

The Russian regional convergence process, 1998-2006: Does the space matter?[¶]

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June 30, 2008

Abstract

This paper investigates the income convergence among Russian regions in the period 1998-2006. It makes two major contributions to a small but growing body of literature on the regional convergence in Russia. First, it identifies spatial regimes using the exploratory spatial data analysis. Second, it examines the impact of spatial effects on the convergence process. Our results show that the overall speed of regional convergence in Russia, being very low by international standards, becomes even lower after controlling for spatial effects. However, when accounting for the spatial regimes, we find a significant regional convergence among high income regions located near other high income regions. A possible explanation for this phenomenon relies on positive spill-over effects.

Keywords: Regional convergence; σ -convergence; β -convergence; spatial regimes; spatial effects

JEL classification: C21; O47; R12

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1 Introduction

After initial slump in the economic performance in the beginning of the 1990s (in the aftermath of the collapse of the Soviet Union), the Russian economy shows robust signs of economic development. In the recent period, 1999-2006, the average annual growth rates of the Gross Domestic Product were about 6.7%. During the same period the unemployment rate has declined from 12.6% up to 7.2%. Despite recent surge in inflation, the forecasters still predict high growth rates for Russia in the nearest future. For example, according to the March issue of Consensus Economics, real GDP of Russia is expected to grow 2008-2009 at the annual rate exceeding 6.5%.

However, in a diverse and geographically large federal state like Russia it is important to look beyond the aggregate statistics. The solid economic performance recorded at the aggregate level may mask substantial regional disparities. Indeed, interregional differences in economic development are large in Russia compared to both industrially developed and developing countries.¹ For example, a gap between the poorest and richest parts of EU (level-2 regions) is much lower than between the poorest and richest regions of Russia even if new member states of EU are taken into account.²

High interregional disparities in economic development cause social and political problems. The tax base of poorest regions may not be enough to provide an acceptable minimum of health, education and local public goods (Hanson (2006)). In the Russian case, this is redoubled by low effectiveness of the Russian federal transfer policy (Lavrovski (2003); Desai et al. (2002)). On one hand, a situation, when some regions flourish and enjoy high standard of living, whereas other regions form persistent poverty clusters, may create a fertile soil for social and political unrest. On the other hand, supporting poor regions at the expense of economically developed regions may weaken stimulus for development of the latter.

In many large or small countries regional economic disparities make a serious challenge to regional development policies. Shankar and Shah (2003) Extremely uneven regional development is a very serious problem in Russia, it remains unresolved from the beginning of the transition period. The acuteness of this issue is well reflected both in official programs of economic development and in a stream of newspaper publications.³ Section

¹See, among others Shankar and Shah (2003); Benini and Czyzewski (2007)

²See Krueger (2007).

³For example, Grigoriev L. and Urozhaeva U. "Regionalnoe izmerenie: glubina mnogoobrasia", Vedomosti, 150, 07.06.2005; Kress V. "Regionalnaya politika: pooshrenie prostranstva", Vedomosti, 150, 15.08.2006; Litvak J. "Economicheskaya politika: rost i

“Spatial development” is for a long time an obligatory part of the program of the long run socio-economic development of Russian Federation. However, many experts claim that most of the policy measures aimed to reduce regional disparities failed, the Federal Programme “Reducing differences in socio-economic development of the regions of the Russian Federation (2002-2010)” (Sokrashenie razlichiy v socialno-ekonomicheskom razvitii regionov RF(2002-2010)) may be cited as a good example of that.⁴ At the same time, a current strategy dealing with regional disparities does not seem to be clearly elaborated.⁵

Acknowledging importance of regional development in Russia, a considerable scientific literature on the interregional economic disparities emerged (see, cf., [van Selm, 2003](#); [Mikheeva, 2000](#); [Popov, 2001](#); [Dolinskaya, 2002](#); [Fedorov, 2002](#); [Granberg and Zaitseva, 2002a](#); [Yemtsov, 2002](#); [Lavrovski, 2003](#); [Klocvog and Chernova, 2005](#); [Drobyshevsky et al., 2005](#); [Benini and Czyzewski, 2007](#); [Lugovoi et al., 2007](#), *inter alia*). Using wide spectrum of different methodologies including cross-sectional and panel data growth regressions for testing β - and σ -convergence, transition matrix methodology, Gini coefficients, and various polarization measures, a common conclusion emerges that the early transition period has been characterized by rapidly rising economic inequality among Russia’s regions.

Furthermore, as argued in [Fedorov \(2002\)](#), the initially growing economic disparity among Russia’s regions started to level off and eventually showed some signs of reversal in the late 1990s. Indeed, the studies that employ the data available for the more recent period (1994-2002, [Drobyshevsky et al. \(2005\)](#)) and (1998—2002, [Lugovoi et al. \(2007\)](#)) report the significant albeit very small value of the convergence coefficient implying much slower annual convergence rate of about 1% and 0.825%, respectively, than typically reported in the literature (around 2% per annum, e.g., see [Barro and Sala-i-Martin \(1991, 1992\)](#); [Abreu et al. \(2005\)](#)). At the same time, both studies report that they find no empirical support in favor of σ -convergence among the Russia’s regions.

In this paper, we further investigate the important issue of convergence among the Russia’s regions using the latest available data covering the time period from 1998 till 2006. But we make an accent on how different spatial effects may influence or even shape regional convergence.

regioni”, *Vedomosti*, 105, 09.07.2007

⁴see, for example, Granik I. and Nikolaeva D., “Federalnaya programma ne reshila neravenstva regionov”, *Kommersant*, 80, 24.05.2007

⁵see, for example, T. Smoliakova “Mejdu Evropoi i Kitaem. Rossia vibiraet svou model razvitia regionov.”, *Rossiiskaya gazeta*, 4676, 04.06.2008

We distinguish two forms of spatial effects. First, it is the so-called spatial regimes. For example, high (low) income regions may tend to locate close to other high (low) income regions forming regional clusters. In this case there is a significant correlation in levels of regional economic development. Second, it is a spatial correlation in growth rates. For example, rapidly (slowly) growing regions may tend to be located close to other rapidly (slowly) growing regions. Spatial correlation in levels or/and rates of economic development may be a consequence of various interactions between regional economies, such as, for example, technology spillovers, migration, commodity flows and trade. Another reason for spatial interrelations between regions is that administrative division of a country very often does not fully correspond to actual boundaries between different regional markets (see an excellent review of literature in [Abreu et al. \(2005\)](#)).

In our study we also explore a possibility that Russia's regions form clubs of convergence, i.e., when economic convergence within one or more groups (clubs) of regions takes place even if the overall regional convergence is weak or even absent. Following [Durlauf and Johnson \(1995\)](#); [Ertur et al. \(2006\)](#) we identify regional convergence clubs on the base of existing spatial regimes. We allow convergence parameters to differ across four groups of regions: rich regions surrounded by rich regions, poor regions — by poor regions, and rich (poor) regions surrounded by poor (rich) regions respectively.

We investigate the process of convergence among the Russia's regions in terms of real per capita Gross Regional Product (GRP) using two alternative measures. First, it is per capita GRP in 1998 prices, i.e., real per capita GRP. Second, it is the same real per capita GRP, but additionally adjusted on regional specific factors as proposed by [Granberg and Zaitseva \(2002a\)](#). Though this adjustment slightly changes both a distribution of regions across high-income and low-income clusters and regression estimates, the use of both measures leads to similar conclusions.

Our analysis generally confirms empirical results received in few existing studies on regional convergence in Russia. First, the overall β -convergence is slow by international standards. Second, not taking into account a spatial correlation in GRP growth rates leads to biased estimates of β -coefficients. Existing positive spatial correlation in growth rates slightly intensifies convergence indicating that low income regions benefit more from this spatial effect. Third, there is a significant spatial correlation in per capita real GRP; high (low) income regions tend to be located close to other high (low) income regions. These spatial regimes are not continuous zones, they consist of several regional clusters.

Our new important finding is that in spite of the overall weak conver-

gence we detect a statistically significant and rapid convergence among the rich regions surrounded by those alike. This suggests that even that slow process of regional convergence seems to be an artefact of convergence within a group of high income regions. Such a negative for regional cohesion result is redoubled by the facts that this HH club of convergence is based on a stable spatial regime, and its estimated steady state is much more higher than for other regions. This leads to a straightforward conclusion: at the absence of appropriate policy measures substantial economic disparities across Russian regions will persist in the short- and medium-term period.

The rest of the paper is organized as follows. In the next section we describe data and methodology used in the paper. Main empirical results and their discussion are presented in the third section. In the last section we briefly summarize our findings and develop some policy implications of our analysis.

2 Data and Methodology

2.1 Data

The data on the volume index of total GRP, nominal GRP, and average population, which are used to construct the series of the real GRP per capita, were taken from the webpage of Rosstat.⁶ We use data on the level of the subjects of the Russian Federation traditionally excluding from analysis Republic of Chechnya. Official data on GRP of Republic of Kalmikia, Republic of Ingushetia and Chukotsky AO exhibited improbable large fluctuations, and these three regions were also excluded from our analysis.⁷ Therefore, our sample includes 76 regions at the period 1998-2006.

A number of authors, e.g., [Hanson \(2006\)](#); [Lugovoi et al. \(2007\)](#); [Zubarevich \(2005\)](#), claim that when comparing the per capita GRP or, equally, studying the process of convergence one has to take into account rather large regional differences in price level. Therefore, in addition, to the GRP corrected for the price changes over time using the GRP deflator, we considered GRP corrected also for the price differences across space using the purchasing power parity (PPP) factors computed by [Granberg and Zaitseva \(2002a\)](#).

These factors are thought to reflect the price differences in three use components of GRP: private consumption, government consumption, and

⁶Russian Federal State Statistics Service, www.gks.ru

⁷Republic of Ingushetia and Chukotsky AO were also excluded from analysis in [Lugovoi et al. \(2007\)](#)

investment. Therefore they are based on the three price aggregates: 1) cost of a fixed basket of goods and services computed by Rosstat as a proxy for the price of private consumption; 2) the so-called notional cost of a unit of government services calculated by the Russian Ministry of Finance as a proxy for the price of government consumption; 3) expert estimates of investment goods prices as a proxy for the price of investment. The factors were calculated for 1999. However, in this study we apply the same factors for all years in our sample. This depends on the assumption that these factors are good proxies for the levels of GRP deflator.

Alternative measures of regional purchasing power, such as minimum subsistence level, cost of a food products basket or cost of a fixed basket of goods and services provided by Rosstat are not representative enough because they only cover the private consumption component of the GRP. Moreover, in case of the minimum subsistence level the structure of underlying consumption basket varies from region to region, for its structure is determined by the regions themselves.

It should be noted that PPP itself may be not a perfect measure of inter-regional price discrepancies. [Granberg and Zaitseva \(2002b\)](#) point out that, despite all its attractiveness, PPP may lead to an underestimation of the GRP in the richer countries or regions. They indicate two reasons for such a bias: 1) methodological difficulties with selection of representative items and accounting for quality of products; 2) existence of a strong statistical relationship between the PPP and GRP corrected using PPP⁸.

2.2 Exploratory data analysis

In order to measure degree of spatial autocorrelation between real per capita GRP we compute the Moran's I statistic. The spatial dependence is accounted for using an $N \times N$ matrix of spatial weights W , which is based on the distances between the capital cities of each region⁹. Following [Ertur et al. \(2006\)](#), we constructed four distance-decay weights matrices depending on four different distance cutoff values: first quartile (W_{D1}), median (W_{D2}), third quartile (W_{D3}), and fourth quartile (W_{D4}). However, the remoteness of Kaliningrad region relative to other regions made impossible the use of distance-based matrix using the first quartile as a cutoff value. The typical

⁸In fact, the correlation for the regions under study is about -0.4, which is quite high.

⁹The use of a matrix of spatial weights based on the contiguity between the regions is precluded by the existence of the Kalinigrad exclave as well as Sakhalin region, which has an island location.

element of this matrix, w_{ij} , is defined as follows:

$$w_{ij} = \frac{1}{d_{ij}^2} \quad (1)$$

where d_{ij} is the great circle distance between the capital of region i and capital of region j . The choice of capital cities and not the centroids of regions can be justified by the fact that the capitals are often also centers of economic activities, whereas centroids, especially in the big Siberian regions, may be located in wilderness. All the elements on the main diagonal of matrix W are equal to zero. The constructed weights matrix is normalized such that all the elements in each row sum up to one.

Unfortunately, the global Moran's I statistic provides only a general measure of the level of spatial correlation. A significant level of this statistic often hides different spatial regimes. In order to distinguish these regimes one can use the Moran scatterplot suggested by [Anselin \(1993\)](#). It plots the real regional GRP per capita in a certain year against its spatial lag corresponding to the weighted average of real regional per capita incomes of its neighbors. Thus, the Moran scatterplot allows us to distinguish between different spatial regimes that exist among a given region and its neighbors: high (low) income regions surrounded by the regions alike — the upper-right (lower-left) quadrant denoted as HH (LL); low income regions surrounded by high income regions — the lower left quadrant, LH; and high income regions surrounded by low income regions, HL, located in the lower right quadrant. In particular, regions from quadrants HH and LL display the positive spatial dependence pattern whereas regions located in quadrants LH and HL are characterized by a negative spatial association.

2.3 Econometric models

The baseline model typically used in order to assess the unconditional β -convergence has the following form:

$$(y_{i,t+\tau} - y_{i,t}) = \alpha + \beta y_{i,t} + \varepsilon_i \quad (2)$$

where $y_{i,t}$ is the log of real GRP per capita in year t for a region i ; τ is the time span over which convergence is being assessed.

Although this type of model has been very popular in the applied research studying regional convergence, the model is rather restrictive in the sense that it does not allow for interdependence among the regions. As pointed out in [De Long and Summers \(1991\)](#), this is a rather unrealistic

assumption as a certain degree of likeliness in regional characteristics is natural to observe among regions that are in the geographical proximity one to another.

Latest research (e.g., see [Rey and Montouri, 1999](#); [Ertur et al., 2006](#), , inter alia) pointed out that treating individual regions as if they were independent one from another might lead to misspecification of model and therefore to either inefficient or, even more seriously, to biased coefficient estimates. Hence, in order to account for interdependence between regions we explicitly model the spatial dependence in our model. Here we follow [Anselin and Rey \(1991\)](#) and distinguish between two types of models: those with *substantive* spatial dependence and those with *nuisance* dependence. In the former model, the spatial dependence is explicitly accounted by adding the spatial lag of the dependent variable in the benchmark regression:

$$(y_{i,t+\tau} - y_{i,t}) = \alpha + \beta y_{i,t} + \rho W(y_{i,t+\tau} - y_{i,t}) + \varepsilon_i \quad (3)$$

where λ is the spatial autoregressive coefficient; W is the spatial weights matrix. In sequel, we refer to this model as SLM.

In the latter models, the spatial dependence is reflected in a spatially autocorrelated error term:

$$\begin{aligned} (y_{i,t+\tau} - y_{i,t}) &= \alpha + \beta y_{i,t} + u_i \\ u_i &= \lambda W u_i + \varepsilon_i \end{aligned} \quad (4)$$

where λ is the spatial autoregressive coefficient; W is the spatial weights matrix. In sequel, we refer to this model as SEM.

Furthermore, following [Ertur et al. \(2006\)](#) we allowed for economic behavior to be different over space. To this end, we employ the results of the Moran scatterplot, presented above, which allows us grouping of the Russian regions in certain clusters and estimating speed of convergence within those different clusters. The benchmark model with spatial heterogeneity looks as follows

$$\begin{aligned} (y_{i,t+\tau} - y_{i,t}) &= I_{LL}\alpha_{LL} + I_{LH}\alpha_{LH} + I_{HL}\alpha_{HL} + I_{HH}\alpha_{HH} + \\ &+ \beta_{LL}I_{LL}y_{i,t} + \beta_{LH}I_{LH}y_{i,t} + \beta_{HL}I_{HL}y_{i,t} + \beta_{HH}I_{HH}y_{i,t} + \\ &+ \varepsilon_i \end{aligned} \quad (5)$$

where I_{KJ} is the spatial regime dummy, which takes value of 1, if region i belongs to KJ regime with $K, J = \{H, L\}$, and zero, otherwise.

As before, one can introduce the spatial dependence in the model with spatial regimes. The spatial lag model is:

$$\begin{aligned}
(y_{i,t+\tau} - y_{i,t}) &= I_{LL}\alpha_{LL} + I_{LH}\alpha_{LH} + I_{HL}\alpha_{HL} + I_{HH}\alpha_{HH} + \\
&+ \beta_{LL}I_{LL}y_{i,t} + \beta_{LH}I_{LH}y_{i,t} + \beta_{HL}I_{HL}y_{i,t} + \beta_{HH}I_{HH}y_{i,t} + \\
&+ \rho W(y_{i,t+\tau} - y_{i,t}) + \varepsilon_i,
\end{aligned} \tag{6}$$

whereas the spatial error model looks as follows:

$$\begin{aligned}
(y_{i,t+\tau} - y_{i,t}) &= I_{LL}\alpha_{LL} + I_{LH}\alpha_{LH} + I_{HL}\alpha_{HL} + I_{HH}\alpha_{HH} + \\
&+ \beta_{LL}I_{LL}y_{i,t} + \beta_{LH}I_{LH}y_{i,t} + \beta_{HL}I_{HL}y_{i,t} + \beta_{HH}I_{HH}y_{i,t} + \\
&+ \varepsilon_i,
\end{aligned} \tag{7}$$

$$u_i = \lambda W u_i + \varepsilon_i \tag{8}$$

Convergence rate, or speed of convergence, measures by how much the region is approaching its steady state each period and is calculated as:

$$CR = -\frac{\ln(1 + \hat{\beta})}{\tau} \tag{9}$$

where τ is the number of periods, and $\hat{\beta}$ is the coefficient of the initial observation, $\hat{\beta} = \beta$ in models without spatial regimes and $\hat{\beta} = \beta_{KJ}$ in the models with spatial regimes with $K, J = \{H, L\}$. The time necessary for the economies to fill half of the gap, which separates them from their steady state, is called the half-life and is computed as:

$$HL = \frac{\ln(2)}{CR} \tag{10}$$

3 Empirical results and discussion

3.1 Exploratory spatial data analysis

We start our data analysis with computation of the time-evolving dispersion in regional per capita incomes in Russia. Decrease in income dispersion is interpreted as evidence of σ -convergence (see [Quah \(1993\)](#)). Figure 1 displays the time-evolving per capita income dispersion in Russia, as measured by the coefficient of variation calculated using the natural log of real per capita regional incomes. Although it somewhat increased in 2005, the overall impression is that this dispersion tend to decline over time. However, the scale of this reduction was not very large: from 1998 to 2006 the coefficient

of variation declined by only about 0.4 percentage points or about 8%. Such a weak σ -convergence corresponds well to our results on β -convergence (see subsection 3.2 below).

Figure 1 also contains the global Moran’s I statistic used to measure degree of spatial autocorrelation in the data. The statistic is significant in every year in our sample suggesting both the presence and strong persistence of the spatial autocorrelation among the regional per capita incomes in Russia, i.e., those tend to be clustered. That is, regions with relatively high(low) incomes tend to be neighbors of regions with equally high(low) per capita incomes.

The fact that both the Moran’s I statistic and the overall income dispersion tend to decline over time may indicate that the underlying clustering among the Russian regions may evolve. It is quite possible that the convergence process could be more pronounced in some clusters rather than in others, i.e., one could observe spatial heterogeneity among different clusters. At the same time there might be a “pockets” of regions where the incomes per capita are stagnating or even diverging.

Unfortunately, neither the overall coefficient of variation nor the global Moran’s I statistic can be used in order to further investigate difference in regional convergence patterns which calls for tools suitable for a more disaggregate analysis. Hence, we employ the Moran scatterplot, see the upper panel of Figure 2.

The classification of regions is given in Table 1. The rows show distribution of regions by the spatial regimes based on the Moran’s scatterplot in 1998, whereas columns contain such a distribution based on the 2006 data. Two rightmost columns (bottom rows) report the number and share of regions in each regime in 1998 (2006). One can see that in 1998 LL and HH regions together make up about 72% of all the regions as the last column of the table shows. In addition, the classification is quite stable over time, for the 90% of regions remain in the same spatial regime in 2006 compared to 1998 as the number of regions in the main diagonal shows. Thus, these results confirm the significance and persistence of the overall Moran’s I statistic reported earlier.

Table 4 reports the classification of the Russia’s regions by spatial regimes using the PPP-adjusted real per capita GRP in 1998 and 2006 which can be compared to that reported in Table 1. There is a rather large overlap between these two tables.

The main difference between these two classifications is that the LL group of regions became a little smaller after the PPP-adjustment. This happened because most of the regions of the Central Federal District left

the LL group after the adjustment on the purchasing power of incomes. Three regions radically changed their status from low income to high income regions (these are Kostroma, Kursk and Oriol). This triggered transition of the neighboring regions from the LL group to LH group. Changes in the HH group are even less significant. Two regions changed their status from high income to low income (that is Primorski krai and Kamchatka region). This triggered transition of Magadan region and Amur region from the HH group to HL group. However, in spite of these changes, in 1998 LL and HH regions together still make a significant part of all regions (about 62%), and the resulting classification is also very stable in time. Further we discuss the distinguished regimes in more detail.

Comparing Table 1 4 and Table 4 5 allows us to identify those regions, which keep their (high income or low income) status whatever measure of GRP is used. The low income regions may be divided on three large clusters. First, it is regions of the Central Federal District. Second — regions of the South Federal District. These two clusters of regions taken together constitute a continuous zone. The third cluster is the "belt" of South-Siberian regions.

Some of these low income regions form the LH group of regions (that is low income regions located close to high income regions). This group includes Tver region and Pskov region, Kurgan region and several regions from the South of Siberia - Republic of Buriatia, Republic of Tuva and Chita region. The LH status of these regions both in 1998 and 2006 casts doubt on that they derived benefit from the neighborhood with high income regions.

The other low income regions do not have even theoretical opportunities to benefit from the neighborhood with high income regions, because they are surrounded by other low income regions. These regions form the LL spatial regime; this consists mostly of regions from the Central and South Federal districts, these regions form an uninterrupted zone. The LL regime also includes the Republic of Altai located at the South of Siberia.

The HH spatial regime consists of five separated spatial clusters. First, it is Saint-Petersburg and Leningrad region, Murmansk region, Arkhangelsk region and Republic of Karelia. Second — Moscow and Moscow region. Third, it is Sverdlovsk region, Perm region and Republic of Bashkiriya. Fourth, it is Omsk region, Tomsk region, Novosibirsk region and Kemerovo region. Fifth, it is Republic of Saha (Yakutia).

Before turning to the formal econometric analysis, we investigate dynamics of variation of real per capita GRP for the four types of regions that we identified above, see Table 1. Figure 4 displays the coefficient of variation computed for every of four groups indicating strongest decline in

the cross-sectional variance of the per capita incomes in group HH and a noticeable but less evident decline in group LL. The coefficient of variation for group LH shows no signs of a trendwise behavior and for the group HL decline in the variation is only noticeable when one compares the end points of our sample, i.e., years 1998 and 2006, the intermediate values display rather stable pattern. This suggests that for the former two types of regions the σ -convergence is more pronounced than for the latter two types, and it seems to be absent for the regions in the group LH. Such a result indicates that the low-income regions generally do not benefit from being located near the high-income regions.

Figure 5 contains the distributional characteristics of the initial level of per capita GRP and growth rates from 1998 till 2006 in each of the four groups. As seen from the upper panel, there is a substantial gap in the real per capita GRP between low- and high-income regions. The median real per capita GRP for high- and low income regions in 1998 constituted about 9082 and 15826 roubles, respectively. The threshold line dividing regions into high- and low income categories was about 13500 roubles in 1998 and 25000 roubles in 2006. In 2006, the median per capita GRP for high- and low income regions were about 15871 and 30476, respectively, indicating that the gap between these groups of regions increased not only in the absolute but also in relative terms. This can be seen from the respective ratios of reported median values 1.74 and 1.92 for years 1998 and 2006, accordingly.

As evident from the lower panel, the regional group HH experienced the largest variation in the growth rates, followed by the regional group LL. For the unconditional β -convergence to take place one would expect a negative association between initial level of per capita income and the growth rate observed over the period in interest. Such information is presented in Figure 6 where the cross-plot of growth rates against the initial income level is presented along with the correlation coefficient. The highest values of the correlation coefficient -0.441 and -0.406 are observed for the groups HH and LL, respectively, followed by the group HL — -0.340 . For the remaining group LH, the value of the correlation coefficient is very close to zero 0.002 .

Results of our exploratory spatial data analysis may be briefly summarized as follows. Firstly, there exists a persistent spatial correlation in real per capita GRP across Russian regions. Using standard techniques we reveal that the high(low) income regions tend to be located near other high (low) income regions. Moreover, these spatial regimes persist in time. Secondly, there is a weak overall σ - and β -convergence in real per capita GRP. However, both σ - and β -convergence is much more intensive among the regions forming HH and LL spatial regimes. In the following section, we present

the results of formal analysis, which support the results presented in this subsection.

3.2 Econometric results

In this section the estimation results of the econometric models are presented, see Table 2. The first column contains the estimated coefficients of the baseline model given in equation (2). The coefficient estimate of β has an expected negative sign and it is significant at the 5% level. The implied convergence rate is 1% and the half-life is 67 years. This result is similar to estimates received in [Drobyshevsky et al. \(2005\)](#) and [Lugovoi et al. \(2007\)](#); it indicates slow overall convergence in real regional GRP per capita in Russia.

However, one has to be cautious when relying on these results, as the presence of spatial dependence may invalidate them. Therefore, we performed the specification tests on the estimated residuals of equation (2), reported in Table 3. These include the Moran's I statistic adapted to regression residuals, and the Lagrange Multiplier tests (LMerr and LMlag, and their robust versions RLMerr and RLMlag) which could be used in order to decide which form of spatial dependence (substantive or nuisance) is more appropriate in our data at hand, see [Anselin and Florax \(2005\)](#).

As the Moran's I statistic strongly indicates spatial dependence among the Russian regions, we may conclude that the results obtained by estimating the benchmark model might well be erroneous. The application of the Lagrange Multiplier tests are not that informative on which model for spatial dependence should be preferred as the p -values obtained for the LMerr and LMlag tests are equally low and the p -values obtained for the robust versions of those tests (RLMerr and RLMlag) tests does not provide enough statistical evidence for rejection of the null hypothesis of absence of spatial dependence in our data. The likely reason for such a discrepancy between non-robust and robust versions of the LM-tests is inadequate treatment of spatial regimes, whose relevance was evident in the Moran scatterplots as mentioned above.

In order to account for the presence of spatial dependence both SEM and SLM models were estimated, see columns (2) and (3) in Table 2. The estimation results of those models confirm the importance of spatial dependence: both estimates of the spatial lag coefficients, λ and ρ , are positive and highly significant. At the same time, incorporation of spatial effects in the regression model resulted in somewhat lower estimated values of the β coefficient and led to slightly increased values of the half-life 84 and 78.5 years for SEM and SLM, respectively. Such a result suggests that existing

spatial correlation of growth rates slightly intensifies the overall convergence across Russian regions. A similar result was received earlier in [Lugovoi et al. \(2007\)](#).¹⁰ It should be noted that it is not clear *a priori* whether this correlation is due to growth spillovers or this is a result of the simultaneous growth of some regions due to, for example, government support or favorable economic trends.

So far, the regression results obtained either with accounting for spatial dependence or not suggest very slow (if any) convergence process among the Russian regions as measured in terms of real per capita income. In order to check whether the results obtained using the aggregated data mask some heterogeneous developments at the more disaggregated level, we estimated the convergence equations allowing for existence of spatial regimes identified in Subsection 3.1.

First, we estimate the benchmark model but this time allowing for spatial regimes, see equation (5) and the fourth column in Table 2. As seen, allowing for the speed of convergence to differ across spatial groups is justified. Again, the estimate of convergence coefficient for the group of high income regions surrounded by those alike β_{HH} is -0.263 and it is significant at the 1% level. The corresponding convergence rate is 3.8% which is almost as twice as large than 2% usually reported in the convergent literature, and the corresponding half-life period is about 18 years. It is also worthwhile noticing that some rather weak signs of unconditional β -convergence could be observed in the group of low income regions surrounded by those alike. The corresponding estimate of β_{LL} is -0.171 which is only significant at the 10% level. This implies the convergence rate of 2.4% which is lower than that reported for the group of HH regions but it is comparable with the results typically reported in the relevant literature. For the remaining two groups of regions LH and HL the estimates of the β coefficients are not significantly different from zero, indicating that the hypothesis of no unconditional β -convergence cannot be rejected.

As noted in [Ertur et al. \(2006\)](#), the presence of spatial autocorrelation may bias our results. Therefore at the next step we check for the presence of the spatial correlation effects in the residuals of the benchmark model that allows for spatial regimes. The results are reported in the right panel of Table 3. The Moran's I statistic is found significant at the 5% level. Both versions of the Lagrange Multiplier tests indicate that the spatial lag model is more appropriate than the spatial error model.

¹⁰Interestingly, the same result holds for USA ([Rey and Montouri \(1999\)](#)) and for macro-regions of EU ([Ertur et al. \(2006\)](#))

Columns (5) and (6) in Table 2 contain the estimation results of SEM and SLM models with spatial regimes. Observe that the spatial dependence is not detected in the SEM model — a result compatible with the outcome of the Lagrange multiplier tests. On the contrary, the estimated spatial lag coefficient ρ is significant at the 5%. Allowing for spatial correlation somewhat lowered the speed of convergence in the HH group of regions. It is reported 2.8% and 3.1% for the SEM and the SLM models, respectively. The corresponding half-lives are 24.7 and 22.1.

Introduction of spatial effects influences the convergence coefficient β_{LL} to much lesser extent. Its value is reported -0.152 and -0.151 for SEM and SLM, respectively. However, only the latter estimate remains significant at the 10% level. The estimates of β_{LH} and β_{HL} remain insignificantly different from zero.

Table 5 presents the estimation results using the PPP-adjusted GPR. As seen, the estimate of β coefficient is slightly lower than those reported in Table 2 and now they turned to be statistically insignificant implying that the null hypothesis of absence of unconditional β -convergence cannot be rejected at the conventional significance levels. At the same time, λ and ρ are highly significant indicating the presence of positive spatial correlation also in the per capita GRP levels that are expressed in the PPP terms.

When comparing the right panel of Table 5 with that of Table 2, i.e., after the introduction of spatial regimes in the growth regressions, one could observe that the PPP adjustment of the GRP variable qualitatively does not change the conclusions based on the unadjusted data. As before, the strongest evidence for convergence is found among the rich regions whose neighbors are also rich. The corresponding estimate β_{HH} is significant at the 1% level. One also observes statistically weak evidence of the unconditional β -convergence among the regions belonging to group LL. The corresponding estimate β_{LL} is significant at the 10% level. It is also remarkable that even so the coefficient estimates of the spatial dependence λ and ρ are significant at the 10% and 5% levels, the numerical values of the regression coefficient estimates are very similar across all three models.

The PPP adjustment resulted in slightly higher estimates of β_{LL} and much larger estimates of β_{HH} . The latter fact implies that when the income is measured in the PPP terms the speed of convergence among the regions in the group HH is much higher than that reported for the unadjusted income, around 4.5% vs 3%.

3.3 Discussion of results

Our results of the formal analysis conform with those based on the exploratory analysis as reported in subsection 3.1. The strongest evidence of convergence is found among those high income regions whose neighbors are also regions with high income. The convergence rate of these regions is around 3% when the spatial effects are taken into account thus exceeding that typically reported in the convergence literature.

Theoretically, this may have various explanations. First, it is measurement errors, which may bias regression coefficients. However, using the same logic as in [Sala-i-Martin \(1996\)](#), we argue that it is not the case, because along with the β -convergence we also observe a strong σ -convergence, which is not subjected to measurement errors. Second, it is redistributive policy measures. But this explanation is also not plausible, because the federal government usually does not redistribute resources from one high-income regions to others.

Other explanations rely on two kinds of possible externalities. Firstly, it is the so-called threshold externalities. When the level of economic development exceeds certain critical values, production possibilities of a region additionally expand. [Azariadis and Drazen \(1990\)](#) show that threshold externalities are able to produce multiple stable steady states; each of these steady states has a “basin of attraction”, and if initial conditions of an economy are in a certain “basin”, then it will be reaching the correspondent steady state. However, one can argue that if the threshold externalities were the only explanation for the strong convergence of HH regions, convergence within the whole groups of high income regions would be also strong. But it is not the case, the estimate of β -coefficient for all high income regions is far less than for their HH subgroup. Therefore, secondly, there are the so-called (spatial) spillover effects arising from the neighborhood with other high income regions. High income regions attract technologies and resources, and HH regions due to their favorable location benefit from spillover effects. The evidence presented in [Table 6](#) coincides with this explanation. Indeed, the highest rate of real investments is observed in the HH group of regions followed by the H group. The immigration rate and an increase in skilled labor is also higher in HH regions than in the whole group of H regions.

On the contrary, the group of LH regions, i.e, low-income regions located closely to high income regions, do not benefit from the positive spillovers. These regions have stable “low income” status and the lowest rates of investments and immigration. This may be potentially explained by poor investment facilities and underdeveloped infrastructure. For example, de-

velopment of telecommunication and transport facilities plays an important role in regional growth in China [Demurger \(2001\)](#). Indeed, such indicators of the development of regional infrastructure as the road density and number of mobile phones per capita are the lowest in the group of LH regions (see [Table 6](#)).

Another our finding is some albeit statistically weak convergence among low income regions that are also surrounded by those alike. The value of corresponding convergence coefficient implies convergence rate of about 2%, but the coefficient is found to be statistically significant only at the 10% level. Therefore, one should be cautious in interpreting the empirical results concerning low income regions, more definite conclusions will be made when longer time series are available. However, [Table 6](#) may outline a possible explanation for convergence within the LL regions. Comparing characteristics of L and LL regions indicates that the inflow of labor resources (including highly skilled labor) to LL regions is larger than to L regions. These regions attract migrants, because they possess more favorable living conditions, which are able to compensate for lower real wages.¹¹

It is important to note the the estimated steady state of the HH club of convergence is much higher than steady state of the LL club. It indicates that these clubs converge to very different levels of output, and a gap in GRP per capita between these groups of regions will persist in the near future. We also note that analysis of factors, which form these steady states, seems to be a promising line of research for future studies on regional convergence in Russia.

4 Conclusion

This paper investigates the convergence process in real per capita GRP among Russian regions in the period 1998-2006 taking into account spatial correlation both in levels and growth rates and allowing convergence parameters to differ across groups of regions. We confirm some empirical findings received earlier in existing studies on unconditional regional β -convergence in Russia. First, the β -convergence across Russian regions is very slow by international standards. Second, not taking into account a spatial correlation in GRP growth rates leads to biased β -coefficients. Third, there is a significant spatial correlation in per capita real GRP; high (low) income regions tend to be located close to other high (low) income regions.

¹¹See [Oshchepkov \(2007\)](#).

Our central result is that even that weak by international standards process of regional convergence is an artefact of a strong convergence among high income regions located near other high income regions. This club of convergence is based on a stable in time spatial regime, and the estimated steady state for this club of high income regions is much more higher than for other regions. Moreover, this finding is robust with respect to whether we use unadjusted or PPP-adjusted per capita real GRP. All this suggests that there are no any grounds to expect huge interregional economic disparities across Russian regions to disappear or even smooth in the short- and medium-term period.

Taking into account serious negative consequences of persistently high regional disparities, there is a dire necessity of proper regional development policies. Some results of our study may be potentially useful for shaping these policies. We found out that high income regions may benefit from being located near other high income regions, i.e., spillover effects favoring economic growth exist. However, the group of low income regions located close to high income regions (the LH group) do not take advantage of these effects. Therefore, federal policies aimed at the LH group of regions should not solely supply these regions with budget transfers, but also promote regional investment facilities and infrastructure, which would attract spillovers.

References

- Abreu, M., H. L. De Groot, and R. J. Florax (2005). Space and growth: A survey of empirical evidence and methods. *Région et Développement* 21, 13–44.
- Abreu, M., H. L. F. de Groot, and R. J. G. M. Florax (2005). A meta-analysis of β -convergence: The legendary 2%. *Journal of Economic Surveys* 19(3), 389–420.
- Anselin, L. (1993). The Moran scatterplot as an ESDA tool to assess local instability in spatial association. GISDATA Specialist Meeting on GIS and Spatial Analysis, Amsterdam.
- Anselin, L. and R. J. Florax (2005). Small sample properties of tests for spatial dependence in regression models. In L. Anselin and R. J. Florax (Eds.), *New Directions in Spatial Econometrics*. Berlin, Springer.

- Anselin, L. and S. J. Rey (1991). Properties of tests for spatial dependence in linear regression models. *Geographical Analysis* 23, 112–131.
- Azariadis, C. and A. Drazen (1990). Threshold externalities in economic development. *Quarterly Journal of Economics* 105(2), 501–526.
- Barro, R. J. and X. Sala-i-Martin (1991). Convergence across states and regions. *Brookings Papers on Economic Activity* 22(1991-1), 107–182.
- Barro, R. J. and X. Sala-i-Martin (1992). Convergence. *Journal of Political Economy* 100(2), 223–51.
- Benini, R. and A. Czyzewski (2007). Regional disparities and economic growth in Russia: Net growth patterns and catching up. *Economic change and restructuring* 40, 91–135.
- De Long, J. B. and L. H. Summers (1991). Equipment investment and economic growth. *The Quarterly Journal of Economics* 106(2), 445–502.
- Demurger, S. (2001). Infrastructure development and economic growth: An explanation for regional disparities in China? *Journal of Comparative Economics* 29(6).
- Desai, R., L. Freinkman, and I. Goldberg (2002). Fiscal federalism and regional growth. evidence from the Russian Federation in the 1990s. Technical Report 3138, World Bank.
- Dolinskaya, I. (2002). Transition and regional inequality in Russia: Reorganisation or procrastination? Technical Report 02/069, IMF.
- Drobyshevsky, S., O. Lugovoy, E. Astafyeva, D. Polevoy, A. Kozlovskaya, P. Trunin, and L. Lederman (2005). Факторы экономического роста в регионах РФ (Determinants of economic growth in the regions of Russian Federation). Technical report, Institute for the Economy in Transition.
- Durlauf, S. N. and P. A. Johnson (1995). Multiple regimes and cross-country growth behaviour. *Journal of Applied Econometrics* 10(4), 365–84.
- Ertur, C., J. Le Gallo, and C. Baumont (2006). The European regional convergence process, 1980-1995: Do spatial regimes and spatial dependence matter? *International Regional Science Review* 29, 3–34.
- Fedorov, L. (2002). Regional inequality and regional polarization in Russia, 1990-1999. *World Development* 30(3), 443 – 456.

- Granberg, A. and I. Zaitseva (2002a). Growth rates in the national economic space. *Problems of Economic Transition* 45(8), 72–91.
- Granberg, A. and I. Zaitseva (2002b). Производство и использование валового регионального продукта: межрегиональные сопоставления. Статья 2 (Production and use of the gross regional product: Interregional comparisn. Second article). *Rossiiskij ekonomicheskij zhurnal (Russian Economic Journal)* 11-12, 48–70.
- Hanson, P. (2006). Federalism with a Russian face: Regional inequality, administrative capacity and regional budgets in Russia. *Economic change and restructuring* 39, 191–211.
- Klocvog, F. N. and L. S. Chernova (2005). Тенденции и целевой прогноз экономической динамики российских регионов (Tendencies and targetted forecast of economic dynamics of Russian regions). *Problemi prognozirovania (Forecasting issues)* (6), 103–115.
- Krueger, A. (2007). Statistics in focus: Regional gross domestic product in the European Union 2004. Technical report, Eurostat.
- Lavrovski, B. (2003). Территориальная дифференциация и подходы к её ослаблению в Российской Федерации (Geographical differentiation and approaches to its alleviation in Russian Federation). *HSE Economic Journal* 7(4), 524–537.
- Lugovoi, O., V. Dashkeyev, I. Mazayev, D. Fomchenko, and A. Polyakov (2007). Экономико-географические и институциональные аспекты экономического роста регионов России (Economic, geographical, and institutional aspects of regional economic growth in Russia). Technical report, Institute for the Economy in Transition.
- Mikheeva, N. (2000). Differentiation of social and economic situation in the Russian regions and problems of regional policy. Technical Report 99/09, EERC.
- Oshchepkov, A. (2007). Are interregional wage differentials compensative in Russia? DIW Berlin Discussion Paper 750.
- Popov, V. (2001). Reform strategies and economic performance of Russia's regions. *World Development* 29(5), 865–886.
- Quah, D. (1993). Galton's fallacy and tests of the convergence hypothesis. *Scandinavian Journal of Economics* 95(4), 427–43.

- Rey, S. J. and B. D. Montouri (1999). US regional income convergence: A spatial econometric perspective. *Regional Studies* 33(2), 143–156.
- Sala-i-Martin, X. X. (1996). The classical approach to convergence analysis. *Economic Journal* 106(437), 1019–36.
- Shankar, R. and A. Shah (2003). Bridging the economic divide within countries: A scorecard on the performance of regional policies in reducing regional income disparities. *World Development* 31(6), 1421–1441.
- van Selm, B. (2003). Economic performance in Russia's regions. *Europe-Asia Studies* 50(4), 603 – 618.
- Yemtsov, R. (2002). Quo vadis: Inequality and poverty dynamics across Russian regions in 1992 - 2000. Cornell/LSE/Wider Conference on Spatial Inequality and Development.
- Zubarevich, N. (2005). Экономическое развитие регионов (Economic development of regions). In Россия регионов: в каком социальном пространстве мы живём? (*Russia of Regions: In What Social Space Do We Live?*). Independent Institute for Social Policy. Moscow Pomatur.

Appendix

Table 1: Classification of Russian regions by spatial regimes based on the GRP in 1998 and 2006

1998 \ 2006	LL	LH	HL	HH	N_{1998}	$N_{i,1998}/N$
LL	Briansk, Vladimir, Voronezh, Ivanovo, Kaluga, Kostroma, Kursk, Oriol, Riazan, Smolensk, Tambov, Tula, Kaliningrad, Adygeia, Dagestan, Kabarda, Cherkessia, Ossetia, Krasnodar, Stavropol, Astrahan, Volgograd, Rostov, Marii-El, Mordovia, Chuvashia, Penza, Saratov, Ulianovsk, Altai,				30	0.39
LH	Kirov	Tver, Pskov, Udmurtia, Kurgan, Buriatia, Tuva, Altai krai, Chita, Evrei AO		Cheliabinsk	11	0.14
HL			Belgorod, Lipeck, Iaroslavl, Vologda, Tatarstan, Nizhnii Novgorod, Samara, Tiumen, Irkutsk, Habarovsk		10	0.13
HH	Hakassia	Novgorod	Komi, Orenburg, Krasnoiarsk	Mosoblast, Moskva, Karelia, Arhangelsk, Lenoblast, Murmansk, Saint-Petersburg, Bashkiria, Perm, Sverdlovsk, Kemerovo, Novosibirsk, Omsk, Tomsk, Iakutia, Primorie, Amur, Kamchatka, Magadan, Sahalin,	25	0.33
$N_{i,2006}$	32	10	13	21	76	
N_{2006}/N	0.42	0.13	0.17	0.28		

Table 2: Unconditional β -convergence regressions

Parameter	without spatial regimes						with spatial regimes					
	OLS		SEM		SLM		OLS		SEM		SLM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	1.292	***	1.141	***	0.943	**	—	—	—	—	—	—
	0.361		0.314		0.363		2.113	***	1.941	***	1.726	***
α_{LL}	—	—	—	—	—	—	0.552		0.639		0.583	
α_{LH}	—	—	—	—	—	—	0.493		0.744		0.316	
α_{HL}	—	—	—	—	—	—	0.615		1.304		1.392	
α_{HH}	—	—	—	—	—	—	1.023		1.185		0.876	
	—	—	—	—	—	—	0.708		0.660		0.652	
β	-0.079	**	-0.064	**	-0.068	*	3.109	***	2.496	**	2.504	**
	0.039		0.033		0.038		0.988		1.076		1.074	
β_{LL}	—	—	—	—	—	—	-0.171	***	-0.152	**	-0.151	**
	—	—	—	—	—	—	0.061		0.069		0.063	
β_{LH}	—	—	—	—	—	—	0.001		-0.026		-0.001	
	—	—	—	—	—	—	0.066		0.139		0.149	
β_{HL}	—	—	—	—	—	—	-0.049		-0.065		-0.054	
	—	—	—	—	—	—	0.073		0.067		0.066	
β_{HH}	—	—	—	—	—	—	-0.263	**	-0.201	*	-0.222	**
	—	—	—	—	—	—	0.102		0.109		0.109	
λ	—	0.409	***	—	—	—	—	0.271	—	—	—	—
	—	0.140		—	—	—	—	0.158	—	—	—	—
ρ	—	—	—	0.439	***	—	—	—	—	—	0.363	**
	—	—	—	0.132		—	—	—	—	—	0.138	
CR	0.010	—	0.008	—	0.009	—	—	—	—	—	—	—
HaL	67.0	—	84.0	—	78.5	—	—	—	—	—	—	—
CR_{LL}	—	—	—	—	—	—	0.023	—	0.021	—	0.020	—
Ha_{LL}	—	—	—	—	—	—	29.6	—	33.7	—	34.0	—
CR_{HH}	—	—	—	—	—	—	0.038	—	0.028	—	0.031	—
Ha_{HH}	—	—	—	—	—	—	18.2	—	24.7	—	22.1	—
Log-likelihood	44.56	—	47.75	—	48.42	—	50.02	—	50.99	—	52.62	—
AIC	-83.12	—	-87.51	—	-88.83	—	-82.05	—	-81.98	—	-85.24	—
BP test	3.74	**	1.52	—	3.03	*	15.82	**	15.30	**	14.54	*
R^2_{adj}	0.06	—	0.14	—	0.16	—	0.10	—	0.12	—	0.17	—

Notes:

- ‘***’, ‘**’, and ‘*’ denote 1%, 5%, and 10% significance levels, respectively.
- Numbers in brackets are the White-corrected standard errors.
- CR , CR_{LL} , and CR_{HH} denote convergence rate in all, LL, and HH regions, respectively.
- HaL , and HaL_{HH} denote half-life in all and in HH regions, respectively.
- BP test stands for Breusch-Pagan test for heteroscedasticity of residuals.

Table 3: Specification tests

	without spatial regimes			with spatial regimes		
	W_{D2}	W_{D3}	W_{D4}	W_{D2}	W_{D3}	W_{D4}
LMerr	0.008	0.006	0.008	0.218	0.151	0.141
LMlag	0.005	0.004	0.008	0.026	0.021	0.026
RLMerr	0.576	0.846	0.851	0.047	0.080	0.115
RLMlag	0.236	0.411	0.692	0.007	0.012	0.022
SARMA	0.015	0.017	0.028	0.012	0.015	0.024
Residual Moran's I	0.004	0.001	0.001	0.046	0.029	0.028

Table 4: Classification of Russian regions by spatial regimes based on the GRP corrected by the PPP in 1998 and 2006

1998 \ 2006	LL	LH	HL	HH	N_{1998}	$N_{i,1998}/N$
LL	Briansk, Vladimir, Tambov, Tula, Adygeia, Dagestan, Kabarda, Cherkessia, Ossetia, Krasnodar, Stavropol, Astrakhan, Volgograd, Marii-El, Mordovia, Chuvashia, Penza, Saratov, Altai, Altaiskii krai, Primorie,	Riazan, Kaliningrad	Smolensk, Rostov		25	0.33
LH	Tuva, Chita	Voronezh, Ivanovo, Kaluga, Tver, Pskov, Kirov, Ulianovsk, Kurgan, Buriatia, Kamchatka, Jewish Rep.			13	0.17
HL	Hakassia	Kostroma	Belgorod, Kursk, Lipeck, Oriol, Iaroslavl, Tatarstan, Nizhnii, Samara, Tiumen, Krasnoarsk, Irkutsk, Habarovsk, Amur, Magadan		16	0.21
HH		Udmurtia	Sahalin	Mosoblast, Moskva, Karelia, Komi, Arhangelsk, Vologda, Lenoblast, Murmansk, Novgorod, Novosibirsk, Saint-Petersburg, Bashkiria, Orenburg, Perm, Sverdlovsk, Cheliabinsk, Kemerovo, Omsk, Tomsk, Iakutia	22	0.29
N_{2006}	24	15	17	20	76	
N_{2006}/N	0.32	0.20	0.22	0.26		

Table 5: Unconditional β -convergence regressions based on the GRP corrected by the PPP

Parameter	without spatial regimes			with spatial regimes		
	OLS (1)	SEM (2)	SLM (3)	OLS (4)	SEM (5)	SLM (6)
α	1.155 ***	1.009 ***	0.833 ***	—	—	—
α_{LL}	—	—	—	2.386 **	2.308 **	2.009 **
α_{LH}	—	—	—	0.966	0.908	0.889
α_{HL}	—	—	—	-0.588	-0.105	-0.503
α_{HH}	—	—	—	1.589	1.437	1.436
β	-0.064	-0.050	-0.057	0.981	0.570	0.631
β_{LL}	—	—	—	0.942	0.869	0.852
β_{LH}	—	—	—	3.791 ***	3.456 ***	3.476 ***
β_{HL}	—	—	—	1.159	0.995	1.049
β_{HH}	—	—	—	—	—	—
λ	—	0.447 ***	—	-0.196 *	-0.189 *	-0.177 *
ρ	—	0.133	0.458 ***	0.105	0.098	0.095
CR	0.008	0.006	0.007	0.115	0.063	0.086
HaL	83.4	109.0	94.3	0.172	0.156	0.156
CR_{LL}	—	—	—	-0.050	-0.009	-0.033
HaL_{LL}	—	—	—	0.096	0.088	0.087
CR_{HH}	—	—	—	-0.329 ***	-0.295 ***	-0.317 ***
HaL_{HH}	—	—	—	0.119	0.102	0.108
Log-likelihood	42.89	46.79	47.08	—	0.324 *	—
AIC	-79.77	-85.58	-86.16	—	0.151	—
BP test	0.39	1.49	0.38	—	—	0.351 **
R^2_{adj}	0.02	0.13	0.14	—	—	0.136

Notes:

- ‘***’, ‘**’, and ‘*’ denote 1%, 5%, and 10% significance levels, respectively.
- Numbers in brackets are the standard errors.
- CR , CR_{LL} , and CR_{HH} denote convergence rate in all, LL, and HH regions, respectively.
- HaL , and HaL_{HH} denote half-life in all and in HH regions, respectively.
- BP test stands for Breusch-Pagan test for heteroscedasticity of residuals.

Table 6: Characterization of spatial regimes using selected average indicators, 1999-2006

Indicator	H	HH	LH	L	LL
Index of real investment	113.6	114.1	109.8	111.0	111.2
Net migration coefficient	-11.50	4.43	-31.88	-3.38	5.09
Increase in share of workers with higher education in total employment (percentage points)	0.54	0.57	0.58	0.60	0.71
Road density (km per 1000 sq km)	91.1	101.5	84.6	144.3	156.5
Number of mobile phones (per capita)	0.50	0.70	0.27	0.30	0.30

Note: Average index of real investment is a chain coefficient. Net migration coefficient is the difference between inflow and outflow of migrants divided by average population of a region.

Source: all the indicators are taken from Rosstat.

Figure 1: Coefficient of variation (left axis, %) and Moran's I (right axis), 1998-2006

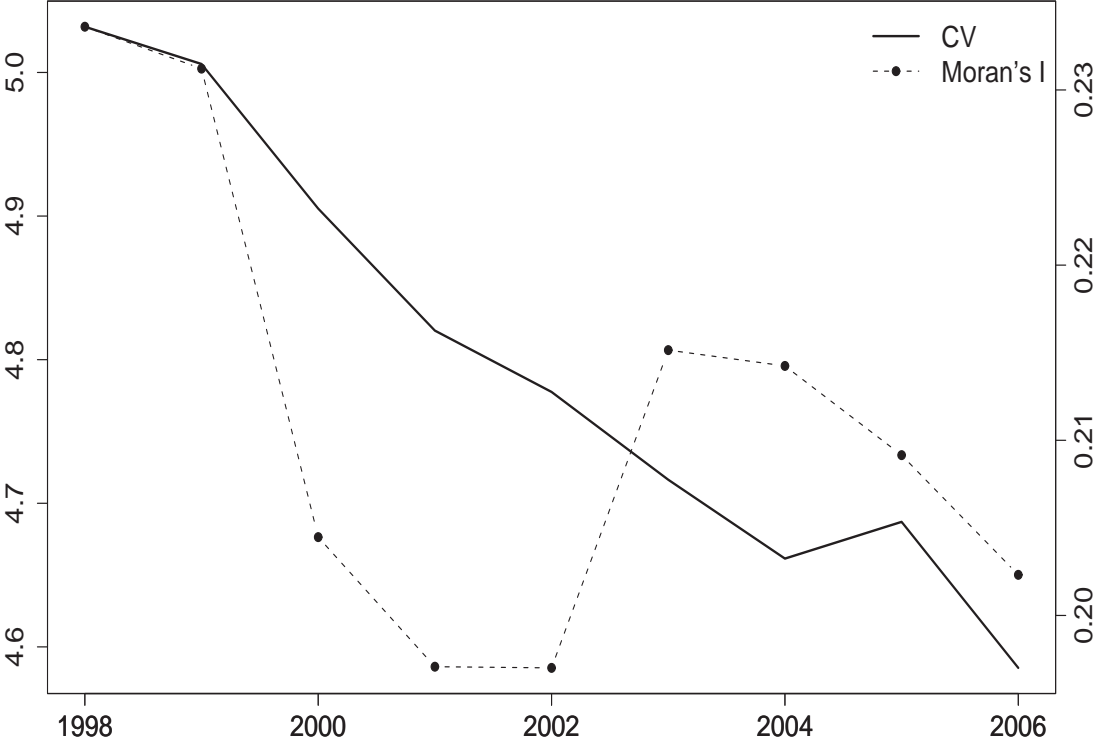
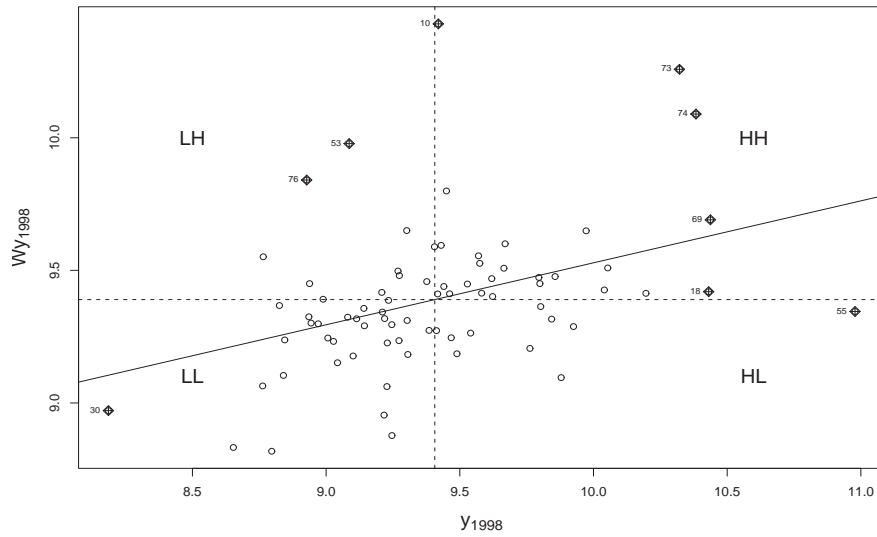
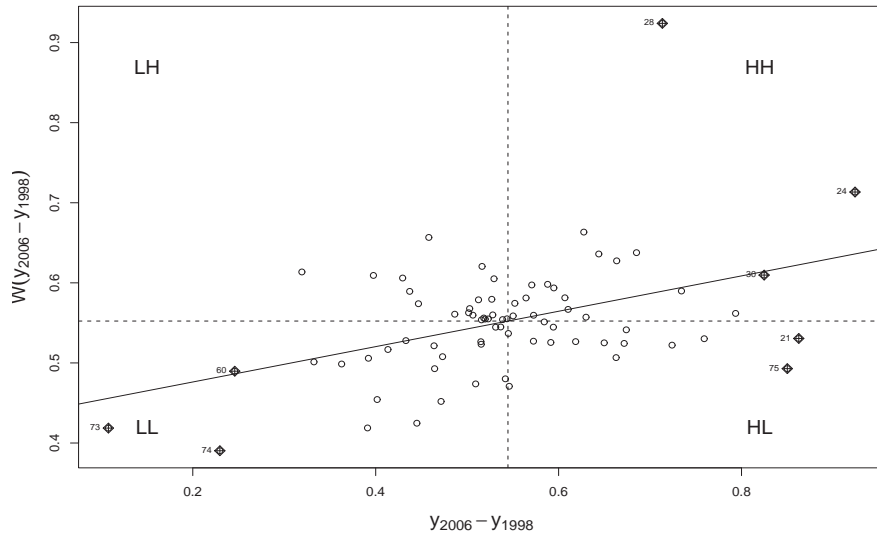


Figure 2: Moran scatter plot, 1998-2006



(a) Real GRP per capita in 1998



(b) Growth of the real GRP per capita in 1998-2006

Figure 3: Distribution of Russian regions by spatial regimes, 1998

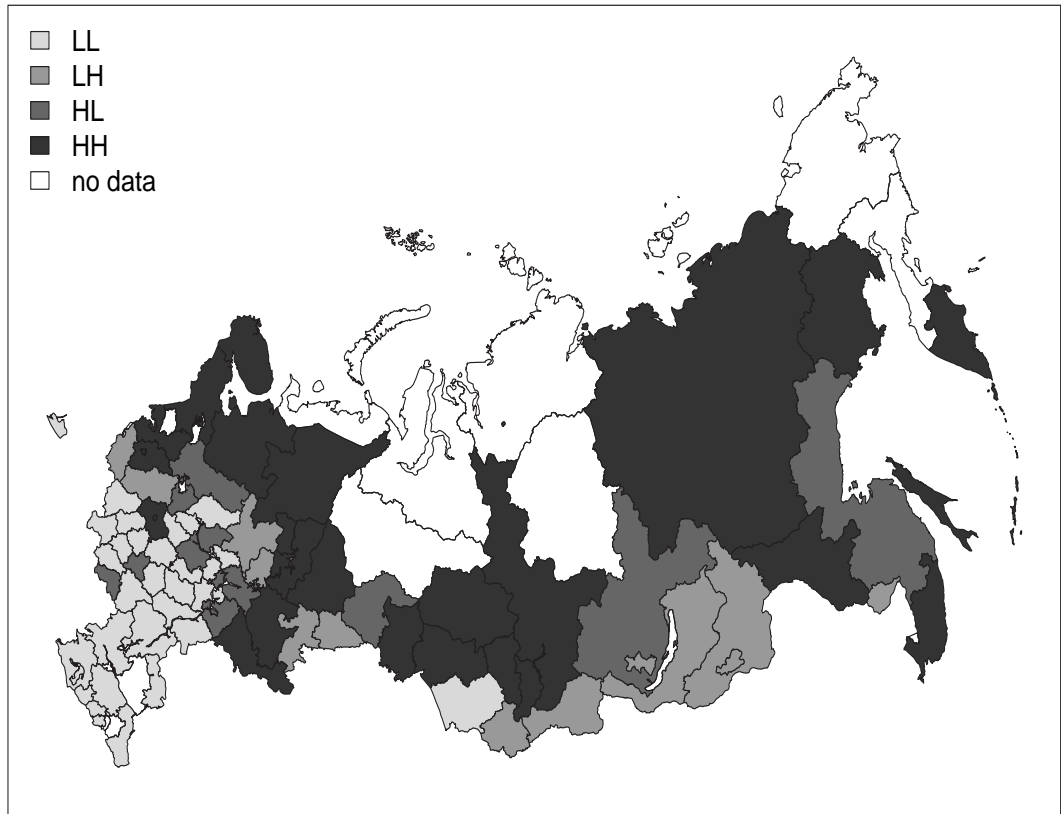


Figure 4: Coefficient of variation (%) across spatial regimes, 1998-2006

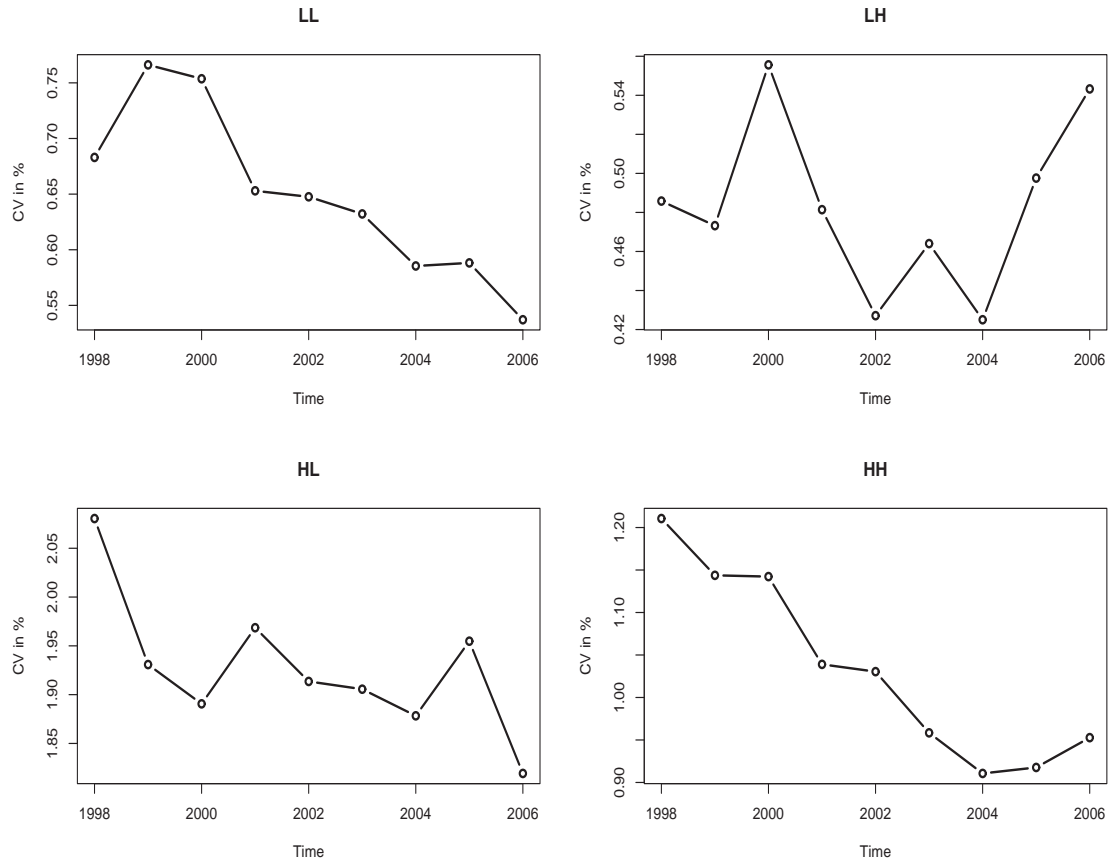
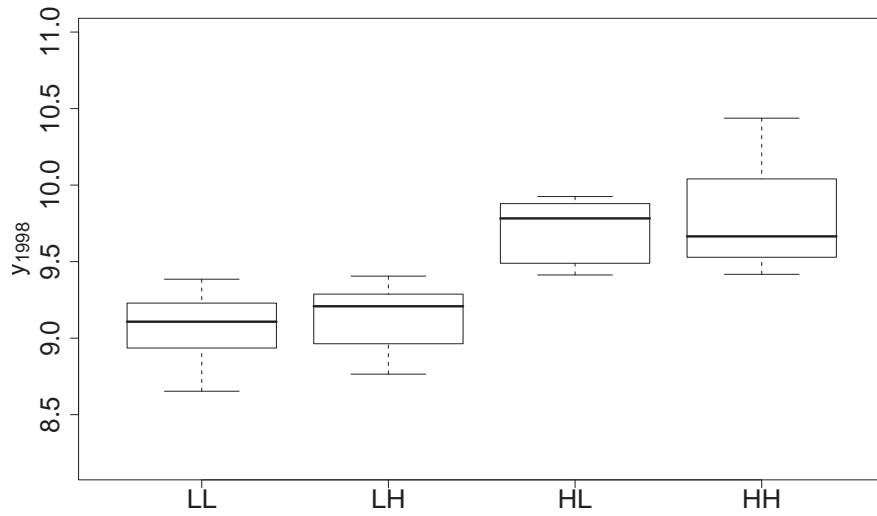
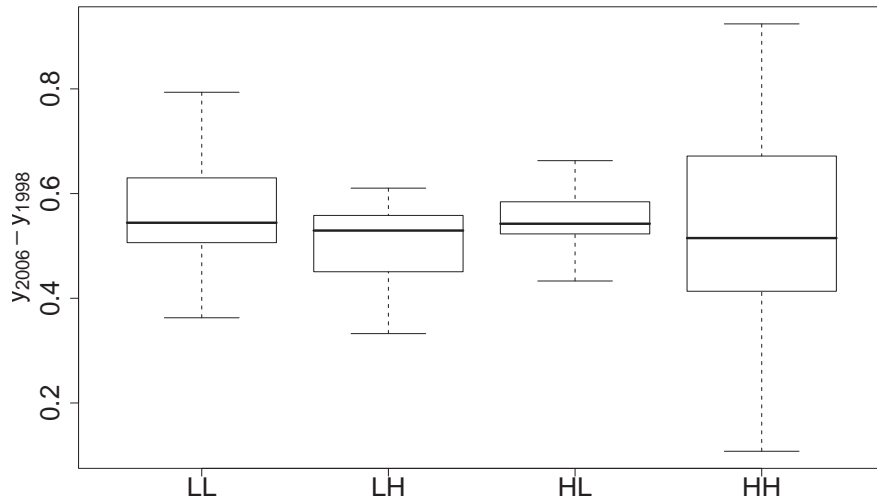


Figure 5: Distribution of real GRP per capita (y_{1998}) and growth of real GRP per capita in 1998-2006 ($y_{2006} - y_{1998}$) by spatial regimes



(a) Real GRP per capita in 1998



(b) Growth of the real GRP per capita in 1998-2006

Figure 6: Real GRP per capita in 1998 (y_{1998}) vs. growth of real GRP per capita ($y_{2006} - y_{1998}$) across spatial regimes

