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Abstract

To be added

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1. Introduction

Ever since the seminal papers by Solow on growth (1956, 1957) has convergence of income levels, often measured with GDP per capita, been on the research agenda. The Solow model predicts that, other things equal, poor countries that have lower per capita incomes and lower capital to labor ratios should grow faster than rich countries. If this prediction of the model were true, then the income gap between rich and poor countries would shrink over time, causing living standards to converge. There is a large literature that shows that convergence only works conditionally: in samples of countries with similar saving and population growth rates income gaps shrink by about 2% per year. In larger samples of countries, after controlling for differences in saving and population growth rates and in levels of human capital, incomes converge by about 2% per year.

An important variant of convergence analysis is convergence of regional incomes or GDP per capita within one country. While regional convergence analysis fulfills better the ceteris paribus condition than does cross country analysis, it is also of great policy relevance. Raising standards of living of poor regions in a country is an important policy aim, since too large income disparities within a country can be destabilizing and can also hamper overall growth. The Russian Federation is a particularly interesting object of study since it is a very large and economically very heterogeneous country with tremendous income disparities. For example, in 2015 the top five regions in the country[2] have gross regional products per capita (in purchasing power parity) that reach levels of rich developed economies while the bottom five regions[3] have gross regional products per capita that place them among the poorest countries of the world (see World Bank, 2017). According to this study, disparities in gross regional product per capita among Russian regions vary by a factor of 17! Figure 1 traces the development of the coefficient of variation of nominal and real gross regional product (GRP) per capita for the period between 1996 and 2015, for which we have reliable and consistent data. It clearly shows that throughout the period disparities are large in international perspective and that sigma-convergence is very limited.

< Figure 1 about here>

[2] These are: Sakhalin Oblast, Tyumen Oblast, Chukotka Autonomous Okrug, Moscow City and Magadan Oblast.

[3] These are: Tuva Republic, Kabardino-Balkar Republic, Karachaevo-Cherkess Republic, Chechnya Republic and Ingush Republic.

Given the importance of regional convergence in Russia there have been many studies on this topic in the last years. We think, however, that our study contributes to the literature in an important fashion. First, we use the longest possible time span in our growth estimates given the availability of reliable and above all across time consistent data. Second, our estimations take spatial correlations into account. Most importantly, all the studies on regional convergence in Russia use ad hoc specifications when estimating growth regressions. It strikes us, therefore, as very worthwhile to develop estimable growth functions that are well grounded in theory. Taking the classic Solow model as a point of departure, we extend this model by adding measures of human capital and of migratory flows and thus arrive at a comprehensive growth model that we then estimate. To the best of our knowledge no study on regional convergence in Russia has done this.

2. Our study and the literature on regional convergence

This literature survey is rather selective as it refers to those papers that strike us as particularly relevant for our study. We look at the state-of-the-art papers that discuss regional convergence in general, and at studies that have Russian convergence as their theme.

2.1 The general literature on regional convergence

To be added

2.2 A relevant selection of papers from the literature on regional convergence in Russia

We start off with the paper by Guriev and Vakulenko (2012) who show that in the first decade of the 21st century wages and income converged across regions but not regional GDP per capita. The authors explain this puzzle by remaining total factor productivity differences among regions. The second important result of the paper deals with labor mobility across regions. In the 1990s according to the authors labor mobility was slowed down by liquidity constraints, which disappeared in the first decade of the new century due to the convergence in real wages and income. This elimination of liquidity constraints allowed disadvantaged regions to break out of the poverty trap boosting migration from relatively low wage and relatively high unemployment regions to relatively high wage and relatively low unemployment regions. In a companion paper Guriev and Vakulenko (2015) hone in on this nexus between regional wage and income convergence and migration. The study by Ivanova (2018) also finds convergence of real wages, however, analyzing convergence at the city level. Looking at city-level data between 1996 and 2013, she establishes conditional sigma-and beta-convergence of real wages in spatially close cities, pointing to important agglomeration effects regarding the evolution of real wages in Russia. Spatial effects are also central to the analysis of the Russian regional convergence process over the years 1998 to 2006 by Kholodilin, Oshchepkov and Siliverstovs (2012). The authors find an important positive spatial correlation in real per capita gross regional product, implying that high-income regions are located for the most part close to other high-income regions and that low-income regions find themselves close to other low-income regions. They also find weak sigma- and beta-convergence across all regions of Russia; however, when looking at the cluster of high-and low-income regions their results demonstrate that both sigma- and beta-convergence are much more pronounced within these clusters. The last paper that we wish to cite is by Kaneva and Untura (2018) who discuss the impact of R&D and knowledge spillovers on the economic growth of Russian regions. Two results of this paper are particularly worth mentioning: expenditures on R&D and on technological innovations contribute to regional growth and thus potentially to regional convergence. In addition, spatial effects turned out to be important when modelling regional growth.[4]

There are three important messages from this brief survey of pertinent papers on regional convergence in Russia. First, when one wants to model regional convergence one needs to include human capital and migratory flows as important determinants of growth. Second, it is vital to include spatial effects in any model to be estimated. Third, all of the discussed papers essentially use ad hoc specifications when estimating growth. None of these studies starts out with a model that is well grounded in the theoretical literature on growth. This lack of comprehensive theoretical underpinnings of the estimated empirical growth models is not only given in the cited literature but also present in the multitude of papers on Russian regional convergence that we did not consider in our brief survey.

3. Theoretical Model

Our theoretical model of regional convergence is based on the classic Solow model (Solow, 1956) augmented with human capital (Mankiew, Romer & Weil, 1992) and taking into account migration (Dolado, Goria & Ichino, 1994).

[4] There are some econometrically well-crafted papers that establish divergence of regional incomes or gross regional product per capita. For example, the paper by Fedorov (2002) establishes strong regional polarization of incomes in the 1990s, while Akhmedjonov, Lau and Izgi (2013) who apply unit root tests for gross regional product per capita series conclude that in the years 2000 to 2008 we observe divergence of GRP per capita for the vast majority or Russia’s regions.

The economy has a Cobb-Douglas production function with labor-augmenting technological progress:

$$Y = HC^{\varphi} \cdot K^{\alpha} \cdot (A \cdot L)^{1-\alpha-\varphi} \quad [1]$$

where Y is output; K is physical capital; HC is human capital; L is labor (natives plus net immigrants); A is the level of technology.

A is assumed to grow exogenously with rate g:

$$A_t = A_0 e^{gt} \ [2]$$

L grows with rate (n + m):

$$L_t = L_0 e^{(n+m)t} \ [3]$$

where n is the growth rate of the native population; m is the net immigration rate, $m = \frac{M}{L}$, M is the net number of new immigrants.

The dynamics of physical capital is described as:

$$\dot{K} = s_k \dot{Y} - \delta_k K \quad [4]$$

where s_k is the fraction of output invested; δ_k is the depreciation rate.

The dynamics of human capital is characterized by the following equation:

$$\dot{HC} = s_h Y - \delta_{hc} HC + m \cdot \varepsilon \cdot HC \quad [4]$$

where s_h is the fraction of output invested in human capital; δ_{hc} is the depreciation rate of human capital; ε is the ratio of HC of immigrants versus natives.

In terms of per effective units of labor (AL) the production function and dynamic equations of physical and human capital look as follows:

$$\mathrm{y} = hc^{\varphi} \cdot k^{\alpha} \qquad [5]$$

$$\dot{k} = s_k y - (g + \delta_k + n + m)k \qquad [6]$$

$$\dot{hc} = s_h y - \big(g + \delta_{hc} + n + m \cdot (1 - \varepsilon)\big) \cdot hc \qquad [7]$$

Equations 6 and 7 suggest that migration should have a negative impact on economic growth, as migration is part of population growth $(n + m)$, which impedes the accumulation of both physical and human capital. However, when $\varepsilon > 1$, migration starts to increase human capital in a region. Theoretically, if $\varepsilon > 2$ and $m > n$, the positive impact of migration on human capital counterbalances the negative impact of the growth of general population, and thus migration may have a positive influence on economic growth (per effective labor).

Finally, applying standard derivations, we receive the theoretical growth equation capturing the dynamics toward steady state:

$$ln(y_t) - ln(y_{t-1}) = -\big(1 - e^{-\lambda t}\big)\ln(y_{t-1}) + \big(1 - e^{-\lambda t}\big)\frac{\alpha}{1-\alpha}\ln(s_t) +$$

$$+\left(1-e^{-\lambda t}\right)\frac{\varphi}{1-\alpha}\ln(HC_t)-\left(1-e^{-\lambda t}\right)\frac{\alpha}{1-\alpha}\ln(n+m+g+\delta)+\left(1-e^{-\lambda t}\right)\frac{\alpha}{1-\alpha}\varepsilon\cdot migr_t+$$
$$+Ln(A_0)+\nu_t \qquad [8]$$

where $migr=\frac{m}{g+\delta+n+m}$.

4. Methodology and Data

4.1 Methodology

Our theoretical model (Equation 8) may be rewritten as a regression as follows:

$$\Delta\ln(y_t)=\beta\ln(y_{t-1})+\beta_1\ln(s_t)+\beta_2\ln(HC_t)-\beta_3\ln(n+g+\delta)+$$
$$+\beta_4 migr_t+region\,FE+Time\,FE\,+\nu_t \quad [9]$$

Compared to the theoretical model, this equation includes two additional variables, $region\,FE$ and $Time\,FE$ reflects, reflecting regional and time fixed effects, respectively. Since the seminal paper by Islam (1995) it is a common practice to include into empirical growth equations region (or country) fixed effects, which allows to control unobserved heterogeneity of regions. More specifically, regional FE control unobserved interregional differences in the initial levels of technological development ($Ln(A_0)$ in Equation 8) as well as other differences (e.g., resource endowments and geo-climatic conditions, see also Islam, 2003). Not taking into account unobserved heterogeneity results in an upward bias in the OLS estimate of β, which implies underestimated rate of convergence.

Time FE, in turn, allow to control the influence of macroeconomic shocks (either positive or negative) affecting all regions in the country. This can be especially important in the Russian case, as the period we consider, 1996-2015, includes both economic crises and recoveries, including the on-going period under sanctions and anti-sanctions (since 2014). Moreover, time FE could control for possible changes in the statistical methodology of calculation of variables by Rosstat.[5]

Although the inclusion of regional FE helps to avoid the omitted variable bias in Equation (9), it creates a bias of another sort. Regional FE are correlated with lagged GRP per capita, which leads to a downward bias in the OLS estimates, known in the literature as the Hurwicz-Nickel bias (Hurwicz, 1950; Nickel, 1981). To avoid this issue, we estimate Equation (9) by system GMM (Arrelano & Bover, 1995; Blundell & Bond, 1998), which became the most

[5] We are aware of, at least, one such change. In 2011, Rosstat changed the definition for internal migration. It started to take into people who moved to another region and stayed there more than 9 months (instead of 12 months before 2011). This led to a visible increase in the amount of internal migration in 2011 compared to 2010 (e.g., see Buranshina & Smirnykh, 2018).

popular approach to estimate dynamic panel data models nowadays, being more efficient than the Arrelano-Bond method (Arrelano & Bond, 1991).

The estimation procedure involves two steps. At the first step, Equation (9) is first-differenced. At the second step, first differences of $\ln(y_{t-1})$ are instrumented not only with lagged levels of y as in the Arrelano-Bond estimator, but also with lagged first differences. Except traditional Sargan-Hansen tests (see Roodman, 2009a), the important diagnostic in this case involves the AR tests for autocorrelation of the residuals. While residuals of the differenced equation should follow AR(1) serial correlation process, they should not exhibit AR(2) process, as in this case the second lags may not serve as valid instruments for current values.

There are also two additional issues related to the estimation of Equation (9). The first issue concerns parameters g and δ. Following Mankiew, Romer & Weil (1992), many existing studies on convergence across different countries or regions assume $(g + \delta)$ = 0.05. However, we are not aware of studies that could justify the use of such assumption in the Russian case. [Although we are aware of, at least, one study that applies this assumption to study convergence across Russian regions, Zemtsov & Smelov, 2018] In order to be one the safe side, we examine how the estimation results may change if we use alternative values for $g + \delta$ (*see Robustness Checks*).

The other issue concerns the frequency of the data used. In a cross-sectional setting, the rate of economic growth at the left-hand side is usually averaged over a long time span (20-25 years or even more, see Barro & Sala-i-Martin, 1991 and many subsequent studies). A panel data setting allows average over periods of different length. A straightforward approach is to use yearly data. However, some recent studies including Barro (2015) and Gennaioli, La Porta & Schleifer (2014) average all variables over (non-overlapping) 5-year periods. On the one hand, averaging variables allow to make results less vulnerable to potential data errors. On the other hand, as formulated by Islam (1995), '…*If we think that the character of the process of getting near to the steady state remains essentially unchanged over the period as a whole, then considering that process in consecutive shorter time spans should reflect the same dynamics*.' Therefore, from the theoretical point of view, averaging over different periods should give similar results. In our study, we employ variables averaged over 3-year non-overlapping periods, but consider alternative averaging schemes as robustness checks.

Estimated coefficients from Equation (9) allow deriving a set of theoretical parameters. First of all, we are interested in the convergence rate $\lambda = \frac{-\ln(1+\beta)}{t}$. We can also drive physical capital share $\alpha = \frac{\beta_1}{\beta+\beta_1}$, human capital share $\varphi = \frac{\beta_2}{\beta}(\alpha - 1)$, and the ratio of human capital of immigrants versus natives $\varepsilon = \frac{\beta_4}{\beta_1}$.

Following existing studies on Russia (e.g., Kholodilin, Oshchepkov & Siliverstovs, 2012; World Bank, 2017), we also take into account possible spatial effects. With this aim, we estimate a version of Equation 9 extended with a spatial lag of dependent variable:

$$\Delta \ln(y_t) = \beta \ln(y_{t-1}) + \beta_1 \ln(s_t) + \beta_2 \ln(HC_t) - \beta_3 \ln(n + g + \delta) + \beta_4 migr_t + region\, FE + \\ + Time\ effects + \beta_5 W \cdot \Delta \ln(y_t) + \nu_t \quad [10]$$

where $W \cdot \Delta \ln(y_t)$ is a spatial lag of $\Delta \ln(y_t)$; W is a spatial weighting matrix (normalized by rows) $w_{ij} = \frac{1}{d_{ij}}$, where d is geographical (arc)distance between regions i and j.

We expect that the estimate of β_5 will be significant and positive, i.e., that growing regions tend to be located closes to other growing regions (either due to growth spill-overs, or because growing regions have similar economic structures pre-determined by similar geo-climatic conditions). Moreover, spatial interdependence between regions may affect the overall convergence process.

The spatial lag of dependent variable complicates the estimation of Equation 10 as this lag is endogenous by nature. We are aware of, at least, two general approaches to estimate such a dynamic panel data model with a spatial lag. The first approach is based on the (quasi-) maximum likelihood estimation. Two its different realizations are developed by Elhorst (2005) and Lee, de Jong, & Yu (2008). The second approach is system GMM that instruments the spatial lag variable like any other RHS endogenous variables (Kukenova & Monteiro, 2009).[6]

In our study, we choose the second approach, system GMM, as it is best suited in cases when there are other potential endogenous variables, except a spatial lag of dependent variable (see Kukenova & Monteiro, 2009 for more details). In our case, all RHS variables may be potentially endogenous (especially migration or human capital). Moreover, using system GMM makes our methodology consistent. [In the Russian context, system GMM has been applied by Buranshina & Smirnykh, 2018; Vakulenko (2015); World Bank (2017)]. In practice, we estimate Equations 9 and 10 in STATA using - xtabond2- module proposed by Roodman (2009b).

4.2 Data

[6] Badinger, Mueller & Tondl (2004) combine system GMM with 'spatial filtering'.

In this paper, we analyze convergence among Russian regions using data for the longest period available, from 1996 to 2015. Traditionally to papers on Russia, we exclude from analysis Chechnya. Most variables we use come from Rosstat regional statistics (statistical yearbook "*Regioni Rossii*").

To measure real GRP per capita we take nominal GRPs, divide them by regional population size, and then adjust them to 1996 prices using physical volume indices.

To measure saving rates we take data on investments (*investicii v osnovnoi capital)* and divide it by GPR.

For human capital we use two alternative measures. First, this is employment in R&D sector. Second, the percentage of employed having higher education.

As a measure of net immigration into the region we use the coefficient of net migration which is net migration divided by regional population.

5. Results

5.1 Estimating the complete model

The main estimation results are presented in Table 1.

[Table 1 near here]

We start with a specification of Equation 9 that does not include regional FE (Column 1). In this case, the OLS estimate of coefficient for the lagged GRP per capita is about -0.005 and not statistically significant. As mentioned above, this estimate may suffer from an upward bias.

Column 2 presents results with regional fixed effects. The estimate of coefficient for the lagged GRP per capita becomes highly significant and large in absolute terms (-0.131), which implies implausible convergence rate among Russian regions of 14% per year. A sharp increase in this coefficient after inclusion of regional FE in line with results of many previous studies (e.g., Barro, 2015; Gennaioli, La Porta & Schleifer, 2014). Such a negative value may reflect the Nickell (downward) bias.

Finally, Column 3 presents estimation results obtained by using system GMM, which allows to avoid the Nickel bias. The estimate of coefficient for the lagged GRP per capita is -0.016 and statistically significant at 5% level. For convenience, all econometric parameters accompanying the application of the system GMM are presented in Table 2 (see the bottom of the first column).

The AR tests for autocorrelation of the residuals suggest that residuals follow AR(1) process but do not exhibit AR(2) process, which indicates that lagged first differences may be used as valid instruments. The number of instruments used in system GMM is 76, which is much less than the total number of observations. Hansen's J tests fail to reject the null hypothesis of joint validity of all instruments at pretty high levels of significance. Therefore, conventional econometric diagnostics do not suggest any technical problems with system GMM estimation in our case.

Table 1 also presents values for the theoretical parameters derived from the estimated coefficients. We find that that coefficients at ln(s) and ln(n+g+δ) are not statistically different from each other in absolute terms, which is in line with the theoretical model (Equation 8). The estimated coefficient for the lagged GRP per capita implies the rate of convergence equal to 1.6% (per year).[7] This estimate is remarkably close to the 2% rate of the 'iron law' of convergence (Abreu, Groot & Florax, 2005; Barro, 2015; Gennaioli, La Porta & Schleifer, 2014), found across many regions and countries.

According to our estimates, physical capital share (α) in the output equals to 0.51, while human capital share (φ) equals to 0.21. As the theoretically grounded growth equation has been never estimated in Russia, we have no examples to compare. Mankiew, Romer & Weil (1992) find that $\alpha \approx \varphi \approx 0.33$.

Finally, we receive that the ratio of HC of immigrants versus natives (ε) is about 3. This suggests that the amount of human capital of moving Russians substantially exceeds the amount of human capital of those who do not migrate.[8] As ε >1, then according to our model, internal migration in Russia may have a positive impact on the output. Again, there are no previous studies on Russia that provide any reference base for our estimate of ε, while existing studies dedicated to internal migration usually do not measure human capital of migrants. Nonetheless, similar to other countries (e.g., see Lkhagvasuren, 2014), it is plausible to expect that internal migrants, on average, have higher amount of human capital than non-migrants.

5.2 Robustness Checks

To assess the stability of our main finings, we performed several robustness checks. None of them altered our results qualitatively.

Firstly, as mentioned above, we tried an alternative value of (g+δ). Using officially published data on stocks of physical capital for the beginning and end of each year and data on

[7] On the one hand, this is higher than the 1% rate typically found in earlier studies on convergence across Russian regions that cover the period from 1990s till about the first half of 2000s (e.g., Drobyshevsky et al., 2005; Kholodilin, Oshchepkov & Siliverstovs, 2012; Lugovoi et al., 2007). On the other hand, some more recent studies provide much larger estimates. For instance, Guriev & Vakulenko (2012) report 4.6% for the period 1995-2010, while Akhmedjonov et al., (2013) find 10% for the period 2000-2008. These results, however, are hardly comparable due to big discrepancies in methodologies.

[8] Dolado, Goria & Ichino (1994) provide estimates for ε ranging from 0.57 to 0.85 for migration between separate OECD countries, which suggests that those who move to another country, on average, have lower amount of human capital than native population. This is in line with a high amount of non-skilled migration from poorer to richer countries within Europe. Migration between Russian regions is the completely different case.

investments we estimated the average depreciation rate (δ) for the period under study equal to about 4% per year. Following Mankiew, Romer & Weil (1992), we also assumed that the rate of technological progress (g) in Russia may be equal to the average long-run growth rate (about 4%). This resulted in an estimate for $(g+\delta)=0.08$.[9]

Secondly, we tried alternative averaging procedures. We averaged all our variables over 6-year intervals instead of 3-year intervals and also we did not average at all, i.e., estimated all specifications using annual panel data as they are.

Thirdly, we used an alternative proxy for human capital, % of employed with higher education instead of employed in R&D sector.

Finally, when estimating specifications with spatial lags we tried alternative spatial weighting matrices (binary and road distance matrices instead of a matrix based on arc-distances).

5.3 What factors contribute to regional convergence?

At the next step, we examined the role of spatial effects, migration, and human capital in the convergence process. To do this, we exclude a corresponding factor from the complete model, estimate resulting specification and compare convergence rate from that specification with the rate derived from the complete model. Table 2 presents estimation results for three such specifications.

[Table 2 near here]

The exclusion of the spatial lag of grp per capita growth raises the estimate for the convergence rate from 1.6% to 1.9%. This suggests that the existing spatial correlation of grp growth among Russian regions contributes to economic convergence.[10] On the contrary, both migration and human capital appear to be strong factors of *divergence,* as the exclusion of them from the growth equation leads to both economically and statistically insignificant parameter of convergence.

6. Conclusion

In this paper, we studied convergence across Russian regions in per capita GRP for the period from 1996 to 2015. The key feature that distinguishes our study from many previous ones is that the empirical growth equation we use is firmly grounded in an extended Solow model,

[9] Alternatively, following a study by Turganbayev (2016) for Kazakhstan, we used the coefficient of liquidation of fixed assets (which equals in Russia to about 1% for the period under study) as a crude proxy for the depreciation rate. When we add it to our estimate for g, we receive the classic 0.05 value for $(g+\delta)$.

[10] Analyzing the period from 1996 to 2008, Kholodilin, Oshchepkov & Siliverstovs (2012) found that spatial effects contribute to divergence. That effect, however, was not economically meaningful (convergence rate altered from 1% to 0.9%).

where human capital and migratory flows are included as additional factors that have a major impact on growth. This allows us to justify the choice of regressors (see Durlauf & Quah, 1999) and derive a set of important theoretical parameters. Additionally, we examine the role of spatial effects in the convergence process.

Our estimate of the convergence rate is 1.6% per year, which suggests that the 2% "iron law" of conditional convergence found across countries may hold for Russia's regions as well. We also find that in the Russian case migration and human capital work as factors impeding convergence across regions. In addition, spatial effects also matter for the convergence process, since they contribute strongly to convergence.

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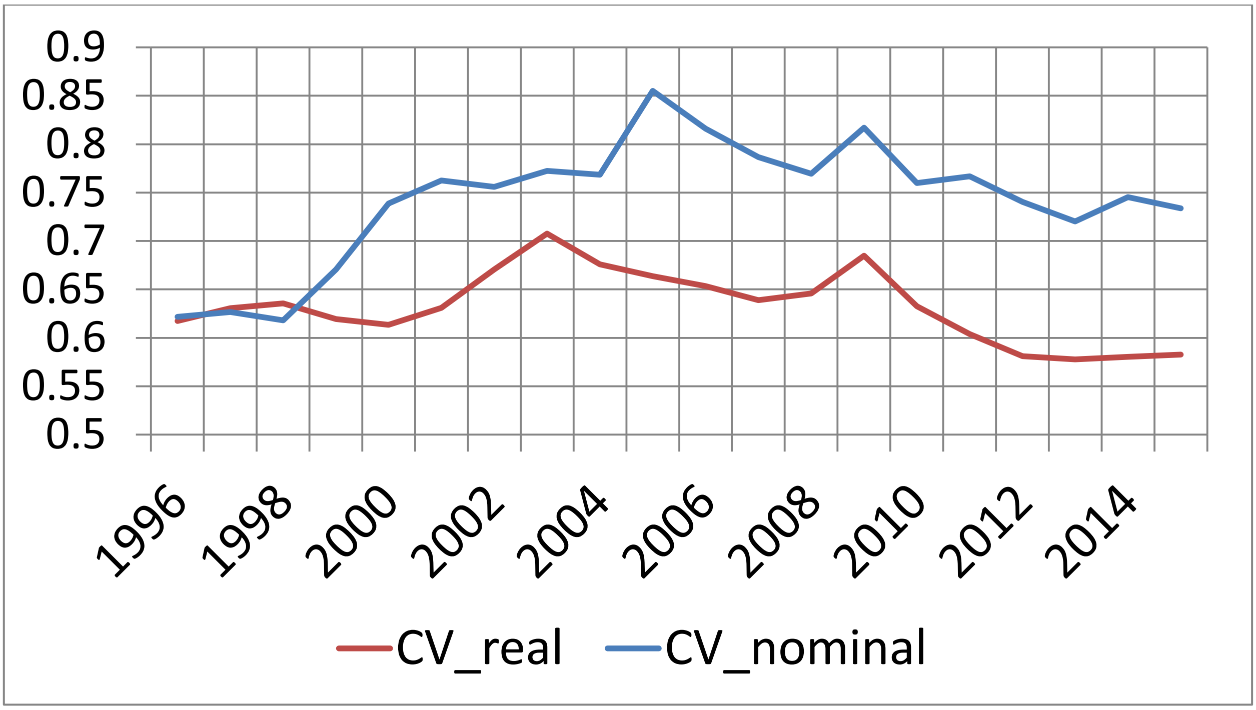
Figure 1

Coefficient of variation (CV) in per capita GRP of Russian regions (*σ-convergence*)



TABLES

Table 1. Growth equation for Russian regions (1996-2015).

DV: change in ln (grp per cap)	OLS	OLS with FE	System GMM
ln (initial grp per cap)	-0.005	-0.131***	-0.016**
	(0.004)	(0.022)	(0.008)
ln(s)	0.014	0.012	0.016
	(0.011)	(0.010)	(0.012)
ln(n+g+δ)	-0.013	-0.016	0.000
	(0.014)	(0.012)	(0.018)
ln(R&D pers)	0.004***	-0.004	0.007***
	(0.001)	(0.006)	(0.003)
migr	-0.028	-0.051*	-0.053
	(0.038)	(0.029)	(0.041)
spatial lag of ln gdp per cap growth	0.654***	0.561***	0.850***
	(0.180)	(0.205)	(0.213)
time effects	YES	YES	YES
region effects	NO	YES	YES
N	393	393	393
Theoretical parameters			
Implied convergence rate (%)	0.48	13.99	1.56
p-value of the F-test on ln(s) + ln(n+g+δ) = 0	0.9558	0.7682	0.4415
Implied α for physical capital	0.75	0.08	0.51
Implied φ for human capital	0.21	-0.03	0.23
Implied ε for migration	1.94	4.26	3.34

Notes: *** significant at 1% level; ** - significant at 5% level; * - significant at 10% level; all variables are averaged over 3-year periods.

Table 2. Exploring factors of convergence of Russian regions (1996-2015).

DV: change in ln grp per cap	Full model	Model without… spatial effects	migration	HC
ln (initial grp per cap)	-0.016**	-0.019**	-0.001	-0.008
	(0.008)	(0.008)	(0.009)	(0.009)
ln(s)	0.016	0.019	0.004	0.015
	(0.012)	(0.012)	(0.011)	(0.012)
ln(n+g+δ)	0.000	-0.011	-0.037	-0.001
	(0.018)	(0.019)	(0.023)	(0.017)
ln(R&D pers)	0.007***	0.008***	0.003	
	(0.003)	(0.003)	(0.003)	
migr	-0.053	-0.047		-0.045
	(0.041)	(0.041)		(0.042)
spatial lag of ln gdp per cap growth	0.850***		0.838***	0.845***
	(0.213)		(0.222)	(0.227)
time effects	YES	YES	YES	YES
region effects	YES	YES	YES	YES
N	393	393	393	393
Theoretical parameters				
Implied convergence rate (%)	1.56	1.90	0.06	0.77
p-value of the F-test on ln(s) + ln(n+g+δ) = 0	0.4415	0.7021	0.2119	0.4586
Implied α physical capital	0.51	0.51	0.87	0.66
Implied φ for human capital	0.23	0.21	0.57	
Implied ε for migration	3.34	2.40		3.00
GMM-related parameters				
N of instruments	76	62	62	62
AB test for AR(1): p-value	0.000	0.000	0.000	0.000
AB test for AR(2): p-value	0.118	0.316	0.111	0.123
Hansen's J test				
Chi-sq (df)	69.11 (64)	54.31(51)	50.55(51)	49.13 (51)
p-value	0.309	0.349	0.492	0.548
Diff-in-Hansen J test				
Chi-sq (df)	41.03 (44)	20.58 (16)	17.67(16)	17.71 (16)
p-value	0.600	0.195	0.344	0.341

Notes: *** significant at 1% level; ** - significant at 5% level; * - significant at 10% level; all variables are averaged over 3-year periods. Estimation method for all specifications: system GMM.