia where migration flows are small, and wages and rents are therefore unlikely to change because of migration.

Unlike Bazzi (2013, Proposition 2), we do not make predictions regarding the impact of inequality on the relationship between income and migration. In our model, the effect of inequality on $M(y_m)$ depends on the functional form of the distribution. Even for the simple case of the uniform distribution (Figure 5), the effect of inequality on $M'(y_m)$ is highly non-linear and hard to test empirically.

5. Empirical specifications and data

5.1. Empirical specifications

We estimate a modified gravity model assuming that migration flows depend positively on the population of both the sending region i and the receiving region j and decreases with the distance between two regions (similarly to the force of gravity between two bodies being proportional to masses of the two bodies and decreasing with distance between them). We use the following log-linear specification of the modified gravity model:

$$\ln M_{i,j,t} = \alpha_{i,j} + \phi \ln income_{i,t} + \varphi \ln income_{j,t} + \sum_{k \in K} \gamma_k \ln X_{k,i,t} + \sum_{k \in K} \delta_k \ln X_{k,j,t} + \sum_{t \in T} \theta_t + \varepsilon_{i,j,t} \quad (1)$$

The dependent variable is the logarithm of the number of migrants who move from region i to region j in year *t.*[6] In order to control for distance, initial conditions and legacies, we include fixed effects $\alpha_{i,j}$ for each pair of regions. We will assume throughout the paper that error terms are not correlated with explanatory variables and fixed effects, and are not serially correlated, so the fixed-effects estimation is not biased.

$X_{k,i,t}$ and $X_{k,j,t}$ are vectors of characteristics of the source and host regions that may change over time, such as population, unemployment rate, characteristics of the housing market (housing price, new flats constructed, square meters of housing per capita), demographic structure (log population, share of young people, share of older people in the population), provision of public goods, e.g., roads, healthcare (doctors per capita and hospital beds per capita), public transportation (buses per capita), education (number of students per capita), inequality and others. These variables include all time-varying factors that may affect productivity and returns to migration, including amenities, human capital and infrastructure. Our model's predictions are related to impact of the change of average income keeping relative income distribution constant; this is why we also control for the changes in Gini coefficients. We also include time dummies to control for common shocks (e.g. changes in macroeconomic environment).

The key variables are $\ln income_{i,t}$ and $\ln income_{j,t}$, the logarithms of per capita real income in the origin and destination regions, correspondingly.

The specification (1) does not automatically rule out endogeneity. Certain right-hand side variables (including income, unemployment, public goods) may depend on migration. We believe however that these effects are negligible since—as shown in Figure 4—migration in Russia is very small (0.5-1.0 per cent of population per year). [7]

As we are especially interested in the effects of liquidity constraints and poverty traps, we will also include squared real per capita income for the sending regions. In the previous Section we discussed why the existence of poverty traps implies a non-monotonic relationship between the income at the origin and the intensity of migration. If financial

[6]The log specification cannot deal with trivial observations. We add 0.5 to all observations. Only 1.7% of observations in the sample have zero number of migrants.
[7] Akhmedov et al. (2005) estimate the labor demand elasticity in Russia at 0.4. Therefore migration of 0.5% results in a decrease in price of 0.5/0.4=1.25%. This is an order of magnitude below the average absolute value of the change in the real wage per year in our data (9.4%).

markets are developed and there are no liquidity constraints then coefficient ϕ should be negative and coefficient φ should be positive. Migration increases with the income at destination and decreases with the income at origin. However, as discussed in the previous Section, in the presence of financial constraints, the coefficient ϕ should be positive for the poorer regions. The relationship between migration and income in origin region $\ln income_{i,t}$ is therefore non-monotonic (as in Figure 5). The simplest way to model such relationship is a regression with the squared log income. Thus, to test the presence of the non-monotonic relationship, we add $(\ln income_{i,t})^2$ to specification (1). Our model predicts a negative coefficient at the squared term.

Another approach to modeling the non-monotonic relationship is the regression with a structural break. Our model (Section 4) implies that for high incomes the slope of the relationship between income in the sending region and migration is negative while for the low incomes the slope is positive. For simplicity, we approximate this relationship with just one kink and run the following regression:

$$\begin{aligned}\ln M_{i,j,t} &= \alpha_{i,j} + a\left(\ln income_{i,t} - \gamma\right) I\left(\ln income_{i,t} \le \gamma\right) + \\ &+ b\left(\ln income_{i,t} - \gamma\right) I\left(\ln income_{i,t} > \gamma\right) + controls_{i,t} + \varepsilon_{i,j,t}\end{aligned} \tag{2}$$

where $I(\cdot)$ is the indicator function, γ is the threshold at which the kink takes place. The specification (2) can also be rewritten as follows:

$$\ln M_{i,j,t} = \begin{cases} \alpha_{i,j} + a\left(\ln income_{i,t} - \gamma\right) + controls_{i,t} + \varepsilon_{i,j,t}, & \ln income_{i,t} \le \gamma, \\ \alpha_{i,j} + b\left(\ln income_{i,t} - \gamma\right) + controls_{i,t} + \varepsilon_{i,j,t}, & \ln income_{i,t} > \gamma. \end{cases}$$

There are two regimes: “before” (to the left of) the threshold: $\ln income_{i,t} \le \gamma$, and “after”(to the right of) the threshold: $\ln income_{i,t} > \gamma$. Our model (in Section 3) would be consistent with the data as long as for some threshold γ we have *b*<0<*a*, and both *a* and *b* are significantly different from zero.

In order to estimate model (2) we use the least squares estimation for transform variables (Hansen, 1999) to extract fixed individual effects (3).

$$\ln M^{*}_{i,j,t} = \beta \ln income^{*}_{i,t}\left(\gamma\right) + controls_{i,t}{}^{*} + \varepsilon^{*}_{i,j,t} \tag{3}$$

where $\ln M^{*}_{i,j,t} = \ln M_{i,j,t} - T^{-1}\sum_{t=1}^{T} \ln M_{i,j,t}$,

$\ln income^{*}_{i,t}\left(\gamma\right) = \begin{pmatrix} \ln income_{i,t} - T^{-1}\sum_{t=1}^{T} \ln income_{i,t} I\left(\ln income_{i,t} \le \gamma\right) \\ \ln income_{i,t} - T^{-1}\sum_{t=1}^{T} \ln income_{i,t} I\left(\ln income_{i,t} > \gamma\right) \end{pmatrix}$ and

$\varepsilon^{*}_{i,j,t} = \varepsilon_{i,j,t} - T^{-1}\sum_{t=1}^{T} \varepsilon_{i,j,t}$, T=15 is the number of years. Therefore, we carry out the transformation of the income variable separately "before" and "after" the threshold point γ. For all other variables we use the conventional within transformation.

Finally, we also use a more flexible, semiparametric, approach to estimating the non-monotonic relationship between migration and income. We assume that there is a parametric relationship between migration and all variables except income in the sending region while the relationship between migration and the income in the sending region is non-parametric:

$$\ln M_{i,j,t} = \alpha_{i,j} + f\left(\ln income_{i,t}\right) + \varphi \ln income_{j,t} + \sum_{k \in K} \gamma_k \ln X_{k,i,t} + \sum_{k \in K} \delta_k \ln X_{k,j,t} + \sum_{t \in T} \theta_t year_t + \varepsilon_{i,j,t} \quad (4)$$

Our approach is based on Baltagi and Li (2002). We use the "xtsemipar" Stata command (Libois and Verardi, 2012). To obtain the non-parametric fit, we use B-splines (Newson, 2001). Following Baltagi and Li (2002), we estimate the curve *f* by regressing residuals from equation (4) on log income in the sending region

$$\hat{\varepsilon}_{i,j,t} = \ln M_{i,j,t} - \hat{\alpha}_{i,j} - \hat{\varphi} \ln income_{j,t} - \sum_{k \in K} \hat{\gamma}_k \ln X_{k,i,t} - \sum_{k \in K} \hat{\delta}_k \ln X_{k,j,t} - \sum_{t \in T} \hat{\theta}_t year_t \quad (5)$$

using a standard non-parametric regression estimator.

To obtain the estimates of the individual fixed effects $\hat{\alpha}_{i,j}$ and regression coefficients, we follow Baltagi and Li's approach and estimate model (4) in first differences using ordinary least squares and approximate first difference of unknown function *f* by series $p^k(\ln income_i)$. Here $p^k(\ln income_i)$ are the first *k* terms of a sequence of functions $p^1(\ln income_i)$, $p^2(\ln income_i)$, etc.

In order to understand the role of financial development, we include an interaction between income and financial development (and control for financial development directly). If our hypothesis of the importance of financial development is correct, we should find that financial development relaxes the liquidity constraints; thus, the positive effect of income in sending regions on migration is less likely. In other words, our theory predicts a negative coefficient at the interaction of financial development and income at the origin region. Unfortunately, the data on financial development only start in 2001 so we present the regressions with financial development as additional evidence (in Section 7).

5.2. Data

We use official data on income per capita, the unemployment rate, GDP and different characteristics of quality of life and economic activity which we mentioned in the previous at the regional level from the Russian Statistical Service (Rosstat, www.gks.ru) for the period of

1995-2010 for 78 regions.[8] We exclude the Republic of Ingushetia and the Republic of Chechnya due to the unavailability of data, as well as 9 autonomous districts (Nenets, Komi-Permyak, Khanty-Mansi, Yamalo-Nenets, Taimyr, Evenk, Ust-Orda Buryat, Agin-Buryat, and Koryak) which are administrative parts of other regions. We restrict ourselves to 1996-2010 as there are no reliable data on deflators before 1995 and because as Rosstat changed methodology of measuring interregional migration before 1996 and after 2010.

In order to take into account price level differences, we deflate incomes by the regional consumer price index (CPI). This allows us to control for region-specific inflation rates that are sufficient for regression models with fixed effects (Section 6).

We use data on incomes rather than on household assets as the latter are not available. However, various sources indicate that the liquid assets of the Russian households during the period of 1996-2010 were very low or virtually trivial, especially in the beginning of transition. During the Soviet times most assets were owned by the state. The personal savings were destroyed by hyperinflation of 1992. The main asset of Russian households – housing – was given to them for free in 1990s but the size (16 and 23 square meters per capita in 1990 and in 2010, respectively) and the quality of this real estate was so poor that the market value of housing remained very small. This is especially true outside Moscow and Saint Petersburg – and even more so in depressed regions where potential migrants want to leave from.[9] The Global Wealth Report (2012) estimates the average value of Russian real estate in 2012 at about $8,000 per adult (about half of the annual GDP per capita). The very same report estimates the average financial assets at only $4000 per adult. Moreover, if one takes into account the acute wealth inequality in Russia (highest in the world except for small Caribbean nations, according to the Global Wealth Report) the median personal wealth is even lower – about $1200 per adult or less than 10% of annual GDP per capita (Global Wealth Report, 2012). The fact that the household assets are very low helps identifying the importance of financial constraints as a barrier to mobility and makes income the key proxy for the ability to move.

We analyze interregional migration data for the period from 1996 to 2010 using region-to-region annual migration flows. These data are collected by the Interior Ministry and are available—albeit not free of charge—from Rosstat. These data reflect the official count of

[8] In some specifications, data on Chukotka are not available. In these cases we have 77 regions.

[9] An important feature of Soviet industrialization was the geographical concentration of production. Believing in economy of scale rather than in competition, Soviet planners have created many one-company towns (which are defined in Russia as settlements where at least 25% employment is within a single firm). Even in 2010, the Russian government's Program for the Support of Monotowns listed 335 monotowns (out of the total of 1099 Russia's towns and cities); their population accounts for a *quarter* of Russia's urban population. In such towns, the largest employer's financial difficulties directly suppress housing prices and further undermine potential migrants' ability to move out (see Friebel and Guriev, 2005).

registered migrants (i.e. of those people who change their registration in this particular year).

We end up with 77*77 observations every year. (We have data on migration for 78 regions but we exclude Chukotka as there are no data for many explanatory variables for this region). Table 6 in the Appendix provides the summary statistics and definition of all the variables we use in our regressions.

As a proxy for financial development we use the ratio of outstanding loans to households and to firms to GDP. Unfortunately, reliable and consistent data on financial development only start in 2001 (and data on mortgages only begin in 2004) so our analysis of the impact of financial development is necessarily limited to 2001-2010. Figure 13 in the Appendix shows that all the indicators of financial development have grown substantially in 2001-2008 and then declined slightly as a result of financial crisis in 2009-10. At the peak, in 2009 the stock of loans to firms, households and mortgage debt was 29%, 14.6% and 3.3% of GDP, correspondingly. This is an impressive growth given that in 2001 lending to households (including mortgages) were essentially trivial, and the loans to firms were only 7% of GDP.

6. Empirical results

In this section we present the results of parametric and semiparametric specifications and then compare the estimates obtained through different methods.

6.1. Linear and quadratic specifications

Table 2 presents the main results for the specification (1). In column 1 we run the specification with linear terms for log income. In column 2, we add squared log income – in order to test for non-monotonicity of the relationship between income and migration. In columns 3 and 4 we re-run specifications 1 and 2 excluding Moscow and Saint Petersburg. Moscow and Saint Petersburg are the only two region-cities in Russia; they are a destination of choice for migrants from all other regions. Therefore, it is important to check whether the results are robust to excluding these two cities.

The main focus of our analysis is on the role of income of the sending region. The first specification (that only includes a linear term) shows that the average effect of income is insignificant. However, once we add a squared income term, we see that the relationship between income and out-migration is non-monotonic: the effect of income on out-migration is positive in poorer regions and negative in richer regions (as predicted by the model). Based on the coefficients at income and at squared income we calculate the peak of the quadratic relationship at 9.2. Using simulation methods for the joint distribution of the coefficients we find that the confidence interval for the peak of the quadratic relationship is (8.7, 10.0).

The effect of income in the receiving region on migration flow is positive. When we add the squared income, the coefficient at the squared income is negative but small. In other words, migrants prefer to move to higher-income regions, but there is a satiation effect. The peak of this quadratic relationship is at 12; this is above any regional incomes in our dataset – thus the effect of income in the receiving region is positive for all region-to-regions migrations in Russia in 1996-2010.

Other coefficients are generally consistent with the gravity model. Migration is correlated with population of both sending and receiving regions – with coefficients being significantly larger than 1. The coefficients at the proxies for public goods, amenities and quality of life are also generally intuitive. People move from regions with high unemployment and infant mortality to regions with low unemployment and infant mortality. Migrants prefer regions with a greater number of doctors and hospital beds per capita. Migrants also prefer regions with higher proportion of women, students, young and old people. They move from regions with higher highway density and higher number of buses per capita (both are measures of costs of mobility). The effects of public goods and demographics should not be overinterpreted however as the measures of public goods provisions co-move together and may reflect omitted variables related to both regional and federal fiscal policy. For the sake of brevity, we do not discuss the role of the public goods in detail. However, we do include these variables in all regressions to control for potential heterogeneity.

We also control for the income distribution through including Gini coefficient for income. The coefficients are significant and negative for both origin and destination regions. The negative coefficient for the destination region probably reflects the aversion to inequality (migrants prefer to migrate to more equal regions). The negative coefficient for the sending region is consistent with importance of poverty traps: those who would like to migrate are probably in the lower income quantiles. Controlling for the average income in the region, a higher Gini coefficient implies that these potential migrants are more likely to be poor and therefore less likely to be able to move.

We include two measures of the real estate market development: availability of housing (in square meters per capita) and price of real estate (in CPI-adjusted rubles per square meter). The effect of real estate market is consistent with the importance of financial constraints – as well as with the existence of Tiebout competition. Migrants leave regions with lower housing prices in favor of regions with higher housing prices. Controlling for income, housing price (in real terms) reflects quality of life. The availability of housing (per capita in square meters) positively affects both the arrivals and the departures of migrants (as the real estate is the most important asset and therefore collateral for most households.

We also include newly constructed flats (using a three-year moving average) but do not find any significant effect.

Table 2. Results of regressions (1) with and without squared terms of log of income. Dependent variable: log of migration.

	1	2	3	4
VARIABLES	Main	With squared income	Without Moscow and Saint Petersburg	Without Moscow and St Petersburg, w/ sq. income
Population i (log)	1.75***	1.80***	1.57***	1.63***
	(0.10)	(0.10)	(0.11)	(0.11)
Population j (log)	1.96***	2.00***	1.74***	1.73***
	(0.10)	(0.10)	(0.10)	(0.11)
Income i (log)	0.03	0.76***	-0.03	0.45**
	(0.02)	(0.16)	(0.02)	(0.19)
Income squared i (log)		-0.04***		-0.03**
		(0.01)		(0.01)
Income j (log)	0.18***	0.70***	0.17***	0.15
	(0.02)	(0.17)	(0.02)	(0.20)
Income squared j (log)		-0.03***		0.00
		(0.01)		(0.01)
Gini i (log)	-0.08*	-0.08*	-0.09**	-0.09**
	(0.04)	(0.04)	(0.05)	(0.05)
Gini j (log)	-0.12***	-0.12***	-0.14***	-0.14***
	(0.04)	(0.04)	(0.05)	(0.05)
Unemployment rate I (log)	0.06***	0.06***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Unemployment rate j (log)	-0.07***	-0.07***	-0.07***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Housing price i (log)	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Housing price j (log)	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Provision of housing i (log)	0.41***	0.40***	0.15*	0.15*
	(0.08)	(0.08)	(0.09)	(0.09)
Provision of housing j (log)	0.62***	0.61***	0.61***	0.61***
	(0.08)	(0.08)	(0.09)	(0.09)
New flats i (moving average, log)	-0.01	-0.002	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
New flats j (moving average log)	-0.01	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	84,666	84,666	80,222	80,222
R2-within	0.308	0.308	0.309	0.310
Number of pairs	5,929	5,929	5,625	5,625

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Variables included in the model but not reported in the table: life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

6.2. Piecewise-linear specification

In the previous section we reported the results with quadratic specifications that imply that the relationship between migration and income in the sending region is non-monotonic. In regions with low incomes, a higher income is associated with higher out-migration – these are the regions in a poverty trap. However, the quadratic specification results in a large confidence interval for the peak of the income-migration relationship. In this subsection, we use a more straightforward method and consider a piecewise-linear specification.

We estimate (3) for different thresholds g. Finally, we find $\hat{g}$ as the threshold with the minimum residual sum of squares (RSS) from equation (3). The minimum RSS is at log real income equal to $\hat{g}=9.0$. Using Hansen's methodology, we test the hypothesis of the significance threshold. The test statistic is F1=112.7, p-value is 0.000. [10] Therefore there are indeed two 'regimes'. We have also tested hypothesis of two thresholds, however, we did not find significant results.

We estimate the 95% confidence interval for the threshold and find that it is (8.9, 9).[11]

Figure 6 presents the coefficient at income to the left of the threshold (coefficient *a*) and coefficient at income to the right of the threshold (coefficient *b*) for different levels of thresholds. We see that for all thresholds below 9.1 the coefficients are consistent with our theory. If income is low, its effect on outward migration is positive (coefficient *a*). If income is high (above the threshold), its effect on outward migration is negative.

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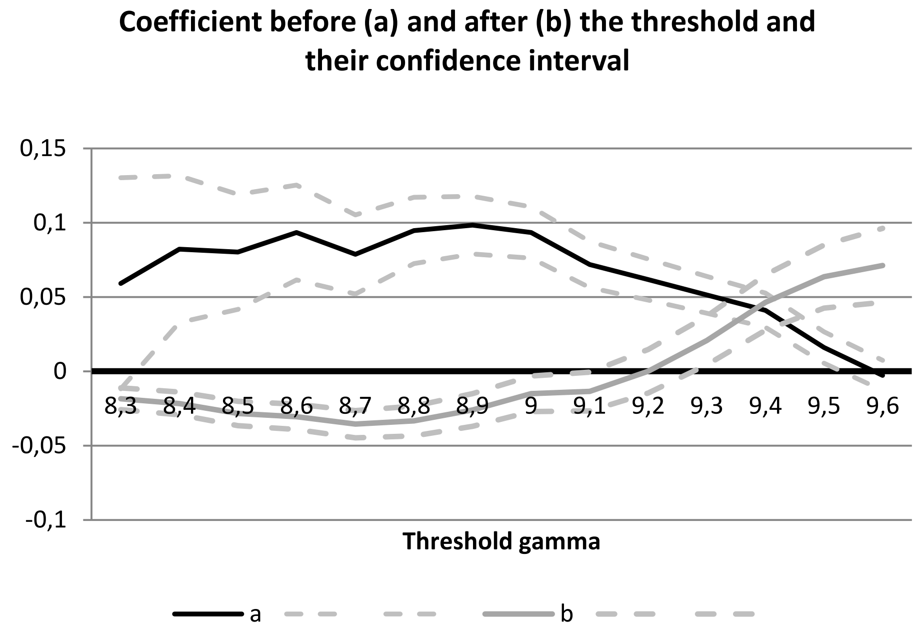
[10]Using bootstrap procedure (Hansen, 1999), we calculate 10%, 5%, 1% critical values for likelihood ratio test. They are 63.2, 68.9, and 80.8, correspondingly.

[11] Confidence interval is defined as a threshold parameter for which likelihood ratio is below the 5% critical value (7.35). This rule and critical value are from Hansen (1999). In our case likelihood ratio is testing null hypothesis that $g=9$.

Figure 6. Results for regressions with structural break for different threshold levels.



Note: Coefficients *a* and *b* represent the relationship between log of migration flow and log of income per capita to the left of the threshold and to the right of the threshold in the regression (2).

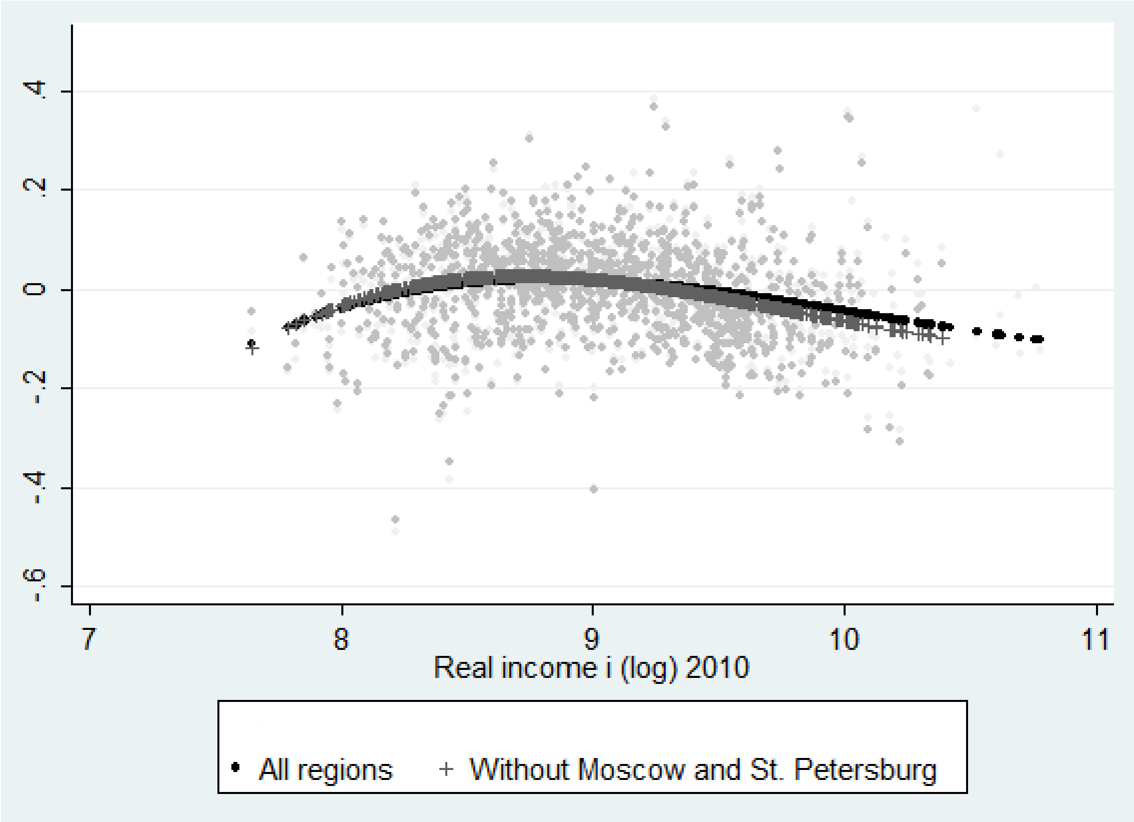
6.3. Semiparametric estimations

In this Section, instead of estimating a quadratic or piecewise-linear relationship between income in the sending region and migration, we use a semiparametric approach (4).

Figure 7 presents the results of this semiparametric estimation. Results for all regions and for the specification without Moscow and Saint Petersburg are very similar. The graphs show that the data are generally consistent with the theoretical predictions. If the regions are poor, increase in income results in higher out-migration; for richer regions, further increase in income results in lower migration. The peak is now somewhat lower: it is reached at log income equal to 8.8 (rather than 9.0 as before). The 95% confidence interval for the peak is (8.6, 9.1)[12]. The log real income at 8.8 implies that the average income is equal to exp(8.8) ≈ 6634 in 2010 rubles and 1.12 Russian average subsistence levels in 2010).

[12] We calculate confidence interval using bootstrap procedure.

Figure 7. Results of semiparametric estimations. Log migration as a function of log real income in the sending region in 2010 rubles.



Note: The graph shows non-parametric fitted value of function *f* from equation (4) which represents the relationship between residuals from the parametric part of the estimation (5) and log of real income in origin region (i). Dots on the graph are actual observations averaged out for each value of the income at origin region (i).

6.4. Discussion of results

In this Section we summarize the estimates of thresholds and peaks of the relationships between the real income in a sending region and intensity of migration. The results of different methods are quite similar. The peak is estimated to be at 9.2 in the quadratic specification, 9.0 in the piece-wise linear specification and 8.8 in the semiparametric specification. The overlap of the three confidence intervals is (8.9,9.0) so we choose 9.0 as our preferred estimate. The value of log real income of 9.0 corresponds to 8103 rubles in 2010 prices per month (about $270 per month or about $3000 per year).

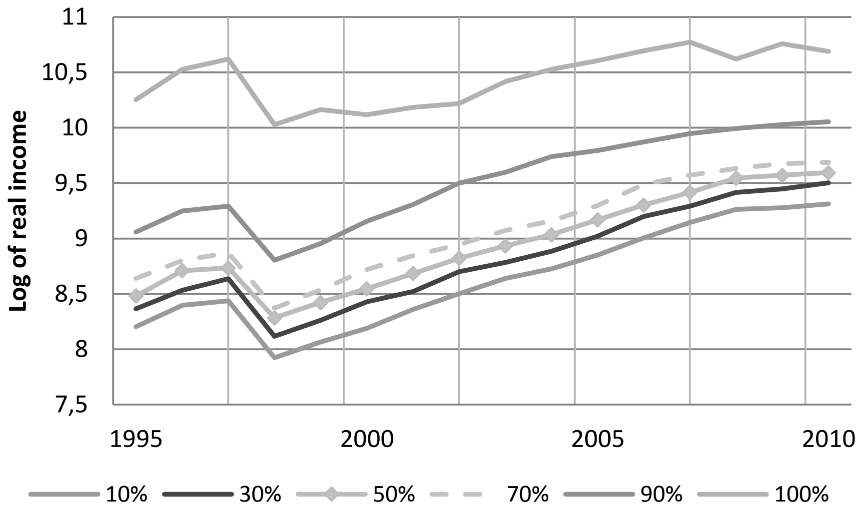
In Figure 8, we plot the evolution of percentiles of interregional income distribution over time. Assuming the critical real income being equal to 9.0, we find which proportion of Russian regions was locked in poverty traps in each year. It turns out that 89.6% of regions were in a poverty trap in 1995, 84.4% – in 2000, 27.2% – in 2005, and 1.3% (i.e., exactly 1 region, Kalmykia) – in 2010. In other words, the number of regions that are in a poverty trap has decreased substantially during 2000s.

Table 3. Estimates of peaks of the relationship between income and migration.

N	Model	Peak (in logarithms of monthly real income)	95% confidence interval	2010 rubles per month
1	Quadratic specification	9.2	(8.7, 10.0)	9897
2	Model with a structural break	9.0	(8.9, 9.0)	8103
3	Semiparametric model	8.8	(8.6, 9.1)	6634

Note: The table presents estimation results for the main specifications of equation (1), (2) and (4).

Figure 8. Evolution of distribution of regions by real income over time.

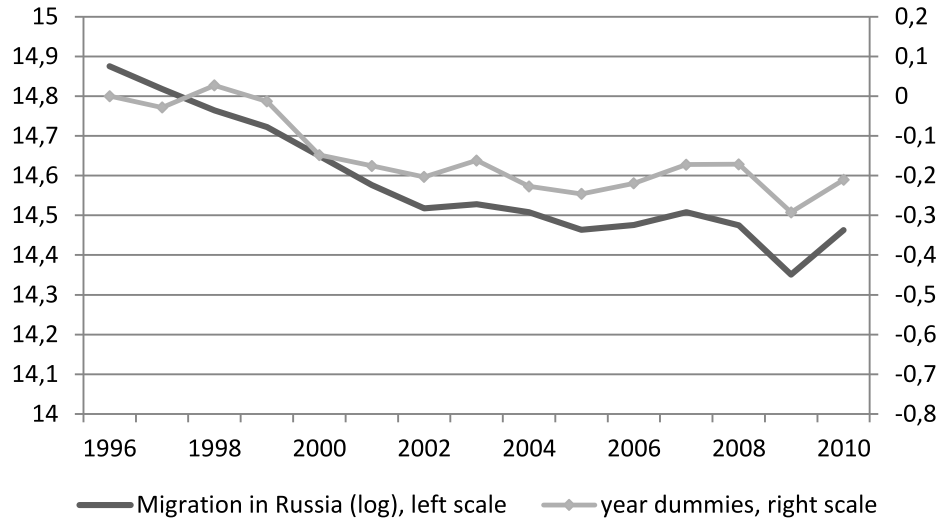


Note: The graph shows the change over time of percentiles of the distribution of Russian regions by log of real income per capita.

Figure 4 implies that while convergence in 1990s was indeed slowed down by poverty traps, the situation changed in 2000s. The overall economic growth let the poor Russian regions "grow out" of their poverty traps. This brought down an important barrier to labor reallocation across Russian regions and resulted in faster interregional convergence between income and wages in 2000s.

How can this be reconciled with falling migration rates in 2000s? In order to understand this, in Figure 10 we plot the year dummies from the main specification Table 2, Column 1) alongside with the annual total migration dynamics (both are in logarithms). The graph shows that there was almost no change in the year dummies in 2000s. This implies that the fall in interregional migration during 2000s was explained precisely by the decreases in the interregional differences. In this sense, the decrease in migration in 2000s is normal. As the barriers to migrations decreased and wages and incomes converged, the number of actual migrants also fell; indeed, the incentives to migrations are no longer as high as they used to be.

Figure 9. Evolution of migration over time: internal migration in Russia in 1996–2010 and time dummies in the main regression (1).



7. Additional evidence and robustness checks

7.1. Regressions for subperiods and subsamples

To check the robustness of our results we estimate equation (1) for the subsamples of close and distant pairs of regions. We also estimate the model for different sub-periods (we consider 1996-2000, 2000-05 and 2005-10).

Table 4 shows the results for geographical sub-samples. Columns 1-2 present the results for pairs of regions that are at most 500 kilometers away from each other. We calculate distance between regions as a railway distance between their capitals. If there is no railway connection between the regions' capitals, we calculate the distance by a highway. Columns 3-4 present the results for the pairs of regions that are 500-2000 kilometers away from each other. The results for the "distant" pairs of regions (more than 2000 kilometers away from each other) are presented in columns 5 and 6.

The coefficients at the income at origins show that the poverty traps only exist for the long distances (this result is similar to Vakulenko et al., 2011). For the long-haul migration (more than 2000 kilometers) we find a familiar non-monotonic relationship with a peak at log income equal to 1.087/(2*0.059)=9.2. If income in the sending region is below this level, the impact of income on migration is positive; if income is above this threshold, the slope of the relationship is negative. This relationship holds neither for the medium-haul nor for short-haul migration. For the intermediate distances (500-2000 kilometers) there is no significant relationship. For the close pairs of regions the relationship is actually U-shaped.

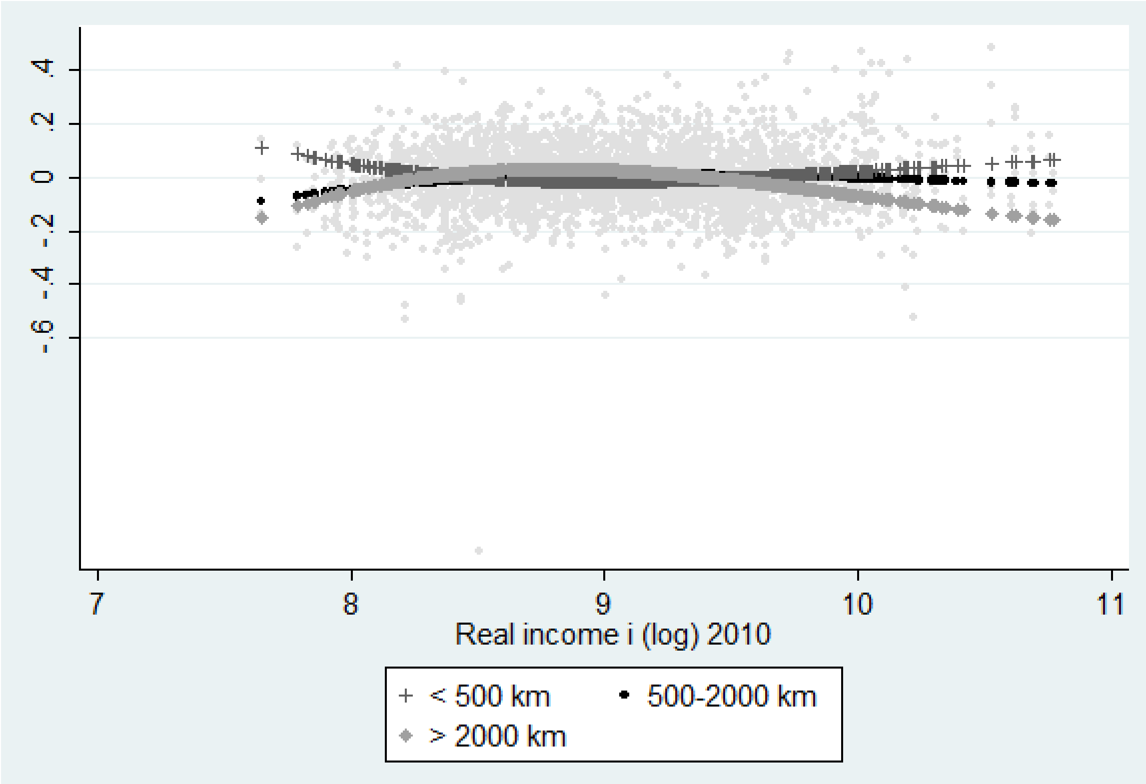
Table 4. Results of regression (1) for different distances between regions. Dependent variable: log of migration.

	1	2	3	4	5	6
VARIABLES	<500 km	<500 km, with squared income	500-2000 km	500-2000 km, with squared income	>2000 km	>2000 km, with squared income
Population i (log)	1.04***	0.94***	1.49***	1.50***	1.85***	1.92***
	(0.26)	(0.25)	(0.14)	(0.14)	(0.15)	(0.15)
Population j (log)	2.24***	2.22***	1.71***	1.75***	2.24***	2.30***
	(0.24)	(0.24)	(0.14)	(0.14)	(0.14)	(0.14)
Income i (log)	0.12**	-1.61***	0.02	0.19	0.04	1.09***
	(0.05)	(0.39)	(0.03)	(0.22)	(0.03)	(0.23)
Income squared i (log)		0.10***		-0.01		-0.06***
		(0.02)		(0.01)		(0.01)
Income j (log)	0.13**	-0.56	0.19***	0.56**	0.18***	0.92***
	(0.05)	(0.41)	(0.03)	(0.25)	(0.03)	(0.25)
Income squared j (log)		0.04*		-0.02		-0.04***
		(0.02)		(0.01)		(0.01)
Unemployment rate i (log)	0.05**	0.05***	0.08***	0.08***	0.04***	0.03**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Unemployment ratej (log)	-0.02	-0.02	-0.07***	-0.07***	-0.07***	-0.08***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	6,246	6,246	31,104	31,104	47,286	47,286
R2-within	0.550	0.556	0.388	0.389	0.276	0.277
Number of pairs	427	427	2,144	2,144	3,356	3,356

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). This table presents the coefficients only for the selected variables of interest. We also include in the model Gini coefficient, provision of housing, housing price, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

Semiparametric results for different distances (presented in Figure 10) produce similar results. The peak for the distant pairs of regions is 8.8 (in terms of the logarithm of real income).

Figure 10. Results of semiparametric model (4) for different distances between regions.

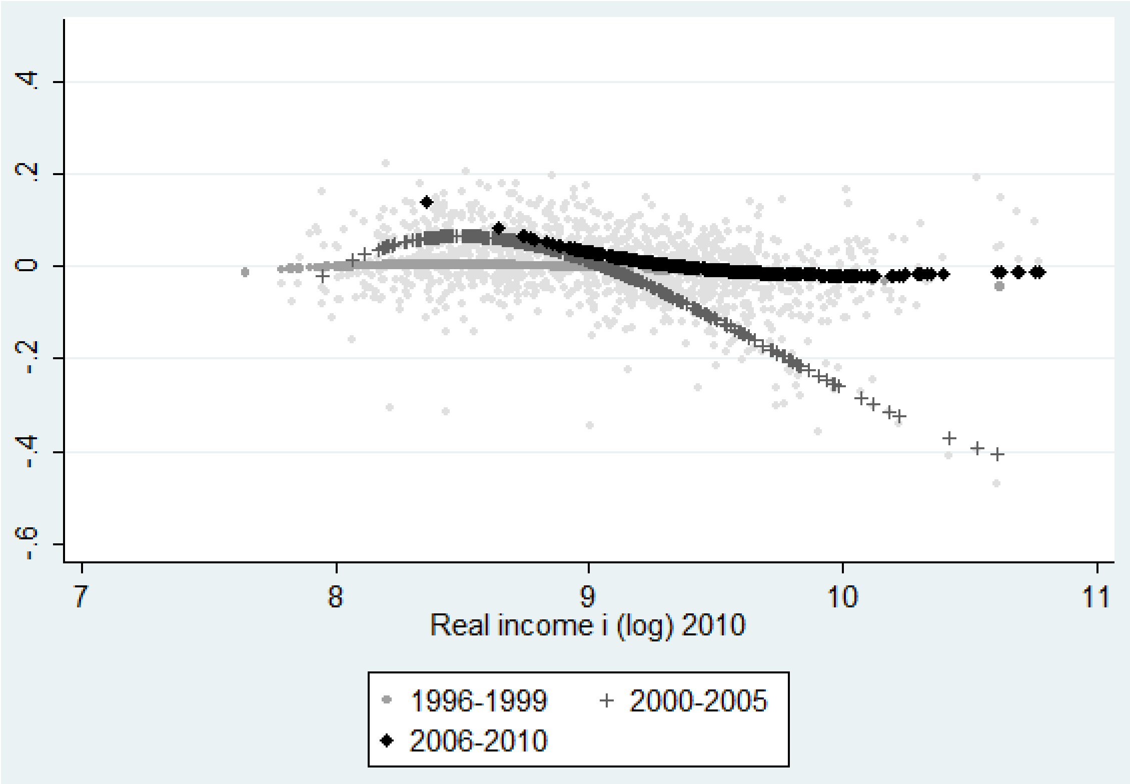


Note: The graph shows non-parametric fitted value of function *f* from equation (4) which represents relationship between residuals from the parametric part (see specification (5)) and log of real income in origin region (i). Dots on the graph are actual observations averaged out for each value of the income at origin region (i).

We have also estimated the relationship between income and migration for different subperiods. Figure 11 presents the results for 1990s, early 2000s and late 2000s.[13] The graphs show that in 1990s the semiparametric relationship is monotonically increasing (the effect of poverty traps dominates). In early 2000s, there is indeed a hill-shaped non-monotonic relationship (consistent with our theory). In 2005-10, the non-monotonicity disappears and the relationship becomes a decreasing one. This is not surprising – in 2005-10, incomes in the vast majority of regions are higher than the thresholds identified above.

[13]The regressions with linear and squared terms for these and other subperiods are reported in Table 7 in the Appendix. The regressions confirm the absence of poverty traps in the 2005-10 period. In 2000-2005 the relationship is non-monotonic with the peak at the similar value of income as in the semiparametric estimation. In 1996-2000, the relationship is increasing.

Figure 1. Results of semiparametric model (4) for different subperiods.



Note: The graph shows non-parametric fitted value of function *f* from equation (4) which represents relationship between residuals from the parametric part (see specification (5)) and log of real income in origin region (i). Dots on the graph are actual observations averaged out for each value of the income at origin region (i).

7.2. Robustness checks

We have run a number of robustness checks. In particular, instead of controlling for pairwise region-to-region fixed effects, we also estimated a model with fixed effects for individual regions (for both i and j). The results (available upon request) were similar. For example, in the quadratic specification, the peak of the relationship between income and migration moved from 9.2 to 9.3.

We have also estimated our main specification with lagged independent variables. The results for one-year and two-year lags are presented in Table 9 and Table 10 in the Appendix. It turns out that specifications with lags have much lower explanatory power. Also, in neither specification we find any significant relationship between lagged income (or lagged squared income) in the sending region and migration. This confirms our choice of the contemporaneous specification (1).

We have also estimated a specification where instead of incomes at origin and destination we included only a difference between them (see Table 8 in the Appendix). We do find that the difference between income at destination and income at origin does have a positive effect on migration. We have also added squared difference and found that the coefficient at squared difference is positive. This is consistent with a conjecture that there is a fixed cost of migration and that the financial constraints are binding.

As yet another robustness check, we also estimate a semiparametric model with nonlinear relationships between migration and income in the destination region. These results are presented in the Figure 14 in the Appendix. The growth in income generally results in higher immigration. This is true for regions with logarithm of income higher than 8.3 (4024 in 2010 rubles); only very few region-years are below this threshold in our data.

We have also estimated the regressions with alternative deflators where we used the regional subsistence levels instead of consumer price indices. We have also run our estimations for 1995-2010; this includes less reliable data on migration from 1995; also, there are no data on real estate prices for 1995. In all cases, the results are similar. The only difference is that in piece-wise linear and quadratic specifications with 1995-2010 data, the peak of the non-monotonic relationship is reach at a lower income. However, the semiparametric analysis provides the same estimate for the peak as in our main specification. Given the problems with the data quality for 1995, we prefer the results from the 1996-2010 panel.

7.3. Financial development

In this section we expand the main specification (1) adding proxies for financial development such as loans to firms, households and mortgage debt as a percent of GDP and their interactions with income. As the data on loans to firms and households are available only since 2001 and data of mortgage debts only start since 2004, the timespan of this analysis is substantially shorter.

Table 5 presents regressions with the ratio of loans to households to GDP (the regressions with alternative measures of financial development are provide in the Table 11 in the Appendix; the results are similar).

In line with our theory, financial development does result in higher outward migration. Moreover, the coefficient at the interaction term between financial development and income is negative. In other words, if this region is more financially developed, liquidity constraints are less binding as a barrier for migration – the outgoing migration is less positively linked to income in the sending region.

We also run regressions with squared income and interaction of financial development and interaction with squared income. Again, consistent with the theory, we find that in the regions with higher level of financial development the coefficient at squared income is more positive (i.e. is closer to zero); therefore in more financially developed regions the non-monotonic relationship between income and migration is less likely to be observed.

Table 5. Regressions (1) with financial development. Dependent variable: log of migration.

VARIABLES	1 Main	2 With squared income	3 Without Moscow and Saint Petersburg	4 Without Moscow and St Petersburg, w/ sq. income
Population i (log)	1.40***	1.33***	1.50***	1.39***
	(0.15)	(0.15)	(0.17)	(0.17)
Population j (log)	2.37***	2.41***	2.10***	2.16***
	(0.14)	(0.14)	(0.16)	(0.16)
Income i (log)	-0.03	-4.14***	-0.03	-5.58***
	(0.05)	(0.84)	(0.05)	(0.95)
Income squared i (log)		0.22***		0.29***
		(0.04)		(0.05)
Income*loans i (log)	-0.02**	-0.63***	-0.02**	-0.89***
	(0.01)	(0.19)	(0.01)	(0.21)
Income squared*loans i (log)		0.03***		0.04***
		(0.01)		(0.01)
Loans i (log)	0.16**	3.13***	0.14*	4.32***
	(0.08)	(0.88)	(0.08)	(0.98)
Income j (log)	0.06	1.35*	0.11**	2.45***
	(0.05)	(0.78)	(0.05)	(0.87)
Income squared j (log)		-0.07*		-0.13***
		(0.04)		(0.05)
Income*loans j (log)	-0.01	0.34*	-0.01	0.83***
	(0.01)	(0.18)	(0.01)	(0.21)
Income squared*loans j (log)		-0.02*		-0.05***
		(0.01)		(0.01)
Loans j (log)	0.11	-1.47*	0.06	-3.69***
	(0.07)	(0.83)	(0.08)	(0.95)
Unemployment rate (log) i	0.03***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Unemployment rate (log) j	-0.05***	-0.05***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	58,223	58,223	55,211	55,211
R2-within	0.104	0.105	0.104	0.106
Number of pairs	5,929	5,929	5,625	5,625

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). We include in the model but not reported such variables as Gini coefficient, provision of housing, housing price, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

8. Concluding remarks

Our analysis of internal migration in Russia helps to understand and quantify barriers to labor mobility and the geographical poverty traps. Using parametric and semiparametric methods we arrive at similar estimates of the barriers to move: residents of regions with annual income below $3000 are likely to be willing but unable to afford the move. We also show how growth of incomes over time helps breaking out of poverty traps.

The finding that the poverty traps are largely gone in today's Russia holds up to the following caveat. Our analysis is carried out at the regional level. Therefore even though there are no regional poverty traps, the traps may still persist at the level of individual towns. While our quantitative estimates are obtained for the regional rather than for the town level, our analysis does provide qualitative insights for policymakers. If the potential migrants would benefit from moving out but cannot finance the move (e.g. because his/her real estate is worthless) then government can and should step in through supporting financial intermediaries that can finance the move.

In order to obtain the quantitative estimates of the parameters of poverty traps, we use a unique case study of Russia in 1990s and 2000s. We need further research to understand whether the income thresholds required to break out of poverty traps are similar in other countries and, if not, how they depend on geography, culture, transportation infrastructure, and on the institutions of labor, financial and real estate markets.

Our analysis shows that lowering barriers to mobility may be accompanied by a decrease rather than an increase in migration per se. Indeed, Russian interregional migration rates have gone down in 2000s; we find that this reduction is explained by lower interregional differences (and therefore lower incentives to migrate). In turn, the interregional differences in wages are lowered not because many workers actually migrate but because their threat to migrate is credible – due to the disappearance of geographical poverty traps and therefore lower barriers to migration. This analysis directly implies that the policymakers should focus on removing barriers to labor mobility (including those driven by financial constraints) rather than on promoting migration per se.

The other interesting implication of our analysis is that convergence in incomes and wages can take place even in the presence of large and persistent interregional differences in GDP per capita – as it has been the case in Russia in 1990s and 2000s. The only way to reconcile convergence in wages and incomes with non-convergence in per capita GDP is as follows. As long as barriers to labor mobility are removed, mobility (or even a threat of mobility) protects workers from employers' monopsony power. At the same time, Russian regions still differ substantially in terms of total factor productivity. These differences may be explained either by interregional differentials in (i) geographical factors, (ii) productivity of inherited capital stock and infrastructure, or (iii) political and economic institutions. Unfortunately, the available data do not allow distinguishing between these three explanations.

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10. Appendix

Table 6. Summary statistics of the variables.

Variable	Definition	Years available	Obs	Mean	Std. Dev.	Min	Max
Migration	Number of people migrated from one region to another in a given year	1995-2010	97344	363.13	2313.11	0.5	67520
Migration (log)	Logarithm of migration	1995-2010	97344	3.91	1.74	-0.69	11.12
Population	Average population per year	1995-2010	97344	1838781	1606615	49056	11500000
Income	Income per capita to subsidence level	1995-2010	97344	2.00	0.79	0.71	6.45
Income (log)	Log of Income per capita to subsidence level	1995-2010	97344	0.63	0.36	-0.34	1.86
Real income	Income per capita (2010 prices)	1995-2010	96096	9602.50	5955.797	2092.72	47747.7
Real income (log)	Log of Income per capita (2010 prices)	1995-2010	96096	9.01	0.550	7.646	10.77
Wage	Wage to subsidence level	1995-2010	91104	2.32	0.82	0.71	7.84
Wage (log)	Log of wage to subsidence level	1995-2010	91104	0.79	0.34	-0.34	2.06
GDP	Real GDP per capita	1996-2010	85176	11011.0	9393.81	1577.72	97736.71
Poverty	Share of population with money income below subsistence level %	1995-2010	96486	26.87	12.51	8.1	77.9
Gini	Gini coefficient (measure of inequality in a region)	1995-2010	96564	0.36	0.05	0.23	0.62
Unemployment rate	Unemployment rate ILO	1995-2010	97344	10.11	4.64	0	32.4
Housing price	Price per square meter deflated by CPI	1996-2010	87828	29234.7	16878.16	4541.54	186018.8
Provision of housing	Availability of dwellings per capita in square meters	1995-2010	97344	20.40	2.84	12.1	31.5
New flats	New flats constructed	1995-2010	97344	30.81	16.44	0.90	122.42
Life expectancy	Life expectancy at birth	1995-2010	97344	65.49	2.88	53.76	74.37

Infant mortality rate	Number of deaths of children under 1 year per 1,000 newborn per year	1995-2010	97344	13.59	5.02	4.28	42.1
Doctors	Number of doctors per 10,000 population	1995-2010	97344	45.69	10.37	27	87.4
Hospital beds	Number of hospital beds per 10,000 population	1995-2010	97344	120.05	23.43	68.1	252.4
Telephones	Number of telephone lines per 100 households	1995-2010	97344	204.09	73.41	42.9	420.4
Highway density	Highway density per 1,000 square km	1995-2010	97344	120.59	98.23	0.8	670
Buses	Number of busses per 100,000 population	1995-2010	97188	62.09	26.26	1	153
Share of young	Share of people less than working-age	1995-2010	97344	19.16	4.09	12.3	35.8
Share of old	Share of people greater than working-age	1995-2010	97344	19.89	4.38	5.2	27.4
Students	Number of students per 10,000 population	1995-2010	97344	334.686	174.3048	0	1256.25
Women	Relation of women to 1,000 men	1995-2010	97344	1137.47	61.69	901	1249
Loans to households	Loans to households, share of GDP	2001-2010	60294	0.061	0.054	0.001	0.267
Loans to firms	Loans to firms, share of GDP	2001-2010	60684	0.137	0.176	0.007	3.064
Mortgage debt	Mortgage debt, share of GDP	2004-2010	42432	0.019	0.017	0.000	0.083

Table 7. Results of regression (1) for different time periods. Dependent variable: log of migration.

	1	2	3	4	5	6
VARIABLES	1996-2000	1996-2000 With squared income	2000-2005	2000-2005 With squared income	2005-2010 With squared income	2005-2010 With squared income
Population i (log)	2.20***	2.23***	2.04***	2.16***	0.97***	0.93***
	(0.31)	(0.32)	(0.31)	(0.32)	(0.21)	(0.21)
Population j (log)	1.22***	1.23***	0.84***	0.94***	2.19***	2.26***
	(0.30)	(0.30)	(0.30)	(0.31)	(0.19)	(0.20)
Income i (log)	0.002	-0.86***	0.04	1.01***	-0.005	-0.72
	(0.05)	(0.25)	(0.04)	(0.33)	(0.05)	(0.67)
Income squared i (log)		0.05***		-0.06***		0.04
		(0.01)		(0.02)		(0.04)
Income j (log)	-0.13***	-0.57**	0.02	0.85**	-0.01	1.11*
	(0.04)	(0.24)	(0.05)	(0.33)	(0.05)	(0.67)
Income squared j (log)		0.03*		-0.05**		-0.06*
		(0.01)		(0.02)		(0.03)
Unemployment rate i (log)	0.05***	0.04***	-0.01	-0.01	0.03**	0.03**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Unemployment rate j (log)	-0.04**	-0.04**	-0.01	-0.02	-0.02*	-0.02*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Observations	25,376	25,376	35,270	35,270	35,574	35,574
R2-within	0.159	0.160	0.105	0.105	0.040	0.040
Number of pairs	5,625	5,625	5,929	5,929	5,929	5,929

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). This table presents the coefficients only for the selected variables of interest. We also include in the model Gini coefficient, provision of housing, housing price, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

Table 8. Results of regressions (1) with the difference between incomes at origin and destination. Dependent variable: log of migration.

	1	2	3	4
VARIABLES	With difference in incomes	With difference in incomes and squares	With difference in income and income in origin	With difference in income and income in origin and squares
Population i (log)	1.83***	1.84***	1.75***	1.81***
	(0.10)	(0.10)	(0.10)	(0.10)
Population j (log)	2.05***	2.05***	1.96***	1.97***
	(0.10)	(0.10)	(0.10)	(0.10)
Ln(income)j – ln(income)i	0.07***	0.07***	0.18***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)
$(\text{Ln(income)j} - \text{ln(income)i})^2$		0.05***		0.05***
		(0.01)		(0.01)
Income i (log)			0.21***	0.96***
			(0.03)	(0.16)
Income squared i (log)				-0.04***
				(0.01)
Gini i (log)	-0.01	-0.02	-0.08*	-0.10**
	(0.04)	(0.04)	(0.04)	(0.04)
Gini j (log)	-0.05	-0.06	-0.12***	-0.14***
	(0.04)	(0.04)	(0.04)	(0.04)
Unemployment rate I (log)	0.06***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
Unemployment rate j (log)	-0.07***	-0.07***	-0.07***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	84,666	84,666	84,666	84,666
R^2-within	0.307	0.308	0.308	0.309
Number of pairs	5,929	5,929	5,929	5,929

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). This table presents the coefficients only for the selected variables of interest. We also include in the model provision of housing, housing price, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

Table 9. Results of regressions with one-year lagged independent variables. Dependent variable: log migration.

VARIABLES	1 Main	2 With squared income	3 Without Moscow and Saint Petersburg	4 Without Moscow and St Petersburg, w/ sq. income
Population i (log), t-1	2.251***	2.284***	2.109***	2.123***
	(0.116)	(0.118)	(0.126)	(0.130)
Population j (log), t-1	1.652***	1.738***	1.519***	1.611***
	(0.114)	(0.115)	(0.124)	(0.128)
Income i (log), t-1	-0.005	0.221	-0.042*	0.039
	(0.023)	(0.166)	(0.024)	(0.199)
Income squared i (log), t-1		-0.013		-0.005
		(0.009)		(0.011)
Income j (log), t-1	0.272***	0.861***	0.254***	0.772***
	(0.023)	(0.168)	(0.025)	(0.205)
Income squared j (log), t-1		-0.033***		-0.029**
		(0.009)		(0.012)
Ginii (log) , t-1	-0.026	-0.025	-0.024	-0.024
	(0.042)	(0.042)	(0.046)	(0.046)
Gini j(log), t-1	-0.288***	-0.285***	-0.287***	-0.286***
	(0.041)	(0.041)	(0.044)	(0.043)
Unemployment rate i(log), t-1	0.051***	0.050***	0.029***	0.029***
	(0.009)	(0.009)	(0.010)	(0.010)
Unemployment rate j(log), t-1	-0.028***	-0.030***	-0.042***	-0.043***
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	78,737	78,737	74,597	74,597
R2-within	0.270	0.271	0.272	0.272
Number of pairs	5,929	5,929	5,625	5,625

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). This table presents the coefficients only for the selected variables of interest. We also include in the model provision of housing, housing price, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

Table 10. Results of regressions with two-year lagged independent variables. Dependent variable: log migration.

VARIABLES	1 Main	2 With squared income	3 Without Moscow and Saint Petersburg	4 Without Moscow and St Petersburg, w/ sq. income
Population i (log), t-2	2.376***	2.343***	2.321***	2.274***
	(0.126)	(0.127)	(0.138)	(0.143)
Population j (log), t-2	1.287***	1.451***	1.058***	1.228***
	(0.124)	(0.127)	(0.135)	(0.142)
Income i (log), t-2	0.005	-0.222	-0.017	-0.283
	(0.024)	(0.166)	(0.025)	(0.203)
Income squared i (log), t-2		0.013		0.015
		(0.009)		(0.012)
Income j (log), t-2	0.311***	1.459***	0.294***	1.249***
	(0.025)	(0.167)	(0.027)	(0.209)
Income squared j (log), t-2		-0.065***		-0.054***
		(0.009)		(0.012)
Ginii (log) , t-2	0.037	0.036	0.046	0.046
	(0.042)	(0.042)	(0.046)	(0.046)
Gini j(log), t-2	-0.334***	-0.331***	-0.341***	-0.340***
	(0.042)	(0.042)	(0.044)	(0.044)
Unemployment rate i(log), t-2	0.022**	0.024**	0.001	0.002
	(0.009)	(0.009)	(0.010)	(0.010)
Unemployment rate j(log), t-2	-0.027***	-0.034***	-0.030***	-0.034***
Observations	72,808	72,808	68,972	68,972
R2-within	0.222	0.223	0.225	0.225
Number of pairs	5,929	5,929	5,625	5,625

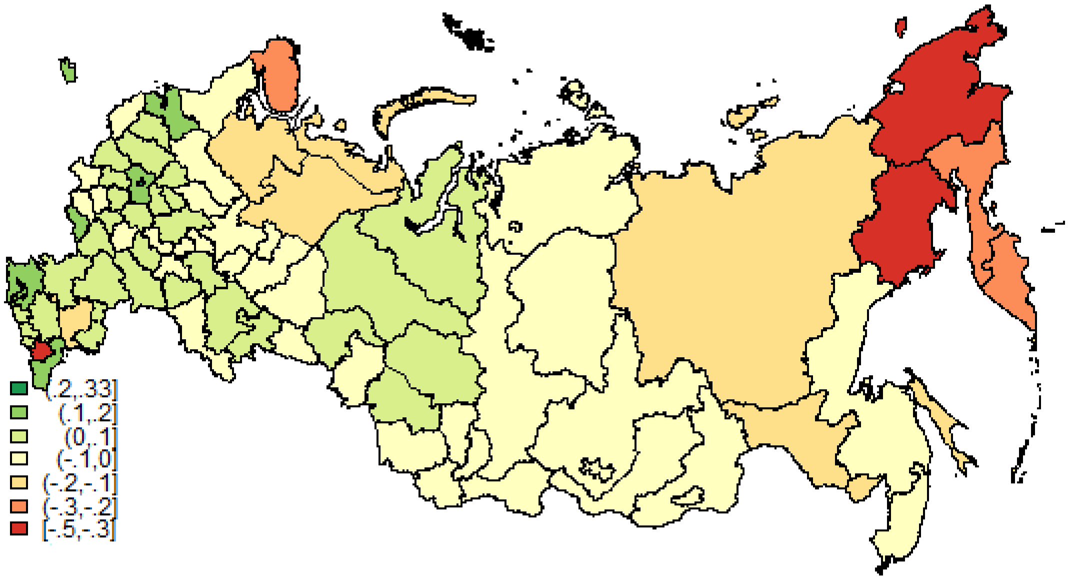
Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). This table presents the coefficients only for the selected variables of interest. We also include in the model provision of housing, housing price, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

Table 11. Regressions with different indicators of financial development (migration model).

VARIABLES	1 Loans to firm	2 Loans to firm with squares	3 All Loans	4 All loans with squares	5 Mortgage debt	6 Mortgage debt with squares
Population i (log)	1.415***	1.396***	1.400***	1.368***	0.737***	0.585**
	(0.150)	(0.153)	(0.151)	(0.153)	(0.243)	(0.246)
Population j (log)	2.321***	2.280***	2.337***	2.306***	2.110***	2.375***
	(0.140)	(0.141)	(0.140)	(0.142)	(0.225)	(0.231)
Income i (log)	0.000	-0.151	-0.005	-0.720	-0.040	-15.118***
	(0.043)	(0.646)	(0.042)	(0.620)	(0.095)	(3.366)
Income squared i (log)		0.008		0.038		0.789***
		(0.034)		(0.033)		(0.174)
Income*fin_devi (log)	-0.024**	0.136	-0.027**	0.016	0.024	-3.170***
	(0.010)	(0.222)	(0.010)	(0.232)	(0.022)	(0.730)
Income squared*fin_devi (log)		-0.009		-0.003		-0.069***
		(0.012)		(0.013)		(0.022)
Fin_devi (log)	0.204**	-0.507	0.232**	0.085	-0.169	15.058***
	(0.090)	(1.033)	(0.096)	(1.074)	(0.204)	(3.510)
Income j (log)	0.042	-0.883	0.040	-0.530	-0.183**	10.629***
	(0.043)	(0.575)	(0.043)	(0.570)	(0.081)	(2.121)
Income squared j (log)		0.050		0.031		-0.567***
		(0.030)		(0.030)		(0.109)
Income*fin_dev j (log)	-0.022**	-0.435**	-0.020*	-0.296	-0.040***	1.276***
	(0.010)	(0.207)	(0.011)	(0.224)	(0.013)	(0.437)
Income squared*fin_dev j (log)		0.023**		0.015		0.167***
		(0.011)		(0.012)		(0.038)
Fin_dev j(log)	0.171*	2.061**	0.166*	1.422	0.398***	-5.906***
	(0.089)	(0.955)	(0.098)	(1.033)	(0.128)	(2.136)
Unemployment rate (log) i	0.032***	0.034***	0.033***	0.036***	0.036**	0.029*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.015)	(0.015)
Unemployment rate (log) j	-0.045***	-0.047***	-0.045***	-0.046***	-0.034**	-0.031**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)	(0.015)
Observations	58,525	58,525	57,919	57,919	29,645	29,645
R2-within	0.103	0.103	0.104	0.105	0.045	0.048
Number of pairs	5,929	5,929	5,929	5,929	5,929	5,929

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). This table presents the coefficients only for the selected variables of interest. We also include in the model Gini coefficient, provision of housing, housing price, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, share of young and old people, number of students, number of women and year dummies.

Figure 12. Net migration for the period of 1995-2010, share of 1995 population.



Source: Rosstat's official data.

Figure 13. Average ratio of outstanding loans to households, loans to firms, and mortgage debt to GDP (%).

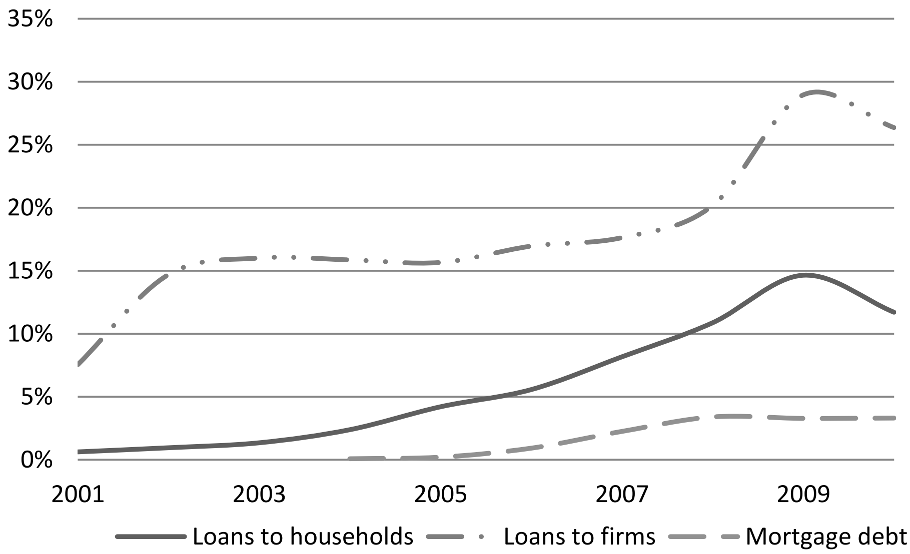
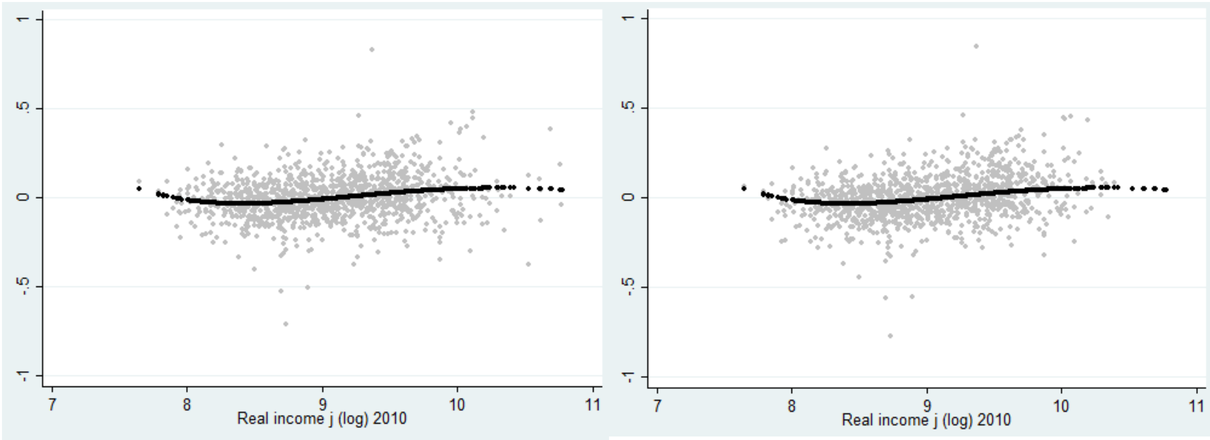


Figure 14. Results of semiparametric regression models for receiving regions.



a) All regions b) Without Moscow and Saint Petersburg

Note: The graph shows non-parametric fitted value of function *f* from equation (4) which represents relationship between residuals from the parametric part of the estimation (5) and log of real income in origin region (i). Dots on the graph are actual observations averaged out for each value of the income at origin region (i).