The Russian regional convergence process: Where does it go?[¶]

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Abstract

This paper investigates the income convergence among Russian regions in the period 1998-2006. It makes two major contributions to rather extensive 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 low by international standards, becomes even lower after controlling for spatial effects. However, when accounting for the spatial regimes, we find a strong regional convergence among high-income regions located near other high-income regions. Our results indicate that estimation of speed of convergence using aggregate data may result in misleading conclusions regarding the nature of convergence process among Russia's regions.

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

JEL classification: C21; O47; R12

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Quintus Horatius Flaccus

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% to 7.2%.

However, in a diverse and geographically large federal state like Russia it is important to look beyond the statistics that is based on aggregate data. 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 (see Shankar and Shah, 2003; Benini and Czyzewski, 2007, among others). For example, a gap between the poorest and richest parts of EU (2-digit NUTS level regions) is much lower than between the poorest and richest regions of Russia even if new member states of EU are taken into account (Krueger, 2007).

Thus, extreme regional inequality represents a very serious problem in Russia as persistent regional economic disparities cause social and political problems and tend to hinder the effectiveness of regional development policies (Shankar and Shah, 2003). Correcting the existing situation constitutes a challenge for regional development policy as the following balance has to be striken. On the one hand, a regional development policy should prevent a situation, when poor regions persistently sink into poverty as it may create a fertile soil for social and political unrest. Moreover, hoping that without federal intervention the poorest regions will escape poverty traps is rather unrealistic. The opportunities for development of these regions are severely limited by their relatively small tax base that is unlikely to be sufficient for provision of an acceptable minimum of health, education, and local public goods (Hanson, 2006). On the other hand, supporting poor regions at the expense of economically developed regions may weaken stimulus for development of the latter.

The acuteness of this issue is well reflected both in official programs of economic development and in a stream of newspaper publications[1]. As a reflection of concern of policy makers the section "Spatial development" is since 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, and the Federal Program "Reducing differences in socio-economic development of the regions of the Russian Federation (2002-2010)" ("Сокращение различий в социально-экономическом развитии регионов РФ (2002-2010)") may be cited as a good example of that[2]. At the same time, a current strategy dealing with regional disparities does not seem to be clearly elaborated[3].

In the same vein, 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 statistically significant, albeit very small, value of the convergence coefficient implying

[1]For example, Grigoriev L. and Urozhaeva U. "Региональное измерение: глубина многообразия" (Regional dimension: Depth of diversity), Vedomosti, №150, 07.06.2005; Kress V. "Региональная политика: поощрение пространства" (Regional policy: Encouraging space), Vedomosti, №150, 15.08.2006; Litvak J. "Экономическая политика: рост и регионы" (Economic policy: Growth and regions), Vedomosti, №105, 09.07.2007; and N. Zubarevich "Стратегия долгосрочного развития: Вспомнить о пространстве" (Long-term development strategy: Remember about space), Vedomosti, №166, 04.09.2008.

[2]See, for example, Granik I. and Nikolaeva D. "Федеральная программа не решила неравенства регионов" (Federal program did not eradicate the regional inequality), Kommersant, №80, 24.05.2007.

[3]See Smoliakova T. "Между Европой и Китаем. Россия выбирает свою модель развития регионов" (Between Europe and China. Russia chooses its regional development model), Rossiiskaya gazeta, №4676, 04.06.2008.

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 Russia's regions.

In this paper, we further investigate convergence process among Russia's regions using the latest available data covering the time period from 1998 until 2006. But in contrast to previous literature, which assumes that the convergence pattern across Russian regions is homogeneous, we allow for differentiated speed of convergence depending on the spatial characteristics of the (groups of) regions. Accounting for spatial characteristics when investigating convergence among the regions is important as 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 spatial correlation in levels of regional economic development. Such spatial correlation could be a consequence of various interactions between regional economies, such as, for example, technology spillovers, migration, and trade. Another reason for spatial interrelations between regions is that administrative division of a country very often does not fully correspond to the actual boundaries between different regional markets (see an excellent review of literature in Abreu et al., 2005). Furthermore, we capitalize on the information delivered by spatial correlation analysis in order to identify regional convergence clubs. Following Durlauf and Johnson (1995) and Ertur et al. (2006), we first classify all regions into the following groups: high-income regions located near other high-income regions, low-income regions located near other low-income regions, high-income regions located near low-income regions, and, conversely, low-income regions located near high-income regions. Second, we allow for convergence speed to differ within each of these groups.

We investigate the process of convergence among Russia's regions in terms of real per capita Gross Regional Product (GRP) using two alternative measures: the real per capita GRP expressed in 1998 prices and the real per capita GRP also expressed in 1998 prices, but additionally adjusted by regional price-related specific factors as proposed by Granberg and Zaitseva (2002a). Though this adjustment slightly changes both a classification of regions into high-income and low-income clusters as well as the estimated speed of convergence, the use of both measures leads to similar conclusions.

Our analysis generally confirms empirical results reported in other studies on regional convergence in Russia. The important novelty of our study is that, in spite of the overall weak convergence typically reported in the earlier studies, we detect a statistically significant and rapid convergence among rich regions located near those alike. This finding is robust across different models and measures of regional income. We also find somewhat weaker statistical evidence on convergence among low-income regions located near those alike. Taken together, our findings suggest a rather disturbing pattern of regional development in Russia. In current situation, both groups of high- and low-income regions form separate convergence clusters that in the absence of an appropriate federal policy will have a tendency to diverge one from another. In fact, our results indicate that weak convergence, typically found at the aggregate level, could mislead a reader into comforting thinking that differences in economic well-being among Russia's regions do tend to diminish, albeit at a somewhat slow pace. Our results could be interpreted as follows: Instead of a comforting but misleading notion of overall weak convergence there is an ongoing polarization of Russian regions and hence in the absence of appropriate policy measures substantial economic disparities across Russian regions are likely to persist in the short and medium run. Neglecting these differences may lead to extremely negative social and political consequences as well as, possibly, pose a serious threat to regional integrity of Russia.

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 section 3. In this section we also summarize our findings and develop some policy implications of our analysis. The final section concludes.

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[4]. The data on Republic of Chechnya were excluded due to their unreliability. In addition, official data on GRP of Republic of Kalmykia, Republic of Ingushetia and Chukotsky AO exhibited improbable large growth-rate fluctuations, and therefore these three regions were also excluded from our analysis as outliers[5]. The autonomous districts (okrugs) were excluded from the analysis, since, firstly, they form a part of the corresponding oblasts and, secondly, the GRP figures for them are

[4]Russian Federal State Statistics Service, `www.gks.ru`.

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

available only starting from 2001. Therefore, our sample includes 76 regions over 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 demand-side components of GRP: private consumption, government consumption, and 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. All these factors were calculated for 1999. However, in this study we obtained the PPPs for other years by multiplying the 1999 PPP by the respective regional GRP deflators. This procedure is based on an assumption that the PPP factors are good proxies for the regional deflators.

Alternative measures of regional purchasing power, such as a 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 regional administration.

It should be noted that the PPP factors itself may be not a perfect measure of interregional 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 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 factors and GRP corrected using these PPP factors[6].

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

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:

$$I = \frac{y'Wy}{y'y} \quad (1)$$

where y is the $N \times 1$ vector of demeaned regional observations of the variable of interest; W is a matrix of spatial weights, which is based in this particular case on the distances between the capital cities of each region[7]. The typical element of this matrix, w_{ij}, is defined as follows:

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

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. 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.

Unfortunately, the global Moran's I statistic provides only a general measure of the level of spatial correlation. An additional information on the strength and the sign of spatial correlation could be derived from 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. As shown in Durlauf and Johnson (1995) and Ertur et al. (2006), the Moran scatterplot allows us to distinguish between different spatial regimes that exist among a given region and its neighbors: high- (low-)income regions located near regions alike — the topright (bottomleft) quadrant denoted as HH (LL); low-income regions located next to high-income regions — the

[7]The 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.

lower left quadrant, LH; and high-income regions located near 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 that appear 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 $\beta-$convergence has the following form:

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

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. In addition, the 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 from each other might lead to misspecification of the model and therefore to either inefficient and/or biased coefficient estimates. Hence, in order to account for interdependence between regions we explicitly account for 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 for by adding the spatial lag of the dependent variable in the benchmark regression:

$$(y_{i,t+\tau} - y_{i,t}) = \alpha + \beta y_{i,t} + \rho W(y_{i,t+\tau} - y_{i,t}) + \varepsilon_i, \tag{4}$$

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

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

$$\begin{aligned}(y_{i,t+\tau} - y_{i,t}) &= \alpha + \beta y_{i,t} + u_i \\ u_i &= \lambda W u_i + \varepsilon_i,\end{aligned} \tag{5}$$

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

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

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

where I_{KJ} is the spatial regime dummy, which takes value of 1, if region i belongs to a regime KJ 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:

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

whereas the spatial error model looks as follows:

$$\begin{aligned}(y_{i,t+\tau} - y_{i,t}) &= I_{LL}\alpha_{LL} + I_{LH}\alpha_{LH} + I_{HL}\alpha_{HL} + I_{HH}\alpha_{HH} + \\ &+ \beta_{LL}I_{LL}y_{i,t} + \beta_{LH}I_{LH}y_{i,t} + \beta_{HL}I_{HL}y_{i,t} + \beta_{HH}I_{HH}y_{i,t} + \\ &+ u_i \\ u_i &= \lambda W u_i + \varepsilon_i.\end{aligned} \tag{8}$$

Convergence rate, or speed of convergence, measures by how much a 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 tends 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 approximately 8%. Such a weak overall σ-convergence corresponds well to our results on overall 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) income tend to be neighbors of regions with equally high (low) per capita income.

The fact that both the Moran's I statistic and the overall income dispersion tend to change over time may indicate that regional growth pattern also undergoes changes. It is quite possible that growth rates within a group (or several groups) of regions start to move more synchronously among themselves than with the rest of regions; i.e., some formation of convergence clusters may be observed resulting in changes in Moran's I statistic. In this case, the convergence process could be more pronounced in some clusters rather than in others; that is, one could observe spatial heterogeneity among different clusters. At the same time, there might be "pockets" of regions where the incomes per capita are stagnating or even diverging. In order to verify it, an analysis of regional growth pattern at a more disaggregated level is needed.

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 scatter plot depicted in 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 scatter plot 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 2 reports the classification of 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. Although, there is a rather large overlap between these two tables the following minor differences in classification of the regions merit a mention. 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 trigged transition of the neighboring regions from the LL group to LH group. Changes in the HH group are even less pronounced. Two regions changed their status from high-income to low-income (that is Primorski krai and Kamchatka region). This trigged 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.

Comparing Tables 1 and 2 allows us to identify those regions, which keep their (high-income or low-income) status irrespective of which measure of GRP is used. The low-income regions may be divided into three large clusters. First, it is the regions of the Central Federal District. Second cluster comprises the 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, Pskov, and Kurgan oblasts as well as several regions in the South of Siberia (Republic of Buriatia, Republic of Tuva, and Chita oblast). The remaining low-income regions that are also located near low-income regions form the LL spatial regime that consists mostly of regions in the Central and South Federal districts, which form a compact area. The LL spatial regime also includes the Republic of Altai located in the South of Siberia.

The high-income regions could be further subdivided into following five spatial clusters. The first cluster is located in the North West encompassing Saint-Petersburg and Leningrad oblast, Murmansk oblast, Arkhangelsk oblast, and Republic of Karelia. The second cluster, which is situated in the Central Russia, includes Moscow and Moscow oblast. The third cluster centered in the Ural mountains comprises Sverdlovsk and Perm oblasts together with Republic of Bashkiria. The fourth cluster, that is located in West Siberia, unifies the Omsk, Tomsk, Novosibirsk, and Kemerovo oblasts. The fifth cluster is located in East Siberia and the Far East.

Before turning to the formal econometric analysis, we investigate the evolution of dispersion of the real per capita GRP over time for the four types of regions that we identified above, see Table 1. Figure 5 displays the coefficient of variation computed for each of four groups indicating strongest decline in the cross-sectional variance of the per capita income 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 trendlike 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.

Figure 6 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 9,082 and 15,826 roubles, respectively. The threshold line dividing regions into high- and low-income categories was about 12,198 roubles in 1998 and 20,965 roubles in 2006. In 2006, the median per capita GRP for high- and low-income regions were about 15,871 and 30,476 roubles, 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, correspondingly.

As evident from the lower panel in Figure 6, 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 7 where the scatterplot 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) with correlation of -0.340. For the remaining group (LH), the value of the correlation coefficient is very close to zero.

Results of our exploratory spatial data analysis can be summarized as follows. Firstly, there exists a non-negligible positive spatial correlation in real per capita GRP across Russian regions. This implies that the high- (low-) income regions tend to be located near other high- (low-) income regions. Moreover, these spatial arrangement is rather stable during the sample period. Secondly, there is a weak overall σ- and β-convergence in real per-capita GRP. However, both σ- and β-convergence is much more pronounced among the regions forming HH and LL spatial regimes. In the following section, we report the results of formal analysis, which support the conclusions based on the descriptive analysis presented in this subsection.

3.2 Econometric results

In this section, estimation results of the econometric models are presented in Tables 3 and 4 for the real per-capita GRP expressed in 1998 prices and the real per-capita GRP also expressed in 1998 prices, but additionally adjusted by regional price-related specific factors as proposed by Granberg and Zaitseva (2002a), respectively.

The first column in Table 3 contains estimated coefficients of the baseline model given in equation (3). The coefficient estimate of β has an expected negative sign and is significant at the 5% level. The implied convergence rate is 1% and the half-life is 67 years. This result is similar to the estimates obtained 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 (3), reported in Table 5. 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 Russian regions, we may conclude that results obtained by estimating the benchmark model might well be erroneous. The application of the Lagrange Multiplier tests is 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 do 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 scatter plots 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 3. 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 accounting for spatial correlation in growth rates slightly lowers the overall speed of convergence across Russian regions. A similar result was reported earlier in Lugovoi et al. (2007).

So far, the regression results obtained either when accounting for spatial dependence or not suggest very slow (if any) convergence process among Russian regions as measured in terms of real per-capita income. In order to check whether 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 (6) and the fourth column in Table 3. 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 located near those alike β_{HH} is -0.263 and is significant at the 1% level. The corresponding convergence rate is 3.8%, which is almost as twice as large as 2% usually reported in the convergence literature, and the corresponding half-life period is about 18 years. It is also worth noticing that some rather weak signs of unconditional β-convergence could be observed in the group of low-income regions located near 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 5. 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.

Columns (5) and (6) in Table 3 contain the estimation results of SEM and SLM with spatial regimes. Observe that the spatial dependence is not detected in SEM—a result compatible with the outcome of the Lagrange multiplier tests reported in Table 5. On the contrary, for SLM 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 SEM and SLM, 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 4 presents the estimation results using the PPP-adjusted GPR. As before, in the left panel we report estimation results of models without spatial dependence, whereas in the right panel—of models, where spatial dependence is explicitly accounted for. As seen from the left panel, the estimate of β coefficient is slightly lower than those reported in Table 3. 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 4 with that of Table 3, 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 though 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

The results of our formal analysis are consistent with those based on the exploratory analysis as reported in subsection 3.1. The strongest evidence of convergence is found among high-income regions neighboring to high-income regions. The convergence rate of such regions is around 3% when the spatial effects are taken into account thus exceeding the rates typically reported in the convergence literature.

In this subsection, we investigate the question of what distinguishes the regions that belong to that group from the rest of regions. For this purpose, we collected the data on regional characteristics including investment, GRP structure, population, labor, and human capital, foreign trade, and nature conditions, see Table 6. According to this table, the HH group has a number of distinguishing features that can well explain their economic well-being. First of all, the group of HH regions is the leader in all investment characteristics. They exhibit the highest investment and savings rate and attract more foreign investments than any other group of regions. The HH regions also take a leading position in trade characteristics such as openness to trade, foreign trade per capita, and foreign trade activity. High levels of investment and trade can be explained by the fact that both Moscow and St. Petersburg belong to this group of regions, but also by the fact that, according to the structure of the GRP, the share of energy sector—that is traditionally export-oriented sector—in industrial production is largest. Also the HH regions are characterized by relatively high share of industrial production in GRP as well as by the lowest share of agricultural sector.

All in all, it appears that the regions that were classified into the HH group possess a number of features that make them to stand out from the rest of regions, on the one hand, but, on the other hand, a certain degree of similarity concerning comparable standards of living, business infrastructure, openness to trade, investment activity, and presence of similar industries (e.g., energy sector) should have facilitated the process of convergence that we were able to detect among these regions. This is indirectly supported by the fact that the investment characteristics vary within the HH group more than within any other group. As predicted by neoclassical models, this may reflect the fact that higher marginal productivity of capital observed in relatively worse-off HH regions attracts additional investment at the expense of investment in relatively better-off HH regions, which, in turn, promotes economic convergence within high-income regions located near other high-income regions. Also the geographical proximity among high-income regions must have positively contributed to convergence process among these regions as supported by our finding of a significant positive spatial correlation in Russia. This must be reflected in the fact that the HH regions are more closely intertwined between themselves rather than with other regions via common goods and commodity flows, labor and capital flows as well as technological transfer.

Our next finding is some, albeit statistically weak, convergence among low-income regions that are located near low-income regions. The value of corresponding convergence coefficient implies convergence rate of about 2%, but the coefficient is found to be statistically significant only at 10% level. Therefore, one should be cautious in interpreting the empirical results concerning low-income regions; more definite conclusions could be drawn when longer time series will be available. However, Table 6 may point out a possible explanation for the convergence among the LL regions. These regions attract migrants, because they possess more favorable living conditions, which are able to compensate for lower real wages (Oshchepkov, 2007).

In sum, we find that the regional convergence process in Russia is not uniform. Therefore, the results based on aggregate data may be misleading. Instead, an analysis at a more disaggregated level should be carried out as only then the differentiated convergence patterns can be detected and convergence clusters can be identified. The existence of these convergence clusters among Russia's regions is not very surprising, given huge regional diversity starting from nature conditions till differences in the industrial structure of GRP. Our findings suggest that the regional divergence process that started in the aftermath of the collapse of the Soviet Union is not over yet: the rich and poor regions tend to cluster with those alike, and so far there is no evidence that the poor regions—even those neighboring rich regions—catch up with economic development of high-income regions. More seriously, it seems that the gap between the poorest and the richest regions, that is already quite extreme by European standards, will not disappear on its own and, in the absence of an appropriate regional policy, it is likely to persist in the medium run.

4 Conclusion

This paper investigates the convergence process in real per-capita GRP among Russian regions in the period 1998-2006. The novelty of our paper is that in addition to modeling of spatial interdependence we allow for differentiated speeds of convergence across different groups of regions instead of measuring an overall speed of convergence as it has been typically done in previous literature investigating regional convergence in Russia. To this end, we employ the exploratory spatial data analysis based on the Moran scatter plot, which allows us to classify all Russia's regions into the following four groups: high-income regions located near other high-income regions, high-income regions located near low-income regions, low-income regions located near high-income regions, and low-income regions located near those alike. Further contributing to the literature, we investigate robustness of our results using two data sets: the GRP corrected for the price changes over time using the GRP deflator and the GRP corrected also for the price differences across space using the purchasing power parity (PPP) factors computed by Granberg and Zaitseva (2002a).

Our main findings can be summarized as follows. First, we find a strong evidence for spatial dependence between regions in Russia, which implies that when addressing a convergence speed these spatial effects must be explicitly accounted for. Second, using the aggregate data we confirm findings reported in previous studies on the presence of very weak, if any, regional β-convergence in Russia. However, our central result is that weak overall convergence found at the aggregate level masks heterogeneous regional convergence patterns that can only be detected if one subdivides regions into the aforementioned groups. More specifically, we find out that a very fast convergence takes place within the group consisting of high-income regions located near those alike. For this group, the convergence speed is about 2.8-3.8%—depending on a model—, which exceeds the "legendary" 2% usually reported in the convergence literature. When we use the PPP-adjusted GRP, the respective convergence speed is even higher and corresponds to

4.4-5.0%. Furhtermore, we find virtually no convergence within the groups of high-income regions neighboring low-income regions and of low-income regions neighboring high-income regions. Lastly, we find some statistical evidence on convergence among low-income regions located near low-income regions.

Our results may be interpreted as follows. The regional divergence process in Russia, spurred by the breakdown of the Soviet Union, still is on-going despite the fact that when looking at the aggregate data there are some very weak signs of its reversal. Unfortunately, our findings point out that these reversal signs seem to be illusory. The convergence takes place but only within the group of high-income regions that are located near regions with similar standards of living. The rest of Russia's regions do not seem to be able to catch up with development characteristic for this group of regions. As a result, the gap between rich and poor regions, which is already quite extreme by European standards, will tend to increase over time unless serious efforts aiming at reducing regional economic disparities will be implemented at the federal level.

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

Table 2: 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	Adygeia, Altai, Altaiskii krai, Astrahan, Briansk, Chuvashia, Dagestan, Cherkessia, Kabarda, Krasnodar, Marii-El, Mordovia, Osetia, Penza, Primorie, Saratov, Stavropol, Vladimir, Volgograd	Kaliningrad, Riazan	Rostov, Smolensk, Tambov, Tula		25	0.33
LH	Chita, Tuva	Buriatia, Ivanovo, Evrei AO, Kaluga, Kamchatka, Kirov, Kurgan, Pskov,Tver, Ulianovsk, Voronezh			13	0.17
HL	Hakassia	Kostroma	Amur, Belgorod, Iaroslavl, Habarovsk, Irkutsk, Krasnoiarsk, Kursk, Lipeck, Magadan, Nizhnii, Oriol, Samara, Tatarstan, Tiumen		16	0.21
HH		Udmurtia	Sahalin	Arhangelsk, Bashkiria, Cheliabinsk, Iakutia, Karelia, Kemerovo, Komi, Lenoblast, Moskva, Mosoblast, Murmansk, Novgorod, Novosibirsk, Omsk, Orenburg, Perm, Saint-Petersburg, Sverdlovsk, Tomsk, Vologda	22	0.29
$N_{i,2006}$ $N_{i,2006}/N$	24 0.32	15 0.20	17 0.22	20 0.26	76	

Table 3: Unconditional β-convergence regressions

Parameter	without spatial regimes			with spatial regimes		
	OLS	SEM	SLM	OLS	SEM	SLM
	(1)	(2)	(3)	(4)	(5)	(6)
α	1.292 ***	1.141 ***	0.943 **		—	—
	(0.361)	(0.314)	(0.363)			
α_{LL}	—	—	—	2.113 ***	1.941 ***	1.726 ***
				(0.552)	(0.639)	(0.583)
α_{LH}				0.493	0.744	0.316
				(0.615)	(1.304)	(1.392)
α_{HL}				1.023	1.185	0.876
				(0.708)	(0.660)	(0.652)
α_{HH}	—	—	—	3.109 ***	2.496 **	2.504 **
				(0.988)	(1.076)	(1.074)
β	-0.079 **	-0.064 **	-0.068 *	—	—	—
	(0.039)	(0.033)	(0.038)			
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
HaL_{LL}	—	—	—	29.6	33.7	34.0
CR_{HH}	—	—	—	0.038	0.028	0.031
HaL_{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 parentheses are the standard errors.

CR, CR_{LL}, and CR_{HH} denote convergence rate in all, LL, and HH regions, respectively.

HaL, HaL_{LL}, and HaL_{HH} denote half-life in all, LL,and in HH regions, respectively.

BP test stands for Breusch-Pagan test for heteroscedasticity of residuals.

Table 4: 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 ***	—	—	—
	(0.406)	(0.378)	(0.380)			
α_{LL}	—	—	—	2.386 **	2.308 **	2.009 **
				(0.966)	(0.908)	(0.889)
α_{LH}	—	—	—	-0.588	-0.105	-0.503
				(1.589)	(1.437)	(1.436)
α_{HL}	—	—	—	0.981	0.570	0.631
				(0.942)	(0.869)	(0.852)
α_{HH}	—	—	—	3.791 ***	3.456 ***	3.476 ***
				(1.159)	(0.995)	(1.049)
β	-0.064	-0.050	-0.057	—	—	—
	(0.043)	(0.040)	(0.039)			
β_{LL}	—	—	—	-0.196 *	-0.189 *	-0.177 *
				(0.105)	(0.098)	(0.095)
β_{LH}	—	—	—	0.115	0.063	0.086
				(0.172)	(0.156)	(0.156)
β_{HL}	—	—	—	-0.050	-0.009	-0.033
				(0.096)	(0.088)	(0.087)
β_{HH}	—	—	—	-0.329 ***	-0.295 ***	-0.317 ***
				(0.119)	(0.102)	(0.108)
λ	—	0.447 ***	—	—	0.324 *	—
		(0.133)			(0.151)	
ρ	—	—	0.458 ***	—	—	0.351 **
			(0.131)			(0.136)
CR	0.008	0.006	0.007	—	—	—
HaL	83.4	109.0	94.3	—	—	—
CR_{LL}	—	—	—	0.027	0.026	0.024
HaL_{LL}	—	—	—	25.4	26.5	28.5
CR_{HH}	—	—	—	0.050	0.044	0.048
HaL_{HH}	—	—	—	13.9	15.9	14.5
Log-likelihood	42.89	46.79	47.08	53.53	55.32	56.06
AIC	-79.77	-85.58	-86.16	-89.06	-90.64	-92.11
BP test	0.39	1.49	0.38	7.05	5.28	7.26
R^2_{adj}	0.02	0.13	0.14	0.18	0.22	0.24

Notes: '***', '**', and '*' denote 1%, 5%, and 10% significance levels, respectively. Numbers in parentheses are the standard errors.

CR, CR_{LL}, and CR_{HH} denote convergence rate in all, LL, and HH regions, respectively.

HaL, HaL_{LL}, and HaL_{HH} denote half-life in all, LL,and in HH regions, respectively.

BP test stands for Breusch-Pagan test for heteroscedasticity of residuals.

Table 5: 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
Residual Moran's I	0.004	0.001	0.001	0.046	0.029	0.028
	without spatial regimes			with spatial regimes		
	W_{D2}	W_{D3}	W_{D4}	W_{D2}	W_{D3}	W_{D4}
LMerr	0.004	0.109	0.128	0.099	0.109	0.128
LMlag	0.003	0.031	0.047	0.030	0.031	0.047
RLMerr	0.605	0.275	0.339	0.309	0.275	0.339
RLMlag	0.364	0.070	0.112	0.081	0.070	0.112
Residual Moran's I	0.001	0.001	0.001	0.022	0.023	0.028

Notes: Table entries are the p-values reported for the specification tests using a mixed regressive-spatial autoregressive model with a spatial autoregressive disturbance is considered. LMerr amounts to testing the null of $\lambda = 0$, given nuisance parameter rho, whereas LMlag amounts for testing the null of $rho = 0$, given the nuisance parameter λ. RLMerr and RLMlag are robust versions of LMerr and LMlag accounting for possible heteroskedasticity.
Residual Moran's I are p-values that correspond to the Moran's I test statistic modified for regression residuals.

The top panel reports the results for the models estimated using the GRP data, whereas the bottom panel—the GRP data adjusted for price-level differences using PPPs.

Table 6: Characterization of spatial regimes using selected average indicators, 1998-2006

	Mean						Coefficient of variation					
Regional characteristics	LL	LH	HL	HH	L	H	LL	LH	HL	HH	L	H
Investment												
Investment rate[1], % of GRP, averaged over 2000-2006	20.9	17.6	20.4	23.2 (23.8)	19.7	22.0	0.26	0.23	0.23	0.43 (0.43)	0.26	0.38
Real growth rate of investment in physical capital[1], %, averaged over 1999-2006	10.9	12.0	11.7	14.2 (14.7)	11.3	13.1	0.46	0.55	0.51	0.44 (0.43)	0.49	0.47
Foreign direct investment per capita[2], dollar USA, averaged over 2003-2006	11.0	9.4	45.5	347.0 (366.0)	10.5	220.1	1.34	0.96	1.49	3.68 (3.67)	1.24	4.43
Foreign investment per capita[2], US dollar, averaged over 2003-2006	29.5	27.9	171.1	669.0 (619.0)	28.9	459.4	1.31	1.14	1.50	2.41 (2.70)	1.24	2.72
Savings rate[3], averaged over 2002-2006	22.0	18.7	21.7	24.6 (25.2)	20.9	23.3	0.24	0.23	0.21	0.50 (0.50)	0.25	0.42
Investment risk[4], averaged over 1998-2006	1.10	1.15	1.02	1.02 (1.04)	1.11	1.02	0.18	0.17	0.16	0.13 (0.12)	0.18	0.14
GRP structure												
Share of industrial production in GRP[1], %, averaged over 1998-2006	24.7	25.6	39.6	37.7 (39.6)	25.0	38.5	0.33	0.34	0.29	0.26 (0.20)	0.33	0.27
Share of agricultural production in GRP[1], %, averaged over 1998-2006	16.9	12.8	9.1	6.3 (7.0)	15.5	7.5	0.37	0.25	0.62	0.71 (0.60)	0.37	0.68
Share of energy sector in industrial production[1], %, averaged over 2000-2006	7.4	2.7	11.0	17.6 (19.0)	5.8	14.8	1.82	1.51	2.03	1.10 (1.03)	1.96	1.39
Population, labor and human capital												
Population[1], million persons, averaged over 1998-2006	1.68	1.06	1.84	2.64 (2.16)	1.47	2.30	0.71	0.56	0.65	0.88 (0.76)	0.73	0.84
Population density[2], persons per sq. km (1 Jan. 2007)	40.3	17.8	25.3	603 (21.5)	32.6	359.8	0.53	0.97	0.92	3.51 (1.46)	0.69	4.51
Urbanization[1], % share of urban population in total population, averaged over 1998-2006	62.5	67.6	73.5	76.5 (74.2)	64.3	75.2	0.21	0.14	0.12	0.15 (0.12)	0.19	0.14
University enrollment rate[2], share of university students in total population, averaged over 2000-2006	3.5	3.2	4.0	4.2 (3.6)	3.4	4.1	0.18	0.26	0.21	0.54 (0.39)	0.21	0.44
Share of employees having higher education in total employment[1], %, averaged over 2000-2006	22.3	19.0	21.5	21.4 (19.5)	21.2	21.4	0.13	0.13	0.14	0.32 (0.14)	0.15	0.25

Continued on next page

Table 6: Characterization of spatial regimes using selected average indicators, 1998-2006 (continued)

	Mean						Coefficient of variation					
Regional characteristics	LL	LH	HL	HH	L	H	LL	LH	HL	HH	L	H
Population growth[1], percent, averaged over 1998-2006	-0.47	-0.99	-0.77	-0.63 (-0.72)	-0.65	-0.69	-1.44	-0.42	-1.01	-0.91 (-0.64)	-1.00	-0.96
Net migration[1], persons per 10000 persons, averaged over 1998-2006	7.4	-29.8	-14.9	-6.6 (-15.9)	-5.3	-10.1	3.71	-1.26	-5.33	-9.62 (-3.55)	-6.71	-6.91
Change in the share of employees having higher education in total employment[2], %, averaged over 2001-2006	0.63	0.56	0.69	0.47 (0.50)	0.61	0.56	0.70	0.70	0.89	0.78 (0.62)	0.70	0.87
Foreign trade												
Openness to trade, foreign trade as a share of GRP[2], %, averaged over 1998-2006	40.8	25.5	49.0	55.2 (51.9)	35.5	52.6	1.29	0.57	0.52	0.42 (0.41)	1.24	0.46
Foreign trade per capita[2], US Dollar, averaged over 1998-2006	489	314	1321	1452 (1168)	429	1397	1.44	0.70	1.17	0.88 (0.54)	1.37	0.99
Foreign trade activity[5]	0.31	0.24	0.54	1.09 (1.06)	0.28	0.85	0.99	1.29	0.61	0.95 (1.02)	1.07	0.99
Nature conditions												
Nature conditions index[6]	4.0	3.7	3.7	3.7	3.9	3.7	0.07	0.12	0.12	0.09	0.09	0.10
Average temperature in January 2006[1], C^0 degrees	-11.5	-17.7	-19.3	-18.2	-13.6	-18.7	-0.41	-0.40	-0.39	-0.48	-0.46	-0.44
Average temperature in July 2006[1], C^0 degrees	19.4	17.1	17.4	16.4	18.6	16.8	0.13	0.10	0.09	0.13	0.13	0.12
Rural population density[2], persons per sq. km, average over 1998-2006	15.0	5.4	7.4	4.7	11.7	5.9	0.61	0.93	0.96	1.36	0.78	1.15

Notes: Numbers in parentheses are the means and coefficients of variation computed for HH regions without Moscow and St. Petersburg.

[1] Rosstat.
[2] Own calculations.
[3] Own calculations using the following formula: Savings rate = investment rate + net exports rate.
[4] Expert Rating Agency: http://www.raexpert.ru/ratings/regions/.
[5] Satarov et al. (2004).
[6] Expert estimates by Yuri Rosich: http://www.geoteka.ru/text.html?page=usl.

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

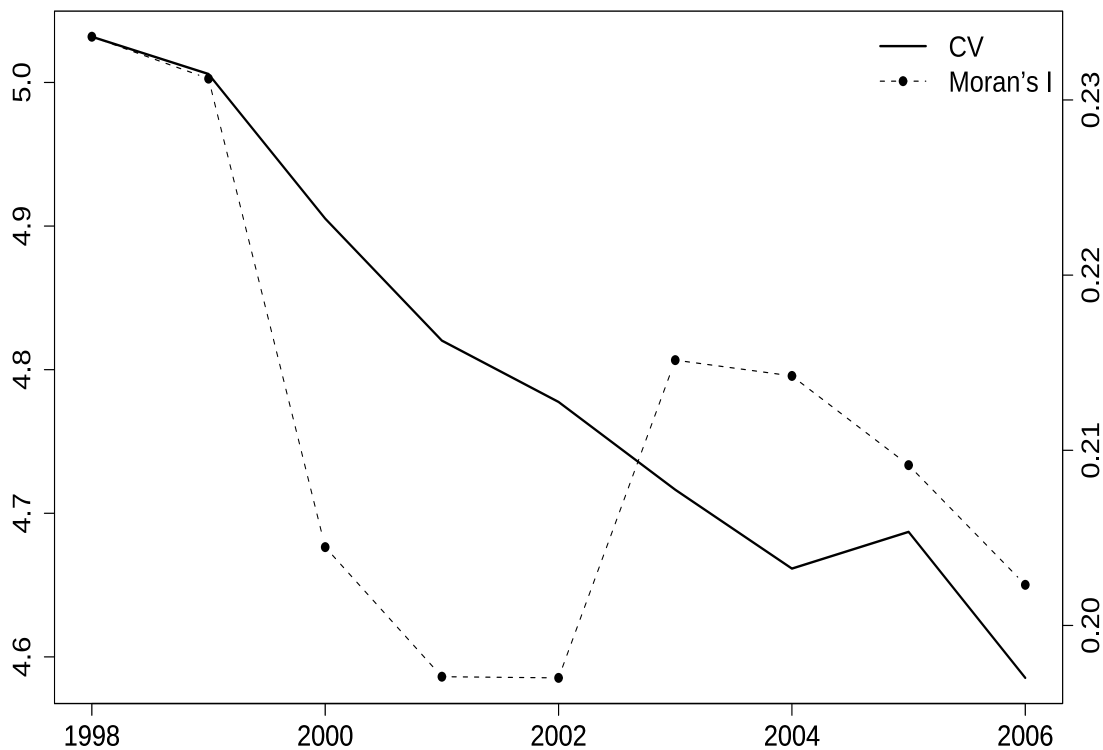


Figure 2: Moran scatter plot: Real GRP per capita, 1998

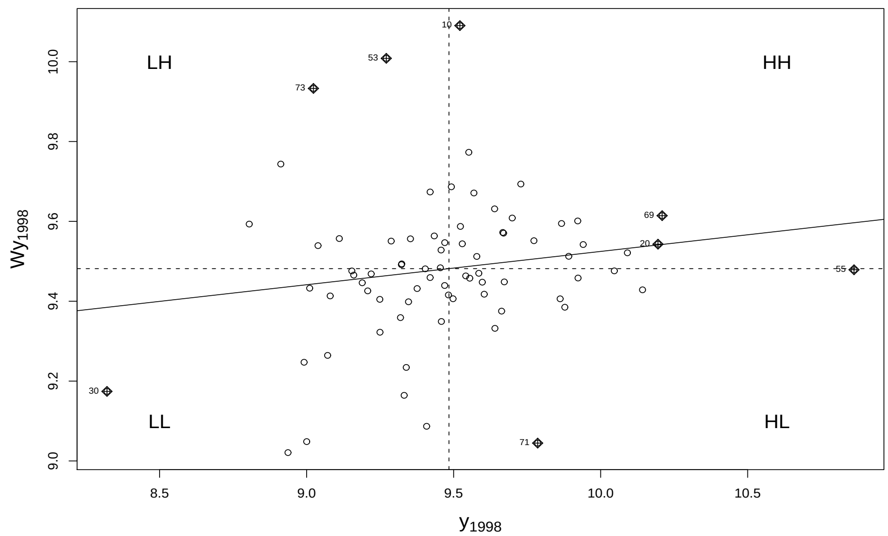


Figure 3: Distribution of Russian regions by spatial regimes, 1998

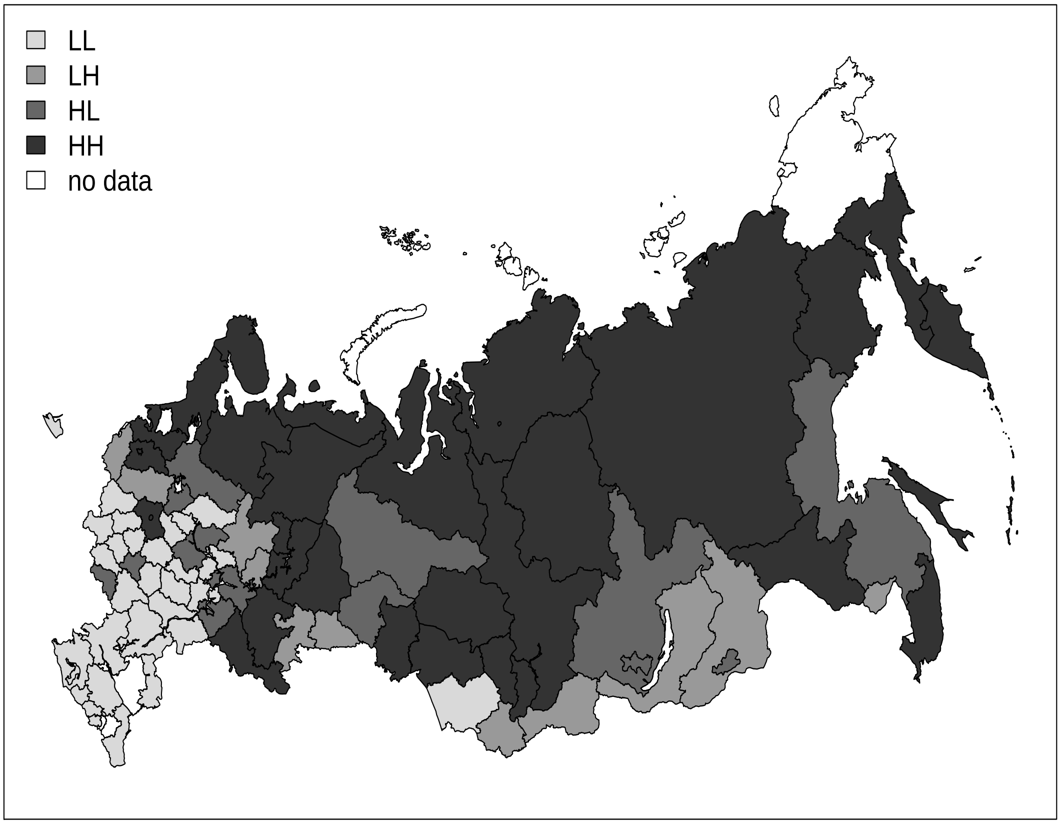


Figure 4: Distribution of Russian regions by spatial regimes (data adjusted for price-level differences using PPPs), 1998

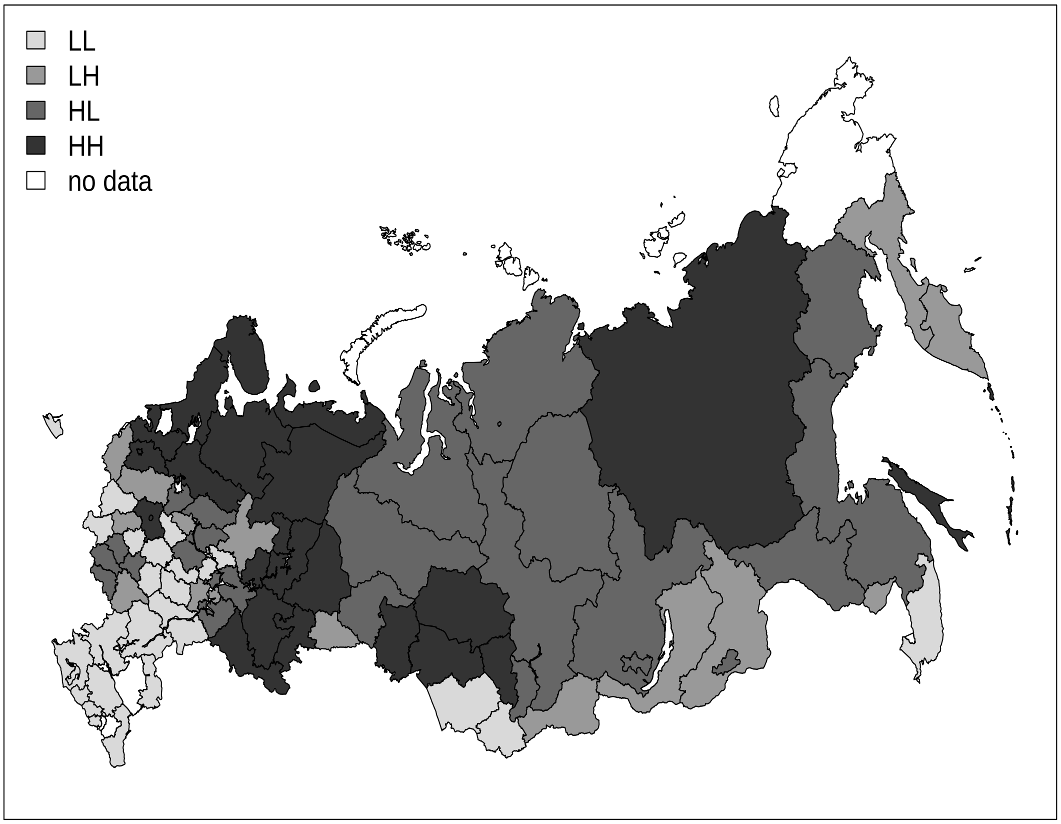


Figure 5: Coefficient of variation (%) across spatial regimes, 1998-2006

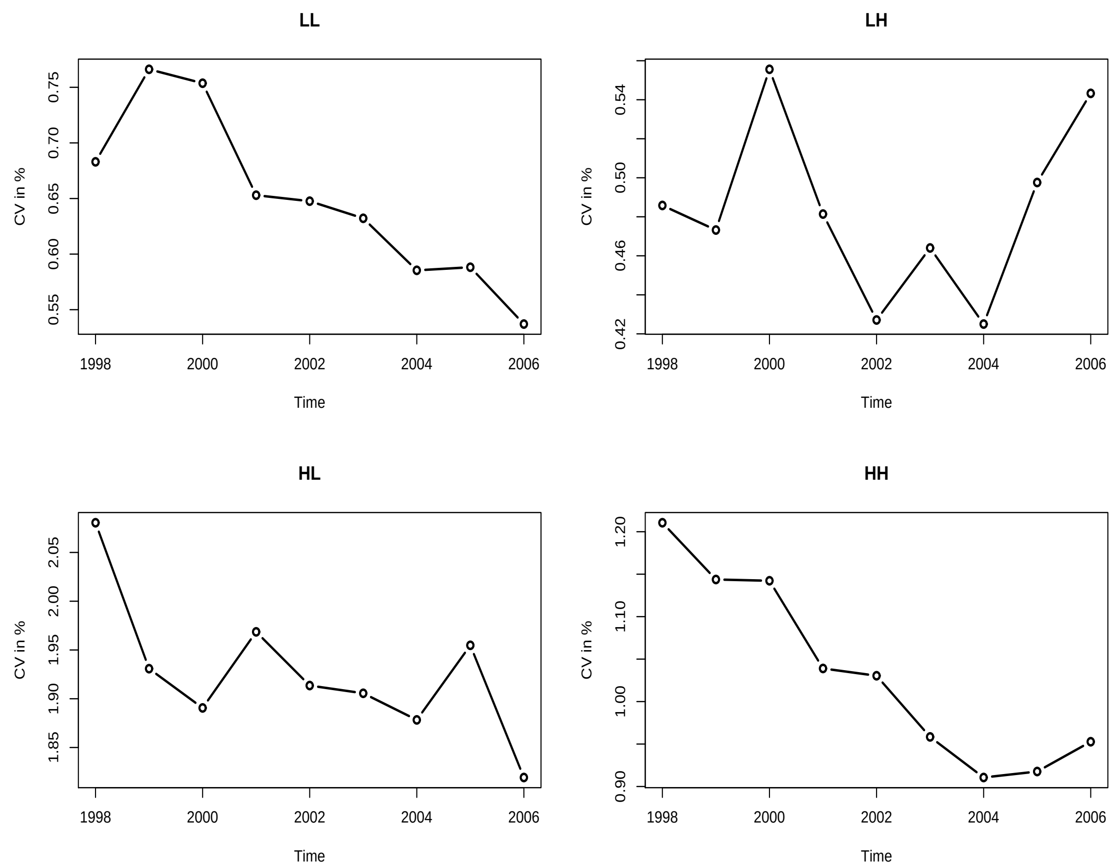
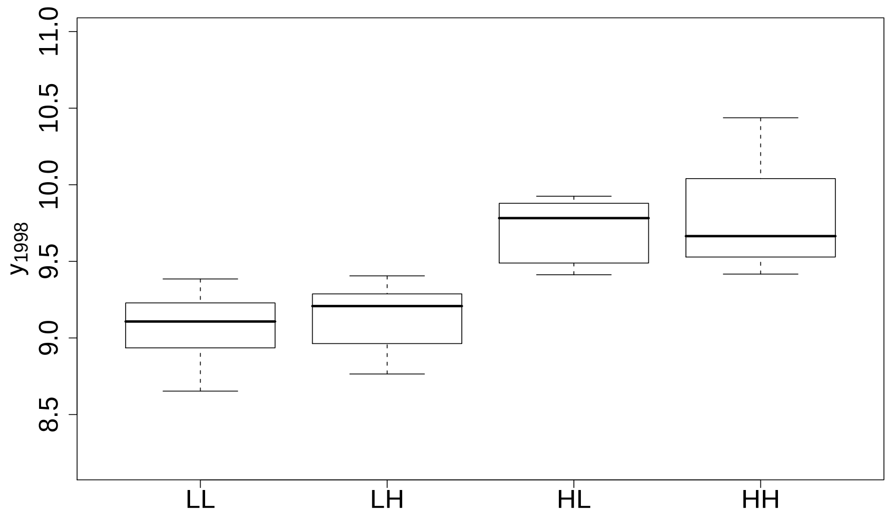
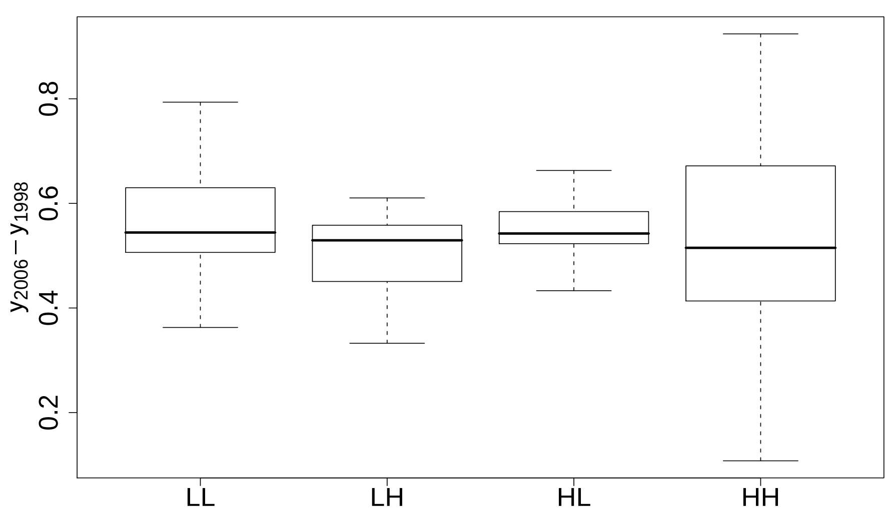


Figure 6: Distribution of real GRP per capita (y_{1998}) and growth of real GRP per capita in 1998-2006 ($y_{2006} - y_{1998}$) by spatial regimes



(a) Real GRP per capita in 1998



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

Figure 7: Real GRP per capita in 1998 (y_{1998}) vs. growth of real GRP per capita ($y_{2006} - y_{1998}$) across spatial regimes