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Convergence between Russian Regions

Sergei Guriev
Elena Vakulenko

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Sergei Guriev[2] and Elena Vakulenko[3]

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Abstract

In this paper we study convergence among Russian regions. We find that while there was no convergence in 1990s, the situation changed dramatically in 2000s. While interregional GDP per capita gaps still persist, the differentials in incomes and wages decreased substantially. We show that fiscal redistribution did not play a major role in convergence. We therefore try to understand the phenomenon of recent convergence using panel data on the interregional reallocation of capital and labor. We find that capital market in Russian regions is integrated in a sense that local investment does not depend on local savings. We also show that economic growth and financial development has substantially decreased the barriers to labor mobility. We find that in 1990s many poor Russian regions were in a poverty trap: potential workers wanted to leave those regions but could not afford to finance the move. In 2000s (especially in late 2000s), these barriers were no longer binding. Overall economic development allowed even poorest Russian regions to grow out of the poverty traps. This resulted in convergence in Russian labor market; the interregional gaps in incomes, wages and unemployment rates are now below those in Europe. The results imply that economic growth and development of financial and real estate markets eventually result in interregional convergence.

Keywords: convergence, economic growth, Russian regions, financial development, migration.

JEL classification: J61, R23.

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[2] New Economic School. E-mail: sguriev@nes.ru

[3] National Research University Higher School of Economics. E-mail: evakulenko@hse.ru, esvakulenko@gmail.com

1. Introduction

This paper studies convergence among Russian regions during Russia's transition from plan to market. The interregional convergence in Russia is important for several reasons. First, Russia represents a unique natural experiment for studying convergence. The allocation of population and of physical capital at the beginning of transition was determined by non-market forces. Soviet industrialization policies often pursued political or geopolitical goals. Even when they reflected economic realities, the economic decision-making was distorted substantially by central planning, price-setting and subsidies. Also, the allocation of production was intended to serve a different country – the Soviet Union (or even the whole Council for Mutual Economic Assistance countries) rather than Russia. In this sense, twenty years ago, the convergence started out with an exogenous allocation which was not driven by market forces and was therefore by definition far away from the steady state market equilibrium.

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 monotowns.[4] Whole towns, cities or even regions relied on a single industry. Therefore the economic restructuring and inter-sectoral reallocation implied not only moving workers or capital between employers in one town – it also required moving workers or capital between cities.

The second important feature of Russian transition was the timing of structural change. The subsidies and price controls (including foreign trade restrictions) were removed virtually overnight in 1992. This created substantial interregional differences (as removal of subsidies and price and foreign trade liberalization made many regional economies non-competitive). However, as financial markets and real estate markets developed slowly, the reallocation in 1990s faced several institutional barriers. In this sense the interregional convergence in Russia is a unique natural experiment for understanding how the markets and institutions matter for reallocation of production factors. While distortions were large already in 1990s, the markets were still underdeveloped. Over time, markets and institutions developed and barriers to reallocation of capital and labor decreased. Comparing the dynamics of convergence in 1990s and in 2000s therefore allows understanding the quantitative importance of market imperfections for factor mobility.

The first glance at the dynamics of interregional dispersion in Russia shows that the data are indeed consistent with the hypothesis that markets and institutions conducive to migration take time to develop. Convergence in incomes, wages and unemployment rates did not happen in 1990s but began only in 2000s, especially in the second half of 2000s (convergence in GDP per capita is still not happening). In this paper we carry out several empirical exercises to

[4] Russian law defines monotowns as town where at least 25% employment is in a single firm. Even now, the Russian government's Program for the Support of Monotowns lists 335 monotowns (out of the total of 1099 Russia's towns and cities) with the total of 25% of Russia's urban population.

understand the role of specific barriers to reallocation and convergence driven by underdevelopment of markets.

Figure 1 . Differences among Russian regions in terms of logarithms of real incomes, real wages, unemployment, real GDP per capita. [5]

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

In particular, while there was no convergence in 1990s (in fact there was even *divergence*), the situation changed dramatically in 2000s. As shown in Figure 1, the convergence process accelerated substantially with interregional differences in incomes and unemployment rates declining sharply in 2005-10. These changes in interregional differences are even statistically significant at 1% level.

The convergence in wages started even earlier (around 2000). Differences in standard deviations of real wage between 2000 and 2005 (or between 2000 and 2010) are significant at 10% level. The gap in GDP per capita remained the same throughout the 2000-10 with a weak convergence in 2005-10. Later in this paper we discuss how we can reconcile convergences in incomes and wages with the lack of convergence (or weak convergence) in GDP per capita.

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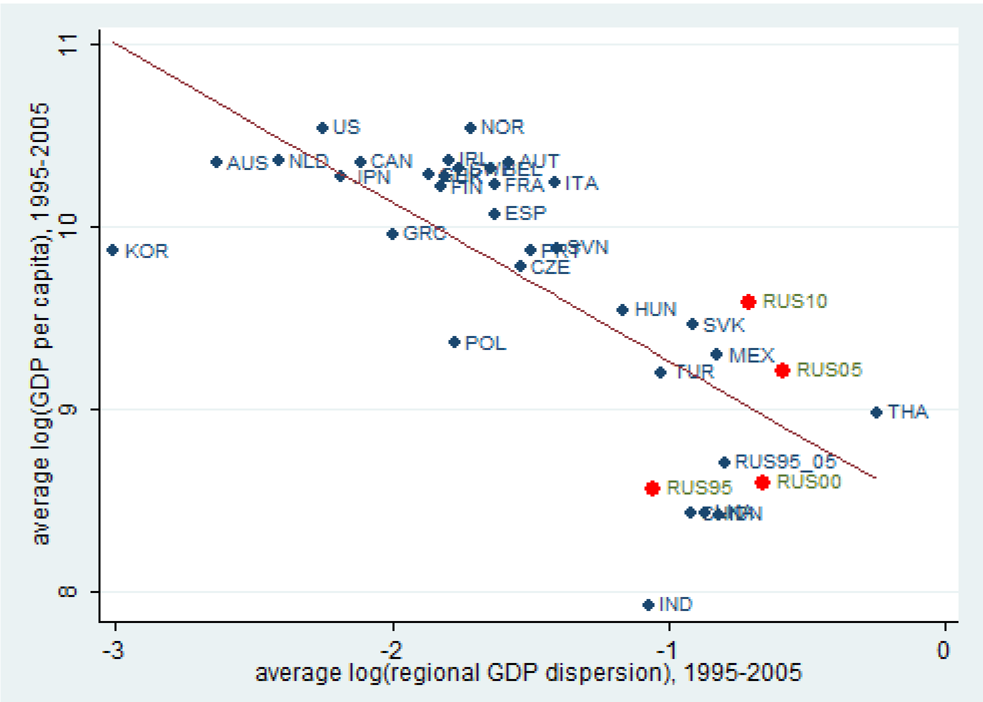
[5] As we discuss in Section 3, we can only build reliable time series back to 1995. However, several papers analyzing convergence in 1990s (see Section 2) imply that there was no convergence in the first half of 1990s so the allocation in 1995 was roughly the same as in 1992. We calculate population-weighted measures of interregional differences in order to make our results internationally comparable. In the Appendix B, we also provide the unweighted measures (Figure 21) even though the incomes, wages and per capita GDP are higher in more populated regions (see the respective correlations in Figure 22), the results are similar.

In order to understand whether the interregional differences are still abnormally high in Russia, we place Russia in the international context using the data recently developed by Che and Spilimbergo (2012). Che and Spilimbergo calculate interregional differences for 32 countries in a compatible way[6] and plot them against GDP per capita (averaged out for 1995-2005, in real PPP-adjusted dollars). Their main finding is that that there is a negative correlation between interregional differences and GDP per capita.

Since Russia was not in Che and Spilimbergo's dataset, we reproduced their calculations for Russia, both for the 1995-2005 average (as they do for the other countries) but also for individual years of 1995, 2000, 2005 and 2010 (

Figure 2). It turns out that while Russia was "abnormally uniform" in early 1990s, it did experience substantial divergence in late 1990s. There was continuing albeit weaker divergence even in early 2000s – so Russia became "abnormally unequal" given its GDP level. Even though there was some convergence in late 2000s, Russia is still "abnormally unequal". Given the fast economic growth in 2000s, Russia should have become substantial "more uniform" – at least given the downward-sloping relationship between income and inter-regional inequality in Che-Spilimbergo's data.

Figure 2. Russia's interregional dispersion in the international context.

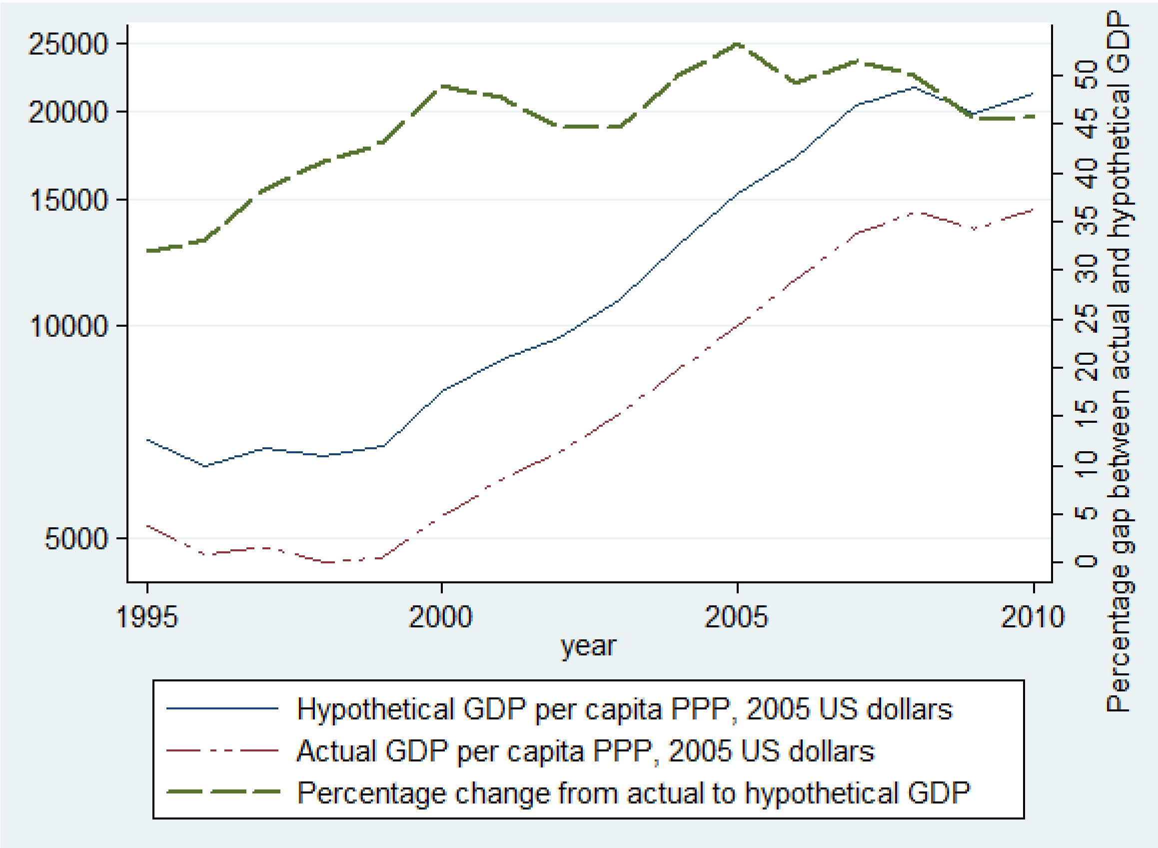


[6] Che and Spilimbergo calculate the population-weighted sum of absolute gaps between regional GDP per capita and national average thus adjusting for the fact that different countries have different numbers of subnational units. They also take into account the fact that data are not available for some regions; they calculate national averages as population-weighted averages using the available sub-national data.

Source: Che and Spilimbergo (2012), Figure 1, and authors' calculations for the trend line[7] and Russia.

The comparison with Che and Spilimbergo's data implies that the interregional differences in Russia are large in terms of international comparisons. To quantify the GDP per capita "cost" of interregional dispersion, Che and Spilimbergo calculate the "hypothetical GDP" – this is the GDP that would be produced if the gap between rich and poor regions were the same as in the US. In their sample the gap between actual and hypothetical GDP varies substantially – from 1.15% for Japan to 48% for Thailand. Figure 3 reproduces their calculations for Russia. The gap between actual and hypothetical GDP in Russia (average for 1995-2005) turns out to be 45% (similar to that of Thailand and much higher than in Mexico, 33%). This gap has grown from 33% in 1995 to 53% in 2005, but the convergence in 2005-10 did reduce the gap to 46% in 2010.

Figure 3. Comparison between hypothetical and actual GDP according to Che and Spilimbergo's methodology.



Source: Che and Spilimbergo (2012) and authors' calculations. Actual and hypothetical GDP are measured in PPP-adjusted 2005 US dollars (left-hand side scale). The gap between the two is measured in percentages (right-hand side scale).

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[7] The trend line is calculated without Russia.

Therefore, understanding the convergence (and the lack thereof) in 1990s and in 2000s is an important issue (both for Russia and for other countries). There can be multiple potential explanations for divergences (or lack of convergence) in 1990s and convergence in 2000s: (i) economic growth simply allowed most Russian regions to grow out of the poverty traps that were widespread in 1990s; (ii) the development of financial and real estate markets reduced the transactions costs of moving therefore reducing the importance of the poverty traps; (iii) development of capital markets increased capital mobility; (iv) federal redistribution reduced interregional differences.

In order to answer this question, we undertake several empirical exercises. First, we decompose the convergence process by sources of income: wages, government transfers and other incomes. Second, we test whether inter-regional migration increased or decreased and which barriers to migrations were binding during this period of time. Third, we undertake a similar study for capital mobility.

The rest of the paper is structured as follows. In the next Section we discuss related literature. Section 3 describes the data. In Section 4, we provide basic facts on interregional convergence and migration. We also decompose convergence in incomes into convergences in its components (such as wages, non-wage incomes, and fiscal transfers). In Section 5 we discuss the labor mobility and the convergence in the labor market. In Section 6 we analyze cross-regional capital flows. In Section 7, we conclude and arrive at policy recommendations.

2. Related literature

In this Section we discuss papers on convergence among Russian regions. Gluschenko (2010) provides an overview of recent work on the inter-regional income inequality in Russia. Table 10 in the Appendix A (developed in Gluschenko, 2010, and extended by us[8]) summarizes the main features of these papers. These papers consider different time spans and different methodologies; they also differ in terms of data, in particular using different regional deflators. Most studies use σ-convergence and—unconditional or conditional—β-convergence methodology (Barro, Sala-i-Martin, 1991). Some studies analyze stochastic convergence where the authors check the stationarity of time series. Finally, some authors use the transition matrix approach (similar to the seminal paper by Quah, 1993) that explores the mobility of regions by income and estimates the Markov transition matrix that contains the probabilities of transition of regions from low-income to high-income categories.

In order to compare the results from different papers, we add a column with estimates of the speed of convergence (for the papers where the authors estimated β-convergence). The β-convergence model assumes a negative relationship between the initial income level and the average annual income growth rate over a given period. Barro and Sala-I-Martin (1991) suggest the following empirical specification for testing (unconditional) β-convergence:

$$(1/T)\log\left(y_{it}/y_{i,t-T}\right)=\alpha-\left[\log\left(y_{i,t-T}\right)\right]\left[\left(1-e^{-\beta T}\right)/T\right]+u_{it} \quad (1)$$

where y_{it} is per capita GDP or income for region i in a moment t. T is a length of the analyzed time period.

In order to calculate the speed of convergence β, one should estimate the coefficient $\hat{b}$ from the regression $(1/T)\log\left(y_{it}/y_{i,t-T}\right)=\alpha+b\log\left(y_{i,t-T}\right)+u_{it}$ and then find

$$\beta=-\frac{\ln\left(1+\hat{b}T\right)}{T} \quad (2)$$

If β>0 (or b<0), regions with lower income grow faster than regions with higher initial income – which means that (unconditional) β-convergence is the case.[9] Notice, however, that β-convergence does not imply decreasing inequality. Indeed, different regions may have different steady-state growth paths. Some regions may "outrun" their growth paths, and thus stay ahead of other regions and some, vice versa, may lag behind their steady-state growth paths.

[8] We added several recent papers. We also added estimates of the *speed* of convergence (in terms of β coefficient in the β-convergence model) wherever applicable.

[9] Conditional β-convergence is the case when the growth rate is negatively correlated with the initial level controlling for other factors that affect growth (e.g., education, saving rates etc.).

The estimate of β allows calculating the time it takes to reduce the inter-regional gap by a factor of two:

$$t_{0.5} = \frac{\ln 2}{\beta} \tag{3}$$

For example, β=7% means that it takes ln 2 / 0.07 = 10 years to reduce the gap by half; if β=2% then it takes 35 years.

The β-convergence is a special case of a more broad definition of convergence, the so-called σ-convergence (decline in the standard deviation or Gini coefficient among regions over time).

According to the studies listed in Table 10 (Appendix A), in 1990s there was no convergence or even divergence among Russian incomes while there was some convergence in (late) 2000s.[10] Below we discuss some of the papers in the table.

Dolinskaya (2002) analyzes the impact of fiscal policy and industry structure on income convergence in Russia 1991-1997 using the transition matrix approach. Her analysis suggests that more successful regions prospered due to their natural resource endowments while continuing to delay restructuring and to support traditional enterprises. The less successful regions were in a "poverty trap" due to their low level of development of competitive industries and lack of resources for the restructuring of the regional economy.

Babetski and Maurel (2002) study the factors of speed of income convergence using the stochastic convergence approach. They estimate the relationship between the speed of convergence and macro-economic stabilization, price liberalization, small-scale privatization, break-up of state-owned enterprises. The authors find that price controls and subsidies for production reduce the speed of convergence in the consumer price index, while privatization increases the speed of convergence. They conclude that the development of market institutions contributes to convergence and government intervention reduces the rate of convergence.

A few papers (Buccellato, 2007, Lugovoy et. al., 2007, Kholodilin et. al, 2009, Zverev, Kolomak, 2010) consider spatial interactions. They show that spatial dimension plays a crucial role in the convergence process in Russia. In particular, Kholodilin et. al. (2009) show that adding spatial lags to the conditional convergence model decreases the speed of convergence.

Solanko (2008) divides regions into rich and poor and finds that there is income convergence only for the rich regions. This result consistent with Kholodilin et. al. (2009) who find that convergence takes place only within the group of high-income regions with similar standards of

[10] For example, Litvintseva et al. (2007) consider dynamics of income quintiles and find that inequality among Russian regions was increasing from 2000 to 2004 (i.e. there was σ-*divergence*). In terms of β-convergence, there was a divergence in GDP in 1990s and weak convergence in 2000s.

living that are located near each other. This is also in line with Andrienko and Guriev (2004) who find that the poorest 30% of Russian regions are in a “poverty trap”. In these regions, the income level is so low that the potential migrants cannot afford to migrate (even though they are willing to). Using panel data, Andrienko and Guriev show that in the poorest regions, out-migration *increases* rather than decreases with income (while in the richer regions there is an intuitive *negative* correlation between income and out-migration).

Kwon and Spilimbergo (2005) study a relationship between income, geographical labor mobility and fiscal policy using panel vector regression approach for 1993-2002. Their analysis of the impulse response functions implies that Russian regions had a very weak response to income shocks. Regional governments have used procyclical fiscal policy, increasing regional expenditures in booms and reducing them in recessions, and inadequate transfer policy. This suggests that in 1990s fiscal policy contributed to rather than mitigated interregional differences.

Our paper differs from the papers above in two important ways. First, we cover the time period of late 2000s where the convergence started to take place. The long time period also allows us to use panel data and to control for fixed effects. Second, we run a whole range of empirical exercises to understand the nature of the recent convergence and test different potential explanations. In this sense, we are the first to notice the recent convergence and offer plausible explanations of why convergence is happening now and why it was not happening before.

As one of the plausible explanations is the role of financial constraints, our paper is related to the work on the non-linear relationship between income at origin and migration. As discussed in Banerjee and Kanbur (1981), Andrienko and Guriev (2004), and Phan and Coxhead (2010), liquidity constraints may result in a non-linear relationship between income and propensity to migrate out of a region. In poor regions, potential migrants are willing to move but may not be able to afford the move; in this case 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 intuition in a simple model of migration decisions of heterogeneous migrants under financial constraints.

3. Data

We use official data on income per capita, gross domestic product (GDP) per capita and wages at the regional level from the Russian Statistical Service (Rosstat)[11] for the period of 1995-2010 for 78 regions.[12] We excluded the Republic of Ingushetia and the Republic of Chechnya due to the unavailability of data, as well as 9 autonomous districts (Nenets, Komi-Perm, Khanty-Mansijsk, Yamalo-Nenets, Taimyr/Dolgano-Nenets, Evenk, Ust-Ordyn Buryat, Aginsk Buryat, and Koryak) which are administrative parts of other regions.

In order to take into account price level differences, we deflate wages and incomes by the regional consumer price index (CPI). [13] This allows us to control for region-specific inflation rates which is sufficient for regression models with fixed effects (Sections 5 and 6). However, when we want to measure the interregional differences in real variables at a given year, we need to use region-specific price *levels*. As a proxy of price level, we use region-specific subsistence level (this is done in Section 4, where we provide basic facts on interregional dispersion and σ-convergence).

In order to understand which factors drive the convergence, we decompose income and GDP into several components. The official Russian data on income divide it into wages, property income, entrepreneurial income, other income (which includes shadow income), and social transfers (such as pension, stipends, grants, social benefits, and social insurance payments). Using this data, we construct three income categories which are (i) wage, (ii) other income (including property, entrepreneurial income and other income) and (iii) transfers. We also decompose GDP into three categories: labor income, capital income, and net business taxes (these data are available from 2002 only).

We analyze interregional migration data for the period from 1995 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 registered migrants (i.e. of those people who change their registration in this particular year). We end up with 77*77 observations every year.[14] Table 11 in the Appendix A provides the summary statistics of all the variables we use in our regressions[15].

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[11] http://gks.ru. Rosstat and many research papers often refer to the regional GDP as GRP (Gross Regional Product) but we prefer to use a more conventional term GDP throughout the paper.

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

[13] There are no reliable regional GDP deflators for the whole period (Granberg and Zaitseva, 2003, only calculate those for 1999-2001). As a robustness check we also use the regional subsistence level in rubles as an alternative deflator; the results are very similar. There are no subsistence level data for 2000; we interpolated this year as an average of 1999 and 2001.

[14] We have data on migration for 78 regions but we exclude Chukotka as there are no data for many explanatory variables for this region.

[15] We fill in some missing data. For Leningrad oblast we take a number of students 0.1 per 1000 population in 1995 as it is in a 1994. For Sakhalin oblast we consider 1 bus per 100 thousand people for 2008 and 2010 – this is the value reported by Rosstat for the year 2009.

4. Decomposition of inter-regional convergence

4.1. Basic facts about convergence

We begin with estimating the basic β-convergence models for three sub-periods – 1995-2000, 2000-2005, and 2005-2010. For each of the sub-periods we run a uni-variate regression of the annual growth rate during the period on the logarithm of the initial level of income. In each case we report the regression coefficient (Table 1). Figure 4 is a graphical presentation of beta-convergence. We carry out this exercise for real incomes, real wages and real GDP per capita. It turns out that there was no convergence in GDP per capita: divergence in 1990s, very weak convergence in early 2000s (the speed of convergence was positive but not significantly different from zero) and weak convergence in late 2000s.

The situation is very different for wages and incomes. There was a slow convergence among Russian regions in terms of real wages and real incomes. This convergence did substantially accelerate in early 2000s for wages and in late 2010s for incomes. In both cases, the speed of convergence β increased to 8 (which—as discussed above—implies that gap is halved every 9 years; indeed, ln2/0.08=8.7).

Table 1. Beta convergence for 95-00, 00-05, 05-10 (%).

Period	Real income per capita		Real wage		Real GDP per capita	
	Regression coefficient b	β,%	Regression coefficient b	β,%	Regression coefficient b	β,%
1995-2000	-4.584*** (1.539)	5.2	-3.790*** (1.372)	4.2	1.228 (1.176)	-1.2
2000-2005	-3.439*** (1.213)	3.7	-6.460*** (0.815)	7.8	-0.818 (0.737)	0.83
2005-2010	-6.757*** (0.884)	8.2	-3.207*** (1.111)	3.5	-1.640*** (0.611)	1.7
1995-2010	-3.444*** (0.457)	4.8	-3.676*** (0.456)	5.3	-0.443 (0.499)	0.45
2000-2010	-4.770*** (0.621)	6.4	-4.739*** (0.599)	6.4	-1.217** (0.463)	1.29

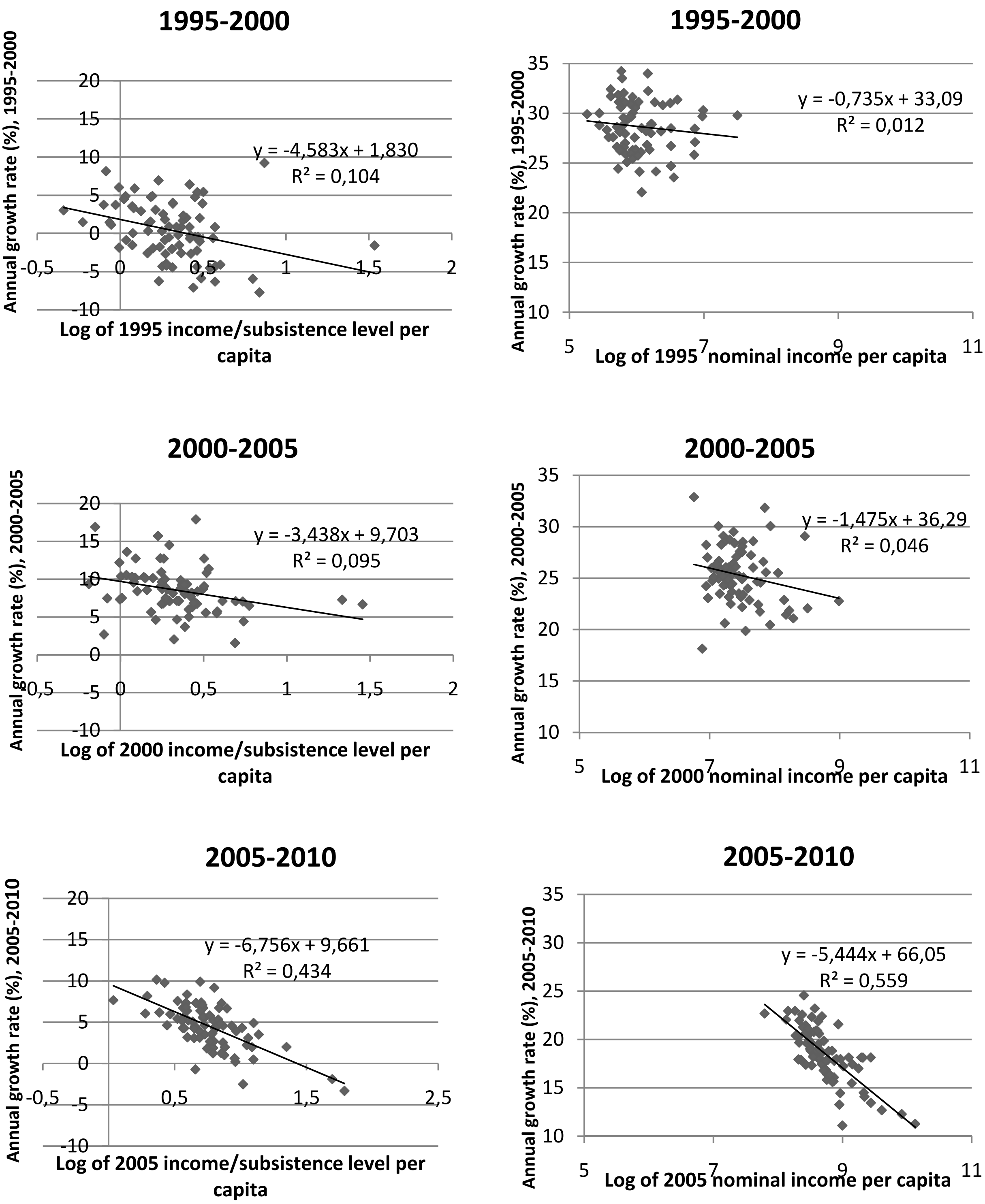
Note: standard errors in parentheses.

We also consider beta-convergence for nominal incomes, wages and GDP. The analysis of the convergence among nominal variables is also very informative. This analysis controls for ruble inflation over time but assumes that at a given moment each ruble of income has the same value in every region (because of interregional trade). This analysis is certainly wrong for the

CPI basket but may be closer to reality for migrants (who travel and therefore can take advantage of lower prices of goods and services in other regions.).

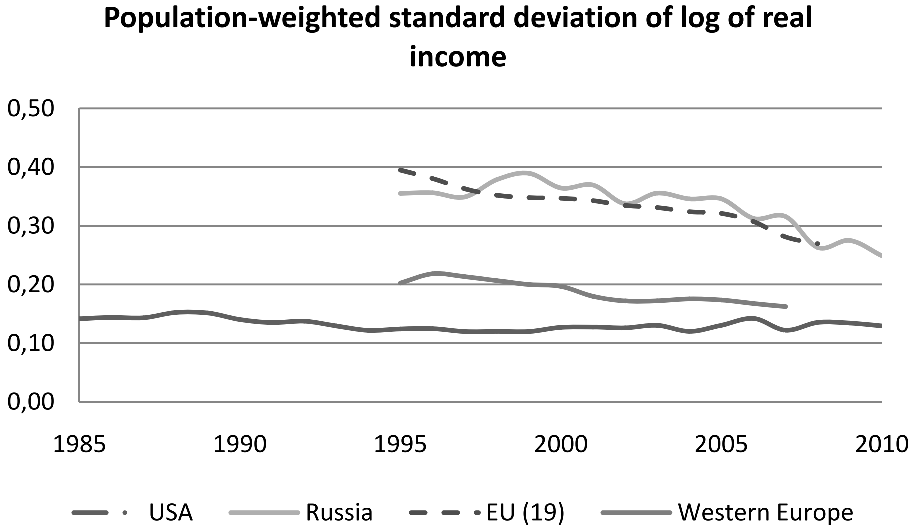
The results of convergences for the nominal variables are presented in the Appendix A (
Table 14). The speeds of convergence of nominal incomes, wages and GDP are lower than for the real values. The highest speed of absolute β-convergence is for nominal income 6.4 in 2005-2010. The nominal wage converges with speed 2.9 in 2000-2005. For the nominal GDP the speed of convergence is the lowest 1.8 in 2005-2010. Sigma-convergence of nominal values is presented in the Figure 25 in the Appendix B. Population-weighted standard deviations for nominal wages and incomes are greater than those for the real variables. This means that part of inter-regional income differentials is explained by differences in price levels across regions. However, the dynamics of standard deviations of nominal wage and income are the same as those for the real values.

Figure 4. Graphical representation of beta-convergence in real and nominal incomes in 95-00, 00-05, 05-10.



In the Introduction we already discussed Russia's sigma-convergence in international perspective in terms of GDP per capita. How does Russia fare internationally in terms of incomes and wages? It turns out that while recent convergence in incomes and wages[16] did not make Russia as equal as the US or Western Europe, Russia is now quite in line with the EU-19 (Figure 5).

Figure 5. Sigma-convergence in the international perspective.



Note: For the EU and Western Europe unit of observation is NUTS-2 region[17].

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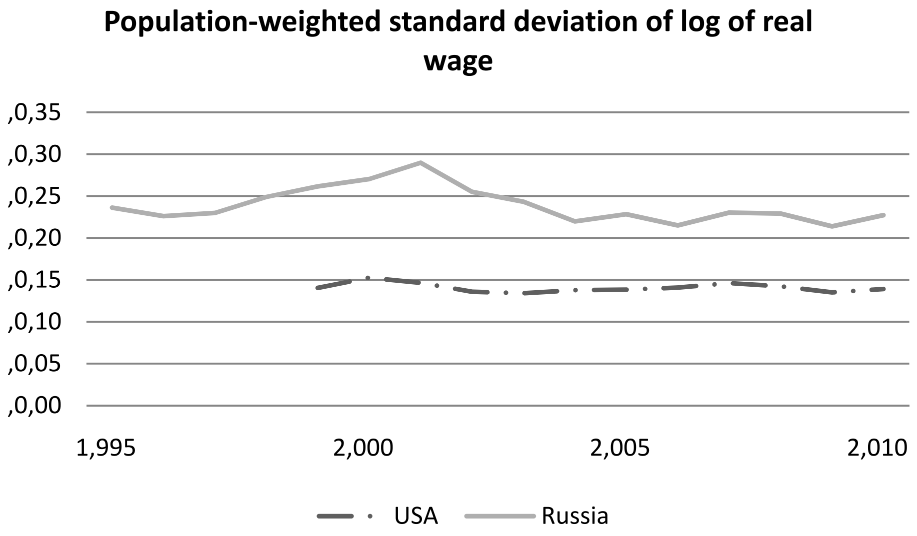
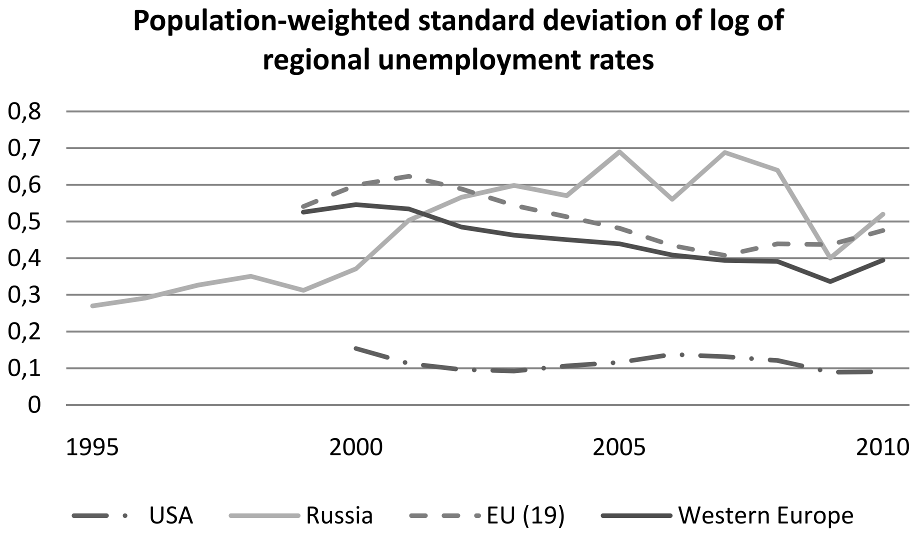
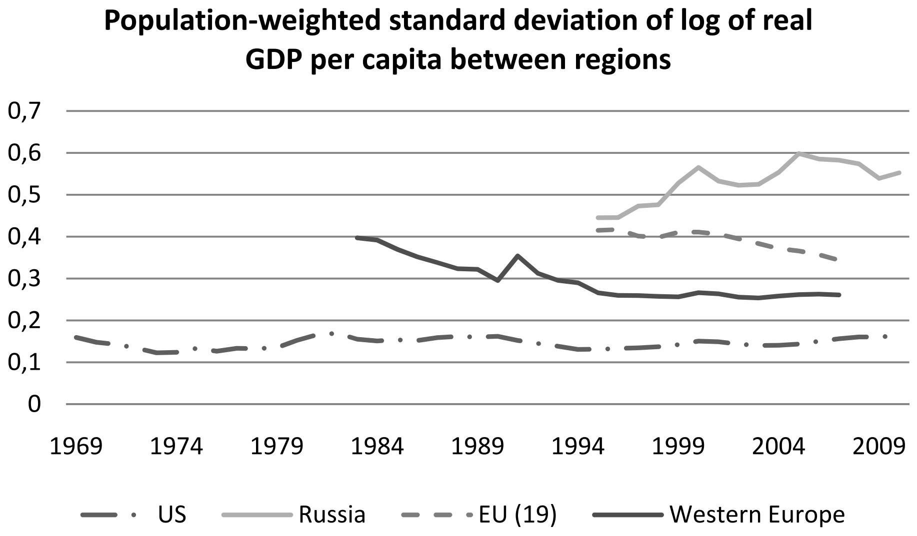
[16] Eurostat reports NUTS-2 level wages only for 1996, 2000, 2004 and 2008.

[17] Data sources: EU, Statistics Database of European Commission, Eurostat http://epp.eurostat.ec.europa.eu. USA Census Bureau www.census.gov . Annual Average Wage/Salary per Job by US State: Bureau of Business & Economic Research http://bber.unm.edu/econ/us-wage.htm
EU (19): Belgium, Czech Republic, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Latvia, Lithuania, Netherlands, Austria, Poland, Portugal, Slovakia, Finland, Sweden, United Kingdom. For EU (19) we consider only those NUTS-2 units for which there is data for each year.
Western Europe: Austria, Belgium, Germany, Ireland, Greece, France, Italy, Netherlands, Norway, Portugal, Finland, Sweden, United Kingdom.


Population-weighted standard deviation of log of real wage
,0,35
,0,30
,0,25
,0,20
,0,15
,0,10
,0,05
,0,00
1,995
2,000
2,005
2,010
USA
Russia


Population-weighted standard deviation of log of regional unemployment rates
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
1995
2000
2005
2010
USA
Russia
EU (19)
Western Europe


Population-weighted standard deviation of log of real GDP per capita between regions
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
1969
1974
1979
1984
1989
1994
1999
2004
2009
US
Russia
EU (19)
Western Europe

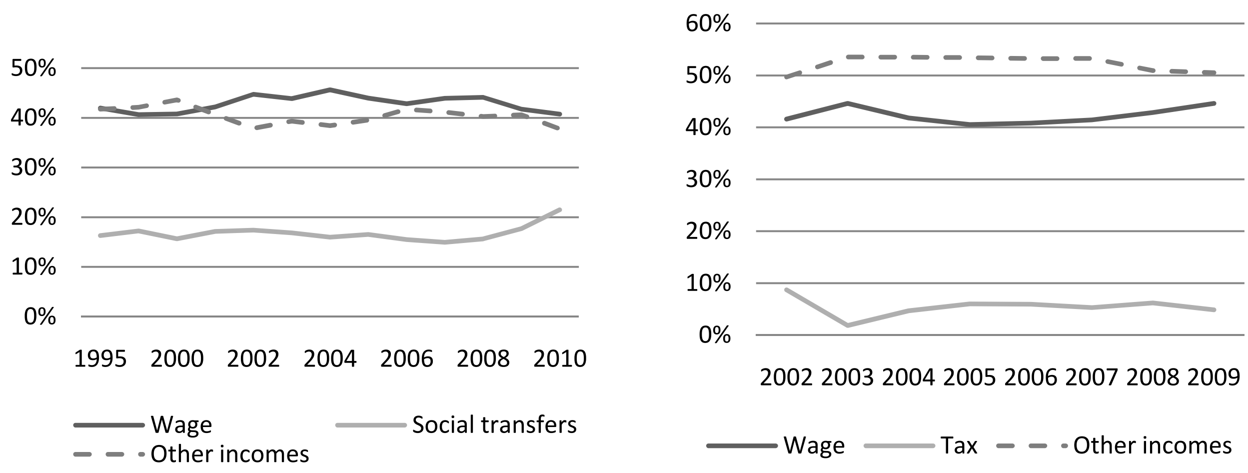
4.2. Decomposition of convergence

What factors drove the acceleration of interregional convergence in 2000s? In order to answer this question, we decompose incomes into (i) wages, (ii) social transfers (from the government budget) and (iii) other incomes. The latter includes rent, dividends, entrepreneurial income. One important caveat in this classification is that informal wages (which are apparently common in Russia, especially in the earlier part of our sample) would be categorized as “other” rather than as “wages”.

Similarly, we decompose GDP into labor share, capital share and fiscal transfers (the data on decomposition of regional GDP are available only since 2002).

The Figure 6 suggests that the share of fiscal transfers was very small. This does not imply that the role of the government in Russia is negligible – substantial part of redistribution may happen through public sector wages and through state-owned companies. The problem is that the Rosstat’s classification that we use counts wages from government or state companies into “wages” rather than government transfers. Unfortunately, we cannot distinguish public sector wages from private sector wages.

Figure 6. Shares of components of incomes (1995, 1999-2010) and GDP per capita (2002-2009).



a) Income components

b) GDP per capita components

In order to decompose the change in interregional dispersion over time we use the standard Gini decomposition methodology developed in Shorrocks (1983). Following Heshmati (2004), firstly, we calculate Gini coefficient as follows:

$$I(Y)=\frac{2}{n^2\mu}\sum_{i=1}^{n}\left(i-\frac{n+1}{2}\right)Y_i \tag{4}$$

where $Y_i=\sum_{k=1}^{K}Y_i^k$ is the sum of the income components, and μ is the mean of Y. We can decompose the expression above to contribution of each component to the inequality in the total income:

$$I(Y)=\sum_{k=1}^{K}\sum_{i=1}^{N}a_i(Y)Y_i^k=\sum_{k=1}^{K}S_k \tag{5}$$

where S_k is a contribution of factor k to overall income inequality. $a_i(Y)=\frac{2}{n^2\mu}\left(i-\frac{n+1}{2}\right)$ is a weight attached to regional i income component k, Y_i^k. The proportional factor contribution in aggregate inequality is calculated as:

$$s_k=S_k/I(Y)=\mathrm{cov}(Y_i,Y)/\sigma^2(Y) \tag{6}$$

With $\sum_k s^k=1$. We estimate population-weighted variance and covariance for the formula (6). The results of Gini decomposition for real income and for real GDP per capita are represented in Figure 7 and Figure 8, correspondingly.

Figure 7. Decomposition of Gini for real income per capita.

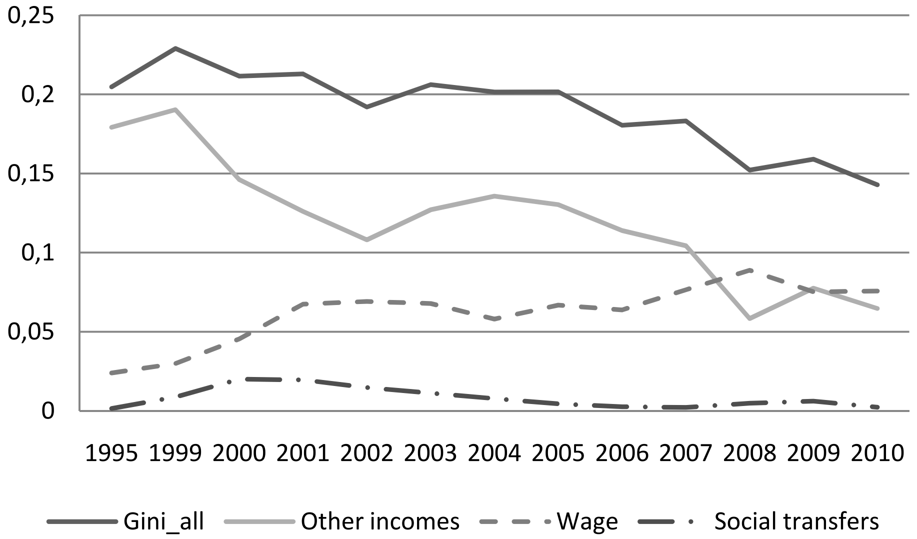
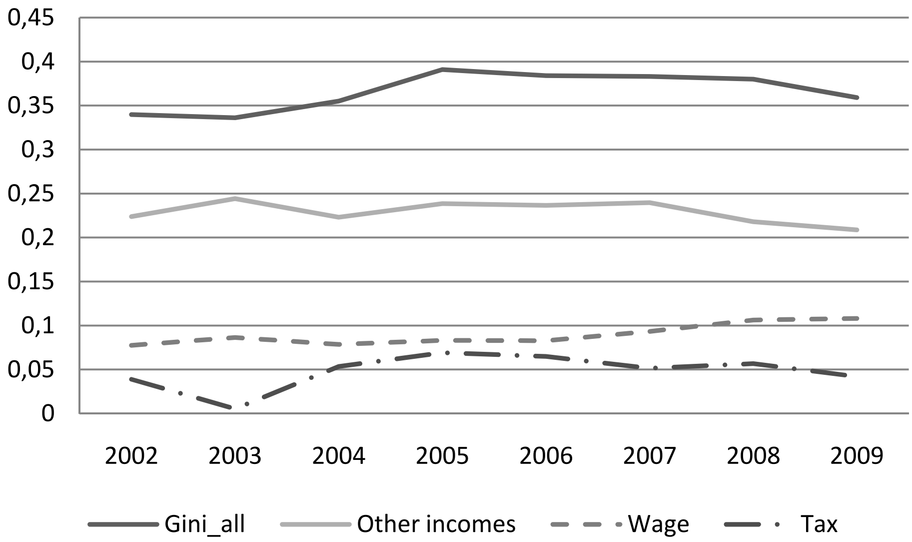


Figure 8. Decomposition of Gini for GDP per capita.



The results can be summarized as follows. Fiscal redistribution always contributed to convergence (as suggested by Zubarevich, 2010, among others) but since its share is very small, the contribution to convergence is also small. As for the role of wages vs. non-wage incomes, wages contributed to convergence in early 2000s while the other incomes did so in later 2000s. The contribution of the latter was much more important than the contribution of the wages, even in early 2000s.

How can we reconcile this with the facts that convergence in wages and incomes was much faster than in GDP per capita? One possible explanation is that much of "non-wage incomes" were actually informal wages while GDP included substantial capital share. There is therefore convergence in both wages and non-wage incomes – due to both labor and capital mobility. It does not however imply convergence in GDP per capita as there are exogenous total factor productivity differentials across regions (e.g. due to institutional inertia or geography) which dictate the differences in GDP per capita.

4.3. Migration rates

Provided the substantial increase in the speed of convergence noted above, it is interesting to check the dynamics of internal migration. It turns out that for some regions migration has been very important in this period but overall it has been decreasing over time.

Figure 9 shows that migration greatly varied across regions. Several regions lost or gained tens of percents of their population due to migration. Most migrants moved from Russia's East and Far East to Russia's European part, especially to Moscow and Saint Petersburg. Figure 23 in the Appendix B shows, however, that migrants also went to other regions: in 2010 the share of all internal migrants to Moscow and Moscow region is 12% (with another 5% going to Saint Petersburg and Leningrad region).

Figure 24 in the Appendix B and Figure 11 presents the structure of migration by distance between origin and destination. This distribution is quite stable. In 1995, 28% migrants (0.28% of population) moved by less than 500 kilometers, while in 2010 this number was 32% (0.19% of population). Share of long-haul migration (more than 2000 km) is decreasing over time from 34% (0.33% of population) at 1995 to 28% at 2010 (0.17% of population).

Figure 9. Net migration for the period of 1995-2010, share of 1995 population.

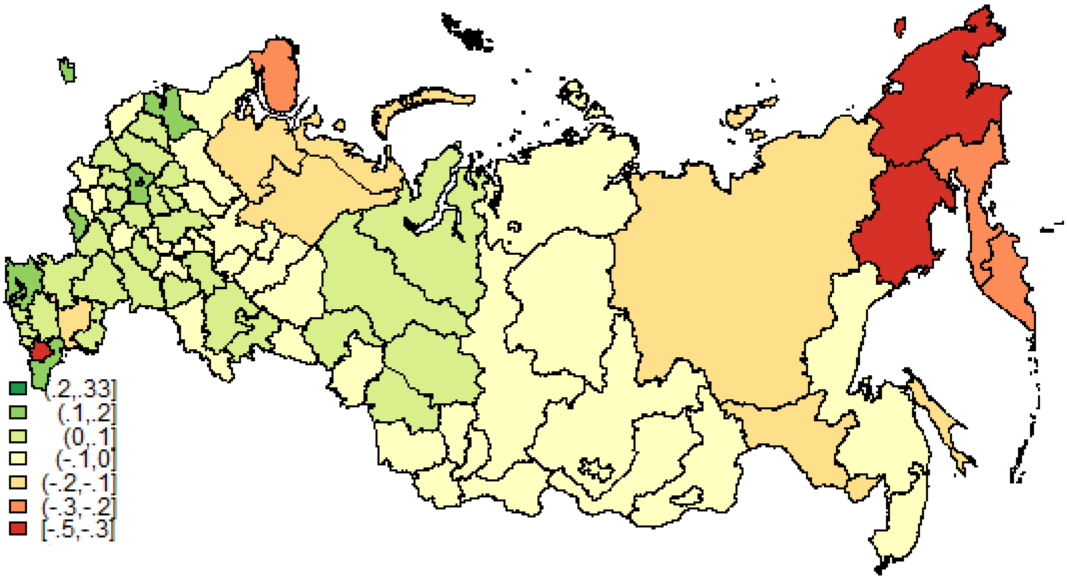


Figure 10. Internal migration (interregional, intraregional, total) in Russia over time as % total Russian population.

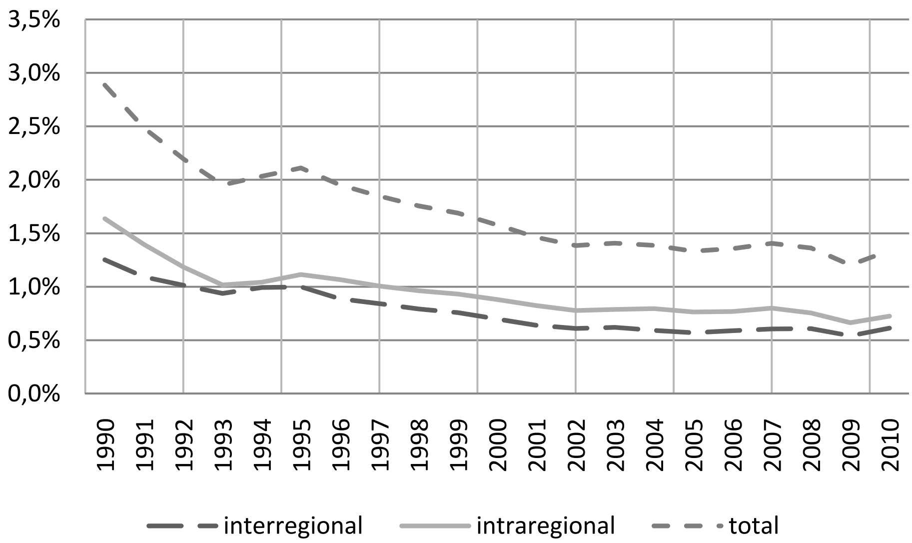
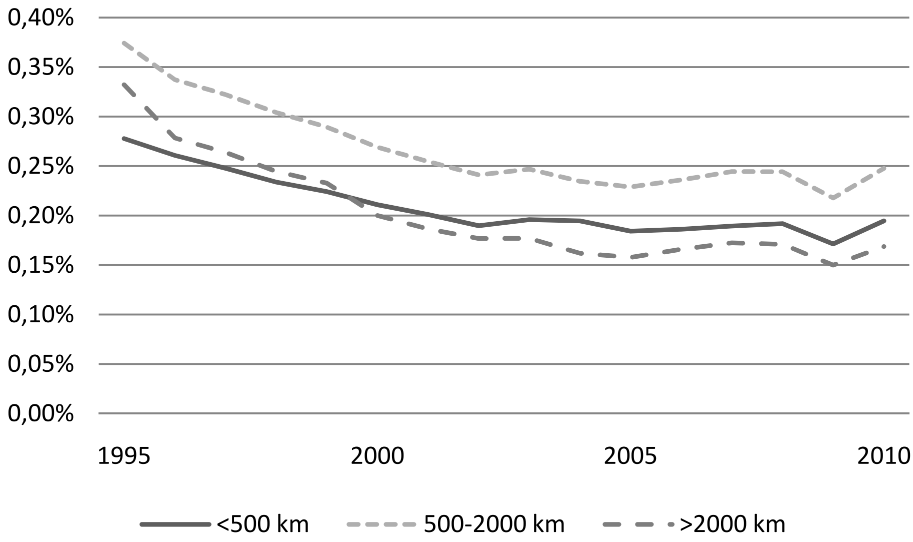


Figure 11. Interregional migration as % of population by distance.

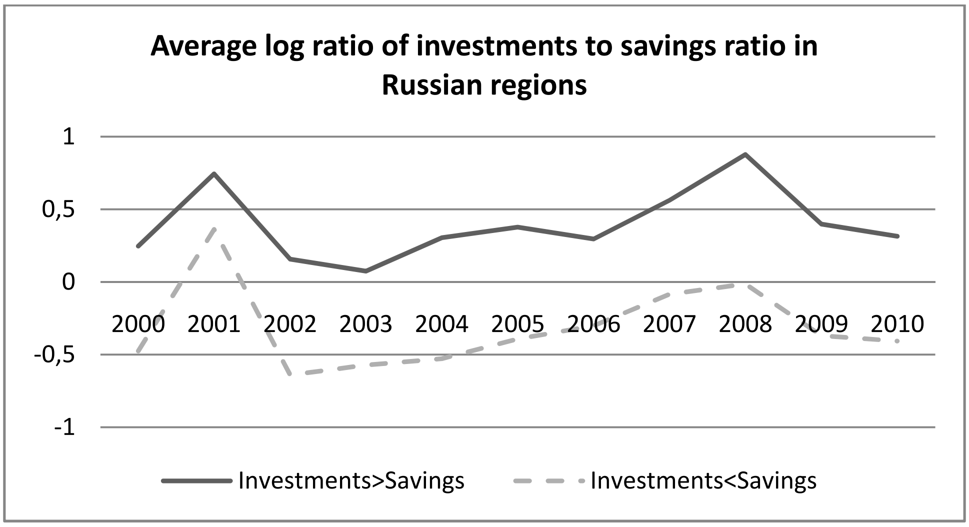


How can we reconcile declining migration with accelerated convergence? Does this mean that migration did not play a major role in convergence? The only consistent explanation is as follows: convergence happened because the barriers to mobility were brought down (e.g. by the development of real estate and financial markets) which resulted in convergence. In the meanwhile, as convergence was happening, the incentives to migrate were being weakened. In the next section we will test whether lower migration was caused by higher barriers to migration (which would not be consistent with convergence!) or by the reduced interregional differentials.

4.4. Capital flows

The data on capital flows in Russia are non-existent. Therefore, we consider the differences between investments and savings for each region. These differences are very substantial. In the Figure 12 below we present the ratio of investment to savings separately for regions where investment over the period 2000-2010 exceeded savings and for the other regions. The average investment to savings ratio is approximately 2.1 from 2000 to 2010 for regions with more investment than savings. From 2001 to 2006 there is a decline of this ratio to 1.7 and from 2006 to 2008 it increases to 6.9 and it is 1.6 at 2010. The reason of sharp increase in this ratio in 2008 is a large investment in the Krasnodar krai – in preparation for the Sochi Winter Olympics 2014. The ratio of investment to savings in the regions where savings exceed investments is approximately 0.77 from 2000 to 2010. This ratio increased from 2002 to 2008 to 1.1 and then decrease to 0.7 at 2010. Dynamics of total investment in Russian region with respect to total savings is the same.

Figure 12. Relationship between investment and savings in Russian regions.



5. Convergence in the labor market

5.1. Empirical specification

We estimate a modified gravity model similar to the one in Andrienko and Guriev (2004). The main idea of 'gravity' models is that migration flow depends positively on number of people in both sending region i and receiving region j and decreases with 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[18]:

$$\ln M_{i,j,t} = \alpha_{i,j} + \phi \ln income_{i,t} + \varphi \ln income_{j,t} + \sum_{k \in K} \gamma_k \ln X_{k,i,t} + \sum_{k \in K} \delta_k \ln X_{k,j,t} + \sum_{t \in T} \theta_t year_t + \varepsilon_{i,j,t} \quad (7)$$

The dependent variable is a logarithm of number of migrants who move from region i to region j in year t[19]. 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[20].

The key variables are $\ln income_i$ and $\ln income_j$ are the logarithms of per capita real income in an origin and destination regions, correspondingly. $X_{k,i,t}$ and $X_{k,i,t}$ are characteristics of the source and host regions that may change over time, such as the unemployment rate, the 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), the 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) etc. We also include time dummies: $year_t$ equals 1 for a year t and 0 otherwise. Definitions of all variables and their descriptive statistics are presented in the Table 11 in the Appendix A.

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 following Subsection

[18] The alternatives include a Poisson model or a negative binominal model. However, as Andrienko and Guriev (2004) show, results are very similar.

[19] 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.

[20] Certainly, even this specification does not rule out endogeneity. For example, such variables as income, unemployment, public goods may depend on migration. We believe however that these effects are negligible since—as shown in Figure 10—migration in Russia is very small (0.5-1.0% per year).

we discuss why the existence of poverty traps implies a non-monotonic relationship between the income at the origin and the intensity of migration.

5.2. A simple model of migrants' poverty traps

If financial markets are developed and there are no liquidity constraints then coefficient ϕ should be negative and coefficient φ should be positive. Migration is the likelier the lower the income at origin and the higher the income at destination. However, as shown in Andrienko and Guriev (2004), for the poorest regions in 1990s, the coefficient ϕ was actually positive. They explained this puzzle through the existence of liquidity constraints and poverty traps. In the very poor Russian regions (in about 30% of the regions hosting about 30% of Russia's population) the potential outgoing migrants wanted but could not afford to leave; so for these regions, an increase in income would result in relaxing the liquidity constraints and *higher* rather than lower outmigration.

In this section we develop a simple model that captures this intuition. Suppose that the migrant receives income y in the origin region (we will refer to the origin region as the "region I") and expects to earn income Y in the destination region ("region j"). Also, there is a cost of migration C to be paid in cash. We assume that this cost is substantially small relatively to the income at destination: $C<Y/2$.

There is a distribution of incomes y in the origin region with cumulative distribution function $F(\cdot)$. There are two periods.

Let us consider the migration outcomes:

1. If $y<C$, the migrant does not have cash to move. She stays in region i, and receives y in the first period and in the second period. The total payoff is 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. The total payoff is $y-C+Y$.
    b. If she stays, then in the second period she receives y. The 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 we assumed above that $C<Y/2$, we have $Y-C>C$, so at least some people migrate.

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

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

Let us now carry out comparative statics with regard to a shift of the whole income distribution at the origin to the right. For simplicity, let us assume that $F(\cdot)=F(y- y_m)$ and it is normalized so that $Ey= y_m$ (so the mean income in the region is y_m). Suppose that the distribution has a finite support (e.g. from y^L to y^H).

How does M depend on y_m? The answer is as follows (assuming that Y>2C):

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

Now we can fully solve the model for all parameter constellations. There can be two cases:

Case 1: $Y-C-y^H<C-y^L$

Parameters	Outcome
$y_m< C-y^H$	$M'(y_m)=0$, M=0, nobody can migrate
$C-y^H < y_m< Y-C-y^H$	$M'(y_m)>0$
$Y-C-y^H < y_m< C-y^L$	$M'(y_m)$ may be either positive or negative[21]
$C-y^L < y_m< Y-C-y^L$	$M'(y_m)<0$
$Y-C-y^L < y_m$	$M'(y_m)=0$, M=0, nobody wants to migrate

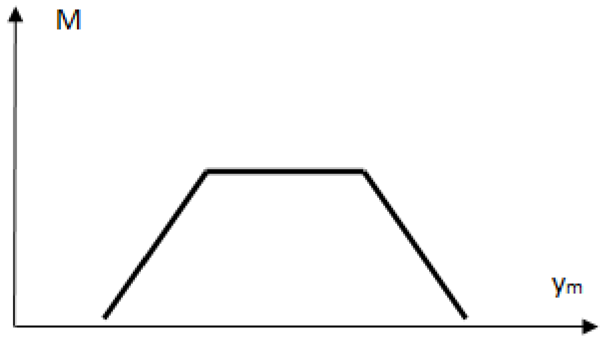
Case 2: $Y-C-y^H>C-y^L$

Parameters	Outcome
$y_m< C-y^H$	$M'(y_m)=0$, M=0, nobody can migrate
$C-y^H < y_m< C-y^L$	$M'(y_m)>0$
$C-y^L < y_m< Y-C-y^H$	$M'(y_m)=0$, M=1, everybody migrates
$Y-C-y^H < y_m< Y-C-y^L$	$M'(y_m)<0$
$Y-C-y^L < y_m$	$M'(y_m)=0$, M=0, nobody wants to migrate

Therefore as the whole income distribution moves to the right, first M increases, then stays constant (in the Case 2) or goes up/down (in the Case 1), then certainly decreases.

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

Figure 13. Migration as a function of the mean income at origin for the case of the uniform distribution of skills (for the case $Y\text{-}C\text{-}y^H > C\text{-}y^L$).



The Figure 13 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 constant 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 the willingness to migrate. If the distribution is not uniform, the middle range of the graph does not have to be constant. In this case the relationship may be non-monotonic.

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

5.3. Regressions

Table 2 presents the main results for the specification (7). 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. Also, 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 results are generally consistent with the gravity model. Migration is correlated with the size 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.[22] 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. The effects of public goods and of 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.

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 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). As both variables are in logs, the sum of the coefficients is the coefficient at the log of the value of housing per capita. 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 – assuming that 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. If we add up the coefficients at the price per square meter and the number of square meters per capita, we find that the value of housing (in real rubles per capita) increases both in-migration and out-migration. The latter effect is consistent with the importance of financial constraints.

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

The main focus of our analysis is on the role of income. It turns out that the effect of income in the receiving region 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. The back-of-the-envelope calculation suggests that the peak of the quadratic relationship is at 12 – which is above the level of income in the richest regions.

The effect of income in the sending region is different. On average, it is either insignificant or negative (naturally, migrants prefer to leave poorer regions). However, once we add a squared

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[22] As discussed in Zubarevich (2005), one should not overemphasize the effect of official measures of public goods – including doctors and hospital beds per capita. The quality of these public goods differs substantially across regions. In what follows we therefore abstain from discussing the role of the public goods. However, we do include them into regressions to control for potential heterogeneity.

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). Using the coefficients at income and at squared income we can find the peak at 9.24. However, the precision of this estimate is very low. The confidence interval is (8.72, 10)[23].

Table 2. Results of regressions with and without squared terms.

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)	1.750***	1.802***	1.572***	1.633***
	(0.099)	(0.098)	(0.109)	(0.111)
Population j (log)	1.964***	2.002***	1.737***	1.734***
	(0.096)	(0.096)	(0.104)	(0.107)
Income i (log)	0.035	0.758***	-0.027	0.450**
	(0.023)	(0.157)	(0.024)	(0.192)
Income squared i (log)		-0.041***		-0.027**
		(0.009)		(0.011)
Income j (log)	0.175***	0.696***	0.169***	0.148
	(0.023)	(0.169)	(0.025)	(0.205)
Income squared j (log)		-0.029***		0.001
		(0.010)		(0.012)
Gini (log) i	-0.084*	-0.082*	-0.093**	-0.092**
	(0.043)	(0.043)	(0.047)	(0.047)
Gini (log) j	-0.124***	-0.123***	-0.143***	-0.143***
	(0.042)	(0.042)	(0.046)	(0.046)
Unemployment rate (log) i	0.062***	0.059***	0.037***	0.036***
	(0.009)	(0.009)	(0.009)	(0.009)
Unemployment rate (log) j	-0.069***	-0.071***	-0.072***	-0.072***
	(0.009)	(0.009)	(0.009)	(0.009)
Housing price i (log)	-0.051***	-0.050***	-0.048***	-0.048***
	(0.011)	(0.011)	(0.012)	(0.012)
Housing price j (log)	0.047***	0.049***	0.055***	0.055***
	(0.011)	(0.011)	(0.011)	(0.011)
Provision of housing i (log)	0.409***	0.404***	0.147*	0.155*
	(0.082)	(0.083)	(0.087)	(0.088)
Provision of housing j (log)	0.617***	0.613***	0.608***	0.608***
	(0.082)	(0.083)	(0.086)	(0.086)
New flats (moving average, log) i	-0.010	-0.005	0.010	0.013
	(0.009)	(0.009)	(0.010)	(0.010)

[23] We calculate confidence interval using simulation methods for the joint distribution of the coefficients.

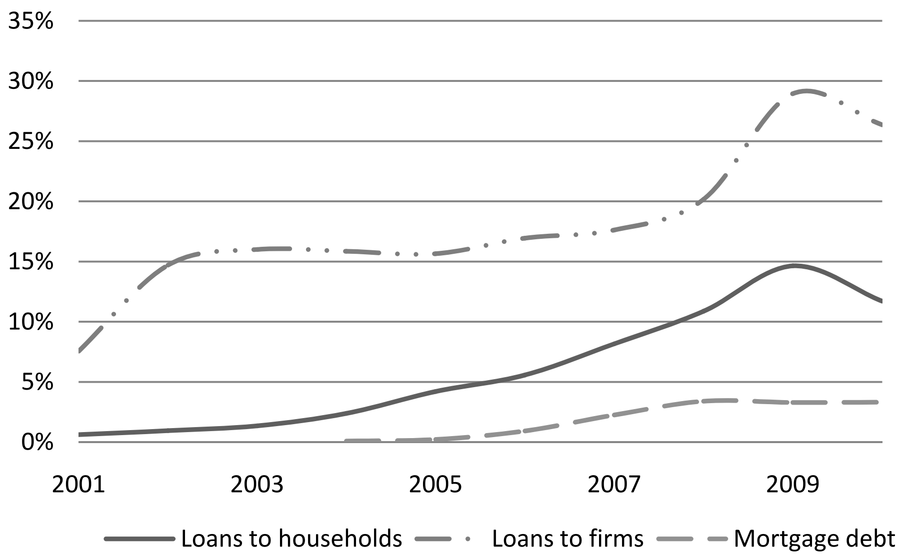
New flats (moving average log) j	-0.006	-0.002	-0.012	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)
Life expectancy (log) i	-0.047	-0.082	0.096	0.067
	(0.201)	(0.201)	(0.208)	(0.208)
Life expectancy (log) j	-0.556***	-0.581***	-0.363*	-0.361*
	(0.191)	(0.191)	(0.199)	(0.199)
Infant mortality rate (log) i	0.039***	0.037**	0.029*	0.028*
	(0.015)	(0.015)	(0.015)	(0.015)
Infant mortality rate (log) j	-0.082***	-0.084***	-0.077***	-0.077***
	(0.016)	(0.016)	(0.016)	(0.016)
Doctors (log) i	0.077	0.121**	0.125**	0.147**
	(0.059)	(0.061)	(0.061)	(0.062)
Doctors (log) j	0.169***	0.200***	0.194***	0.193***
	(0.056)	(0.057)	(0.057)	(0.058)
Hospital beds (log) i	0.043	0.036	-0.002	-0.003
	(0.039)	(0.039)	(0.040)	(0.040)
Hospital beds (log) j	0.311***	0.306***	0.271***	0.271***
	(0.039)	(0.039)	(0.040)	(0.040)
Telephones (log) i	-0.010	-0.035	-0.091***	-0.101***
	(0.026)	(0.026)	(0.027)	(0.028)
Telephones (log) j	-0.163***	-0.180***	-0.154***	-0.154***
	(0.025)	(0.026)	(0.029)	(0.029)
Highway density (log) i	0.037**	0.037**	0.034*	0.034*
	(0.018)	(0.018)	(0.018)	(0.018)
Highway density (log) j	-0.003	-0.003	0.026	0.026
	(0.018)	(0.018)	(0.019)	(0.019)
Buses (log) i	0.027***	0.028***	0.033***	0.033***
	(0.007)	(0.007)	(0.007)	(0.007)
Buses (log) j	-0.015*	-0.015*	-0.027***	-0.027***
	(0.009)	(0.008)	(0.009)	(0.009)
Share of young i, t-1	-0.022***	-0.015***	-0.025***	-0.020***
	(0.005)	(0.005)	(0.006)	(0.006)
Share of young j, t-1	0.056***	0.061***	0.051***	0.050***
	(0.005)	(0.005)	(0.006)	(0.006)
Share of old i, t-1	-0.050***	-0.042***	-0.041***	-0.037***
	(0.004)	(0.004)	(0.004)	(0.005)
Share of old j, t-1	0.023***	0.028***	0.020***	0.020***
	(0.004)	(0.005)	(0.005)	(0.005)
Students i (log), t-1	-0.077***	-0.074***	-0.085***	-0.082***
	(0.009)	(0.009)	(0.009)	(0.009)
Students j (log), t-1	0.102***	0.104***	0.111***	0.111***
	(0.011)	(0.011)	(0.011)	(0.011)
Women i (log), t-1	0.469**	0.497**	-1.387***	-1.223***
	(0.229)	(0.224)	(0.286)	(0.293)
Women j (log), t-1	-3.058***	-3.038***	-3.725***	-3.732***

	(0.216)	(0.212)	(0.290)	(0.299)
Year dummies included[24]	Yes	Yes	Yes	Yes
Observations	84,666	84,666	80,222	80,222
R-squared[25]	0.308	0.308	0.309	0.310
Number of id	5,929	5,929	5,625	5,625

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

While increased mobility may be explanation by an increase in incomes, the liquidity traps may also be relaxed due to financial development. In 2000s, Russia has experienced a rapid development of financial sector. As shown in Figure 14, all indicators of financial development have grown substantially in 2001-2008[26]. As a result of financial crisis there was a slight decline in 2009-10. At the peak, in 2009 the average level loans to firms, households and mortgage debt was 29%, 14.6% and 3.3% of GDP, correspondingly.

Figure 14. Average ratio of loans to households and firms, and mortgage debt to GDP (%).



In order to understand the role of financial development, we add a proxy for financial development to the regressions above. We also include an interaction between income and financial development. 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

[24] Results with year dummies are in Appendix A Table 12.
[25] For all fixed effect models R^2 within are presented.
[26] We show the means; the evolution of medians is quite similar. For mortgage debt we only have data from 2004 to 2010.

predicts a negative coefficient at the interaction of income and financial development at the origin region.

Table 3 presents regressions with financial development. As a proxy for financial development, we use a ratio of loans to households to GDP[27]. We have also estimated this specification with alternative measures of financial development and obtained similar results (see Table 17 in the Appendix A).

We find the predicted result: financial development results in higher outward migration. Moreover, the coefficient at the interaction term is negative: migration is less linked to income in the sending region if this region is more financially developed.

Table 3. Regressions with financial development.

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)	1.399***	1.332***	1.502***	1.390***
	(0.153)	(0.155)	(0.166)	(0.168)
Population j (log)	2.370***	2.412***	2.096***	2.165***
	(0.143)	(0.145)	(0.157)	(0.158)
Income i (log)	-0.028	-4.143***	-0.033	-5.580***
	(0.049)	(0.844)	(0.051)	(0.946)
Income squared i (log)		0.216***		0.292***
		(0.044)		(0.050)
Income*loans i (log)	-0.020**	-0.633***	-0.018**	-0.887***
	(0.008)	(0.189)	(0.009)	(0.213)
Income squared*loans i (log)		0.031***		0.045***

[27] This variable is *loans* in the
In order to understand the role of financial development, we add a proxy for financial development to the regressions above. We also include an interaction between income and financial development. 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 income and financial development at the origin region.
Table 3 presents regressions with financial development. As a proxy for financial development, we use a ratio of loans to households to GDP. We have also estimated this specification with alternative measures of financial development and obtained similar results (see Table 17 in the Appendix A).

We find the predicted result: financial development results in higher outward migration. Moreover, the coefficient at the interaction term is negative: migration is less linked to income in the sending region if this region is more financially developed.

Table 3.

		(0.010)		(0.012)
Loans i (log)	0.155**	3.134***	0.144*	4.321***
	(0.077)	(0.876)	(0.081)	(0.985)
Income j (log)	0.058	1.346*	0.114**	2.452***
	(0.048)	(0.779)	(0.051)	(0.870)
Income squared j (log)		-0.070*		-0.130***
		(0.041)		(0.046)
Income*loans j (log)	-0.010	0.336*	-0.006	0.828***
	(0.008)	(0.181)	(0.009)	(0.207)
Income squared*loans j (log)		-0.019*		-0.046***
		(0.010)		(0.011)
Loans j (log)	0.110	-1.474*	0.057	-3.687***
	(0.075)	(0.833)	(0.079)	(0.948)
Gini (log) i	-0.088	-0.027	-0.046	-0.025
	(0.085)	(0.089)	(0.096)	(0.098)
Gini (log) j	-0.208**	-0.253***	-0.357***	-0.448***
	(0.088)	(0.091)	(0.099)	(0.101)
Unemployment rate (log) i	0.035***	0.034***	0.031***	0.031***
	(0.011)	(0.011)	(0.012)	(0.012)
Unemployment rate (log) j	-0.049***	-0.046***	-0.063***	-0.058***
	(0.010)	(0.011)	(0.011)	(0.011)
Housing price i (log)	-0.032**	-0.033**	-0.029*	-0.029*
	(0.015)	(0.015)	(0.016)	(0.016)
Housing price j (log)	0.058***	0.062***	0.048***	0.055***
	(0.015)	(0.015)	(0.016)	(0.016)
Provision of housing i (log)	0.534***	0.439***	0.561***	0.429**
	(0.164)	(0.163)	(0.170)	(0.169)
Provision of housing j (log)	0.388***	0.407***	0.400***	0.427***
	(0.142)	(0.143)	(0.149)	(0.151)
New flats (moving average, log) i	-0.047***	-0.042***	-0.046***	-0.040***
	(0.012)	(0.012)	(0.013)	(0.013)
New flats (moving average log) j	0.046***	0.043***	0.046***	0.041***
	(0.012)	(0.013)	(0.013)	(0.013)
Life expectancy (log) i	0.699**	0.753***	0.689**	0.737***
	(0.272)	(0.271)	(0.281)	(0.280)
Life expectancy (log) j	-1.503***	-1.546***	-1.168***	-1.202***
	(0.255)	(0.255)	(0.264)	(0.262)
Infant mortality rate (log) i	0.063***	0.071***	0.056***	0.060***
	(0.017)	(0.017)	(0.018)	(0.018)
Infant mortality rate (log) j	-0.066***	-0.068***	-0.065***	-0.063***
	(0.018)	(0.018)	(0.019)	(0.019)
Year dummies included[28]	Yes	Yes	Yes	Yes
Public goods included	Yes	Yes	Yes	Yes

[28] Coefficients at the year dummies and public goods are in the Table 13 in the Appendix A.

Observations	58,223	58,223	55,211	55,211
R-squared	0.104	0.105	0.104	0.106
Number of id	5,929	5,929	5,625	5,625

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.4. Structural breaks

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 section we use a piece-wise linear specification that allows us understanding whether there is significant change in the slope of the income-outmigration relationship at a certain income threshold. In particular, we run the following regression:

$$\ln M_{i,j,t} = \alpha_{i,j} + a \ln income_{i,t} I\left(\ln income_{i,t} \le \gamma\right) + b \ln income_{i,t} I\left(\ln income_{i,t} > \gamma\right) + \text{other variables} + \varepsilon_{i,j,t} \tag{8}$$

where $I(\cdot)$ is the indicator function, γ is a threshold. An alternative way of writing (8) is:

$$\ln M_{i,j,t} = \begin{cases} \alpha_{i,j} + a \ln income_{i,t} + \text{other variables} + \varepsilon_{i,j,t}, & \ln income_{i,t} \le \gamma, \\ \alpha_{i,j} + b \ln income_{i,t} + \text{other variables} + \varepsilon_{i,j,t}, & \ln income_{i,t} > \gamma. \end{cases}$$

Thus in our case there are two regimes: "before" (to the left of the threshold: y<y*) and "after" (to the right of the threshold: y>y*).

To estimate model (8) we use least squares estimation for transform variables (Hansen, 1999) to extract fixed individual effects (9).

$$\ln M^*_{i,j,t} = \alpha_{i,j} + \beta \ln income^*_{i,t}\left(\gamma\right) + \text{other variables}^* + \varepsilon^*_{i,j,t} \tag{9}$$

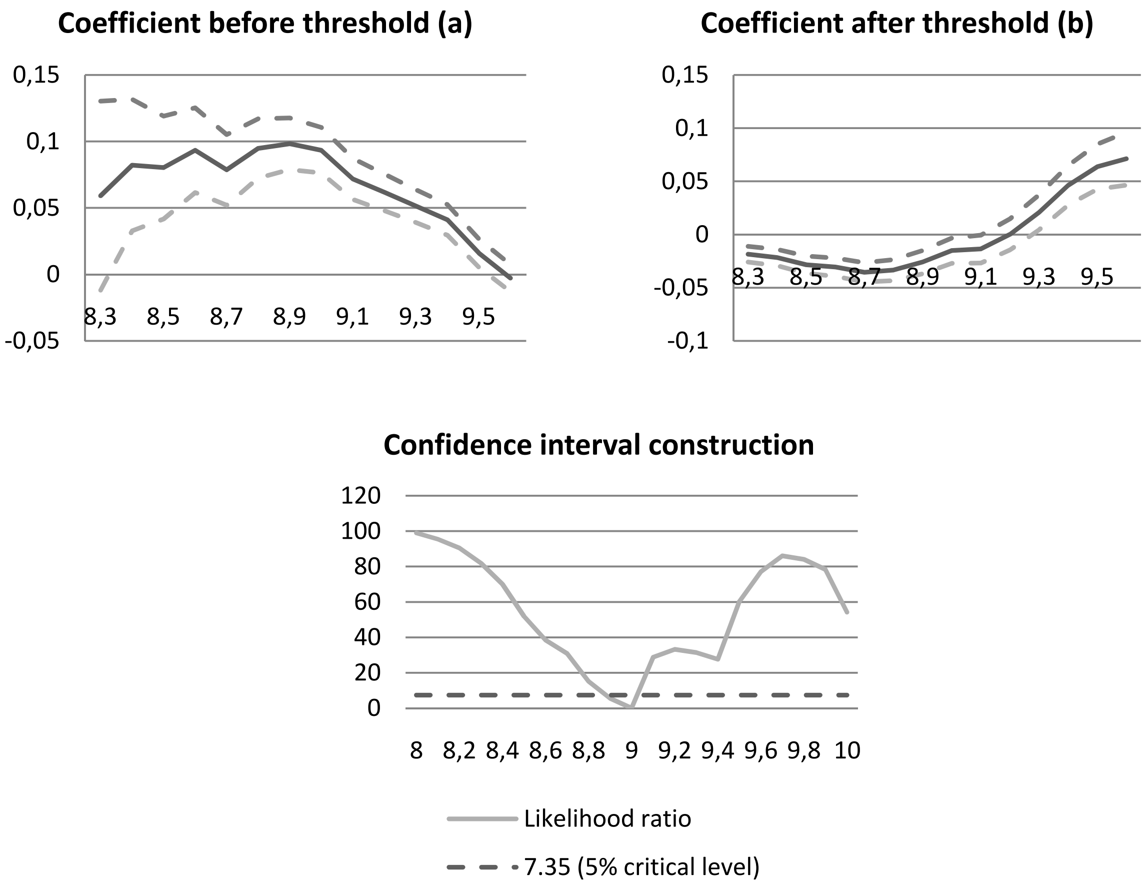
where $\ln M^*_{i,j,t} = \ln M_{i,j,t} - T^{-1} \sum_{t=1}^{T} \ln M_{i,j,t}$,

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

$\varepsilon^*_{i,j,t} = \varepsilon_{i,j,t} - T^{-1} \sum_{t=1}^{T} \varepsilon_{i,j,t}$, T is a number of years.

Then we estimate (9) for different thresholds γ. Finally, $\hat{\gamma}$ is the threshold for which we receive minimum residual sum of squares (RSS) from equation (10). Figure 15 presents our estimation of equation (9). The minimum RSS is at log real income equal to 9. Using Hansen's methodology[29,] we test hypothesis of significance threshold. The test statistic is F1=112.7[30], p-value=0.000.Therefore we have two 'regimes'[31]. We also calculate 95% confidence interval for threshold (Figure 15). In our case the confidence interval for threshold is (8.9, 9)[32].

Figure 15. Results for regressions with structural break for different threshold levels.



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[29] For Hansen procedure we need a balanced panel. There is no price of housing for all regions and all periods. Thus we estimate model without this variable. The estimation of the threshold parameter is the same for balanced and unbalanced panel.

[30] 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.

[31] We have also tested hypothesis of two thresholds, however, we did not find significant results.

[32] 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 $\gamma = 9$.

5.5. Semiparametric estimations

In this Section, instead of estimating a quadratic or piece-wise-linear relationship between income in the sending region and migration, we use a semiparametric approach. We suppose that there is parametric form for all variables except real income in sending region (see Eq. 10):

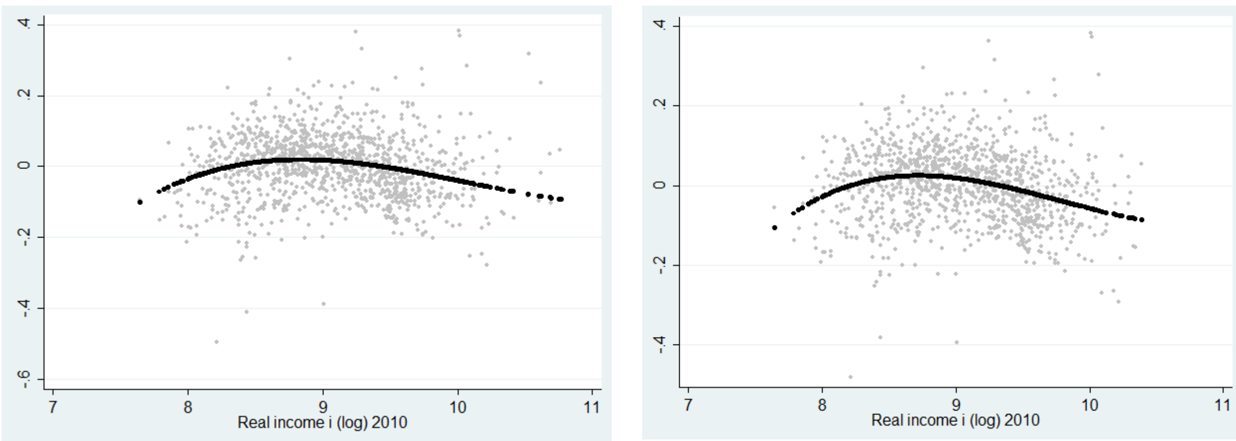
$$\ln M_{i,j,t} = \alpha_{i,j} + f\left(\ln income_{i,t}\right) + \varphi \ln income_{j,t} + \sum_{k \in K} \gamma_k \ln X_{k,i,t} + \sum_{k \in K} \delta_k \ln X_{k,j,t} + \sum_{t \in T} \theta_t year_t + \varepsilon_{i,j,t} \quad (10)$$

Our approach is based on method from Baltagi and Li, (2002). The authors prove that the curve f can be estimated by regressing residuals from equation (10) on log income in the sending region using a standard non-parametric regression estimator[33].

$$\hat{\varepsilon}_{i,j,t} = \ln M_{i,j,t} - \hat{\alpha}_{i,j} - \hat{\varphi} \ln income_{j,t} - \sum_{k \in K} \hat{\gamma}_k \ln X_{k,i,t} - \sum_{k \in K} \hat{\delta}_k \ln X_{k,j,t} - \sum_{t \in T} \hat{\theta}_t year_t \quad (11)$$

To obtain the estimates of the individual fixed effects $\hat{\alpha}_{i,j}$ and regression coefficients, the authors suggest estimate model (11) in first differences using ordinary least squares and approximate first difference of unknown function f by series $p^k\left(\ln income_i\right)$. Here $p^k\left(\ln income_i\right)$ are the first k terms of a sequence of functions $\left(p^1\left(\ln income_i\right), p^2\left(\ln income_i\right)...\right)$.

Figure 16. Results of semiparametric models.



a) All regions

b) Without Moscow and Saint

[33] We use xtsemipar command for Stata written by Libois and Verardi (2012). To perform the non-parametric fit we use B-splines (Newson, 2001).

Petersburg

Figure 16 presents the results of the semiparametric estimation. Results for all regions and without Moscow and Saint Petersburg are quite 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)[34]. The log real income at 8.8 implies that the average income is equal to exp(8.8) $\approx$ 6634 in 2010 rubles and 1.12 Russian average subsistence levels in 2010).

We also estimate a semiparametric model with nonlinear relationships between migration and income in a receiving region. These results are presented in the Figure 26 in the Appendix B. The growth in income results in higher immigration. However, it is true only for regions with logarithm of income more than 8.3 (4024 in 2010 rubles). Before this point the growth in income results in lower in-migration, because the income is very small.

5.6. Robustness checks and additional evidence

To check the robustness of our results we estimate equation (7) for subsamples of close and distant 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 which 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 which 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 large distances (this result is similar to Vakulenko et al., 2011).

Table 4. Results for different distances between pairs of regions (short)[35].

VARIABLES	(1) <500 km	(2) <500 km With squared income	(3) 500-2000 km	(4) 500-2000 km With	(5) >2000 km	(6) >2000 km With squared

[34] We calculate confidence interval using bootstrap procedure.

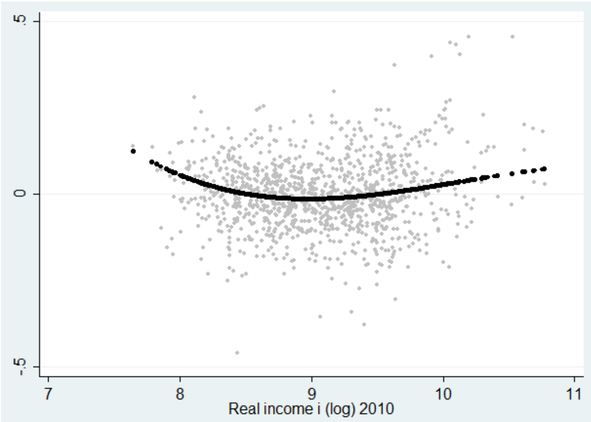
[35] We present only part of results in this section. The full estimation results are in Appendix A Table 15.

				squared income		income
Population i (log)	1.041***	0.940***	1.488***	1.497***	1.846***	1.921***
	(0.257)	(0.252)	(0.144)	(0.142)	(0.148)	(0.147)
Population j (log)	2.244***	2.217***	1.714***	1.745***	2.242***	2.297***
	(0.241)	(0.240)	(0.142)	(0.144)	(0.144)	(0.143)
Income i (log)	0.124**	-1.610***	0.016	0.187	0.041	1.087***
	(0.052)	(0.392)	(0.033)	(0.221)	(0.032)	(0.235)
Income squared i (log)		0.098***		-0.010		-0.059***
		(0.022)		(0.012)		(0.013)
Income j (log)	0.130**	-0.556	0.190***	0.560**	0.178***	0.919***
	(0.052)	(0.410)	(0.032)	(0.247)	(0.032)	(0.250)
Income squared j (log)		0.039*		-0.021		-0.042***
		(0.023)		(0.014)		(0.014)
Unemployment rate (log) i	0.048**	0.048***	0.082***	0.082***	0.041***	0.035**
	(0.019)	(0.018)	(0.012)	(0.012)	(0.014)	(0.014)
Unemployment rate (log) j	-0.020	-0.018	-0.068***	-0.069***	-0.073***	-0.077***
	(0.019)	(0.018)	(0.012)	(0.012)	(0.014)	(0.014)
Observations	6,246	6,246	31,104	31,104	47,286	47,286
R-squared	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

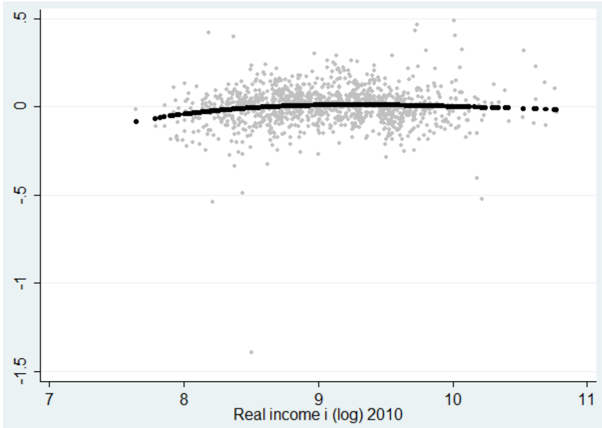
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Semiparametric results for different distances are presented in Figure 17. The results for the distant regions (more than 500 km) differ from those for the nearby regions. The results (presented in the Table 4) are consistent with main regressions above. The peak for distant pairs of regions is 8.8 (in terms of the logarithm of real income).

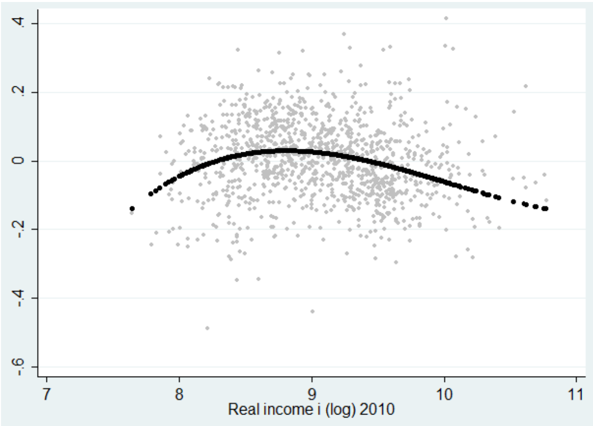
Figure 17. Results of semiparametric model for different distances.



a) Distance <500 km



b) Distance 500-2000 km



c) Distance >2000 km

Table 5 presents results for different subperiods. For each subperiod, we estimate two specifications: the main equation (7) and the equation with squared income term. The main result is the absence of poverty trap in 2005-10 period. There is a strange result for 1996-2000 time period: positive sign for squared income in origin region. Table 18 shows that it is effect of crisis in 1998. It was a structural break for real income in this year. We estimate model separately before and after crisis and receive that sign for squared income in sending region is negative in 90th before and after crisis.

Table 5. Results for different time periods[36].

VARIABLES	(1) 1996-2000	(2) 1996-2000 With squared income	(3) 2000-2005	(4) 2000-2005 With squared income	(5) 2005-2010 With squared income	(6) 2005-2010 With squared income

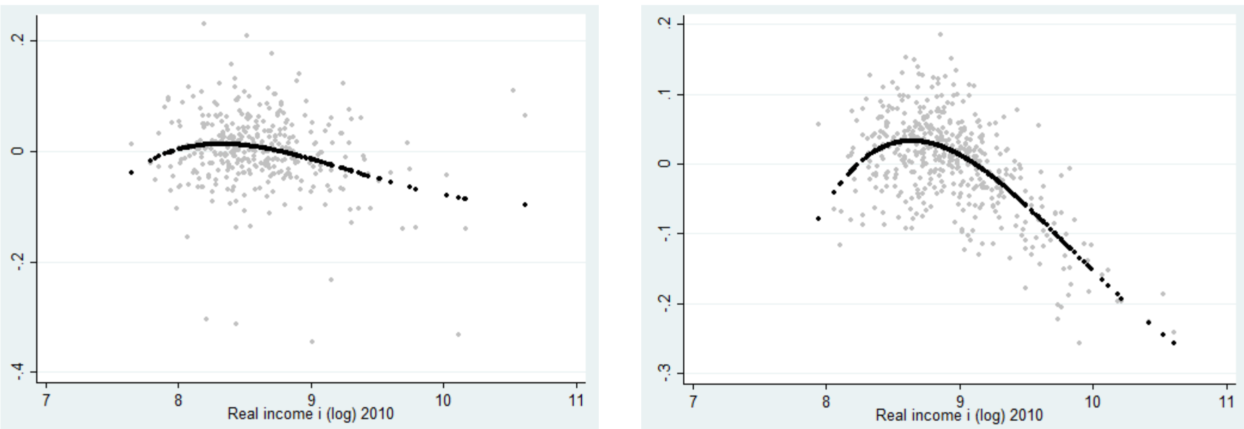
[36] We present only part of results in this section. The full estimation results are in Appendix A Table 16.

Population i (log)	2.196***	2.232***	2.043***	2.155***	0.974***	0.930***
	(0.315)	(0.316)	(0.312)	(0.317)	(0.208)	(0.214)
Population j (log)	1.216***	1.235***	0.843***	0.939***	2.189***	2.259***
	(0.298)	(0.299)	(0.304)	(0.312)	(0.193)	(0.200)
Income i (log)	0.002	-0.859***	0.044	1.015***	-0.005	-0.721
	(0.048)	(0.246)	(0.044)	(0.328)	(0.050)	(0.674)
Income squared i (log)		0.050***		-0.056***		0.038
		(0.014)		(0.019)		(0.035)
Income j (log)	-0.132***	-0.571**	0.017	0.846**	-0.013	1.106*
	(0.044)	(0.245)	(0.045)	(0.333)	(0.051)	(0.670)
Income squared j (log)		0.025*		-0.048**		-0.059*
		(0.014)		(0.019)		(0.035)
Unemployment rate (log) i	0.047***	0.044***	-0.006	-0.013	0.033**	0.031**
	(0.016)	(0.016)	(0.015)	(0.015)	(0.013)	(0.013)
Unemployment rate (log) j	-0.038**	-0.040**	-0.012	-0.018	-0.025*	-0.023*
	(0.017)	(0.017)	(0.015)	(0.015)	(0.013)	(0.013)
Observations	25,376	25,376	35,270	35,270	35,574	35,574
R-squared	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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

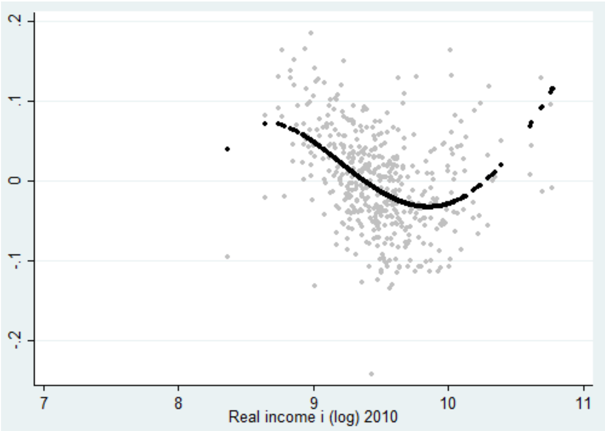
The results of the semiparametric estimations for different time periods are presented in the Figure 18. The graphs show that for 1995-2000 the threshold is 4580 in 2010 rubles. For 2000-2005 it is 5430 and there is no poverty trap for 2005-2010.

Figure 18. Results of semiparametric model for different subperiods.



a) 1996-2000

b) 2000-05



c) 2005-10

5.7. Convergence in the Russian labor market: discussion of evidence

In the Table 6 below summary results of all threshold and peak estimations for the logarithm of real income in a sending region are presented[37]. The results of different methods are quite similar.

Table 6. Table of summary results.

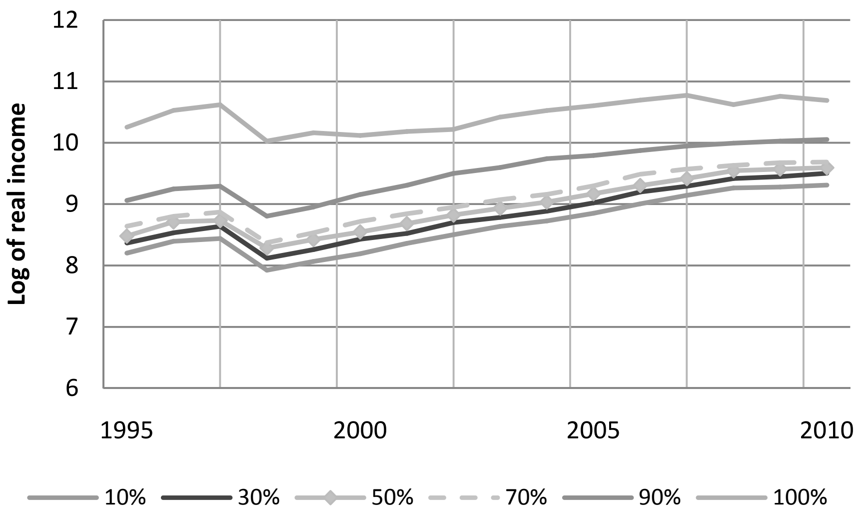
N	Model	Peak/Threshold (logarithm)	95% confidence interval	Russian rubles 2010
1	With squared income	9.24	(8.72, 10)	10301
2	Models with structural break	9	(8.9, 9)	8103
3	Semiparametric model	8.8	(8.6, 9.1)	6634

[37] These are results for the main specification of migration model (Table 2, Column 1) for all regions and for the period 1996-2010.

The log real income equal to 9 corresponds to 8103 rubles in 2010 prices. In other words, 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. (See Therefore, the number of regions which are in poverty trap is decreasing over time.

Figure 19 where we plot the evolution of percentiles of interregional income distribution over time[38]). Therefore, the number of regions which are in poverty trap is decreasing over time.

Figure 19. Number of regions above and below thresholds over time.



The evidence above suggests that while convergence in 1990s was indeed slowed down by poverty rates, the situation changed in 2000s. The overall economic growth let the poor Russian regions "grow out" of their poverty traps. In addition, financial development relaxed liquidity constraints. This brought down the most important barriers to labor reallocation across Russian regions and resulted in faster convergence between income and wages in 2000s.

How can this be reconciled with falling migration rates in 2000s? In order to understand this, we plot the year dummies from the main specification (Table 2, Column 1). We see that there was almost no change in the year dummies in 2000s (Figure 20). In other words, while migration was falling, this fall was explained precisely by the decreases in interregional differences – and not by certain secular downward trend in migration. 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 as the incentives to migrations are no longer as high as they used to be. Also, once we compare Russian migration rates to migration rates in other countries (

[38] Percentiles for income with respect to subsistence level are presented in the Figure 27 in the Appendix B.

Table 7), we see the interregional migration in Russia comparable to that in the EU-27 (while still much lower than in other countries). However, it is difficult to compare the results of internal interregional migration within countries through different methodology, definition of migration, sources of data and size of regions are quite different.

Figure 20. Evolution of migration over time: internal migration in Russia in 1996–2010 and time dummies in the main regression.

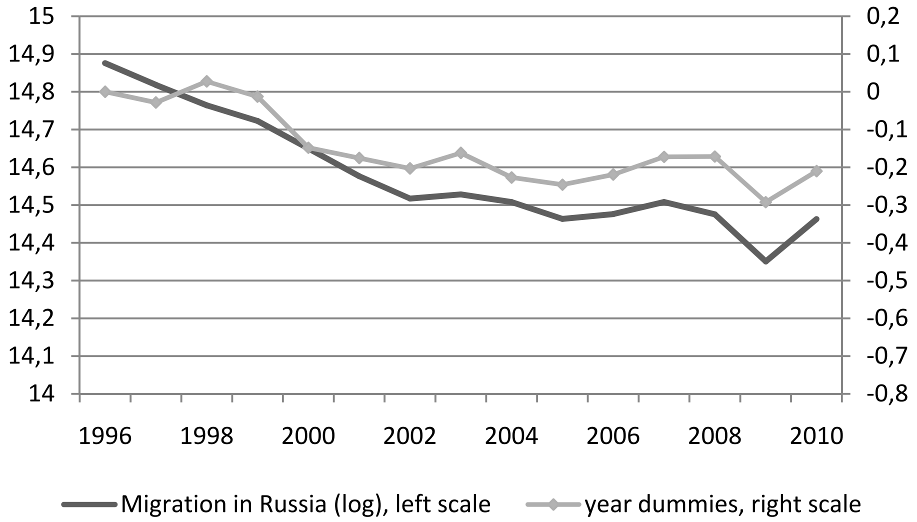


Table 7. Migration rates in Russia and in other countries (interregional migration), % of population[39].

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Russia	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5	
USA	3.1	2.8	2.7	2.6	2.6	2.0	1.7	1.6	1.6		
EU (27)			0.4	0.4	0.4	0.3	0.4	0.4			
New Zealand		10.0					9.7				
Japan	2.2	2.2	2.2	2.1	2.1	2.1	2.1	2.1	2.0	2.0	
Canada							2.9				

[39] Source: authors calculations. http://gks.ru Rosstat Russia
http://www.e-stat.go.jp Portal Site of Official Statistics of Japan
http://www.stats.govt.nz Statistics New Zealand
http://www.census.gov/ United States Census Bureau
http://epp.eurostat.ec.europa.eu Eurostat
www.statcan.gc.ca Statistics Canada
http://www.stats.gov.cn National Bureau Statistics of China

China											3.0

6. Integration of capital markets

6.1. Hypothesis and empirical specifications

As there are no data on interregional capital flows, we estimate those using the data on savings and government deficit. The net capital flows to the region can be estimated through an identity CapFlows=I-S+D, where I is an investment in capital assets. S is population savings, and D is the deficit of (consolidated) budget.[40]

Our specification is as follows:

$$capital\ \ flow_{i,t} = \alpha_i + \beta_1 R_{i,t-1} + \beta_2 Inc_{i,t} + \beta_3 \left(K/E\right)_{i,t-1} + \sum_{t\in T} \theta_t year_t + \text{other variables} + \varepsilon_{i,t} \quad (12)$$

where R is a lag of logarithm of capital income per unit of capital[41]. Inc is income per capita. K/E is the lagged capital to employment ratio. We also include fixed effects α_i for each region, time dummies $year_t$, logarithm of population, provision of public goods, e.g., roads, healthcare (doctors per capita and hospital beds per capita), public transportation (buses per capita).

We also test whether the capital market is integrated, i.e. investment in a region is a function of the savings in the very same region.

$$Inv_{it} = \alpha_i + \beta_1 S_{it} + \beta_2 BInc_{it} + \beta_3 BExp_{it} + \beta_4 R_{it} + \beta_5 \left(K/E\right)_{it} + \text{other variables} + \varepsilon_{it} \quad (13)$$

where Inv is a logarithm of investment in fixed capital, S is savings, $BInc$ and $BExp$ are government budget's income and expenditure correspondingly. We also include the same control variables as in the equation (13).

If the coefficient β_1 is positive and significant, capital market is regionally segmented. If the coefficient β_1 is not significant, this implies that capital flows are not generally constrained by regional borders.

[40] Since regional GDP equals C+I+G+TradeSurplus as well as C+S+T, trade deficit is I-S+(G-T), where G is government spending and T is government revenues. On the other hand, capital inflows are equal to trade deficit.
[41] We divide capital share of the regional GDP by capital assets in the region. These data are only available from 2002. This is why the model for capital flows can only be estimated for 2002-2009.

6.2. Results

The Table 8 below presents the results for the net capital inflows. We find that capital flows to regions with lower incomes and wages. This is consistent with neoclassical growth theory and suggests that capital flows may also be an important source of convergence.

In all specifications, we find that capital flows to regions with higher returns to capital; this probably reflects the quality of investment climate. We find no effect of pre-existing stock of capital. This may be due to the fact that the old capital may be outdated.

Table 8. Results for the net capital inflows.

Dependent variable – capital inflows	(1) Main	(2) With income	(3) With income, without wage	(4) Different income components	(5) Different income components, w/o returns to capital
Capital income per unit of capital t-1 (log)	0.016***	0.018***	0.015***	0.013**	
	(0.006)	(0.006)	(0.006)	(0.006)	
Other incomes (as a part of income per capita) t-1 (log)				0.002	0.009***
				(0.005)	(0.003)
Wage (as a part of income per capita) t-1 (log)				-0.038**	-0.029***
				(0.018)	(0.009)
Social transfers (as a part of income per capita)[42] t-1 (log)				-0.008	0.011
				(0.018)	(0.008)
Income per capita (log) t-1		-0.018	-0.027**		
		(0.013)	(0.012)		
Wage (log) t-1	-0.058***	-0.047**			
	(0.022)	(0.023)			
Capital to employment t-1	0.012	0.011	0.007	0.014	0.022***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.006)
Population (log)	0.046	0.056	0.059	0.037	0.078**
	(0.063)	(0.064)	(0.064)	(0.064)	(0.039)
Unemployment	-0.001	-0.001	-0.001	-0.001	-0.001

[42] The three income subcategories (social transfers, other incomes, wages) are defined in Section 4.2.

	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Telephones	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Buses	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Doctors	0.002**	0.002**	0.002**	0.002***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Number of hospitals	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highway density	-0.000	-0.000	-0.000**	-0.000*	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
year2003	-0.081**	-0.092***	-0.044*	-0.060*	-0.001
	(0.032)	(0.033)	(0.023)	(0.036)	(0.003)
year2004	-0.067**	-0.076***	-0.036*	-0.050	-0.002
	(0.027)	(0.028)	(0.019)	(0.031)	(0.003)
year2005	-0.056**	-0.064***	-0.030*	-0.040	0.003
	(0.023)	(0.023)	(0.016)	(0.026)	(0.004)
year2006	-0.045**	-0.051***	-0.024*	-0.033	0.001
	(0.018)	(0.019)	(0.013)	(0.021)	(0.004)
year2007	-0.028**	-0.033**	-0.013	-0.019	0.008**
	(0.014)	(0.014)	(0.010)	(0.016)	(0.004)
year2008	-0.004	-0.007	0.004	0.001	0.018***
	(0.008)	(0.009)	(0.006)	(0.011)	(0.004)
year2009	-0.001	-0.002	0.001	0.001	0.010***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)
Observations	622	622	622	622	856
R-squared	0.167	0.182	0.182	0.173	0.181
Number of regions	78	78	78	78	78

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In order to understand whether there are substantial barriers to capital flows, we estimate a panel regression for investment per capita as a function of savings per capita. We find that there is no significant relationship which rejects the hypothesis that there are interregional barriers to capital mobility (

Table 9).

Table 9. Results for investments per capita.

VARIABLES	(1) 2002-2009	(2) 2002-2005	(3) 2005-2009
Savings per capita (log)	0.021	0.035	0.010
	(0.030)	(0.045)	(0.040)
Budget income per capita (log)	0.014	-0.175	0.346*
	(0.162)	(0.213)	(0.202)
Budget expenditure per capita (log)	0.215	0.263	0.061
	(0.168)	(0.206)	(0.203)
Capital income per unit of capital (log)	0.265***	0.389***	0.102
	(0.058)	(0.082)	(0.079)
Capital to employed	-0.037	0.484**	-0.358**
	(0.111)	(0.237)	(0.156)
Population (log)	2.668***	-0.824	1.514
	(0.837)	(1.899)	(1.662)
Wage (log) t-1	0.540***	0.870***	-0.127
	(0.196)	(0.298)	(0.332)
Unemployment	-0.007	-0.005	-0.017**
	(0.006)	(0.010)	(0.008)
Telephones	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)
Buses	-0.002*	0.000	-0.001
	(0.001)	(0.002)	(0.001)
Doctors	0.003	-0.001	0.016*
	(0.007)	(0.013)	(0.009)
Number of hospitals	-0.001	-0.002	-0.002
	(0.002)	(0.004)	(0.002)
Highway density	-0.001**	0.001	-0.000
	(0.000)	(0.001)	(0.000)
year2003	-0.003	-0.232*	
	(0.077)	(0.127)	
year2004	0.031	-0.319	
	(0.118)	(0.204)	
year2005	0.118	-0.364	
	(0.158)	(0.277)	
year2006	0.185		0.204***
	(0.200)		(0.079)
year2007	0.381		0.539***
	(0.242)		(0.148)
year2008	0.477*		0.799***
	(0.288)		(0.226)
year2009	0.297		0.807***
	(0.332)		(0.299)
Observations	617	309	385
R-squared	0.914	0.810	0.826
Number of regions	78	78	78

*** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses

7. Conclusions and policy implications

In this paper, we analyze convergence among Russian regions. Unlike 1990s, when Russian regions did not converge or even diverge, in 2000s (especially in the late 2000s) there was a substantial convergence in incomes and wages. By 2010, this resulted in reduction of the inter-regional differences in incomes to European levels.

In order to understand why convergence did not happen in 1990s and did start in 2000s, we carried out a number of empirical exercises. First, we decomposed the convergence in incomes into convergence in wages, government transfers, and other incomes. We also compared convergence in incomes to convergence in GDP per capita (which has not happened). Second, we ran panel regressions for inter-regional migration. Since we have detailed data for gross region-to-region migration, we were able to analyze main determinants and barriers for labor mobility. Third, we ran panel regressions for capital flows. As the data for inter-regional capital flows are not available, our analysis was limited to the study of net capital inflows for each region and therefore was not as detailed as that of the labor reallocation.

Our results are as follows. While direct government transfers did contribute to convergence, their role has been negligible (as the share of transfers in income is very small). It may well be the case that government redistribution has contributed to reallocation through public sector and government companies' wages but our data do not allow do single out this effect. We found that in early 2000s convergence was explained mainly by wages while in later years convergence was due to convergence in other incomes. Once again, the data limitations did not allow us to distinguish the role of entrepreneurial and capital income from that of the informal wages. Interestingly, despite income convergence, there was no convergence in GDP per capita among Russian regions. Inter-regional dispersions in GDP per capita remain high not only by European standards but also by standards of less developed countries.

Our panel regressions show that reduction in barriers to labor mobility has played an important role in convergences in wages and incomes. We show that some regions lost tens of percents of their populations over the last 15 years while some other regions gained tens of percents. In 1990s, labor mobility from poor to rich regions was slowed down by liquidity constraints. The migrants from poor regions were willing to move but—because of the underdevelopment of financial and real estate markets—they were not able to move. Our results shows that in these regions the increase in income resulted in higher (rather than lower) outward migration – increase in income allowed breaking out of the poverty traps. Using several parametric and semiparametric specifications we identify the critical threshold of income that allowed for overcoming liquidity constraints. While in 1990s tens of regions were below this threshold (and therefore were locked in the poverty trap), by 2010 only one region was below the threshold. In this sense, overall economic growth allowed Russian regions to overcome liquidity constraints through simply growing out of the poverty traps. We run additional tests to show that financial development has also contributed to relaxing liquidity constraints.

Lowering barriers to labor mobility resulted in convergence in wages and incomes which was followed by a reduction of the labor mobility per se. Inter-regional migration rates have gone down in 2000s. We show that this reduction is explained by lower inter-regional differences (and therefore lower incentives to migrate).

Our analysis of capital flows is limited by the lack of detailed data. But our study of panel data on net capital inflows and investment shows that, first, capital does flow to regions with higher return to capital and with lower wages and incomes – and thus contributes to convergence. Second, investment in Russian regions is not correlated to savings – which suggests that capital market is not regionally segmented. As our data on capital are limited to 2000s, we cannot compare the recent years to 1990s, but at least we can argue that recently, capital market was functioning well and was contributing to convergence.

The results above do imply that the combination of convergence in wages and incomes and non-convergence in GDP per capita is a puzzle. The only way to reconcile these facts is as follows. While there is a functioning market for geographical reallocation of labor and capital, Russian regions still differ substantially in terms of total factor productivity. These differences may be explained either by (i) geographical factors, (ii) productivity of inherited capital stock, or (iii) political and economic institutions. The geographical factors are exogenous and cannot be changed, while the role of inherited capital stock will continue to decrease over time due to capital reallocation. Institutional factors are endogenous to changes in political system and in federalism. We do not have data to distinguish between these three explanations – including more detailed data on capital stock and panel data on investment and business climate. This analysis is therefore part of the future research agenda.

What are the policy implications of our analysis? One important result is that, in order to ensure inter-regional convergence in incomes and wages, one does not need convergence in GDP per capita. As long as barriers to labor and capital mobility are removed, mobility (or even a threat of mobility) protects workers. Therefore the very fact of remaining large inter-regional dispersion in GDP per capita should not serve as a justification for government intervention (e.g. region-specific government investment).

As reducing barriers to mobility is important for convergence, this is exactly where the policies can contribute the most. Developing financial and housing markets and improving investor protection is the best policy to reduce inter-regional difference in income. These factors have already reduced income differentials among Russian regions.

We should however provide an important caveat. Our analysis is done at the regional level. We therefore do not address the sub-regional level and have nothing to say on the need for town-level government interventions. There may well be many cases where individual towns (e.g. so called mono-towns) are locked in poverty traps. In those cases government intervention may be justified and desirable. Our results show that poverty traps did exist in Russia in 1990s at the regional level. These may well still exist at the town level even now. We cannot extrapolate the quantitative value of the income threshold we identified for the poverty traps from regional to town level but our analysis provides very clear qualitative criteria for government intervention. If the average citizen of a town 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. Therefore our analysis is fully consistent with government's mono-towns restructuring program.

8. References

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9. Appendix

9.1. Appendix A: Tables

Table 10. Studies of income inequality among Russian regions.

Paper	Time span	Income indicator	Regional price deflator	Main method of analysis	The speed of convergence β
Mikheeva (1999, 2000)	1990-1996	GDP Personal incomes	- CPI	β-convergence	-2% (GDP per capita), -3.5% (Real personal income)
Carluer, Sharipova (2004)	1985-1999 1994-1999 1995-2000	Personal incomes GDP Industrial production	- - -	β-convergence	-0.78% Income (1985-99) 13.6% GDP (1994-99) -0.92% Industrial output (1995-2000)
Solanko (2006, 2008)	1992-2005	Personal incomes	CPI	β-convergence	3% (for initially rich region)
Ledyaeva, Linden (2008)	1996-2005	GDP	-	β-convergence	1.24%
Melnikov (2005, 2007, 2008)	1995-2004 1997-2005	GDP Personal incomes	Cost of the PC basket	β-convergence	No convergence before 2000 9.44% (GDP 2000-2004) 3.66% (personal income)
Lugovoy et al. (2007)	1998-2004	GDP	From Granberg and Zaitseva (2003)	β-convergence	2.9-3.1%
Kholodilin et. al (2009)	1998-2006	GDP	From Granberg and Zaitseva (2003)	β-convergence	2%
Buccellato (2007)	1999-2004	GDP	-	β-convergence	3.6%
Berkowitz, DeJong (2002, 2003, 2005)	1993-1997 1993-2000	Personal incomes	CPI	Causal cross-sectional analysis	-0.1% (1993-1997) 0.1% (1993-2000)

Berkowitz, DeJong (2010)	1993-2007	Personal incomes	Cost of the PC basket + CPI	Causal cross-sectional analysis	4.5% (1993-2000) 7.8% (2000-2007)
Berkowitz, Jackson (2006)	1995-2001	Personal incomes (by quintile)	-	Causal cross-sectional analysis	Convergence
Ahrend (2005)	1995-1997 1994-1998 1991-1998	GDP Personal incomes Industrial production	- CPI	Causal cross-sectional analysis	No convergence (GDP) 4.3% (income) -1.4% (industrial production)
Babetski, Maurel (2002)	1995-1999	Personal incomes	CPI (?)	Time series analysis	Weak convergence
Kwon, Spilimbergo (2005)	1993-2002	GDP (?)	CPI (?)	Time series analysis	Convergence
Bradshaw, Vartapetov (2003)	1990-2001	Personal incomes, GDP	Cost of staples basket, subsistence minimum	σ-convergence	Divergence
Galbraith et. al (2004)	1990-2000	Payroll	-	σ-convergence	Divergence
Litvintseva et al. (2007)	2000-2004	Personal incomes (by quintile)	Cost of the PC basket + CPI(?)	σ-convergence	Divergence
Fedorov (2002)	1990-1999	Personal incomes, personal expenditures	CPI	Polarization	Divergence (slowly in 1998-1999)
Balatskii and Saakyants (2006)	1998-2004	GDP	-	Polarization (?)	Divergence
Dolinskaya (2002)	1991-1997	Personal incomes	CPI	Transition probability matrices	Divergence
Carluer (2005)	1985-1999	Personal incomes	-	Transition probability matrices	-0.78% (1985-99) 1% (1993-99) -4% (1991-93) 0.5% (1985-91) σ-divergence
Yemtsov (2005)	1994-2000	Personal incomes	Minimum subsistence level	σ-convergence, transition probability	Divergence

				matrices	
Lavrovsky and Shiltsin (2009)	2000-2005	GDP	-	Transition probability matrices	Divergence
Herzfeld (2008)	1999-2004	GDP	-	Convergence clubs, transition probability matrices	Divergence
Iodchin (2007)	1996-2003	GDP per worker	CPI	β-convergence, σ-convergence	σ-divergence 0.64%
Uschev, Chirkova (2008)	1998-2004	GDP	-	β-convergence	2.4%
Libman (2006, 2009)	1990-2004 2000-2004	Personal incomes GDP	- CPI	β-convergence	4.4% (1990-95) 2.5% (1996-99) 2.4% (2000-04) 5.7% (1990-2004) 6.8% (2000-04) GDP
Gerasimova (2009)	1995-2007	Personal incomes	-	σ-convergence	Convergence
Zverev, Kolomak (2010)	1995-2006	GDP Budget income Budget expenditure	-	β-convergence, σ-convergence	No convergence (GDP) 9,3% (Budget income) 14% (Non tax income) 4,7% (general expenditures) 3,4% (expenditures for education) 1,9% (Expenditure for housing and public utilities) 17,1% (Social policy)
Kolomak (2010)	1995-2007	Personal incomes	-	β-convergence	1.7%
Mahler (2011)	2002-2008	GDP	CPI	Theil index	Divergence
Akhmedjonov, Lau, Izgi (2013)	2000-2008	GDP	PPP	Time series analysis	Divergence

Source: Gluschenko (2010), authors' calculations.

Table 11. 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
Fund coefficient	Income ratio of 10% rich population to 10% poor population	1995-2010	96564	11.64	4.62	4.5	49.1
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 1000 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
Homicides	Number of reported homicides and attempts to murder	1995-2010	97344	348.42	300.84	7	1749
Mobile telephones	Number of registered mobile phones, thousand	2000-2010	65442	1808.09	4228.42	0.1	39688.8
Pollution	Emissions into the air from stationary sources	1995-2010	97344	253.27	488.06	0	4179
Crime	Number of crime reported, per 100,000 population	1995-2010	97344	2077.76	676.41	430	4941
Share of unprofitable firms	Share of unprofitable firms	2000-2010	66924	37.73	9.08	16.3	70.3
Urban	Towns residents %	1995-2010	97344	69.33	12.50	23.6	100
Capital flow	Net capital flow per capita	2000-2010	936	0.01	0.03	-0.10	0.31
Capital income (log)	Log of capital income (share of GDP) per unit of capital	2002-2010	624	-1.72	0.38	-3.22	-0.45
Other incomes (as a part of income per capita)	Part of income per capita, rubles	1999-2010	936	2913.30	2562.31	202.76	20442.24
Social transfers (as a part of income per capita)	Part of income per capita, rubles	1999-2010	936	1185.90	976.82	77.52	5762.99
Wage (as a part of income per capita)	Part of income per capita, rubles	1999-2010	936	3306.66	3395.92	143.22	30573.77
Capital to labor ratio (log)	Log of capital to labor ratio	1995-2010	1248	5.93	0.76	3.64	8.75
Investment (log)	Log of investment in capital	1995-	1248	9.39	1.64	4.54	13.87

	assets	2010					
Savings (log)	Log of population savings per capita	2000-2010	927	-4.49	1.35	-9.71	-1.65
Budget income (log)	Log of consolidate budget incomes per capita	1995-2010	1247	-4.73	1.20	-7.21	-0.81
Budget expenditures (log)	Log of consolidate budget expenditures per capita	1995-2010	1247	-4.70	1.19	-7.26	-1.07
Loans to households	Loans to households with respect to GDP	2001-2010	60294	0.061	0.054	0.001	0.267
Loans to firms	Loans to firms with respect to GDP	2001-2010	60684	0.137	0.176	0.007	3.064
Mortgage debt	Mortgage debt with respect to GDP	2004-2010	42432	0.019	0.017	0.000	0.083

Table 12. Results of regressions with and without squared terms (migration model).

VARIABLES	(1) Main	(2) Squared income	(3) Without Moscow and Saint-Petersburg	(4) Without Moscow and Saint Petersburg, squared income
Population i (log)	1.750***	1.802***	1.572***	1.633***
	(0.099)	(0.098)	(0.109)	(0.111)
Population j (log)	1.964***	2.002***	1.737***	1.734***
	(0.096)	(0.096)	(0.104)	(0.107)
Income i (log)	0.035	0.758***	-0.027	0.450**
	(0.023)	(0.157)	(0.024)	(0.192)
Income squared i (log)		-0.041***		-0.027**
		(0.009)		(0.011)
Income j (log)	0.175***	0.696***	0.169***	0.148
	(0.023)	(0.169)	(0.025)	(0.205)
Income squared j (log)		-0.029***		0.001
		(0.010)		(0.012)
Gini (log) i	-0.084*	-0.082*	-0.093**	-0.092**
	(0.043)	(0.043)	(0.047)	(0.047)
Gini (log) j	-0.124***	-0.123***	-0.143***	-0.143***
	(0.042)	(0.042)	(0.046)	(0.046)
Unemployment rate (log) i	0.062***	0.059***	0.037***	0.036***
	(0.009)	(0.009)	(0.009)	(0.009)
Unemployment rate (log) j	-0.069***	-0.071***	-0.072***	-0.072***
	(0.009)	(0.009)	(0.009)	(0.009)
Housing price i (log)	-0.051***	-0.050***	-0.048***	-0.048***
	(0.011)	(0.011)	(0.012)	(0.012)
Housing price j (log)	0.047***	0.049***	0.055***	0.055***
	(0.011)	(0.011)	(0.011)	(0.011)
Provision of housing i (log)	0.409***	0.404***	0.147*	0.155*
	(0.082)	(0.083)	(0.087)	(0.088)
Provision of housing j (log)	0.617***	0.613***	0.608***	0.608***
	(0.082)	(0.083)	(0.086)	(0.086)
New flats (moving average, log) i	-0.010	-0.005	0.010	0.013
	(0.009)	(0.009)	(0.010)	(0.010)
New flats (moving average log) j	-0.006	-0.002	-0.012	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)
Life expectancy (log) i	-0.047	-0.082	0.096	0.067
	(0.201)	(0.201)	(0.208)	(0.208)
Life expectancy (log) j	-0.556***	-0.581***	-0.363*	-0.361*
	(0.191)	(0.191)	(0.199)	(0.199)

Infant mortality rate (log) i	0.039***	0.037**	0.029*	0.028*
	(0.015)	(0.015)	(0.015)	(0.015)
Infant mortality rate (log) j	-0.082***	-0.084***	-0.077***	-0.077***
	(0.016)	(0.016)	(0.016)	(0.016)
Doctors (log) i	0.077	0.121**	0.125**	0.147**
	(0.059)	(0.061)	(0.061)	(0.062)
Doctors (log) j	0.169***	0.200***	0.194***	0.193***
	(0.056)	(0.057)	(0.057)	(0.058)
Hospital beds (log) i	0.043	0.036	-0.002	-0.003
	(0.039)	(0.039)	(0.040)	(0.040)
Hospital beds (log) j	0.311***	0.306***	0.271***	0.271***
	(0.039)	(0.039)	(0.040)	(0.040)
Telephones (log) i	-0.010	-0.035	-0.091***	-0.101***
	(0.026)	(0.026)	(0.027)	(0.028)
Telephones (log) j	-0.163***	-0.180***	-0.154***	-0.154***
	(0.025)	(0.026)	(0.029)	(0.029)
Highway density (log) i	0.037**	0.037**	0.034*	0.034*
	(0.018)	(0.018)	(0.018)	(0.018)
Highway density (log) j	-0.003	-0.003	0.026	0.026
	(0.018)	(0.018)	(0.019)	(0.019)
Buses (log) i	0.027***	0.028***	0.033***	0.033***
	(0.007)	(0.007)	(0.007)	(0.007)
Buses (log) j	-0.015*	-0.015*	-0.027***	-0.027***
	(0.009)	(0.008)	(0.009)	(0.009)
Share of young i, t-1	-0.022***	-0.015***	-0.025***	-0.020***
	(0.005)	(0.005)	(0.006)	(0.006)
Share of young j, t-1	0.056***	0.061***	0.051***	0.050***
	(0.005)	(0.005)	(0.006)	(0.006)
Share of old i, t-1	-0.050***	-0.042***	-0.041***	-0.037***
	(0.004)	(0.004)	(0.004)	(0.005)
Share of old j, t-1	0.023***	0.028***	0.020***	0.020***
	(0.004)	(0.005)	(0.005)	(0.005)
Students i (log), t-1	-0.077***	-0.074***	-0.085***	-0.082***
	(0.009)	(0.009)	(0.009)	(0.009)
Students j (log), t-1	0.102***	0.104***	0.111***	0.111***
	(0.011)	(0.011)	(0.011)	(0.011)
Women i (log), t-1	0.469**	0.497**	-1.387***	-1.223***
	(0.229)	(0.224)	(0.286)	(0.293)
Women j (log), t-1	-3.058***	-3.038***	-3.725***	-3.732***
	(0.216)	(0.212)	(0.290)	(0.299)
year1997	-0.029***	-0.020**	-0.017	-0.014
	(0.010)	(0.010)	(0.011)	(0.011)
year1998	0.027	0.064***	0.004	0.019
	(0.020)	(0.020)	(0.022)	(0.022)
year1999	-0.013	0.020	-0.015	-0.002
	(0.020)	(0.021)	(0.022)	(0.023)
year2000	-0.148***	-0.112***	-0.144***	-0.131***
	(0.025)	(0.025)	(0.027)	(0.027)

year2001	-0.175***	-0.124***	-0.123***	-0.106***
	(0.032)	(0.032)	(0.036)	(0.036)
year2002	-0.203***	-0.144***	-0.130***	-0.112***
	(0.038)	(0.038)	(0.043)	(0.043)
year2003	-0.162***	-0.086*	-0.062	-0.039
	(0.045)	(0.046)	(0.052)	(0.052)
year2004	-0.227***	-0.136***	-0.119**	-0.091
	(0.051)	(0.052)	(0.058)	(0.059)
year2005	-0.246***	-0.142**	-0.123*	-0.091
	(0.056)	(0.058)	(0.064)	(0.065)
year2006	-0.219***	-0.103	-0.099	-0.062
	(0.062)	(0.064)	(0.070)	(0.072)
year2007	-0.172***	-0.050	-0.056	-0.017
	(0.066)	(0.068)	(0.075)	(0.076)
year2008	-0.172**	-0.045	-0.061	-0.019
	(0.069)	(0.071)	(0.078)	(0.079)
year2009	-0.292***	-0.165**	-0.177**	-0.135*
	(0.069)	(0.071)	(0.078)	(0.080)
year2010	-0.210***	-0.090	-0.101	-0.061
	(0.070)	(0.071)	(0.079)	(0.080)
Observations	84,666	84,666	80,222	80,222
R-squared	0.308	0.308	0.309	0.310
Number of id	5,929	5,929	5,625	5,625

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13. Regressions with financial development (migration model).

VARIABLES	(1) Main	(2) With squared income	(3) Without Moscow and Saint Petersburg	(4) Without Moscow and Saint Petersburg, with squared income
Population i (log)	1.399***	1.332***	1.502***	1.390***
	(0.153)	(0.155)	(0.166)	(0.168)
Population j (log)	2.370***	2.412***	2.096***	2.165***
	(0.143)	(0.145)	(0.157)	(0.158)
Income i (log)	-0.028	-4.143***	-0.033	-5.580***
	(0.049)	(0.844)	(0.051)	(0.946)
Income squared i (log)		0.216***		0.292***
		(0.044)		(0.050)
Income*loans i (log)	-0.020**	-0.633***	-0.018**	-0.887***
	(0.008)	(0.189)	(0.009)	(0.213)
Income squared*loans i (log)		0.031***		0.045***
		(0.010)		(0.012)

Loans i (log)	0.155**	3.134***	0.144*	4.321***
	(0.077)	(0.876)	(0.081)	(0.985)
Income j (log)	0.058	1.346*	0.114**	2.452***
	(0.048)	(0.779)	(0.051)	(0.870)
Income squared j (log)		-0.070*		-0.130***
		(0.041)		(0.046)
Income*loans j (log)	-0.010	0.336*	-0.006	0.828***
	(0.008)	(0.181)	(0.009)	(0.207)
Income squared*loans j (log)		-0.019*		-0.046***
		(0.010)		(0.011)
Loans j (log)	0.110	-1.474*	0.057	-3.687***
	(0.075)	(0.833)	(0.079)	(0.948)
Gini (log) i	-0.088	-0.027	-0.046	-0.025
	(0.085)	(0.089)	(0.096)	(0.098)
Gini (log) j	-0.208**	-0.253***	-0.357***	-0.448***
	(0.088)	(0.091)	(0.099)	(0.101)
Unemployment rate (log) i	0.035***	0.034***	0.031***	0.031***
	(0.011)	(0.011)	(0.012)	(0.012)
Unemployment rate (log) j	-0.049***	-0.046***	-0.063***	-0.058***
	(0.010)	(0.011)	(0.011)	(0.011)
Housing price i (log)	-0.032**	-0.033**	-0.029*	-0.029*
	(0.015)	(0.015)	(0.016)	(0.016)
Housing price j (log)	0.058***	0.062***	0.048***	0.055***
	(0.015)	(0.015)	(0.016)	(0.016)
Provision of housing i (log)	0.534***	0.439***	0.561***	0.429**
	(0.164)	(0.163)	(0.170)	(0.169)
Provision of housing j (log)	0.388***	0.407***	0.400***	0.427***
	(0.142)	(0.143)	(0.149)	(0.151)
New flats (moving average, log) i	-0.047***	-0.042***	-0.046***	-0.040***
	(0.012)	(0.012)	(0.013)	(0.013)
New flats (moving average log) j	0.046***	0.043***	0.046***	0.041***
	(0.012)	(0.013)	(0.013)	(0.013)
Life expectancy (log) i	0.699**	0.753***	0.689**	0.737***
	(0.272)	(0.271)	(0.281)	(0.280)
Life expectancy (log) j	-1.503***	-1.546***	-1.168***	-1.202***
	(0.255)	(0.255)	(0.264)	(0.262)
Infant mortality rate (log) i	0.063***	0.071***	0.056***	0.060***
	(0.017)	(0.017)	(0.018)	(0.018)
Infant mortality rate (log) j	-0.066***	-0.068***	-0.065***	-0.063***
	(0.018)	(0.018)	(0.019)	(0.019)
Doctors (log) i	0.094	0.076	0.103	0.085
	(0.081)	(0.081)	(0.083)	(0.083)
Doctors (log) j	0.019	0.016	0.007	-0.010
	(0.084)	(0.084)	(0.086)	(0.086)
Hospital beds (log) i	0.029	0.037	0.041	0.051
	(0.046)	(0.046)	(0.047)	(0.047)
Hospital beds (log) j	0.305***	0.301***	0.261***	0.249***
	(0.047)	(0.047)	(0.048)	(0.048)

Telephones (log) i	-0.040	-0.005	-0.047	-0.018
	(0.031)	(0.032)	(0.033)	(0.033)
Telephones (log) j	-0.002	-0.004	-0.007	-0.003
	(0.031)	(0.032)	(0.034)	(0.034)
Highway density (log) i	0.046**	0.032*	0.035*	0.020
	(0.019)	(0.019)	(0.020)	(0.020)
Highway density (log) j	-0.050**	-0.048**	-0.028	-0.031
	(0.020)	(0.020)	(0.021)	(0.021)
Buses (log) i	0.031***	0.028***	0.038***	0.035***
	(0.009)	(0.009)	(0.009)	(0.009)
Buses (log) j	-0.041***	-0.038***	-0.055***	-0.048***
	(0.009)	(0.009)	(0.010)	(0.010)
Share of young i, t-1	-0.012	-0.022***	0.000	-0.006
	(0.008)	(0.008)	(0.009)	(0.009)
Share of young j, t-1	0.062***	0.065***	0.044***	0.044***
	(0.008)	(0.008)	(0.009)	(0.009)
Share of old i, t-1	0.012*	-0.005	0.021***	0.001
	(0.007)	(0.008)	(0.007)	(0.008)
Share of old j, t-1	-0.016**	-0.011	-0.030***	-0.022***
	(0.007)	(0.008)	(0.008)	(0.008)
Students i (log), t-1	-0.080***	-0.085***	-0.082***	-0.087***
	(0.021)	(0.021)	(0.022)	(0.022)
Students j (log), t-1	0.111***	0.111***	0.108***	0.106***
	(0.021)	(0.021)	(0.022)	(0.022)
Women i (log), t-1	-1.593**	-1.244	-2.859***	-3.324***
	(0.791)	(0.797)	(0.954)	(0.957)
Women j (log), t-1	-6.050***	-6.226***	-4.615***	-4.812***
	(0.806)	(0.814)	(1.013)	(1.018)
year2002	-0.001	-0.007	0.000	0.004
	(0.014)	(0.015)	(0.017)	(0.018)
year2003	0.057**	0.040	0.057*	0.059*
	(0.027)	(0.028)	(0.035)	(0.035)
year2004	0.022	-0.001	0.018	0.021
	(0.039)	(0.040)	(0.050)	(0.050)
year2005	0.031	0.007	0.026	0.036
	(0.051)	(0.052)	(0.064)	(0.064)
year2006	0.101	0.080	0.081	0.103
	(0.064)	(0.065)	(0.079)	(0.080)
year2007	0.179**	0.164**	0.152*	0.189**
	(0.075)	(0.076)	(0.091)	(0.093)
year2008	0.197**	0.192**	0.160	0.211**
	(0.082)	(0.083)	(0.099)	(0.101)
year2009	0.096	0.100	0.054	0.123
	(0.086)	(0.088)	(0.103)	(0.106)
year2010	0.175**	0.184**	0.126	0.196*
	(0.086)	(0.087)	(0.102)	(0.105)
Observations	58,223	58,223	55,211	55,211

R-squared	0.104	0.105	0.104	0.106
Number of id	5,929	5,929	5,625	5,625

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14. Beta convergence for 95-00, 00-05, 05-10 (%) nominal income.

Period	Nominal income per capita		Nominal wage		Nominal GDP per capita	
	Estimation coefficient b	β	Estimation coefficient b	β	Estimation coefficient b	β
1995-2000	-0.736 (0.742)	0.7	-2.275*** (0.566)	2.4	1.205 (1.064)	-1.1
2000-2005	-1.475* (0.763)	1.5	-2.734*** (0.462)	2.9	-0.588 (0.709)	0.5
2005-2010	-5.445*** (0.554)	6.4	-2.349*** (0.395)	2.5	-1.736*** (0.652)	1.8
1995-2010	-2.347*** (0.314)	2.9	-2.241*** (0.238)	2.7	-0.455 (0.485)	0.4
2000-2010	-3.356*** (0.410)	4	-2.492*** (0.307)	2.9	-1.194** (0.478)	1.2

Table 15. Results for different distances between pairs of regions (migration model).

VARIABLES	(1) <500 km	(2) <500 km With squared income	(3) 500-2000 km	(4) 500-2000 km With squared income	(5) >2000 km	(6) >2000 km With squared income
Population i (log)	1.041***	0.940***	1.488***	1.497***	1.846***	1.921***
	(0.257)	(0.252)	(0.144)	(0.142)	(0.148)	(0.147)
Population j (log)	2.244***	2.217***	1.714***	1.745***	2.242***	2.297***
	(0.241)	(0.240)	(0.142)	(0.144)	(0.144)	(0.143)
Income i (log)	0.124**	-1.610***	0.016	0.187	0.041	1.087***
	(0.052)	(0.392)	(0.033)	(0.221)	(0.032)	(0.235)
Income squared i (log)		0.098***		-0.010		-0.059***
		(0.022)		(0.012)		(0.013)
Income j (log)	0.130**	-0.556	0.190***	0.560**	0.178***	0.919***
	(0.052)	(0.410)	(0.032)	(0.247)	(0.032)	(0.250)
Income squared j (log)		0.039*		-0.021		-0.042***
		(0.023)		(0.014)		(0.014)
Gini (log) i	-0.174**	-0.157*	-0.008	-0.012	-0.182***	-0.164***
	(0.085)	(0.087)	(0.061)	(0.061)	(0.064)	(0.063)
Gini (log) j	-0.046	-0.050	-0.149**	-0.156***	-0.152**	-0.138**
	(0.087)	(0.087)	(0.059)	(0.059)	(0.063)	(0.063)
Unemployment rate (log) i	0.048**	0.048***	0.082***	0.082***	0.041***	0.035**
	(0.019)	(0.018)	(0.012)	(0.012)	(0.014)	(0.014)
Unemployment rate (log) j	-0.020	-0.018	-0.068***	-0.069***	-0.073***	-0.077***
	(0.019)	(0.018)	(0.012)	(0.012)	(0.014)	(0.014)
Housing price i (log)	-0.002	-0.004	0.004	0.005	-0.076***	-0.074***
	(0.025)	(0.024)	(0.014)	(0.014)	(0.016)	(0.016)
Housing price j (log)	0.037	0.032	0.064***	0.064***	0.045***	0.046***
	(0.025)	(0.024)	(0.015)	(0.015)	(0.015)	(0.015)
Provision of housing i (log)	0.548***	0.531***	0.588***	0.590***	0.256**	0.237**
	(0.181)	(0.172)	(0.127)	(0.127)	(0.117)	(0.117)
Provision of housing j (log)	0.895***	0.917***	0.894***	0.898***	0.468***	0.453***
	(0.160)	(0.157)	(0.129)	(0.130)	(0.111)	(0.111)
New flats (moving average, log) i	-0.113***	-0.129***	-0.060***	-0.059***	0.019	0.027**
	(0.024)	(0.023)	(0.015)	(0.015)	(0.012)	(0.012)

New flats (moving average log) j	0.074***	0.068***	0.026*	0.029*	-0.029**	-0.023*
	(0.024)	(0.024)	(0.015)	(0.015)	(0.012)	(0.012)
Life expectancy (log) i	0.297	0.461	-0.132	-0.146	0.182	0.128
	(0.483)	(0.476)	(0.298)	(0.298)	(0.279)	(0.277)
Life expectancy (log) j	0.608	0.541	-1.246***	-1.269***	-0.364	-0.405
	(0.467)	(0.463)	(0.291)	(0.292)	(0.265)	(0.265)
Infant mortality rate (log) i	0.043	0.045	0.045**	0.045**	0.044**	0.038*
	(0.028)	(0.027)	(0.022)	(0.022)	(0.021)	(0.021)
Infant mortality rate (log) j	-0.036	-0.036	-0.080***	-0.080***	-0.089***	-0.094***
	(0.034)	(0.033)	(0.021)	(0.021)	(0.023)	(0.023)
Doctors (log) i	0.049	-0.040	0.302***	0.313***	0.052	0.112
	(0.144)	(0.148)	(0.084)	(0.085)	(0.082)	(0.083)
Doctors (log) j	0.168	0.112	0.251***	0.276***	0.091	0.133*
	(0.132)	(0.137)	(0.081)	(0.083)	(0.078)	(0.079)
Hospital beds (log) i	0.335***	0.363***	0.102*	0.097*	-0.016	-0.018
	(0.092)	(0.095)	(0.053)	(0.053)	(0.059)	(0.059)
Hospital beds (log) j	0.186**	0.206**	0.270***	0.260***	0.367***	0.366***
	(0.092)	(0.094)	(0.053)	(0.053)	(0.057)	(0.057)
Telephones (log) i	0.054	0.111*	0.011	0.004	-0.060	-0.090**
	(0.064)	(0.066)	(0.036)	(0.036)	(0.037)	(0.037)
Telephones (log) j	-0.191***	-0.163***	-0.187***	-0.201***	-0.129***	-0.150***
	(0.061)	(0.061)	(0.036)	(0.037)	(0.037)	(0.038)
Highway density (log) i	0.120***	0.106***	0.054**	0.056**	0.006	0.003
	(0.037)	(0.038)	(0.025)	(0.025)	(0.026)	(0.026)
Highway density (log) j	-0.107***	-0.103***	-0.026	-0.023	0.010	0.008
	(0.037)	(0.038)	(0.027)	(0.027)	(0.027)	(0.027)
Buses (log) i	0.009	-0.002	0.024**	0.025**	0.029***	0.029***
	(0.019)	(0.019)	(0.012)	(0.012)	(0.009)	(0.009)
Buses (log) j	-0.034*	-0.038*	-0.052***	-0.050***	-0.005	-0.005
	(0.020)	(0.021)	(0.011)	(0.011)	(0.012)	(0.012)
Share of young i, t-1	-0.006	-0.020	-0.028***	-0.027***	-0.029***	-0.018**
	(0.013)	(0.014)	(0.008)	(0.007)	(0.008)	(0.008)
Share of young j, t-1	0.061***	0.055***	0.079***	0.082***	0.037***	0.045***
	(0.013)	(0.013)	(0.008)	(0.008)	(0.008)	(0.008)
Share of old i, t-1	-0.044***	-0.058***	-0.022***	-0.020***	-0.048***	-0.037***
	(0.015)	(0.016)	(0.007)	(0.008)	(0.006)	(0.006)
Share of old j, t-1	0.027*	0.018	0.023***	0.027***	0.025***	0.033***

	(0.014)	(0.015)	(0.008)	(0.008)	(0.006)	(0.006)
Students i (log), t-1	-0.043**	-0.048***	-0.103***	-0.102***	-0.061***	-0.055***
	(0.018)	(0.018)	(0.012)	(0.012)	(0.015)	(0.014)
Students j (log), t-1	0.023	0.018	0.092***	0.093***	0.117***	0.121***
	(0.019)	(0.020)	(0.013)	(0.012)	(0.020)	(0.020)
Women i (log), t-1	1.665***	1.922***	0.141	0.136	-0.119	-0.013
	(0.458)	(0.483)	(0.307)	(0.305)	(0.372)	(0.361)
Women j (log), t-1	-1.335***	-1.368***	-4.237***	-4.227***	-2.481***	-2.410***
	(0.443)	(0.489)	(0.320)	(0.318)	(0.326)	(0.320)
year1997	-0.064***	-0.075***	-0.032**	-0.029**	-0.028*	-0.015
	(0.023)	(0.025)	(0.013)	(0.014)	(0.016)	(0.016)
year1998	0.004	-0.057	0.003	0.018	0.023	0.079**
	(0.037)	(0.041)	(0.028)	(0.029)	(0.031)	(0.032)
year1999	-0.007	-0.062	-0.039	-0.027	-0.029	0.024
	(0.040)	(0.043)	(0.028)	(0.029)	(0.034)	(0.033)
year2000	-0.040	-0.099*	-0.150***	-0.137***	-0.201***	-0.142***
	(0.048)	(0.052)	(0.034)	(0.035)	(0.041)	(0.041)
year2001	-0.070	-0.159**	-0.142***	-0.123***	-0.254***	-0.173***
	(0.065)	(0.074)	(0.043)	(0.045)	(0.054)	(0.053)
year2002	-0.090	-0.194**	-0.181***	-0.159***	-0.288***	-0.196***
	(0.079)	(0.090)	(0.052)	(0.054)	(0.063)	(0.062)
year2003	-0.056	-0.192*	-0.135**	-0.105	-0.257***	-0.142*
	(0.097)	(0.112)	(0.062)	(0.064)	(0.075)	(0.074)
year2004	-0.076	-0.242*	-0.190***	-0.154**	-0.344***	-0.207**
	(0.110)	(0.129)	(0.070)	(0.073)	(0.084)	(0.084)
year2005	-0.128	-0.318**	-0.208***	-0.166**	-0.371***	-0.216**
	(0.120)	(0.143)	(0.077)	(0.080)	(0.092)	(0.092)
year2006	-0.178	-0.391**	-0.201**	-0.153*	-0.340***	-0.166
	(0.132)	(0.157)	(0.086)	(0.090)	(0.102)	(0.102)
year2007	-0.175	-0.401**	-0.173*	-0.123	-0.289***	-0.106
	(0.138)	(0.165)	(0.092)	(0.096)	(0.109)	(0.109)
year2008	-0.189	-0.424**	-0.187*	-0.134	-0.287**	-0.097
	(0.143)	(0.171)	(0.097)	(0.101)	(0.113)	(0.113)
year2009	-0.337**	-0.575***	-0.301***	-0.248**	-0.412***	-0.221*
	(0.143)	(0.171)	(0.098)	(0.102)	(0.114)	(0.114)
year2010	-0.262*	-0.486***	-0.234**	-0.184*	-0.320***	-0.140
	(0.139)	(0.165)	(0.099)	(0.103)	(0.115)	(0.115)
	(6.144)	(6.321)	(5.187)	(5.351)	(5.794)	(6.068)
Observations	6,246	6,246	31,104	31,104	47,286	47,286
R-squared	0.550	0.556	0.388	0.389	0.276	0.277
Number of id	427	427	2,144	2,144	3,356	3,356

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16. Results for different time periods (migration model).

VARIABLES	(1) 1996-2000	(2) 1996-2000 With squared income	(3) 2000-2005	(4) 2000-2005 With squared income	(5) 2005-2010 With squared income	(6) 2005-2010 With squared income
Population i (log)	2.196***	2.232***	2.043***	2.155***	0.974***	0.930***
	(0.315)	(0.316)	(0.312)	(0.317)	(0.208)	(0.214)
Population j (log)	1.216***	1.235***	0.843***	0.939***	2.189***	2.259***
	(0.298)	(0.299)	(0.304)	(0.312)	(0.193)	(0.200)
Income i (log)	0.002	-0.859***	0.044	1.015***	-0.005	-0.721
	(0.048)	(0.246)	(0.044)	(0.328)	(0.050)	(0.674)
Income squared i (log)		0.050***		-0.056***		0.038
		(0.014)		(0.019)		(0.035)
Income j (log)	-0.132***	-0.571**	0.017	0.846**	-0.013	1.106*
	(0.044)	(0.245)	(0.045)	(0.333)	(0.051)	(0.670)
Income squared j (log)		0.025*		-0.048**		-0.059*
		(0.014)		(0.019)		(0.035)
Gini (log) i	-0.091*	-0.081*	-0.066	-0.040	0.074	0.073
	(0.047)	(0.047)	(0.096)	(0.097)	(0.173)	(0.173)
Gini (log) j	0.086*	0.092**	0.040	0.063	-0.274	-0.271
	(0.046)	(0.046)	(0.099)	(0.100)	(0.173)	(0.172)
Unemployment rate (log) i	0.047***	0.044***	-0.006	-0.013	0.033**	0.031**
	(0.016)	(0.016)	(0.015)	(0.015)	(0.013)	(0.013)
Unemployment rate (log) j	-0.038**	-0.040**	-0.012	-0.018	-0.025*	-0.023*
	(0.017)	(0.017)	(0.015)	(0.015)	(0.013)	(0.013)
Housing price i (log)	-0.069***	-0.075***	-0.016	-0.020	0.014	0.014
	(0.013)	(0.013)	(0.019)	(0.019)	(0.020)	(0.020)
Housing price j (log)	0.062***	0.059***	0.049**	0.045**	0.051**	0.051**
	(0.013)	(0.013)	(0.019)	(0.019)	(0.020)	(0.020)
Provision of housing i (log)	0.144	0.102	0.587***	0.446**	0.236	0.205
	(0.144)	(0.143)	(0.198)	(0.208)	(0.190)	(0.193)
Provision of housing j (log)	0.114	0.092	0.323	0.203	0.600***	0.649***
	(0.154)	(0.153)	(0.207)	(0.216)	(0.174)	(0.177)
New flats (moving	-0.032	-0.038	-0.027	-0.016	-0.007	-0.008

average, log) i						
	(0.024)	(0.024)	(0.019)	(0.019)	(0.021)	(0.021)
New flats (moving average log) j	0.103***	0.100***	0.049**	0.058***	-0.046**	-0.045**
	(0.024)	(0.024)	(0.019)	(0.019)	(0.020)	(0.020)
Life expectancy (log) i	-0.535	-0.462	-0.485	-0.514	0.376	0.416
	(0.372)	(0.375)	(0.397)	(0.396)	(0.368)	(0.364)
Life expectancy (log) j	-0.364	-0.327	0.285	0.260	-1.048***	-1.111***
	(0.391)	(0.391)	(0.390)	(0.389)	(0.351)	(0.349)
Infant mortality rate (log) i	-0.009	-0.008	0.028	0.030	0.056**	0.060***
	(0.031)	(0.031)	(0.024)	(0.024)	(0.023)	(0.023)
Infant mortality rate (log) j	-0.016	-0.016	-0.017	-0.015	-0.064**	-0.069***
	(0.031)	(0.031)	(0.025)	(0.025)	(0.026)	(0.025)
Doctors (log) i	0.089	0.062	0.332**	0.398***	-0.085	-0.089
	(0.106)	(0.106)	(0.147)	(0.150)	(0.095)	(0.095)
Doctors (log) j	0.541***	0.527***	-0.135	-0.079	0.060	0.066
	(0.107)	(0.107)	(0.142)	(0.145)	(0.112)	(0.112)
Hospital beds (log) i	-0.329***	-0.318***	0.018	-0.004	-0.111*	-0.111*
	(0.095)	(0.095)	(0.087)	(0.087)	(0.061)	(0.061)
Hospital beds (log) j	-0.181**	-0.175*	0.341***	0.322***	0.102*	0.103*
	(0.090)	(0.090)	(0.088)	(0.088)	(0.062)	(0.062)
Telephones (log) i	-0.040	-0.062	-0.041	-0.087*	0.009	0.015
	(0.057)	(0.057)	(0.041)	(0.044)	(0.065)	(0.065)
Telephones (log) j	-0.364***	-0.376***	0.022	-0.017	-0.041	-0.049
	(0.060)	(0.061)	(0.040)	(0.044)	(0.069)	(0.069)
Highway density (log) i	-0.216**	-0.190**	0.037	0.036	0.055**	0.052**
	(0.097)	(0.096)	(0.026)	(0.026)	(0.022)	(0.022)
Highway density (log) j	0.313***	0.327***	0.036	0.035	0.012	0.016
	(0.105)	(0.105)	(0.030)	(0.030)	(0.022)	(0.022)
Buses (log) i	-0.130***	-0.134***	0.018	0.015	0.045***	0.041***
	(0.041)	(0.041)	(0.014)	(0.014)	(0.014)	(0.014)
Buses (log) j	0.126***	0.124***	0.018	0.015	-0.067***	-0.060***
	(0.041)	(0.041)	(0.015)	(0.015)	(0.014)	(0.014)
Share of young i, t-1	-0.021	-0.019	-0.025*	-0.014	-0.021	-0.025*
	(0.017)	(0.016)	(0.013)	(0.013)	(0.014)	(0.015)
Share of young	0.112***	0.114***	0.064***	0.072***	0.010	0.016

j, t-1						
	(0.017)	(0.017)	(0.013)	(0.014)	(0.015)	(0.016)
Share of old i, t-1	-0.060***	-0.058***	-0.053***	-0.044***	0.028**	0.022
	(0.016)	(0.016)	(0.008)	(0.009)	(0.013)	(0.014)
Share of old j, t-1	0.047***	0.048***	0.034***	0.042***	-0.046***	-0.037**
	(0.015)	(0.015)	(0.009)	(0.009)	(0.013)	(0.014)
Students i (log), t-1	-0.119***	-0.116***	-0.051***	-0.048**	-0.086*	-0.087*
	(0.019)	(0.019)	(0.019)	(0.019)	(0.049)	(0.049)
Students j (log), t-1	0.069***	0.071***	0.072***	0.074***	0.064	0.066
	(0.020)	(0.020)	(0.018)	(0.017)	(0.048)	(0.048)
Women i (log), t-1	-4.754**	-3.748*	1.377***	1.247***	-2.014	-2.402
	(2.209)	(2.229)	(0.303)	(0.305)	(1.944)	(1.955)
Women j (log), t-1	8.585***	9.098***	-2.325***	-2.436***	0.664	1.269
	(2.125)	(2.154)	(0.295)	(0.299)	(1.909)	(1.918)
year1997	0.034**	0.035**				
	(0.016)	(0.016)				
year1998	-0.026	-0.029				
	(0.034)	(0.034)				
year1999	0.031	0.039				
	(0.039)	(0.038)				
year2000	0.013	0.028				
	(0.050)	(0.050)				
year2001			-0.043	-0.001		
			(0.029)	(0.031)		
year2002			-0.076	-0.007		
			(0.047)	(0.050)		
year2003			-0.051	0.060		
			(0.064)	(0.072)		
year2004			-0.127	0.019		
			(0.081)	(0.091)		
year2005			-0.142	0.034		
			(0.097)	(0.109)		
year2006					0.014	0.013
					(0.022)	(0.022)
year2007					0.054	0.053
					(0.035)	(0.035)
year2008					0.032	0.030
					(0.044)	(0.044)
year2009					-0.071	-0.074
					(0.050)	(0.051)
year2010					0.027	0.022
					(0.055)	(0.058)

Observations	25,376	25,376	35,270	35,270	35,574	35,574
R-squared	0.159	0.160	0.105	0.105	0.040	0.040
Number of id	5,625	5,625	5,929	5,929	5,929	5,929

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17. 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_dev i (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_dev i (log)		-0.009		-0.003		-0.069***
		(0.012)		(0.013)		(0.022)
Fin_dev i (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)
Housing price i (log)	-0.033**	-0.030*	-0.032**	-0.031**	0.047**	0.031
	(0.015)	(0.016)	(0.015)	(0.016)	(0.023)	(0.023)
Housing price j (log)	0.048***	0.044***	0.050***	0.048***	0.069***	0.051**
	(0.015)	(0.015)	(0.016)	(0.016)	(0.023)	(0.024)
Provision of housing i (log)	0.656***	0.638***	0.577***	0.571***	0.231	0.187

	(0.160)	(0.160)	(0.160)	(0.160)	(0.204)	(0.203)
Provision of housing j (log)	0.508***	0.523***	0.471***	0.469***	0.591***	0.805***
	(0.140)	(0.140)	(0.139)	(0.139)	(0.183)	(0.186)
New flats (moving average, log) i	-0.049***	-0.051***	-0.046***	-0.049***	-0.014	0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.025)	(0.025)
New flats (moving average log) j	0.039***	0.041***	0.040***	0.041***	-0.103***	-0.090***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.024)	(0.024)
Life expectancy (log) i	0.561**	0.575**	0.587**	0.600**	0.435	0.800
	(0.273)	(0.272)	(0.273)	(0.271)	(0.511)	(0.522)
Life expectancy (log) j	-1.436***	-1.435***	-1.400***	-1.384***	-1.671***	-1.680***
	(0.257)	(0.257)	(0.257)	(0.257)	(0.498)	(0.495)
Infant mortality rate (log) i	0.051***	0.052***	0.059***	0.062***	0.029	0.032
	(0.017)	(0.017)	(0.017)	(0.017)	(0.026)	(0.027)
Infant mortality rate (log) j	-0.071***	-0.070***	-0.066***	-0.064***	-0.076**	-0.071**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.030)	(0.030)
Doctors (log) i	0.174**	0.151*	0.170**	0.144*	-0.154	-0.116
	(0.084)	(0.084)	(0.083)	(0.084)	(0.109)	(0.109)
Doctors (log) j	-0.155*	-0.138	-0.126	-0.118	0.164	0.173
	(0.088)	(0.090)	(0.087)	(0.087)	(0.117)	(0.117)
Hospital beds (log) i	-0.017	-0.016	-0.008	-0.010	-0.088	-0.109
	(0.046)	(0.046)	(0.045)	(0.045)	(0.070)	(0.070)
Hospital beds (log) j	0.327***	0.323***	0.323***	0.323***	0.007	-0.014
	(0.047)	(0.047)	(0.046)	(0.046)	(0.070)	(0.070)
Telephones (log) i	-0.043	-0.033	-0.035	-0.020	0.031	0.040
	(0.032)	(0.032)	(0.032)	(0.032)	(0.077)	(0.077)
Telephones (log) j	-0.007	-0.004	-0.010	-0.008	0.176**	0.166**
	(0.031)	(0.031)	(0.031)	(0.032)	(0.083)	(0.083)
Highway density (log) i	0.049**	0.046**	0.048**	0.045**	0.075*	0.056
	(0.019)	(0.019)	(0.019)	(0.019)	(0.044)	(0.043)
Highway density (log) j	-0.041**	-0.039*	-0.041**	-0.041**	-0.061	-0.042
	(0.020)	(0.020)	(0.020)	(0.020)	(0.043)	(0.043)
Buses (log) i	0.028***	0.029***	0.029***	0.029***	0.045***	0.041**
	(0.008)	(0.009)	(0.008)	(0.009)	(0.016)	(0.016)
Buses (log) j	-0.030***	-0.036***	-0.036***	-0.040***	-0.077***	-0.057***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.017)	(0.017)
Share of young i, t-1	-0.009	-0.013	-0.011	-0.016*	0.002	-0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.020)	(0.020)
Share of young j, t-1	0.064***	0.061***	0.061***	0.059***	0.009	0.008
	(0.008)	(0.009)	(0.008)	(0.009)	(0.022)	(0.022)
Share of old i, t-1	0.005	0.001	0.008	-0.000	-0.006	-0.032
	(0.006)	(0.008)	(0.007)	(0.008)	(0.020)	(0.021)
Share of old j, t-1	-0.024***	-0.027***	-0.022***	-0.025***	-0.054***	-0.030
	(0.007)	(0.008)	(0.007)	(0.008)	(0.017)	(0.019)
Students i (log), t-1	-0.099***	-0.104***	-0.091***	-0.098***	-0.139**	-0.152**
	(0.022)	(0.022)	(0.021)	(0.021)	(0.066)	(0.066)
Students j (log), t-1	0.113***	0.113***	0.110***	0.110***	0.147**	0.158**

	(0.021)	(0.021)	(0.021)	(0.021)	(0.066)	(0.066)
Women i (log), t-1	-1.763**	-1.993**	-1.924**	-2.055**	0.003	-0.337
	(0.778)	(0.819)	(0.773)	(0.809)	(2.398)	(2.386)
Women j (log), t-1	-6.543***	-6.159***	-6.303***	-6.074***	0.379	2.917
	(0.806)	(0.843)	(0.798)	(0.839)	(2.277)	(2.282)
year2002	0.010	0.007	0.011	0.008		
	(0.014)	(0.015)	(0.014)	(0.015)		
year2003	0.080***	0.070**	0.079***	0.069**		
	(0.027)	(0.028)	(0.027)	(0.028)		
year2004	0.046	0.029	0.044	0.026		
	(0.037)	(0.039)	(0.037)	(0.039)		
year2005	0.058	0.037	0.056	0.033		
	(0.047)	(0.049)	(0.047)	(0.049)		
year2006	0.135**	0.111*	0.133**	0.107*		
	(0.061)	(0.062)	(0.061)	(0.063)		
year2007	0.212***	0.186***	0.214***	0.187***	-0.004	-0.031
	(0.070)	(0.072)	(0.071)	(0.073)	(0.028)	(0.029)
year2008	0.230***	0.204***	0.236***	0.211***	-0.029	-0.070
	(0.076)	(0.077)	(0.077)	(0.078)	(0.043)	(0.044)
year2009	0.143*	0.119	0.144*	0.123	-0.075	-0.127**
	(0.080)	(0.081)	(0.081)	(0.083)	(0.052)	(0.054)
year2010	0.222***	0.202**	0.223***	0.208**	0.041	-0.017
	(0.081)	(0.082)	(0.082)	(0.083)	(0.061)	(0.063)
Gini (log) i	-0.126	-0.150	-0.119	-0.131	0.384*	0.580***
	(0.087)	(0.092)	(0.086)	(0.092)	(0.204)	(0.201)
Gini (log) j	-0.145	-0.099	-0.132	-0.103	-0.308	-0.309
	(0.089)	(0.094)	(0.089)	(0.094)	(0.211)	(0.210)
Observations	58,525	58,525	57,919	57,919	29,645	29,645
R-squared	0.103	0.103	0.104	0.105	0.045	0.048
Number of id	5,929	5,929	5,929	5,929	5,929	5,929

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18. Results for different periods (before and after crisis 1998).

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	1996-2000	1996-1997	1995-1997	1998-2010	1998-2000
Population i (log)	1.802***	2.156***	0.177	1.755***	1.689***	1.846***
	(0.098)	(0.314)	(1.651)	(0.499)	(0.116)	(0.572)
Population j (log)	2.002***	1.158***	8.857***	2.101***	2.071***	1.189**
	(0.096)	(0.298)	(1.709)	(0.511)	(0.110)	(0.595)
Income i (log)	0.758***	-0.718***	2.148	0.274	1.089***	3.587***
	(0.157)	(0.238)	(2.321)	(0.670)	(0.171)	(0.539)
Income squared i (log)	-0.041***	0.044***	-0.117	-0.011	-0.060***	-0.215***

	(0.009)	(0.013)	(0.133)	(0.038)	(0.010)	(0.033)
Income j (log)	0.696***	-0.431*	-4.939*	-5.407***	0.600***	-1.691***
	(0.169)	(0.238)	(2.530)	(0.726)	(0.178)	(0.533)
Income squared j (log)	-0.029***	0.019	0.251*	0.309***	-0.024**	0.101***
	(0.010)	(0.013)	(0.145)	(0.041)	(0.010)	(0.032)
Gini (log) i	-0.082*	-0.124***	-0.188	0.068	0.011	-0.140*
	(0.043)	(0.045)	(0.115)	(0.047)	(0.052)	(0.077)
Gini (log) j	-0.123***	0.049	0.523***	0.035	-0.142***	0.061
	(0.042)	(0.045)	(0.114)	(0.047)	(0.052)	(0.079)
Unemployment rate (log) i	0.059***	0.061***	0.041	-0.002	0.053***	0.093***
	(0.009)	(0.016)	(0.030)	(0.023)	(0.009)	(0.027)
Unemployment rate (log) j	-0.071***	-0.023	-0.094***	-0.034	-0.080***	-0.043*
	(0.009)	(0.017)	(0.032)	(0.024)	(0.009)	(0.025)
Housing price i (log)	-0.050***	-0.084***	0.041		-0.033***	-0.014
	(0.011)	(0.013)	(0.033)		(0.012)	(0.022)
Housing price j (log)	0.049***	0.050***	0.129***		0.038***	0.024
	(0.011)	(0.013)	(0.031)		(0.012)	(0.024)
Provision of housing i (log)	0.404***	-0.017	2.046***	0.681**	0.356***	-0.001
	(0.083)	(0.140)	(0.789)	(0.282)	(0.093)	(0.205)
Provision of housing j (log)	0.613***	-0.027	2.064***	-0.250	0.556***	-0.607***
	(0.083)	(0.149)	(0.668)	(0.340)	(0.088)	(0.211)
New flats (moving average, log) i	-0.005	-0.042*	0.132	0.045	-0.014	0.018
	(0.009)	(0.024)	(0.082)	(0.045)	(0.010)	(0.040)
New flats (moving average log) j	-0.002	0.096***	-0.245***	-0.063	-0.000	0.056
	(0.009)	(0.024)	(0.086)	(0.044)	(0.010)	(0.040)
Life expectancy (log) i	-0.082	-0.942***	-2.174	-2.179***	-0.014	-1.558***
	(0.201)	(0.339)	(1.403)	(0.385)	(0.223)	(0.590)
Life expectancy (log) j	-0.581***	-0.806**	2.378	0.910**	-0.774***	-0.562
	(0.191)	(0.368)	(1.517)	(0.418)	(0.211)	(0.596)
Infant mortality rate (log) i	0.037**	0.008	-0.112	-0.220***	0.052***	-0.042
	(0.015)	(0.030)	(0.077)	(0.048)	(0.015)	(0.048)
Infant mortality rate (log) j	-0.084***	0.000	0.090	-0.013	-0.090***	-0.047
	(0.016)	(0.030)	(0.072)	(0.044)	(0.016)	(0.049)

Doctors (log) i	0.121**	0.109	0.861***	0.434***	0.116*	-0.134
	(0.061)	(0.106)	(0.333)	(0.133)	(0.066)	(0.178)
Doctors (log) j	0.200***	0.574***	0.613*	0.123	0.215***	0.927***
	(0.057)	(0.108)	(0.330)	(0.122)	(0.063)	(0.181)
Hospital beds (log) i	0.036	-0.363***	-1.974***	-1.008***	0.012	0.054
	(0.039)	(0.095)	(0.316)	(0.209)	(0.040)	(0.184)
Hospital beds (log) j	0.306***	-0.220**	0.903***	0.047	0.353***	-0.137
	(0.039)	(0.089)	(0.310)	(0.194)	(0.041)	(0.178)
Telephones (log) i	-0.035	-0.040	-0.601***	-0.099	-0.062**	0.072
	(0.026)	(0.057)	(0.214)	(0.094)	(0.029)	(0.119)
Telephones (log) j	-0.180***	-0.354***	-0.244	0.155*	-0.112***	-0.240**
	(0.026)	(0.058)	(0.212)	(0.094)	(0.028)	(0.119)
Highway density (log) i	0.037**	-0.182*	-0.190	0.169	0.045**	-0.679***
	(0.018)	(0.096)	(0.223)	(0.125)	(0.018)	(0.165)
Highway density (log) j	-0.003	0.335***	0.686**	-0.050	0.003	0.531***
	(0.018)	(0.105)	(0.273)	(0.111)	(0.019)	(0.183)
Buses (log) i	0.028***	-0.137***	-0.146	-0.221***	0.028***	0.047
	(0.007)	(0.040)	(0.148)	(0.076)	(0.007)	(0.063)
Buses (log) j	-0.015*	0.121***	-0.013	0.036	-0.018**	0.032
	(0.008)	(0.040)	(0.140)	(0.068)	(0.009)	(0.064)
Share of young i, t-1	-0.015***	-0.020	0.066	0.075***	-0.009	-0.008
	(0.005)	(0.015)	(0.050)	(0.026)	(0.006)	(0.037)
Share of young j, t-1	0.061***	0.113***	0.068	0.071**	0.057***	0.051
	(0.005)	(0.014)	(0.056)	(0.028)	(0.006)	(0.035)
Share of old i, t-1	-0.042***	-0.043***	-0.052	-0.056***	-0.022***	0.016
	(0.004)	(0.015)	(0.035)	(0.018)	(0.005)	(0.040)
Share of old j, t-1	0.028***	0.063***	-0.068*	0.099***	0.022***	0.028
	(0.005)	(0.015)	(0.037)	(0.018)	(0.005)	(0.039)
Students i (log), t-1	-0.074***	-0.113***	-0.151**	-0.109***	-0.070***	-0.101***
	(0.009)	(0.019)	(0.059)	(0.032)	(0.013)	(0.033)
Students j (log), t-1	0.104***	0.073***	-0.173***	0.026	0.125***	0.129***
	(0.011)	(0.020)	(0.051)	(0.027)	(0.013)	(0.035)
Women i (log), t-1	0.497**	-4.706**	11.180*	5.122***	-0.202	-13.926***
	(0.224)	(2.153)	(6.380)	(1.694)	(0.218)	(4.318)
Women j (log),	-3.038***	8.140***	-4.240	-9.608***	-2.809***	15.657***

t-1						
	(0.212)	(2.046)	(6.800)	(1.736)	(0.223)	(4.331)
year1996	-0.064***			-0.146***		
	(0.020)			(0.026)		
year1997	-0.084***	0.031**	0.014	-0.143***		
	(0.018)	(0.013)	(0.049)	(0.049)		
year1998	0.000					
	(0.000)					
year1999	-0.043***				-0.053***	-0.017
	(0.011)				(0.012)	(0.032)
year2000	-0.175***				-0.194***	-0.078
	(0.018)				(0.018)	(0.058)
year2001	-0.187***				-0.204***	
	(0.025)				(0.027)	
year2002	-0.207***				-0.234***	
	(0.032)				(0.035)	
year2003	-0.149***				-0.184***	
	(0.040)				(0.044)	
year2004	-0.199***				-0.234***	
	(0.046)				(0.050)	
year2005	-0.206***				-0.241***	
	(0.052)				(0.056)	
year2006	-0.167***				-0.202***	
	(0.058)				(0.064)	
year2007	-0.113*				-0.150**	
	(0.063)				(0.069)	
year2008	-0.109*				-0.142**	
	(0.066)				(0.072)	
year2009	-0.229***				-0.256***	
	(0.066)				(0.072)	
year2010	-0.154**				-0.184**	
	(0.067)				(0.073)	
Observations	84,666	25,376	9,661	17,328	75,005	15,715
R-squared	0.308	0.159	0.068	0.140	0.226	0.108
Number of id	5,929	5,625	5,037	5,776	5,929	5,625

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

9.2. Appendix B: Figures

Figure 21. Unweighted standard deviation between regions, logs of real wages, real incomes, real GDP per capita and unemployment rate.

Figure 22. Dynamic of correlation between logs of real wage, real income, real GDP, unemployment and population.

Figure 23. Migration to Moscow and Saint Petersburg as a share of total migrants (%).

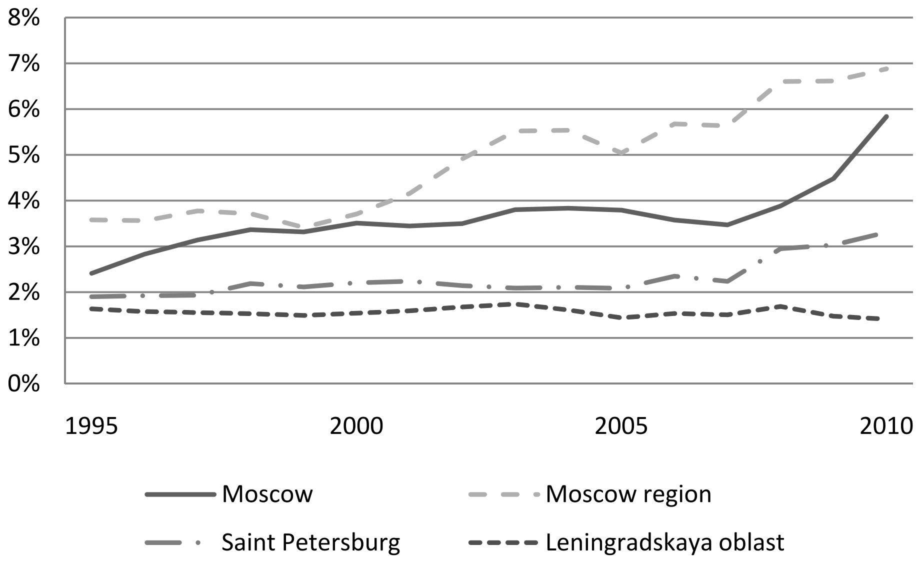


Figure 24. Interregional migration with respect to internal migration (%) by distance.

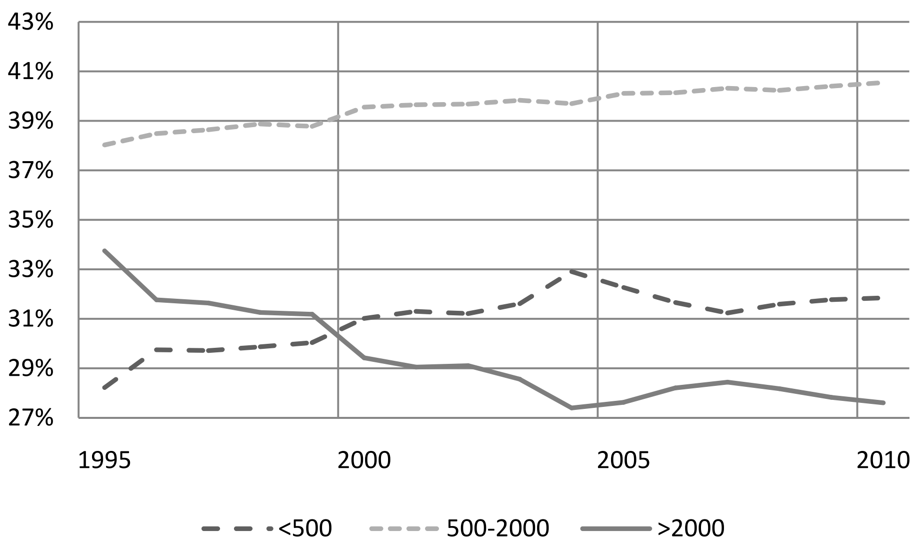
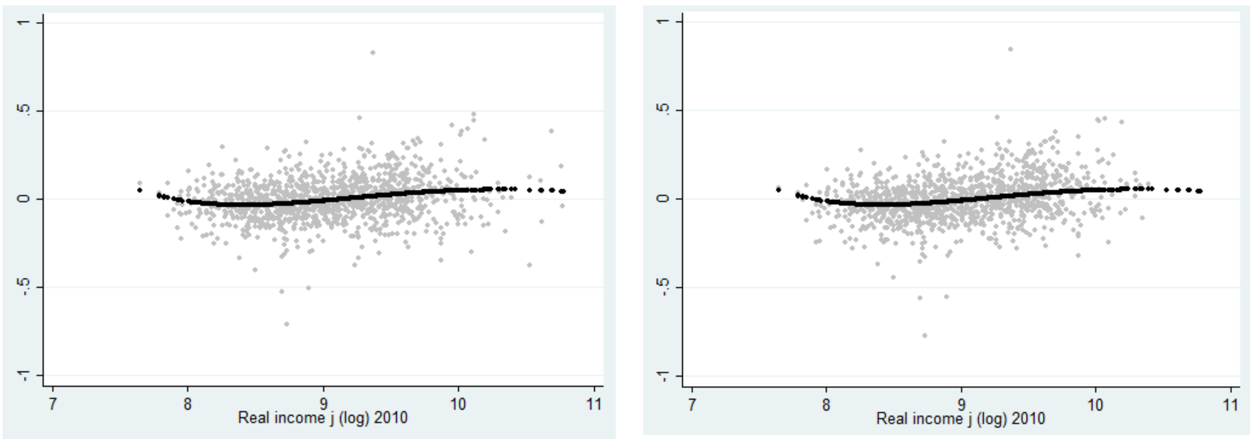


Figure 25. Population weighted standard deviation between regions, logarithms of nominal incomes, nominal wages, unemployment, nominal GDP per capita.

Figure 26. Results of semiparametric regression models for receiving regions.



a) All regions

b) Without Moscow and Saint Petersburg

Figure 27. Number of regions above and below thresholds over time for log of income to minimum living standards.