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

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ABSTRACT

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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 relation-ship between income and migration. In richer regions, higher incomes result in lower migration outflows. However, in the poorest regions, an increase in incomes results in higher emigration. This is consistent with the presence of geographical poverty traps: potential migrants want to leave the poor regions but cannot afford to 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. Journal of Comparative Economics 43 (3) (2015) 633–649. Sciences Po, Paris, France; CEPR, London, United Kingdom; National Research University Higher School of Economics, Moscow, Russia.

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. 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 driven by high transportation, psychological or informational costs of moving. These costs are reinforced by the underdevelopment of financial markets. Even when returns to mobility exceed the costs of migration, potential migrants with low earnings and assets may not be able to finance their move. Essentially, these migrants are locked in geographical poverty traps.

An 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

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mobility, we need to estimate the change of migration in response to change in external circumstances that allows the breaking out of poverty traps at least for some potential migrants. This may involve a substantial decrease in migration costs, or progress in financial development, or an increase in income (keeping the moving costs constant).

In this paper we study interregional migration in Russia in 1996–2010 when both a breakthrough in financial development and rapid growth in income took place. Russia offers a unique setting for an empirical study of barriers to internal migration and of geographical poverty traps. First, it is a large and diverse country with a substantial potential for geographical labor reallocation. The initial allocation of labor at the beginning of the transition was far from the spatial equilibrium in a market economy. Before the 1990s, Soviet industrialization policies often pursued political or geopolitical rather than economic goals. Even when they reflected economic realities, allocation decisions were distorted substantially by central planning, price controls and subsidies. Not surprisingly, the transition involved moving millions of people between Russian regions. Second, Russia experienced a dramatic growth in incomes during the 2000s. According to the IMF data, Russia's GDP per capita in constant prices grew by 80% between 1996 and 2010.

We use a panel dataset of the gross annual migration flows between Russian regions in 1996–2010. We estimate the relationship between income at the origin region and gross 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 us to take into account the distance between origin and destination and other time-invariant variables that can affect the informational, cultural, or psychological 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 us to control for regional fixed effects, e.g. region i's cultural or psychological propensity to move or region j's attractiveness to migrants.

The presence of geographical poverty traps implies a non-monotonic relationship between the income at the region of origin and the migration outflows. If the incomes are low, financial constraints are likely to bind. Potential migrants with low income are willing to move but are unable to fund the costs of migration. Hence, the higher the income at the region of origin, the higher the migration outflows. On the other hand, for sufficiently high income, financial constraints are no longer important, and the effect of income on migration now works in the opposite direction. Indeed, controlling for income at destination, a higher income at home decreases the economic returns on migration.

In order to estimate a non-monotonic (hill-shaped) relationship between income and migration outflows, we use both semiparametric and parametric methods. We allow for a piece-wise linear and for a quadratic relationship between income and migration. All three approaches (semiparametric, piece-wise linear, and quadratic) deliver similar quantitative results. We find that the relationship between income and migration outflows is indeed hill-shaped; it peaks at about $3000 per year (at 2010 exchange rate). We interpret the fact that the relationship is non-monotonic as evidence of the existence of poverty traps. We also argue that once incomes are above the threshold of $3000 per year (which is true for almost all Russian regions in the late 2000s), financial constraints are no longer binding, so that the regions have broken out of these poverty traps.

While the relationship between migration and income is non-monotonic for income at origin, we find 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. Moreover, consistent with standard predictions from migration theory (see, for example, Moretti, 2011), we also document that migrants tend to go from regions with high unemployment and worse public goods to regions with lower 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 long-distance migration rather than migration to nearby regions. This is intuitive as costs of migration are likely to increase with distance. We also provide additional evidence using the data on the financial development of Russian regions. Unfortunately, these data are only available from 2001 (and some of the series start only in 2004). We find that financial development relaxes the financial constraints on 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, a higher income is more likely to have a negative rather than positive impact on migration. In other words, poverty traps are less likely to emerge in the regions with more developed financial markets.

Our empirical strategy assumes that while incomes push and pull migration flows there is no reverse causality. Migration could affect average income directly if the incomes of a large number of incoming or outgoing migrants were different from the region's average income. Essentially, we assume that differences in incomes are driven by local productivity shocks and that migration is too small to affect local labor market outcomes. While this assumption is often made in the literature on internal migration, it is especially likely to hold in our setting. Indeed, in Russia in 1996–2000, the average annual migration rate was only 0.5–1.0% of total population and therefore could hardly affect incomes and other socio-economic variables in the origin and destination regions. We also run a number of additional checks to rule out the effect of migration on incomes. In particular, we exclude regions with large cumulative net migration flows (above 10% or below −10% of population over fifteen years).

Our paper contributes to the literature on the effect of financial constraints on migration. The general theory of spatial labor allocation (see, for example, the survey in Moretti, 2011) predicts that 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, at least since the seminal paper by Banerjee and Kanbur (1981), the literature has suggested that in the presence of financial constraints, the relationship between income and migration outflows may become non-monotonic. Hatton and Williamson (2005) and Williamson (2006) argue that poverty traps and the non-monotonic relationship between income and outgoing migration have indeed been important for long-distance migration in the last 200 years. De Haas (2009) and Human Development Report (2009) state that financial constraints and poverty traps remain relevant for modern international migration as well.

The recent empirical literature generally finds a positive effect of incomes, wages, or wealth on (long-distance) migration outflows for the poorest regions; this can be interpreted as evidence of the importance of financial constraints for migration. Recent papers use both individual and aggregate data. Most individual-level studies show that financial constraints do matter for migration (see Dustmann and Okatenko, 2014 on sub-Saharan Africa and Asia regions, Mendola, 2008; Sharma and Zaman, 2013 on Bangladesh, Beam et al., forthcoming and McDonald and Valenzuela, 2012 on the Philippines, and Friebel and Guriev, 2005 on Russia). Some other studies (e.g., Beegle et al., 2011 on Tanzania and Abramitzky et al., 2013 on Norway) find no significant effects. The papers that use aggregate data find evidence in favor of the importance of financial constraints (see Andrienko and Guriev, 2004; Gerber, 2006 for Russia, McKenzie and Rapoport, 2007; Angelucci, forthcoming on Mexico, Phan and Coxhead, 2010 on Vietnam, Michálek and Podolák, 2010 on Slovakia, Horváth, 2007 on Czech Republic, Golgher et al., 2008 and Golgher, 2012 on Brazil, and Bazzi, 2013 on Indonesia).[1]

We contribute to this literature in several ways. First, we use a major quasi-natural experiment of transition from a command economy where the original allocation of labor was very different from long-run market equilibrium. This has created a large potential for migration. Moreover, the transition to a market economy involved a dramatic growth in incomes. The regions that were initially locked in geographical poverty traps eventually broke out of them. 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 which produce similar quantitative estimates of barriers to mobility. We find that the income threshold for the poverty traps is $3000 per year. This estimate may be specific for Russia in the 1990s and 2000s. It is likely that this threshold depends on geography, technology, institutions, and culture and would therefore be different in other developing countries. However, the very fact that different methods deliver a similar result suggests that such analysis can be a useful policy tool for the other economies as well. Once policymakers obtain a quantitative estimate of the threshold income, they can identify the regions that are locked in poverty traps and then target such regions with mobility-enhancing policies. (Our analysis implies that regions with income above the threshold are not locked in traps so there is no need for policy intervention.) As we find that both income growth and financial development matter, policy makers may use both income support policies and improving access to financing, especially for the poorest residents.

The rest of the paper is structured as follows. In Section 2, we describe our hypotheses, empirical specifications and the data. In Section 3 we present 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 the three different methodologies provide strikingly similar results. In Section 4 we discuss additional evidence including regressions for subperiods and subsamples, as well as regressions with proxies for financial development. These variables are only available for a short period of time; this is why we present these results as additional evidence rather than include them into the main empirical section. In Section 5, we conclude and discuss the policy implications of our results.

2. Hypotheses, empirical specifications and data

2.1. Hypotheses

We assume that migration decisions are made by rational individuals who compare the migration costs and the differences in utility functions in the origin and destination regions. The potential migrant's utility depends on income, public goods and real estate prices.

We also allow for financial constraints: even if a potential migrant wants to migrate but has no cash to finance the move, he/she stays in the origin region. In Appendix B, we develop a simple illustrative model with heterogeneous migrants and financial constraints that predicts an inverted-U-shape relationship between the average income in the sending region and migration outflows.

The non-monotonicity arises as there are two effects of an increase in income on migration. The conventional effect of willingness to move results in a negative relationship: if income at home is higher, the migrants are less willing to move. There is also a countervailing effect of financial constraints: if the income is higher, the migrants are more likely to be able

[1] The paper closest to ours is Andrienko and Guriev (2004) who study internal migration in Russia in 1990s. Our analysis is different 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 and find that both provide the same quantitative estimates of the income threshold of the poverty trap.

to finance the move. If the average income is low, the effect of financial constraints dominates, and migration increases with average income. If the average income is high, financial constraints are no longer binding, the effect of the willingness to move dominates and migration outflows decrease with higher average income.

We will test the presence of this inverted U shape using non-linear and piecewise-linear parametric specifications as well as semi-parametric specifications.

2.2. 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 decrease with the distance between the 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:

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

The dependent variable is the logarithm of the number of migrants M who move from region i to region j in year t.[2] In order to control for distance, initial conditions and pre-transition legacies, we include fixed effects $\alpha_{i,j}$ for each pair of regions. $X_{k,i,t}$ and $X_{k,j,t}$ are vectors of the characteristics of the source and the destination regions which 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, proportion of women[3]), provision of public goods, e.g., roads, healthcare (doctors per capita and hospital beds per capita), public transportation (buses per capita), education (one-year time lag of number of students per capita), inequality and others. These variables include all time-varying factors that may affect productivity and returns on migration, including amenities, human capital and infrastructure. Our model's predictions are related to the 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 $year_i$ to control for common shocks (e.g. changes in the 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, respectively.

Parameters ϕ, φ, γ_k, δ_k, θ_t are the coefficients in the model. Finally, $\varepsilon_{i,j,t}$ is the error term which is normally distributed with a zero mean. We assume throughout the paper that the error terms are not correlated with explanatory variables and fixed effects. We allow for the intragroup correlation of the error terms for each pair of regions i, j; this is why we use robust standard errors clustered for each pair. As a robustness check, we also estimate models with the robust standard errors two-way clustered separately by regions i and j, assuming heteroskedasticity within groups.

As we are especially interested in the effects of liquidity constraints and poverty traps, we also include the 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 origin and the intensity of migration. If financial markets are developed and there are no liquidity constraints then coefficient ϕ should be negative and coefficient φ should be positive. Migration increases with income at destination and decreases with income at origin. However, as discussed above, in the presence of financial constraints, the coefficient ϕ should be positive for the poorer regions. The relationship between migration and income in the origin region ln $income_{i,t}$ is therefore non-monotonic (see Fig. 8 in the Appendix B). The simplest way to model such a 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 a non-monotonic relationship is a regression with a structural break. Our model (in the Appendix B) implies that for high incomes the slope of the relationship between income in the sending region and migration is negative while for low incomes the slope is positive. For simplicity, we approximate this relationship with one kink and run the following regression:

$$\ln M_{i,j,t} = \alpha_{i,j} + a(\ln income_{i,t} - \gamma) I(\ln income_{i,t} \leqslant \gamma) + b(\ln income_{i,t} - \gamma) I(\ln income_{i,t} > \gamma) + controls_{i,t} + \varepsilon_{i,j,t} \quad (2)$$

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:

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

There are two regimes: "before" (to the left of) the threshold: ln $income_{i,t} \leqslant \gamma$, and "after" (to the right of) the threshold: ln $income_{i,t} > \gamma$. The non-monotonic relationship is consistent with the data if for some threshold γ we have $b < 0 < a$, and both a and b are significantly different from zero.

We use the least squares estimate for the transformed variables (Hansen, 1999) to extract fixed individual effects:

[2] 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.

[3] All demographic variables except log population are included in the model with one-year lag.

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

where $\ln M^*_{i,j,t} = \ln M_{i,j,t} - T^{-1}\sum_{j=1}^{T} \ln M_{i,j,t}$, $\ln income^*_{i,t}(\gamma) = \begin{pmatrix} \ln income_{i,t} - T^{-1}\sum_{t=1}^{T} \ln income_{i,t} I(\ln income_{i,t} \leqslant \gamma) \\ \ln income_{i,t} - T^{-1}\sum_{t=1}^{T} \ln income_{i,t} I(\ln income_{i,t} > \gamma) \end{pmatrix}$ 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. 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 income in the sending region is non-parametric:

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

Our approach is based on Baltagi and Li (2002). We use the "xtsemipar" Stata command (Libois and Verardi, 2013). To obtain the non-parametric fit, we use B-splines (Newson, 2000). Following Baltagi and Li (2002), we estimate the curve f by regressing residuals from Eq. (4)

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

on log income in the sending region 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 on migration of income in sending regions 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 4.2).

The theoretical model in the Appendix B effectively assumes that income distribution within regions does not change over time. Under this assumption, the change in average income represents a shift in the whole distribution. In reality, inequality within regions did grow over time (the unweighted average of within-region Gini coefficients increased from 31% in 1995 to 39% in 2010). However, the change in equality was small compared to the change in incomes: the regional fixed effects explain 61% of variation in Gini coefficients (for comparison, the regional fixed effects explain only 17% of variation in average incomes). The cross-regional differentials in Gini coefficients remain roughly constant. Regions, which had a higher Gini coefficient in 1995, were also likely to have a higher Gini coefficient in 2010.

In order to control for the effect of the change in inequality, we include $Gini_{it}$ and $Gini_{jt}$ in all specifications. Also, in Section 4.1 we run a regression with average incomes of upper and lower quantiles of the income distribution.

In all the specifications above, we assume that income, unemployment, public goods, and real estate market conditions in both the sending and receiving regions do not depend on migration flows.[4] These assumptions are common in the migration literature (see, e.g. Kline, 2010). Essentially, we assume that incomes and other labor market outcomes are driven by productivity shocks and do not depend on migration decisions. Also, we assume that the supply of real estate in the host region is perfectly elastic; therefore rents do not depend on migration.

These assumptions are realistic in the context of Russia. The migration flows are small: 0.5–1.0% of the population per year and therefore are not likely to have a substantial impact on the incomes in either the sending and receiving regions. To understand the quantitative implications of such migration rates for wages, we can use the estimate of the labor demand elasticity in Russia of 0.4 (Akhmedov et al., 2005). Then migration inflow of 0.5% results in a wage decrease 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%).

In order to check that our results are not driven by the regions with high *cumulative* migration over the whole 1995–2010 period, we also estimate our regressions for the subsample of regions with net cumulative migration flows below 10% and above −10% of the region's population. We also use a 15% threshold as a robustness check.

The alternative explanations of our findings related to the impact of migration flows on incomes are also not consistent with trends in income inequality and in inter-regional convergence. Indeed, suppose that for some reasons in the 1990s a substantial part of the least productive workers moved so that higher migration outflows were correlated with growth in average income; and in the later years (again, for whatever reasons) the most productive workers moved, so higher migration outflows were correlated with lower income growth. It is theoretically plausible. However, this explanation would imply (a) faster interregional convergence in the 1990s than in the 2000s and (b) a fall in the interregional inequality over

[4] In her paper on the effect of the elite change in Russian regions on the small business development Shurchkov (2012) uses a more sophisticated identification strategy. Her instrumental variable is the interaction of Putin time dummy with distance to Moscow regional dummy. Unfortunately, we cannot use this instrument as time dummies, geographical characteristics and their interactions have a direct effect on migration flows – not just through their impact on business development and income.

time. Since we observe the opposite (see Appendix A), we can safely assume that the impact of migration on the change in average income has not been important, at least in 1996–2010 in Russia.

2.3. 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 section at the regional level from the Russian Statistical Service (Rosstat, www.gks.ru) for the period of 1995–2010 for 77 regions (see Table 5 in the Online Appendix). We exclude Ingushetia, Chechnya, and Chukotka 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 Rosstat changed the 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 which are sufficient for regression models with fixed effects.

We use data on incomes rather than on household assets as the latter are not available. However, various sources indicate that liquid assets of Russian households in 1996–2010 were very low, especially at the beginning of transition. During Soviet times most assets were owned by the state. Personal savings were destroyed by the hyperinflation of 1992. The main asset of Russian households—housing—was given to them for free in the 1990s but the size (16 and 23 square meters per capita in 1990 and 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 live.[5] The Global Wealth Report (2012) estimates the average value of Russian real estate in 2012 at about \$8000 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 the acute wealth inequality in Russia is taken into account (the 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 household assets are very low helps identify the importance of financial constraints as a barrier to mobility and makes income the key proxy for the ability to move.

The region-to-region annual migration flows are collected by the Interior Ministry and are available from Rosstat. These data reflect the official count of registered migrants (i.e. of those people who change their registration in this particular year).

We end up with $77 * 77 = 5929$ observations every year. Table 5 in the Online Appendix provides summary statistics and the definitions of all the variables used in our regressions.

As a proxy for financial development we use the ratio of outstanding household and business loans 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. Fig. 11 in the Online Appendix shows that all the indicators of financial development grew substantially in 2001–2008 and then declined slightly as a result of the financial crisis in 2009–2010. At the peak in 2009 the stock of loans to firms, households and mortgage debt was 29%, 14.6% and 3.3% of GDP, respectively. This is impressive growth given that in 2001 lending to households (including mortgages) were essentially trivial, and business loans were only 7% of GDP.

3. Results

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

3.1. Linear and quadratic specifications

Table 1 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 the 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 the destination of choice for migrants from all other regions. In these cities the assumption that real estate supply is perfectly elastic is less likely to hold so real incomes may be endogenous to migration. Also, these cities are special as their financial and real estate markets are more developed so financial constraints are less likely to bind even at the same levels of income. Another distinction is that the expectation of future income growth in these cities may be substantially higher than in the rest of the country. This is outside our model, which essentially assumes equal expected future growth rates across regions. Finally, the labor markets in these cities—at least in

[5] 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).

Table 1
Results of regressions (1) with and without squared terms of log of income. 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
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)
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)
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)
Observations	84,666	84,666	80,222	80,222
R2-within	0.308	0.308	0.309	0.310
Number of pairs	5929	5929	5625	5625

Note: Robust standard errors in parentheses. Variables included in the model but not reported in the table: housing price, stock of housing, new flats, life expectancy, infant mortality rate, number of doctors, number of hospital beds, number of telephones, highway density, number of buses, one-year time lag of share of young and old people, number of students, proportion of women and year dummies. The standard errors are clustered at the level of pairs of regions.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

some occupations—are more likely to be internationally integrated; and our model ignores international migration. 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 (which 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 that the quadratic relationship peaks at log income being equal to 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).

When we exclude Moscow and Saint Petersburg, the results are similar, although the coefficients are smaller. This can be explained by the fact that returns to moving to Moscow and Saint Petersburg are higher due to the expectations of higher future income, not just the higher current income in these cities.[6]

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-region migrations in Russia in 1996–2010.

Other coefficients are generally consistent with the gravity model. Migration is correlated with the population of both the 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 a higher proportion of women, students, young and old people. They move from regions with a higher highway density and a higher number of buses per capita (both

[6] We have also run regressions excluding Moscow and Saint Petersburg as sending regions but keeping them as receiving regions. Results (available on request) are also similar; the coefficients at income and income squared in the sending region are the same as in the Columns 3 and 4, while for the receiving regions the coefficients are similar to those in the Columns 1 and 2.

are measures of costs of mobility). The effects of public goods and demographics should not be over-interpreted 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 public goods in detail. However, we do include these variables in all regressions to control for potential heterogeneity.

We also control for income distribution through including Gini coefficients 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 real estate market development: the availability of housing (in square meters per capita) and the price of real estate (in CPI-adjusted rubles per square meter). The effect of the real estate market is consistent with the importance of financial constraints and 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 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.

3.2. 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 γ. Finally, we find $\hat{\gamma}$ as the threshold with the minimum residual sum of squares (RSS) from Eq. (3). The minimum RSS is reached at log real income equal to 9.0. Using Hansen's methodology (Hansen, 1999), we test the hypothesis of the significance threshold. The test statistic is $F1 = 112.7$, p-value is 0.000.[7] Therefore there are indeed two 'regimes'. We have also tested the hypothesis of two thresholds, however, we did not find significant results.

We estimate the 95% confidence interval for the threshold to be (8.9, 9).[8]

Fig. 1 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.

3.3. 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).

Fig. 2 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, an increase in income results in higher out-migration; for richer regions, a 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).[9] The log real income at 8.8 implies that the average income is equal to exp(8.8) = 6634 rubles in 2010.

3.4. Discussion of results

In this section we summarize the estimates of the thresholds and peaks of the relationships between real income in the sending region and the intensity of migration. The results of different methods are quite similar (see Table 2). 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 per month in 2010 prices per month (about $270 per month or about $3000 per year at 2010 exchange rate).

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

[8] 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 $\gamma = 9.0$.

[9] We calculate confidence interval using bootstrap procedure.

Table 2
Estimates of the peak 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 Eqs. (1), (2) and (4).

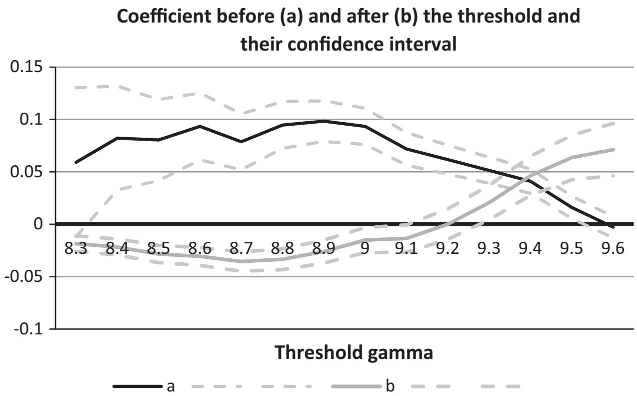

Fig. 1. Results for regressions with structural break for different threshold levels. Note: Coefficients *a* and *b* represent the relationship between log of migration flow and log of income per capita to the left of the threshold and to the right of the threshold in the regression (2).

Fig. 2. 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 Eq. (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 are the actual observations averaged out for each value of the income at origin region (*i*).

In Fig. 3, we plot the evolution of percentiles of interregional income distribution over time. Assuming the critical real income being 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 decreased substantially during the 2000s.

Fig. 3 implies that while convergence in the 1990s was indeed slowed down by poverty traps, the situation changed in the 2000s. The overall economic growth let the poorer 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 (see Appendix A for the data on the evolution of interregional differences in incomes, wages, unemployment rates and GDP per capita in Russia and other countries).

While Russian regions did break out of the geographical poverty traps in the 2000s, lowering barriers to migration did not result in increase of migration (see Fig. 4). In order to understand this, in Fig. 4 we also plot the year dummies from the main

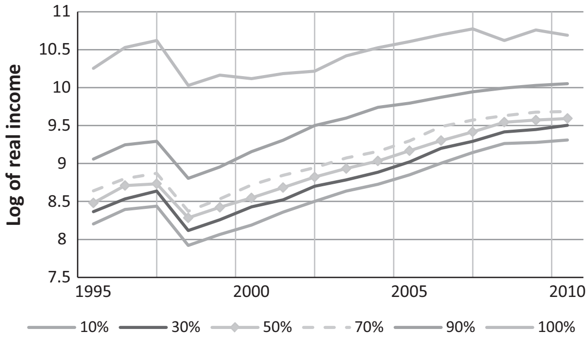

Fig. 3. Evolution of distribution of regions by real income over time. Note: The graph shows the change over time of percentiles of the distribution of Russian regions by log of real income per capita.

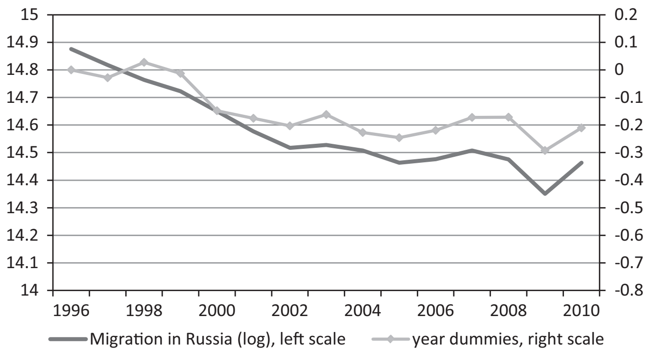

Fig. 4. Evolution of migration over time: internal migration in Russia in 1996–2010 and time dummies in the main regression (1).

specification (Table 1). 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 is explained precisely by the decreases in the interregional differences. In this sense, the decrease in migration in the 2000s is normal. As the barriers to migration decreased, the threat of migration from poorer regions became credible. This has resulted in growth of wage and incomes in these regions. Therefore interregional differences in wages and incomes decreased, the number of actual migrants also fell – as the incentives to migrate were no longer as high as they used to be.

We have also carried out a counterfactual estimation of the number of migrants that would have moved if there were no poverty traps. We have replaced each actual observation M_{ijt} to the left of the peak in Fig. 2 with a counterfactual number of migrants that we have estimated by extrapolating leftwards the trend on the right of the peak. We have also normalized all the time dummies so that our counterfactual would predict the same average migration in 2010 (the year where poverty traps were fully eradicated). The results of this back-of-the-envelope calculation are as follows: in 1990s, migration would have been higher by 25%, in 2000–2003 – by 14%, and in 2004–2010 – only by 2%. In total, more than 4 million additional migrants would have moved. A caveat is due. Without reliable data on within-region income distribution, we cannot provide credible microfoundations for this extrapolation. Also, this exercise does not take into account general equilibrium effects; such a substantial change in migration flows could have affected incomes, unemployment, public goods and other determinants of future migration. In this sense, this estimate should be treated only as a back-of-the-envelope calculation.

4. Additional evidence and robustness checks

4.1. Regressions for subperiods and subsamples

To check the robustness of our results we estimate Eq. (1) for the subsamples of close and distant pairs of regions. We also estimate the model for different sub-periods: 1996–2000, 2000–2005 and 2005–2010.

Table 6 in the Online Appendix shows the results for geographical sub-samples. Columns 1–2 present the results for pairs of regions that are at most 500 km away from each other. We calculate the distance between regions as a railway distance between their capitals. If there is no railway connection between the regional capitals, we calculate the distance by a highway. Columns 3–4 present the results for the pairs of regions that are 500–2000 km away from each other. Columns 5–6 present the results for the pairs of regions more than 2000 km away from each other.

The coefficients of 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 km) 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 medium-haul nor for short-haul migration. For the intermediate distances (500–2000 km) there is no significant relationship. For the close pairs of regions the relationship is U-shaped.

Semiparametric results for different distances (presented in Fig. 13 in the Online Appendix) produce similar results. The peak for the distant pairs of regions is 8.8 (in terms of the logarithm of real income).

We have also estimated the relationship between income and migration for different subperiods. Fig. 9 in the Online Appendix presents the results for the 1990s, the early 2000s and the late 2000s.[10] The graphs show that in the 1990s the semiparametric relationship is monotonically increasing (the effect of poverty traps dominates). In the early 2000s, there is indeed a hill-shaped non-monotonic relationship (consistent with our theory). In 2005–2010, the non-monotonicity disappears and the relationship becomes a decreasing one. This is not surprising, in 2005–2010 incomes in the vast majority of regions were higher than the thresholds identified above.

We also ran the regressions for the different quantiles of the within-region income distribution to see which parts of the distribution drive our results. Unfortunately, Russian data does not allow us to carry out such tests. The official statistics do report quintiles of income distribution for Russian regions. Unfortunately, these quintiles are constructed based on two moments of the distribution (average income and Gini coefficient) assuming that the income distribution is lognormal. Therefore for each region-year we only have two degrees of freedom. We ran regressions with the split of the income distribution into two subsamples—below and above a certain percentile. We present the results in Table 13 in the Online Appendix for the following thresholds: 10%, 33%, 50%, 66%, 90%. (For example, in the second column the variable IncomeLower is the average income of the lower third of the population while the variable IncomeUpper is the average income of the upper two thirds.) The results suggest that the poorer part of the distribution is financially constrained (the coefficient of income is positive). The richer part is not constrained as the coefficient at income is not significant, or negative.

Given the importance for the Russian economy of the growth in global commodity prices, we have also checked whether our results are driven by the resource-rich regions. Column 5 in Table 12 in the Online Appendix presents the results for the subsample where the share of natural resources in GDP is below 25% (thus excluding top ten resource rich regions). The results remain similar.

Finally, we consider the issue of the endogeneity of income to migration. As we argued above, annual internal migration in Russia has on average been very low and was therefore unlikely to affect the incomes. On the other hand, in certain regions, the cumulative migration over the whole 1995–2010 period has been substantial (see Fig. 10 in the Online Appendix for the map of these regions). Table 12 shows that our results are not driven by these regions. In Column 4, we exclude the regions where cumulative inflows or cumulative outflows have been above 15% of population, in Column 3 we have also checked the 10% threshold and found similar results.

4.2. Robustness checks

We ran 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 estimated our main specification with lagged independent variables. The results for one-year and two-year lags are presented in Tables 9 and 10 in the Online Appendix. It turns out that specifications with lags have much lower explanatory power. Also, in neither specification do 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 also estimated a specification where instead of incomes at origin and destination we included only a difference between them (see Table 8 in the Online Appendix). We 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 the squared difference is positive. This is consistent with the 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 Fig. 12 in the Online Appendix. Growth in income generally results in higher immigration. This is true for regions with the logarithm of income higher than 8.3 (4024 rubles in 2010); only very few region-years are below this threshold in our data.

We also ran the regression including foreign direct investments (FDI) in both sending and receiving regions. As this variable is not available for all region-years, the sample is smaller; therefore we only report these results in the Online Appendix (Table 11). The results are similar: the coefficients at FDI are not significant, and the coefficients at income do not change.

We have checked whether our results depend on international migration. Unfortunately, the official data on international migration are not reliable. Individuals that work and live permanently abroad can still maintain registration in Russia and

[10] The regressions with linear and squared terms for these and other subperiods are reported in Table 7 in the Online Appendix. The regressions confirm the absence of poverty traps in the 2005–2010 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.

Table 3
Panel regressions 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
R^2-within	0.104	0.105	0.104	0.106
Number of pairs	5929	5929	5625	5625

Note: Robust standard error in parentheses. 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, one-year time lag of share of young and old people, number of students, proportion of women and year dummies.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

will be counted as living in Russia for statistical purposes. (In case of internal migration, to get registered in the destination region, one has to deregister in the origin region.) In order to check the robustness of the results, we re-estimate our specification excluding the regions with noticeable international migration; namely, we exclude the regions where international migration inflows are above 10% of the internal migration inflows and/or international migration outflows are above 10% of the internal migration outflows. The results do not change (see the last Column in Table 12).

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 reached 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.

We have also added proxies for financial development such as loans to firms, households and mortgage debt as a percentage of GDP and their interactions with income. As the data on loans to firms and households are available only since 2001 and data on mortgage debts since 2004, the timespan of this analysis is substantially shorter.

Table 3 presents regressions with the ratio of household loans to GDP (the regressions with alternative measures of financial development are provide in the Table 14 in the Online Appendix; the results are similar). In all regressions we include fixed effects for pairs of regions. Therefore we control for all historical legacies in terms of interregional differentials in accumulated wealth, financial development and links between origin and destination regions.

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 have also run regressions with squared income and the interaction of financial development with squared income. Again, consistent with the theory, we find that in the regions with a 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 a non-monotonic relationship between income and migration is less likely to be observed.

5. 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 income growth and financial development help regions break out of poverty traps.

Our quantitative estimates of the parameters of poverty traps are based on the data from Russia in the 1990s and the 2000s. Further research is needed 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 labor, financial and real estate markets. However, the qualitative result that geographical poverty traps are an important yet solvable policy problem is likely to extend beyond Russia.

We find 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 the 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 becomes credible (due to the disappearance of geographical poverty traps and therefore lower barriers to migration). This analysis directly implies that policymakers should focus on removing barriers to labor mobility (including those driven by financial constraints) rather than on promoting migration per se.

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Appendix A

A.1. Interregional differentials, convergence and migration in Russia

In this Appendix, we provide the basic trends in interregional differentials and migration in Russia and put them into the international perspective.

Fig. 5 in Appendix A 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

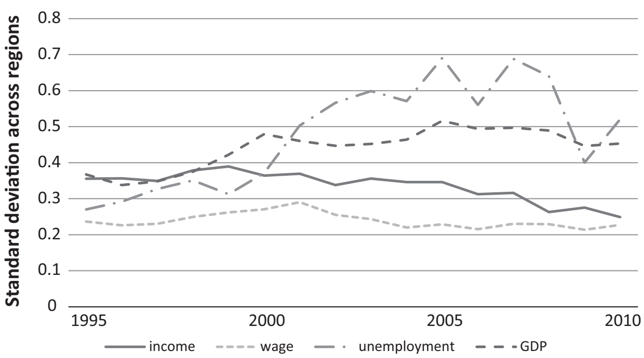

Fig. 5. Differences between Russian regions in terms of logarithms of real incomes, real wages, unemployment, and real GDP per capita. (We calculate population-weighted measures of interregional differences in order to make our results internationally comparable. The results for the unweighted measures are very similar (available upon request).) Note: The graph shows $\sqrt{\frac{1}{P}\sum_{i=1}^{N}P_i(X_{it}-\overline{X}_t)^2}$, 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 $\overline{X}_t$ 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.

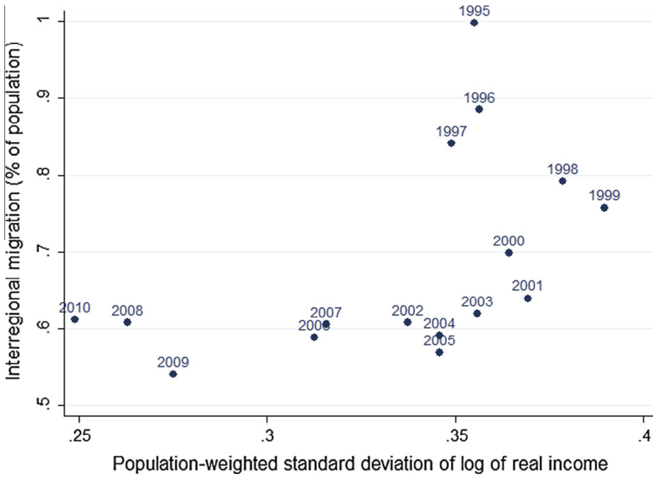

Fig. 6. Interregional migration rates and interregional differences in real incomes. Note: Population-weighted standard deviation of log of real income is $\sqrt{\frac{1}{P}\sum_{i=1}^{N}P_i(X_{it}-\overline{X}_t)^2}$, where X_{it} is the log of real income in region i in year t, and $\overline{X}_t$ is the population average log of real income in year t. P and P_i are population in Russia and region i, respectively.

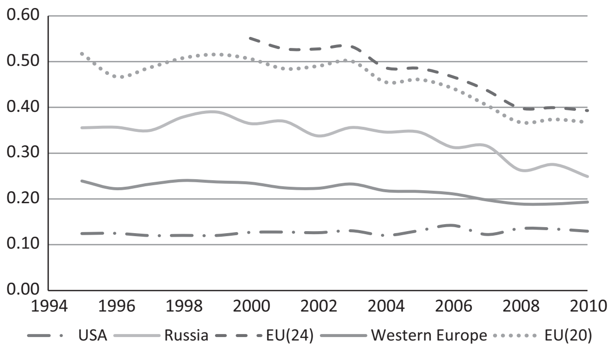

Fig. 7. Russian convergence in the international perspective: population-weighted standard deviation of logarithm of real income across subnational units in Russia, Europe and the United States. Note: The graph shows $\sqrt{\frac{1}{P}\sum_{i=1}^{N}P_i(X_{it}-\overline{X}_t)^2}$, where X_{it} is the log of real income in region i in year t, and $\overline{X}_t$ 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, Eurostat http://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.

were increasing rather than decreasing. The situation changed dramatically in 2000s. Interregional differences in unemployment rates declined sharply in 2005–2010. 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.[11]

The interregional convergence in incomes in Russia was taking place along with the decreasing migration (Fig. 6 in Appendix A). This is also 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

[11] The fact that there is convergence in incomes and wages and no convergence in GDP per capita is consistent with falling barriers to mobility. 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.

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.

Are the interregional differences in Russia still large compared to other countries? While the 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 (Fig. 7 in Appendix A). This is quite striking given that EU also had a decade of fast convergence.

Appendix B

B.1. A simple model of geographical poverty traps

In this Appendix 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 is not correlated with the income at origin. We denote the expected income at destination Y.

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: $C < Y/2$ (otherwise there will be no migration in equilibrium).

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 $y \geqslant C$, 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 $y \geqslant C$ *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 4 in Appendix B). Let us discuss the intuition behind the results presented in Table 4 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 $Y - C - y^H > C - y^L$ 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

Table 4
Relationship between average income and migration for different levels of average income in a region.

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

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

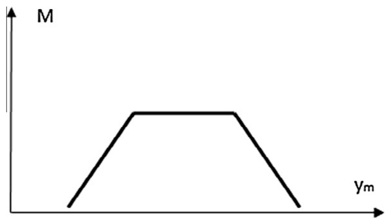

Fig. 8. Migration as a function of the mean income at origin for the case of the uniform distribution of incomes at origin (for the case $Y - C - y^H > C - y^L$).

to be interested in migration $y_m + y^H < Y - C$. 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.

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 Fig. 8 in Appendix B illustrates the relationship for the Case 2 ($Y - C - y^H > C - y^L$). In the Case 1 ($Y - C - y^H < C - y^L$), 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 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.

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 $y_m < \min\{C - y^L, Y - C - y^H\}$), and there is a decreasing part for high y_m(for $y_m > \max\{C - y^L, Y - C - y^H\}$).

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 (Fig. 8 in Appendix B), the effect of inequality on $M'(y_m)$ is highly non-linear and hard to test empirically.

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jce.2015.02.002.

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