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Estimating a Comprehensive Model of Russian Regional Convergence¹

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Abstract

In this paper, we study convergence in per capita GRP across Russian regions in the period from 1996 to 2015. To this purpose, we estimate growth equations, which are directly derived from a neoclassical growth model, augmented with human capital and migration. To our knowledge, this is the first paper on regional convergence in Russia that arrives at estimable growth functions using such a derivation explicitly. We also include a term for spatial interdependencies of the growth experience of Russian regions. Our main estimates establish a convergence rate of 1.6% per year. According to our findings, human capital together with interregional migration work as factors impeding convergence between Russian regions. On the other hand, spatial interdependencies between Russian regions contribute to convergence, albeit only marginally.

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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 country² have gross regional products per capita (in purchasing power parity) that reach levels of rich developed economies while the bottom five regions³ 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 very selective as it refers to those papers that strike us as particularly relevant for our study. We look at important and state-of-the-art papers that discuss regional convergence in general and that have migration and spatial correlations as a focus, and at studies that have Russian convergence as their theme.

2.1 Migration and spatial correlations as a focus in the general literature on convergence

Many early papers on regional convergence in the context of capitalist economies, which have migration as an important driver, take their inspiration from the seminal paper by Barrow and Sala-i-Martin (1991). It strikes us, therefore, as worthwhile to set the stage by presenting their main cross section equation, which many authors have estimated with different data sets. This equation looks in a generic fashion as follows:

$$\left(\frac{1}{T}\right) \log \left(\frac{y_{r,t}}{y_{r,t-T}}\right) = \alpha - \left[\frac{1-e^{-\beta T}}{T}\right] [\log(y_{r,t-T})] + \gamma m_{r,t} + x_{r,t} + \varepsilon_{r,t} \quad (0),$$

where $y_{r,t}$ is the per capita income in region r in the 12 months ending at date t ; T is the number of years spanned by the data, while β is the annual rate at which the economy of the region converges to its own long-run state and γ is the coefficient of the annual net migration rate $m_{r,t}$. In addition, the variable $y_{r,t-T}$ is per capita income in region r at the beginning of the period, x is a vector of other control variables and $\varepsilon_{r,t}$ is a white noise error term.

The authors analyze and estimate the rate of convergence β , that is, the rate at which actual income per capita or GDP per capita approaches its steady state. In a neoclassical growth model

the convergence coefficient depends on the productivity of capital and the level of saving. The principal innovation in the studies of Barrow and Sala-i-Martin is to put migration as an important focus of the analysis. In a neoclassical framework with homogeneous labor, positive net migration will increase the rate of convergence since labor will migrate from poor to rich countries or regions because of higher wage rates. Positive net migration will lower the capital-labor ratio in this scenario, hence the productivity of capital will be diluted and diminishing returns to capital per worker will set in more rapidly, leading *ceteris paribus* to a higher convergence coefficient. When labor is not homogeneous and migrants bring with themselves human capital and raise the productivity of capital, positive net migration can contribute to divergence. The authors then provide a careful analysis of the empirical patterns of convergence and of net migration across the 48 U.S. continental states, using 10 year-intervals for the most part with data from 1900 to 1988 and taking account of endogeneity issues connected with migration. The upshot of their results can be summarized as follows: convergence of income per capita proceeds at around 2 percent, and migration contributes very marginally to this convergence. The authors get qualitatively similar results when looking at convergence of gross state product, for which they only have data from 1963 to 1986. The empirical analysis of convergence across 74 regions within the European Union also confirms the results gotten for the United States.

The paper by Ozgen, Nijkamp and Poot (2010) performs a meta-analysis of studies that assess the effect of net internal migration on income growth and conversion. Their analysis is rigorous and consistent insofar as the authors only take papers into their sample that estimate cross section equations essentially identical to the one developed by Barrow and Sala-i-Martin. Spending considerable time to address the various pitfalls of meta-analysis – for example, they investigate publication bias very carefully – the authors look at 67 comparable effect sizes of β and γ from 12 studies. They summarize their results in the following way: “As a result of synthesizing the empirical work, we conclude that the overall effect of net migration on growth is positive, but small. A one percentage point increase in the net migration rate [.....] increases the rate of growth in per capita income by 0.1 percentage points.” This summarized evidence of the 12 studies implies that in contrast to the results found by Barrow and Sala-i-Martin internal net migration contributes to divergence rather than convergence, albeit in a very marginal fashion.

The two papers that are closest to our approach are by Dolado, Goria and Ichino (1994) and by Boubtane, Dumont and Rault (2016). The earlier study by Dolado et al. was the first to develop a structural growth model that introduced migration as a factor of growth and was augmented by human capital. The authors then estimated this model using data from 23 OECD countries for the

period between 1960 and 1985. Having acknowledged the seminal contribution by Dolado et al., we, however, prefer to concentrate on the second study by Boubtane et al., which has an identical approach, but has empirical evidence that is more credible and also more relevant for our study. For, this second study, by employing system GMM estimation, uses more appropriate techniques to take account of the endogeneity issues connected to migration. In addition, in the past internal migratory flows were one order of magnitude larger than cross-country migration. Only since the 1980s do we see international migration surge dramatically. Boubtane et al. use data from 22 OECD countries in the years 1986 to 2006, when international migratory flows were large and a substantial part of migrants had high skill levels. In contrast, the period under investigation by Dolado et al. was characterized by relatively limited international migration and most of the migrants were unskilled and working in the manufacturing sector. Hence looking at the evidence from Boubtane et al. strikes us as more informative.

Their theoretical model highlights the ambiguous effect of net migration on growth; this effect depends on the relative human capital contribution of foreign- and native-born migrants, net migration rates of foreign-born and natives as well as on the parameters of the production function. In the augmented Solow model there are, as already stated above, two countervailing forces brought on by positive net migration: capital dilution as more workers are spread over the existing capital stock, and the contribution of migrants to the accumulation of human capital, which increases the productivity of capital. Only if the latter factor dominates the former will migration positively affect growth. The careful econometric analysis leads the authors to arrive at the following central conclusion: “The results show that in the short run, taking into account the skill composition of foreign-born migrants, a 50% increase in the net migration rate of foreign-born migrants would increase GDP per worker by three-tenths of a percentage point per year [.....]. The long-run effect of foreign-born migration on GDP per worker is, on average 2 % per year.”

The second strand of literature, which is particularly relevant for our study, deals with spatial effects when analyzing regional convergence. Not taking into account these spatial effects, leads to omitted variable bias and thus to misleading inferences about regional convergence. The paper by Rey and Montouri (2010) demonstrates this for the convergence process in the United States in an exemplary fashion. The authors undertake a very careful analysis of the question whether per capita income growth is clustered in groups of states, that is, whether there is spatial autocorrelation in the regional income per capita data. They find very convincing evidence that this is indeed the case and conclude that empirical models of regional convergence that ignore these spatial effects are clearly misspecified. Employing data from 1929 to 1994, they estimate

an average rate of convergence of roughly 2 % when spatial effects are ignored, while this estimate is lower when the convergence rate is estimated with a maximum likelihood spatial error model. Goodness of fit tests in the form of the Akaike Information Criterion show that the spatial error model fits the data best, implying that the models à la Barrow and Sala-i-Martin are misspecified due to omitted spatial dependence. Modelling this spatial dependence is hence crucial when one wants to arrive at unbiased estimates of regional convergence.

Econometric issues are at the center of the paper by Badinger, Müller and Tondl (2004) who discuss the need to develop models that take account of both spatial dependence and endogeneity issues when estimating regional convergence of pro capita income. Using data from 212 NUTS 2 European regions for the years 1985 to 1999 the authors proceed in two steps: first they filter out the spatial effects from the data, then they apply standard estimators for dynamic panel data. In their illuminating econometric exercise they show that neglecting spatial dependence leads to an implausible convergence coefficient that implies divergence, while applying a GMM estimator in first differences or a system GMM estimator leads to a convergence coefficient that implies convergence. The authors also provide evidence that the GMM estimator in first differences might be plagued by weak instruments and that the system GMM estimator should be preferred when estimating regional convergence.

2.2 Relevant papers from the literature on regional convergence in Russia

We begin with a very recent and general paper by Durand-Lasserve and Blöchliger (2018) on regional convergence in Russia. The authors estimate an empirical error-correction model that in its essence is based on the results of an exploratory analysis of the drivers of regional disparities in Russia and uses official Rosstat regional data for the period 2004 – 2015. To address endogeneity issues and omitted variable bias, they employ system GMM estimation and include regional fixed effects in their specifications. Their results imply a convergence rate of gross regional product which is around 2% and thus in line with the “iron law of convergence” highlighted by Barrow (2015). One central result of their regressions points to the importance of human capital for regional growth.

The paper by Guriev and Vakulenko (2012) comes to different conclusions regarding convergence. The authors 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 large 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 paper by Vakulenko (2016) also has its focus on migration as it analyzes the impact of migration on wages, income and the unemployment rate at the regional level. Using data from 1995 to 2010, the author estimates a dynamic panel data model, which includes spatial effects. Her main result states that migration does not affect regional sigma-convergence in any meaningful way.

The study by Ivanova (2018) finds convergence of real wages; however, she analyzes 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 turn 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

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 of Russia's regions. Lehmann and Silvagni (2012), straddling the years 1995 – 2010 in their estimations, also establish divergence, albeit weak, of gross regional product per capita in Russia.

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 model of regional convergence is based on the classic Solow model (Solow, 1956) augmented with human capital (Mankiw, Romer & Weil, 1992) and migration (Dolado, Goria & Ichino, 1994). 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:

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

L grows with rate (n + m):

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

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. Immigration increases the amount of human capital in the region if $\varepsilon > 0$.⁵

⁵ Following Dolado, Goria & Ichino (1994), migrants are not assumed to bring significant amounts of physical capital with them.

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

$$y = hc^\varphi \cdot k^\alpha \quad [5]$$

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

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

Equations 6 and 7 suggest that immigration has a negative impact on economic growth in the region as migration contributes to the overall population growth ($n + m$), which, in turn, impedes the accumulation of both physical and human capital (per effective labor). As a result, migration from poor to rich regions should contribute to regional convergence, which is the standard prediction of a neoclassical growth theory (see Barro & Sala-i-Martin, 2004).

However, Equation 7 indicates that when $\varepsilon > 1$, migration starts to increase the stock of human capital in a region. Moreover, when $\varepsilon > 2$ and $> n$, i.e., when the immigration rate is larger than the native population growth rate, the positive impact of immigration on human capital counterbalances the negative impact of the total population growth. As a result, immigration will have a positive influence on economic growth (per effective labor), which means that interregional migration may impede regional convergence.

Equations [6] and [7] imply steady state levels of physical and human capital (when $\dot{k} = 0$ and $\dot{hc} = 0$) as follows:

$$k^* = \left(\frac{s_k}{g + \delta_k + n + m} \right)^{\frac{1-\varphi}{1-\alpha-\varphi}} \left(\frac{s_{hc}}{g + \delta_k + n + m(1-\varepsilon)} \right)^{\frac{\varphi}{1-\alpha-\varphi}} \quad [8]$$

$$hc^* = \left(\frac{s_k}{g + \delta_k + n + m} \right)^{\frac{\alpha}{1-\alpha-\varphi}} \left(\frac{s_{hc}}{g + \delta_k + n + m(1-\varepsilon)} \right)^{\frac{1-\alpha}{1-\alpha-\varphi}} \quad [9]$$

Substituting [8] and [9] into the production function [5] and taking logs (and assuming that $\delta_{hc} = \delta_k$) gives steady state output per capita:

$$\begin{aligned} \ln(y^*) = & \frac{\alpha}{1-\alpha-\varphi} \ln(s_k) + \frac{\varphi}{1-\alpha-\varphi} \ln(s_{hc}) - \frac{\alpha}{1-\alpha-\varphi} \ln(g + \delta + n + m) - \\ & - \frac{\varphi}{1-\alpha-\varphi} \ln(g + \delta + n + m - \varepsilon \cdot m) \quad [10] \end{aligned}$$

The last term may rewritten as

$$\begin{aligned} \frac{\varphi}{1-\alpha-\varphi} \ln(g + \delta + n + m - \varepsilon \cdot m) = & \frac{\varphi}{1-\alpha-\varphi} \ln \left((g + \delta + n + m) \cdot \left(1 - \frac{\varepsilon \cdot m}{g + \delta + n + m} \right) \right) = \\ & \frac{\varphi}{1-\alpha-\varphi} \ln \left((g + \delta + n + m) \right) + \frac{\varphi}{1-\alpha-\varphi} \ln \left(1 - \frac{\varepsilon \cdot m}{g + \delta + n + m} \right) \quad [11] \end{aligned}$$

Further, assuming that $\ln(1-x) \approx -x$, the steady state output per capita is:

$$\begin{aligned} \ln(y^*) = & \frac{\alpha}{1-\alpha-\varphi} \ln(s_k) + \frac{\varphi}{1-\alpha-\varphi} \ln(s_{hc}) - \frac{\alpha + \varphi}{1-\alpha-\varphi} \ln(g + \delta + n + m) - \\ & - \frac{\varphi}{1-\alpha-\varphi} \cdot \varepsilon \cdot \frac{m}{g + \delta + n + m} \quad [12] \end{aligned}$$

Finally, as noted by Mankiew, Romer & Weil (1992), Equation [12] may be rewritten in terms of human capital stock:

$$\ln(y^*) = \frac{\alpha}{1-\alpha} \ln(s_k) + \frac{\varphi}{1-\alpha} \ln(hc^*) - \frac{\alpha}{1-\alpha} \ln(g + \delta + n + m) - \frac{\alpha}{1-\alpha} \cdot \varepsilon \cdot \frac{m}{g+\delta+n+m} \quad [13]$$

In practice, the choice between Equation [12] and Equation [13] should depend on “whether the available data on human capital correspond more closely to the rate of accumulation or to the level of human capital.” (Mankiew, Romer & Weil, 1992, p.418).

The pace of convergence of output to its steady state level is given by:

$$\ln(y_t) - \ln(y_{t-1}) = (1 - e^{-\lambda\tau})(\ln(y^*) - \ln(y_{t-1})) \quad [14]$$

where τ the period between moment t and $t-1$; λ is the rate of convergence.

Finally, the theoretical growth equation capturing the dynamics toward the steady state is:

$$\begin{aligned} \ln(y_t) - \ln(y_{t-1}) = & -(1 - e^{-\lambda\tau}) \ln(y_{t-1}) + (1 - e^{-\lambda\tau}) \frac{\alpha}{1-\alpha} \ln(s_{kt}) + \\ & + (1 - e^{-\lambda\tau}) \frac{\varphi}{1-\alpha} \ln(hc_t) - (1 - e^{-\lambda\tau}) \frac{\alpha}{1-\alpha} \ln(g + \delta + n + m) + (1 - e^{-\lambda\tau}) \frac{\alpha}{1-\alpha} \varepsilon \cdot migr_t + \\ & + (1 - e^{-\lambda\tau}) \ln(A_0) + v_t \quad [15] \end{aligned}$$

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

4. Methodology and Data

4.1 Methodology

Our theoretical model (Equation 15) may be rewritten as a regression as follows:

$$\begin{aligned} \Delta \ln(y_t) = & \beta \ln(y_{t-1}) + \beta_1 \ln(s_{kt}) + \beta_2 \ln(hc_t) - \beta_3 \ln(g + \delta + n + m) + \\ & + \beta_4 migr_t + regionFE + TimeFE + v_t \quad [16] \end{aligned}$$

Compared to the theoretical model, this equation includes two additional variables, *regionFE* and *TimeFE*, reflecting regional and time fixed effects, respectively. Since the seminal paper by Islam (1995) it is common practice to include into empirical growth equations region (or country) fixed effects, which allows to control for unobserved heterogeneity of regions. More specifically, regional FE control for unobserved interregional differences in the initial levels of technological development ($\ln(A_0)$ in Equation 15) as well as other differences, like resource endowments and geo-climatic conditions; on this see Islam (2003). Not taking into account unobserved heterogeneity results in an upward bias in the OLS estimate of β , which implies an underestimated rate of convergence.

Time fixed effects, in turn, allow to control for the influence of macroeconomic shocks (either positive or negative) affecting all regions in the country. This can be especially important in the Russian case, since the period that we consider, 1996-2015, includes both economic crises

and recoveries, including the since 2014 on-going period of sanctions and anti-sanctions. Moreover, time fixed effects can in principle control for possible changes in the statistical methodology of calculation of variables by Rosstat.⁶

Although the inclusion of regional FE helps to avoid the omitted variable bias in Equation (9), it creates a bias of another sort. Regional fixed effects 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; Nickell, 1981). To avoid this bias, we estimate Equation 16 by system GMM (Arrelano & Bover, 1995; Blundell & Bond, 1998), which has become the most popular approach to estimate dynamic panel data models, as it is more efficient than the Arrelano-Bond method (Arrelano & Bond, 1991).

The estimation procedure involves two steps. As a first step, Equation 16 is first-differenced. As a second step, the 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. Apart from traditional Sargan-Hansen tests (see Roodman, 2009a), the important diagnostic in this case involves the tests for autocorrelation of the residuals. While residuals of the differenced equation should follow an AR(1) serial correlation process, they should not exhibit an AR(2) process, since in this case the second lags may not serve as valid instruments for current values.

There are also three additional issues related to the estimation of Equation 16. The first issue concerns parameters g and δ . Following Mankiew, Romer & Weil (1992), many existing studies on convergence across different countries or regions assume $g + \delta = 0.05$. Although we are not aware of studies that justify the use of such an assumption in the Russian case, we are aware of, at least, one study that applies this assumption to study convergence across Russian regions (Zemtsov & Smelov, 2018). We also assume $g + \delta = 0.05$ in our main regressions, but as a robustness check we use alternative values to see whether the estimated results change in this case.

The second 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, for example Barro & Sala-i-Martin, 1991). A panel data setting allows averaging 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 enables us to make results less vulnerable to potential data errors. On the other hand, as

⁶ 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).

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 a 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.

Finally, the third issue relevant in the Russian context relates to large price differentials across regions. However, some previous studies show that possible adjustments of regional GDPs for price differentials almost do not affect neither the scale of variation in GDP nor the relative order of regions and have almost no effect on convergence results. (e.g., see Kholodilin, Oshchepkov & Siliversotvs, 2012; Durand-Lasserve & Blöchliger, 2018). Therefore, for the sake of simplicity, we use regional GDPs without price corrections.

The estimated coefficients from Equation 16 allow us to derive a set of crucial theoretical parameters. First of all, we are interested in the convergence rate $\lambda = \frac{-\ln(1+\beta)}{t}$. We can also derive the physical capital share $\alpha = \frac{\beta_1}{\beta+\beta_1}$, the human capital share $\varphi = \frac{\beta_2}{\beta}(\alpha - 1)$, and the ratio of human capital of immigrants versus that of natives $\varepsilon = \frac{\beta_4}{\beta_1}$.

Following existing studies on convergence in 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 16 extended with a spatial lag of the dependent variable:

$$\Delta \ln(y_t) = \beta \ln(y_{t-1}) + \beta_1 \ln(s_t) + \beta_2 \ln(HC_t) - \beta_3 \ln(n + g + \delta) + \beta_4 \text{migr}_t + \text{region FE} + \\ + \text{Time effects} + \beta_5 W \cdot \Delta \ln(y_t) + v_t \quad [17]$$

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 closer 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, as suggested by studies reviewed in Section 2.1.

The spatial lag of the 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 (quasi-) maximum likelihood estimation. Two different realizations of this approach 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).⁷

In our study, we choose the second approach, system GMM, as it is best suited in cases when there are other potential endogenous variables in addition to a spatial lag of the dependent variable (see Kukenova & Monteiro, 2009, for more details). In our case, all RHS variables may be potentially endogenous, especially immigration or human capital. By using system GMM as our estimation method, we generate consistent estimates of the coefficients on all potentially endogenous variables.⁸⁹

4.2 Data

In this paper, we analyze convergence among Russian regions using data for the longest period available, from 1996 to 2015. Like traditionally done in papers on Russia, we exclude Chechnya from the analysis. Most variables we use come from Rosstat regional statistics, i.e., the statistical yearbooks “*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 kapital*) and divide it by GPR. For human capital we use two alternative measures. First, employment in the R&D sector, and second, the percentage of employed having higher education. We normalize both variables by total population. As a measure of net immigration into a region we use the coefficient of net migration, which is calculated as 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 the specification of Equation 17, which does not include regional fixed effects (Column 1). In this case, the OLS estimate of the coefficient on lagged GRP per capita is

⁷ Badinger, Mueller & Tondl (2004) combine system GMM with ‘spatial filtering’.

⁸ In the Russian context, system GMM has been applied by Buranshina & Smirnykh, 2018; Vakulenko (2016); World Bank (2017).

⁹ In practical terms, we estimate Equations 9 and 10 in STATA using –the `xtabond2`- module proposed by Roodman (2009b).

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 the coefficient on lagged GRP per capita becomes highly significant and large in absolute terms (-0.131), which implies an implausible convergence rate among Russian regions of 14% per year. Such a sharp increase in this coefficient after the inclusion of regional FE is 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 avoids the Nickel bias. The estimate of the coefficient on lagged GRP per capita is -0.016 and statistically significant at the 5% level. To maintain uniformity in the rows of Table 1, we present all the test parameters in connection with the application of the system GMM at the bottom of the first column of Table 2.

The AR tests for autocorrelation of the residuals suggest that residuals follow an AR(1) process but do not exhibit an 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 $\ln(n+g+\delta)$ are not statistically different from each other in absolute terms, which is in line with the theoretical model (Equation 15). The estimated coefficient on lagged GRP per capita implies a rate of convergence equal to 1.6% per year.¹⁰ 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, the share of physical capital in output (α) equals 0.51, while the share of human capital (φ) is equal to 0.21. As theoretically grounded growth equations have not been estimated for Russia before, we cannot rigorously compare our estimates to previous ones as far as results for Russia are concerned. However, estimated measures in the literature are

¹⁰ 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 larger estimates. For instance, Durand-Lasserve & Blöchliger (2018) find about 2.5%, 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.

close to ours. Durand-Lasserve & Blöchliger (2018) estimate a version of the Cobb-Douglas production function for cross-sections of Russian regions in 2005 and 2015 and establish α to be equal to about 0.5. At the same time, according to statistics of the national accounts of Rosstat, in the period 2006-2013 the physical capital share in Russia was in the range from 0.29 to 0.35 with the average value of 0.32. If the share of tax incomes is equally distributed between the shares of labor and physical capital, this increases the share of physical capital up to 0.42. Our estimates are also remarkably close to the estimates by Mankiew, Romer & Weil (1992) who obtained $\alpha=0.48$ and $\varphi=0.23$ for a sample of 98 countries, and $\alpha=0.38$ and $\varphi=0.23$ for the sub-sample of 22 OECD countries.¹¹

Finally, our estimates imply that the ratio of human capital of immigrants versus that of natives (ε) is about 3. This suggests that the amount of human capital coming with migrants from other regions substantially exceeds the amount of human capital of the native population.¹² As $\varepsilon > 1$, then, according to our model, interregional migration in Russia may have a positive impact on the output of the receiving (relatively rich) region and thus impede economic convergence between regions. Again, there are no previous studies on Russia that provide any benchmark 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 interregional movers in Russia have, on average, a higher amount of human capital than non-movers in receiving regions.

5.2 Robustness Checks

To assess the stability of our main findings, we performed several robustness checks. None of them altered our results qualitatively. First, as mentioned above, we try an alternative value of $(g+\delta)$. Using officially published data on stocks of physical capital for the beginning and end of each year and data on investments we estimate the average depreciation rate (δ) for the period under study to equal 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, which is about 4%. This results in an estimate for $(g+\delta)$ of 0.08.¹³ As a second robustness check, we exclude the period from 1996 to 1999 from our analysis as the Russian

¹¹ As labor share was declining over last years in most developed countries (e.g., see OECD, 2018), one may expect that these estimates for capital share for the current period should be higher.

¹² Dolado, Goría & Ichino (1994) provide estimates for ε ranging from 0.57 to 0.85 for immigration in OECD countries, which suggests that those who move to OECD countries, on average, have lower amount of human capital than native population. However, we may expect that for migration within one country ε should be higher.

¹³ 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 $(g+\delta)$.

economy was exposed in these years to strong and systemic negative transition shocks. Third, we use an alternative proxy for human capital, the percent of employed with higher education instead of the employed in the R&D sector. Finally, when estimating specifications with spatial lags we tried alternative spatial weighting matrices, namely 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 the resulting specification, and compare the convergence rate from that specification with the rate derived from the complete model. Table 2 presents estimation results for three such specifications. In column 1, we repeat the GMM estimates and the implied theoretical parameters of the full specification shown in Table 1.

[Table 2 near here]

We find that the exclusion of the human capital proxy from the full specification leads to a significant decrease in the coefficient on the lagged value of *grp* per capita. This is in line with the original study by Mankiew, Romer & Weil (1992), who show that the inclusion of a human capital proxy leads to faster rate of convergence. This implies that human capital is a factor of divergence. It is also noteworthy that the exclusion of human capital leads to a larger implied α : while in the full specification $\alpha = 0.51$, in the specification without the human capital proxy α becomes 0.66. Such an increase in α is again in line with the seminal study by Mankiew, Romer & Weil (1992).

As Table 2 shows, the exclusion of the migration variable from our complete equation leads to both an economically and statistically insignificant parameter of convergence. This suggests that migration is a strong factor of *divergence* in the Russian case, which is consistent with the high estimate of ε in the full model. This result differs from that of Vakulenko (2016), who finds that migration has no impact on income convergence between Russian regions in the period 1995-2010. However, our result is qualitatively similar to results of some cross-national studies (e.g., Boubtane, Dumont & Rault, 2016; Huber & Tondl, 2012).

Finally, we find that 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 means that the existing spatial correlation of GRP growth among Russian regions contributes to their economic convergence. This, in turn, suggests that economic growth in regions with relatively high level of GRPs tend to spill over to regions with relatively low levels of GRP. This effect, however, is not ‘economically’ strong.

6. Summary and Conclusions

In this paper, we studied convergence in per capita GRP across Russian regions in the period from 1996 to 2015, the longest period for which data are available. The key feature that distinguishes our study from many previous ones is that we estimate growth equations that are directly derived from the classic Solow model, augmented with human capital and migration. Therefore, our paper presents, strictly speaking, the first empirical test for the applicability of the standard growth model to Russian regional economic development. Estimating theoretically grounded equations allows us to justify the choice of explanatory variables, and thus avoid the criticism raised about *ad hoc* approaches to specifying empirical growth equations, as voiced by Durlauf and Quah, 1999; and Durlauf, Kourtellos & Tan, 2008, among others. Our estimates also allow us to derive a set of plausible parameters of the augmented growth model.

Our main specification provides an estimate for convergence rate equal to 1.6% per year, which is remarkably close to the 2% “iron law” of (conditional) convergence. In our view, this finding suggests that the general (long-run) dynamics of the economic development of Russian regions may be analyzed within the framework of a neoclassical growth model, despite existing strong structural differences between Russian regional economies.

According to our estimates, human capital together with interregional migration work as factors impeding convergence between Russian regions. In contrast, spatial interdependencies between Russian regions contribute to convergence, although their effect is not economically strong.

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Figure 1

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

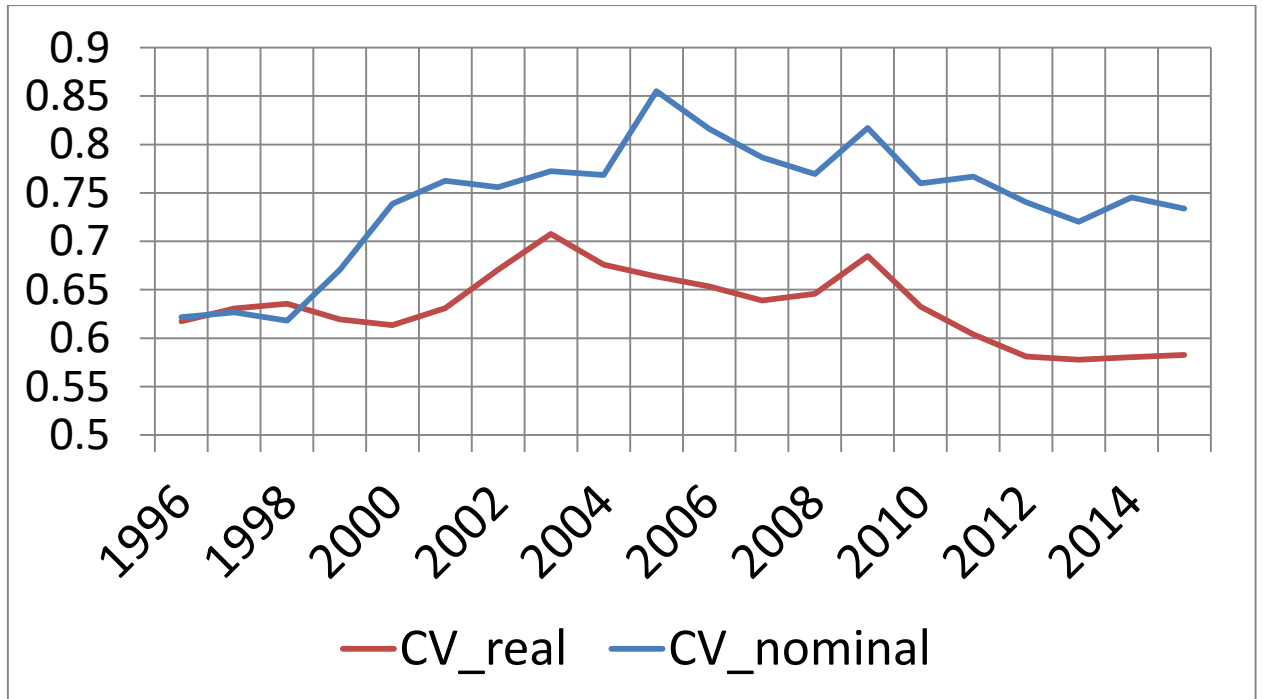


Table 1. Estimated growth equation for the panel of Russian regions (1996-2015).

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
<i>Theoretical parameters</i>			
Implied convergence rate (%)	0.48	13.99	1.56
p-value of the F-test on $\ln(s) + \ln(n+g+\delta) = 0$	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. Standard errors robust to heteroscedasticity and clusterization within regions are in parentheses. All variables are averaged over 3-year periods.

Table 2. Estimated growth equation for the panel of Russian regions (1996-2015) without human capital, migration, or spatial effects.

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

Notes: *** significant at 1% level; ** - significant at 5% level; * - significant at 10% level. Standard errors robust to heteroscedasticity and clusterization within regions are in parentheses. All variables are averaged over 3-year periods. Estimation method for all specifications: system GMM.