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THE SPATIAL ECONOMIC IMPACT OF R&D EXPENDITURES: A SPATIAL PANEL DATA ANALYSIS OF GERMANY

Asst. Prof. İsmail KOÇ (Ph.D.)*

Recep KOÇ (Ph.D.)**

ABSTRACT

The paper examines the impact of R&D expenditures on gross domestic product (GDP) at the NUTS 1 level in Germany. Using the spatial panel data analysis method, the existence of spatial dependencies among regions was investigated, and the findings revealed positive spatial effects. Based on the tests conducted, the Random Effects Spatial Error Panel Data Model was identified and accepted as the appropriate model for this paper. It was determined that a one-unit increase in R&D expenditures leads to a 7% increase in GDP at a 1% significance level. Furthermore, the model was found to have an explanatory power of 63%, demonstrating that it is both statistically significant and reliable. The paper is significant as it emphasizes the multiplier effect that highlights the spatial impacts of R&D expenditures. Additionally, the heterogeneity among regions was found to have a meaningful spatial relationship with economic performance, leading to the development of an econometric model proposal in this context.

Keywords: *R&D Expenditures, Gross Domestic Product, Spatial Panel Data Analysis, Germany.*

JEL Classification Codes*: O30, O32, C23, R11.*

1. INTRODUCTION

Regional development is a critical policy domain aimed at reducing economic inequalities, ensuring sustainable growth, and enhancing social welfare. Regional R&D investments contribute to increasing technological potential and accelerating economic growth through innovation (Tatlı, 2023, p. 766). Private R&D activities not only create knowledge spillovers that support economic growth at both regional and spatial levels (Autant-Bernard and LeSage, 2011) but also promote regional development through positive externalities that extend to neighboring regions. Countries that maximize investments in human capital tend to outperform others in enhancing societal welfare and improving income distribution (Esener, 2020, p. 25).

* Sakarya University of Applied Sciences, Sapanca Vocational School, Department of Accounting and Taxation, Sakarya/ Türkiye, E-mail: ismailkoc@subu.edu.tr.
International Guest Researcher, Stuttgart University of Applied Sciences (HFT Stuttgart), Germany.
** Suleyman Demirel University, Institute of Social Sciences, Isparta/ Türkiye, E-mail: reckoc@hotmail.com.

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The geographic concentration of production shapes the spatial distribution of innovation and facilitates knowledge dissemination. Particularly, the distance to the source of knowledge is highlighted as a determinant factor influencing access to knowledge and innovation processes (Audretsch and Feldman, 1994). These findings demonstrate that knowledge externalities play a significant role in areas with concentrated innovative activities, directly impacting economic growth and sectoral performance.

The promotion of knowledge production through R&D incentives accelerates not only the development of individual regions but also regional convergence processes. Andersson and Karlsson (2007) showed that spatial dependency enables knowledge resources in a specific region to positively impact the growth of other regions, with this effect being more pronounced among functionally interconnected regions. In this context, R&D incentives serve as a crucial policy tool that strengthens the interaction between knowledge dissemination and regional development.

Germany, with its economically robust federal structure, has been implementing effective policies to reduce interregional development disparities for many years. As one of Europe's economic leaders, Germany allocates 3.11% of its GDP to R&D expenditures, ranking among the highest-spending countries in Europe alongside Sweden (3.57%) and Finland (3.09%). This figure significantly exceeds the European Union (2.22%) and Eurozone (2.25%) averages, underscoring Germany's economic leadership (Eurostat, 2025). As one of the most advanced countries globally in terms of production and R&D capacity, Germany has achieved remarkable success in reducing interregional inequalities through its regional policies (Yıldızak, 2020, p. 211).

The regional distribution of R&D expenditures in Germany has created pronounced spatial effects on economic development and innovation. According to 2021 data, the four regions with the highest R&D expenditures are Baden-Württemberg (€30.35 billion), Bayern (€22.54 billion), Nordrhein-Westfalen (€16.37 billion), and Stuttgart (€15.54 billion). R&D investments in these regions not only boost local economic outputs but also support economic activities in neighboring regions through spatial externalities, thereby extending regional development to a broader area (Eurostat, 2025).

Spatial econometrics, unlike traditional econometrics, accounts for spatial heterogeneity and spatial dependence. LeSage (1999) emphasized that these two issues must be considered in analyses involving spatial data. Although Anselin (2009) and Paelinck (2012) did not provide a direct definition of spatial econometrics, Paelinck and Klaassen (1979) articulated five foundational principles underpinning the field. These principles include spatial independence, asymmetry, the effects of spatial distances, differences between ex-ante and ex-post interactions, and the explicit modeling of topology in spatial models.

Expanding on these principles, Paelinck (2012) noted that spatial independence is addressed within the context of income-generating models and gravity models. Spatial asymmetry holds critical significance concerning consumption behaviors and income disparities in trade flows. Another principle, referred to as "allotopy," highlights the distance-dependent effects of exogenous variables. The importance of employing local models in ex-ante preferences was underscored, along with the necessity of incorporating topological variables. Strategically structuring spatial models requires the careful selection of appropriate distance metrics.

According to Anselin (1988, 2001), spatial econometrics differs from traditional econometrics by accounting for spatially specific effects such as spatial dependence and spatial heterogeneity. These spatial effects violate the Gauss-Markov assumptions of traditional econometrics, leading to issues of dependence and variation within the data structure. As a result, alternative estimation methods must be employed in spatial econometrics. The field encompasses a wide range of applications, including spatial interaction models, urban density analyses, and regional economic models, offering more accurate and meaningful analyses through techniques that explicitly address spatial dimensions.

Models used to identify spatial effects are based on the mathematical representation of spatial dependence and spatial heterogeneity (Anselin, 2003). Spatial dependence can model neighborhood effects through weight matrices, incorporating spatially lagged dependent variables, explanatory variables, or error terms. Prominent models in this context include the Spatial Lag Model, the Spatial Cross-Regressive Model, and the Spatial Error Model (Anselin, 2009). Moreover, spatial dependence determines the influence of one unit on others and the intensity of these interactions, which are explained within the framework of neighborhood and topology concepts (Anselin, 1988).

In spatial growth regressions, while the influence of initial income levels diminishes over time, long-term regional incomes depend not only on their own regional characteristics but also on those of neighboring regions, the structure of spatial connectivity, and the strength of spatial dependence (LeSage and Fisher, 2008). Therefore, models examining regional income and growth dynamics must account for spatial dependence. The spatial weight matrix (W) is a critical component in such analyses, characterized as an N x N matrix where each cell (w_ij) represents the neighborhood relationship between observations. In the basic definition, w_ij = 1 if a neighborhood relationship exists, and w_ij = 0 otherwise (Anselin et al., 2008).

Studies employing spatial econometric methods reveal that economic activities in Germany are characterized by spatial dependence, with the economic performance of one region exerting a significant influence on neighboring regions (Anselin, 1988). In this context, spatial weight matrices and spatial panel data models emerge as crucial tools for examining the impact of R&D expenditures on gross domestic product (GDP).

Spatial panel econometric studies typically focus on analyzing regional economic heterogeneity and spatial dependence in developed countries. However, research specifically investigating the impact of R&D expenditures on GDP at the NUTS 1 level in Germany remains scarce. While numerous studies address Germany’s economic performance, a majority concentrate on topics such as regional GDP disparities (Niebuhr, 2006; Südekum, 2008; Fuchs-Schündeln and Izem, 2012; Bräuninger and Niebuhr, 2005; Jeleskovic and Loeber, 2023), the effects of innovation and R&D expenditures (Naimoğlu, 2021; Kaya, 2019; Yaman, Çetin, and Dulupçu, 2020), and spatial interactions and dependence, among other areas.

In studies focusing on Germany’s regional development and R&D expenditures, elements such as spatial interactions and spatial dependence are frequently examined. Panel data models are employed in such analyses to elucidate the level of interaction within spatial relationships. Nonetheless, this paper offers an innovative contribution to the literature by providing a unique perspective on the spatial effects of R&D expenditures on GDP at Germany’s federal level. Through its emphasis on spatial econometric analysis, it seeks to deepen the understanding of the interplay between regional R&D investments and economic outcomes, highlighting the broader implications of spatial dependencies.

2. LITERATURE REVIEW

The paper aims to examine the impact of R&D expenditures on regional economic performance in Germany's NUTS 1-level regions and how these effects are shaped within the framework of spatial dependence. The primary objective of the paper is to analyze the direct and indirect effects of R&D expenditures on economic growth and to uncover the dynamics of this relationship using spatial econometric methods.

Table 1, provides a summary of significant studies addressing regional economic performance and R&D activities in Germany. These studies analyze key aspects such as employment growth, GDP increase, spatial knowledge spillovers, and sectoral dynamics across different periods. Early studies identified labor factors, infrastructure investments, and sectoral structures as critical determinants of employment growth. In later years, the positive impact of sectoral concentration and industrial structure on GDP growth was emphasized.

Table 1. Selected Studies on Regional Growth in Germany

Paper	Period	Units of Analysis (Regions)	Results	Methods Used
Schröder (1968)	1950-1956, 1956-1962	32 administrative districts, West Germany	Employment growth influenced by structural factors, labor force, climate, transport, taxes, and services	Analysis of structural and economic factors
Kau (1970)	1961-1962	335 district regions, West Germany	Employment growth in food and beverage industries affected by agricultural employment, population, GDP per employee	Regression analysis using economic and demographic variables
Koll (1977)	1961-1970	143 districts, 34 regions, Bavaria	GDP growth driven by agglomeration, industrial structure, and infrastructure investments	Cross-sectional analysis
Reimers (1981)	1960-1970	73 regions, West Germany, Denmark, Norway, Sweden	Employment growth in 10 industries tied to initial employment shares in the population	Iterative variable selection for identifying key factors
Bröcker, Peschel, Reimers (1983)	1960-1970	73 regions, West Germany, Denmark, Norway, Sweden	Employment growth in 34 industries linked to initial employment shares in the population	Iterative variable selection
Bröcker (1989)	1970-1978, 1978-1982	87 regions, West Germany	Employment growth in secondary and tertiary sectors influenced by regional economic conditions	Iterative variable selection
Herz, Röger (1995)	1957-1988	75 spatial planning regions	GDP per capita shows evidence of absolute and conditional β-convergence with declining speed over time	Convergence analysis
Seitz (1995)	1980-1990	328 districts, 167 labor market regions	Growth in GVA per employee observed across four sectors	Growth rate analysis
Schalk, Untiedt (1996)	1978-1989	151 labor market regions, West Germany	Regional technological efficiency enhances β-convergence significantly	Convergence analysis incorporating technological efficiency
Funke, Strulik (1999)	1970-1994	11 federal states, West Germany	Panel regression confirms significant regional economic dynamics	Panel regression
Niebuhr (2001)	1976-1996	71 spatial planning regions, West Germany	GVA per employee demonstrates spatial autocorrelation and conditional β-convergence	Spatial autocorrelation and convergence analysis
Funke, Niebuhr (2005a)	1976-1996	71 spatial planning regions, West Germany	Conditional β-convergence identified with the presence of convergence clubs	Spatial econometric modeling
Funke, Niebuhr (2005b)	1976-1996	71 spatial planning regions, West Germany	Spatial knowledge spillovers significantly affect regional GVA per employee	Spatial econometric modeling with knowledge spillover effects
Kosfeld, Eckey, Dreger (2006)	1992-2000	180 labor market regions, Germany	σ-convergence observed in East and unified Germany, not in West Germany	Convergence analysis using spatial econometric methods
Brunow, Hirte (2009)	1996-2005	180 labor market regions, Germany	GDP per capita shows conditional β-convergence with effects of age structure analyzed through quantile regression	Conditional convergence analysis and quantile regression
Alecke, Mitze, Untiedt (2011)	1994-2006	225 labor market regions, Germany	GRW subsidies show redistribution effects and positive growth impacts	Spatial econometric analysis focusing on policy effects

Source: (Werner, 2016, S. 133).

Research focusing on spatial dependence and knowledge spillovers highlighted the contributions of interregional economic interactions to growth. Recent studies have demonstrated that economic support programs not only foster growth but also contribute to reducing regional inequalities. These findings underscore the relevance of spatial econometric methods as a valuable guide in the design of regional development policies.

Table 2. Selected Studies on Regional Growth in Germany

Paper	Period	Regions	Key Features / Findings	Conclusions	Methodology Used
Autant-Bernard & LeSage (2011)	1992-2000	94 French Regions	French patents, private, and public research expenditures analyzed by industry and region.	- Knowledge production function estimated. - Examines spatial spillovers in own- and other-industry sectors. - Largest effects come from private R&D that spills across industries.	Panel data analysis with a knowledge production function; spatial spillover effects analyzed at regional and sectoral levels.
Fritsch and Slavtchev (2011)	1992-2007	97 Western German Regions	Regional R&D expenditures, especially university research, positively impact innovation outputs.	Strengthening university research is key to enhancing regional innovation capabilities.	Statistical analysis of R&D expenditures and innovation outputs.
Broekel and Brenner (2011)	1995-2006	270 German Regions	R&D investments' impact on growth is influenced by sectoral structure and interregional interactions.	Policies should focus on regional specialization and fostering interregional R&D collaboration.	Panel data analysis to evaluate interregional R&D effects.
Crescenzi and Rodríguez-Pose (2012)	1995-2006	202 European Regions (including Germany)	Impact of R&D on growth is shaped by institutional quality and social capital.	Institutional quality and social capital are critical for maximizing R&D benefits.	Cross-sectional econometric analysis of regional data.
Brachert, Titze and Kubis (2011)	2000-2006	97 German Regions	Regional R&D intensity in high-tech sectors positively impacts employment growth.	Promoting R&D in high-tech industries can drive employment growth.	Panel data analysis focusing on R&D intensity and employment.
Broekel, T. (2013)	2000-2010	270 labor market regions in Germany	Collaborative R&D subsidies enhance innovation efficiency, benefiting low-capacity regions.	Policies should promote collaboration, especially in low-capacity regions.	Panel data analysis to assess effects of regional collaborative projects.
Eickelpasch and Fritsch (2015)	2000-2012	39 Eastern German Regions	R&D support programs positively influence regional innovation and economic performance.	Regional R&D programs should address specific regional needs and gaps.	Analysis of program impact on regional innovation indicators.
Sanso-Navarro and Vera-Cabello (2017)	1990-2010	France, Germany, Italy, Spain	Long-term relationship between R&D and knowledge stocks; knowledge spillovers are critical.	Innovation policies should target increasing knowledge spillovers and absorptive capacity.	Unit root tests and cointegration techniques to analyze dynamic relationships between R&D and knowledge stocks.

Fusillo et al. (2023)	2004-2019	NUTS-2 regions in EU-13	Participation in Global Network of Embodied R&D (GNRD) enhances technological diversification.	Increased GNRD exposure supports diversification into unrelated technologies.	Panel data analysis using GNRD data to measure exposure and its effect on diversification.

Source: Compiled by the author.

In the post-2010 period, various studies in Germany have investigated the relationship between regional R&D activities and economic growth. Below, a complementary table is presented, summarizing some of these studies and their findings, providing a more comprehensive understanding of this dynamic.

Table 2 summarizes findings from significant studies on the impact of regional R&D activities on economic growth in Germany and Europe. Fritsch and Slavtchev (2011) highlight the pivotal role of R&D expenditures on university research in boosting regional innovation outputs, while Broekel and Brenner (2011) emphasize the influence of sectoral structures and interregional interactions on growth. Additionally, Crescenzi and Rodríguez-Pose (2012) underline the importance of institutional quality and social capital in enhancing the effectiveness of R&D investments. Eickelpasch and Fritsch (2015) demonstrate that regional R&D support programs not only foster innovation performance but also contribute to economic growth. Broekel (2013) notes that collaborative R&D subsidies enhance innovation efficiency in low-capacity regions, thereby reducing regional inequalities. Sanso-Navarro and Vera-Cabello (2017) draw attention to the long-term impact of knowledge stocks on growth and the critical importance of knowledge spillovers, while Fusillo et al. (2023) emphasize the role of participation in global R&D networks in driving technological diversification. These studies underscore the necessity for regional development policies to leverage R&D investments and collaboration as strategic tools and highlight the importance of fostering innovation ecosystems to reduce interregional inequalities.

Van Oort (2007) analyzed the spatial and sectoral composition effects of agglomeration economies in the Netherlands, emphasizing the importance of relationships between non-adjacent cities for economic growth. The paper highlighted the critical role of non-adjacent urban regimes in understanding spatial growth dynamics, particularly in the context of the Randstad region and medium-sized cities. These findings demonstrate the significance of broader spatial effects on economic growth, extending beyond local growth models (Van Oort, 2007, pp. 27–28)Similarly, Brunow and Hirte (2009) offered a novel perspective by examining the impact of the age structure of human capital on regional productivity. The paper revealed a U-shaped distribution of productivity based on age, with the 30–39 age group exhibiting lower productivity compared to other age groups. Addressing productivity differences between Germany’s eastern and western states, the paper underscores the necessity of considering workforce composition and regional disparities in policy design (Brunow and Hirte, 2009).

In this context, it is evident that the effectiveness of regional development policies varies according to the characteristics of the areas targeted. Specifically, R&D investments are influenced by regional dynamics such as technological capacity, human capital, and innovation infrastructure. Celli, Cerqua, and Pellegrini (2021) found that while the European Union's Regional Policy generally contributes positively to economic growth, R&D investments in the least developed regions fail to deliver the anticipated additional benefits. Their paper underscores the importance of tailoring policies to regional needs and highlights the positive impacts of initiatives such as the Smart Specialization Strategy (S3) on local development.

Finally, the paper by Strelkov, Hirzalla, and Samokhvalov (2024) reveals that the success of R&D investments is closely linked to the infrastructure and connectivity of countries. High levels of public investment, foreign direct investment (FDI), and European Union funding, combined with strong academia-industry linkages in the Czech Republic and Hungary, have enhanced R&D success in these countries. In contrast, the lack of these elements in countries like Bulgaria and Poland has limited their R&D activities (Strelkov, Hirzalla and Samokhvalov, 2024, p. 11). These studies in the literature demonstrate that the impact of R&D investments on economic growth is shaped not only by local factors but also by spatial and regional dynamics. Therefore, to formulate effective policies, it is essential to conduct detailed analyses of regional disparities and local needs.

3. DATA AND METHODOLOGY

In this paper, which investigates the spatial effects of R&D expenditures on gross domestic product (GDP) at the regional level across Germany's federal regions, the data spans the years 2013 to 2022. The year 2022 stands out as the most recent year available in the dataset for this time frame, adding a degree of relevance for analyzing current economic policies. Due to the panel nature of the data, encompassing both temporal and cross-sectional dimensions, panel data analysis will be conducted. The analysis will be performed using STATA 14.2. The dependent variable in the paper is GDP at the NUTS 1 level, while the independent variable is R&D expenditures.

Table 3. Dataset Variables

Variable	Unit	Value	Source
Gross Domestic Product (GDP)	loggdp	Nominal	EUROSTAT
Research and Development Expenditures	logrd	Nominal	BUNDESAMT

The variables are defined under the assumption that R&D expenditures will increase regional income as a result of innovation production. Similar studies have been presented in the literature. Additionally, to ensure the linear nature of the variables and to determine the extent to which changes in R&D expenditures explain the elasticity coefficient of GDP at the NUTS1 level in Germany, the nominal values of the data have been logarithmized.

As mentioned in the paper, due to the cross-sectional and time-series nature of the data, as well as the search for spatial dependence, a spatial panel data analysis will be conducted. The use of spatial panel data models and the selection of an appropriate model to analyze the impact of R&D expenditures on GDP under the presence of spatial dependence represents an innovative methodological approach. Furthermore, modeling spatial dependence for Germany's NUTS1 regions in this manner can contribute significantly to spatial economic analyses.

The first step in econometric research is the collection of data to be used in the model. This data can be cross-sectional, time-series, or panel data (Güriş and Çağlayan, 2018). Panel data models are employed when data exhibit both cross-sectional and time-series characteristics. By incorporating a spatial weight matrix into the model, spatial panel data models are developed (Oguzturk and Koç, 2023).

In spatial panel data analysis, the general linear regression model that includes spatial dependencies is shown in Equation 1. In this function, y_t represents the dependent variable, $\rho W y_t$ denotes the spatial lag of the dependent variable, $X_t\beta$ represents explanatory variables, and $WX_t\Theta$ accounts for spatial cross-effects. In Equation 2, $\lambda W\mu_t$ represents the spatial dependence in the error term. To determine whether fixed or random effects are appropriate, the LR and Hausman tests are employed (Elhorst, 2017).

$$y_t = \rho W y_t + X_t\beta + WX_t\Theta + \mu \ + a_t \imath_N + \mu_t \tag{1}$$

$$\mu_t = \lambda W \mu_t + \varepsilon_t \tag{2}$$

The determination of whether the paper employs fixed or random effects depends on the values taken by the lag and error terms in Equations 1 and 2. In the general spatial panel data model, if the ρ and ϴ parameters are not significant, the error model is selected. Conversely, if the λ and ϴ parameters are not significant, the lag model is chosen (Yerdelen Tatoğlu, 2020). The models resulting from the tests are presented in Table 4 (Oguzturk & Koç, 2023).

Tablo 4. Spatial Panel Data Models

Spatial Panel Durbin Model (SDM)	Formula	Criterion
General Spatial Panel Model (SAC)	$y_t = a_t \imath_N + \rho W y_t + X_t\beta + WX_t\Theta + \varepsilon_t$	$\lambda = 0$
Spatial Panel Lag Model (SAR)	$y_t = a_t \imath_N + \rho W y_t + X_t\beta + \mu_t$, $\mu_t = \lambda W \mu_t + \varepsilon_t$	$\Theta = 0$
Spatial Panel Error Model (SEM)	$y_t = a_t \imath_N + \rho W y_t + X_t\beta + \varepsilon_t$	$\lambda = \Theta = 0$
Spatial Panel Durbin Error Model (SDEM)	$y_t = a_t \imath_N + X_t\beta + \mu_t$, $\mu_t = \lambda W \mu_t + \varepsilon_t$	$\rho = \ \Theta = 0$
Spatial Panel Durbin Model (SDM)	$y_t = a_t \imath_N + X_t\beta + \mu_t$, $\mu_t = \lambda W \mu_t + \varepsilon_t$	$\rho = 0$

Spatial panel data models are categorized into fixed and random effects. The fixed effects model varies only at the intercept level and includes spatial error and spatial lag models. In random effects models, error terms exhibit spatial dependence, and unobserved effects are incorporated into the model. The selection of an appropriate model depends on the presence of unit effects and the correlation between variables. If unit effects are present, fixed or random effects models are used; otherwise, classical spatial models are preferred (Yerdelen Tatoğlu, 2020).

Accordingly, the analysis will begin by calculating the LM tests and probability values for spatial models. Here, the presence of unit effects will be assessed. If the probability values of the LM tests are significant at the 1% significance level, the null hypothesis of no cross-sectional dependence, which questions the existence of unit effects, will be rejected, and the presence of unit effects will be accepted. The tests to be used are shown in the table below.

Table 5. Tests for Determining Unit (Spatial) Effects

Test Name	Symbol	Hypothesis (H_0)	Description
Breusch-Pagan LM Test	lmec1	H_0: No cross-sectional dependence	Conducts a basic cross-sectional dependence test
Breusch-Pagan Adjusted LM Test (ALM)	lmec2	H_0: No cross-sectional dependence	Used for small sample adjustments
Sosa-Escudero and Yoon LM Test	lmec3	H_0: No cross-sectional dependence	Applied for more flexible hypotheses
Sosa-Escudero and Yoon Adjusted LM Test (ALM)	lmec4	H_0: No cross-sectional dependence	Adjusted for small sample sizes

The Breusch-Pagan LM Test is a Lagrange Multiplier (LM) test used to assess cross-sectional dependence in a panel data model, specifically testing cross-sectional dependence for unit effects (Breusch and Pagan, 1980). This test evaluates whether spatial dependence exists in the error terms of a fixed effects model and is considered an LM test for spatial error dependence. If spatial dependence is detected, it implies that standard estimators may not be efficient (Anselin, 1988).

The Breusch-Pagan Adjusted LM Test (ALM) is an alternative version of the Breusch-Pagan LM Test, designed to test cross-sectional dependence for unit effects. Compared to the standard LM test, it is adapted for smaller samples and performs better in situations with large N and small T. It is used in fixed unit effects models but incorporates adjustments to yield more consistent results (Pesaran, 2004).

The Sosa-Escudero and Yoon LM Test introduces a different Lagrange Multiplier approach for detecting cross-sectional dependence. This test is better suited for cases where certain specific assumptions are relaxed and can be applied in both random and fixed unit effects models (Sosa-Escudero & Bera, 2008, p. 77).

The Sosa-Escudero and Yoon Adjusted LM Test (ALM) is a variation or adjustment of the LMEC3 test. It aims to identify cross-sectional dependence more accurately. This test is particularly useful for small samples or under model specification adjustments. As an enhanced version of the LM test, it performs better under local misspecification and yields more robust results even when errors are not normally distributed. Unit effects, used to model individual heterogeneity, are analyzed through cross-sectional dependence tests. These tests assess unit effects under the assumption of independence or with adjustments. The Breusch-Pagan and Sosa-Escudero and Yoon tests allow for a combined evaluation of both phenomena.

If the null hypothesis of no unit effects is rejected, the nature of the effect—whether fixed or random—will be tested through the Hausman Test using the SDM and SAR models. If the null hypothesis in the Hausman Test is rejected at the 1% significance level, fixed effects estimators are considered consistent. If accepted, random effects estimators are deemed consistent. If one of these tests is significant while the other is not, cross-sectional independence tests will be conducted to assess the presence of autocorrelation and to perform correlation tests.

In subsequent tests, spatial dependence will be sought, determined using Moran's I and its extended variants. Additionally, LM tests will be used to evaluate error and lag models. Comparisons across classical, fixed effects, and random effects models will be summarized in a table. Based on the results of these tests, the most appropriate model will be identified for the analysis. The selected model will then be transformed into an exponential function for interpretation.

4. ANALYSIS

To determine the appropriate model for the paper's analysis, as previously mentioned, the estimator for unit effects was first tested. The test results are presented in the table below.

Table 6. Tests for Identifying Unit Effects

	sdm	**sac**	**Sem**	**sar**
lmec1	661.2113	660.8904	660.8904	660.8904
lmec1p	7.4e-146	9.6e-146	9.6e-146	9.6e-146
lmec2	487.3091	486.8269	486.8269	486.8269
lmec2p	5.5e-108	7.0e-108	7.0e-108	7.0e-108
lmec3	25.71792	25.70779	25.70779	25.70779
lmec4	3.95e-07	3.97e-07	3.97e-07	3.97e-07
lmec4p	22.07508	22.06415	22.06415	22.06415
	2.62e-06	2.64e-06	2.64e-06	2.64e-06

The Breusch-Pagan LM, Breusch-Pagan ALM, Sosa-Escudero Yoon LM, and Sosa-Escudero Yoon ALM tests, along with their probability values, were used to examine unit effects within the

SDM and SAC models. As a result, at the 1% significance level, the null hypothesis of no unit effects was rejected, indicating that unit effects are significant. Consequently, the Hausman test was employed to determine whether the effect is fixed or random in the spatial panel data model. The results are presented below.

Table 7. Hausman Test

	Sdmre	sarre
lmhsfe	-27.38254	-3.967395
lmhsfep	1.13e-06	.1375597

As a result of the Hausman test, the test statistic for the sdmre test was found to be significant at the 1% significance level, whereas the sarre test was not found to be significant. Consequently, the alternative hypothesis indicating a systematic difference between fixed and random effects is accepted based on the sdmre results. To confirm that the paper's model aligns with fixed effects, a correlation test was conducted. The correlation test results, including the Pesaran test and the Breusch-Pagan LM test for cross-sectional dependence, were significant at the 1% significance level. This indicates the presence of autocorrelation among the units, leading to the acceptance of the alternative hypothesis. In other words, the gross domestic product (GDP) model for regions exhibits correlation among residuals. Additionally, a high correlation was observed between regions. Given the presence of spatial autocorrelation, additional tests were applied to determine the extent and nature of spatial autocorrelation. These tests are summarized in Table 8.

Table 8. Tests for Selecting the Spatial Model

Test	**Classical (Pooled) Spatial Panel Data Model**	**Random Effects Spatial Panel Data Model**	**Fixed Effects Spatial Panel Data Model**
GLOBAL Moran MI	0.3173 (0.0000)	0.5422 (0.0000)	-0.1867 (0.0015)
GLOBAL Geargy GC	0.6284 (0.0000)	0.3263 (0.0000)	0.7438 (0.0294)
GLOBAL Getis-Ords GO	-0.3173 (0.0000)	-1.9656 (0.0000)	0.6768 (0.0015)
Moran MI Error Test	5.0753 (0.0000)	2.7457 (0.0016)	-0.7395 (0.4596)
LM Error (Burridge)	23.8391 (0.0000)	67.1627 (0.0000)	7.9633 (0.0048)
LM Error (Robust)	20.0804 (0.0000)	67.1606 (0.0000)	7.9634 (0.0048)
LM Lag (Anselin)	3.7593 (0.0525)	0.0028 (0.9581)	0.0000 (0.9978)
LM Lag (Robust)	0.0006 (0.9808)	0.0006 (0.9797)	0.0000 (0.9950)
LM SAC	23.8396 (0.0000)	67.1633 (0.0000)	7.9634 (0.0187)
LM SAC	1,5958 (0,4503)	10,8672 (0,0044)	17,4954 (0,0002)

In Table 8, test statistics for three potential models for spatial panel data analysis were calculated. Although the statistical values were significant at the 1% significance level, the Classical Spatial Error Panel Data Model was not accepted as the paper's model due to the prior acceptance of the alternative hypothesis indicating the presence of unit effects. Following the acceptance of unit effects, the Hausman test results revealed that the sdmre test was significant at the 1% level, leading to the acceptance of the fixed effects estimator. Conversely, the sarre test was not significant at the 1%, 5%, or 10% levels, suggesting that the random effects estimator should be considered.

Subsequently, cross-sectional independence tests, which examine the presence of spatial correlation, were conducted to determine whether fixed or random effects should be accepted. These tests were significant at the 1% level. The autocorrelation tests performed for both fixed and random effects models indicated that all statistical values were significant at the 1% level for the random effects model, making it the more acceptable option. Notably, the Moran I Error Test for the Fixed Effects Spatial Panel Data Model was not significant. The lack of significance in the Moran I Error Test suggests that the error terms are spatially independent. Furthermore, while the LM Error Test and the Robust LM Error Test were significant at the 1% level, the LM Lag Test and the Robust LM Lag Test were not significant at any level, leading to the acceptance of the Random Effects Spatial Error Panel Data Model as the final model for the paper.

Table 9 presents the accepted model, the Random Effects Spatial Error Panel Data Model, along with the results of other potential models, including the pooled and fixed effects models, for comparison purposes. Although the statistical values for the Classical Spatial Error Panel Data Model were significant, they hold no practical relevance due to the presence of unit effects. This model is included in the table only for comparative purposes.

Given the presence of unit effects, the determinant value of the fixed and random effects models—i.e., the proportion of the model explained—is moderately high at 65%. For the Fixed Effects Model, it was determined that a one-unit increase in R&D expenditures resulted in a 6.6% increase in GDP. In the model selection tests, the Random Effects Model, which had a significant Moran I Error Test at the 1% level, showed that a one-unit increase in R&D expenditures led to a 7% increase in GDP. This finding underscores the robustness of the Random Effects Spatial Error Panel Data Model in explaining the spatial dynamics of R&D expenditures on GDP.

Table 9. Analysis Report

		Test statistic	p-value
Classical Spatial Error Panel Data Model	Model	$\text{loggdp}= 5.268772 + 0.9999204 \text{ logrd} + (I-0.4330972\times W)^{-1}\,\epsilon$	
	logrd	0.9999204	0.0000
	cons	5.268772	0.0000
	λ (Lamda)	0.4330972	0.0000
	$R^2 = 0.7157$		
Random Effects Spatial Error Panel Data Model	Model	$\text{loggdp}= 10.70381 + 0.070381 \text{ logrd} + (I-0.9263792\times W)^{-1}\,\epsilon$	
	logrd	0.070381	0.0000
	cons	10.70381	0.0000
	λ (Lamda)	0.9263791	0.0000
	R^2:0.6510 (within)		
Effects Spatial Error Panel Data Model	Model	$\text{loggdp}=0.0662038 \text{ logrd} + (I-0.9267563\times W)^{-1}\,\epsilon$	
	logrd	0.06662038	0.0000
	λ (Lamda)	0.9267563	0.0000
	R^2:0.6510 (within)		

The Random Effects Spatial Error Panel Data Model is presented in the following table as:

$$\text{loggdp} = 10.70381 + 0.070381\text{logrd} + (I - 0.9263791 \times W)^{-1}\,\epsilon \tag{3}$$

If the inverse of the loggdp variable is taken, the following equation is obtained:

$$\text{gdp} = e^{10.70381 + 0.070381\text{logrd} + (I-0.9263791\times W)^{-1}\,\epsilon} \tag{4}$$

By applying the exponential property of logarithms, the equation becomes:

$$e^{0.070381\log(rd)} = rd^{0.070381} \tag{5}$$

Substituting this into the expanded equation, the following expression is obtained:

$$\text{gdp} = e^{10.70381}\; rd^{0.070381}\; e^{(I-0.9263792\times W)^{-1}}\epsilon \tag{6}$$

Since $e^{10.70381}$ is a constant, it can be replaced with A, yielding the final model:

$$\text{gdp} = A\; rd^{0.070381}\; e^{(I-0.9263792\times W)^{-1}}\epsilon \tag{7}$$

As seen in the final equation, a one-unit increase in the rd variable impacts the dependent variable gdp by 7%.

5. CONCLUSION

This paper analyzed the impact of R&D expenditures on regional economic performance in Germany's NUTS 1-level regions and examined how these effects are shaped by spatial dependence. The findings reveal that R&D expenditures have a positive and significant impact on regional GDP levels. According to the Random Effects Spatial Error Panel Data Model, a one-unit increase in R&D expenditures leads to an approximately 7% increase in regional GDP levels. This result highlights the critical role of R&D investments in achieving regional economic growth objectives.

Spatial dependence tests demonstrated that R&D expenditures in one region not only affect that region's economic performance but also significantly influence neighboring regions. The results of the Moran I test and LM error tests support the presence of strong spatial dependence and its implications for economic growth. Consequently, the Random Effects Spatial Error Panel Data Model was determined to be the most appropriate model for this analysis. While the Moran I Error Test indicated that the error terms are spatially independent, the presence of autocorrelation between regions was observed. The findings suggest that the random effects model provides a more explanatory analytical framework that accounts for unit effects.

The results of this paper are consistent with the literature, emphasizing the positive and significant effects of R&D expenditures on regional economic performance. For instance, Funke and Niebuhr (2005) highlighted the role of spatial knowledge spillovers and geographical proximity in enhancing the impact of R&D investments on regional productivity in Germany. Similarly, this paper demonstrates that R&D expenditures not only strengthen economic growth dynamics in the regions where they are made but also extend these effects to neighboring regions. Moreover, while Brunow and Hirte (2009) examined the influence of human capital age structures and regional disparities on productivity, this paper identified the indirect effects of R&D expenditures within the context of spatial dependence.

Furthermore, this paper aligns with the findings of Celli, Cerqua, and Pellegrini (2021), who emphasized the need for regional development policies to be tailored to local dynamics. The results underscore the importance of planning R&D investments within a framework of regional cooperation and coordination. In conclusion, the findings support the views in the literature on spatial knowledge spillovers, locally adaptive policies, and regional disparities, clearly demonstrating the critical role of R&D investments in regional development, particularly in the context of Germany.

The paper's findings highlight the pivotal role of increasing R&D expenditures in the formulation of regional development strategies in Germany. These investments, coupled with their indirect effects on neighboring regions, strengthen the dynamics of economic growth within a framework of spatial dependence. The results underscore the importance of planning R&D investments through regional cooperation and coordination, suggesting that policymakers should manage resource allocation more efficiently by considering spatial dependence. This paper contributes to the literature on the analysis of spatial dependence and the impact of R&D expenditures on economic performance, serving as a valuable guide for the design of regional development policies.

REFERENCES

Alecke, B., Mitze, T., and Untiedt, G. (2011) "Regional Growth Effects of Economic Support Programs in Germany", Journal of Regional Science, 51(3), 507–535.

Anselin, L. (1988) “Spatial Econometrics: Methods and Models”, New York: Springer Science and Business Media.

Anselin, L. (2001) "Spatial Econometrics", In B. H. Baltagi (Ed.), A Companion to Theoretical Econometrics, 311–330, Blackwell.

Anselin, L., Le Gallo, J., and Jayet, H. (2008) "Spatial Panel Econometrics", In L. Matyas and P. Sevestre (Eds.), The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice , 3rd ed., 625–662), Berlin: Springer.

Audretsch, D. B., and Feldman, M. P. (1996) "RandD Spillovers and the Geography of Innovation and Production", The American Economic Review, 86(3), 630–640.

Autant-Bernard, C., and LeSage, J. P. (2011) “Quantifying Knowledge Spillovers Using Spatial Econometric Models”, 51(3), s. 471-496.

Bräuninger, M., and Niebuhr, A. (2005) "Convergence, Trade, and Factor Mobility in German Regions", Review of Regional Research, 25(2), 99–118.

Breusch, T., and Pagan, A. (1980) "The Lagrange Multiplier Test and Its Applications to Model Specification in Econometrics", The Review of Economic Studies, 47(1), 239–253.

Bröcker, J. (1989) "Agglomeration and Regional Employment Growth in Secondary and Tertiary Sectors", Regional Studies, 23(5), 433–449.

Bröcker, J., Peschel, K., and Reimers, H. (1983) "Structural Change and Regional Employment Growth in Northern Europe", Regional Science and Urban Economics, 13(3), 389–408.

Brunow, S., and Hirte, G. (2009) "The age Pattern of Human Capital and Regional Productivity: A Spatial Econometric Paper on German Regions", Papers in Regional Science, 88(4), 799–824.

Celli, V., Cerqua, A., and Pellegrini, G. (2021) "Does R&D Expenditure Boost Economic Growth in Lagging Regions?", Social Indicators Research.

Elhorst, J. P. (2017) "Spatial Panel Data Analysis", In S. Shekhar, H. Xiong, and X. Zhou (Eds.), Encyclopedia of GIS (2nd ed., pp. 2050–2058). Cham, Switzerland: Springer International Publishing.

Eurostat. (2025) "Total intramural R&D Expenditure (GERD) by Sectors Of Performance". Access Data: 15.01.2025, https://ec.europa.eu/eurostat/databrowser/view/tipsst10/default/table?lang=en.

Fritsch, M., and Wyrwich, M. (2021) "Regional Entrepreneurial Culture and Economic Development in Germany", Small Business Economics, 56(4), 1735-1751.

Fuchs-Schündeln, N., and Izem, R. (2012) "Explaining the regional Differences in Economic Transition: The Case of Post-Unification Germany", American Economic Review, 102(5), 1671–1701.

Funke, M., and Niebuhr, A. (2005a) "Regional Economic Growth: Convergence Clubs in Germany", Applied Economics, 37(6), 665–675.

Funke, M., and Niebuhr, A. (2005b) "Knowledge Spillovers and Regional Growth: Evidence from Germany", Regional Studies, 39(1), 143–153.

Funke, M., and Strulik, H. (1999) "Regional Growth and Panel Regression in West Germany", Journal of Economic Dynamics and Control, 23(7), 1197–1214.

Gülmez, A., and Yardımcıoğlu, F. (2012) "OECD Ülkelerinde Ar-Ge Harcaması ve Ekonomik Büyüme İlişkisi: Panel Eşbütünleşme ve Panel Nedensellik Analizi (1990-2010)", Maliye Dergisi, 163(Temmuz-Aralık), 335–353.

Güriş, S., and Çağlayan, T. (2018) "Mekansal Yapı İktisadi Büyümeyi Etkiler Mi: OECD Ülkeleri Örneği", Finansal Araştırmalar Dergisi, 10(19), 277–290.

Herz, B., and Röger, W. (1995) "Convergence in Regional GDP Per Capita in Germany", Jahrbuch für Regionalwissenschaft, 15(1), 9–28.

Jeleskovic, V., and Loeber, S. (2023) "How Industrial Clusters Influence the Growth of the Regional GDP: A Spatial-Approach", Papers.

Kau, J. B. (1970) "Agricultural Employment and Regional Growth in West Germany", Regional Studies, 4(2), 147–155.

Kaya, D. G. (2019) "AR-GE Harcamalarının Gelişimi: TR-AB Üzerine Bir Değerlendirme", Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi, 33(3), 791–812.

Kogler, D. F., Essletzbichler, J., and Rigby, D. L. (2017) "Knowledge Bases, Related Variety, and Regional Growth in Germany", Economic Geography, 93(3), 256–285.

Koll, W. (1977) "Wirtschaftswachstum und Industrieentwicklung in Bayern", Zeitschrift für Wirtschaftsgeographie, 21(4), 290–305.

Kosfeld, R., Eckey, H.-F., and Dreger, C. (2006) "Regional Income Convergence in Germany, 1992-2000", Empirical Economics, 31(1), 45–62.

LeSage, J. P. (1999) “The Theory and Practice of Spatial Econometrics”, Toledo, Ohio, United States: University of Toledo. Access data: 01.01.2025, https://www.spatial-econometrics.com/html/sbook.pdf.

LeSage, J. P., and Fisher, M. M. (2008) "Spatial Growth Regressions: Model Specification, Estimation and Interpretation", Spatial Economic Analysis, 3(3), 275–304.

Naimoğlu, M. (2021) "Enerji Alanında Yapılan AR-GE Harcamalarının Enerji Tüketimi Üzerine Etkisi: Almanya Örneği", Bingöl Üniversitesi Sosyal Bilimler Enstitüsü Dergisi(22), 97–118.

Niebuhr, A. (2001) "Convergence and Spatial Dependence in German Regions", Regional Studies, 35(6), 445–456.

Niebuhr, A. (2006) "Spatial Effects of European Integration: Do Border Regions Benefit Average?", Review of Regional Research, 26(2), 123–151.

Oguzturk, B. S., and Koç, R. (2023) "Türkiye’nin 100. Yılında Sosyal Sermaye ve İnovasyonun Bölgesel Açıdan Durumu Üzerine Mekânsal Ekonometrik Bir Analiz", Süleyman Demirel Üniversitesi Vizyoner Dergisi, 14(100. Yıl Özel Sayısı), 1–25.

Paelinck, J. H. (2012) “Spacial Econometrics: A Personal Overview”, University of Economics in Katowice. Access data: 01.01.2025, https://www.ue.katowice.pl/fileadmin/_migrated/content_uploads/9_J.H.P.Paelinck_Spatial_econometrics....pdf.

Paelinck, J. H., and Klaasen, L. H. (1979) “Spatial Econometrics (Studies in Spatial Analysis)”, Farnborough: Saxon House.

Pesaran, M. H. (2004) "General Diagnostic Tests for Cross Section Dependence in Panels", IZA Discussion Paper No. 1240. Access data: 01.01.2025, https://docs.iza.org/dp1240.pdf

Reimers, H. (1981) "Employment Growth in Northern Europe: A Regional Analysis", Scandinavian Journal of Economics, 83(2), 246–261.

Schalk, H. J., and Untiedt, G. (1996) "Technological Efficiency and Regional Growth in West Germany", Applied Economics Letters, 3(10), 677–681.

Schröder, H. (1968) "Die Bedeutung der Beschäftigung für das Regionale Wachstum in Westdeutschland", Papers in Regional Science, 20(3), 203–218.

Seitz, H. (1995) "Regional Economic Growth and Sectoral Contributions in Germany", Economic Modelling, 12(3), 312–324.

Sosa-Escudero, W., and Bera, A. K. (2008) "Tests for Unbalanced Error-Components Models Under Local Misspecification", The Stata Journal, 8(1), 68–78.

Südekum, J. (2008) "Convergence or Divergence? Regional Response to Market Integration in the EU", Regional Science and Urban Economics, 38(4), 359–374.

Van Oort, F. G. (2007) "Spatial and Sectoral Composition Effects of Agglomeration Economies in the Netherlands", Papers in Regional Science, 86(1), 5–30.

Werner, A. (2016) "Empirische Analyse der Determinanten regionalen Wachstums in Deutschland". İçinde Wachstumsdeterminanten in Deutschland. Springer Gabler, Wiesbaden.

Yaman, H., Çetin, D., and Dulupçu, M. A. (2020) "OECD Ülkelerinde Ar-Ge Harcamaları ve İleri Teknoloji İhracatı: Bir Panel Veri Analizi", Anadolu Üniversitesi Sosyal Bilimler Dergisi, 20(3), 192–208.

Yerdelen Tatoğlu, F. (2020) "İleri Panel Veri Analizi Stata Uygulamaları (4 b.)", İstanbul: Beta.

KATKI ORANI / *CONTRIBUTION RATE*	**AÇIKLAMA / *EXPLANATION***	**KATKIDA BULUNANLAR / *CONTRIBUTORS***
Fikir veya Kavram / *Idea or Notion*	Araştırma hipotezini veya fikrini oluşturmak / *Form the research hypothesis or idea*	Asst. Prof. İsmail KOÇ (Ph.D.) Recep KOÇ (Ph.D.)
Tasarım / *Design*	Yöntemi, ölçeği ve deseni tasarlamak / *Designing method, scale and pattern*	Asst. Prof. İsmail KOÇ (Ph.D.) Recep KOÇ (Ph.D.)
Veri Toplama ve İşleme / *Data Collecting and Processing*	Verileri toplamak, düzenlenmek ve raporlamak / *Collecting, organizing and reporting data*	Asst. Prof. İsmail KOÇ (Ph.D.) Recep KOÇ (Ph.D.)
Tartışma ve Yorum / *Discussion and Interpretation*	Bulguların değerlendirilmesinde ve sonuçlandırılmasında sorumluluk almak / *Taking responsibility in evaluating and finalizing the findings*	Asst. Prof. İsmail KOÇ (Ph.D.) Recep KOÇ (Ph.D.)
Literatür Taraması / *Literature Review*	Çalışma için gerekli literatürü taramak / *Review the literature required for the study*	Asst. Prof. İsmail KOÇ (Ph.D.) Recep KOÇ (Ph.D.)

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