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Spatial Econometric Analysis of Regional Capital Investments in Ukraine

Abstract

The aim of this paper is to identify and quantify spatial dependence in the distribution of capital investments across Ukrainian regions, to determine the type of spatial relationships (spatial lag versus spatial error), and to decompose the total effect of gross regional product on capital investments into direct and indirect (spillover) components. Spatial dependence is a fundamental characteristic of regional economic processes; however, in the context of Ukrainian regional studies, the spatial dimension of capital investment distribution remains insufficiently explored. Classical econometric models that treat regions as isolated units produce biased and inefficient parameter estimates when interregional interactions are present. This gap is particularly significant for Ukraine, where institutional heterogeneity, uneven spatial development, and the impact of armed conflict create complex patterns of regional interdependence. The empirical basis consists of a balanced panel of 25 regional units (24 oblasts and the city of Kyiv) over the period 2016–2021, yielding 150 observations. The spatial interaction structure is defined by a first-order queen contiguity weight matrix based on GADM Level-1 shapefiles. Estimation is performed via maximum likelihood using the R packages splm, plm, and spdep. The study compares spatial autoregressive (SAR) and spatial error (SEM) models with fixed and random effects. Model selection relies on Baltagi–Song–Koh LM tests and the spatial Hausman test. The analysis confirms statistically significant spatial dependence in regional capital investments. The elasticity of capital investments with respect to gross regional product is consistently above unity ($\beta \approx 1.19–1.27$), indicating procyclical investment behaviour consistent with the accelerator theory. The effect decomposition reveals an indirect spatial effect of 0.196, approximately 14 percent of the total effect, confirming the existence of interregional investment spillovers. The spatial Hausman test favours fixed-effects specifications ($\chi^2 = 18.71$, $p < 0.001$). Ignoring spatial interactions underestimates the impact of economic growth on investments by 14–16 percent, which has direct implications for regional investment policy design and post-war recovery strategies.

DOI: https://doi.org/10.30525/2500-946X/2026-2-12

Keywords
spatial econometrics, capital investments, gross regional product, spatial autocorrelation, panel data, SAR model, regional economy

JEL: C21, C23, R12, E22

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1 Introduction

Spatial econometrics, as developed in the works of Anselin (1988) and LeSage and Pace (2009), proceeds from the assumption that the value of an economic variable in one region depends on the values of the same variable in neighbouring regions – the phenomenon known as spatial autocorrelation. The global Moran's I indicator of spatial autocorrelation is calculated as a weighted correlation between regional values of an indicator and the average value in neighbouring regions. A positive value of I indicates clustering – the grouping of regions with similar levels of the indicator – whereas a negative value points to spatial heterogeneity, where regions with high values border regions with low values (LeSage & Pace, 2009).

In the context of investment analysis, spatial autocorrelation means that the volumes of capital investments in a particular oblast may depend on analogous indicators in neighbouring oblasts through mechanisms of bank competition for clients, labour and capital migration, and shared infrastructural links. For the conditions of the armed conflict in Ukraine, Capoani and Martini (2026) developed a spatial gravity model demonstrating that proximity to the conflict zone has a statistically significant negative effect on economic activity both directly and through spatial spillovers. The relevance of the present study is determined by the need to account for spatial dependence when modelling regional investment processes, since ignoring interregional interactions leads to biased and inefficient parameter estimates.

2 Literature Review

The fundamental principles of spatial econometrics were laid down in the works of Anselin (1988), who proposed a systematic approach to the specification, estimation, and testing of models with spatial dependence. LeSage and Pace (2009) developed this apparatus further, in particular by proposing a methodology for decomposing the effects of explanatory variables on direct, indirect (spillover), and total components in models with a spatial lag of the dependent variable. For the Ukrainian context, Shkurpat (2006) demonstrated the existence of statistically significant spatial autocorrelation of labour productivity across regions. Chen et al. (2022) empirically confirmed the existence of positive spatial spillovers in the sphere of digital finance using the example of Chinese provinces, which supports the universality of the mechanisms of spatial diffusion of financial processes. Capoani and Martini (2026) examined the spatial dimension of the economic consequences of the armed conflict in Ukraine by means of a gravity model. Baltagi, Song, and Koh (2003) developed a series of LM tests for diagnosing spatial dependence in panel data, which have become a standard instrument of spatial panel econometrics.

The empirical analysis was carried out using R software packages: splm (Millo & Piras, 2012) for estimating spatial panel models, plm (Croissant & Millo, 2008) for standard panel specifications, and spdep (Bivand, Pebesma, & Gómez-Rubio, 2013) for constructing spatial weight matrices and testing spatial autocorrelation. The spatial structure of regions was built on the basis of GADM shapefiles (GADM, 2022).

At the same time, the available literature has insufficiently addressed the question of spatial interrelations specifically in the sphere of capital investments for the regions of Ukraine, particularly in view of the specificity of institutional heterogeneity, the unevenness of spatial development, and the impact of the armed conflict. The present study aims to fill this gap through the application of spatial panel models to the analysis of regional investment flows.

3 Purpose of the Study

The purpose of the article is to identify and quantify spatial dependence in the distribution of capital investments among the regions of Ukraine on the basis of spatial panel models, to determine the type of spatial interrelations (spatial lag or spatial error), and to decompose the impact of gross regional product on capital investments into direct and indirect components.

4 Materials and Methods

The empirical base of the study consists of a balanced panel of N = 25 regional units (24 oblasts and the city of Kyiv, excluding the temporarily occupied Autonomous Republic of Crimea and the city of Sevastopol) for the period T = 6 years (2016–2021), forming a total sample of 150 observations. The dependent variable is the natural logarithm of the volume of capital investments in region i in year t (ln CapInv_it), expressed in thousands of hryvnias at actual prices. The main explanatory variable is the natural logarithm of gross regional product (ln GRP_it), expressed in millions of hryvnias at actual prices. The logarithmic specification of both variables allows the estimated coefficient to be interpreted as the elasticity of capital investments with respect to gross regional product. The data sources were official publications of the State Statistics Service of Ukraine on capital investments by regions (State Statistics Service of Ukraine, n.d.-a) and on gross regional product at actual prices (State Statistics Service of Ukraine, n.d.-b).

The spatial structure of regional interaction is defined by a first-order queen contiguity matrix, constructed on the basis of the administrative boundaries of the oblasts of Ukraine according to GADM Level-1 shapefiles (GADM, 2022). The spatial weight matrix W of dimension 25 × 25 is row-standardised, where each element is represented as:

$$w^*_{ij} = w_{ij} / \sum_j w_{ij} \quad (1)$$

where w_{ij} = 1 if regions i and j share a common border, and w_{ij} = 0 otherwise.

The baseline specification of the model can be written as:

$$ln\ CapInv_{it} = \alpha_i + \beta \cdot ln\ GRP_{\_it} + \varepsilon_{it}, \quad (2)$$

where α_i is the fixed individual effect of the region.

The spatial extension of the model involves the inclusion of a spatial lag of the dependent variable (SAR model) or a spatially correlated error (SEM model):

$$SAR: ln\ CapInv_{it} = \alpha i + \rho\ W\ ln\ CapInv_{jt} + \beta \cdot ln\ GRPit + \varepsilon it, \quad (3)$$

$$SEM: ln\ CapInv_{it} = \alpha i + \beta \cdot ln\ GRP_{it} + u_{it}, \text{ where } u_{it} = \lambda \cdot W \cdot u_{jt} + e_{it}. \quad (4)$$

Estimation was carried out in the R environment (version 4.5.3) using the packages splm (Millo & Piras, 2012), plm (Croissant & Millo, 2008), and spdep (Bivand et al., 2013). The estimation method is maximum likelihood (ML). The choice between specifications is justified by means of the Baltagi–Song–Koh LM tests (Baltagi, Song, & Koh, 2003) and the spatial Hausman test (LeSage & Pace, 2009).

5 Results

At the first stage, a standard panel model with fixed individual effects (within-estimator) was estimated without taking spatial dependence into account. The results are presented in Table 1.

The estimated elasticity coefficient $\beta = 1.232$ is statistically significant at the highest level ($p < 0.001$) and indicates that an increase in gross regional product by 1% is associated with an increase in capital investments in the corresponding region by approximately 1.23%. A coefficient value exceeding unity indicates a more than proportional response of investments to growth in regional output, which is consistent with the accelerator theory of investment. The within coefficient of determination ($R^2 = 0.860$) shows that variation in gross regional product explains about 86% of the intra-regional (temporal) variation in capital investments.

For a justified choice between the spatial lag model (SAR), the spatial error model (SEM), and a non-spatial specification, a series of Baltagi–Song–Koh LM tests was conducted (Baltagi et al., 2003). The results are presented in Table 2.

The standard LM tests reject the null hypothesis of the absence of spatial dependence both in the form of a spatial lag ($p = 0.038$) and in the form of a spatial error ($p = 0.023$) at the 5% significance level. At the same time, the robust versions of the tests, which allow the type of spatial dependence to be distinguished in the presence of both forms (Baltagi et al., 2003), do not demonstrate statistical significance either for the spatial lag ($p = 0.565$) or for the spatial error ($p = 0.281$). Such a picture is typical for panels with a relatively small number of spatial units ($N = 25$), where the statistical power of the robust tests is limited. Therefore, both models were estimated, and the choice was justified by additional criteria.

The results of estimating three alternative spatial specifications are presented in Table 3.

The SAR FE model demonstrates an estimate of the spatial lag parameter $\rho = 0.141$, which is positive and at the borderline of statistical significance ($p = 0.050$). This indicates the presence of a moderate positive effect of spatial spillover of investments: an increase in capital investments in adjacent regions is associated with growth of investments in the given region. The coefficient on ln GRP equals 1.187 and remains highly significant. The SEM FE model fixes the spatial error autocorrelation parameter $\lambda = 0.221$, which is statistically significant ($p = 0.017$), confirming the presence of spatially correlated unobserved factors common to neighbouring regions. The value of the log-likelihood for SEM FE (108.147) is slightly higher than

TABLE 1 Results of the FE model (within-estimator) without spatial effects

Parameter	Estimate	Std. error	t-statistic	p-value
β (ln GRP)	1.2316	0.0451	27.328	$< 2.22 \cdot 10^{-16}$
R^2 (within)	0.8604			
Adj. R^2	0.8322			
F-statistic	746.82			$< 2.22 \cdot 10^{-16}$

Note. Balanced panel: N = 25, T = 6, total number of observations – 150. Dependent variable – ln CapInv_it. Significance level: *** $p < 0.001$. Source: calculated by the author in the R environment (plm package) on the basis of data from the State Statistics Service of Ukraine

TABLE 2 LM tests for spatial dependence (within model)

Test	Statistic	p-value	Conclusion
LM-lag	4.3279	0.0375	Significant at the 5% level
LM-error	5.1573	0.0232	Significant at the 5% level
Robust LM-lag	0.3319	0.5645	Not significant
Robust LM-error	1.1613	0.2812	Not significant

Source: calculated by the author in the R environment (splm package, slmtest function)

TABLE 3 Comparison of spatial panel models (ML estimates)

Parameter	SAR FE	SEM FE	SAR RE
ρ (spatial lag)	0.1408 (p = 0.050)		0.0805 (p = 0.309)
λ (spatial error)		0.2211 (p = 0.017)	
β (ln GRP)	1.1871 (p < 0.001)	1.2297 (p < 0.001)	1.2665 (p < 0.001)
Constant			–2.5309 (p < 0.001)
Log-likelihood	107.077	108.147	

Note. FE — fixed effects, RE — random effects. Estimation method — maximum likelihood. Significance level: *** $p < 0.001$, * $p < 0.05$. Source: calculated by the author in the R environment (splm package, spml function) for SAR FE (107.077). The SAR RE model demonstrates a statistically insignificant spatial lag (ρ = 0.081, p = 0.309), which confirms the need to use fixed effects.

For a formal choice between specifications with fixed and random effects, the spatial Hausman test was carried out (LeSage & Pace, 2009). The results are presented in Table 4.

The obtained value χ^2 = 18.714 (p < 0.001) rejects the null hypothesis, indicating the presence of correlation between regional individual effects and the explanatory variables. Accordingly, the specification with fixed effects is correct, while the random-effects model is inconsistent.

The decomposition of the impact effects for the SAR FE model is presented in Table 5.

The direct effect (1.198) is close to the coefficient of the baseline FE model and reflects the intra-regional elasticity of investments with respect to regional output. The indirect effect (0.196) quantitatively estimates the scale of spatial spillovers: each percent of growth in gross regional product in neighbouring oblasts generates an additional approximately 0.2 percentage points of growth in capital investments in the given region. The total effect (1.394) demonstrates that, with account for spatial multipliers, the real impact of economic growth on investments is 16.4% greater than indicated by the standard non-spatial estimate (1.394 / 1.198 ≈ 1.164).

6 Discussion

The obtained results are consistent with the theoretical positions of spatial econometrics (Anselin, 1988; LeSage & Pace, 2009) and confirm the presence of interregional investment flows in Ukraine analogous to the financial flows recorded in the study by Chen et al. (2022) on the example of Chinese provinces. The elasticity of capital investments with respect to gross regional product, which steadily exceeds unity (β = 1.19–1.27), is consistent with the accelerator model of investment and indicates the procyclical character of investment activity in the regions of Ukraine.

The presence of an indirect spatial effect of 0.196 can be explained by infrastructural links (transport corridors, supply chains), labour migration between neighbouring oblasts, and competition among banks for clients, which stimulates the distribution of credit products in neighbouring markets. These results confirm the conclusions of Shkurpat (2006) regarding the significance of spatial autocorrelation for macroeconomic indicators of Ukrainian regions, extending them to the sphere of capital investments. For the conflict zone, these flows between regions, on the contrary, have a negative character, which is consistent with the model of Capoani and Martini (2026), which demonstrates that proximity to military actions reduces investment attractiveness not only of directly affected oblasts but also of adjacent ones.

The slightly higher value of the log-likelihood for SEM FE (108.15) compared with SAR FE (107.08) may indicate that spatial dependence in this panel is generated to a greater extent by common unobserved shocks (for example, macroeconomic or regulatory) that simultaneously affect adjacent regions, rather than by direct flows of investments between oblasts. At the same time, both specifications confirm the presence of spatial dependence, which is the key result of this study.

Certain limitations of the analysis conducted should be noted. The number of spatial units (N = 25) is relatively small, which may affect the asymptotic properties of ML estimates of the spatial parameters. The model includes only one explanatory variable (GRP), which creates a potential risk of bias due to omitted variables. The data are used in actual (nominal) prices without deflation, which is partly compensated by the logarithmic specification and the presence of time effects but does not completely eliminate this problem. In addition, GRP is available only up to 2021 inclusive, which limits the possibility of evaluating the impact of the full-scale invasion of 2022.

TABLE 4 Spatial Hausman test (SAR FE versus SAR RE)

Indicator	Value
χ^2-statistic	18.714
Degrees of freedom	2
p-value	$8.63 \cdot 10^{-5}$

Source: calculated by the author in the R environment (splm package, sphtest function)

TABLE 5 Decomposition of the effects of ln GRP on ln CapInv (SAR FE)

Type of effect	Estimate	Interpretation
Direct	1.198	A 1% increase in the region's GRP raises its capital investments by approximately 1.20%
Indirect	0.196	A 1% increase in the GRP of neighbouring regions raises the region's investments by approximately 0.20%
Total	1.394	Aggregate (own + spatial) effect of a 1% increase in GRP

Source: calculated by the author in the R environment (splm package, effects function)

7 Conclusions

The spatial panel analysis carried out of the dependence of regional GDP on investment flows allows the following main conclusions to be formulated. Regional capital investments in Ukraine are characterised by statistically significant spatial dependence, which is confirmed by the standard Baltagi–Song–Koh LM tests both for the spatial lag ($p = 0.038$) and for the spatial error autocorrelation ($p = 0.023$). The elasticity of capital investments with respect to gross regional product is steadily greater than unity ($\beta = 1.19–1.27$), which indicates the procyclical character of investment activity. The spatial Hausman test unequivocally confirms the advantage of models with fixed effects ($\chi^2 = 18.71$, $p < 0.001$). The decomposition of effects in the SAR FE model reveals an indirect spatial effect of 0.196, which constitutes approximately 14% of the total effect. This means that ignoring spatial interrelations leads to an underestimation of the impact of economic growth on investments by 14–16%. In Ukraine, the active movement of financial and investment flows between regions facilitates the spread of the positive impact of economic growth in some regions to others.

The prospects for further research are connected with extending the panel by including additional explanatory variables, in particular volumes of bank lending, indicators of proximity to the conflict zone, and indicators of institutional quality, as well as with comparing alternative specifications of spatial weight matrices (distance-based, economic) and with extending the data to 2022–2024.

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Received on: 19th of April, 2026
Accepted on: 25th of May, 2026
Published on: 30th of June, 2026