

SPATIAL AUTOCORRELATION OF REGIONAL INFLATION IN RUSSIA: ITS EXISTENCE AND HETEROGENEITY

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This research examines whether regional inflation in Russia exhibits spatial autocorrelation (SA) and to what extent this phenomenon is determined by the spatial pattern of a country (in other words whether spatial autocorrelation is heterogeneous).

Given that Russian regions are not closed economies, i.e. they interact and trade with one each other (exporting/importing good and services), an inflation level in a particular region depends not only on its internal economic, social, geographical and other features, but also on the same features of other regions of the country. It is highly likely that higher level of inflation in a particular region may induce acceleration in the price growth in other regions and vice versa (spillover effects). The detection of this phenomenon suggests the presence of *spatial autocorrelation* in the levels of regional inflation. One may expect the highest spatial autocorrelation among the levels of inflation of regions that are considered as ‘neighbors’ (usually determined as territories that share common borders), because of the highest expected (usually) similarity of their socio-economic features. This may be expressed in the first order SAR model:

$$\pi_t = \rho W \pi_t + \varepsilon_t \quad (1)$$

$\varepsilon_t \sim N(0, \sigma^2 I_N)$ – is the vector of homoscedastic independent errors, π_t – is the vector of regional levels of inflation.

In this research regional CPIs (consumer price indexes) are used as the quantitative measure of inflation. There are 79 Russian regions in the data set. The time span includes fifteen years, namely from 2002 to 2016.

Several metrics, based on different spatial weights matrixes with distance thresholds (i.e. weights equal to zero whenever distance between a pair of regions exceeds the threshold), are applied to test for spatial autocorrelation. These metrics are Moran’s I, APLE (approximate profile likelihood estimator) and ML estimator of SAR model (1).

In this study, inferences on statistical significance for Moran’s I and APLE statistics are based on both permutation and Monte-Carlo tests, while LR test is used to test for significance of ML estimates of SAR model (1).

Results suggest that, at first, statistically significant spatial autocorrelation (that is measured and tested with different metrics and statistical tests) is observed for almost all examined years (there is no statistically significant SA for 2002 and 2012 years, as our analysis shows). Second, enhancement in distance threshold in spatial weight matrix leads to concurrent increase in values of SA in all metrics, except Moran’s, (in other words, spatial autocorrelation grows as additional variation, coming from the regions, is taken into the analysis). Based on this, we conclude that spatial autocorrelation, detected with listed above methods, among Russian regional levels of inflations exhibits heterogeneity pattern.

For further analysis of spatial heterogeneity and of the spillover effects that it induces, a spatial panel econometric model with two matrixes is used:

$$\begin{aligned} \mathcal{A}\pi &= \mathbb{X}\beta + \varepsilon \\ \varepsilon &\sim \varepsilon | \mathbb{X} \sim \text{Normal}(0, \sigma^2 I_{TN}) \\ \pi | \mathbb{X} &\sim \text{Normal}(\mathcal{A}^{-1} \mathbb{X}\beta, \sigma^2 (\mathcal{A}^{-1})' \mathcal{A}^{-1}) \end{aligned}$$

$I_{TN} = (I_T \otimes I_N)$ is $TN \times TN$ identity matrix;

$\mathcal{A} = (I_T \otimes A)$ is $TN \times TN$ matrix of spatial filters for panel;

$A = (I_N - \rho_1 W_1) * (I_N - \rho_2 W_2)$ - sequential spatial filter;

ρ_1 - 1-st scalar, ρ_2 - 2-d scalar;

$$W_1 = \left\{ \frac{1}{d_{ij}} \mid d_{ij} \leq X \text{ km.} \right\};$$

$$W_2 = \left\{ \frac{1}{d_{ij}} \mid d_{ij} > X \text{ km.} \right\};$$

X – matrix of explanatory variables.

The results are presented in Table 1. In this research, we are mostly interested in estimates of ρ_1 , ρ_2 and ρ (ρ is the SA coefficient for the model with one spatial weight matrix), that is why the estimates of other parameters are not reported. The reported coefficients (ρ_1 , ρ_2 and ρ) represent coefficients of spatial autocorrelation when spatial interaction is absorbed and formed with the certain spatial weight matrix. Because the data set has the panel structure, the estimates of ρ_1 , ρ_2 and ρ represent resulted average SA for the whole time span of fifteen years.

Table 1. Results of estimation.

Parameters of spatial autocorrelation	Estimates							
	Model 1 (one matrix)				Model 2 (two matrixes)			
	W500	W1000	W2000	WID	W500	W1000	W2000	WID
ρ	0.48	0.57	0.65	0.72	-	-	-	-
ρ_1	-	-	-	-	0.38	0.68	0.77	-
ρ_2	-	-	-	-	0.76	0.65	0.43	-
$\text{CORR}(\hat{\pi}; \pi)^2$	30.4	29.6	30.1	30.8	32.3	33.7	33.1	-
RMSE	312.9	294.3	270.7	250.9	234.0	212.6	221.5	-
LR for $H_0: \rho = 0$	287.7	435.4	630.2	805.2	1065	1178	1087	-

Results of estimation, at first, strongly demonstrate that there is the heterogeneity of statistically significant spatial autocorrelation of levels of inflation of Russian regions (i.e. that spatial autocorrelation is highly depended on the distance between the regions) during examined period of time. Second, the magnitude of detected spatial autocorrelation is almost equal for regions that are within 1000 km. and outside this distance. Third, we quantify the spillover (indirect) effects, then test their estimates for statistical significance (we fail to accept their insignificance). The calculations show that indirect effects for the models without distance threshold is almost equal to the spillover effect for the models with threshold of 1000 km (the distance for which SA's heterogeneity is eliminated).

Obtained results may be used for forecasting, namely for predictions of proliferation of inflationary shocks among Russian regions (that is, how an accelerated price grows occurred in a source-region transfers to other regions).

References:

1. E.V. Semerikova, O.A. Demidova, «Analysis of regional unemployment in Russia and Germany: spatial econometric approach», *Spatial Economics*, 2015, vol. 2
2. J. Paul Elhorst, Donald J Lacombe, Gianfranko Piras, On model specification and parameter space definitions in higher order spatial econometric models, *Regional Science and Urban Economics*, 2012, vol. 42
3. A.S. Brandsma, R.H. Ketellapper, A biparametric approach to spatial autocorellation, *Environment and Planning A*, 1979, vol. 11