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Regional per capita income differences: Spatial and hierarchical dependencies

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ABSTRACT
Relevance. Regional differences in per capita income are a matter of concern for many countries for many reasons, including the threat that such regional disparities pose to national security. Multiple tools and methods are used to investigate these disparities and fix them. The use of lower level aggregated data and the analysis that takes into account spatial interactions thus become particularly relevant because it allows us to reveal the diversity of interactions at the micro-level.
Research objective. This study aims to determine the significance of spatial relationships at different levels of data aggregation and hierarchical dependencies in per capita income and highlight the level of administrative division (regional or municipal) that has the greatest impact on per capita income.
Methods and data. The analysis relies on the data from 2,270 municipalities in 85 Russian regions. The Hierarchical Spatial Autoregressive Model (HSAR) was used to distinguish both spatial and hierarchical effects. We used three specifications of the model: with estimates of the spatial interaction on the higher level (spatial error at the regional level), on the lower level (spatial lag at the municipal level), and on both levels.
Results. Spatial interactions explain the observed variation of per capita income at the municipal level data at both the higher (regional) and lower (municipal) levels but the model with the estimated spatial interaction on the higher level was better.
Conclusion. Despite the importance of spatial interactions at the lower level, models that take into account spatial interactions only at the upper level may better explain the observed differences in some cases. Our findings contribute to the rather scarce research literature on spatial relationships on several levels of administrative division. We have shown that for each specific case it is important to identify not only the factors but also the spatial effects in relation to this or that level of the territorial hierarchy.

KEYWORDS
per capita income, municipal economy, regional economy, spatial effects, hierarchical effects, HSAR

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Региональные различия в доходах на душу населения: пространственные и иерархические зависимости

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АННОТАЦИЯ
Актуальность. Региональные различия в доходах на душу населения беспокоят многие страны, в том числе из-за угрозы национальной безопасности. В поисках путей снижения дифференциации доходов разрабатываются новые инструменты и методы. Среди направлений совершенствования инструментальной базы анализа выделяются переход на менее агрегированные данные и включение в оценку пространственных взаимодействий, которые в совокупности позволяют увидеть и учесть все многообразие проявления экономических явлений на микроуровне.
Цель исследования. Это исследование направлено на определение значимости пространственных связей на разных уровнях агрегации данных, иерархических зависимостей в доходах на душу населения и выделение уровня административного деления (регионального или муниципального), оказывающего наибольшее влияние на его изменение.

КЛЮЧЕВЫЕ СЛОВА
среднедушевой доход, городское хозяйство, региональная экономика, пространственные эффекты, иерархические эффекты, HSAR

БЛАГОДАРНОСТИ
Работа выполнена при выполнении государственного задания Министерства науки и высшего образования Российской Федерации (шифр FZWU-2020-0027).

Данные и методы. Анализ проводился на данных 2270 муниципальных образований в разрезе 85 субъектов Российской Федерации. Для выделения пространственных и иерархических эффектов применялась иерархическая пространственная модель (HSAR) в трех спецификациях: с оценками пространственного взаимодействия на верхнем уровне (пространственная ошибка на региональном уровне), нижнем уровне (пространственное отставание на муниципальном уровне) и на обоих уровнях.
Результаты. Пространственные эффекты объясняют наблюдаемую вариацию муниципальных образований по доходам на душу населения как на верхнем (региональном), так и на нижнем (муниципальном) уровнях, но модель с оценкой пространственного взаимодействия на верхнем уровне имеет более высокое качество.
Выводы. Несмотря на важность пространственных взаимодействий на нижнем уровне, модели, учитывающие пространственные взаимодействия только на верхнем уровне, в некоторых случаях могут лучше объяснить наблюдаемые различия. Этот вывод позволяет дополнить достаточно редкие и дискуссионные исследования пространственных отношений, учитывающих зависимости одновременно на нескольких уровнях административного деления. Он показывает, что каждый случай нуждается в конкретизации не только факторов, но пространственных эффектов применительно к уровню территориальной иерархии.

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人均收入地区差异：空间和等级的依赖性

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摘要
现实性：人均收入的地区差异是许多国家关注的问题，因为这对国家安全存在威胁。为了缩减收入差异，很多国家正在开发新的工具和方法。本文在改进分析工具时，关注到以前较少汇总的数据，并将空间相互作用纳入评估。这些都使我们有可能在微观层面看到和考虑经济现象的所有表现形式。
研究目**标：**本研究旨在确定不同数据集合中空间的重要性，以及等级依赖对人均收入的决定性。并且会对人均收入差异影响最大的行政区域进行区分确定。
数据和方法：分析基于俄罗斯联邦 85 个组成实体的2270 个城市数据。为了突出空间和层次效应，研究在三个方面使用异质性空间自回归模型（HSAR）：上层的空间相关性（区域级别的空间误差），下层的空间相关性（城市级别的空间滞后）以及两个层级的空间相互作用。
研究**结果：**空间分析解释了上层（区域级别）和下层（城市级别）的人均收入变化。模型显示上层的空间交互效率更高。
结论：尽管下层空间交互作用很重要，但仅考虑上层空间交互作用的模型在某些情况下可以更好地解释观察到的差异。这一结论使得相当罕见和有争议的空间关系研究成为可能。而研究也同时考虑了多个行政区划级别的依赖关系。它表明，每个案例不仅需要说明具体因素，还需要描述与地域等级相关的空间效应。

关键词
人均收入，城市经济，区域经济，空间效应，等级效应，异质性空间自回归模型

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Introduction

Concerning the problem of regional disparities, the disparities in the level of income are among the most widely discussed economic problems (Malkina, 2014), because they are perceived as a threat to economic security (Kupreshchenko & Fedotova, 2016).

In Russia, there is a serious problem of regional per capita income differentiation (Malkina, 2014; Zubarevich & Safronov, 2019). The analysis of the data for 2004–2012 showed that 'an increase in intraregional differentiation is accompanied by a decrease in interregional differentiation of incomes' (Malkina, 2014). 'Positive trends in the distribution of regions by income and poverty levels slowed down in the 2010s, and during the crisis of 2014–2017 the positive trend turned into negative' (Zubarevich & Safronova, 2019). For a better understanding of regional disparities, there are three main areas of interest that are widely discussed in international research literature but are still underexplored in Russia.

First of all, this study of per capita income differences should be shifted from the regional to municipal level. The studies of uneven development may focus on various administrative levels: national (country), regional (states in the USA, Brazil and Australia, provinces of Canada and China, regions of Russia, NUTS 2 in the European Union), municipal (counties in the USA and China, municipalities in Russia and Brazil, local areas in Australia, NUTS 3 in the EU), local levels (cities and villages). The disparities become even more prominent on the lower levels (Gustafsson & Shi, 2002; Siddique & Khan, 2021), where the differences between municipalities are added to the differences between the countries and the regions within these countries.

Secondly, it is important to understand how the context (determinants) of the higher (regional) level affects the situation on the lower (municipal) level. It is obvious that the region determines the policy in relation to municipalities and redistributes funds between the government budgets of the lower level. Hierarchical models are best suited to capture these relationships (Díaz-Dapena et al., 2017; Díaz-Dapena et al., 2018; Yusupov et al., 2019).

Finally, spatial interaction must be taken into account. In an open economy, neighboring territories are connected by commodity flows, technology spillovers and labor migration. It's necessary to 'more accurately capture the role of location and account for spatial dependence in the economic growth process' (Pede, 2013). Spatial connections may have different gradients (Breau & Saillant, 2016; Demidova, 2015).

Considering the above, the purpose of this work is to determine the significance of spatial relationships at different levels of data aggregation and hierarchical dependencies in per capita income and to highlight the level of administrative division (regional or municipal) that has the greatest impact on the change in per capita income.

To achieve this goal, the following tasks need to be addressed. First, we are going to review the research literature on the topic to reveal the factors included into the models of population income. We also show the potential of the new class of models for investigating the spatial effects at two levels of data aggregation for income analysis. Next, we are going to conduct a test to identify hierarchical and spatial effects in the data in order to explore the possibility of using new models to analyze per capita income. We will build models with estimated spatial interaction on the higher level (spatial error at the regional level, lower level (spatial lag at the municipal level) and both levels (spatial error at the regional level and spatial lag at the municipal level simultaneously). We will also conduct a comparative analysis and identify the model with the highest predictive ability. Finally, the conclusions will be drawn about the potential use of this new class of models in regional studies.

The practical significance of this study has two aspects. First, as was said above, it tests a new class of models taking into account spatial interactions at two levels of data aggregation. To this end, I will rely on the data for Russia, which is one of the largest and unevenly developing countries in the world, in order to discuss the advantages and disadvantages of the method. Second, the study has far-reaching implications in terms of public policy. It is a commonly known fact that the directions of spatial effects at the level of municipalities and Russian regions are different. Until recently, however, there have been very few methods that could be used to distinguish between the effects on the level of regions and municipalities. This is the research gap that this article aims to address. Our might be of interest to a wide range of specialists and analysts dealing with regional governance issues.

Literature review

Regional differences in per capita income are a concern for many countries, especially large ones. For example, Breau & Saillant (2016) discuss regional disparities as a persistent feature of Canada's economic landscape. They use the data of 287 Canadian census divisions to explore the East-West and urban-rural gradients of regional income disparities. Diaz Dapena et al. (2017, p. 5050) observe that the general trend of income per capita growth 'coexists with different intra-state behavior's across Brazilian geography'. They use the data of 4,067 municipalities from 27 states to show a wide intra-regional heterogeneity which manifests itself as divergence in the south-eastern states and as convergence in inland states. Ngarambe et al. (1998) analyze 1,257 counties in the south of the U.S. in the 1970s and 1980s and demonstrate that increased income inequality is a price to be paid for rapid economic growth.

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Thus, there is considerable research literature on income growth on the national level (Higgins et al., 2006; Roth, 2010; Pede, 2013).

Among the various factors that affect per capita income and its growth, the relationship between income per capita volume and inequality appears to be the most difficult for analysis. Some researchers conclude that inequality has a negative impact on per capita income (Ngarambe et al., 1998; Roth, 2010; De Jesus et al. 2019), while others believe that this impact is positive (Breau & Saillant, 2016) or insignificant (Pede, 2013). The in-depth analysis by Fallah & Partridge (2007) showed a different inequality-growth linkage between more and less populated counties consistent with a different transmission mechanism of economic incentives, agglomeration economies, and social capital between more and less urban counties. They divided the observations into two groups and found that the Gini coefficient for the rural US counties is negative and statistically significant at the 1% level. On the contrary, for metropolitan counties, inequality produces the opposite effect with the regression term being positive and significant at the 1% level. Dividing the sample into high and low poverty non-metro counties made it possible to identify, that income inequality has a much more negative impact on percent change in per capita income in high-poverty non-metro counties (Fallah & Partridge, 2007).

Human capital is considered an important determinant of income, which is associated with both higher labor productivity and an increase in the share of innovative products in production. One of the key indicators characterizing human capital is the level of education (Díaz-Dapena, 2017; Breau & Saillant, 2016; Fallah & Partridge, 2007; Higgins et al., 2006). Fallah & Partridge (2007) take into account the percentage of the population over 25 years old that falls into five education attainment categories running from high school graduate to graduate degree. Breau & Saillant (2016) include in the model the percentage of the labor force with a bachelor's degree or higher. Higgins et al. (2006) used the percentage of population with high school diploma. As a rule, education has a positive effect on per capita income but not always. For example, Higgins et al. (2006) showed that per capita personal income in US is positively and significantly related to the percentages of the population with bachelor's degree or more, and not significantly to the percentages of the population with college education. Pede (2013) takes into account five categories of human capital variables in the growth model: percentage of county population with a high school degree, college degree, associate's degree, Bachelor's degree, or graduate degree. He expected 'that these categories of educational attainment will have different effects on income growth' (Pede, 2013, p. 119). His results showed that not all categories have a significant positive impact. Čadil et al. (2014) suggested that one of the reasons for such different impact may be over-education and unsuitable education.

Some control variables were included in the model. As a control variable, researchers use the population size to control for agglomeration effects (Fallah & Partridge, 2007). This variable does not always have a positive effect. For example, the coefficient of the growth of population is negative and significant in OLS model and not significant in the multilevel model (Díaz Dapena et al., 2017).

Productivity is considered as the source of growth in real income per capita in a basic tenet of economic science (Gordon & Dew-Becker, 2005). So it may also be include to the per capita income model.

Per capita income depends on the number of people employed, because wages and entrepreneurial income are generally higher than social benefits. A large number of unemployed people living in the territory reduces its average value of the per capita income. In confirmation of this, studies show that the unemployment rate has a negative relationship with the growth in the natural logarithm of the real average total income growth (Breau & Saillant, 2016), growth in the log of real per capita money income (Stansel, 2005), the logged difference of county-level income per-capita (Roth, 2010).

The factor determining the high per capita incomes may be similarly high incomes in the neighboring territories. The population may move in search of higher incomes. Accordingly, the equalization of social benefits by the state happens together with the equalization of wages as a result of the balance in the labor market, and hence the income of the population as a whole, which is why 'any analysis on income inequality must consider space and geography alongside other significant socioeconomic correlates' (Siddique & Khan, 2021, p. 18). In view of this consideration, two Russian studies – by Demidova (2015) and Ivanova (2017) – have included not just panel data models but spatial panel data models.

Methodology and data

With regard to regional economy, all data characterizing the development of territories (in any aggregation: street, quarter, city/district, region, country) are simultaneously hierarchically structured and spatially organized. In the late 20th century, the prevalent view was that such data are both spatial and hierarchical in nature (Car, Frank, 1994). In the early 21st century, Anselin & Cho (2002, p. 284) noted that 'incorporating spatially varying coefficients is a hierarchical approach toward modeling the spatial variation of the model parameters across observations'. Despite this, it was only in the last decade that the spatial component started to be directly included in hierarchical models or the hierarchical data structure started to be taken into account.

One of the first works in which the combination of tools for hierarchical and spatial analysis was used is the study by G. Dong and R. Harris (2014). To study the land prices variation in China, they built several models that take into account hierarchical and spatial effects. In more recent studies, the HSAR models were used to study the growth of GDP per capita in Europe (Díaz-Dapena, 2018), the cost of land in Poland (Cellmer et al., 2019), suicides in the United States (Tu et al., 2020), the rate of GRP growth in Russia (Bukina et al., 2017). By combining the two approaches, these studies considered both the heterogeneity and spatial dependence of the data, which makes this method more informative compared to classical models (Cellmer et al., 2019).

Spatial econometrics models explain the processes characterized by spatial autocorrelation (Anselin & Cho, 2002). In multilevel (hierarchical) modelling, the key role is played by the hierarchy of data, which can be also applied to explain the processes characterized by spatial heterogeneity (Goldstein, 2010; Raudenbush et al., 2011; Oshchepkov & Shirokanova, 2020). HSAR models are applied in the case of both spatial and hierarchical effects. The former can be identified by calculating the Global Moran's Index (Anselin & Cho, 2002); the latter, by using the test of homogeneity of lower level variance (Raudenbush et al., 2011) and ICC or VPC (intraclass correlation coefficient (Oshchepkov & Shirokanova, 2020)), variance partition coefficient (Goldstein, 2010).

The general formula of the HSAR model can be presented as follows (Dong & Harris 2014; Dong et al., 2016; Cellmer et al., 2019):

Lower level (municipality):

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \\ + \beta_{3j}X_{3ij} + \rho W^{M} Y_{ij} + r_{ij}, \quad (1)$$

Higher level (region):

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_{1j} + \gamma_{02}Z_{2j} + b_0, \quad (2)$$

$$b_0 = \lambda W^{R}\beta_0 + u_0, \quad (3)$$

where Y_{ij} is a dependent variable, the volume of social payments and taxable cash income per capita in the municipality; X_{1ij}, an independent variable, the ratio of the number of employees of large, medium-sized enterprises and non-profit organizations to the resident population of the city / municipality; X_{2ij}, an independent variable, labor productivity; X_{3ij}, the number of resident population; Z_1, independent variable, the share of workers with higher education in the structure of the labor force; Z_{2j}, independent variable, Gini coefficient; W^M, W^R is the matrix of neighborhood at the lower (municipal) and higher (regional) level, respectively; λ, ρ *are the* spatial autoregressive coefficients; r_{ij}, u_0, model errors at the municipal and regional levels; i is the index for affiliation to the observation of the lower level (in this case, municipality); j, the index for affiliation of the lower level observations to the higher-level observation (in this case, Russian region).

The main focus in the model is made on spatial interactions, namely (1) explaining how the income of the population of one territory correlates with the income of the population in neighboring territories at the level of municipalities (ρ) and how strongly the residuals of the model grouped at the level of the region correlate (λ). If $\lambda = 0$, then a spatial lag model is considered that takes into account the hierarchical data structure. If $\rho = 0$, then a model that takes into account the spatial error of data grouped at the level of regions. If $\lambda = 0$ and $\rho = 0$, then we are talking about a simple hierarchical model with random effects that does not take into account spatial interactions.

Calculations were performed in the *R* package – HSAR (Dong et al., 2016).

The volume of social payments and taxable cash income per capita in the municipality was considered as a dependent variable.

The independent variables were the following:

– the ratio of the number of employees of large, medium-sized enterprises and non-profit organizations to the resident population of the city / municipality;

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– labor productivity as the ratio of the volume of shipped goods of own production, performed works and services (excluding small businesses) in relation to the population;

– the size of resident population;

– the share of workers with higher education in the structure of the labor force;

– Gini coefficient.

The last two indicators are presented at the regional level (85 observations), while the rest, at the municipal level (2270 observations). The description of the data is presented in Table 1.

The analysis was carried out on the basis of the data from 2,270 municipalities in 85 constituent entities of the Russian Federation in 2019, which is 96.7% of the total number of municipalities. The study relied on the statistical data provided by the Federal State Statistics Service. The assessment does not include data on closed cities and districts as well as individual small territories for which data are not available in order to comply with the requirement to ensure the confidentiality of primary statistical data received from organizations in accordance with the provisions of the Federal State Statistics Service.

The spatial weights matrix formalizes the assumption that the territory under consideration has a connection with neighboring territories. The analysis used a binary matrix that takes into account the first-order neighborhood. At the level of municipalities, the neighborhood of municipalities limited to the territory of the islands was determined taking into account their geographical proximity. Thus, Novaya Zemlya of Arkhangelsk region was considered as neighboring in relation to the Zapolyarny District of the Nenets Autonomous District, which is the closest to it; Elizovsky district to the Ust-Bolsheretsky district of Kamchatka region; Aleutsky district to the Ust-Kamchatsky district of Kamchatka region; the urban districts of Yuzhno-Kurilsky, Kurilsky, Korsakovsky located on the islands are connected to the Severokurilskiy urban district of Sakhalin region and to each other.

Results

To find out whether the HSAR models are suitable for the purpose of this analysis, we tested for both spatial and hierarchical effects.

Calculations have shown that there is a spatial autocorrelation of the volume of social payments and taxable cash income per capita (Moran's I = 0.645). The Local Moran's I values (see Figure 1) show that there is a direct relationship of territories with high values of the indicator (high-high) in the north and north-east of the country and the territories united by low values of the indicator (low-low cluster) in the west and south of the country.

The test of homogeneity of level-1 variance shows the significance of the hierarchical effects (χ^2 statistic = 408.7, degrees of freedom = 81, p-value = 0.000). These results indicate that there is variability among the 2,347 lower level units in terms of the residual within-region (i.e. higher level) variance. The high value of the ICC indicates the significance of the hierarchical effects in the way similar to the previous criterion (ICC = 71.2%).

The modeling results are presented in Table 1.

Table 1

General characteristics of the variables

Variable	Mean	Standart Deviation	Minimum	Maximum
Lower level (municipality)				
Volume of social payments and taxable cash income per capita, million rubles / person	0.25	0.19	0.07	2.79
Ratio of the number of employees of large, medium-sized enterprises and non-profit organizations to the resident population of the city / municipality, coef.	0.19	0.13	0.03	1.94
Ratio of the volume of shipped goods of own production, performed works and services (excluding small businesses) in relation to the population, million rubles / person	0.55	2.67	0.001	64.8
Population, thousand people	63.67	311.35	0.7	12615.25
Higher level (region)				
Share of workers with higher education in the structure of the labor force, %	31.71	5.40	22.00	50.26
Gini coefficient, coef.	0.37	0.02	0.33	0.44

Source: compiled by the authors based on statistical data of the Federal State Statistics Service.

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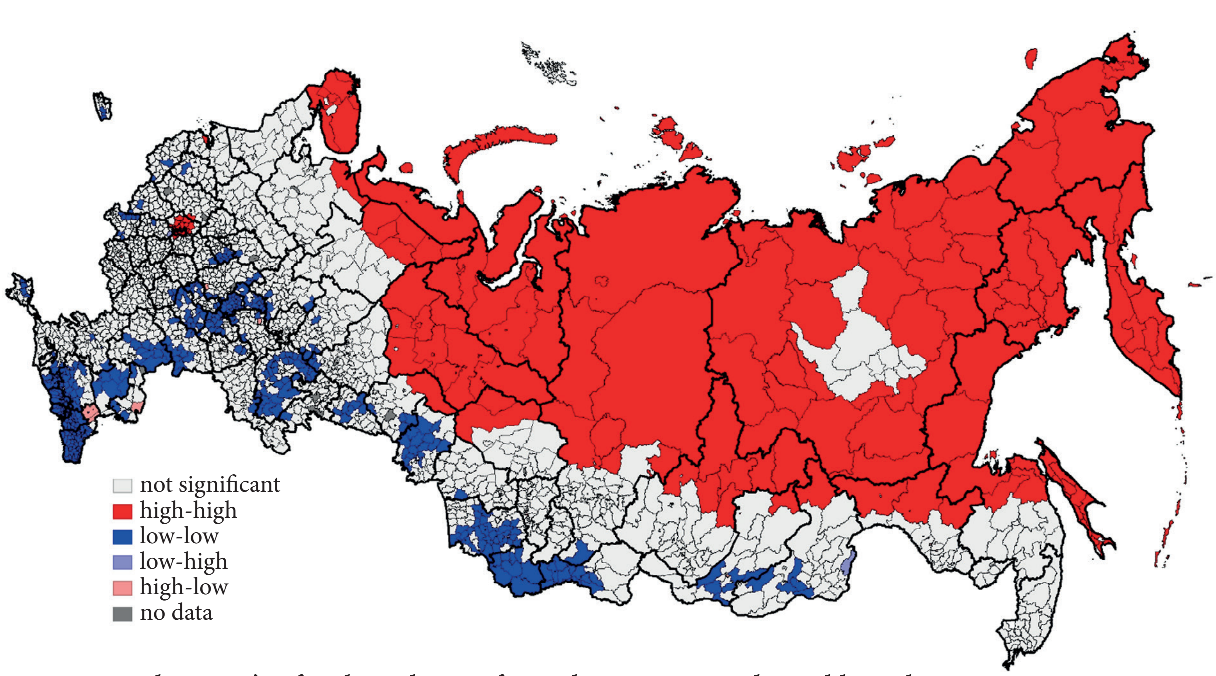

Figure 1. *Local Moran's I for the volume of social payments and taxable cash income per capita in 2019*
Source: the authors' calculations are based on statistical data: database of indicators of municipalities provided by the Federal State Statistics Service. URL: https://gks.ru/dbscripts/munst/ (Accessed: 21.02.2021)

Table 2

Results of estimations: depended variable – the volume of social payments and taxable cash income per capita

Variable	HSAR model with an estimate of the spatial dependence on		
	higher levels	lower level	both levels
Intercept, α	–0.3 (0.12)	–0.422 (0.173)	–0.207 (0.093)
Independent variables at the municipal (lower) level			
Ratio of the number of employees of large, medium-sized enterprises and non-profit organizations to the resident population of the city / municipality	0.00056 (0.00006)	0.0005 (0.00006)	0.0005 (0.00006)
Ratio of the volume of shipped goods of own production, performed works and services (excluding small businesses) in relation to the population, million rubles / person	0.035 (0.0009)	0.033 (0.0008)	0.033 (0.0009)
Population	0.00005 (0.00001)	0.00006 (0.00001)	0.00005 (0.00001)
Independent variables at the regional (higher) level			
Share of workers with higher education in the structure of the labor force	0.00698 (0.00192)	0.0035 (0.002)	0.0043 (0.0012)
Gini coefficient	0.39 (0.331)	1.267 (0.425)	0.182 (0.255)
Spatial interaction			
Spatial lag at the municipal level, ρ	–	0.255 (0.022)	0.252 (0.019)
Spatial error at the regional level, λ	0.954 (0.023)	–	0.967 (0.018)
Diagnostics			
Pseudo R squared	0.727	0.713	0.717
Deviance Information Criteria (DIC)	215187.3	230536.7	228254.5
Variance Component: municipal level, σ^2 regional level, τ^2	 0.0101 (0.0003) 0.004 (0.0008)	 0.0096 (0.0003) 0.011 (0.002)	 0.0096 (0.0003) 0.0018 (0.0004)
Log-likelihood	–99636.4	–105316.6	–105781.8

* standard error in brackets
Source: compiled by the authors

In total, three HSAR specifications were built: models with the estimated spatial interaction on the higher level (spatial error at the regional level[1]), lower level (spatial lag at the municipal level[2]) and both levels (spatial error at the regional level and spatial lag at the municipal level simultaneously). For all models, the hierarchical effects were estimated (variance component). Standard deviation values for the variation component, spatial lag and error indicate the significance of both hierarchical and spatial effects. In the absence of the spatial interactions estimate at any of the levels, the variation component at this level increased. This suggests that spatial interactions explain the observed variation at both the higher and lower levels.

It can, however, be noted that the model of the best quality is the model with estimated spatial interaction on the higher level. This model has higher Pseudo R and Log-likelihood, lower Deviance Information Criteria than other models.

As for the included factors, all of them, except for the Gini coefficient, have shown a significant positive direct influence on the dependent variable in all the three specifications. They all have a positive direct influence on the dependent variable. These results agree with the evidence from other countries. For example, Breau & Saillant (2016), exploring the data of 287 Canadian census divisions, found that the unemployment rate has a significant negative effect and the spatial lag has a significant positive effect on real average total income. Our study used the inverse unemployment rate: the ratio of the number of employees of large, medium-sized enterprises and non-profit organizations to the resident population of the city / municipality. Therefore, the negative impact of the unemployment rate correlates with the positive impact of the indicator we use on the dependent variable. Fallah & Partridge (2007) estimate the income growth model on the data of 3,028 US metropolitan counties [15]. They have shown that the population shares (high school graduates, four-year college graduates, and holders of a graduate degree) are all positively correlated with the per-capita income growth. Ngarambe et al. (1998), based on the data of 1,257 counties in the US South, found the positive impact of the percentage of people 25 years old and over who have completed 12 years or more of school on family income growth. Roth (2010) exploring 3,141 counties in US in 1977–2000 found a negative impact of the unemployment rate and a positive impact of the percentage of residents holding a college degree on per-capita income growth.

Fallah & Partridge (2007) have demonstrated that the Gini's regression coefficient is negative and significant at the 1% level. The same result is obtained by Ngarambe et al. (1998). The results of Breau & Saillant (2016) are even more interesting: the Gini regression coefficient for the rural US counties is negative and statistically significant at the 1% level while for metropolitan counties, inequality produces the opposite effect with the regression term being positive and significant at the 1% level. Pede (2013) found that the Gini coefficient has a significant and positive influence on the income growth.

In our study, the growth of the indicator is not considered. The Gini coefficient has a positive and significant effect on per capita income in the models with the estimated spatial interaction on the higher (with the spatial error at the regional level) and lower level (with the spatial lag at the municipal level), and not significant in the model with the estimated spatial interaction on both levels.

Discussion and implications

We use county-level data from 2,270 Russian municipalities to study the differences in per capita income. Municipal-level data are valuable for this purpose because they capture intra-regional and inter-regional heterogeneity. Accordingly, not only regional differences are taken into account, but also different connections at the municipal level, such as the center-periphery, urban-rural. These new tools enable us to divide the effects into several levels, and moreover, evaluate the spatial effects on each of these levels. The inclusion of spatial matrices at the two levels of data aggregation – municipal and regional – helped us investigate how the proximity of territories affects the incomes of the population.

The results obtained are of great importance for regional policy-making. In fact, it has been established that spatial dependencies can be assessed both at the municipal level and at the regional level. Therefore, he spatial models of income in Russia built both by using the data of the

[1] Takes into account the spatial autocorrelation of error terms.

[2] Takes into account the spatial autocorrelation of the dependent variable, namely the relationship between its values in neighboring territories.

municipal level (Ivanova, 2017) and the data of the constituent entities of the Russian Federation (Demidova, 2015) will be significant. At the municipal level, in addition to the existing dependencies at the regional level, such as higher incomes in the north and northeast of the country, center and periphery effects are added.

Our research based on the inclusion of matrices at both levels of data aggregation leads us to the following conclusions. A model that takes into account only the proximity of the region in relation to the region with high incomes, without taking into account municipal spatial effects, has a higher quality, which means it allows better forecasting. Accordingly, the regional effects in the fight against poverty will be more predictable. This does not mean that the problems of poverty at the level of municipalities are not so significant. It should be emphasized at this point once again that the model with the inclusion of spatial matrices at both levels was significant. On the contrary, all estimates indicate that the differences between municipal districts with higher and lower incomes are higher than the differences between regions with higher and lower incomes of the population. We can assume that due to the fact that the model takes into account the hierarchy of objects and the nesting of municipalities in regions, it links intermunicipal differences with the characteristics of the regions, determining the need for a more in-depth study of interlevel interaction. Thus, spatial relationships are not so simple and their hierarchy should be considered in more detail.

Our findings give a more detailed understanding of spatial interactions. The proposed methodology provides opportunities for examining these interactions on the regional and municipal levels at the same time, thus creating potential paths for future research.

Our study may be also of interest for policy-makers and public administrators since it shows how the changes observed in some territories affect the changes in the neighboring territories. Given the country's administrative-territorial division, it is important to better understand how the changes in one municipal district can affect situation in the neighboring municipal district belonging to another Russian region.

We found that the level of spatial connection can change the significance of other factors. The Gini index is significant in the models that take into account only spatial relationships at the municipal level. In the future, it is necessary to examine the reasons why the significance of the Gini coefficient falls in the models that take into account regional spatial effects. This will require us to expand the range of factors taken into account in the model.

In further studies, it could be more productive to use a distance matrix instead of a neighbourhood matrix in models.

Despite the above-described shortcomings, it was shown that the new class of models expands the possibilities for studying the processes in the national economy, which seems a promising area for future research.

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